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## Climate change and occupational health: Are there limits to our ability to adapt?

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# Climate Change and Occupational Health: Are There Limits to Our Ability to Adapt?

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## **Climate Change and Occupational Health: Are There Limits to Our Ability to Adapt?**

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### **ABSTRACT**

This study considers the relationship between temperature and occupational health. The results indicate that both high and low temperatures increase injury rates and that high temperatures have more severe adverse effects in warmer climates, which suggests that avoiding the adverse effects of high temperatures may be easier for workers when hot days are rarer. While research on the effect of temperature on mortality finds substantial capacity for adaptation with current technology, the results presented here suggest that outdoor workers face challenges in adapting to high temperatures.

**JEL Classification Codes:** I1, J2, Q5

**Key Words:** adaptation, climate change, labor force participation, occupational health, temperature

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# 1 Introduction

The greenhouse gasses accumulating in the earth’s atmosphere are poised to raise global temperatures considerably in a relatively short period of time. While air conditioning and outdoor avoidance are promising strategies for mitigating the adverse effects of high temperatures in many contexts, these approaches are not feasible in all situations. In particular, the hundreds of millions of workers around the world exposed to outdoor temperatures as part of their jobs may face additional adaptation challenges relative to the rest of the population. The health of workers matters because health and productivity are linked and because occupational injuries and illnesses have an estimated annual cost of nearly \$300 billion in the United States (Leigh 2011) and approximately \$3 trillion globally (Takala et al. 2014). Knowing if high temperatures affect occupational health and understanding how workers respond to high temperatures have important implications for preparing for climate change, for assessing the social costs of greenhouse gas emissions, and for developing a deeper understanding of the health effects of temperature more broadly. But despite considerable attention being devoted to understanding the impact of temperature on a variety of outcomes and behaviors, little is currently known about the effect of temperature on workers’ health.<sup>1</sup>

An important finding from much of the economics research on the effect of temperature on health is that while both high and low temperatures have adverse health effects, people have demonstrated a substantial capacity to adapt to their climates. One piece of evidence that adaptation has occurred is that hot days have less severe effects in warmer climates than in cooler climates, largely because the higher frequency of hot days in warmer climates has led to greater investments in air cooling technology in these places (Barreca et al. 2016; Heutel, Miller, and Molitor 2017). Given that air conditioning technology appears to be the main adaptive mechanism, though, workers’ capacity for adapting to a higher distribution of temperatures remains unclear.

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<sup>1</sup>Discussions of the lack of research on the potential effects of climate change on occupational health are common. For example, on the National Institute for Occupational Safety and Health’s science blog, Kiefer et al. (2014) state, “There has been considerable research and planning with regard to the public health and environmental aspects of climate change, but little on its effects on workers.”

Data limitations present a major challenge for studying the impact of temperature on occupational health. Linking temperature to occupational health requires data on workers' health outcomes that can be matched closely to the weather that workers experienced on a particular day, but most publicly available data with occupational health information (e.g. the National Health Interview Survey; the Survey of Occupational Injuries and Illnesses) only contain state or region identifiers and the year of illnesses and injuries.

To assess the effects of temperature on occupational health, I construct two data sets with daily occupational health outcomes matched to daily weather information. The first data set draws on workers' compensation (WC) administrative data from Texas and consists of daily Metropolitan Statistical Area (MSA) claim rates for each of Texas's 66 self-contained MSAs matched to weather data from the National Climatic Data Center.<sup>2</sup> An advantage of using data from Texas is that climate change will result in many places in the United States moving towards rather than away from the Texas climate, which means the results provide insights into the effect of temperature on workers in a climate that more places will resemble in the future. However, focusing only on a place with a climate that is warmer than most of the rest of the United States would limit the study's ability to provide insights into the degree to which adaptation or avoidance behaviors can mitigate the adverse effects of temperature. To consider the effects of temperature on occupational health for a wider variety of climates, I draw on data on injuries and illnesses from the mining industry to create a data set with daily injury rates for various outdoor, above-ground mining sites across the United States along with the weather experienced at the site each day.

I use these data sets to estimate models with time and place fixed effects to identify the effect of temperature on occupational health measures through plausibly random short-run variations in temperature. Using the Texas data set, I find evidence that both high and low temperatures are detrimental to workers' health. A day with a high temperature of 86°F to 88°F increases three-day claim rates by 2.1 to 2.8 percent relative to days with temperatures

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<sup>2</sup>I use the term MSA to mean Core Based Statistical Areas, which include both metropolitan and micropolitan statistical areas as identified by the Census Bureau. Micropolitan areas are urban clusters of at least 10,000 and fewer than 50,000 people, while metropolitan areas are urban clusters of at least 50,000 people.

of 59°F to 61°F, while a day with temperatures over 100°F increases three-day claim rates by 3.5 to 3.7 percent. A day with a high temperature under 35°F increases three-day claim rates by 3.4 to 5.8 percent relative to days with temperatures of 59°F to 61°F. With the mining analysis, I test for heterogeneous effects of temperature based on a site's temperature norms. Whereas adaptation and acclimation hypotheses would predict that the adverse effects of a hot day would be smaller in warmer climates, the results from the mining analysis suggest that a hot day has more detrimental effects on occupational health in warmer climates than in cooler climates. With the mining data, I find no evidence that cold temperatures affect injury rates, though as I discuss later, the mining data have limitations in picking up injuries and illnesses that the cold is likely to affect

Overall, these results provide strong evidence that extreme temperatures affect occupational health. While in other aspects of life, people have been able to adapt to high temperatures through air conditioning technology, many workers do not appear to be able to do so. Instead, finding that hot days are more harmful in warmer climates suggests that the potential for workers to engage in avoidance behavior may be more limited in places where extreme temperatures are common. To test for differences in avoidance behavior based on temperature norms, I draw on data on hours worked from the monthly Current Population Survey (CPS). Estimating models with MSA and year-month fixed effects, I find statistically significant differences in the effect of hot and cold days on hours worked based on climate for a sample of temperature-exposed workers. An additional day above 90°F decreases weekly hours worked more in cooler climates than in warmer climates, while an additional day with a high below 40°F decreases weekly hours worked more in warmer climates than in cooler climates.

These results are relevant for assessing the costs of climate change, as they indicate that the health effects of extreme temperatures go beyond the illnesses that often dominate the discussion of the potential health effects of climate change. Furthermore, much research indicates that people can adapt to warm climates, which means that using the estimated effects of high temperatures now to assess damages from future distributions of temperatures likely overstates some of the costs of climate change. But the results from this study highlight that workers

who have to be outside as part of their jobs may face additional challenges in adapting to high temperatures relative to the rest of the population.

## 2 Background

### 2.1 Related Literature

Most relevant to this paper is the research that examines the impact of temperature on labor force participation and economic output, which includes Behrer and Park (2017), Deryugina and Hsiang (2014), and Graff Zivin and Neidell (2014). This research finds that high temperatures lower economic output and lead outdoor workers to reduce their hours worked. Other studies consider how other environmental factors, such as pollution (e.g., Chang et al. 2016; Graff Zivin and Neidell 2012; Hanna and Oliva 2015; Isen, Rossin-Slater, and Walker 2017) and rain (e.g., Connolly 2008), affect workers and show that other environmental factors affect labor force participation and productivity as well.<sup>3</sup> This study contributes to this literature by examining the impact of temperature on workers' health and by assessing workers' ability to adapt to their environments with currently available technology.

Also relevant to this study is the epidemiology literature that has considered the impact of temperature on occupational health. The vast majority of these studies focus only on illnesses related to high temperatures and find that higher temperatures are associated with more heat-related illnesses (e.g., Adam-Poupart et al. 2014; Argaud et al. 2007; Hajat, O'Connor, and Kosatsky 2010; Luber and McGeehin 2008; Nelson et al. 2011; Xiang et al. 2014a). The few studies that consider the impact of temperature on a broader set of occupational health outcomes use data from a single city or from a small area and identify the impact of temperature using time-series variation in temperature in summer months (e.g., Morabito et al. 2006; Xiang et al. 2014b). These studies yield mixed evidence about the impact of temperature on non-illness

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<sup>3</sup>Refer to Dell, Jones, and Olken (2014), Deschenes (2014), and Heal and Park (2015) for excellent reviews of the economics research on climate. Refer to Graff Zivin and Neidell (2013) for a review of research on the effects of other environmental factors.

health issues.<sup>4</sup> My contributions relative to these studies are to use econometric methods that account for seasonality and other confounding factors, to consider how mitigating responses may lead to different effects of temperature in different climates, and to characterize the effects of a full range of temperatures, including low temperatures.

Another related economics literature examines the relationship between work and health more generally (e.g., Anderson and Marmot 2012; Case and Deaton 2005; Fletcher, Sindelar, and Yamaguchi 2011; Guardado and Ziebarth 2018; Morefield, Ribar, and Ruhm 2012; Schmitz 2016). This paper contributes to this literature by providing evidence on how the environment factors into this relationship. Additionally, as people with lower incomes and less education comprise a disproportionate share of workers exposed to outdoor temperatures, this study also has implications for the literatures that examine the income-health and education-health gradients (e.g., Clark and Royer 2013; Conti, Heckman, and Urzua 2010; Lleras-Muney 2005). Finally, this paper also relates to the economics research on the effects of temperature on health more broadly by focusing on a setting that is not conducive to some of the primary methods for mitigating the effects of high temperatures.<sup>5</sup>

## 2.2 Physiological Effects of Temperature and Mitigating Factors

The physiological health effects of extreme temperatures arise because these temperatures can push the body's core temperature outside of its healthy ranges (Seltenrich 2015). High temperatures can increase heart and respiratory rates, reduce blood pressure, and damage internal organs, which can lead to sunstroke, syncope, cramps, exhaustion, and fatigue, as well as

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<sup>4</sup>For example, Morabito et al. (2006) find that work-related hospital admissions in Tuscany are highest when daytime temperatures are in the high 70s and that daytime temperatures around 90°F are associated with as many hospitalizations as daytime temperatures around 70°F, while Xiang et al. (2014b) find no evidence that consecutive days with temperatures above 95°F lead to more injuries in Adelaide for workers on average. Focusing on a single temperature indicator variable as in Xiang et al. rather than characterizing the full effect of temperature makes interpreting the estimates difficult because the reference days likely have high temperatures as well. These studies' reliance on time series variation is also problematic if there is seasonality in the nature of work and in work-related injuries.

<sup>5</sup>The literature on the health effects of temperature has grown in recent years and includes Barreca (2012), Barreca et al. (2016), Burgess et al. (2014), Deschenes and Greenstone (2011), Deschenes and Moretti (2009), Heutel, Miller, and Molitor (2017), Karlsson and Ziebarth (2017), Mullins and White (2018), and White (2017). Much of this research focuses on the mortality effects of temperature, though some of the more recent studies consider the effects of temperature on non-mortality health outcomes as well.



acute cardiovascular and respiratory failure. As fatigue is often a contributing factor for injuries, high temperatures also have the potential to increase injury rates. Cold temperatures cause veins and arteries to narrow, blood to become more viscous, and the body to lose heat, which depletes energy. The direct adverse effects of cold temperatures include frostbite and hypothermia. As cold weather causes muscles to tighten and restricts blood flow, cold temperatures can lead to muscle strains and sprains as well as other injuries (Scott et al. 2016). At temperatures below 32°F, ice may form, which may increase the prevalence of falls or motor vehicle accidents.

In addition to temperature having direct effects on health, a number of lab experiments show that people’s ability to perform various tasks declines at both high and low temperatures (Hancock, Ross, and Szalma 2007; Hancock and Vasmatazidis 2003; Pilcher, Nadler, and Busch 2002). This performance decline appears to occur for a variety of tasks, including psychomotor, perceptual, and cognitive tasks, and has the potential to lead to increased injury rates.<sup>6</sup>

Despite the physiological effects of temperature extremes, people can mitigate temperature’s potential adverse effects in several ways. Air conditioning has proven to be an especially effective way to adapt to high temperatures. Another way to mitigate temperature’s adverse effects is to avoid being outside during extreme temperatures. Consistent with workers being able to engage in avoidance behavior, Graff Zivin and Neidell (2014) find that workers in outdoor industries reduce their labor supply on hot days.<sup>7</sup>

Mitigation decisions are influenced by the distribution of likely temperatures. For example, as the expected number of hot days rises, the benefits from purchasing an air conditioner rise, which is why people in warmer climates are more likely to have residential air conditioning than people in cooler climates. Differences in the adoption of air conditioning can explain almost all of the differential effects of high temperatures on mortality across time and space (Barreca et al.

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<sup>6</sup>A number of recent studies show that students perform worse on tests on particularly hot days, which is consistent with high temperatures affecting cognitive task completion (Cho 2017; Garg, Jagnani, and Taraz 2017; Goodman et al. 2018; Graff Zivin, Hsiang, and Neidell 2015; Park 2017).

<sup>7</sup>While this section focuses on air conditioning and labor supply responses, there are many potential ways of adapting to extreme temperatures. Appendix A discusses the possibility that MSAs where dangerous temperatures are common have adapted by specializing in work that can be performed in climate-controlled environments and presents evidence that is inconsistent with climate-based specialization of labor having already shaped the distribution of temperature-exposed jobs in the United States.

2016; Heutel, Miller, and Molitor 2017). But the interaction between temperature distributions and mitigation decisions is complex and does not necessarily imply less detrimental effects of high temperatures where high temperatures are common. For example, the temperature threshold at which people will engage in avoidance behavior to mitigate the adverse effects of high temperatures will rise as high temperatures become more common if the marginal cost of avoidance increases with avoidance duration. Construction workers in states like Washington or Wisconsin may be able to avoid working or to avoid doing their most dangerous work on the relatively small number of days each year that temperatures reach 90°F, while construction workers in Texas will likely have higher thresholds for engaging in avoidance behavior.

Whether a 95°F day will have a more detrimental effect on occupational health in a warmer climate or in a cooler climate is unclear for two reasons. First, air conditioning technology, which is the adaptive mechanism that appears to be responsible for hot days having less severe mortality effects in warmer climates, is less effective outside than inside. Thus, for outdoor workers the benefits of pursuing adaptive technologies may be small relative to the costs, even in places where dangerously high temperatures are common. Second, the marginal cost of engaging in avoidance behavior likely increases faster for work than for non-work settings. While people who do not work outside can likely engage in avoidance behavior for long periods of time without repercussions, firms may discourage extended or repeated delays that arise from workers engaging in avoidance behaviors.

It should be noted that temperature affecting occupational health does not necessarily imply the existence of frictions that make the adverse impact of temperature on occupational health sub-optimally high. The theory of compensating wage differentials suggests that firms must pay workers higher wages to take additional risks, meaning that workers are likely paid more for outdoor work in places where dangerous temperatures are common. Moreover, firms with experience-rated WC premiums would be expected to internalize the costs of temperature's effect on occupational health because they pay for the increased WC costs of occupational health incidents from extreme temperatures through higher premiums. However, the many firms that are not fully experience-rated likely do not bear the entire cost of the occupational health

effects of temperature that their workers experience, which likely provides them with incentives to take a sub-optimal number of precautions to protect workers from extreme temperatures.<sup>8</sup>

### 2.3 Temperature-Exposed Workers in the United States

I now characterize temperature-exposed workers in the United States using the 2014 American Community Survey (ACS), which is the Census Bureau’s annual survey that collects demographic, social, economic, and housing information on one percent of the U.S. population. I classify workers’ exposure to temperature in two ways. First, I classify workers in the following industries as being exposed to outdoor temperatures: agriculture, forestry, fishing, and hunting; construction; manufacturing; mining; and transportation. These industries are often listed in government reports as being exposed to outdoor temperatures and vulnerable to climate change (e.g., Jacklitsch et al. 2016), and this classification has been used elsewhere in the research literature (e.g., Graff Zivin and Neidell 2014). Under this classification, 23 percent of the U.S. workforce is employed in an industry with high exposure to outdoor temperatures.

A drawback of characterizing workers’ temperature exposure using industry is that there is considerable heterogeneity in exposure within industry. For example, the construction industry consists of laborers, carpenters, civil engineers, accountants, and secretaries. While laborers and carpenters are likely exposed to outdoor temperatures frequently, accountants and secretaries likely rarely are and civil engineers are likely only occasionally exposed. Classifying workers based on industry means that many workers who are rarely exposed to outdoor temperatures are classified as being exposed to them regularly. To obtain a more granular measure of temperature exposure, I match the ACS data to data from the Occupational Information Network (O\*NET), which is a Bureau of Labor Statistics (BLS) tool that collects and summarizes occupational information from job incumbents, occupational experts, and occupational analysts. Relevant to

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<sup>8</sup>For more information on compensating wage differentials, refer to Guardado and Ziebarth (2018), Kniesner et al. (2012), Powell and Shan (2012), and Viscusi and Aldy (2003). For more information on experience rating in WC and its effects on firms’ and workers’ safety incentives, refer to Campolieti and Hyatt (2006), Hunt and Dillender (2017), and Ruser (1991). For discussions about how insurance and institutions can lead to frictions that prevent people and firms from internalizing the full costs of weather events, refer to Annan and Schlenker (2015) and Kahn (2005).

this study are O\*NET’s variables about how often an occupation is outside and how often an occupation works in a non-climate-controlled building, both of which are measures of exposure to outdoor temperatures.<sup>9</sup>

Panel A of Table 1 shows characteristics of U.S. workers by their occupational temperature exposure. The first column displays characteristics of workers in industries with high exposure to outdoor temperatures, the second column displays characteristics of workers in other industries, the third column displays characteristics of workers in occupations that are exposed to outdoor temperatures more than one day per week, and the fourth column displays characteristics of workers in occupations that are never exposed to outdoor temperatures as part of their jobs. Panel B of Table 1 shows the equivalent information for Texas workers. The main differences in the demographic characteristics of workers with different temperature exposures come from their gender and education. Only 22 percent of workers in high-exposure industries are female and only 19 percent have bachelors’ degrees, while 55 percent of workers in other industries are female and 37 percent have bachelors’ degrees. The differences are even starker when workers’ temperature exposure is characterized using O\*NET data. Just 9 percent of U.S. workers in high-exposure occupations have a bachelor’s degree, and only 9 percent are female. In contrast, 70 percent of U.S. workers who are never exposed to outdoor temperatures are female and 38 percent have a bachelor’s degree.

Texas has similar characteristics to the nation as a whole except for Texas’s high share of Hispanic workers. In Texas, 37 percent of workers are Hispanic, while only 17 percent of workers in the United States as a whole are Hispanic. Among Hispanic people, the shares with high exposure to temperature are similar in both Texas and the rest of the nation. The difference in the Hispanic share between Texas and the rest of the nation has the potential to affect the generalizability of the results that use Texas WC data if temperatures affect Hispanics differently

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<sup>9</sup>Since the ACS classifies occupations using Census occupation codes and the O\*NET classifies occupations using the Standard Occupational Classification (SOC) codes, merging O\*NET data to the ACS requires a crosswalk between Census codes and SOC codes, which I obtain from the BLS. When the Census occupation codes cannot be matched to the level of granularity in O\*NET, I assign the temperature exposure of the least-exposed occupation in the broader set of SOC matches. In Section 4, I follow the same approach with CPS data, which also uses Census occupation codes.

than non-Hispanics. While I am unaware of any research that suggests that biological reactions to temperature vary by race or ethnicity, Hispanics are much more likely to lack documentation and therefore may not file for WC at the same rate conditional on being injured as non-Hispanic workers. Texas having a larger share of undocumented immigrants likely biases the estimates of the level effects downward with the Texas WC analysis but should not have an effect in percentage terms as long as Hispanic workers' participation in WC conditional on being injured is unrelated to temperature.

### **3 The Effect of Temperature on Occupational Health**

#### **3.1 Evidence from Texas Workers' Compensation Medical Claims Data**

##### **Texas Workers' Compensation Insurance and the Medical Claims Data**

To examine the effect of temperature on workers' health, I first use WC administrative data that contain information on all medical bills paid for by WC insurers in Texas. WC insurance is regulated at the state level, and benefits to injured workers are set by the state. While WC insurance pays for medical care immediately after an injury occurs, injured workers become eligible for income replacement benefits after missing 3-7 days of work, depending on the state. In Texas, injured workers become eligible for income replacement benefits after missing at least seven days of work.

The raw data consist of all medical bills paid for by Texas WC from 2006 to 2014. Each bill contains the cost of the bill, the International Classification of Diseases (ICD-9) code for the bill, the zip code where treatment was received, the date treatment was received, the birth month of each claimant, the gender of the claimant, and a unique identifier for each claim. Since the data contain information about the underlying claims as well as all treatment, they allow for distinguishing between claims and bills. Each injury or illness has one claim associated with it, while each claim generally consists of multiple bills. I create an intermediate data set with

claims as the unit of observation and restrict attention to claimants ages 18 to 64. I define the claim's MSA as the MSA of the first place of treatment.

As the data do not contain the date that the injury occurred, I define the claim's start date to be the first day that medical treatment was received. For certain kinds of injuries, the injury date and the date of first treatment likely coincide. For other types of injuries, workers may not receive treatment immediately. As discussed in more detail below, the empirical strategy accounts for the possible mismeasurement of the date that occupational health incidents began by allowing workers multiple days to report injuries.

I use ICD-9 codes from the first day of treatment to create a series of indicator variables that describes the medical issue that underlies each claim. First, I create an indicator equal to one if the provider specifically identifies a condition as being an illness stemming from the heat. To consider the possibility that temperature affects injury rates, I create another indicator variable equal to one if the claim is for an injury. Because research often finds differences in treatment and reporting patterns based on how traumatic and visible injuries are, I create an indicator equal to one if the claim is related to an open wound, a crushing injury, or a fracture and another indicator variable equal to one if the claim is for a strain, sprain, bruise, or other muscle-related issue.<sup>10</sup>

Table 2 contains descriptive statistics for this intermediate data set, which consists of 1,916,590 claims. Males account for 60 percent of all claims in Texas, likely because males tend to work in more dangerous and physical jobs. Injury ICD-9 codes account for the vast majority of claims at 91.3 percent. I next collapse this intermediate data set to the MSA level to produce daily counts of claims. I then combine the counts of claims with monthly MSA employment data from the BLS's Local Area Unemployment Statistics (LAUS) and create daily rates of claims per 100,000 workers for all 66 self-contained MSAs in Texas.

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<sup>10</sup>For examples of research that considers differences based on visibility/trauma of an injury, refer to Bronchetti and McInerney (2017), Campolieti and Hyatt (2006), Card and McCall (1996), Dillender (2015), and Hansen (2016). The corresponding ICD-9 codes are as follows: illnesses from the heat: 992; injuries: 710 to 740 and 800 to 959; open wound, crushing, and fracture injuries: 800 to 829, 870 to 898, and 925 to 929; sprain, strain, bruise, and muscle-related injuries: 710 to 739, 840 to 848, and 920 to 924. Claims can have multiple ICD-9 codes on the first day of treatment, so some claims fall into multiple classifications.

An important feature of the Texas WC system is that purchasing WC insurance is optional. While several states exempt small firms from the requirement to purchase WC insurance, Texas and Oklahoma are the only states that do not require firms to purchase WC insurance regardless of their size. As firms that do not purchase WC insurance can be sued for negligence by injured employees, WC insurance is still widely purchased in Texas despite not being mandatory, and 81 percent of Texas workers work for firms with WC insurance as of 2012 (Texas Department of Insurance 2012). Given that non-subscription is unlikely to be related to transitory temperature fluctuations, the empirical approach will still yield unbiased estimates of the effect of temperature on WC claims in Texas. As the baseline estimates are calculated per 100,000 workers, the estimates in levels are a lower bound of what the effect of temperature would be if everyone in Texas was covered by WC insurance. If temperature has the same effect on workers covered by WC insurance and on those not covered by WC insurance, then the estimates could be proportionately scaled to account for the fact that 19 percent of Texas workers are not covered. But as firms with fewer than ten employees comprise a majority of non-subscribing firms (Texas Department of Insurance 2012) and as small firms tend to have much lower injury rates than larger firms (Bureau of Labor Statistics 2016), it is likely the case that injury rates are lower at non-subscribing firms. To be conservative, I do not scale the estimates to account for non-subscription.

The estimates in percent terms will not be majorly affected by non-subscription if non-subscribing firms account for a disproportionately small share of overall injuries or if the effect of temperature is similar for non-subscribing firms in percent terms. If, however, workers who are more sensitive to temperature select into work at firms without WC insurance or if firms that do not purchase WC insurance take fewer precautions to protect their workers from extreme temperatures, the estimates in percent terms would likely be larger if everyone in the state was covered by WC insurance. As noted above, though, small firms are more likely to opt out of WC insurance and have lower injury rates, which suggests the results may not be dramatically different if all workers in Texas were covered by WC insurance. Still, it is important to remember that while non-subscription does not hinder the ability of this study to produce valid estimates

of the effect of temperature on WC claims in Texas, it does mean that some injuries arising from temperature are likely not reflected in the estimates. Other than not being compulsory, Texas WC is generally similar to other states' WC programs along most dimensions (Morantz 2010).

The weather data come from the National Climatic Data Center Summary of the Day Data. These data contain the daily maximum temperatures, the daily minimum temperatures, and daily precipitation for numerous weather stations throughout the United States. I incorporate all of this information into the analysis but focus on the maximum temperatures since most work is done during the day, meaning that more work is done closer to the day's maximum temperature than to the day's minimum temperature. To calculate an MSA's weather measures, I take an inverse-distance weighted average of all the valid measurements from stations that are located within 124 miles (200 kilometers) of each MSA's centroid.<sup>11</sup> I restrict the sample to include only weekdays since most work is done during the week.<sup>12</sup> The main analysis sample includes 154,968 MSA-days.

Texas's size means that different parts of the state can experience substantially different weather than other parts on any given day. Appendix B contains figures that display the total number of days of 100°F or more and the total number of days with low temperatures below 32°F for selected MSAs and illustrates the variation in temperature across Texas.

## **Estimation and Results**

Graph A of Figure 1 shows means of monthly claim rates per 100,000 workers for all claims and for claims for injuries. For both series, mean rates peak in August. Graph B of Figure 1 shows means of monthly heat-related claim rates per 100,000 workers and shows that these types of claims peak in the summer and do not occur in the winter. Drawing causal inferences from these graphs is difficult because different types of work are done in different seasons. Also,

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<sup>11</sup>This approach follows Deschenes and Greenstone (2011). Results are similar if I simply use information the weather station closest to each MSA's centroid. Also following Deschenes and Greenstone, I only use a station's information for years in which the station has valid measurements for the full year.

<sup>12</sup>This sample restriction is made at the end of the construction of the analysis data set, so the claims and weather for the day after a Friday are Saturday's claims and weather rather than Monday's claims and weather.



some months have more holidays and missed work, which results in lower injury rates in those months for reasons unrelated to temperature.

To obtain estimates of the effect of temperature, I estimate fixed effect models of the following form:

$$y_{jt} = \delta_t + \gamma_{jm} + \alpha * othweather_{jt} + \beta * temperature_{jt} + \epsilon_{jt}, \quad (1)$$

where  $j$  indexes the MSA,  $t$  indexes the calendar date,  $m$  indexes the year and month,  $y$  represents the various dependent variables,  $\delta$  is a vector of calendar date fixed effects,  $\gamma$  is a vector of MSA-year-month fixed effects, *othweather* is a vector that includes controls for the day's precipitation as well as for the precipitation and temperature on the days surrounding the day of observation, and *temperature* represents the day's temperature. For specifications that include days with precipitation, I control for indicator variables for a day's precipitation falling into one of the following bins: greater than or equal to 0.05 inches but less than 0.50 inches, greater than or equal to 0.50 inches but less than 1.00 inch, greater than or equal to 1.00 inch but less than 2.00 inches, and greater than or equal to 2.00 inches.<sup>13</sup>

I specify *temperature* as a vector of indicator variables for the day's high temperature falling into three-degree temperature bins. I include all temperatures below 35°F in one bin and all temperatures over 100°F in another. The indicator variable for 59°F to 61°F is omitted, so all estimates can be interpreted as the effect of a given temperature bin relative to the effect of a day with a high temperature of 59°F to 61°F. I weight the regressions by the number of employed people in the MSA in the month of the observation. I display the *temperature* coefficients in graphs along with 95-percent confidence intervals for each estimate calculated using robust standard errors clustered at the MSA level. Standard errors and point estimates are shown in tables in Appendix C.

The controls in Equation (1) are extensive. The  $\delta$  coefficients account for the fact that baseline injury rates may be different on Tuesdays and Fridays, that baseline injury rates are

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<sup>13</sup>To avoid classifying days with heavy dew or a light drizzle as being rainy, I consider a day to have positive precipitation if it has at least 0.05 inches of precipitation. When the sample is restricted to days without precipitation, the controls for the day's precipitation are excluded.

different in December versus June, and that injury rates may be different in 2011 compared to 2006 for idiosyncratic reasons other than temperatures. The  $\gamma$  coefficients account for the fact that MSAs may have different economic conditions or employment patterns in July of 2011 versus March of 2011 as well as the fact that MSAs may have different baseline claim levels for reasons unrelated to temperature. These controls mean that identification of the effect of temperature comes from different MSAs experiencing different temperatures on the same day.<sup>14</sup>

As explained earlier, the claim's start date is defined as the earliest date medical treatment was received. Since treatment may not be received on the day that an injury occurs, a critical decision for the empirical implementation is how long to allow workers to report and receive treatment for an occupational health incident. Not allowing enough time for workers to receive treatment for their injuries might fail to produce valid estimates of the effect of temperature because health issues from one day's temperature could be attributed to another day's temperature. But allowing too much time for workers to receive treatment will introduce unnecessary noise into the estimation.

To consider how a day's temperature affects claim rates over the next several days, I begin by controlling for the weather during the five days before and the four days after the day of observation and estimating separate regressions of the effect of a day's temperature on health outcomes the day of the temperature as well as up to four days after the day's temperature. Figure 2 shows the various estimates separately for all days and for days without precipitation. The first two graphs in Figure 2 display estimates of the effect of a day's temperature on that day's WC claims. The results suggest that same-day claim rates start rising with temperature once temperatures reach the 70s. A day of 86°F to 88°F increases claim rates by 0.309 to 0.329 per 100,000 workers, or by 5.0 to 5.2 percent, relative to a day with a high temperature of 59°F to 61°F, while a day above 100°F increases claim rates by 0.484 to 0.507, or by 7.6 to 8.2 percent. The results do not provide strong evidence that low temperatures affect same-day

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<sup>14</sup>As temperature is plausibly exogenous in the short run, less extensive controls than those in Equation (1) should produce similar results. Appendix B verifies that the results are robust across a variety of specifications. Appendix B also assesses the validity of Equation (1) by focusing on settings where temperature would be expected to have smaller or no effects on occupational health and verifies that the empirical strategy indeed estimates smaller effects of temperature in these settings.

claim rates.

Graphs C and D display estimates of the effect of a day's temperature on the next day's claim rates. For days with high temperatures in the mid-forties and below, claim rates rise as the daily high falls. Graphs C and D provide no evidence that high temperatures have next-day effects. These results are consistent with cold weather being more likely to affect strains, sprains, and other muscle-related issues (Scott et al. 2016), which are often not treated on the day of the injury. Graphs E and F display estimates of the effect of a day's temperature on claims two days later and indicate that cold temperatures still increase claim rates two days after the day of the original temperature observation. The estimates of the effect of a day's temperature on claim rates three and four days later are displayed in graphs G through J and do not suggest that temperature still affects claims three and four days later, suggesting that all of the effect of a day's temperature appears to have been realized by the third day after the day of the temperature observation.

Since the effect of a day's temperature is realized during that day and the subsequent two days, I focus on three-day claim rates for the remainder of the analysis rather than show the analysis separately for each day after a day's temperature. To account for the serial correlation of weather, I control for the temperature and precipitation two days prior to and two days after the day of the observation, which means that the previous weather that affects today's three-day claim rates is controlled for as is the subsequent two days' weather that is correlated with today's temperature and also affects today's three-day claim rates. The coefficients on the current day's temperature bins isolate the effect of a day's temperature on claiming over the next three days. Given the similarities between the analysis that controls for precipitation and the analysis that excludes days with precipitation in Figure 2, I include days with precipitation for the remainder of the analysis and control for the precipitation indicator variables.

It is important to note that this empirical strategy will not capture the impact of temperature on occupational health issues that take years to develop or on occupational health issues that are not treated until after three days have passed since they occurred. As long as the date of first treatment of past medical issues or of slow-developing medical issues is not related to

a day's high temperature in a way that is not captured by the controls for the previous two days' high temperatures, the main implication of these health issues not being captured by the empirical strategy is that the estimates will be attenuated.

Figure 3 shows coefficients on the temperature indicators for a variety of specifications with three-day claim rates per 100,000 workers as the dependent variable. Graph A displays the baseline temperature coefficients from Equation (1) and confirms that both high and low temperatures have harmful effects on occupational health. A day with a high temperature of 86°F to 88°F raises three-day claim rates by 0.333 per 100,000 workers, or by about 2.1 percent relative to claim rates when temperatures range from 59°F to 61°F. A day with a high temperature above 100°F raises three-day claim rates by 0.553 per 100,000 workers, or by about 3.5 percent relative to when temperatures range from 59°F to 61°F. A day with a high temperature below 35°F increases three-day claim rates by 0.922 claims per 100,000 workers, or by about 5.8 percent.

Graphs B through F consider a variety of alternative specifications. An alternative to computing rates as in the baseline specification is to set the dependent variable to be the log or inverse hyperbolic sine (IHS) of claims. A concern with specifying the dependent variable in rates is that regressions with the rate as the dependent variable may be more sensitive to outliers than a regression that uses a log or IHS transformation as the dependent variable because these alternative transformations tend to downweight outliers. Taking the log or IHS of the dependent variable also allows the coefficients to be interpreted as percent changes in three-day claim rates. The estimates with IHS of three-day claim counts as the dependent variable are shown in graph B of Figure 3 and follow a similar pattern as the estimates that use claim rates as the dependent variable. These estimates indicate that high temperatures of 86°F to 88°F increase three-day claim rates by 2.8 percent, that high temperatures above 100°F increase three-day claim rates by 3.7 percent, and that high temperatures below 35°F increase three-day claim rates by 3.4 percent.

As previously explained, I focus on high temperatures because high temperatures are most likely more relevant to occupational health than low temperatures are since more work is done

during the day. In graphs C through E, I consider the implications of this decision. While the point estimates may fall and the standard errors may become larger with the inclusion of controls for the day's low temperatures because daily high and low temperatures are highly correlated with each other, the coefficients on the high temperatures falling to zero might suggest that the daily low temperatures are more relevant than assumed by the main specification. In graph C, I set the dependent variable to be three-day claim rates and control for the daily low temperature. The point estimates on colder daily highs fall, but the point estimates display a similar pattern. Graphs D and E display coefficients on low temperatures in three-degree temperature bins. The regression for graph E controls for the day's high temperatures, while the regression for graph D does not. When daily high temperatures are not controlled for, the distribution of coefficients follows a similar pattern as the main estimates. When controls are included for high temperatures, the coefficient estimates on the daily low temperature bins fall towards zero and are no longer statistically significant. Overall, these estimates suggest that high temperatures are the relevant temperatures to consider.

Figure 2 showed that the qualitative conclusions are unaltered regardless of whether days with precipitation are included or excluded from the analysis, suggesting that precipitation does not confound the analysis. Apart from precipitation confounding the analysis, though, the interaction between temperature and precipitation may matter. For instance, cold weather may be especially harmful on days with precipitation, since ice may form. In contrast, though, a day with extreme temperatures may not have similar effects when it is raining because people may be less likely to work. As climate change will alter precipitation patterns, interactive effects of temperature and precipitation are relevant for assessing the potential impacts of climate change. To test for differential effects of temperature on days with precipitation, I allow days with precipitation to have separate day, MSA-year-month, and other weather effects in Equation (1) and then supplement Equation (1) with terms for the interaction of each temperature bin with an indicator variable for the day having precipitation. Graph F of Figure 3 displays the estimates on the temperature-precipitation interaction terms, which are estimates of the differential effects of temperature on days with precipitation. The profile of estimates does not

provide strong evidence that temperature has interactive effects with precipitation.

While hot temperatures are common across Texas, humidity levels vary. According to the Köppen classification, which is a climate classification scheme that divides the earth into five basic climates, the eastern side of the state consists of mostly humid subtropical climates, while the western side of the state consists of semi-arid and desert climates. As the names imply, humid subtropical climates are much more humid than desert and semi-arid climates. Based on the Köppen climate regions, I test for differential effects of temperature for MSAs in humid climates by interacting an indicator for an MSA being in a humid climate with the day fixed effects and the weather variables. Graph G displays the coefficients on the interaction of the temperature bins and the indicator for being in a humid climate and provides no evidence of differential effects of temperature based on an MSA's typical humidity.

Temperatures may have different effects depending on previous days' weather. For instance, extreme temperatures may have larger effects if they are a shock than if people have time to acclimate to them. Alternatively, consecutive days of extreme temperatures may intensify their effects or may make avoiding working during the temperature extremes more difficult. In graph H of Figure 3, I test for differential effects of a cold day in the fall or of a hot day in the spring by supplementing Equation (1) with interactions of select temperature bins with indicator variables for spring and fall. As spring and fall are seasons when temperatures are in transition, extreme temperatures are much less common and are more likely to be shocks during these seasons. While the results are imprecisely estimated for lower temperatures, the estimates of the effect of hot days in spring are negative and marginally statistically significant, suggesting that hot days may have less of an effect in spring than in the rest of the year. These results are inconsistent with acclimation being a major mitigating factor of the effect of temperature on occupational health.

Figure 4 considers the types of claims that temperature affects. As explained earlier, high temperatures can have direct physiological effects, which can include heat stroke, sunstroke, heat syncope, heat cramps, heat exhaustion, and heat fatigue. Graph A focuses solely on claims with ICD-9 codes of 992, which is the ICD-9 code for illnesses from the heat. The results show a strong

effect of high temperatures on these kinds of claims. The estimates first become statistically significant once temperatures reach the mid-80s and appear to rise non-linearly as temperatures rise. A day with a high temperature above 100°F increases the rate of heat-related claims by 0.072 per 100,000 workers.

As explained in Section 2, temperatures also have the potential to affect injury rates. Whether or not injuries are affected is important since injuries comprise the majority of work-related medical issues. Graph B considers the effect of temperature on injury claims and reveals a pattern that mirrors the estimates for all claims. While the effects do not increase as dramatically as they do for claims identified by medical providers as being heat-related, the level effects for injuries are much higher.

Graphs C and D consider two broad types of injuries. Graph C focuses on the effect of temperature on claims for open wounds, crushing injuries, and fractures, which are injuries that are visible, traumatic, or require immediate care. Graph D focuses on the effect of temperature on claims for sprains, strains, bruises, and muscle issues, which are typically less visible on the day of the injury and may not be debilitating until they have had time to swell. The results presented in graphs C and D confirm that the main effects of low temperatures appear to be accounted for by increases in swelling injuries, while high temperatures appear to result in larger percent increases in more traumatic injuries.

Even with the large increases in claim rates arising from temperatures at both extremes, if the medical issues caused by temperature extremes are not costly to treat or do not result in the need for further treatment, then climate change may still not have major occupational health implications. Graphs A and B of Figure 5 consider medical treatment 3 to 30 and 31 to 180 days after claims begin. Both sets of results indicate that high and low temperatures lead to medical issues that require subsequent treatment. A day below 35°F increases the rate of claims that require treatment 3 to 30 days later by 6.3 percent and the rate of claims that require treatment 31 to 180 days later by 7.0 percent. The equivalent numbers are 1.7 percent and 2.4 percent for days with highs of 86°F to 88°F and 3.0 and 2.6 percent for days with highs

above 100°F.<sup>15</sup>

Graphs C and D of Figure 5 examine whether the claims that arise from temperature extremes have six-month medical costs that are above or below the median six-month spending, which is \$1,257 in 2014 dollars. The estimates suggest that a majority of the claims resulting from low temperatures have above-median spending, while the claims resulting from high temperatures are more evenly split.<sup>16</sup>

Appendix B considers heterogeneous effects of temperature based on age. The results show similar patterns for younger and older workers, though the estimated effects of cold temperatures appear to be larger for older workers than for younger worker. The effects of high temperatures appear to be similar for younger and older workers.

## 3.2 Evidence from Mining Injury Data

### Mining Safety and Health Administration Data

The preceding analysis indicates that high temperatures have sizable effects on occupational health in a warm climate. To extend the analysis beyond Texas, I now draw on data from the U.S. Department of Labor’s Mining Safety and Health Administration (MSHA), which is tasked with tracking and improving workplace safety for the U.S. mining industry. To construct the analysis data set, I combine information from three MSHA data sets. The first is a site-level data set that has basic information about each site, including its zip code and whether the site is an underground mine, a surface mine, or a facility. The second data set contains quarterly employment information for each site, including the number of workers working in a mill, an open pit quarry, and an office. To restrict attention to workers who are likely experiencing

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<sup>15</sup>A potential concern with the interpretation of the results as presenting evidence that extreme temperatures affect occupational health is that workers may falsely report injuries to avoid working in uncomfortable temperatures. Given that low temperatures do not have same-day effects, that high temperatures affect fractures and open wounds, both of which would be difficult to fake, and that many of these medical issues are still being treated throughout the year, malingering does not seem to be a plausible explanation for the increase in claim rates.

<sup>16</sup>The WC data used for this project cover most of 2015, which allows for follow-up care and six-month costs to be calculated for claims that occur throughout the whole sample period. I did not include 2015 data in most of the analysis because the data for the last few months of 2015 are incomplete and because the diagnosis codes switch from ICD-9 to ICD-10 in the middle of 2015.



temperatures reflective of the temperatures at the weather stations, I focus on non-office workers working at surface mines. In contrast to work in underground mines, work at surface mines is performed outdoors in the open air.

The third data set consists of information on injuries and illnesses that occur at each site. Federal law requires all employers in the mining industry to notify MSHA of all occupational injuries and illnesses that require medical treatment beyond first aid. Site operators must report certain types of injuries immediately and must submit a form for all other injuries within ten business days of the injury. Reporting can be done online and is estimated by MSHA to take half an hour. Site operators who fail to report injuries are subject to fines. These data contain information on the date of the injury, the site where the injury occurred, and the injured worker's occupation. As with the employment data, I focus on injuries and illnesses for non-office workers.

I merge these three data sets with the weather data to create a site-day level data set with daily injury rates per 100,000 workers, the weather of each day, and the weather of the surrounding days.<sup>17</sup> I focus the analysis on sites that operate each year from 2006 to 2014 so that the time period is consistent with the Texas WC analysis. To ease the computational burden of the analysis, I restrict the sample to sites that employ at least 5 workers each year, which leaves 1,114 sites. As with the previous analysis, I focus only on weekdays. From 2006 to 2014, these sites had 13,013 weekday injuries. The resulting data set consists of 2,538,188 site-days.

The Texas data have several advantages over the MSHA data. One is that the Texas WC data represent a much wider set of occupations and industries than the mining data, making the results more generalizable.<sup>18</sup> Another advantage is that the WC data contain information on approximately two million injuries from an underlying population of over 10 million workers,

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<sup>17</sup>For ease of discourse, I use the term *injuries* to refer to injuries and illnesses. I compute the rate per 100,000 workers to make the results comparable to the Texas WC results, though most sites employ fewer than 100 workers at a time. As with all the analysis for this study, I include only information from the continental United States, meaning sites in Alaska, Hawaii, Puerto Rico, and the Virgin Islands are excluded.

<sup>18</sup>While a disadvantage in some ways, the mining data representing a few occupations from a single industry has the advantage of demonstrating the effect of temperature on some of the most temperature-exposed workers.

which facilitates the thorough analysis presented in the previous section. A third advantage is that the WC data capture a fuller set of injuries. Compared to WC data, injury data recorded by employers tend to miss illnesses and injuries that are often not treated on the day of the injury. Instead, employer-recorded data are better at capturing traumatic injuries that are easier to observe and relate to the workplace, such as surface and open wounds and traumatic injuries to bones. Injuries like strains, sprains, and other muscle-related injuries—i.e., cold-weather injuries—as well as most illnesses are underreported in these data (Boden and Ozonoff 2008; Rosenman et al. 2006; Ruser 2008). For this reason, the main analysis focuses on same-day injury rates and the discussion centers on the effects of high temperatures.<sup>19</sup>

Despite the drawbacks of the mining data, they have a major advantage over the WC data in that the mining sample spans 47 states, which allows for testing for heterogeneous effects based on temperature norms. As explained earlier, it is possible that workers in warmer climates may be able to adapt or acclimate to the heat and that the effects of a hot day will be much more severe in other parts of the country. Alternatively, it is also possible that workers in cooler parts of the country may have better options in terms of shifting work to avoid dangerous work on hot days.

Several features of the mining industry are relevant for interpreting the analysis. One is that safety in the mining industry is regulated by the Mining Safety and Health Act while safety in other industries is regulated by the Occupational Safety and Health Act. Despite a different law regulating safety in the mining industry, safety regulations tend to be similar for mining and for other industries, though the mining industry has additional safety regulations that are specific to mining risks (Johnson 1987). One of the most meaningful differences between mining jobs and other jobs is that mining jobs tend to be more physically demanding than other jobs. For example, according to O\*NET data, quarry work is more physically demanding than 89 percent of jobs, while being a millwright is more physically demanding than 97 percent of other occupations. High physical demands have the potential to exacerbate the risks from extreme

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<sup>19</sup>Estimates of the effect of temperature on subsequent days do not provide evidence of delayed effects and are shown in Appendix D.

temperatures, meaning occupational health in the mining industry might be especially sensitive to temperature.

## Estimation and Results

The empirical approach with the mining data can still be represented by Equation (1), except that  $j$  now indexes the site rather than the MSA. The basic models include controls for precipitation, the weather of the previous two days and subsequent two days, site-year-month fixed effects, and day fixed effects. As the goal of this analysis is to provide separate estimates for sites in different climates, I first calculate the mean daily high temperature in June through September for each site and then categorize sites as being in warmer or cooler climates based on their location in this distribution. I consider sites in the top quartile of this distribution to be in warmer climates and sites in the bottom quartile of this distribution to be in cooler climates. The top quartile includes all sites with a mean summer high temperature of 89.9°F or above, while the bottom quartile includes all sites with a mean summer high temperature of 81.3°F or below.

Figure 6 displays the estimates of the effect of temperature on same-day claim rates separately for sites in warmer climates, cooler climates, and the middle 50 percentiles of the summer temperature distribution, both for the sample of all days and for the sample of days with no precipitation. As can be seen in graphs A and B, injury rates begin rising with temperature once temperatures reach the mid-70s or mid-80s at sites in warmer climates. A day with temperatures over 100°F increases injury rates by 6.92 per 100,000 workers, which is a 67.0 percent increase from when the temperature is 59°F to 61°F. Note that the estimated effects of temperature are likely larger with the mining data because the mining analysis focuses exclusively on workers with high exposure to outdoor temperatures and because mining jobs are physically demanding.

Graphs C and D of Figure 6 display the equivalent estimates for sites in the middle of the summer temperature distribution, while graphs E and F show estimates for sites in the bottom quartile of the summer temperature distribution. A similar pattern of estimates is not observed

for sites in cooler climates, regardless of whether or not days with precipitation are included. These results are consistent with the notion that adapting to high temperatures through air conditioning is not an option for outdoor workers and that engaging in avoidance behavior to prevent the adverse effects of high temperatures becomes more difficult for workers as high temperatures become more common.

The final two graphs in Figure 6 display estimates of the differential effects of temperature at sites in warmer climates versus all other sites in a single regression. To obtain these estimates, I allow sites in warm climates to have separate day fixed effects and separate effects for each weather variable. The interactions between the temperature bins and the warm climate indicator are estimates of the differential impact of temperature on sites in warmer climates. The point estimates indicate that the effects of higher temperatures are statistically significantly larger in warmer climates at at least the ten-percent level for three out of the five hottest temperature bins. For days with no precipitation, the estimated effects of high temperatures are statistically significantly larger in warmer climates at the five-percent level for three out of four of the hottest temperature bins.

Unlike with the Texas WC data, the mining data have information on whether injuries resulted in missed work. Figure 7 replicates the analysis in Figure 6 using the rate of time-loss injuries as the dependent variable. The results show that high temperatures affect time-loss injuries in warmer climates, which supports the finding from the Texas WC analysis that many of the injuries that are caused by high temperatures are not trivial. Again, the results provide no evidence that high temperatures have similar effects in cooler climates.

A potential concern with analysis that uses data for the whole United States is that while many regions have experienced warming over the past few decades, others have experienced slight cooling (Burke and Emerick 2016). Failing to account for these trends could lead to biased estimates if these trends are correlated with trends in injury rates. Note that the site-year-month fixed effects in the main specifications account for any region- or site-specific trends because including site-year-month fixed effects means that identification of the temperature coefficients comes from comparing injury rates within a site-year-month combination. To assess

the possibility that regional trends would hinder the analysis without the site-year-month fixed effects and to consider the robustness of the estimates more generally, Appendix D displays estimates from models that replace the site-year-month fixed effects with site fixed effects and from models that replace the site-year-month fixed effects with site fixed effects and with state-year fixed effects. Regardless of the level of fixed effects included, the estimates are generally similar to the original estimates, which suggests that regional trends in warming are not a major concern for the analysis.

## 4 Extensions

### 4.1 Avoidance Behavior: The Effect of Temperature on Hours Worked

The results presented in Section 3.2 indicate that the occupational health effects of high temperatures are larger in warmer climates, which is consistent with adapting to high temperatures through air conditioning being difficult for outdoor workers and with engaging in avoidance behavior to prevent the adverse effects of high temperatures being easier when high temperatures are rare. Avoidance behavior can take many forms. If a worker divides her time between a climate-controlled space and a non-climate-controlled space, one possible avoidance strategy for the worker would be to arrange her work so that she is in the climate-controlled space when outdoor temperatures are at their most dangerous levels. Alternatively, even if workers spend all their time outside, they can redistribute their tasks so that they do more dangerous tasks during more favorable temperatures. For instance, a construction worker may avoid high-beam work on particularly hot days and may instead do tasks on the ground, where dizziness or fatigue would have less severe effects. Finally, a worker may simply work less once temperatures reach dangerous levels. In this section, I use basic monthly CPS data to examine this third type of avoidance behavior.

To consider the effect of temperature on hours worked, I use data from the 2006 to 2014 basic monthly CPS collected by the BLS. Each month the CPS asks respondents to report their

hours worked at their main jobs as well as their hours worked at all other jobs during the week that contains the twelfth day of the month. The systematic reference week of the CPS is crucial to this analysis as it allows the temperature conditions faced by workers to be matched to the week for which they report hours worked.<sup>20</sup>

Only one other study has examined the effect of temperature on time use. Using the 2003 to 2006 American Time Use Surveys (ATUS), Graff Zivin and Neidell (2014) examine how temperature affects people's time allocation among indoor leisure, outdoor leisure, and work. Most relevant to the current study are their findings about the effect of temperature on hours worked, which indicate that a day with a high temperature above 85°F decreases time allocated to labor. Graff Zivin and Neidell do not find evidence of an effect of low temperatures on hours worked, though they cannot rule out meaningful effects.

As its name implies, the ATUS is uniquely suited to studying many dimensions of time use. In addition to allowing for matching a day's time use to the same day's weather, the ATUS also allows Graff Zivin and Neidell (2014) to consider the effects of temperature on leisure and on intraday labor substitution.<sup>21</sup> Despite the ATUS's advantages, the basic monthly CPS has a major advantage over the ATUS in that the sample sizes in the basic monthly CPS are much larger than those in the ATUS, which makes the CPS more conducive to heterogeneity analysis.

To evaluate the effect of temperature on hours worked, I restrict the CPS sample to workers ages 18 to 64 who report their hours worked and their occupations in the previous week and are located in one of the 254 MSAs consistently identified in the CPS during the time period

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<sup>20</sup>Refer to Bureau of Labor Statistics (2017a) for an overview of the CPS and its collection procedures. To avoid interviewing households during holidays, November and December sometimes have reference weeks that do not include the twelfth day of the month. To avoid assigning workers the wrong temperatures, I exclude observations from November and December from the analysis.

<sup>21</sup>Having hours worked at the day level also facilitates the study of interday substitution, which is not possible with hours worked at the week level. For instance, if a particularly hot day results in zero hours being worked on that day but twice as many hours being worked the following day, daily data can identify this interday substitution, while the strongest conclusion that could be reached with weekly data would be that the hot day did not affect weekly hours worked. Graff Zivin and Neidell (2014) find no evidence that high or low temperatures cause interday substitution of labor.

studied.<sup>22</sup> I match the CPS data to the O\*NET data and focus on the subset of workers who are in occupations that are exposed to outdoor temperatures more than one day per week. Since the CPS only contains information about one week in each month, the estimation strategy can no longer rely on within-month variation to identify the impact of temperature. Instead, I now estimate models of the following form:

$$y_{ijm} = \gamma_j + \delta_m + \lambda * X_{ijm} + \alpha * othweather_{jm} + \beta * temperature_{jm} + \epsilon_{ijm}, \quad (2)$$

where  $i$  indexes the individual,  $\gamma$  is a vector of MSA fixed effects,  $\delta$  is a vector of year-month fixed effects,  $X$  is a vector of demographic and job characteristics that includes controls for race, sex, age, years of education, usual hours worked, occupation, and industry, and  $othweather$  is the number of weekdays in the reference week that fell into each precipitation bin and the number of weekend days in each temperature and precipitation bin. The  $temperature$  variable is now the number of weekdays in the reference week with highs in each temperature bin.

This part of the analysis ultimately seeks to test for heterogeneous effects of high or low temperatures in places where they are rare compared to places where they are common. By definition, places experience uncommonly high or low temperatures rarely, meaning cooler MSAs experience only a few days over 100°F over the time period. Also, unlike with the occupational health analysis, the CPS data also must be aggregated to the week level rather than to the day level, which introduces noise into the estimation. Thus, despite the CPS’s large sample sizes, precision remains an issue. To improve precision, I use ten-degree temperature bins and set 90°F and above as the hottest bin and 40°F and below as the coldest temperature bin. I omit the number of days that are 50°F to 59°F, so the coefficients on the temperature bins can be interpreted as the effect of an additional day with a temperature in that bin on hours worked relative to hours worked when all five workdays are in the 50s.

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<sup>22</sup>I drop workers with imputed hours or occupations because the Census “hot deck” matching procedure used for imputation does not restrict donor matches to individuals in the same local area, which can result in biased estimates in area-level analysis. Refer to Autor, Katz, and Kearney (2008), Buchmueller, DiNardo, and Valletta (2011), and Lemieux (2006) for discussions about potential bias of the hot decking procedure. Despite concerns about bias from imputation, the results are very similar when observations with imputed hours and occupations are included.

The coefficients on the temperature bins from estimating Equation (2) are shown in Figure 8. Graph A shows the basic results for all MSAs. Each day with a high below 40°F decreases weekly hours worked by 0.185 hours on average, which is a 0.5 percent decline from when temperatures are in the 50s. The estimated effect of a day above 90°F is a statistically insignificant -0.045 hours per week. Graphs B, C, and D display the results separately for MSAs with different temperature norms.<sup>23</sup> The coefficient estimates on the number of days below 40°F are negative for all three climates, but the point estimate is largest in warmer climates. The point estimate for the effect of an additional day with a high below 40°F is -1.011 for warmer MSAs, -0.160 for cooler MSAs, and -0.107 for all other MSAs. The point estimate of -1.011 translates into a 2.6 percent decline in weekly hours worked for each day with highs below 40°F in warmer climates. The results in graph D suggest that additional hot days decrease hours worked in cooler climates. An additional day with a high above 90°F decreases weekly hours worked in cooler climates by 0.364 hours per week, which is equivalent to a 0.9 percent decline in weekly hours worked. I do not find evidence that high temperatures affect weekly hours worked in other MSAs.

To compute estimates of the differences in effects, I allow MSAs in different climates to have separate year-month fixed effects and *othweather* effects and then supplement Equation (2) with the interaction of the number of days in each ten-degree temperature bin with an indicator for the specific climate type in question. Graph E displays estimates of the differences in the effects of temperature in warmer MSAs compared to all other MSAs. A day with a high below 40°F decreases hours worked by 0.602 per week more in warmer MSAs than in all other MSAs. Graph F shows estimates of the differential effects of temperature in cooler MSAs relative to all other MSAs. A day with a high above 90°F decreases hours worked in a week by 0.392 more in MSAs in cooler climates than MSAs in other climates.

Since all people in a year-month-MSA combination experience the same temperatures in the CPS, the CPS analysis cannot rely on temperature variation from within a year-month-MSA

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<sup>23</sup>To keep the results comparable, I use the same cutoffs for characterizing temperature norms as in the mining analysis of 81.3°F and 89.9°F.



combination. Instead, the baseline CPS specification assumes that any MSA-specific shocks or trends are not systematically correlated with both temperatures and hours worked. To relax the assumption of no region-specific trends, Figure 9 displays estimates from models that supplement Equation (2) with state-year fixed effects. The estimates being sensitive to these additional controls might suggest that states with MSAs that experienced temperature shocks in a particular year experienced broader changes to hours worked and would raise doubts about the empirical strategy's ability to isolate the effects of temperature. The estimates in Figure 9, however, are similar to their corresponding estimates from Figure 8, providing no evidence that unobserved state-level trends hinder the empirical strategy.

The results presented in this section provide evidence that outdoor workers in warmer climates reduce their hours worked more in response to low temperatures while outdoor workers in cooler climates reduce their hours more in response to high temperatures.<sup>24</sup> These results are consistent with three possible explanations. First, workers in warmer areas may be able to avoid working on colder days more easily than they can avoid working on hot days since hot days are too common to avoid. Second, workers in warmer areas may be able to acclimate to high temperatures, and since high temperatures do not affect them, they do not need to adjust their labor force participation. Third, workers in warmer areas may have been able to adapt to high temperatures in ways that mean they do not have to adjust their hours worked, whereas workers in cooler climates have not adapted in the same ways and therefore have to reduce hours. While this study cannot rule out the possibility of acclimation or differential technology adoption, considering these hours-worked results along with the occupational health results suggests that differences in the feasibility of avoidance behavior explain part of the differential hours-worked responses between workers in warmer and cooler environments.

The estimates imply that all five weekdays being over 90°F would reduce hours worked for outdoor workers in cooler climates by approximately 4.5 percent, which may seem small relative

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<sup>24</sup>These results differ from Graff Zivin and Neidell (2014) in two main ways. First, I find evidence that workers adjust their hours in response to cold temperatures. Second, I find evidence of heterogeneous effects based on temperature normals. It should be noted that our studies use different samples and have different focuses. Also, neither finding from this analysis is ruled out by their confidence intervals.

to the reduced effect of high temperatures on injury rates in cooler climates relative to warmer climates documented in the mining analysis. But three factors are important to remember when comparing the effect sizes from the mining analysis and the CPS analysis. First, even though the CPS analysis focuses on temperature-exposed workers, workers in the mining analysis still have higher levels of temperature exposure than the majority of the workers in the CPS sample. Presumably, workers with more exposure to outdoor temperatures experience greater hours reductions in response to higher temperatures in cooler climates. A direct comparison of the effect sizes in mining analysis and the CPS analysis would require replicating the CPS analysis with only miners at surface mines, which is not possible because the CPS does not contain enough observations of miners for meaningful analysis and because the types of mines that miners work at are not observable in CPS data. Second, not working is just one type of avoidance behavior. Other types of avoidance behavior, like delaying certain kinds of work, cannot be measured in the CPS but would also likely be able to mitigate the impact of high temperatures on injury rates in cooler climates. Finally, the hours reductions coming from temperature would arguably be the most dangerous hours, meaning the likelihood of experiencing an injury during the marginal hour likely would have been high relative to the typical hour of work.

While the main analysis focused on the effect of temperature on hours worked for workers exposed to outdoor temperatures at least one day per week, temperature also has the potential to affect hours worked for indoor workers since low temperatures can be associated with dangerous driving conditions, which can increase travel costs to work. Indoor workers may also adjust their hours worked in response to extreme temperatures if the buildings where they work are not climate-controlled or are costly to climate control. However, the effect of temperature being the same for all workers regardless of their temperature exposure would cast doubt on the hypothesis that the effect temperature on hours worked is largely driven by workers with high exposure to outdoor temperatures engaging in avoidance behavior.

To consider the effect of temperature on workers with less exposure to outdoor temperatures, Figure 10 replicates the analysis shown in Figure 8 with the sample of workers from the CPS that is exposed to outdoor temperatures less than one day per week. None of the specifications

in Figure 10 show any effect of high temperatures on hours worked. While there is some evidence that low temperatures reduce hours worked in warmer climates, the size of the effects is small relative to the size of the effects for outdoor workers. For instance, the estimated effect of a day with a high below 40°F in a warm climate of -0.266 shown in graph B is statistically insignificant and roughly one-fourth of the magnitude of the estimated effect on outdoor workers. Overall, these results do not suggest that the effect of temperature on hours worked is the same for workers with less exposure to outdoor temperatures and for workers with more exposure to outdoor temperatures.

## 4.2 The Costs of Extreme Temperatures

The estimates from this study allow for a back-of-the-envelope calculation of the total costs of extreme temperatures that currently arise from avoidance and from occupational health issues in a warm climate like Texas. The estimates presented in Section 3.1 suggest that WC claims arising from extreme temperatures do not have dramatically different costs than other WC claims. Under the assumption that WC claims arising from temperature have the average cost of a work-related injury of \$20,500 in 2014 dollars (Leigh 2011), each day with a high temperature above 90°F leads to costs from occupational health incidents of \$0.08 per worker, and each day with a high temperature below 40°F leads to costs from occupational health incidents of \$0.15 per worker.<sup>25</sup> As about 10 percent of workers work outside at least one day per week and as these workers have an average hourly wage of \$18 in 2014 dollars, the implied cost of the reduction in hours worked from each day with a high below 40°F is about \$1.82 per worker in warmer climates when averaged across all workers.<sup>26</sup>

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<sup>25</sup>To make the estimates from the Texas WC analysis comparable to the estimates from the CPS analysis, I estimate a model for the Texas WC analysis that computes estimates of the effect of a day with a high temperature below 40°F and the effect of a day with a high temperature above 90°F. Appendix B discusses this specification and displays the estimates.

<sup>26</sup>The share of workers who work outside at least one day per week and their average hourly wage come from the 2014 ACS. Note that this calculation assumes that the hours reductions from the CPS come entirely from avoidance rather than from missed work due to an occupational injury. Even if the injuries documented in the WC analysis result in a full week of work being missed on average, the estimated impact of a day with a high below 40°F on hours worked coming from occupational injuries could only account for about 0.3 percent of the hours effect documented in the CPS analysis.

Combining the costs from avoidance and occupational health incidents indicates that a day with a high temperature below 40°F increases costs by \$1.97 in warm climates. Given that Texas MSAs averaged 4.5 weekdays with highs below 40°F from 2006 to 2014, these estimates imply that days with highs below 40°F resulted in \$8.87 in costs coming from avoidance and occupational health issues per worker per year from 2006 to 2014 in Texas. As the CPS analysis did not indicate that outdoor workers in warmer climates reduced their hours worked in response to high temperatures, the entire cost of a day above 90°F in warmer climates comes from occupational health incidents. From 2006 to 2014, Texas MSAs averaged 79.2 weekdays with highs above 90°F each year, which implies an average annual cost of days above 90°F of \$6.34 per worker. As Texas averaged about 11 million workers from 2006 to 2014, these estimates imply average total annual costs of days with high temperatures above 90°F of \$69.7 million in Texas and average total annual costs of days with high temperatures below 40°F of \$97.6 million. As has been discussed elsewhere in this paper, this study likely does not capture all of the adverse effects of temperature on occupational health or the full effect of temperature on different types of avoidance behaviors, meaning that these cost calculations are lower-bound estimates of the current cost of days with extreme temperatures in a warm climate.

### 4.3 Implications of Climate Change

Despite its size giving it more climate variation than most other states, Texas is still one of the hottest states in the country. However, as asserted in the introduction, considering the impact of temperature in Texas is useful since climate change is expected to lead to other states' climates more closely resembling Texas's current climate, which would lead to the results from the Texas analysis pertaining to a higher share of U.S. workers in the future.

Figure 11 illustrates the shift of the rest of the United States towards the Texas climate. Graph A of Figure 11 displays the average share of days with highs that fell into various temperature bins for the nine Census divisions from 2006 to 2014, while graph B graphs the predicted distribution of daily high temperatures for 2070 to 2099 for each Census division calculated

from the Hadley Climate Model 3 under the assumption of no major emission changes.<sup>27</sup> In both graphs, Texas’s temperature distribution in 2006 to 2014 is represented by a thick red line. Figure 11 shows that while Texas currently averages more hot days than all Census divisions, by the end of the century, the temperature distribution in the rest of the United States will match Texas’s current temperature distribution much more closely than it does now.

## 5 Discussion and Conclusion

This study constructs and studies two data sets that link temperature and a broad set of occupational health outcomes. Using a data set derived from Texas WC claims, I find strong evidence that both hot and cold temperatures have adverse effects on workers’ health. Once daily high temperatures reach the 70s or low 80s, higher temperatures are associated with worse health outcomes. Illnesses identified by medical professionals as being directly related to the heat see the sharpest increase, but higher temperatures appear to affect a broad swath of injuries. A day with a high temperature over 100°F increases same-day claim rates by 7.6 to 8.2 percent and three-day claim rates by 3.5 to 3.7 percent. Three-day claim rates also begin to rise as high temperatures fall below 40°F. A day with a high temperature below 35°F increases three-day claim rates by 3.4 to 5.8 percent.

To be able to consider heterogeneous effects of high temperature on occupational health based on temperature norms, I draw on injury data from the mining industry. These data confirm that high temperatures are harmful to workers’ health in warm climates like Texas, but they provide no evidence that high temperatures harm workers’ health in cooler climates, which indicates that workers in climates where hot days are rare are better able to deal with a hot day than workers in climates where hot days are common.

These results are consistent with avoidance behavior being more feasible when high temperatures are rare. Using CPS data, I provide evidence that avoiding working during extreme

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<sup>27</sup>The Hadley climate model is a general circulation model that uses both atmospheric and oceanic data for its forecasts and was one of the main models used by the International Panel on Climate Change’s Special Report on Emissions Scenarios. For more information on this model, refer to Collins, Tett, and Cooper (2001).

temperatures is easier when extreme temperatures are rare. The CPS analysis indicates that high temperatures result in larger decreases in hours worked in cooler places than in warm places. Similarly, cold temperatures reduce hours worked more in places that are normally warm than they do in places that often experience cold temperatures.

These results are policy-relevant as countries around the world continue to grapple with climate change and decide what actions to take now to prevent temperatures from continuing to rise in the future. The evidence of adaptation from the literature on the mortality effects of temperature suggests reason for optimism that the negative effects of high temperatures can be mitigated using currently available technology. But the analysis presented in this paper suggests less cause for optimism in terms of our ability to deal the occupational health effects of high temperatures.

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Table 1: Demographic Characteristics of Temperature-Exposed Workers

	High-Exposure Industries	Other Industries	High-Exposure Occupations	Low-Exposure Occupations
<b>A. United States</b>				
% Male	78	45	91	30
% Ages 18 to 35	32	41	36	38
% Ages 36 to 50	38	33	37	34
% Ages 51 to 64	30	26	27	27
% with High School Degree	85	93	82	95
% with Bachelor's Degree	19	37	9	38
% White	77	74	79	75
% Black	9	12	8	12
% Hispanic	21	16	24	14
n	300,390	1,010,158	133,706	396,584
<b>B. Texas</b>				
% Male	81	46	93	31
% Ages 18 to 35	35	43	38	41
% Ages 36 to 50	38	34	38	34
% Ages 51 to 64	27	23	24	24
% with High School Degree	78	90	70	93
% with Bachelor's Degree	20	33	7	33
% White	78	74	80	74
% Black	9	13	7	13
% Hispanic	43	35	53	32
n	26,236	79,831	10,969	31,580

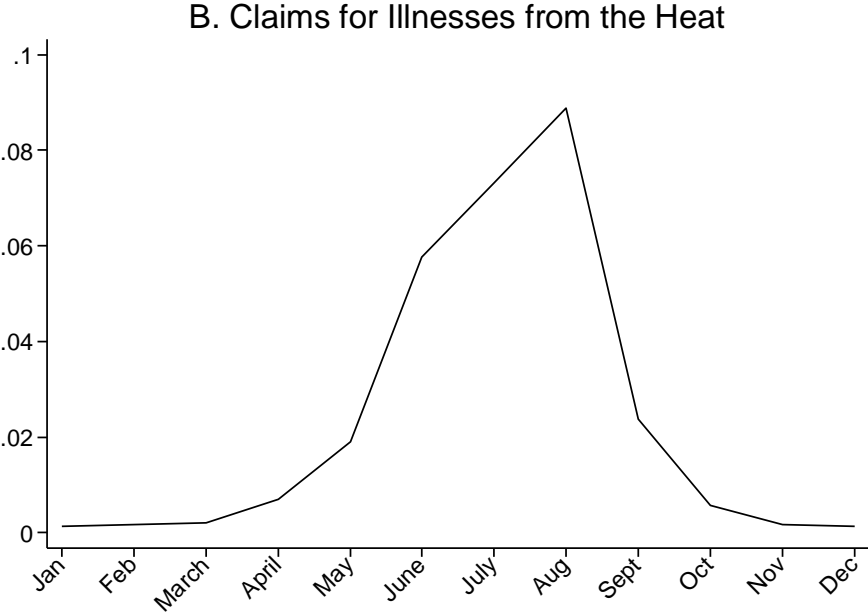
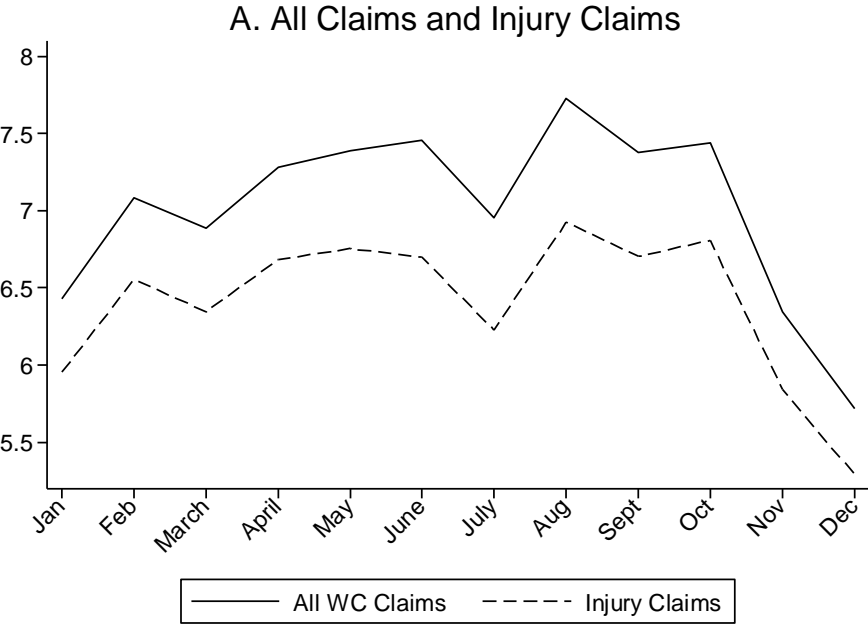
Notes: The data come from the 2014 ACS. High-exposure industries include agriculture, forestry, fishing, and hunting; construction; manufacturing; mining; and transportation. High-exposure occupations are those that are exposed to outdoor temperatures at least one day per week according to O\*NET data. Low-exposure occupations are those that are never exposed to outdoor temperatures according to O\*NET data. The means are weighted using ACS weights.

Table 2: Characteristics of WC Claims

% Male	60.0
% Ages 18 to 35	39.5
% Ages 36 to 50	37.7
% Ages 51 to 64	22.8
% Claims for Illnesses from the Heat	0.4
% Injury Claims	91.3
% Open Wound, Crushing, and Fracture Claims	23.0
% Sprain, Strain, Bruise, and Muscle-Related Claims	65.0
n	1,916,590

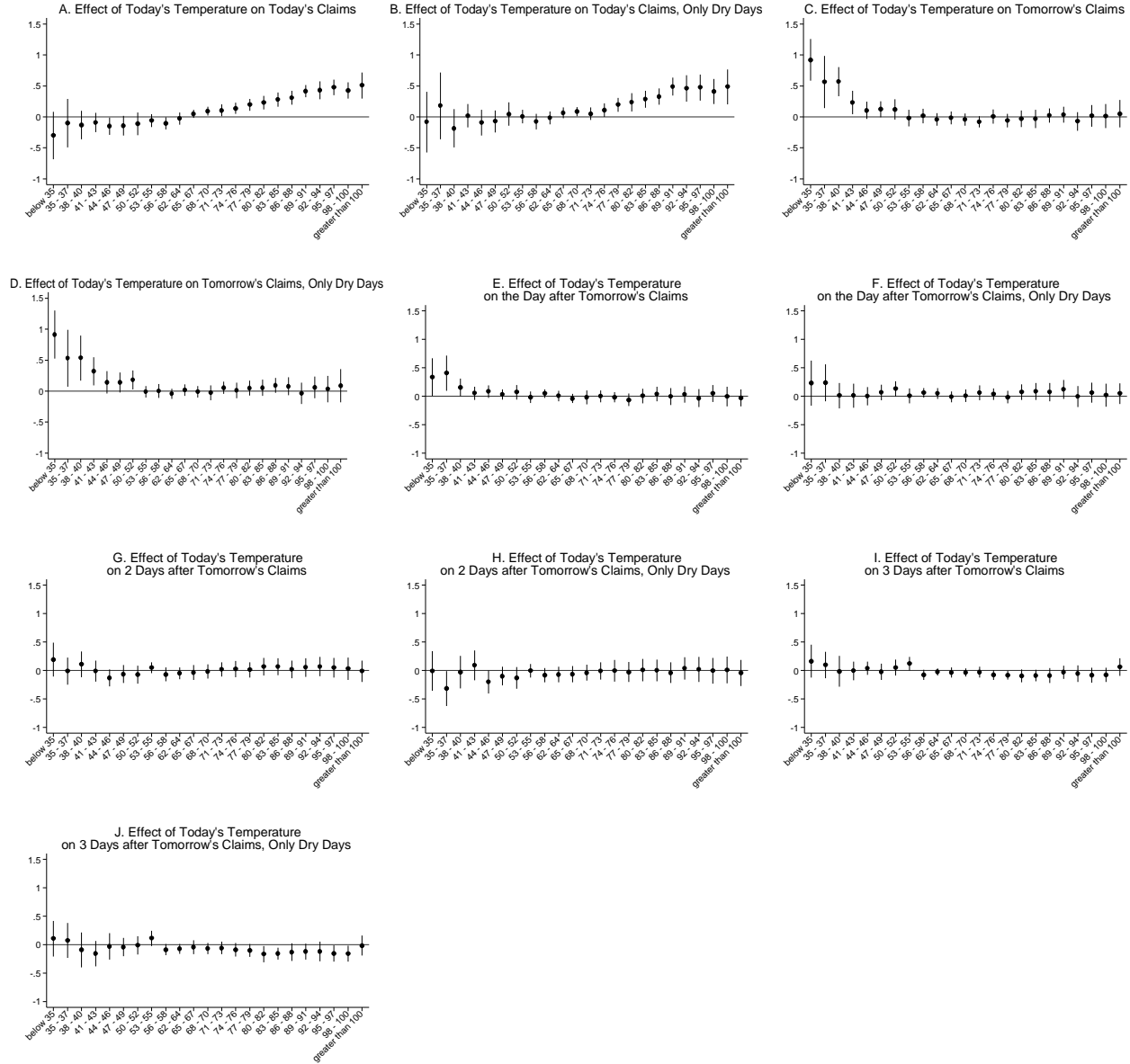
Notes: The data come from 2006 to 2014 Texas WC claims.

Figure 1: Mean of Daily Claims per 100,000 Workers by Month



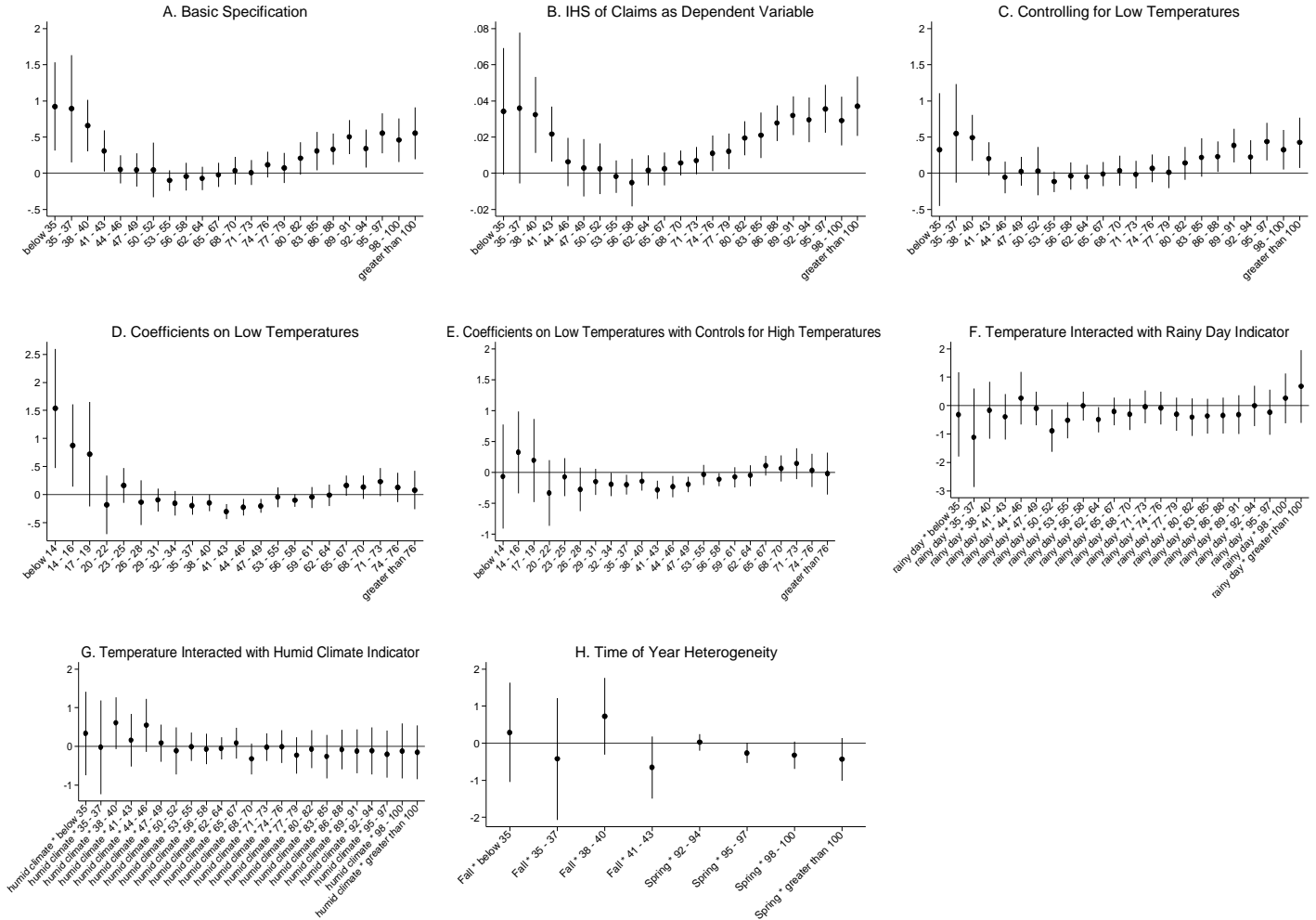
Notes: The graphs show means of daily claims per 100,000 workers by month. The sample includes 154,968 MSA-days. The underlying claim data come from 2006 to 2014 Texas WC claims and contain information on 1,916,590 claims, 1,749,452 claims for injuries, and 6,760 claims for illnesses from the heat. The means are weighted by the MSA’s employment during the month of the observation from LAUS data.

Figure 2: The Effect of Temperature on Daily Claim Rates per 100,000 Workers



Notes: Each graph displays coefficient estimates from a single regression of Equation (1) along with 95-percent confidence intervals calculated using standard errors clustered at the MSA level. The sample includes 154,968 MSA-days and 124,964 MSA-days without precipitation. The underlying claim data come from 2006 to 2014 Texas WC claims and contain information on 1,916,590 claims. All regressions control for day fixed effects, year-month-MSA fixed effects, precipitation indicator variables, and high temperature and precipitation indicator variables for each of the previous five days and subsequent four days. The mean of the D.V. at 59°F to 61°F for each graph is as follows: A: 6.2; B: 6.2; C: 5.4; D: 5.4; E: 4.3; F: 4.4; G: 4.2; H: 4.2; I: 4.5; J: 4.5. Each regression is weighted by the MSA's employment during the month of the observation from LAUS data.

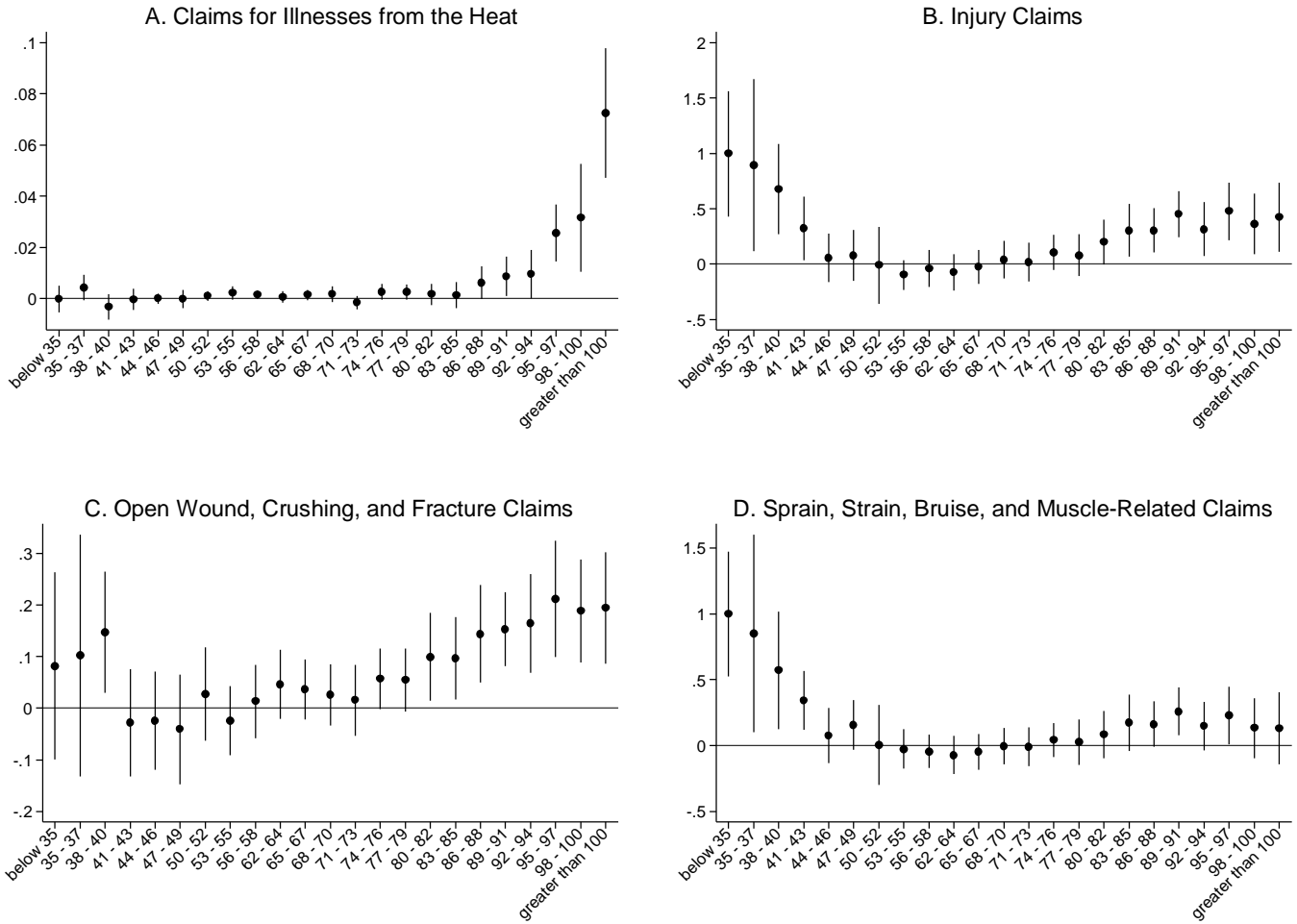
Figure 3: The Effect of Temperature on Three-Day Claim Rates per 100,000 Workers



Notes: Each graph displays coefficient estimates from a single regression of Equation (1) along with 95-percent confidence intervals calculated using standard errors clustered at the MSA level. The sample includes 154,968 MSA-days. The underlying claim data come from 2006 to 2014 Texas WC claims and contain information on 1,916,590 claims. All regressions control for day fixed effects, year-month-MSA fixed effects, precipitation indicator variables, and high temperature and precipitation indicator variables for the previous two days and subsequent two days. The regressions for graphs C through E also include controls for low temperatures for the day of observation and for the previous two days and subsequent two days. The regression in graph D omits high temperature controls. The regression for graph F also includes interactions of the weather controls, of the day fixed effects, and of the year-month-MSA fixed effects with a rainy day indicator, while the regression for graph G also includes interactions of the weather controls and of the day fixed effects with an indicator for being in a humid climate. The mean of the three-day claim rate per 100,000 workers at 59°F to 61°F is 15.8. Each regression is weighted by the MSA’s employment during the month of the observation from LAUS data.

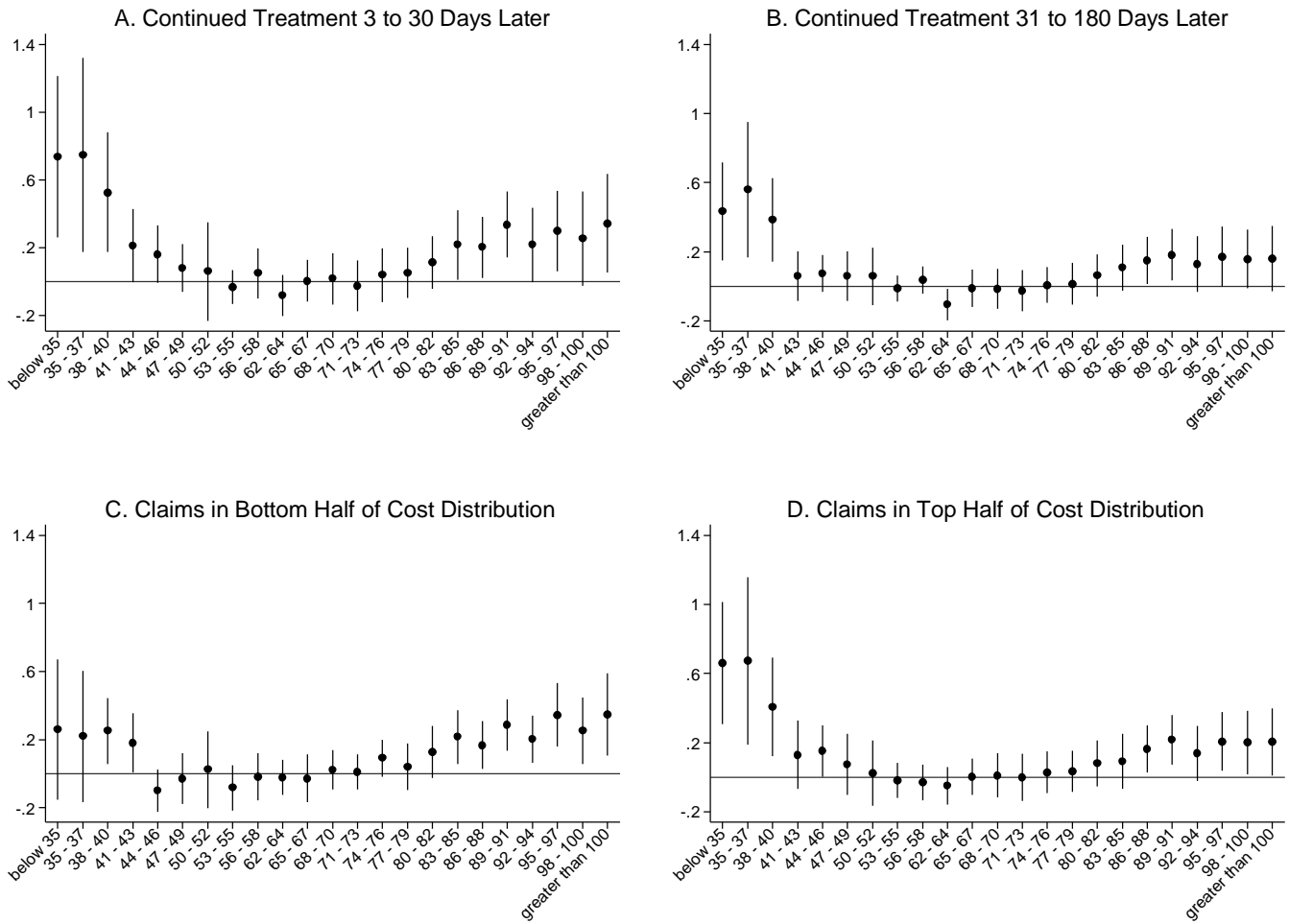


Figure 4: The Effect of Temperature on Three-Day Claim Rates per 100,000 Workers for Different Types of Claims



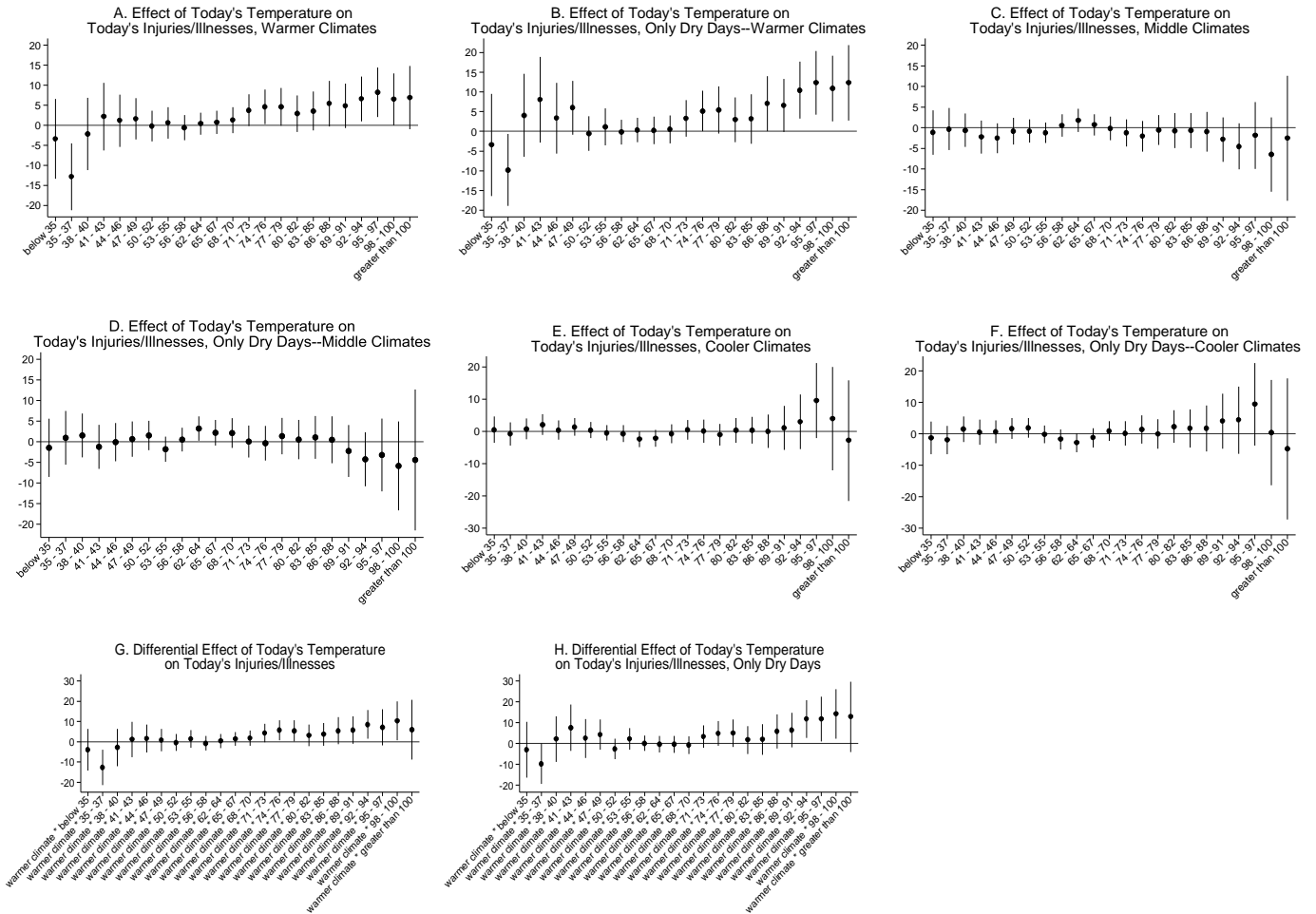
Notes: Each graph displays coefficient estimates from a single regression of Equation (1) along with 95-percent confidence intervals calculated using standard errors clustered at the MSA level. The sample includes 154,968 MSA-days. The underlying claim data come from 2006 to 2014 Texas WC claims. The underlying number of claims for each regression is as follows: A: 6,760; B: 1,749,452; C: 441,553; D: 1,244,996. All regressions control for day fixed effects, year-month-MSA fixed effects, precipitation indicator variables, and high temperature and precipitation indicator variables for the previous two days and subsequent two days. The mean of the D.V. at 59°F to 61°F for each graph is as follows: A: 0.0; B: 14.6; C: 3.6; D: 10.6. Each regression is weighted by the MSA's employment during the month of the observation from LAUS data.

Figure 5: The Effect of Temperature on Three-Day Claim Rates per 100,000 Workers, Follow-Up Treatment and Medical Costs



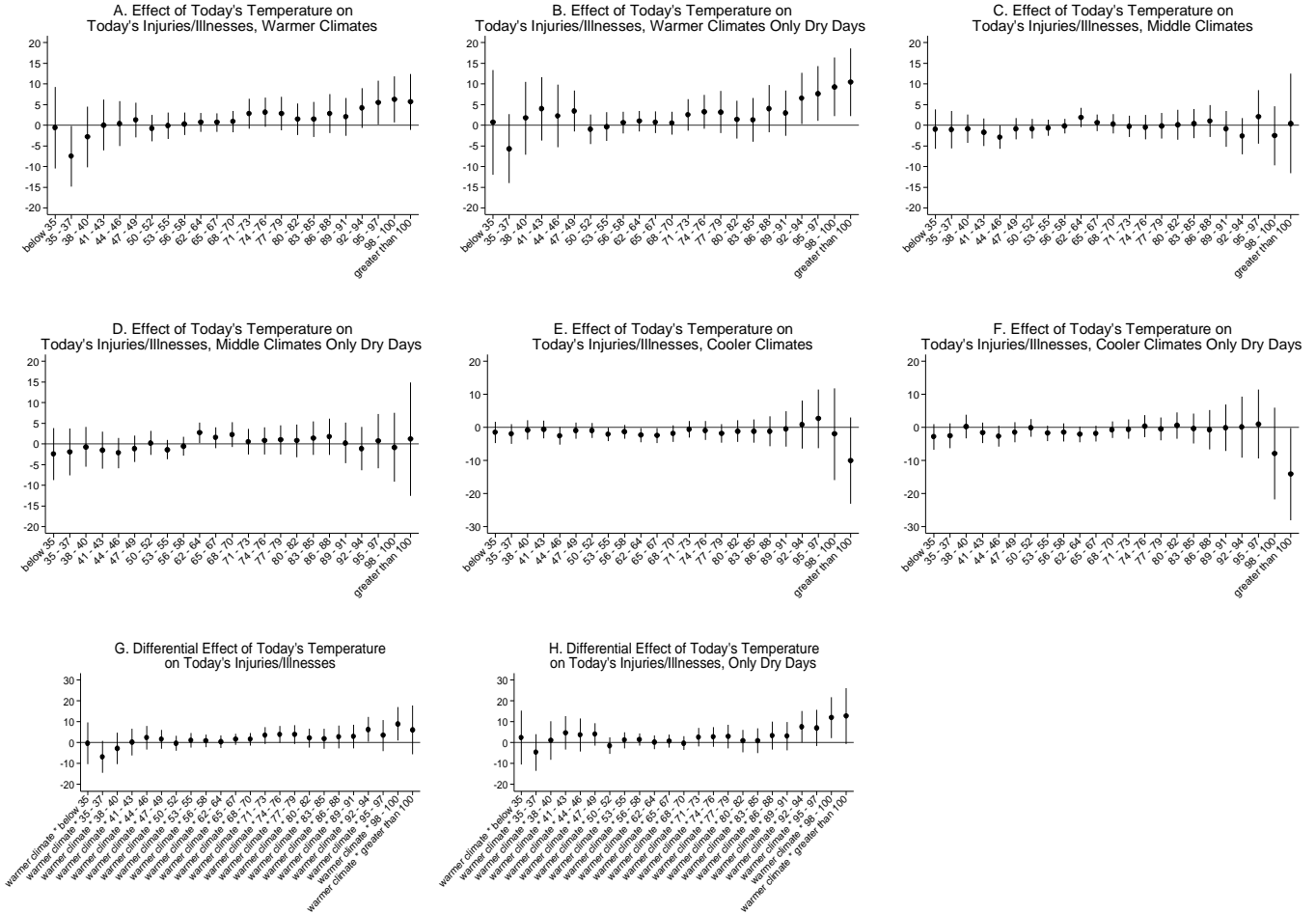
Notes: Each graph displays coefficient estimates from a single regression of Equation (1) along with 95-percent confidence intervals calculated using standard errors clustered at the MSA level. The sample includes 154,968 MSA-days. The underlying claim data come from 2006 to 2014 Texas WC claims. The underlying number of claims for each regression is as follows: A: 678,621; B: 266,236; C: 958,295; D: 958,295. All regressions control for day fixed effects, year-month-MSA fixed effects, precipitation indicator variables, and high temperature and precipitation indicator variables for the previous two days and subsequent two days. The mean of the D.V. at 59°F to 61°F for each graph is as follows: A: 11.6; B: 6.2; C: 8.9; D: 8.8. Each regression is weighted by the MSA’s employment during the month of the observation from LAUS data.

Figure 6: The Effect of Temperature on Daily Injury Rates per 100,000 Workers in Mining Data



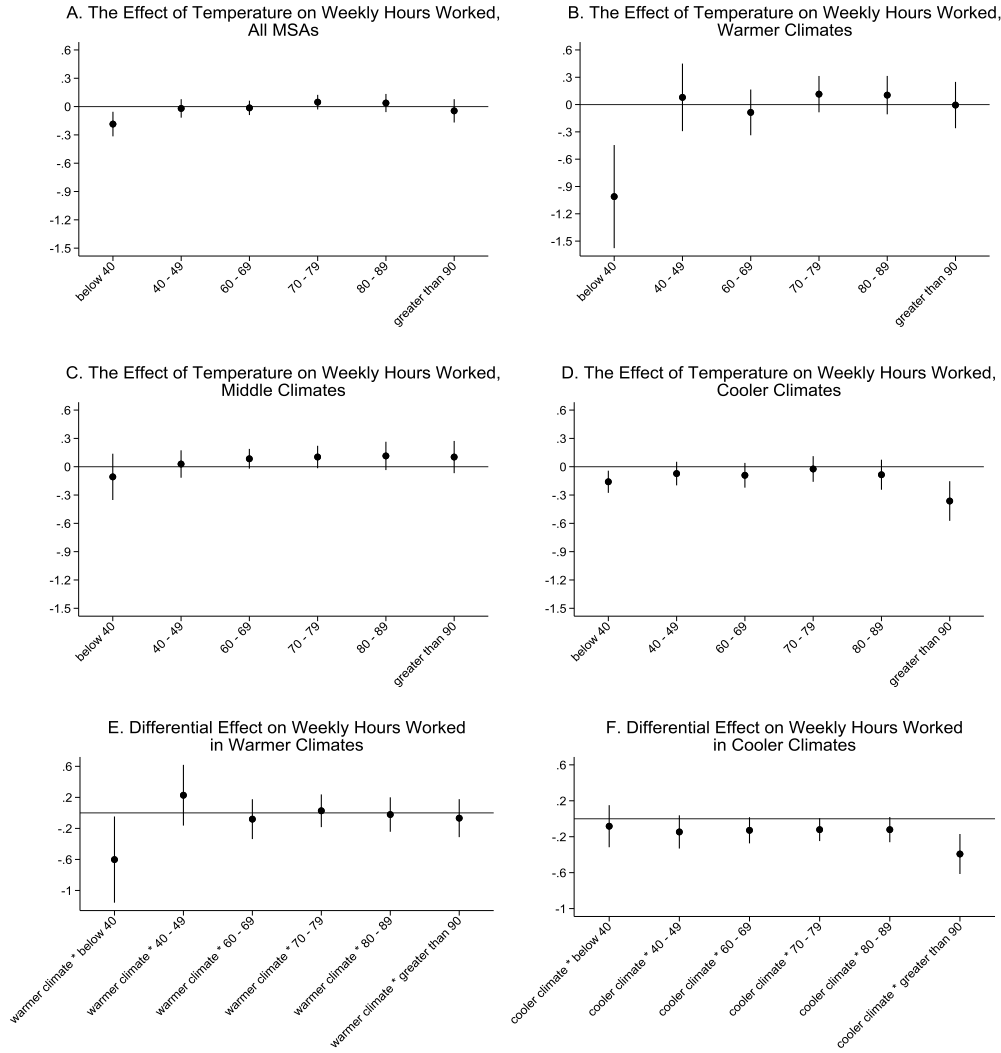
Notes: Each graph displays coefficient estimates from a single regression of Equation (1) along with 95-percent confidence intervals calculated using standard errors clustered at the site level. The sample size for each regression is as follows: A: 652,744; B: 504,027; C: 1,310,184; D: 899,973; E: 652,744; F: 416,433; G: 2,615,672; H: 1,820,433. The underlying injury data come from 2006 to 2014 MSHA logs. The underlying number of injuries for each regression is as follows: A: 4,100; B: 2,853; C: 4,786; D: 3,334; E: 4,127; F: 2,862; G: 13,013; H: 9,049. All regressions control for day fixed effects, year-month-site fixed effects, precipitation indicator variables, and high temperature and precipitation indicator variables for the previous two days and subsequent two days. The regressions for graphs G and H also include interactions of the weather controls and of the day fixed effects with an indicator for a site being in a warmer climate. The mean of daily injury rates at 59°F to 61°F for each graph is as follows: A: 10.3; B: 10.9; C: 10.9; D: 10.1; E: 10.1; F: 9.0; G: 10.5; H: 9.9. Each regression is weighted by the number of workers at each site.

Figure 7: The Effect of Temperature on Daily Time-Loss Injury Rates per 100,000 Workers in Mining Data



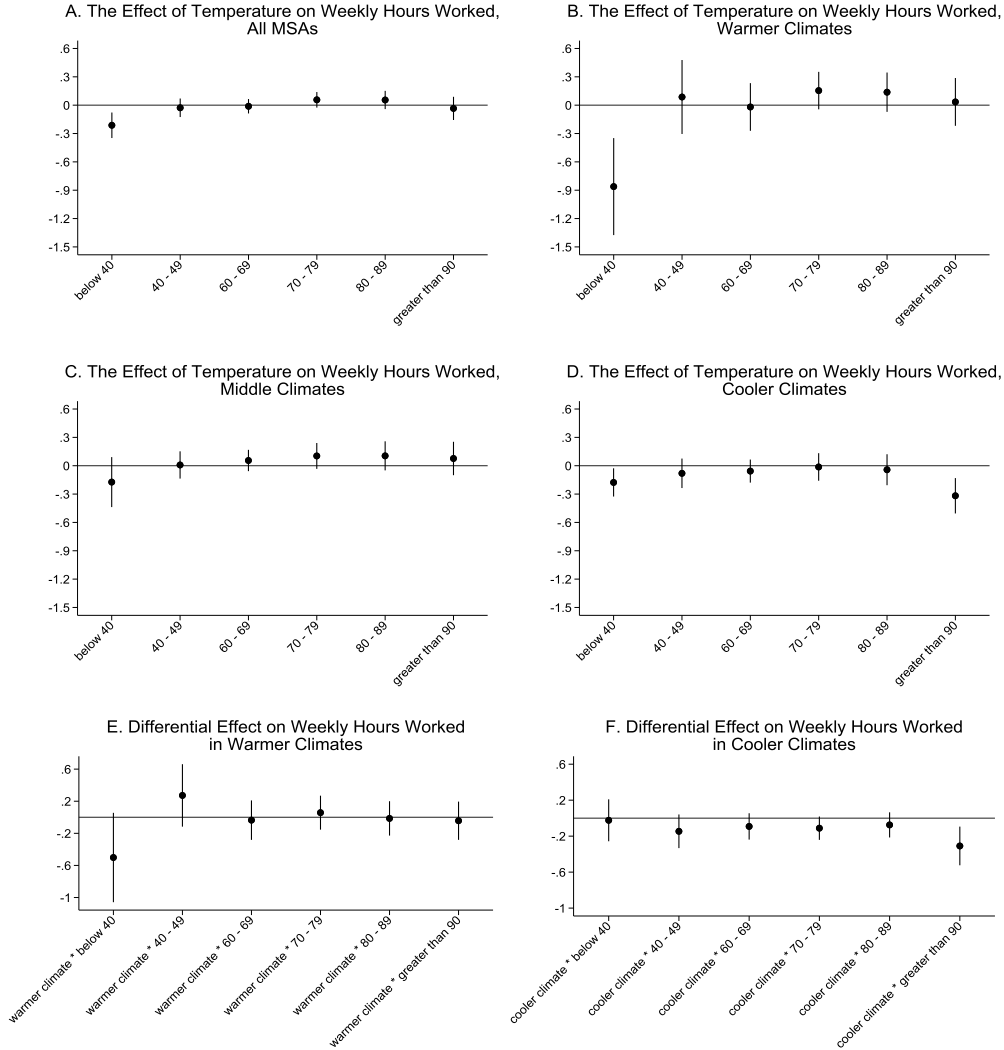
Notes: Each graph displays coefficient estimates from a single regression of Equation (1) along with 95-percent confidence intervals calculated using standard errors clustered at the site level. The sample size for each regression is as follows: A: 652,744; B: 504,027; C: 1,310,184; D: 899,973; E: 652,744; F: 416,433; G: 2,615,672; H: 1,820,433. The underlying injury data come from 2006 to 2014 MSHA logs. The underlying number of injuries for each regression is as follows: A: 2,791; B: 1,923; C: 3,068; D: 2,174; E: 2,395; F: 1,635; G: 8,254; H: 5,732. All regressions control for day fixed effects, year-month-site fixed effects, precipitation indicator variables, and high temperature and precipitation indicator variables for the previous two days and subsequent two days. The regressions for graphs G and H also include interactions of the weather controls and of the day fixed effects with an indicator for a site being in a warmer climate. The mean of daily injury rates at 59°F to 61°F for each graph is as follows: A: 7.0; B: 7.3; C: 7.3; D: 7.0; E: 6.8; F: 5.6; G: 7.1; H: 6.6. Each regression is weighted by the number of workers at each site.

Figure 8: The Effect of Temperature on Weekly Hours Worked for Workers Exposed to Outdoor Temperatures More than One Day per Week



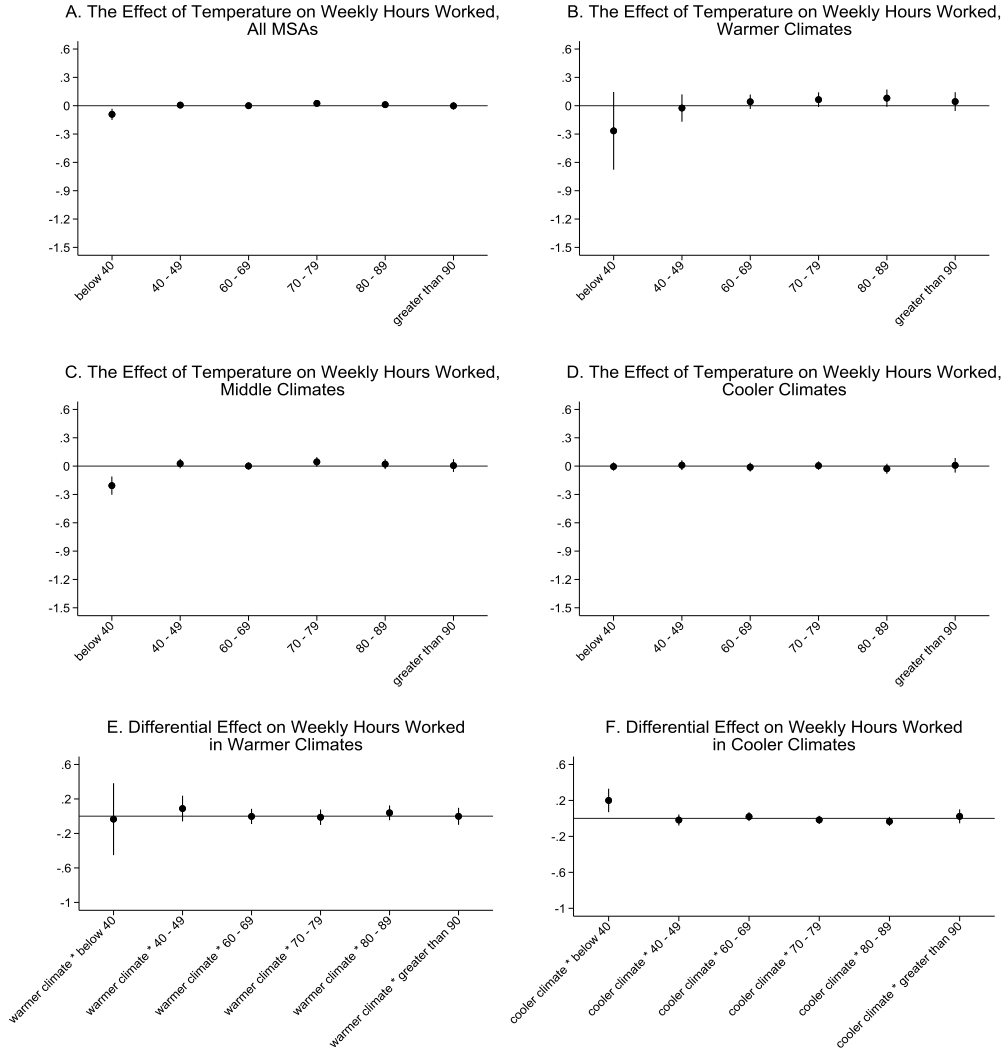
Notes: Each graph displays coefficient estimates from a single regression of Equation (2) along with 95-percent confidence intervals calculated using standard errors clustered at the MSA level. The sample size for each regression is as follows: A: 325,395; B: 65,758; C: 145,549; D: 114,088; E: 325,395; F: 325,395. The data on workers come from the 2006 to 2014 monthly CPS. The sample includes workers exposed to outdoor temperatures more than one day per week. All regressions control for MSA fixed effects, year-month fixed effects, the number of days in each precipitation bin, the number of weekend days in each temperature and precipitation bin, and the individual's race, sex, age, education, usual hours worked, occupation, and industry. The regression for graph E also includes interactions of the weather controls and of the year-month fixed effects with an indicator for an MSA being in a warmer climate. The regression for graph F also includes interactions of the weather controls and of the year-month fixed effects with an indicator for an MSA being in a cooler climate. The mean of hours worked when each day of the reference week has high temperatures of 50°F to 59°F for each graph is as follows: A: 39.1; B: 38.7; C: 39.0; D: 39.2; E: 39.1; F: 39.1. Each regression is weighted using CPS weights.

Figure 9: The Effect of Temperature on Weekly Hours Worked for Workers Exposed to Outdoor Temperatures More than One Day per Week, Robustness to Including State-Year Fixed Effects



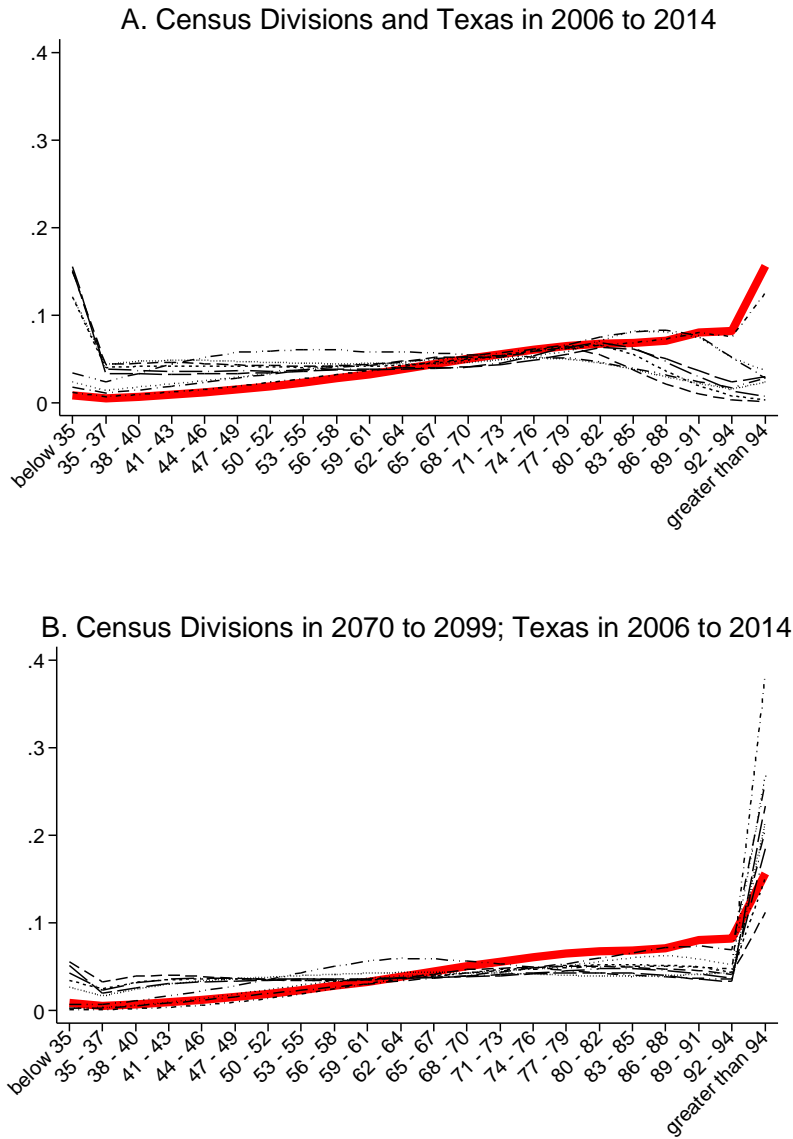
Notes: Each graph displays coefficient estimates from a single regression of Equation (2) along with 95-percent confidence intervals calculated using standard errors clustered at the MSA level. The sample size for each regression is as follows: A: 325,395; B: 65,758; C: 145,549; D: 114,088; E: 325,395; F: 325,395. The data on workers come from the 2006 to 2014 monthly CPS. The sample includes workers exposed to outdoor temperatures more than one day per week. All regressions control for MSA fixed effects, year-month fixed effects, state-year fixed effects, the number of days in each precipitation bin, the number of weekend days in each temperature and precipitation bin, and the individual's race, sex, age, education, usual hours worked, occupation, and industry. The regression for graph E also includes interactions of the weather controls and of the year-month fixed effects with an indicator for an MSA being in a warmer climate. The regression for graph F also includes interactions of the weather controls and of the year-month fixed effects with an indicator for an MSA being in a cooler climate. The mean of hours worked when each day of the reference week has high temperatures of 50°F to 59°F for each graph is as follows: A: 39.1; B: 38.7; C: 39.0; D: 39.2; E: 39.1; F: 39.1. Each regression is weighted using CPS weights.

Figure 10: The Effect of Temperature on Weekly Hours Worked for Workers Exposed to Outdoor Temperatures Less than One Day per Week



Notes: Each graph displays coefficient estimates from a single regression of Equation (2) along with 95-percent confidence intervals calculated using standard errors clustered at the MSA level. The sample size for each regression is as follows: A: 3,078,897; B: 531,363; C: 1,403,654; D: 1,143,880; E: 3,078,897; F: 3,078,897. The data on workers come from the 2006 to 2014 monthly CPS. The sample includes workers exposed to outdoor temperatures less than one day per week. All regressions control for MSA fixed effects, year-month fixed effects, the number of days in each precipitation bin, the number of weekend days in each temperature and precipitation bin, and the individual's race, sex, age, education, usual hours worked, occupation, and industry. The regression for graph E also includes interactions of the weather controls and of the year-month fixed effects with an indicator for an MSA being in a warmer climate. The regression for graph F also includes interactions of the weather controls and of the year-month fixed effects with an indicator for an MSA being in a cooler climate. The mean of hours worked when each day of the reference week has high temperatures of 50°F to 59°F for each graph is as follows: A: 37.4; B: 37.0; C: 37.8; D: 37.3; E: 37.4; F: 37.4. Each regression is weighted using CPS weights.

Figure 11: Temperature Distributions of Texas and Census Divisions



Notes: The thick red line in both graphs represents the distribution of daily high temperatures of Texas from 2006 to 2014. Graph A also displays the distribution of daily high temperatures for each Census region from 2006 to 2014, while graph B displays the predicted distribution of daily high temperatures for each Census region from 2070 to 2099 using the Hadley 3 climate forecast model.



# Appendices

## A Appendix: Industrial and Occupational Distributions by Temperature Normals

The results from this study suggest that temperatures at either tail of the temperature distribution are harmful to workers and provide little evidence that temperature-exposed workers can adapt to temperature extremes. A type of adaptation that the main analysis does not consider could involve specialization of labor based on the distribution of temperature norms. Climate-based specialization of labor might involve today's warmer areas shifting towards work that is conducive to climate-controlled environments as the earth warms and today's cooler areas shifting towards temperature-exposed work. Though this type of specialization may be able to mitigate the harmful effects of climate change on workers, the potential for this type of specialization may be limited as many temperature-exposed jobs are location-dependent. For instance, many jobs are based on the locations of natural resources, while construction and transportation jobs are typically required broadly.<sup>1</sup> Furthermore, non-climate-related factors, such as the availability of cheap land, also factor into firms' location decisions. In addition, much of the industrial composition of the United States has likely arisen for historical reasons, and relocating can be costly for both firms and workers.

If occupational specialization based on climate is cost-effective, it plausibly would have already partially occurred. To consider the presence of and potential for this type of specialization, I examine the correlation between an MSA's frequency of dangerous temperatures and its share of temperature-exposed jobs. A strong negative correlation between the number of days with dangerous temperatures and temperature-exposed employment shares would provide

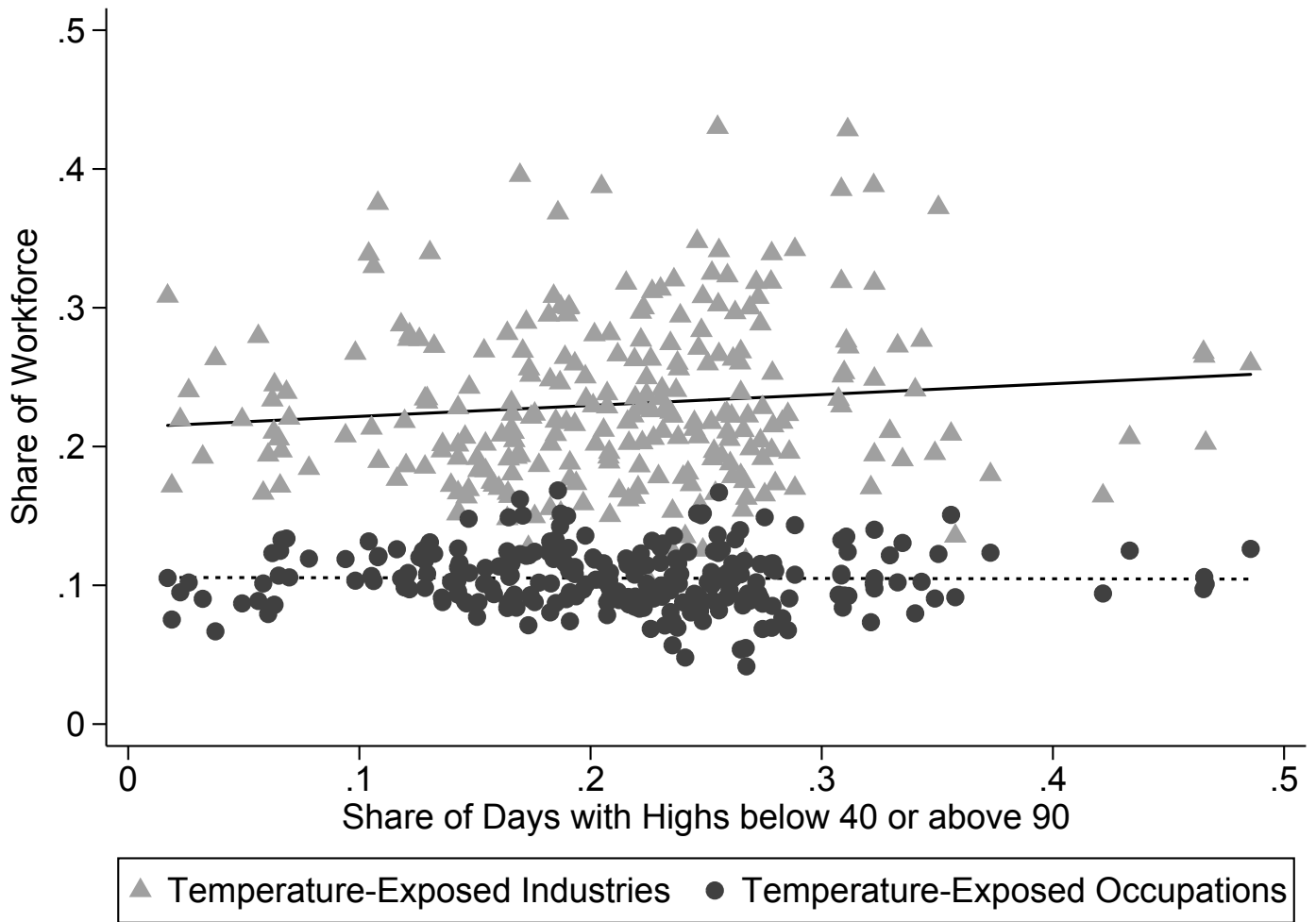
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<sup>1</sup>Climate change will not shift the distribution of mineral resources. However, as agriculture often requires specific climates, the location of the agriculture industry may shift as the climate changes. Construction and transportation will still be required broadly as the climate changes, though demand for these industries is affected by the distribution of people, which may be altered by climate change. Because tourism is likely heavily influenced by climate, climate change will likely alter the location of tourism jobs. Refer to Butsic, Hanak, and Valletta (2011) for a discussion about how climate change could affect the locations of tourism jobs.

suggestive evidence that temperature-based specialization of labor is cost-effective, that it has already occurred, and that it can continue to occur as the distribution of temperatures changes. No correlation between dangerous temperature shares and temperature-exposed employment shares may suggest that the potential for adaptation through specialization is currently limited.

Figure A.1 plots the share of workers in high-exposure industries and occupations for each MSA identifiable in the ACS along with the MSA's share of days from 2006 to 2014 with highs above 90°F or below 40°F. Regardless of how temperature-exposed jobs are defined, the correlation coefficient between temperature-exposed work and dangerous temperatures is small. When defining temperature exposure based on industry, the correlation coefficient is 0.108. When defining temperature exposure based on occupation, the correlation coefficient is -0.009. While this descriptive analysis does not rule out specialization either now or in the future, these patterns are not supportive that climate-based specialization of labor has already shaped the distribution of temperature-exposed jobs in the United States.

Figure A.1: Correlation between MSAs' Share of Days with Dangerous Temperatures and Share of Workforce in Temperature-Exposed Jobs



Notes: The share of dangerous days is from 2006 to 2014. The industry shares come from the 2014 ACS. The occupation shares come from the 2014 ACS and the O\*NET.

## **B Appendix: Additional Analysis of Texas Climate and Data**

### **B.1 Texas Temperatures**

Figure B.1 shows the total number of days of 100°F or more by year for Amarillo, Austin, Dallas-Ft. Worth, Laredo, and Lubbock. Laredo experienced more days 100°F or more than the other MSAs most years, but the magnitudes of the difference vary by year. Other MSAs' relative rankings vary more over time. For example, while Austin usually has more days 100°F or more than Dallas, Dallas has more in some years. The rankings of Amarillo and Lubbock also vary by year. Figure B.2 shows the total number of days with low temperatures below 32°F for each of the five MSAs and also displays variation in temperature across time and geography.

Figure B.1: Total Days with Highs over 100°F by Year for Selected MSAs

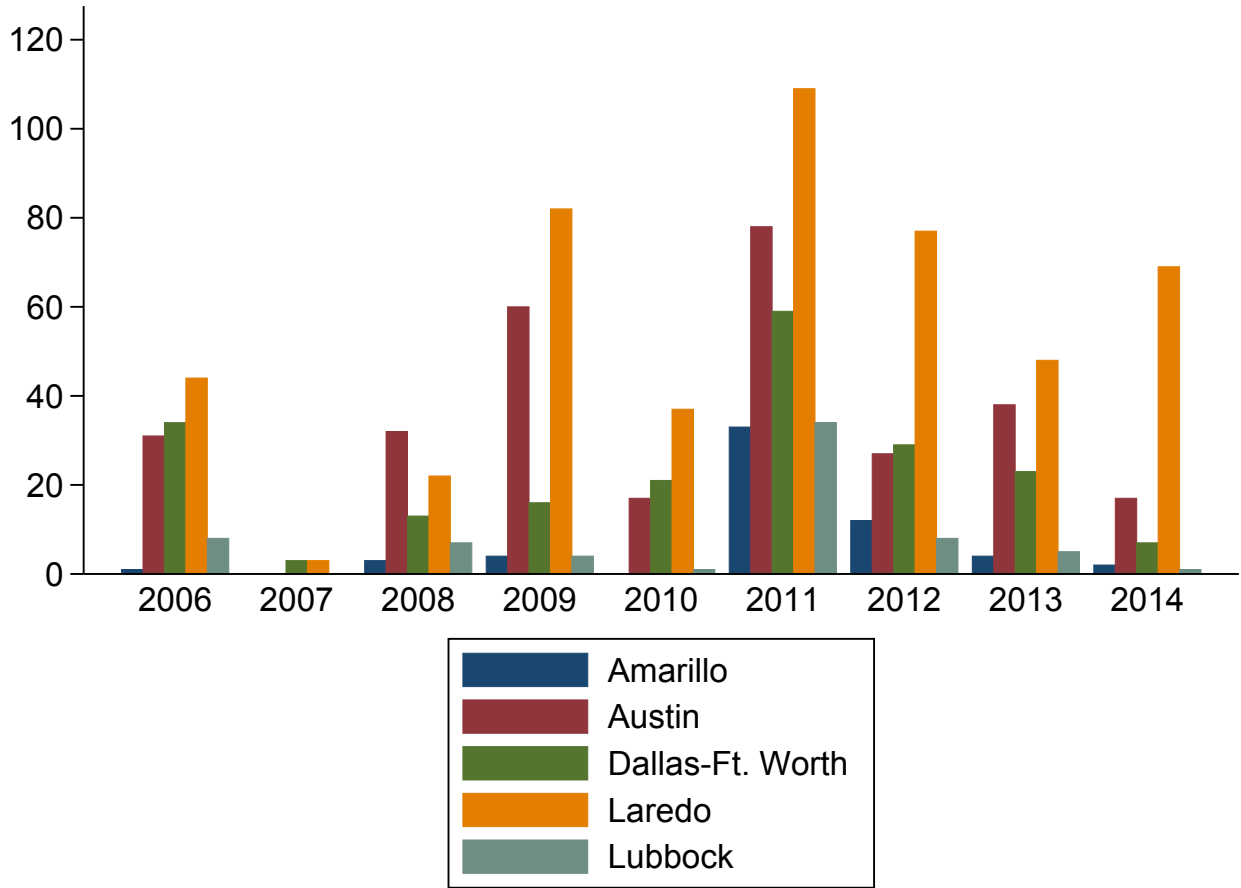
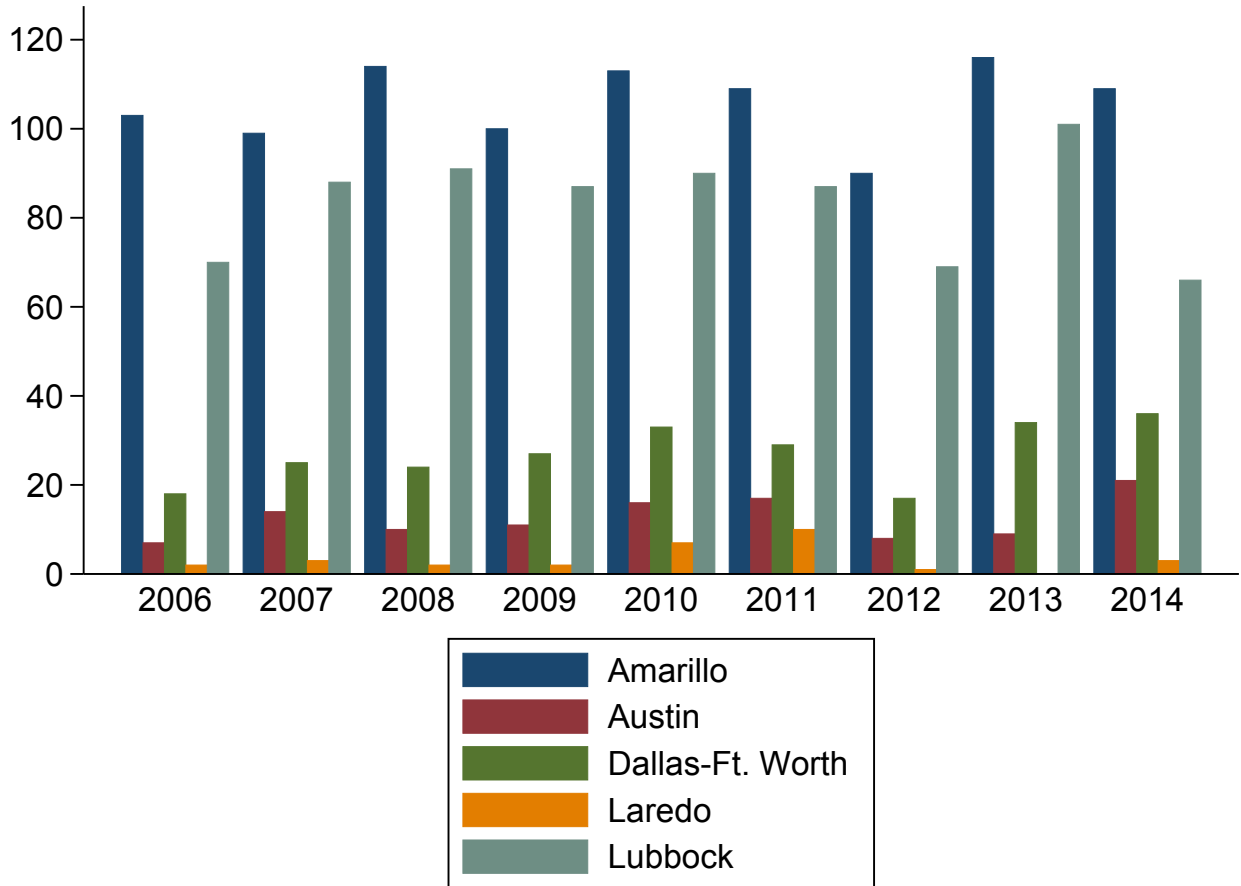


Figure B.2: Total Days with Lows Less than 32°F by Year for Selected MSAs



## B.2 Alternative Specifications with Daily Data

Figure B.3 considers additional specifications for the Texas WC results. For comparison, graph A of Figure B.3 displays the original estimates with three-day claim rates as the dependent variable. The regression underlying graph A controls for day fixed effects, year-month-MSA fixed effects, precipitation indicator variables, and high temperature and precipitation indicator variables for each of the previous two days and subsequent two days. The year-month-MSA fixed effects in this main specification allow each MSA to have a different baseline claim rate in each year and month combination and thus account for MSA-specific shocks that are correlated with temperature. These shocks could arise from chance, which in principle should not hinder the empirical strategy even absent the year-month-MSA fixed effects, or from temperature affecting economic conditions, which could lead to more or less work being done in hot or cold months. Two potential concerns arise with the inclusion of these controls. First, one may be interested in temperature's effects on health through its effect on economic conditions. That is, a heat wave or cold wave reducing agricultural yields and therefore lowering injuries for an entire season because fewer workers are needed is an indirect effect of extreme temperatures on occupational health that may be important to document. Second, the year-month-MSA fixed effects may absorb the effect of multiple hot or cold days occurring together in a particular month, which could be problematic if multiple days of extreme temperatures have interactive effects.

To consider the sensitivity of the results to these controls, graph B in Figure B.3 shows temperature coefficients from a specification that replaces the year-month-MSA fixed effects with separate year-MSA fixed effects and month-MSA fixed effects. This specification no longer allows each year, month, and MSA combination to have a different baseline claim rate, but it still allows MSAs to have different economic conditions each year and different monthly seasonality. The results from this specification are very similar to the original results. Graph C shows temperature coefficients from a specification that replaces the year-month-MSA fixed effects from the original specification with MSA fixed effects. Thus, this specification allows MSAs to have different baseline claim rates but assumes common time trends and seasonality

across Texas. The estimated effects of hotter temperatures rise slightly in this specification, but the coefficients are still generally similar to those in the original specification.

Another set of extensive controls in Equation (1) is the fixed effects for each calendar date. One advantage of these fixed effects is that they control for seasonality and state-wide economic conditions very flexibly. However, given that weather is plausibly random within a given month, such extensive controls are likely unnecessary. Another advantage of the day fixed effects is that they can account for certain days having fewer injuries regardless of their temperature because less work is done on them. For instance, far fewer claims occur during Christmas and the surrounding days relative to other times of the year because less work is done during Christmastime, which could be problematic if not accounted for because late December is prone to cold shocks but not to heat shocks. Again, though, as temperature is plausibly random within a given month, less exhaustive time controls should be sufficient for obtaining unbiased estimates even if some of the identifying variation comes from claim rates on non-holidays being compared to claim rates on holidays.

To consider the sensitivity of the results to the day fixed effects, graph D of Figure B.3 displays temperature coefficients from the same specification as in graph C but with the day fixed effects replaced with day-of-week fixed effects and with year-month fixed effects. Rather than try to make individual judgments about each holiday, I exclude days with 500 or fewer state-wide claims (4.7 percent of the sample) from this specification as well as days from December 22 to January 5 (an additional 1.8 percent of the sample).<sup>1</sup> Even with this drastically different specification, the results in graph D are very similar to the original estimates, especially for the effects of high temperatures. While only one of the coefficients on low temperatures is statistically significant in this specification, the point estimates for low temperatures follow a pattern that is similar to the original estimates.

Graphs A through D of Figure B.3 show that the results are not sensitive to model specification. Even with drastically different levels of fixed effects, the results remain similar, which is reassuring about the validity of the approach taken in the main text.

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<sup>1</sup>The results are similar if I do not make these restrictions.



As another way to assess the validity of the main specification, I next focus on settings where extreme temperatures would be expected to have smaller effects or no effect at all on occupational health and verify that the empirical strategy indeed finds smaller effects of temperature in these settings. Graph E of Figure B.3 shows baseline estimates of the effect of a day's temperature on same-day claim rates from a specification that controls for day fixed effects, year-month-MSA fixed effects, precipitation indicator variables, and the precipitation and temperature during the two days before and two days after the day of observation.<sup>2</sup>

As with all the specifications in the main analysis, the regression underlying graph E excludes weekends since less work is done on weekends, meaning that the effects of temperature on occupational health during weekends would be expected to be considerably lower than its effects during the week. As a credibility test of the main specification, I next estimate the effect of a weekend day's temperature on that day's claim rates by restricting the sample to include only weekends. These effects being larger than or similar in size to the estimated effects of temperature on weekdays would raise concerns about the ability of Equation (1) to isolate the effect of a day's temperature. The estimated effects of temperature on same-day claim rates for weekends are shown in graph F of Figure B.3. As would be expected, the estimates are much smaller than the estimated effects of temperature on weekdays.

Graphs G through J of Figure B.3 display estimates of the effect of future temperatures on previous days' same-day claim rates. Future temperatures have the potential to affect the current day's claims if people are forward looking and do more work or do more dangerous work on the current day if the weather during the next few days is predicted to be extreme. Still, large effects of future weather could also raise concerns that Equation (1) does not isolate the effects a given day's temperature. In graphs G through J, the sample is again restricted to weekdays. Graphs G and H report coefficients on the next day's temperature bins, while graphs I and J report coefficients on the temperature bins two days after the day of observation. To account for the fact that future days' high temperatures may be correlated with the current day's low temperatures, the specifications in graphs H and J include controls for low temperatures for the

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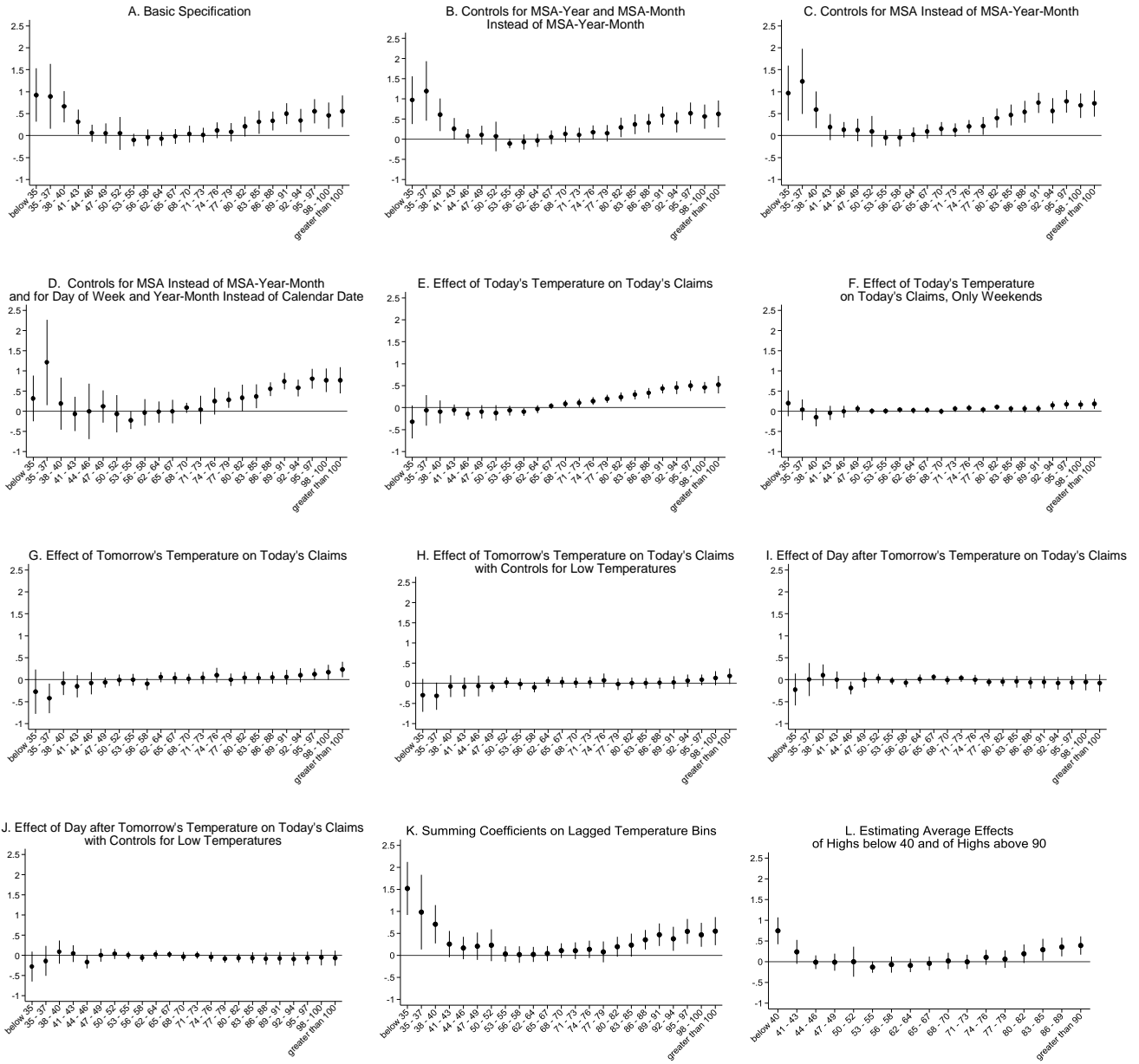
<sup>2</sup>These estimates are equivalent to graph A of Figure 2 without as many weather leads and lags.

day of the observation as well as for the surrounding days. Overall, the coefficients on future high temperatures are small and are mostly statistically insignificant, which is reassuring that Equation (1) isolates the effect of the current day's temperature.

An alternative to estimating the impact of a day's temperature on three-day claim rates is to sum the lagged temperature indicator variables when the dependent variable is the daily claim rates to obtain estimates of the full impact of temperature. An example of a study adopting this approach is Barreca et al. (2016), who use monthly data and sum the effect of the current month's estimated effect of temperature on monthly mortality and the lagged month's estimated effect of temperature on monthly mortality to obtain the full effect of temperature on mortality. Graph K shows estimates of the effect of temperature on claim rates obtained from estimating the impact of temperature on daily claim rates with temperature lags and then summing the effect of today's temperature on today's claim rates, the effect of yesterday's temperature on today's claim rates, and the effect of the day before yesterday's temperature on today's claim rates. The estimated effect of a day with a high below 35°F rises, but the estimates are generally similar to the main estimates.

Finally, estimates of the effect of a day's high temperature being above 90°F and of the effect of day's high temperature being below 40°F are necessary for the back-of-the-envelope cost calculation in Section 4.2. To obtain these estimates, I set the highest temperature bin equal to one for days with highs of at least 90°F and the lowest temperature bin equal to one for days with highs below 40°F. I set the second highest temperature bin equal to one for days with highs of 86°F to 89°F so that the reference group is still days with high temperatures of 59°F to 61°F. As with the main analysis, I set the dependent variable to be three-day claim rates. The results are shown in graph L of Figure B.3. The estimates imply that each day with a high below 40°F increases three-day claim rates by 0.746 per 100,000 workers and that each day with a high above 90°F increases three-day claim rates by 0.391 per 100,000 workers.

Figure B.3: Alternative Specifications of the Effect of Temperature on Claim Rates per 100,000 Workers



Notes: Each graph displays coefficient estimates from a single regression of Equation (1) along with 95-percent confidence intervals calculated using standard errors clustered at the MSA level. The sample size for each regression is as follows: A-C, E, and G-L: 154,968; D: 144,804; F: 61,974. The underlying claim data come from 2006 to 2014 Texas WC claims and contain information on 1,916,590 claims. In graphs A through D and L, the dependent variable is three-day claim rates. In graphs E through K, the dependent variable is same-day claim rates. The baseline specification controls for day fixed effects, year-month-MSA fixed effects, precipitation indicator variables, and high temperature and precipitation indicator variables for the previous two days and subsequent two days. Alterations to the baseline specification are described in the text. The mean of the D.V. at the omitted category for each graph is as follows: A-C: 15.8; D: 17.1; E: 6.2; F: 1.1; G: 6.2; H: 6.2; I: 6.3; J: 6.3; K: 6.2; L: 15.8. Each regression is weighted by the MSA's employment during the month of the observation from LAUS data.

### B.3 Aggregating Data to the Annual Level

Economics research on the effect of temperature on mortality often aggregates temperature and mortality information to the annual level and then estimates fixed effects models using data with a long panel of years. With mortality, conducting the analysis at the annual level has an advantage over conducting the analysis at the daily level in that the annual approach estimates the effect of temperature on mortality rates net of any near-term displacement effects. As older and sicker people are most susceptible to dying from temperature shocks, netting out near-term displacement allows mortality studies to focus on deaths that would not have occurred soon absent the temperature shock. Compared to mortality analysis at the annual level, analysis of mortality with daily data would have to be much more careful in considering the time profile of the effects. With occupational health, analysis with annual data would still have an advantage over analysis with daily data in terms of potentially capturing more claims. As explained in the main text, the baseline specification does not capture effects of temperature on occupational health issues that take years to develop or on occupational health issues that are not treated until after three days have passed since they occurred.

Despite the advantages of annual data, daily data also have advantages over more aggregated data. As Deschenes (2014) explains, daily data allow for a more detailed characterization of the effect of temperature than annual data do. Aggregating to the annual level also has a complication with occupational health in that year-to-year temperature fluctuations may affect economic conditions, which means that temperature has the potential to affect occupational injuries indirectly through its effect on employment. As the goal of this study is to consider the effect of temperature on workers facing the same economic conditions, daily data are useful because they allow for estimating models that hold economic conditions fixed. Perhaps most importantly, daily data can also help with precision, which is especially useful for outcomes that have not been reasonably well-documented across the country for decades, as is the case with mortality.

As Figure 2 of the main text shows, the effect of temperature appears to be realized soon

after the day of observation, so aggregating temperature and WC claim information to the annual level has the potential to introduce noise into the estimation. To consider the feasibility of conducting the Texas WC analysis at the annual level, I aggregate the Texas WC data to the annual level and then estimate models of the following form:

$$y_{jt} = \delta_t + \gamma_j + \alpha * precipitation_{jt} + \beta * temperature_{jt} + \epsilon_{jt}, \quad (3)$$

where  $j$  indexes the MSA,  $t$  indexes the year,  $y$  is the annual rate of claims per 100,000 workers, *precipitation* is the number of days in the year with precipitation in each precipitation bin, and *temperature* is the number of days in the year with high temperatures in each temperature bin. I use the same bins and omitted category as with the CPS analysis, so the coefficient on a given temperature bin can be interpreted as the effect of an additional day with a temperature in that bin relative to an additional day in the 50s.

Each regression with the annual data has 594 observations. Figure B.4 displays *temperature* coefficients from separate regressions of Equation (3). In graph A, the dependent variable is the annual claim rate per 100,000 workers. The estimated effects of temperature shown in graph A of Figure B.4 are all statistically insignificant and have wide confidence intervals. The 95-percent confidence interval for the effect of an additional day with a high above 90°F is -2.7 to 2.9 claims per 100,000 workers, while the 95-percent confidence interval for the effect of an additional day with a high below 40°F is -5.0 to 4.1 claims per 100,000 workers. Thus, these estimates cannot come close to ruling out meaningful effect sizes, including the effect sizes documented in the main analysis.

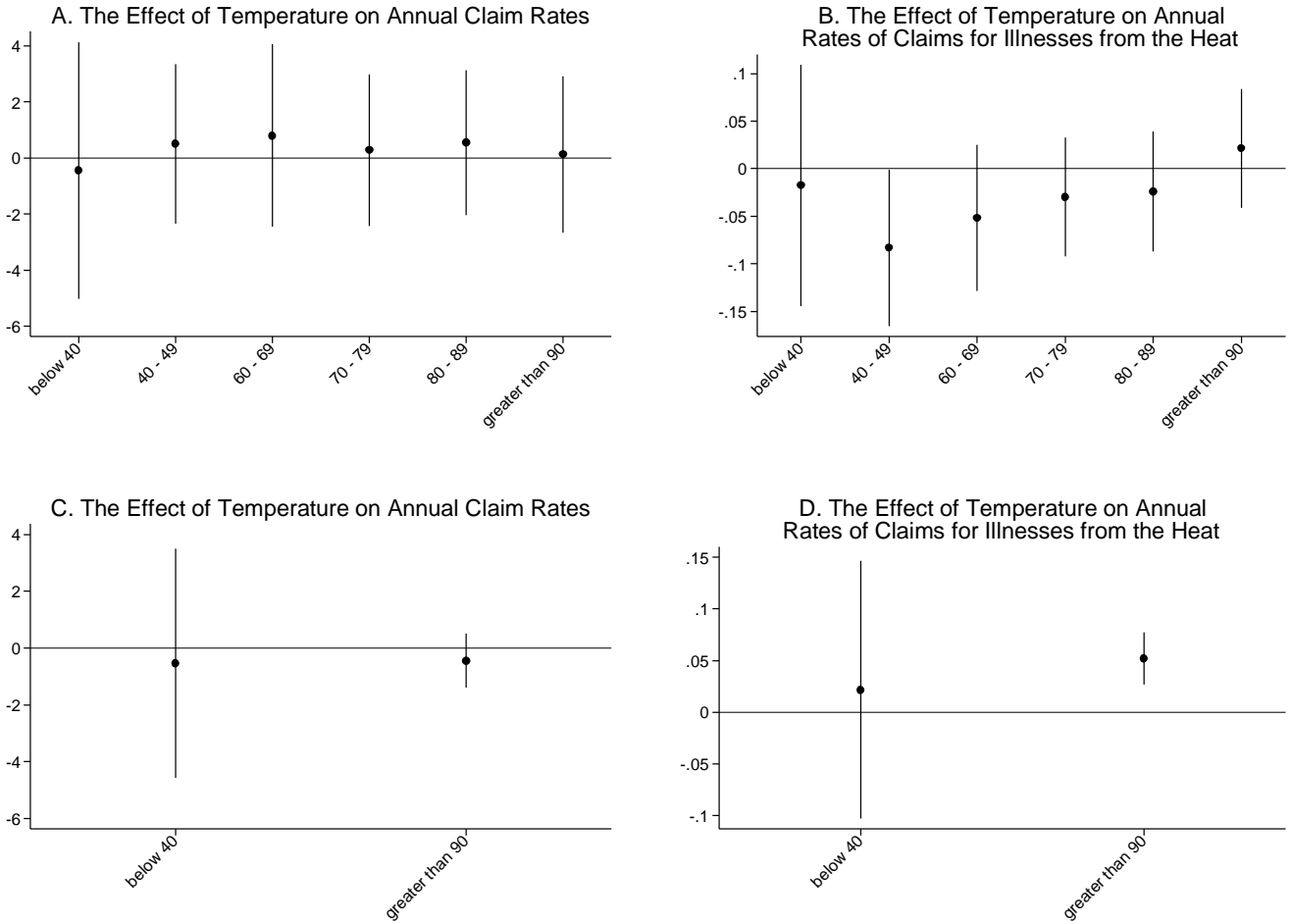
Graph B focuses solely on the effect of temperature on rates of claims for illnesses arising from the heat, as these types of claims would likely be easier to tie to temperature. Even with this outcome, though, Equation (3) can neither identify nor rule out meaningful effects of temperature. Graphs C and D broaden the size of the reference group by replacing the *temperature* vector in Equation (3) with only two variables, one equal to the number of days in the year with highs below 40°F and another equal to the number of days in the year with

highs above 90°F. With claim rates as the dependent variable, the coefficients on the two temperature variables are still imprecise and can neither identify nor rule out meaningful effects of temperature. With rates of claims for illnesses arising from the heat as the dependent variable, the point estimate of the effect of a day with a high above 90°F is now statistically significant and indicates that each additional day with a high above 90°F increases the annual rate of claims for illnesses arising from the heat by 0.05 per 100,000 workers, which is in line with the estimates from the daily analysis.

Other levels of aggregation in between annual and daily levels are also possible. For example, the data could be aggregated to the semiannual, year-month, or week level. As would be expected, the analysis becomes more precise as the level of aggregation becomes finer. However, the estimates are still generally too imprecise for meaningful analysis even at the year-month level.

This analysis in this appendix highlights the advantage of using daily data to study the occupational health effects of temperature. To the best of my knowledge, no data set exists with high quality occupational health measures, narrowly identifiable geographies, a long time series, and wide geographic coverage. As such, daily data enables analysis that would not otherwise be possible.

Figure B.4: The Effect of Temperature on Annual Claim Rates per 100,000 Workers, Analysis at the Annual Level



Notes: Each graph displays coefficient estimates from a single regression of Equation (3) along with 95-percent confidence intervals calculated using standard errors clustered at the MSA level. The sample includes 594 MSA-years. The underlying claim data come from 2006 to 2014 Texas WC claims. The underlying number of claims for each regression is as follows: A and C: 1,916,590; B and D: 6,760. All regressions control for MSA fixed effects, year fixed effects, and the number of days in the year with precipitation in each precipitation bin. The mean of the D.V. for each graph is as follows: A and C: 1,977; B and D: 7.0. Each regression is weighted by the number of workers in an MSA during the year of the observation from LAUS data.

## B.4 Heterogeneity by Age

Previous research has found that elderly people and young children are most susceptible to the effects of temperature. If the effects of high temperatures are driven solely by older workers, then a possible avenue for adaptation to climate change would be for workers to shift out of temperature-exposed jobs as they age. But younger workers being sensitive to high temperatures too suggests fewer options in terms of shifting younger workers to temperature-exposed jobs. I now test for differential effects of temperature based on age.

As the LAUS employment data do not contain separate MSA-level employment estimates by age, I use employment information from the ACS to compute the claim rates and weights. Because of confidentiality concerns, the ACS does not provide identifiers for small areas, so only 28 MSAs are included in the analysis.<sup>3</sup> Graph A of Figure B.5 considers how the results from using information available in the ACS compare to the baseline results when not accounting for age. The coefficients presented in graph A follow a similar pattern as the baseline results presented in Figure 3 and indicate that using information from the ACS does not drastically alter the results.

Graph B shows estimates separately for workers ages 18 to 40, while graph C shows estimates separately for workers ages 41 to 64. The estimated effects of cold temperatures appear to be larger for older workers than for younger workers, while the effects of high temperatures appear to be similar for both age groups. Graph D shows estimates of the differential effects of temperature on older workers from a single regression and confirms that the effects of cold temperatures are statistically significantly larger for older workers than for younger workers.<sup>4</sup> High temperatures appear to have similar adverse effects on both age groups.

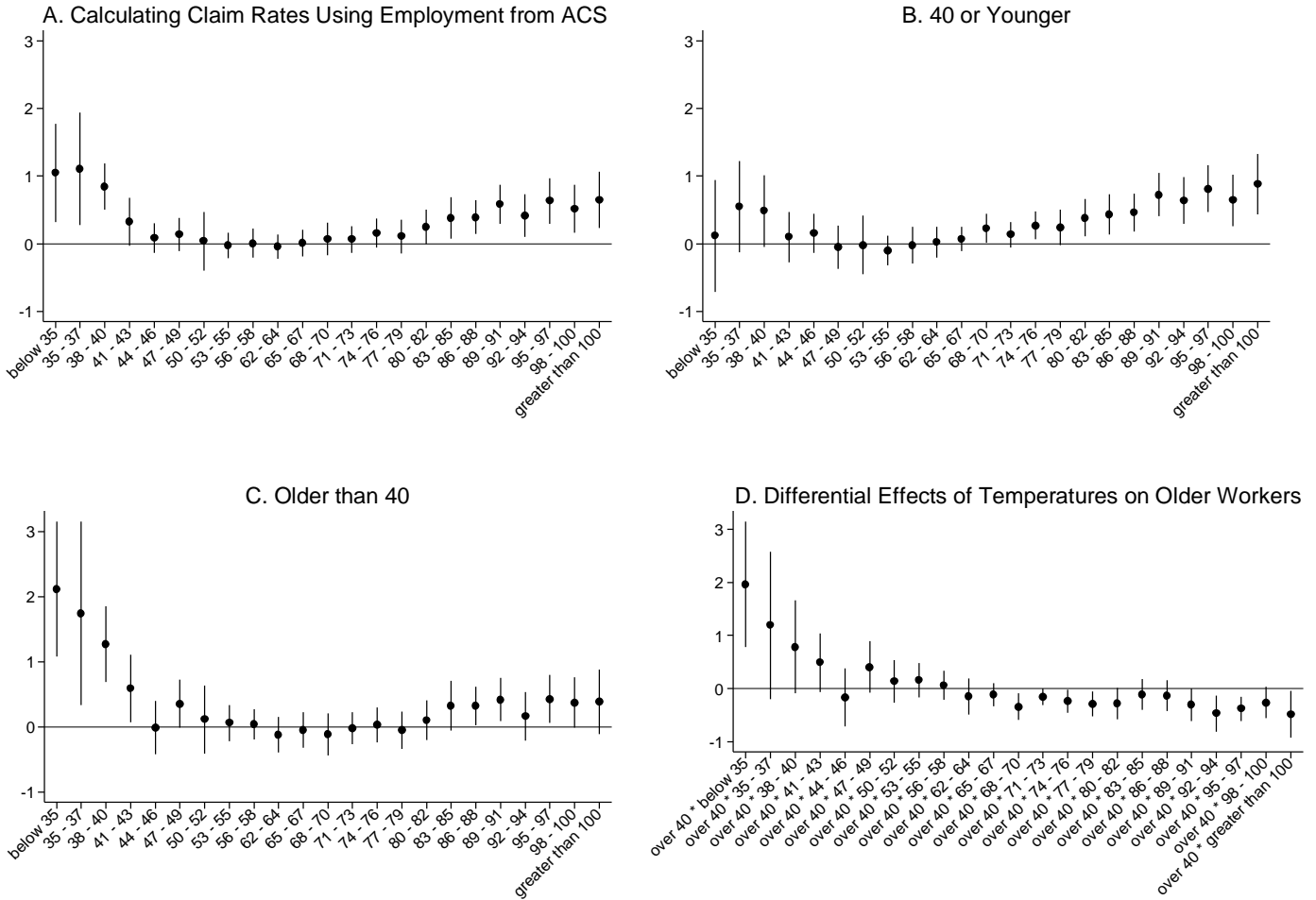
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<sup>3</sup>I assign people to MSAs using the ACS's Public Use Micro Areas (PUMAs) variable. I obtain the crosswalk from PUMAs to MSAs from the Missouri Census Data Center. As the ACS does not include the month of the observation, all employment estimates are at the year level, meaning that the MSA-year-month fixed effects now absorb variation in employment across months within a year.

<sup>4</sup>To obtain the estimates in graph D, I create a sample with two observations for each MSA and day combination, one that includes claim rates and employment for older individuals and another that includes claim rates and employment for younger individuals. I include the daily high temperatures as controls and allow older and younger age groups to have different day and year-month-MSA fixed effects, as well as different effects from the surrounding weather.



Figure B.5: The Effect of Temperature on Three-Day Claim Rates per 100,000 Workers, Heterogeneity by Age

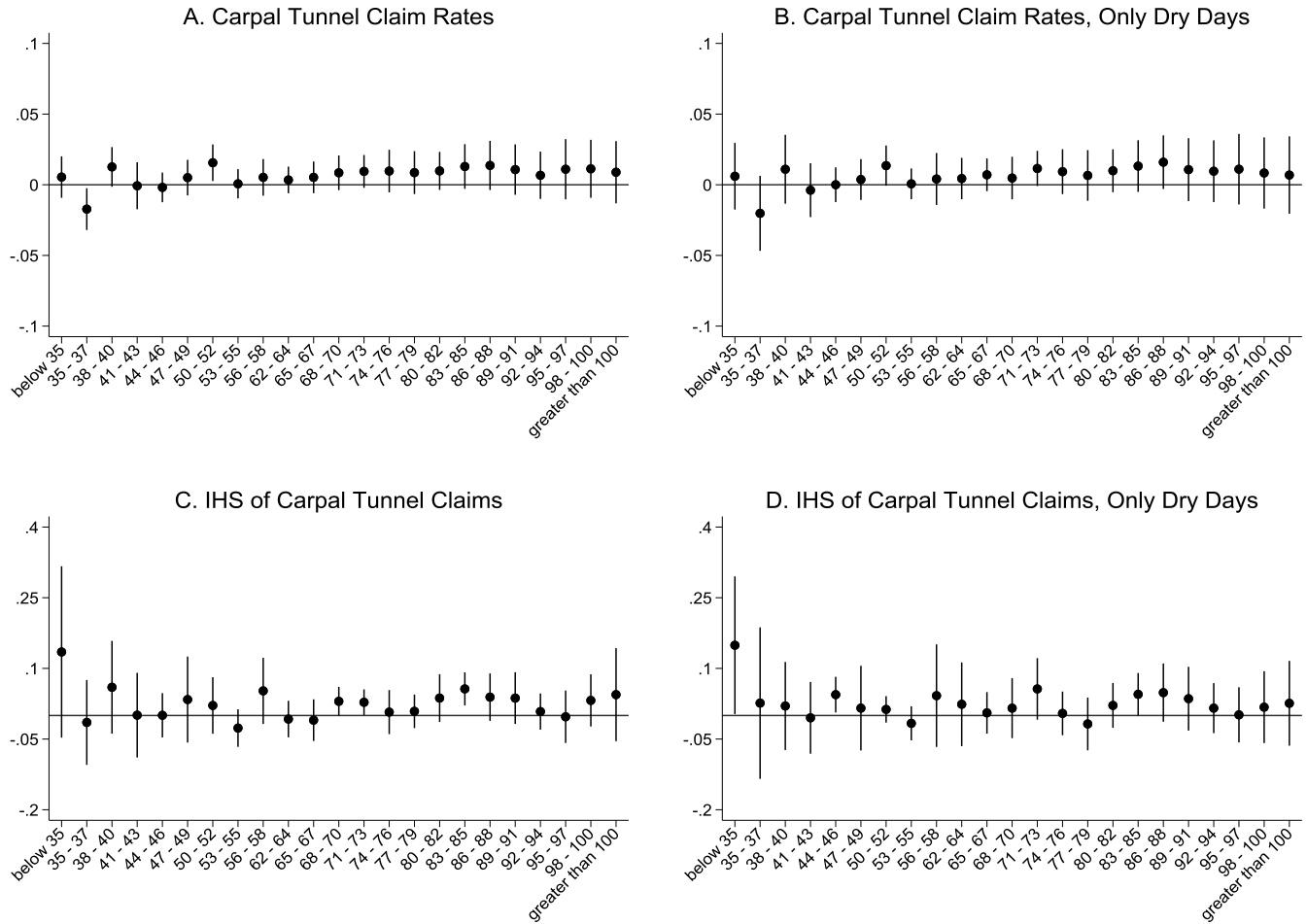


Notes: Each graph displays coefficient estimates from a single regression of Equation (1) along with 95-percent confidence intervals calculated using standard errors clustered at the MSA level. The sample size for each regression is as follows: A through C: 62,614; D: 125,228. The underlying claim data come from 2006 to 2014 Texas WC claims. The underlying number of claims for each regression is as follows: A and D: 1,808,773; B: 936,486; C: 872,287. All regressions control for day fixed effects, year-month-MSA fixed effects, precipitation indicator variables, and high temperature and precipitation indicator variables for the previous two days and subsequent two days. The regression for graph D also controls for interactions of being an observation from the over-40 sample. The mean of three-day claim rates at 59°F to 61°F for each graph is as follows: A and D: 16.2; B: 15.4; C: 17.3. Each regression is weighted by the number of workers in age group in an MSA during the year of the observation estimated from ACS data.

## B.5 Carpal Tunnel Syndrome Claims

Figure B.6 shows estimates of the effect of temperature on three-day claim rates for carpal tunnel syndrome. Since carpal tunnel syndrome develops over an extended period of time, the empirical strategy indicating that a day's temperature affects claims for carpal tunnel syndrome would raise doubts about the validity of the empirical strategy and may suggest that temperature merely affects the timing of reporting of injuries without actually affecting occupational health. But regardless of whether the analysis focuses on all days or just on days without precipitation, the results shown in Figure B.6 do not suggest that temperature extremes are associated with changes in the reporting of carpal tunnel syndrome. The lack of a relationship holds when the three-day claim rate per 100,000 workers is the dependent variable and when the IHS of three-day claim counts is the dependent variable.

Figure B.6: The Effect of Temperature on Three-Day Carpal Tunnel Syndrome Claims per 100,000 Workers



Notes: Each graph displays coefficient estimates from a single regression of Equation (1) along with 95-percent confidence intervals calculated using standard errors clustered at the MSA level. The sample includes 154,968 MSA-days and 124,964 MSA-days without precipitation. The underlying claim data come from 2006 to 2014 Texas WC claims and contain information on 8,903 carpal tunnel claims. All regressions control for day fixed effects, year-month-MSA fixed effects, precipitation indicator variables, and high temperature and precipitation indicator variables for the previous two days and subsequent two days. The mean three-day carpal tunnel claim rate per 100,000 workers at 59°F to 61°F is 0.1. Each regression is weighted by the MSA’s employment during the month of the observation from LAUS data.

# C Appendix: Estimates Corresponding to Figures

Table C.1: Estimates from Figure 2, Graphs A through F

Dependent variable: daily claims per 100,000 workers relative to day temperature observed	Day of temperature		Day after day of temperature		Two days after day of temperature	
below 35	-0.302 (0.192)	-0.085 (0.246)	0.921*** (0.168)	0.913*** (0.195)	0.337** (0.164)	0.231 (0.197)
35 - 37	-0.101 (0.195)	0.179 (0.269)	0.562*** (0.211)	0.529** (0.230)	0.406** (0.154)	0.237 (0.163)
38 - 40	-0.130 (0.116)	-0.183 (0.154)	0.567*** (0.118)	0.534*** (0.182)	0.158** (0.078)	0.012 (0.112)
41 - 43	-0.091 (0.077)	0.018 (0.094)	0.232** (0.094)	0.320*** (0.113)	0.052 (0.059)	0.011 (0.106)
44 - 46	-0.150** (0.069)	-0.094 (0.103)	0.105 (0.069)	0.141 (0.090)	0.083 (0.055)	0.002 (0.081)
47 - 49	-0.142* (0.080)	-0.073 (0.090)	0.124* (0.064)	0.141* (0.080)	0.032 (0.045)	0.066 (0.069)
50 - 52	-0.111 (0.092)	0.046 (0.094)	0.120 (0.081)	0.183** (0.077)	0.071 (0.063)	0.130* (0.067)
53 - 55	-0.060 (0.052)	0.005 (0.054)	-0.021 (0.067)	-0.013 (0.046)	-0.018 (0.050)	0.008 (0.065)
56 - 58	-0.103** (0.049)	-0.076 (0.062)	0.016 (0.059)	0.000 (0.056)	0.046 (0.038)	0.060 (0.042)
62 - 64	-0.029 (0.050)	-0.016 (0.052)	-0.043 (0.051)	-0.041 (0.041)	0.005 (0.046)	0.049 (0.048)
65 - 67	0.049 (0.032)	0.064 (0.044)	-0.017 (0.052)	0.016 (0.047)	-0.039 (0.041)	-0.009 (0.048)
68 - 70	0.094** (0.035)	0.087** (0.037)	-0.042 (0.049)	-0.010 (0.047)	-0.019 (0.060)	0.009 (0.055)
71 - 73	0.107** (0.048)	0.052 (0.051)	-0.079* (0.045)	-0.027 (0.059)	-0.001 (0.052)	0.060 (0.065)
74 - 76	0.139*** (0.045)	0.108** (0.054)	0.005 (0.058)	0.054 (0.048)	-0.018 (0.045)	0.037 (0.049)
77 - 79	0.195*** (0.048)	0.196*** (0.056)	-0.058 (0.055)	0.011 (0.063)	-0.062 (0.055)	-0.015 (0.056)
80 - 82	0.230*** (0.054)	0.234*** (0.074)	-0.031 (0.068)	0.050 (0.060)	0.005 (0.063)	0.074 (0.069)
83 - 85	0.277*** (0.057)	0.286*** (0.069)	-0.034 (0.074)	0.057 (0.065)	0.040 (0.064)	0.083 (0.075)
86 - 88	0.309*** (0.057)	0.329*** (0.067)	0.023 (0.057)	0.093 (0.061)	-0.004 (0.075)	0.072 (0.081)
89 - 91	0.414*** (0.049)	0.489*** (0.073)	0.035 (0.065)	0.079 (0.072)	0.032 (0.072)	0.120 (0.083)
92 - 94	0.429*** (0.072)	0.458*** (0.106)	-0.073 (0.075)	-0.037 (0.087)	-0.033 (0.078)	-0.006 (0.093)
95 - 97	0.477*** (0.063)	0.473*** (0.105)	0.016 (0.087)	0.061 (0.088)	0.047 (0.075)	0.062 (0.087)
98 - 100	0.426*** (0.065)	0.411*** (0.100)	0.014 (0.096)	0.032 (0.107)	-0.005 (0.086)	0.021 (0.101)
greater than 100	0.507*** (0.105)	0.484*** (0.140)	0.050 (0.111)	0.088 (0.134)	-0.029 (0.075)	0.046 (0.090)
Corresponding graph	A	B	C	D	E	F
Unit of observation	MSA-day	MSA-day	MSA-day	MSA-day	MSA-day	MSA-day
Number of MSAs	66	66	66	66	66	66
n	154,968	124,964	154,968	124,964	154,968	124,964
Fixed effects	yr-mth-MSA	yr-mth-MSA	yr-mth-MSA	yr-mth-MSA	yr-mth-MSA	yr-mth-MSA
	day	day	day	day	day	day
Mean of D.V. at 59°F to 61°F	6.2	5.2	5.4	5.4	4.3	4.4

Notes: Each column displays coefficient estimates from a single regression of Equation (1). Standard errors are clustered at the MSA level and are shown in parentheses below the estimates. The underlying claim data come from 2006 to 2014 Texas WC claims and contain information on 1,916,590 claims. All regressions control for day fixed effects, year-month-MSA fixed effects, precipitation indicator variables, and high temperature and precipitation indicator variables for each of the previous five days and subsequent four days. The sample in columns B, D, and F includes only days without precipitation, and thus the regressions do not include controls for the precipitation on the day of observation. Each regression is weighted by the MSA's employment during the month of the observation from LAUS data.

Table C.2: Estimates from Figure 2, Graphs G through I

Dependent variable: daily claims per 100,000 workers relative to day temperature observed	Three days after day of temperature		Four days after day of temperature	
below 35	0.192 (0.149)	-0.008 (0.174)	0.163 (0.145)	0.106 (0.157)
35 - 37	-0.012 (0.119)	-0.318** (0.153)	0.097 (0.116)	0.074 (0.154)
38 - 40	0.109 (0.114)	-0.028 (0.143)	-0.016 (0.136)	-0.091 (0.155)
41 - 43	-0.011 (0.092)	0.090 (0.130)	-0.008 (0.083)	-0.157 (0.113)
44 - 46	-0.132* (0.075)	-0.200* (0.102)	0.040 (0.059)	-0.028 (0.117)
47 - 49	-0.062 (0.080)	-0.099 (0.082)	-0.023 (0.071)	-0.039 (0.080)
50 - 52	-0.073 (0.078)	-0.130 (0.097)	0.050 (0.070)	-0.010 (0.080)
53 - 55	0.048 (0.048)	-0.003 (0.060)	0.120** (0.060)	0.112* (0.067)
56 - 58	-0.068 (0.061)	-0.083 (0.063)	-0.078* (0.045)	-0.087* (0.050)
62 - 64	-0.048 (0.053)	-0.069 (0.069)	-0.026 (0.031)	-0.073 (0.044)
65 - 67	-0.035 (0.066)	-0.065 (0.072)	-0.033 (0.044)	-0.043 (0.062)
68 - 70	-0.016 (0.062)	-0.039 (0.071)	-0.032 (0.036)	-0.066 (0.049)
71 - 73	0.020 (0.063)	-0.008 (0.075)	-0.028 (0.047)	-0.057 (0.055)
74 - 76	0.026 (0.072)	-0.005 (0.097)	-0.079* (0.044)	-0.089 (0.059)
77 - 79	0.011 (0.067)	-0.026 (0.089)	-0.083** (0.038)	-0.099* (0.057)
80 - 82	0.067 (0.077)	0.008 (0.098)	-0.094 (0.057)	-0.167** (0.071)
83 - 85	0.065 (0.075)	-0.000 (0.096)	-0.088* (0.050)	-0.155*** (0.052)
86 - 88	0.021 (0.077)	-0.040 (0.091)	-0.089 (0.066)	-0.133* (0.078)
89 - 91	0.052 (0.082)	0.039 (0.098)	-0.032 (0.058)	-0.120* (0.071)
92 - 94	0.069 (0.085)	0.019 (0.110)	-0.054 (0.074)	-0.116 (0.086)
95 - 97	0.050 (0.086)	-0.006 (0.113)	-0.082 (0.067)	-0.154** (0.072)
98 - 100	0.032 (0.098)	0.010 (0.118)	-0.078 (0.063)	-0.160** (0.070)
greater than 100	-0.014 (0.093)	-0.043 (0.115)	0.059 (0.078)	-0.016 (0.088)
Corresponding graph	G	H	I	J
Unit of observation	MSA-day	MSA-day	MSA-day	MSA-day
Number of MSAs	66	66	66	66
n	154,968	124,964	154,968	124,964
Fixed effects	yr-mth-MSA	yr-mth-MSA	yr-mth-MSA	yr-mth-MSA
Mean of D.V. at 59°F to 61°F	day	day	day	day
	4.2	4.2	4.5	4.5

Notes: Each column displays coefficient estimates from a single regression of Equation (1). Standard errors are clustered at the MSA level and are shown in parentheses below the estimates. The underlying claim data come from 2006 to 2014 Texas WC claims and contain information on 1,916,590 claims. All regressions control for day fixed effects, year-month-MSA fixed effects, precipitation indicator variables, and high temperature and precipitation indicator variables for each of the previous five days and subsequent four days. The sample in columns H and J includes only days without precipitation, and thus the regressions do not include controls for the precipitation on the day of observation. Each regression is weighted by the MSA's employment during the month of the observation from LAUS data.

Table C.3: Estimates from Figure 3, Graphs A - C and F - H

Dependent variable	Three-day claims per 100,000 workers	IHS(Three-day claim counts)	Three-day claims per 100,000 workers	Three-day claims per 100,000 workers	Three-day claims per 100,000 workers	Three-day claims per 100,000 workers
below 35	0.922*** (0.305)	0.034* (0.018)	0.327 (0.390)	-0.311 (0.742)	0.334 (0.540)	0.293 (0.672)
35 - 37	0.892** (0.370)	0.036* (0.021)	0.552 (0.341)	-1.128 (0.867)	-0.023 (0.608)	-0.429 (0.823)
38 - 40	0.657*** (0.178)	0.032*** (0.011)	0.491*** (0.159)	-0.160 (0.501)	0.599* (0.335)	0.731 (0.518)
41 - 43	0.311** (0.142)	0.022*** (0.008)	0.199* (0.114)	-0.395 (0.403)	0.156 (0.340)	-0.656 (0.421)
44 - 46	0.053 (0.097)	0.006 (0.007)	-0.058 (0.109)	0.257 (0.465)	0.544 (0.342)	
47 - 49	0.045 (0.115)	0.003 (0.008)	0.025 (0.100)	-0.099 (0.295)	0.083 (0.240)	
50 - 52	0.046 (0.188)	0.003 (0.007)	0.031 (0.167)	-0.884** (0.373)	-0.116 (0.305)	
53 - 55	-0.102 (0.072)	-0.002 (0.004)	-0.117 (0.072)	-0.522 (0.318)	-0.010 (0.183)	
56 - 58	-0.046 (0.095)	-0.005 (0.007)	-0.039 (0.095)	-0.016 (0.253)	-0.068 (0.196)	
62 - 64	-0.072 (0.081)	0.002 (0.004)	-0.051 (0.084)	-0.492** (0.224)	-0.054 (0.142)	
65 - 67	-0.024 (0.084)	0.002 (0.005)	-0.012 (0.083)	-0.205 (0.245)	0.083 (0.199)	
68 - 70	0.034 (0.096)	0.006 (0.003)	0.036 (0.104)	-0.306 (0.276)	-0.329 (0.202)	
71 - 73	0.011 (0.086)	0.007* (0.004)	-0.020 (0.096)	-0.041 (0.288)	-0.021 (0.181)	
74 - 76	0.120 (0.089)	0.011** (0.005)	0.067 (0.096)	-0.085 (0.289)	-0.007 (0.212)	
77 - 79	0.075 (0.104)	0.012** (0.005)	0.016 (0.112)	-0.306 (0.292)	-0.238 (0.237)	
80 - 82	0.206* (0.112)	0.019*** (0.005)	0.138 (0.114)	-0.408 (0.333)	-0.069 (0.247)	
83 - 85	0.306** (0.132)	0.021*** (0.006)	0.218 (0.133)	-0.370 (0.305)	-0.264 (0.282)	
86 - 88	0.333*** (0.108)	0.028*** (0.005)	0.229** (0.105)	-0.349 (0.319)	-0.081 (0.256)	
89 - 91	0.501*** (0.118)	0.032*** (0.005)	0.384*** (0.116)	-0.316 (0.343)	-0.127 (0.286)	
92 - 94	0.342** (0.131)	0.029*** (0.006)	0.224* (0.117)	-0.015 (0.355)	-0.117 (0.307)	0.017 (0.112)
95 - 97	0.553*** (0.139)	0.036*** (0.007)	0.436*** (0.130)	-0.234 (0.397)	-0.202 (0.306)	-0.265* (0.136)
98 - 100	0.454*** (0.150)	0.029*** (0.007)	0.325** (0.138)	0.255 (0.438)	-0.121 (0.357)	-0.327* (0.185)
greater than 100	0.553*** (0.180)	0.037*** (0.008)	0.421** (0.174)	0.669 (0.640)	-0.153 (0.350)	-0.436 (0.290)
Corresponding graph	A	B	C	F	G	H
Unit of observation	MSA-day	MSA-day	MSA-day	MSA-day	MSA-day	MSA-day
Number of MSAs	66	66	66	66	66	66
n	154,968	154,968	154,968	154,968	154,968	154,968
Fixed effects	yr-mth-MSA day	yr-mth-MSA day	yr-mth-MSA day	yr-mth-MSA day	yr-mth-MSA day	yr-mth-MSA day
Mean of D.V. at 59°F to 61°F	15.8	3.3	15.8	15.8	15.8	15.8

Notes: Each column displays coefficient estimates from a single regression of Equation (1). Standard errors are clustered at the MSA level and are shown in parentheses below the estimates. The underlying claim data come from 2006 to 2014 Texas WC claims and contain information on 1,916,590 claims. All regressions control for day fixed effects, year-month-MSA fixed effects, precipitation indicator variables, and high temperature and precipitation indicator variables for the previous two days and subsequent two days. The regression in column C also includes controls for low temperatures for the day of observation and for the previous two days and subsequent two days. The regression in column F also includes interactions of the weather controls, of the day fixed effects, and of the year-month-MSA fixed effects with a rainy day indicator. The regression in column G also includes interactions of the weather controls and of the day fixed effects with an indicator for being in a humid climate. Column F displays the coefficients on the rainy day indicator interacted with the temperature bins. Column G displays the coefficients on the indicator for being in a humid climate interacted with the temperature bins. Column H displays the coefficients on fall and spring indicator variables interacted with the temperature bins. Each regression is weighted by the MSA's employment during the month of the observation from LAUS data.

Table C.4: Estimates from Figure 3, Graphs D and E

Dependent variable for each specification: Three-day claims per 100,000 workers		
below 14	1.536*** (0.532)	-0.070 (0.422)
14 - 16	0.874** (0.367)	0.324 (0.333)
17 - 19	0.722 (0.466)	0.189 (0.336)
20 - 22	-0.181 (0.261)	-0.332 (0.266)
23 - 25	0.164 (0.155)	-0.077 (0.153)
26 - 28	-0.139 (0.199)	-0.276 (0.177)
29 - 31	-0.096 (0.101)	-0.154 (0.107)
32 - 34	-0.152 (0.111)	-0.195** (0.095)
35 - 37	-0.191** (0.084)	-0.198** (0.081)
38 - 40	-0.146* (0.074)	-0.145* (0.074)
41 - 43	-0.300*** (0.068)	-0.285*** (0.074)
44 - 46	-0.224*** (0.075)	-0.229*** (0.086)
47 - 49	-0.199*** (0.062)	-0.195*** (0.062)
53 - 55	-0.047 (0.087)	-0.041 (0.082)
56 - 58	-0.102* (0.056)	-0.117** (0.053)
59 - 61	-0.049 (0.093)	-0.080 (0.083)
62 - 64	-0.011 (0.094)	-0.054 (0.086)
65 - 67	0.164* (0.090)	0.108 (0.081)
68 - 70	0.136 (0.104)	0.062 (0.107)
71 - 73	0.225* (0.126)	0.143 (0.125)
74 - 76	0.129 (0.132)	0.032 (0.135)
greater than 76	0.082 (0.172)	-0.021 (0.170)
Corresponding graph	D	E
Unit of observation	MSA-day	MSA-day
Number of MSAs	66	66
n	154,968	154,968
Fixed effects	yr-mth-MSA day	yr-mth-MSA day
Mean of D.V. at 59°F to 61°F	15.8	15.8

Notes: Each column displays coefficient estimates on bins for low temperatures from a single regression of Equation (1). Standard errors are clustered at the MSA level and are shown in parentheses below the estimates. The underlying claim data come from 2006 to 2014 Texas WC claims and contain information on 1,916,590 claims. All regressions control for day fixed effects, year-month-MSA fixed effects, precipitation indicator variables, and low temperature and precipitation indicator variables for the previous two days and subsequent two days. The regression in column D also includes controls for high temperatures on the day of observation and for the previous two days and subsequent two days. Each regression is weighted by the MSA's employment during the month of the observation from LAUS data.

Table C.5: Estimates from Figure 4

Dependent variable: claim type per 100,000 workers	Illnesses from the heat	Injuries	Open wounds, crushing injuries, and fractures	Sprains, strains, bruises, and muscle-related issues
below 35	-0.000 (0.003)	0.996*** (0.283)	0.082 (0.091)	0.999*** (0.237)
35 - 37	0.004* (0.002)	0.892** (0.389)	0.103 (0.117)	0.853** (0.376)
38 - 40	-0.003 (0.003)	0.676*** (0.204)	0.147** (0.059)	0.571** (0.223)
41 - 43	-0.000 (0.002)	0.323** (0.144)	-0.028 (0.052)	0.342*** (0.112)
44 - 46	-0.000 (0.001)	0.059 (0.110)	-0.024 (0.048)	0.077 (0.105)
47 - 49	-0.000 (0.002)	0.079 (0.115)	-0.041 (0.053)	0.159* (0.094)
50 - 52	0.001 (0.001)	-0.010 (0.173)	0.028 (0.045)	0.006 (0.152)
53 - 55	0.002 (0.001)	-0.097 (0.067)	-0.024 (0.033)	-0.025 (0.075)
56 - 58	0.001* (0.001)	-0.039 (0.084)	0.013 (0.036)	-0.043 (0.064)
62 - 64	0.001 (0.001)	-0.074 (0.082)	0.047 (0.033)	-0.071 (0.073)
65 - 67	0.001 (0.001)	-0.027 (0.077)	0.036 (0.029)	-0.047 (0.069)
68 - 70	0.002 (0.002)	0.041 (0.085)	0.026 (0.030)	-0.005 (0.069)
71 - 73	-0.002 (0.001)	0.018 (0.088)	0.015 (0.035)	-0.007 (0.074)
74 - 76	0.003* (0.002)	0.107 (0.081)	0.057* (0.030)	0.044 (0.065)
77 - 79	0.003* (0.002)	0.082 (0.095)	0.054* (0.030)	0.027 (0.086)
80 - 82	0.002 (0.002)	0.197* (0.101)	0.100** (0.043)	0.083 (0.090)
83 - 85	0.001 (0.003)	0.305** (0.118)	0.096** (0.040)	0.174 (0.108)
86 - 88	0.006* (0.003)	0.305*** (0.100)	0.144*** (0.047)	0.164* (0.087)
89 - 91	0.009** (0.004)	0.450*** (0.105)	0.153*** (0.036)	0.260*** (0.090)
92 - 94	0.010** (0.005)	0.316** (0.122)	0.164*** (0.048)	0.149 (0.092)
95 - 97	0.026*** (0.006)	0.476*** (0.129)	0.212*** (0.056)	0.229** (0.109)
98 - 100	0.032*** (0.011)	0.363** (0.137)	0.188*** (0.050)	0.133 (0.115)
greater than 100	0.072*** (0.013)	0.425*** (0.156)	0.194*** (0.054)	0.132 (0.137)
Corresponding graph	A	B	C	D
Unit of observation	MSA-day	MSA-day	MSA-day	MSA-day
Number of MSAs	66	66	66	66
n	154,968	154,968	154,968	154,968
Underlying number of claims	6,760	1,749,452	441,553	1,244,996
Fixed effects	yr-mth-MSA day	yr-mth-MSA day	yr-mth-MSA day	yr-mth-MSA day
Mean of D.V. at 59°F to 61°F	0.0	14.6	3.6	10.6

Notes: Each column displays coefficient estimates from a single regression of Equation (1). Standard errors are clustered at the MSA level and are shown in parentheses below the estimates. The underlying claim data come from 2006 to 2014 Texas WC claims. All regressions control for day fixed effects, year-month-MSA fixed effects, precipitation indicator variables, and high temperature and precipitation indicator variables for the previous two days and subsequent two days. Each regression is weighted by the MSA's employment during the month of the observation from LAUS data.



Table C.6: Estimates from Figure 5

Dependent variable: Claim type per 100,000 workers	Continued treatment 3 to 30 days later	Continued treatment 31 to 180 days later	Bottom half of cost distribution	Top half of cost distribution
below 35	0.736*** (0.238)	0.434*** (0.142)	0.260 (0.206)	0.662*** (0.177)
35 - 37	0.747** (0.287)	0.558*** (0.196)	0.219 (0.193)	0.673*** (0.242)
38 - 40	0.525*** (0.177)	0.384*** (0.120)	0.251** (0.097)	0.406*** (0.142)
41 - 43	0.210* (0.108)	0.058 (0.072)	0.182** (0.087)	0.129 (0.099)
44 - 46	0.161* (0.086)	0.074 (0.053)	-0.099 (0.062)	0.152** (0.075)
47 - 49	0.078 (0.071)	0.059 (0.071)	-0.029 (0.075)	0.074 (0.088)
50 - 52	0.058 (0.146)	0.057 (0.083)	0.024 (0.113)	0.023 (0.094)
53 - 55	-0.035 (0.050)	-0.013 (0.038)	-0.083 (0.067)	-0.019 (0.050)
56 - 58	0.048 (0.074)	0.037 (0.040)	-0.017 (0.069)	-0.029 (0.052)
62 - 64	-0.084 (0.061)	-0.105** (0.045)	-0.022 (0.052)	-0.050 (0.055)
65 - 67	0.003 (0.062)	-0.010 (0.054)	-0.026 (0.070)	0.003 (0.053)
68 - 70	0.015 (0.076)	-0.014 (0.058)	0.023 (0.057)	0.011 (0.064)
71 - 73	-0.026 (0.075)	-0.024 (0.059)	0.011 (0.052)	0.000 (0.068)
74 - 76	0.037 (0.079)	0.008 (0.051)	0.091* (0.054)	0.029 (0.060)
77 - 79	0.050 (0.073)	0.014 (0.061)	0.041 (0.068)	0.034 (0.060)
80 - 82	0.112 (0.078)	0.063 (0.061)	0.127* (0.076)	0.079 (0.067)
83 - 85	0.215** (0.103)	0.108 (0.066)	0.215*** (0.079)	0.091 (0.079)
86 - 88	0.201** (0.091)	0.150** (0.068)	0.168** (0.070)	0.165** (0.068)
89 - 91	0.335*** (0.097)	0.183** (0.074)	0.286*** (0.076)	0.215*** (0.072)
92 - 94	0.216* (0.110)	0.129 (0.081)	0.203*** (0.070)	0.139* (0.080)
95 - 97	0.297** (0.119)	0.171* (0.087)	0.346*** (0.093)	0.207** (0.085)
98 - 100	0.252* (0.139)	0.157* (0.085)	0.253** (0.097)	0.202** (0.092)
greater than 100	0.343** (0.147)	0.160* (0.094)	0.349*** (0.121)	0.205** (0.097)
Corresponding graph	A	B	C	D
Unit of observation	MSA-day	MSA-day	MSA-day	MSA-day
Number of MSAs	66	66	66	66
n	154,968	154,968	154,968	154,968
Underlying number of claims	678,621	266,236	958,295	958,295
Fixed effects	yr-mth-MSA day	yr-mth-MSA day	yr-mth-MSA day	yr-mth-MSA day
Mean of D.V. at 59°F to 61°F	11.6	6.2	8.9	8.8

Notes: Each column displays coefficient estimates from a single regression of Equation (1). Standard errors are clustered at the MSA level and are shown in parentheses below the estimates. The underlying claim data come from 2006 to 2014 Texas WC claims. All regressions control for day fixed effects, year-month-MSA fixed effects, precipitation indicator variables, and high temperature and precipitation indicator variables for the previous two days and subsequent two days. Each regression is weighted by the MSA's employment during the month of the observation from LAUS data.

Table C.7: Estimates from Figure 6

Dependent variable for all specifications: Daily injury rate per 100,000 workers								
below 35	-3.401 (5.063)	-3.444 (6.580)	-1.132 (2.738)	-1.471 (3.594)	0.504 (2.081)	-1.366 (2.639)	-3.935 (5.269)	-2.904 (6.857)
35 - 37	-12.855*** (4.247)	-9.801** (4.632)	-0.313 (2.597)	0.952 (3.317)	-0.799 (1.814)	-2.044 (2.300)	-12.706*** (4.463)	-9.676* (4.950)
38 - 40	-2.158 (4.586)	4.078 (5.362)	-0.606 (2.044)	1.528 (2.707)	0.767 (1.636)	1.421 (2.044)	-2.816 (4.729)	2.118 (5.561)
41 - 43	2.140 (4.283)	7.980 (5.524)	-2.249 (2.041)	-1.240 (2.720)	2.072 (1.640)	0.495 (2.048)	1.231 (4.454)	7.632 (5.720)
44 - 46	1.136 (3.331)	3.304 (4.549)	-2.519 (1.842)	-0.100 (2.362)	0.392 (1.501)	0.586 (1.820)	1.595 (3.517)	2.475 (4.746)
47 - 49	1.621 (2.633)	6.010* (3.465)	-0.855 (1.653)	0.638 (2.182)	1.369 (1.387)	1.660 (1.676)	0.846 (2.842)	4.316 (3.700)
50 - 52	-0.218 (1.951)	-0.547 (2.230)	-0.789 (1.441)	1.516 (1.815)	0.375 (1.259)	1.853 (1.596)	-0.320 (2.156)	-2.584 (2.510)
53 - 55	0.603 (2.014)	1.143 (2.395)	-1.199 (1.263)	-1.813 (1.553)	-0.473 (1.218)	-0.223 (1.437)	1.437 (2.191)	2.197 (2.634)
56 - 58	-0.601 (1.605)	-0.181 (1.594)	0.539 (1.399)	0.520 (1.466)	-0.728 (1.334)	-1.825 (1.616)	-0.710 (1.849)	0.139 (1.858)
62 - 64	0.378 (1.397)	0.359 (1.579)	1.748 (1.429)	3.198** (1.503)	-2.449* (1.253)	-2.894* (1.531)	0.329 (1.768)	-0.257 (2.035)
65 - 67	0.736 (1.467)	0.252 (1.755)	0.684 (1.290)	2.181 (1.583)	-2.151 (1.307)	-1.320 (1.544)	1.379 (1.724)	-0.339 (2.071)
68 - 70	1.268 (1.636)	0.522 (1.807)	-0.150 (1.470)	2.111 (1.838)	-0.727 (1.483)	0.865 (1.570)	1.773 (1.916)	-0.738 (2.149)
71 - 73	3.770* (2.012)	3.260 (2.343)	-1.254 (1.671)	0.053 (1.974)	0.463 (1.568)	0.111 (1.957)	4.341* (2.299)	3.391 (2.712)
74 - 76	4.650** (2.187)	5.171** (2.594)	-2.112 (1.898)	-0.361 (2.137)	0.079 (1.823)	1.325 (2.292)	5.745** (2.519)	4.827 (3.021)
77 - 79	4.587* (2.395)	5.438* (3.036)	-0.541 (1.827)	1.368 (2.246)	-1.088 (1.711)	-0.103 (2.369)	5.338** (2.678)	5.009 (3.404)
80 - 82	2.907 (2.343)	2.967 (2.883)	-0.707 (2.158)	0.526 (2.427)	0.301 (1.929)	2.260 (2.637)	3.171 (2.746)	1.704 (3.383)
83 - 85	3.589 (2.481)	3.170 (3.197)	-0.667 (2.162)	1.051 (2.642)	0.350 (2.125)	1.670 (3.072)	3.594 (2.867)	1.946 (3.722)
86 - 88	5.372* (2.900)	7.020** (3.552)	-0.980 (2.438)	0.476 (2.895)	0.039 (2.630)	1.694 (3.703)	5.526 (3.371)	5.868 (4.183)
89 - 91	4.866* (2.806)	6.569* (3.402)	-2.865 (2.733)	-2.241 (3.205)	1.050 (3.456)	3.959 (4.444)	5.864* (3.447)	6.428 (4.223)
92 - 94	6.606** (2.842)	10.452*** (3.688)	-4.509 (2.838)	-4.264 (3.333)	2.964 (4.291)	4.321 (5.413)	8.624** (3.590)	11.763** (4.583)
95 - 97	8.240*** (3.129)	12.326*** (4.094)	-1.893 (4.127)	-3.211 (4.495)	9.515 (5.904)	9.317 (6.642)	7.155 (4.532)	11.784** (5.465)
98 - 100	6.481** (3.276)	10.876** (4.235)	-6.501 (4.577)	-5.865 (5.489)	3.901 (8.136)	0.389 (8.501)	10.358** (4.920)	14.201** (6.046)
greater than 100	6.924* (4.003)	12.306** (4.840)	-2.564 (7.713)	-4.416 (8.702)	-2.867 (9.500)	-4.821 (11.403)	6.025 (7.547)	12.834 (8.615)
Corresponding graph	A	B	C	D	E	F	G	H
Climate	warmer	warmer	middle	middle	cooler	cooler	all	all
Unit of observation	site-day	site-day	site-day	site-day	site-day	site-day	site-day	site-day
Number of sites	278	278	558	558	278	278	1,114	1,114
n	652,744	504,027	1,310,184	899,973	652,744	416,433	2,615,672	1,820,433
Number of injuries	4,100	2,853	4,786	3,334	4,127	2,862	13,013	9,049
Fixed effects	yr-mth-site day	yr-mth-site day	yr-mth-site day	yr-mth-site day	yr-mth-site day	yr-mth-site day	yr-mth-site day	yr-mth-site day
Mean of D.V. at 59°F to 61°F	10.3	10.9	10.9	10.1	10.1	9.0	10.5	9.9

Notes: Each column displays coefficient estimates from a single regression of Equation (1). Standard errors are clustered at the site level and are shown in parentheses below the estimates. The underlying injury data come from 2006 to 2014 MSHA logs. All regressions control for day fixed effects, year-month-site fixed effects, precipitation indicator variables, and high temperature and precipitation indicator variables for the previous two days and subsequent two days. The regressions in columns G and H also include interactions of the weather controls and of the day fixed effects with an indicator for a site being in a warmer climate. Columns G and H display interactions between the temperature bins and a warmer climate indicator. Each regression is weighted by the number of workers at each site.

Table C.8: Estimates from Figure 7

Dependent variable for all specifications: Daily time-loss injury rate per 100,000 workers								
below 35	-0.577 (5.007)	0.717 (6.439)	-0.914 (2.428)	-2.476 (3.205)	-1.544 (1.649)	-2.876 (1.961)	-0.304 (5.130)	2.445 (6.605)
35 - 37	-7.511** (3.739)	-5.661 (4.221)	-1.058 (2.302)	-1.936 (2.907)	-2.019 (1.515)	-2.543 (1.911)	-6.863* (3.890)	-4.661 (4.459)
38 - 40	-2.882 (3.729)	1.693 (4.503)	-0.855 (1.744)	-0.723 (2.444)	-0.785 (1.476)	0.246 (1.823)	-2.792 (3.859)	0.975 (4.708)
41 - 43	0.047 (3.134)	3.996 (3.910)	-1.696 (1.677)	-1.511 (2.268)	-0.596 (1.354)	-1.655 (1.588)	0.204 (3.269)	4.676 (4.085)
44 - 46	0.365 (2.761)	2.225 (3.856)	-2.895** (1.436)	-2.204 (1.877)	-2.545* (1.343)	-2.658* (1.601)	2.295 (2.904)	3.705 (4.024)
47 - 49	1.269 (2.126)	3.433 (2.517)	-0.832 (1.307)	-1.139 (1.630)	-0.955 (1.233)	-1.476 (1.539)	1.568 (2.290)	3.967 (2.734)
50 - 52	-0.697 (1.608)	-0.976 (1.810)	-0.819 (1.227)	0.227 (1.485)	-0.916 (1.138)	-0.124 (1.356)	-0.291 (1.792)	-1.466 (2.042)
53 - 55	-0.119 (1.642)	-0.356 (1.769)	-0.635 (0.998)	-1.384 (1.199)	-2.112** (1.019)	-1.799 (1.160)	1.121 (1.781)	1.138 (1.959)
56 - 58	0.346 (1.383)	0.626 (1.327)	-0.204 (0.912)	-0.546 (1.146)	-1.335 (1.071)	-1.516 (1.369)	0.913 (1.533)	1.491 (1.532)
62 - 64	0.684 (1.165)	0.960 (1.246)	1.861 (1.194)	2.711** (1.249)	-2.305** (1.096)	-2.149* (1.214)	0.504 (1.516)	0.216 (1.660)
65 - 67	0.661 (1.130)	0.727 (1.348)	0.615 (1.006)	1.504 (1.286)	-2.463** (1.127)	-1.843 (1.212)	1.529 (1.348)	0.719 (1.599)
68 - 70	0.910 (1.317)	0.486 (1.392)	0.321 (1.188)	2.247 (1.520)	-1.831 (1.269)	-0.721 (1.279)	1.621 (1.562)	-0.220 (1.685)
71 - 73	2.809 (1.843)	2.517 (1.951)	-0.304 (1.312)	0.529 (1.593)	-0.549 (1.270)	-0.529 (1.470)	3.413* (2.041)	2.631 (2.230)
74 - 76	3.147* (1.797)	3.266 (2.080)	-0.479 (1.503)	0.754 (1.690)	-0.927 (1.478)	0.389 (1.700)	3.933* (2.069)	2.734 (2.411)
77 - 79	2.797 (2.062)	3.186 (2.594)	-0.125 (1.591)	1.021 (1.796)	-1.832 (1.437)	-0.404 (1.763)	3.779 (2.310)	2.926 (2.859)
80 - 82	1.450 (1.953)	1.364 (2.310)	0.124 (1.858)	0.749 (2.024)	-1.134 (1.657)	0.587 (2.014)	2.123 (2.328)	0.755 (2.743)
83 - 85	1.405 (2.155)	1.293 (2.682)	0.378 (1.787)	1.403 (2.065)	-1.107 (1.760)	-0.360 (2.296)	1.819 (2.465)	0.870 (3.039)
86 - 88	2.817 (2.410)	4.021 (2.906)	1.010 (1.966)	1.762 (2.225)	-1.142 (2.319)	-0.681 (3.029)	2.725 (2.805)	3.373 (3.392)
89 - 91	2.022 (2.303)	2.944 (2.801)	-0.882 (2.218)	0.240 (2.487)	-0.425 (2.736)	-0.083 (3.563)	2.950 (2.859)	3.077 (3.457)
92 - 94	4.199* (2.437)	6.530** (3.140)	-2.636 (2.250)	-1.133 (2.652)	0.918 (3.692)	0.127 (4.693)	6.357** (3.039)	7.620** (3.844)
95 - 97	5.478** (2.684)	7.696** (3.386)	1.979 (3.302)	0.667 (3.361)	2.625 (4.519)	1.022 (5.292)	3.437 (3.810)	7.118 (4.423)
98 - 100	6.247** (2.835)	9.280** (3.606)	-2.558 (3.624)	-0.793 (4.242)	-2.046 (7.040)	-7.895 (7.030)	9.010** (4.110)	11.977** (4.963)
greater than 100	5.647 (3.427)	10.407** (4.181)	0.434 (6.143)	1.165 (7.007)	-10.050 (6.631)	-14.144** (7.075)	6.176 (5.960)	12.733* (6.801)
Corresponding graph	A	B	C	D	E	F	G	H
Climate	warmer	warmer	middle	middle	cooler	cooler	all	all
Unit of observation	site-day	site-day	site-day	site-day	site-day	site-day	site-day	site-day
Number of sites	278	278	558	558	278	278	1,114	1,114
n	652,744	504,027	1,310,184	899,973	652,744	416,433	2,615,672	1,820,433
Number of injuries	2,791	1,923	3,068	2,174	2,395	1,635	8,254	5,732
Fixed effects	yr-mth-site day	yr-mth-site day	yr-mth-site day	yr-mth-site day	yr-mth-site day	yr-mth-site day	yr-mth-site day	yr-mth-site day
Mean of D.V. at 59°F to 61°F	7.0	7.3	7.3	7.0	6.8	5.6	7.1	6.6

Notes: Each column displays coefficient estimates from a single regression of Equation (1). Standard errors are clustered at the site level and are shown in parentheses below the estimates. The underlying injury data come from 2006 to 2014 MSHA logs. All regressions control for day fixed effects, year-month-site fixed effects, precipitation indicator variables, and high temperature and precipitation indicator variables for the previous two days and subsequent two days. The regressions in columns G and H also include interactions of the weather controls and of the day fixed effects with an indicator for a site being in a warmer climate. Columns G and H display interactions between the temperature bins and a warmer climate indicator. Each regression is weighted by the number of workers at each site.

Table C.9: Estimates from Figure 8

Dependent variable for all specifications: Hours worked in reference week						
below 40	-0.185*** (0.066)	-1.011*** (0.283)	-0.107 (0.124)	-0.160*** (0.059)	-0.602** (0.282)	-0.083 (0.119)
40 - 49	-0.020 (0.050)	0.079 (0.186)	0.029 (0.073)	-0.073 (0.063)	0.228 (0.199)	-0.147 (0.094)
60 - 69	-0.014 (0.039)	-0.086 (0.126)	0.084 (0.053)	-0.091 (0.066)	-0.081 (0.130)	-0.129* (0.074)
70 - 79	0.047 (0.039)	0.115 (0.100)	0.103* (0.060)	-0.024 (0.068)	0.027 (0.107)	-0.121* (0.065)
80 - 89	0.038 (0.049)	0.104 (0.105)	0.115 (0.076)	-0.085 (0.080)	-0.021 (0.113)	-0.121* (0.071)
greater than 90	-0.045 (0.063)	-0.005 (0.127)	0.103 (0.086)	-0.364*** (0.106)	-0.068 (0.124)	-0.392*** (0.113)
Corresponding graph	A	B	C	D	E	F
Climate	all	warmer	middle	cooler	all	all
Unit of observation	individual	individual	individual	individual	individual	individual
Number of MSAs	254	60	108	86	254	254
n	325,395	65,758	145,549	114,088	325,395	325,395
Fixed effects	yr-mth MSA	yr-mth MSA	yr-mth MSA	yr-mth MSA	yr-mth MSA	yr-mth MSA
Mean of D.V. at 50°F to 59°F	39.1	38.7	39.0	39.2	39.1	39.1

Notes: Each column displays coefficient estimates from a single regression of Equation (2). Standard errors are clustered at the MSA level and are shown in parentheses below the estimates. The data on workers come from the 2006 to 2014 monthly CPS. The sample includes workers exposed to outdoor temperatures more than one day per week. All regressions control for MSA fixed effects, year-month fixed effects, the number of days in each precipitation bin, the number of weekend days in each temperature and precipitation bin, and the individual's race, sex, age, education, usual hours worked, occupation, and industry. The regression in column E also includes interactions of the weather controls and of the year-month fixed effects with an indicator for an MSA being in a warmer climate. The regression in column F also includes interactions of the weather controls and of the year-month fixed effects with an indicator for an MSA being in a cooler climate. Column E displays interactions between the temperature bins and a warmer climate indicator. Column F displays interactions between the temperature bins and a cooler climate indicator. Each regression is weighted using CPS weights.

Table C.10: Estimates from Figure 9

Dependent variable for all specifications: Hours worked in reference week						
below 40	-0.213*** (0.069)	-0.862*** (0.257)	-0.173 (0.133)	-0.177** (0.075)	-0.502* (0.283)	-0.024 (0.118)
40 - 49	-0.028 (0.050)	0.086 (0.196)	0.008 (0.073)	-0.080 (0.078)	0.272 (0.198)	-0.146 (0.095)
60 - 69	-0.011 (0.039)	-0.019 (0.126)	0.055 (0.057)	-0.057 (0.061)	-0.036 (0.125)	-0.092 (0.074)
70 - 79	0.057 (0.042)	0.154 (0.099)	0.104 (0.069)	-0.013 (0.073)	0.057 (0.108)	-0.111* (0.066)
80 - 89	0.055 (0.049)	0.137 (0.104)	0.105 (0.078)	-0.042 (0.082)	-0.014 (0.109)	-0.075 (0.071)
greater than 90	-0.034 (0.062)	0.035 (0.126)	0.077 (0.089)	-0.318*** (0.094)	-0.043 (0.121)	-0.309*** (0.109)
Corresponding graph	A	B	C	D	E	F
Climate	all	warmer	middle	cooler	all	all
Unit of observation	individual	individual	individual	individual	individual	individual
Number of MSAs	254	60	108	86	254	254
n	325,395	65,750	145,548	114,080	325,395	325,395
	yr-mth	yr-mth	yr-mth	yr-mth	yr-mth	yr-mth
Fixed effects	MSA	MSA	MSA	MSA	MSA	MSA
	st-yr	st-yr	st-yr	st-yr	st-yr	st-yr
Mean of D.V. at 50°F to 59°F	39.1	38.7	39.0	39.2	39.1	39.1

Notes: Each column displays coefficient estimates from a single regression of Equation (2). Standard errors are clustered at the MSA level and are shown in parentheses below the estimates. The data on workers come from the 2006 to 2014 monthly CPS. The sample includes workers exposed to outdoor temperatures more than one day per week. All regressions control for MSA fixed effects, year-month fixed effects, state-year fixed effects, the number of days in each precipitation bin, the number of weekend days in each temperature and precipitation bin, and the individual's race, sex, age, education, usual hours worked, occupation, and industry. The regression in column E also includes interactions of the weather controls and of the year-month fixed effects with an indicator for an MSA being in a warmer climate. The regression in column F also includes interactions of the weather controls and of the year-month fixed effects with an indicator for an MSA being in a cooler climate. Column E displays interactions between the temperature bins and a warmer climate indicator. Column F displays interactions between the temperature bins and a cooler climate indicator. Each regression is weighted using CPS weights.

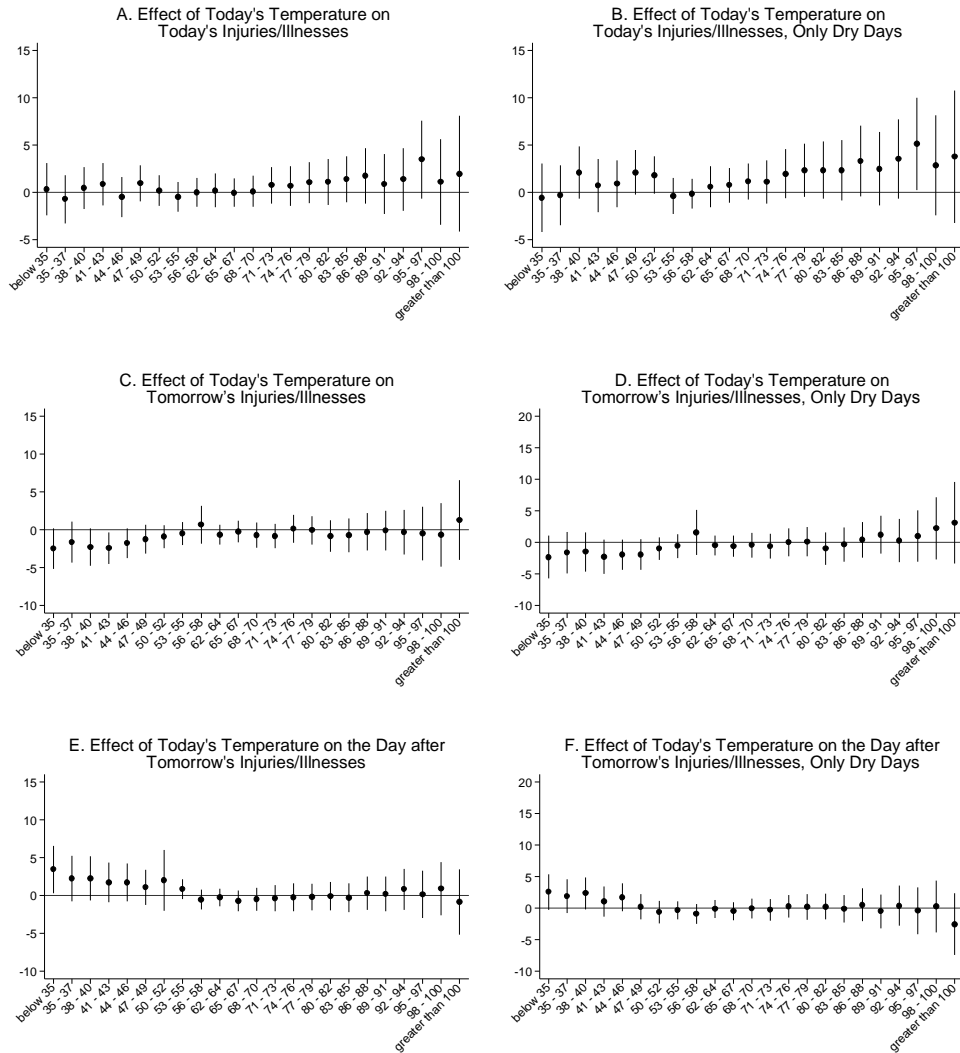
Table C.11: Estimates from Figure 10

Dependent variable for all specifications: Hours worked in reference week						
below 40	-0.091*** (0.030)	-0.266 (0.206)	-0.207*** (0.049)	-0.005 (0.022)	-0.034 (0.212)	0.200*** (0.067)
40 - 49	0.006 (0.015)	-0.025 (0.072)	0.027 (0.025)	0.010 (0.026)	0.089 (0.076)	-0.018 (0.031)
60 - 69	0.000 (0.014)	0.042 (0.038)	0.001 (0.019)	-0.011 (0.024)	-0.003 (0.045)	0.020 (0.025)
70 - 79	0.025* (0.015)	0.064 (0.039)	0.045* (0.025)	0.005 (0.022)	-0.012 (0.045)	-0.016 (0.023)
80 - 89	0.011 (0.016)	0.080* (0.046)	0.021 (0.026)	-0.028 (0.027)	0.039 (0.043)	-0.033 (0.026)
greater than 90	-0.002 (0.020)	0.044 (0.050)	0.006 (0.034)	0.009 (0.039)	-0.001 (0.050)	0.023 (0.039)
Corresponding graph	A	B	C	D	E	F
Climate	all	warmer	middle	cooler	all	all
Unit of observation	individual	individual	individual	individual	individual	individual
Number of MSAs	254	60	108	86	254	254
n	3,078,897	531,363	1,403,654	1,143,880	3,078,897	3,078,897
Fixed effects	yr-mth MSA	yr-mth MSA	yr-mth MSA	yr-mth MSA	yr-mth MSA	yr-mth MSA
Mean of D.V. at 50°F to 59°F	37.4	37.0	37.8	37.3	37.4	37.4

Notes: Each column displays coefficient estimates from a single regression of Equation (2). Standard errors are clustered at the MSA level and are shown in parentheses below the estimates. The data on workers come from the 2006 to 2014 monthly CPS. The sample includes workers exposed to outdoor temperatures less than one day per week. All regressions control for MSA fixed effects, year-month fixed effects, the number of days in each precipitation bin, the number of weekend days in each temperature and precipitation bin, and the individual's race, sex, age, education, usual hours worked, occupation, and industry. The regression in column E also includes interactions of the weather controls and of the year-month fixed effects with an indicator for an MSA being in a warmer climate. The regression in column F also includes interactions of the weather controls and of the year-month fixed effects with an indicator for an MSA being in a cooler climate. Column E displays interactions between the temperature bins and a warmer climate indicator. Column F displays interactions between the temperature bins and a cooler climate indicator. Each regression is weighted using CPS weights.

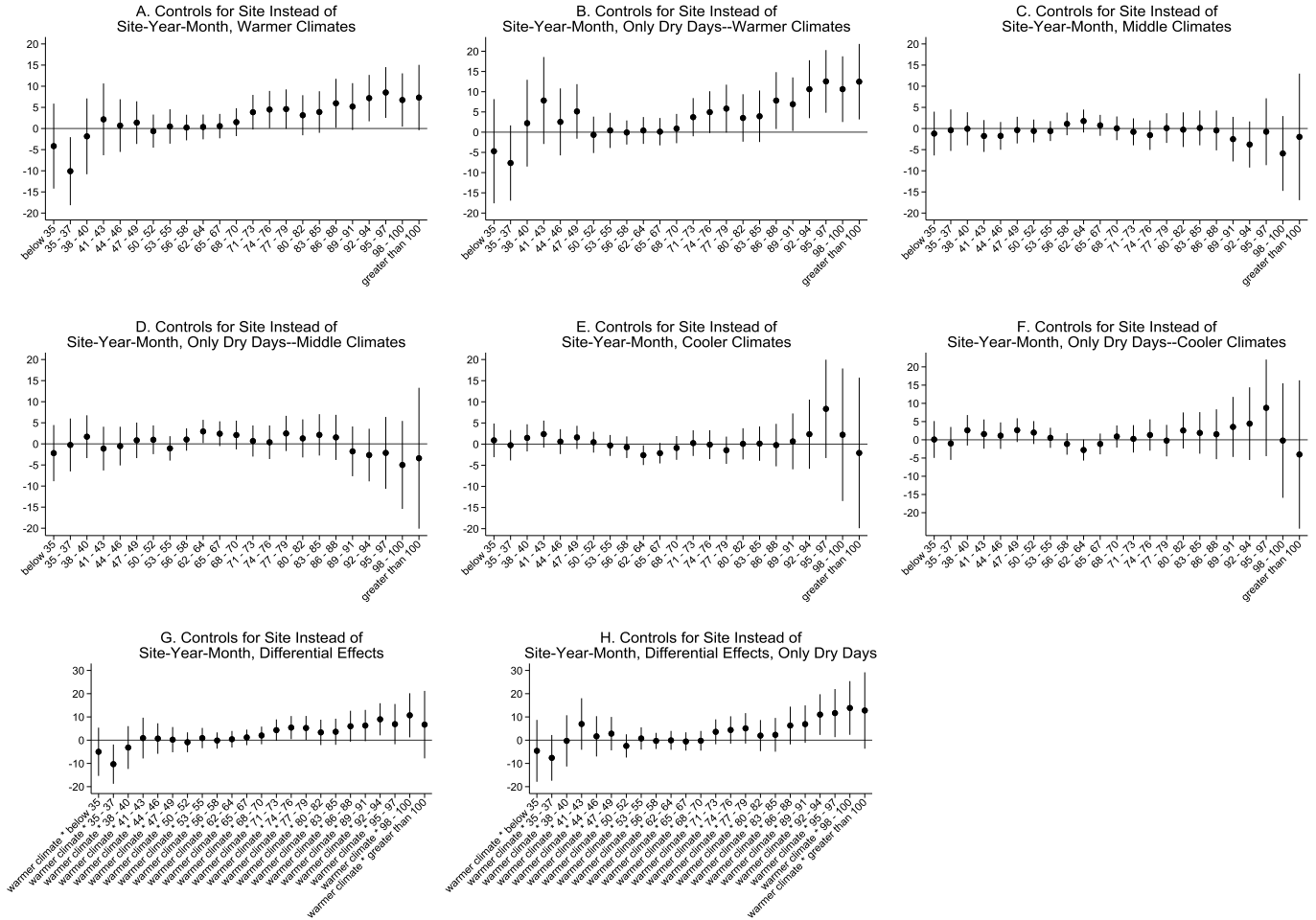
# D Appendix: Additional Analysis of Mining Data

Figure D.1: The Effect of Temperature on Daily Injuries per 100,000 Workers in Mining Data



Notes: Each graph displays coefficient estimates from a single regression of Equation (1) along with 95-percent confidence intervals calculated using standard errors clustered at the site level. The sample includes 2,615,672 site-days and 1,820,433 site-days without precipitation. The underlying injury data come from 2006 to 2014 MSHA logs and contain information on 13,013 injuries. All regressions control for day fixed effects, year-month-site fixed effects, precipitation indicator variables, and high temperature and precipitation indicator variables for the previous two days and subsequent two days. The mean of the D.V. at 59°F to 61°F for each graph is as follows: A: 10.5; B: 9.9; C: 9.3; D: 9.1; E: 7.4; F: 7.6. Each regression is weighted by the number of workers at each site.

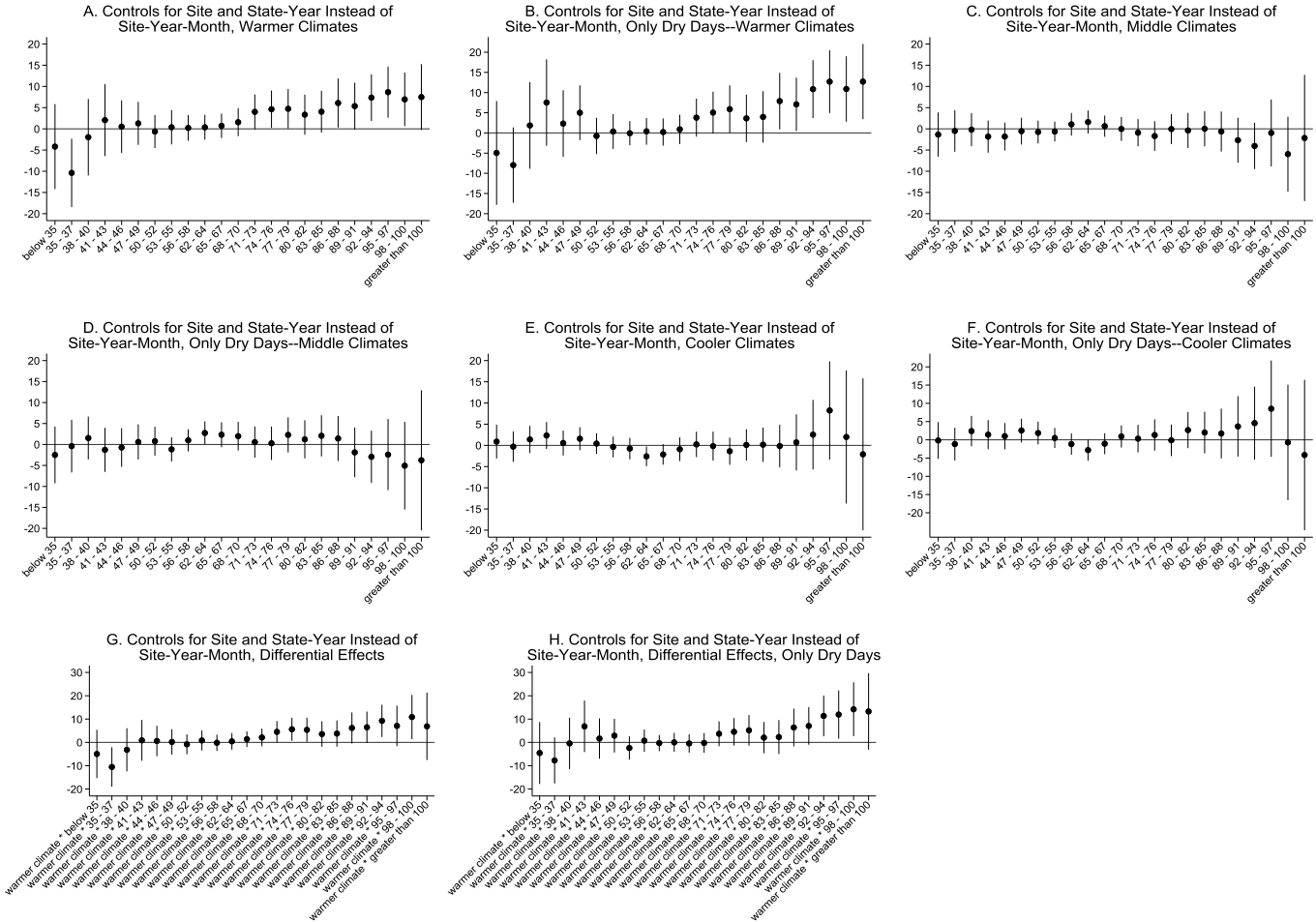
Figure D.2: The Effect of Temperature on Daily Injuries per 100,000 Workers in Mining Data, Site Fixed Effects Instead of Site-Year-Month Fixed Effects



Notes: Each graph displays coefficient estimates from a single regression of Equation (1) along with 95-percent confidence intervals calculated using standard errors clustered at the site level. The sample size for each regression is as follows: A: 652,744; B: 504,027; C: 1,310,184; D: 899,973; E: 652,744; F: 416,433; G: 2,615,672; H: 1,820,433. The underlying injury data come from 2006 to 2014 MSHA logs. The underlying number of injuries for each regression is as follows: A: 4,100; B: 2,853; C: 4,786; D: 3,334; E: 4,127; F: 2,862; G: 13,013; H: 9,049. All regressions control for day fixed effects, site fixed effects, precipitation indicator variables, and high temperature and precipitation indicator variables for the previous two days and subsequent two days. The regressions for graphs G and H also include interactions of the weather controls and of the day fixed effects with an indicator for a site being in a warmer climate. The mean of daily injury rates at 59°F to 61°F for each graph is as follows: A: 10.3; B: 10.9; C: 10.9; D: 10.1; E: 10.1; F: 9.0; G: 10.5; H: 9.9. Each regression is weighted by the number of workers at each site.



Figure D.3: The Effect of Temperature on Injuries per 100,000 Workers in Mining Data, Site Fixed Effects and State-Year Fixed Effects Instead of Site-Year-Month Fixed Effects



Notes: Each graph displays coefficient estimates from a single regression of Equation (1) along with 95-percent confidence intervals calculated using standard errors clustered at the site level. The sample size for each regression is as follows: A: 652,744; B: 504,027; C: 1,310,184; D: 899,973; E: 652,744; F: 416,433; G: 2,615,672; H: 1,820,433. The underlying injury data come from 2006 to 2014 MSHA logs. The underlying number of injuries for each regression is as follows: A: 4,100; B: 2,853; C: 4,786; D: 3,334; E: 4,127; F: 2,862; G: 13,013; H: 9,049. All regressions control for day fixed effects, site fixed effects, state-year fixed effects, precipitation indicator variables, and high temperature and precipitation indicator variables for the previous two days and subsequent two days. The regressions for graphs G and H also include interactions of the weather controls and of the day fixed effects with an indicator for a site being in a warmer climate. The mean of daily injury rates at 59°F to 61°F for each graph is as follows: A: 10.3; B: 10.9; C: 10.9; D: 10.1; E: 10.1; F: 9.0; G: 10.5; H: 9.9. Each regression is weighted by the number of workers at each site.