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

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Abstract

Despite many workers being regularly exposed to outdoor temperatures as part of their jobs, little is known about the effect of temperature on occupational health. This study assembles and analyzes two data sets that link occupational health outcomes and temperature. Using a data set that consists of daily occupational injury and illness rates constructed from Texas workers' compensation claims data, I find that 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. A day with high temperatures below 35°F increases three-day claim rates by 3.4 to 5.8 percent. To consider how the effects of temperature vary across climates, I construct a data set with daily injury rates from mining sites around the United States. The results indicate that sites in warmer climates experience worse effects of high temperatures than sites in cooler climates, suggesting that avoiding the adverse effects of higher temperatures may be easier for workers when there are fewer hot days. Using data from the monthly Current Population Survey, I show that high temperatures reduce hours worked of temperature-exposed workers more in cooler climates than in warmer climates, while low temperatures reduce hours worked more in warmer climates than in cooler climates. While research on the effect of temperature on mortality finds substantial capacity for adaptation with current technology, the results presented in this paper highlight that the ease of adaptation varies across contexts. In some important settings, the effects of high temperatures may intensify as the earth warms.

Keywords: 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 settings, the hundreds of millions of workers around the world exposed to outdoor temperatures as part of their jobs may have limited avoidance or adaptation options 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 alone (Leigh 2011). Knowing if high temperatures affect occupational health and understanding how workers respond to high temperatures have important implications for preparing for climate change and for assessing the social costs of greenhouse gas emissions.

Despite considerable attention being devoted to understanding the impact of temperature on a variety of outcomes and behaviors, little is currently known about the effects of temperature on workers' health. The research that has explored the effects of temperature on workers has focused on productivity and finds that high temperatures are associated with lower productivity.[1] A lack of an understanding of how temperature affects occupational health is a recognized hole in the literature.[2] The economics literature on the health effects

[1]This research mostly includes studies of indoor air temperature (Cachon, Gallino, and Olivares 2012; Niemela et al. 2002; Seppanen, Fisk, and Faulkner 2003) and finds that productivity falls with temperature once temperatures reach a certain point, though the estimated thresholds across studies range from 60°F to the 80s. Other related studies consider the effect of temperature on economic output across countries (Dell, Jones, and Olken 2012; Heal and Park 2013; Hsiang 2010) or on income across counties in the United States (Deryugina and Hsiang 2014) and tend to find that temperatures outside an optimal range lower output and income. Refer to Dell, Jones, and Olken (2014), Deschenes (2014), and Heal and Park (2015) for reviews of the economics research on climate.

[2]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." In their review of research about occupational health and temperature, Gubernot, Anderson, and Hunting (2013) state that "few studies examine or characterize the incidence of occupational heat-related illnesses and outcomes. More research on the effects of occupational heat exposure is needed to identify and implement evidence-based policies and interventions."

of temperature is small in general and focuses almost exclusively on mortality and the elderly (Barreca 2012; Barreca et al. 2016; Burgess et al. 2014; Deschenes and Greenstone 2011; Deschenes and Moretti 2009; Heutel, Miller, and Molitor 2017). An important finding from this literature is that while both high and low temperatures increase mortality rates, 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 mortality 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). The near-exclusive focus on mortality is a recognized weakness in the literature. According to Deschenes (2014), "At the conceptual level, the main limitation of the existing literature is that mortality and hospitalizations have been exclusively studied, and so little is known about the potentially large "lower level" effects of temperature extremes on chronic conditions and quality of life."

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 and 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 matched to weather data from the National Climatic Data Center.[3] 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

[3]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.

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. If workers can adapt to high temperatures with currently available technology, they arguably would have done it already in Texas. However, a possible concern about drawing conclusions about the effect of temperature on occupational health from Texas data is that acclimation, adaption, or avoidance behavior may be more or less feasible in a warm climate than in a cooler climate. 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 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 high temperatures of 86°F to 88°F increases three-day claim rates by 2.1 to 2.8 percent relative to days with temperatures 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 high temperatures 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. Taking advantage of the fact that the WC data allow future treatment to be linked to a medical issue that began months earlier, I find that many of the claims that arise from extreme temperatures require additional treatment in the days and months after they begin.

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 effect 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 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 from the monthly Current Population Survey (CPS) and take advantage of the fact that the CPS questions about hours worked in the past week refer to the same, identifiable week for all respondents each month. 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 mortality effects. Furthermore, a lot of 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.[4] But the results from this study highlight that the cost and ease of adaptation to higher temperatures with current technology are context-specific. In some important settings, the effects of high temperatures may intensify as high temperatures become more common.

In addition to contributing to the economics literature that studies the effects of temper-

[4]Assessing the costs of climate change is challenging. Refer to Nordhaus (2011), Nordhaus (2014), and Stern (2007) for examples of Integrated Assessment Models that seek to quantify the costs of carbon and climate change and to Burke et al. (2015), Heal (2017), Lemoine (2017), Lemoine and Traeger (2012), Millner, Dietz, and Heal (2013), and Pindyck (2013) for critiques and discussions of these models and for discussions of economic issues relevant to assessing future costs of climate change.

ature and people's responses to their environments, this study also contributes to the body of research that seeks to understand the relationship between work and health (e.g., Case and Deaton 2005; Fletcher, Sindelar, and Yamaguchi 2011; Morefield, Ribar, and Ruhm 2012; Schmitz 2016). Additionally, as low-income and low-educated people make up a disproportionate share of workers exposed to outdoor temperatures, this study 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).

The paper proceeds as follows. The next section discusses the potential effect of temperature on occupational health and possible factors that may mitigate these effects. Section 3 characterizes the workers in the United States in temperature-exposed jobs. Section 4 discusses the occupational health analysis. Section 5 considers avoidance behavior, the predicted future distribution of temperatures, and the possibility that the current industrial composition of MSAs reflects adaptive efforts. Section 6 provides a discussion and concludes.

2 The Potential Effects of Temperature on Occupational Health

The physiological health effects of temperatures at either tail of the temperature distribution arise because these temperatures can push the body's core temperature outside of its healthy ranges.[5] 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 acute cardiovascular and respiratory failure. Physical exertion, which is a common component of many jobs vulnerable to environmental stresses, can exacerbate the likelihood that high temperatures affect workers' health. As fatigue is often a contributing factor for injuries, high temperatures also have the potential to increase injury rates.

[5] The information in the first two paragraphs of this section comes from Seltenrich (2015).

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.

Apart from the direct effects of temperature, a number of lab experiments show that people's ability to perform various tasks declines at both high and low temperatures (Hancock and Vasmatzidis 2003; Hancock, Ross, and Szalma 2007; 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.[6]

Despite the physiological effects of temperature extremes, several factors may mitigate the effect of temperature on occupational health. First, workers are likely healthier than the rest of the population, and people who select into temperature-exposed jobs may be able to handle temperature extremes better than people who do not. This selection into vulnerable jobs has the potential to mitigate the effects of temperatures, especially in light of previous research that finds that the elderly and infants are the most vulnerable to the effects of temperature (Deschenes, Greenstone, and Guryan 2009; Deschenes and Greenstone 2011; Graff Zivin and Shrader 2016).

A second factor that may minimize the adverse effects of temperature on occupational health is that the human body has the ability to physically change in response to its environment. These acclimation responses can include changes in skin blood flow, metabolic rate, oxygen consumption, and core temperatures (Armstrong and Maresh 1991; Graff Zivin and Neidell 2014). Physiological acclimation can occur in as little as two weeks (Wagner et al. 1972) and can potentially lessen the adverse effects of extreme temperatures in places where

[6] 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; Graff Zivin, Hsiang, and Neidell 2015; Park 2017).

extreme temperatures are common.

A third factor that may mitigate the effects of temperature is that people may be able to avoid working or doing their most dangerous or strenuous work during temperature extremes. As evidence that workers can engage in avoidance behavior, Graff Zivin and Neidell (2014) find that workers in outdoor industries reduce their labor supply on hot days.

Finally, extreme temperatures may not affect workers' health because workers may be able to adapt to extreme temperatures in a variety of ways. For instance, short-run behavioral adaptations during periods of high temperatures include drinking more water, wearing different clothes, and spending more time in the shade, all of which the National Institute for Occupational Safety and Health recommends. Longer-term adaptive strategies include investing in technology that alters temperature or in technology aimed at reducing labor needs in vulnerable industries. However, the main adaptive tools that Barreca et al. (2016) find have ameliorated the mortality effects of temperature in the past several decades—air conditioning and heating—are not available for many workers, meaning the capacity for vulnerable workers to adapt may be limited.[7]

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 indus-

[7] Research often considers avoidance behavior to be a form of adaptation (e.g, Deschenes and Greenstone 2011 and Graff Zivin and Neidell 2014). In this paper, I consider them to be separate ways to mitigate the effects of temperature on occupational health to distinguish between minimizing the effects of temperature while continuing to work and perform the same tasks at the same time of day (adaptation) and minimizing the effects of temperature by choosing not to work or not to do certain tasks when temperatures are dangerous (avoidance).

tries 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 a lot of 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 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.[8]

Panel A of Table 1 shows characteristics of U.S. workers by their occupational temper-

[8]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. As many Census occupation codes cannot be matched to the level of granularity in O*NET, the occupations of 54 percent of workers in the 2014 ACS cannot be matched to a unique occupation in O*NET. For instance, the 2010 Census code of 0950 (Other Financial Specialists) matches to an SOC code of 13-2099 in the BLS crosswalk, but the O*NET has different entries for SOC codes of 13-2099.02 (Risk Management Specialists) and 13-2099.04 (Fraud Examiners, Investigators and Analysts). For the ACS observations that do not have a unique match in the O*NET, I assign the temperature exposure of the least-exposed occupation in the broader set of SOC matches when determining which workers are exposed to outdoor temperatures more than once per week and the temperature exposure of the most-exposed occupation when determining which workers are never exposed to outdoor temperatures. While this incomplete match means the O*NET-matched data are not good for estimating the number of workers with different temperature exposures, this approach means that workers who are classified as being regularly or never exposed to temperature are unlikely to be misclassified. In Section 5, I follow the same approach with CPS data, which also uses Census occupation codes.

ature 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 once 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 occupations that are exposed to temperature have a bachelor's degree, and only 9 percent are female. In contrast, 70 percent of U.S. workers who are never exposed to temperature 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 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 participate in WC at the same rate conditional on being injured as non-Hispanic workers (McInerney 2016). 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.

4 The Effect of Temperature on Occupational Health

4.1 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 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.[9]

Texas differs from all states other than Oklahoma in that Texas employers are not required to purchase WC insurance. Despite this, 81 percent of Texas workers work for firms with WC insurance as of 2012 (Texas Department of Insurance 2012). Other than not being compulsory, Texas WC is generally similar to other states' WC programs along most dimensions (Morantz 2010).[10] The WC insurer pays medical providers a fixed amount for services performed and must report all WC medical spending to TDI, which compiles the information into the data set used in this paper.[11] The non-compulsory nature of WC insurance in Texas will bias the estimates of the effects in levels towards zero since some workers will not be eligible to file a WC claim. However, the estimated effects in percent terms will remain

[9] For a thorough overview of WC, refer to Sengupta and Baldwin (2015).

[10] Relatively few studies have examined firms' decisions to opt out of WC insurance in Texas (Morantz 2010). An exception is Butler (1996), who finds that safety levels are likely similar between subscribing and non-subscribing firms.

[11] Employers in Texas may self-insure or purchase insurance from an insurance company. Both self-insurers and insurance companies are subject to TDI's reporting requirements.

unbiased since non-subscription is unrelated to transitory temperature fluctuations.

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 start date of the claim as the earliest date medical treatment was received and the MSA as the MSA of the first place of treatment.[12]

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.[13]

Table 2 contains descriptive statistics for this intermediate data set, which consists of

[12]Approximately 94 percent of the U.S. population belongs to an MSA, and approximately 92 percent of Texas WC claims were first treated in a Texas MSA. An alternative to using MSA as the level of geography is to use county, which has an advantage in that all of the U.S. population can be assigned to a county. The advantage of using MSA codes is that many temperature-exposed workers, such as those in construction, may be likely to cross county boundaries for work, so they may experience weather across an MSA. In results available upon request, I have verified that the main analysis is robust to aggregation at the county level.

[13]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.

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 each MSA in Texas.

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.[14] I restrict the sample to include only weekdays since most work is done during the week. The main analysis sample includes 154,968 MSA-days.

The Texas Climate

There are several advantages to using data from Texas to study the effects of high temperatures. First, while high temperatures are common across Texas, Texas's size means that different parts of the state can experience substantially different weather than other parts on any given day or in a particular month. Second, as explained earlier, if places can adapt to high temperatures with the available technology, Texas likely would have already adapted. Third, climate change will move the climates of most states towards the climate of Texas rather than away from it. Finally, according to the Köppen climate classification, Texas has

[14] 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.

multiple climates. On the eastern side of the state, the climate is mostly humid subtropical, while the western side of the state consists of semi-arid and desert climates. Thus, I can test for differential effects of temperature based on climate zone.

Despite hot summers being the norm in Texas, there is considerable heterogeneity by location. Figure 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 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.

Estimation and Results

Graph A of Figure 3 shows means of monthly claim rates per 100,000 workers for all claims and for claims arising from injuries. For both series, mean rates peak in August. Graph B of Figure 3 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, 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 exact date, m indexes the year and month, y

represents the various dependent variables, δ is a vector of day fixed effects, γ 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 a given day, 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: less than 0.05 inches but greater than 0 inches, 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.[15] 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.

The extensive controls in Equation (1) mean that the estimation strategy requires few assumptions. The δ coefficients account for the fact that baseline injury rates may be different on Tuesdays rather than Fridays, that baseline injury rates are different in December versus June, and that injury rates may be different in 2011 compared to 2006 for idiosyncratic reasons other than temperatures. The γ 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. The main assumption of the estimation strategy is that temperatures are

[15] While the paper considers possible interactive effects of temperature and precipitation in Figure 5, the first goal of the analysis is to understand the effects of temperature on occupational health apart from the effect of precipitation. A potential concern with including days with precipitation in the analysis is that precipitation and temperature can be correlated (Auffhammer et al. 2013) and precipitation may have its own effect on labor force participation (Connolly 2008) or on occupational health, which has the potential to confound the analysis. Therefore, I begin by estimating separate specifications for days without precipitation. 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 more than 0.05 inches of precipitation. When the sample is restricted to days without precipitation, the controls for the day's precipitation are excluded.

determined independently of workers' health.[16]

A critical decision for the empirical implementation is how long to allow workers to report and receive treatment for an occupational health incident. Certain injuries, such as fractures or open wounds, likely receive immediate treatment, while others, such as sprains or strains, may not be treated until a few days have passed. Not allowing enough time for workers to report their injuries and receive treatment will fail to produce valid estimates of the effect of temperature because health issues from one day's temperature will be attributed to another day's temperature. But allowing workers too much time to report and receive treatment will introduce unnecessary noise into the estimation.

To consider how to specify the dependent variable and what number of surrounding days' weather to control for, I begin by controlling for the weather during the five days before and the four days after a particular day 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 4 shows the various estimates separately for all days and for days without precipitation. As with all the figures that display estimates, the bars in Figure 4 represent the 95-percent confidence interval for each estimate calculated using robust standard errors clustered at the MSA level. All point estimates are shown in tables in the appendix. The first two graphs in Figure 4 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 claim rates.

Graphs C and D display estimates of the effect of a day's temperature on the next day's

[16] While the estimation strategy has the advantage of requiring few assumptions to estimate the impact of temperature on common measures of occupational health, it should be noted that it will not capture the impact of temperature on conditions like cancer that may take years to develop.

claim rates. For days with high temperatures in the mid-forties and below, claim rates rise as the daily high falls. I find 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, which display estimates of the effect of a day's temperature on claims two days later, tell a similar story. Two days later there is still some evidence that a cold day causes an increase in claim rates. However, all of the effect of a day's temperature appears to have been realized by the third day. The estimates of the effect of today's temperatures on claim rates three and four days later, displayed in graphs G through J, do not indicate an effect of temperature.

Based on the analysis shown in Figure 4, I define the dependent variables based on three-day claim rates for the main WC analysis and control for the weather three days prior and two days after the day of the observation, which means that preceding weather that affects today's occupational health outcomes is controlled for as is the future weather that is correlated with today's temperature and also affects three-day claim rates. Given the similarities between the analysis that controls for precipitation and the analysis that excludes days with precipitation in Figure 4, I include days with precipitation for the remainder of the analysis and control for the precipitation indicator variables.

Figure 5 shows coefficients on the temperature indicators for a variety of specifications with the three-day claim rate 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 high temperatures of 86°F to 88°F raises 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 injury rates by 0.553 per 100,000 workers, or by about 3.5 percent relative to claim rates when temperatures range from 59°F to 61°F. A day with high temperatures 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. Because 8.8 percent of the observations in the sample have three-day claim counts of zero, I consider the robustness of the results to taking the IHS of three-day claim counts, which approximates the log transformation but has the advantage of being defined at zero. The estimates with IHS of three-day claim counts as the dependent variable are shown in graph B of Figure 5 and tell a similar story 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.[17]

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

[17]For more information on the IHS transformation, refer to Pence (2006). The results are almost identical if I instead use the log(three-day claim counts + 1), which is defined for all MSA-days.

the point estimates display a similar pattern. Graphs D and E display coefficients on low temperatures in three-degree temperature bins. The regression in graph E controls for the day's high temperatures, while the results in graph D do 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 long statistically significant. Overall, these estimates suggest that high temperatures are the relevant temperatures to consider.

Figure 4 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 supplement Equation (1) with controls for the day's temperature, allow days with precipitation to have separate day, MSA-year-month, and other weather effects, and interact each temperature indicator with an indicator variable for the day having precipitation. Graph F of Figure 5 displays the estimates on the 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.

An advantage of studying Texas is that Texas spans multiple climates. According to the Köppen climate types, most of east Texas has a humid subtropical climate, while west Texas is comprised 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 for MSAs east of the 98th meridian in graph G. I find 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. On the other hand, 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 5, I test for differential effects of a cold day in the fall or of a hot day in the spring by including each day's temperature as a control and then interacting select temperature bins with indicators 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. Although 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.

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. On the other hand, younger workers being sensitive to high temperatures too suggests fewer options in terms of shifting younger workers to temperature-exposed jobs. I next 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.[18] Graph A of Figure 6 considers how the

[18] 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, meaning that the MSA-year-month fixed effects now absorb variation in employment across months within a year.

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 5 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.[19] High temperatures appear to have similar adverse effects on both age groups.

Figure 7 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 are not as

[19] 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.

dramatic as they are 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 8 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 to 88 and 3.0 and 2.6 percent for days with highs above 100°F.[20]

Graphs C and D of Figure 8 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 induced by low temperatures have above-median spending, while the claims induced by high temper-

[20] 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.

atures are more evenly split.[21]

4.2 Evidence from Mining Injury Data

Mining Safety and Health Administration Data

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 temperatures reflective of the temperatures at the weather stations, I focus on non-office workers working in surface mines.

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 immediately notify MSHA of all occupational injuries and illnesses that require medical treatment beyond first aid. 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

[21] 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.

surrounding days.[22] 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 contain a much wider set of occupations and industries than the mining data, making the results more generalizable.[23] Another advantage is that the WC data contain information on approximately two million injuries from an underlying population of over 10 million 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.[24]

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

[22]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 employer 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.

[23]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.

[24]Estimates of the effect of temperature on subsequent days do not provide evidence of delayed effects and are shown in the appendix.

effects based on temperature norms. It is possible that Texans 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.

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 model includes controls for precipitation, the weather of the previous three days and proceeding 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 9 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.

Graphs C and D in Figure 9 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.

The final two graphs in Figure 9 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 of other weather. I also include the day's temperature as a control and then interact the temperature bins with being in a warmer climate. The interactions between temperature bins and being in warmer climates 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 10 replicates the analysis in Figure 9 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.

5 Extensions

5.1 Avoidance Behavior: The Effect of Temperature on Hours Worked

Research on the effects of temperature on mortality finds evidence that people are capable of adapting to their climates. One piece of evidence consistent with adaptation is that hot days have smaller mortality effects in warmer climates than in cooler climates (e.g., Barreca et al. 2016; Heutel, Miller, and Molitor 2017). The results presented in Section 4, however, indicate that the occupational health effects of high temperatures are likely larger in warmer climates, suggesting that temperature-exposed workers may not able to adapt in similar ways as the rest of the population. Instead, the results presented in Section 4 are consistent with the idea that engaging in avoidance behavior during high temperatures is easier when high temperatures are rare. Avoidance behavior varying by temperature norms would be expected in settings where the marginal cost of missing work increases with the amount of work missed or where the cost of delaying certain tasks increases with the length of the delay.[25]

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.

[25]These conditions are met in many settings. For instance, many crops have typical harvesting or planting windows of a few weeks, while many industries operate with incentivized deadlines or tasks that must be done sequentially. In these industries, the marginal cost of delaying tasks increases as delays increase.

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 the design of this study as it allows the temperature conditions faced by workers to be matched to the week for which they report hours worked.[26] In addition to hours worked, other information collected in the CPS used in this study includes the industry and occupation of the worker's main job, the worker's usual hours worked, and various demographic characteristics of the worker.

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.[27] 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 con-

[26]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.

[27]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.

ducive to heterogeneity analysis. At approximately 4.5 million observations, the sample size with identifiable MSA codes from the 2006 to 2014 CPS has over 160 times as many workers with narrowly identified geographies as the 2003 to 2006 ATUS does at 27,482.[28] This increased sample size allows for focusing more narrowly on occupations exposed to outdoor temperatures and for a more precise analysis of differential effects of temperature based on temperature norms.

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 studied.[29] 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 no longer relies on within-month variation. Instead, I now estimate models of the following form:

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

where i indexes the individual, γ is a vector of MSA fixed effects, δ 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 previous week that fell into each precipita-

[28]The ATUS is collected from a randomly selected person over the age of 15 from each household finishing its eighth month in the CPS. In addition to only conducting one interview from one person from each household, the ATUS sample size is smaller because it excludes some households oversampled by the CPS and because only about half of respondents chosen for the ATUS complete the survey. The current study also has a larger sample size because it uses more years of data. For more information on the ATUS's sampling procedures, refer to the Bureau of Labor Statistics (2017b).

[29]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.

tion 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.

The coefficients on the temperature bins from estimating Equation (2) are shown in Figure 11. 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.[30] 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

[30]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.

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. I control for separate indicator variables for the number of days in each possible temperature bin and interact 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.

The results presented here provide evidence that workers in warmer climates reduce their hours worked more in response to low temperatures while workers in cooler climates reduce their hours more in response to high temperatures.[31] 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 methods to adapt to high temperature so that they do not have to adjust their hours worked, whereas workers in cooler climates have not adopted the same technologies and therefore have to reduce hours. While this study cannot rule out the possibility of acclimation or adaptation, considering these hours-worked results along with the occupational health results suggests that differences in

[31] 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 can be ruled out by their confidence intervals.

the feasibility of avoidance behavior explain part of the differential hours-worked responses between warmer and cooler environments.[32]

5.2 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. Graph A of Figure 12 displays the average share of days with highs that fell into various temperature bins for Texas counties as well as for counties in the nine Census divisions from 2006 to 2014.[33] Texas's distribution is represented by the thick red line and shows that counties in Texas averaged more days with daily high temperatures of 95°F or higher than any of the Census divisions. During this same time period, Texas counties averaged fewer days at the bottom end of the temperature distribution than any of the Census divisions.

As asserted in the introduction, Texas is an especially useful laboratory for considering the implications of climate change because climate change will move other states towards the Texas climate. To demonstrate the relevance of the Texas environment in assessing the impact of climate change, graph B of Figure 12 graphs Texas's temperature distribution from 2006 to 2014 with 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.[34] Only two Census divisions are predicted to have a smaller share of days with highs of 95°F or higher than Texas had from 2006 to 2014.

Despite resulting in fewer days with low temperatures that are dangerous for workers, climate change will result in more days that are dangerous for workers on net under the

[32]It should be noted that, especially with cold weather, firms, workers, and local governments can almost certainly adapt at least partially. Towns' investments in cold-adaptive infrastructure and technology and people's knowledge of how to drive on slick roads are part of why a light snow can shut down a southern city while having minimal effects on northern cities.

[33]I use counties for this part of the analysis because counties are all self-contained in states and Census divisions. Some states are warmer than Texas, but they are in divisions with states that have fewer days over 95°F than Texas.

[34]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).

assumption of no emission changes. According to the Hadley Climate Model 3, U.S. counties will average 30.0 fewer days with high temperatures of 40°F or below, 65.8 more days 80°F or above, and 76.1 more days of 95°F or above. The effects of climate change will not be felt equally across the country. For example, New England will average 40.7 fewer days under 40°F per year and 40.4 more days of at least 95°F, while the Southern Atlantic states will average 12.0 fewer days under 40°F per year and 83.6 more days of at least 95°F.

5.3 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 Section 4 cannot 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.[35] 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 firms.

If occupational specialization based on climate is cost-effective, it plausibly would have

[35] 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.

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 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 13 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.

6 Discussion and Conclusion

This study constructs and studies the first data sets to my knowledge to link temperature and occupational health. 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 high temperatures 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 at odds with an adaptation/acclimatization story. With the available technology, workers in warmer climates do not appear to be able to adapt to high temperatures. Instead, 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 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 and indicates that the adverse effects of hot days on workers may intensify as hot days become more common due to climate change.

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Table 1: Demographic Characteristics of Temperature-Exposed Workers

	High-Exposure Industries	Other Industries	High-Exposure Occupations	Low-Exposure Occupations
A. United States				
% 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. Texas				
% 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 IPUMS 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 once 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 IPUMS 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.

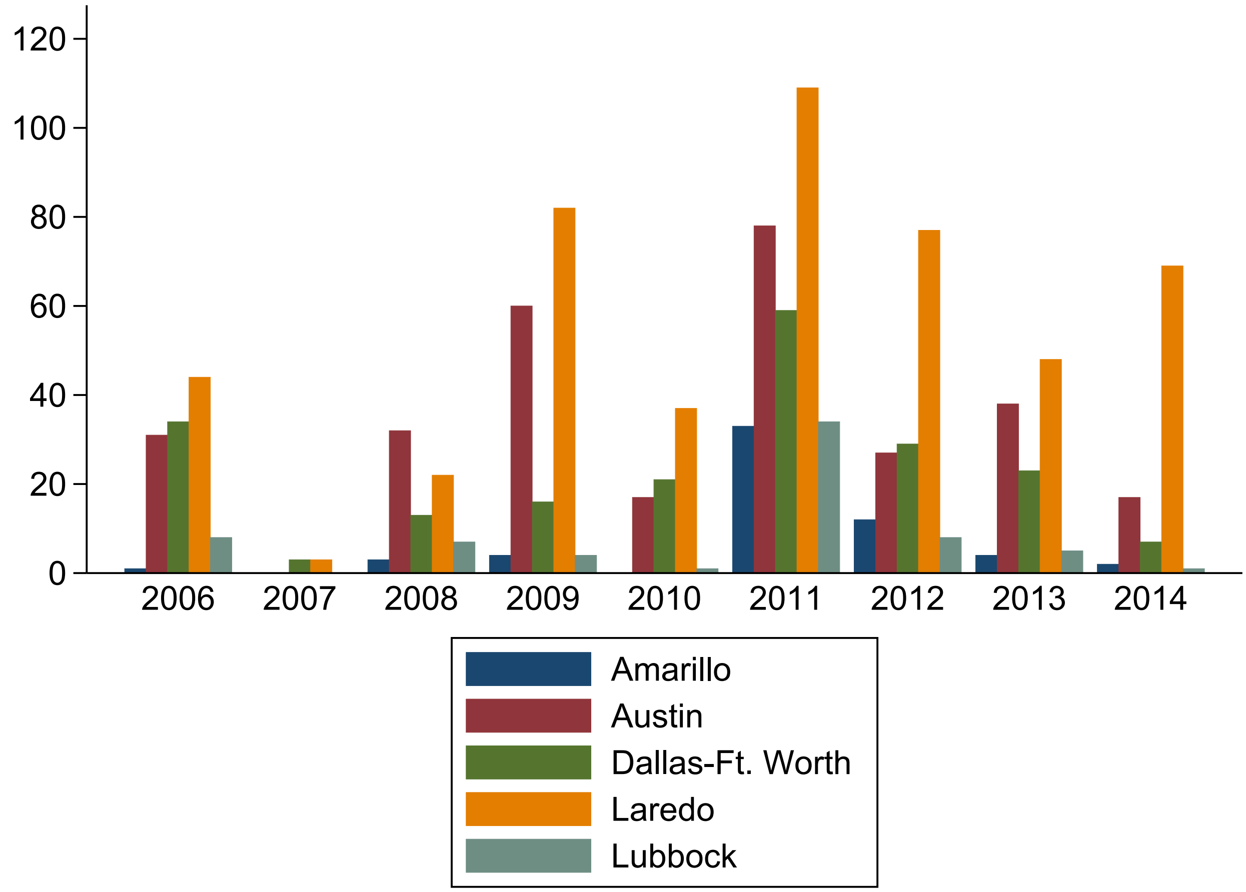

Figure 1: **Total Days with Highs over 100°F by Year for Selected MSAs.**

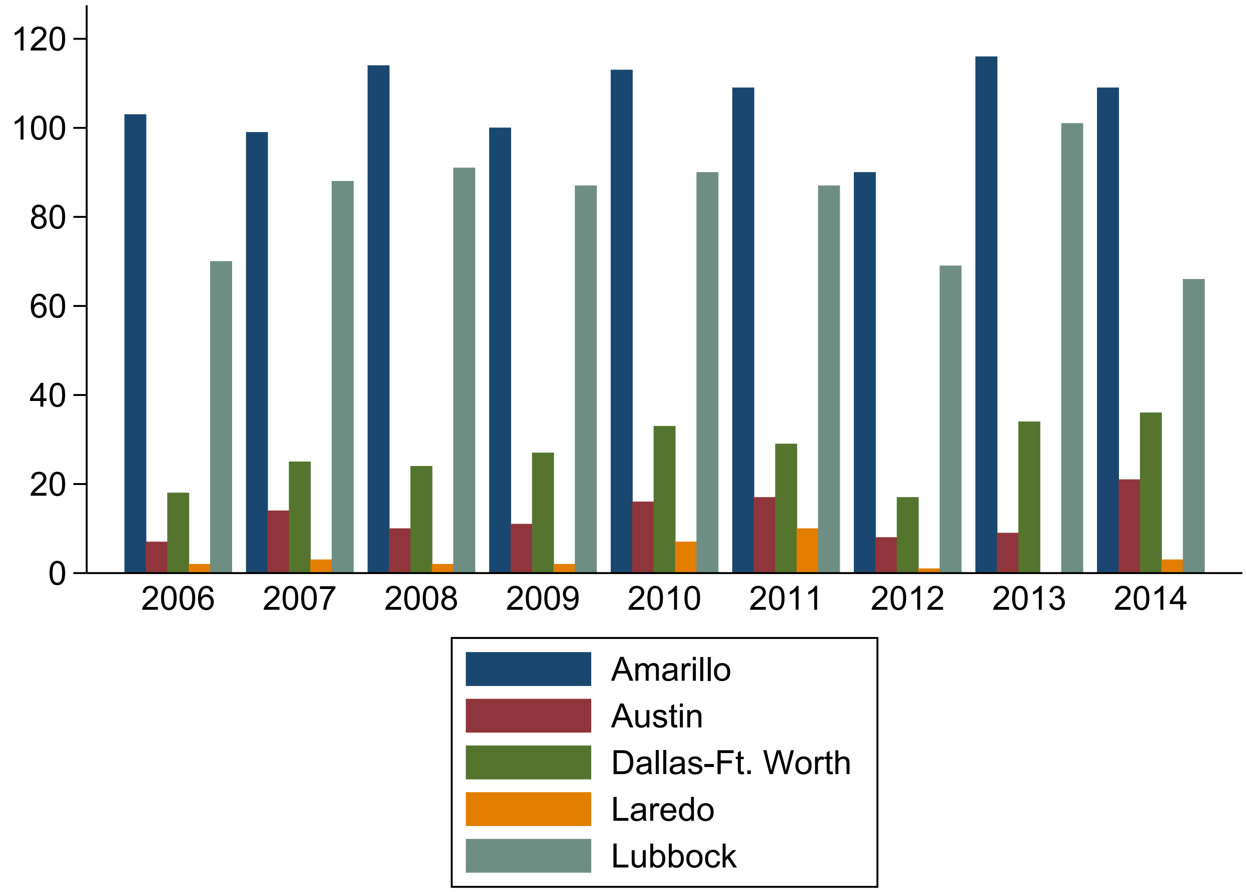

Figure 2: **Total Days with Lows Less than 32°F by Year for Selected MSAs.**

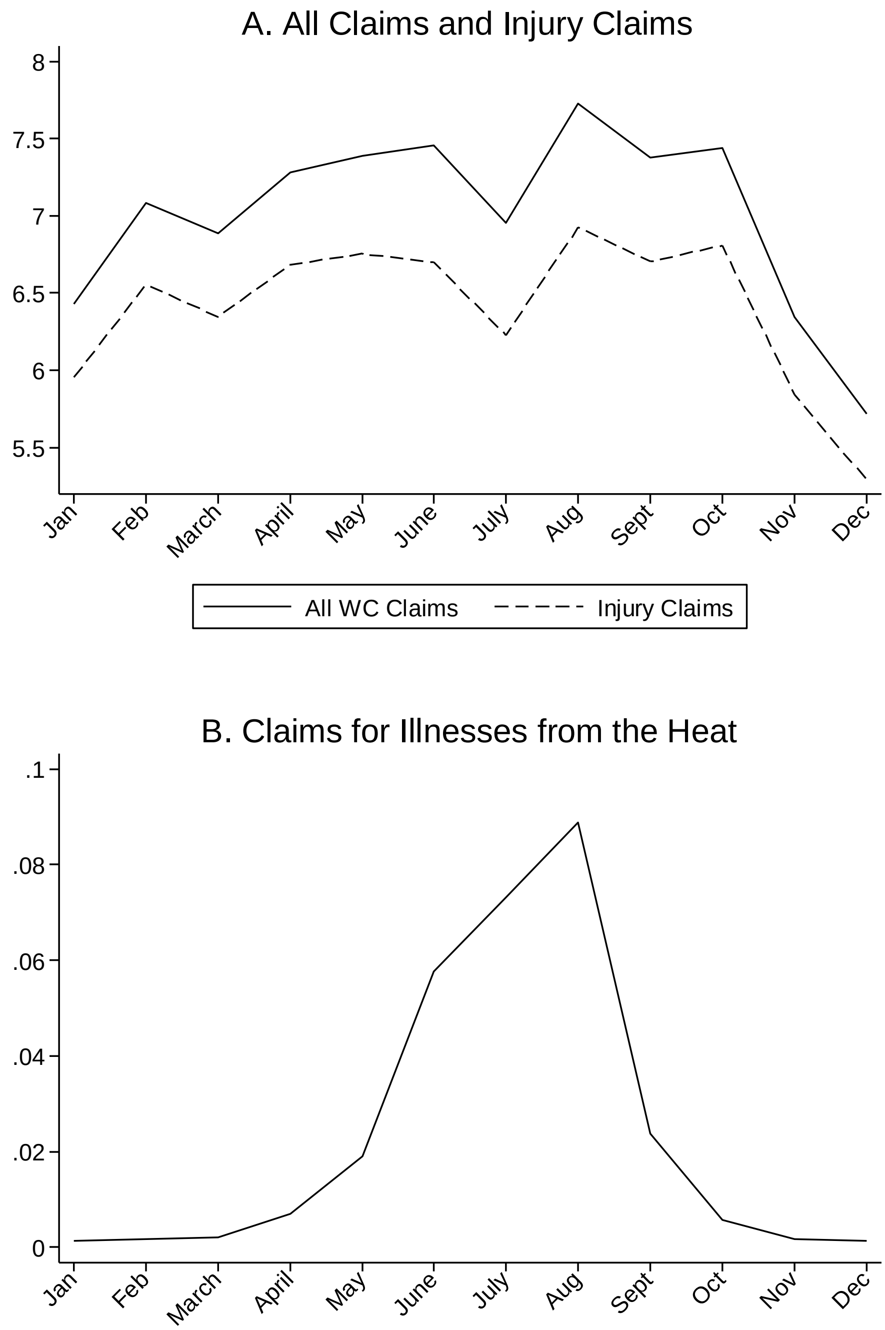

Figure 3: **Mean of Daily Claims per 100,000 Workers by Month.** The data come from 2006 to 2014 Texas WC claims. The unit of observation is an MSA-day. The means are weighted using the number of workers in an MSA during the month of the observation from LAUS data.

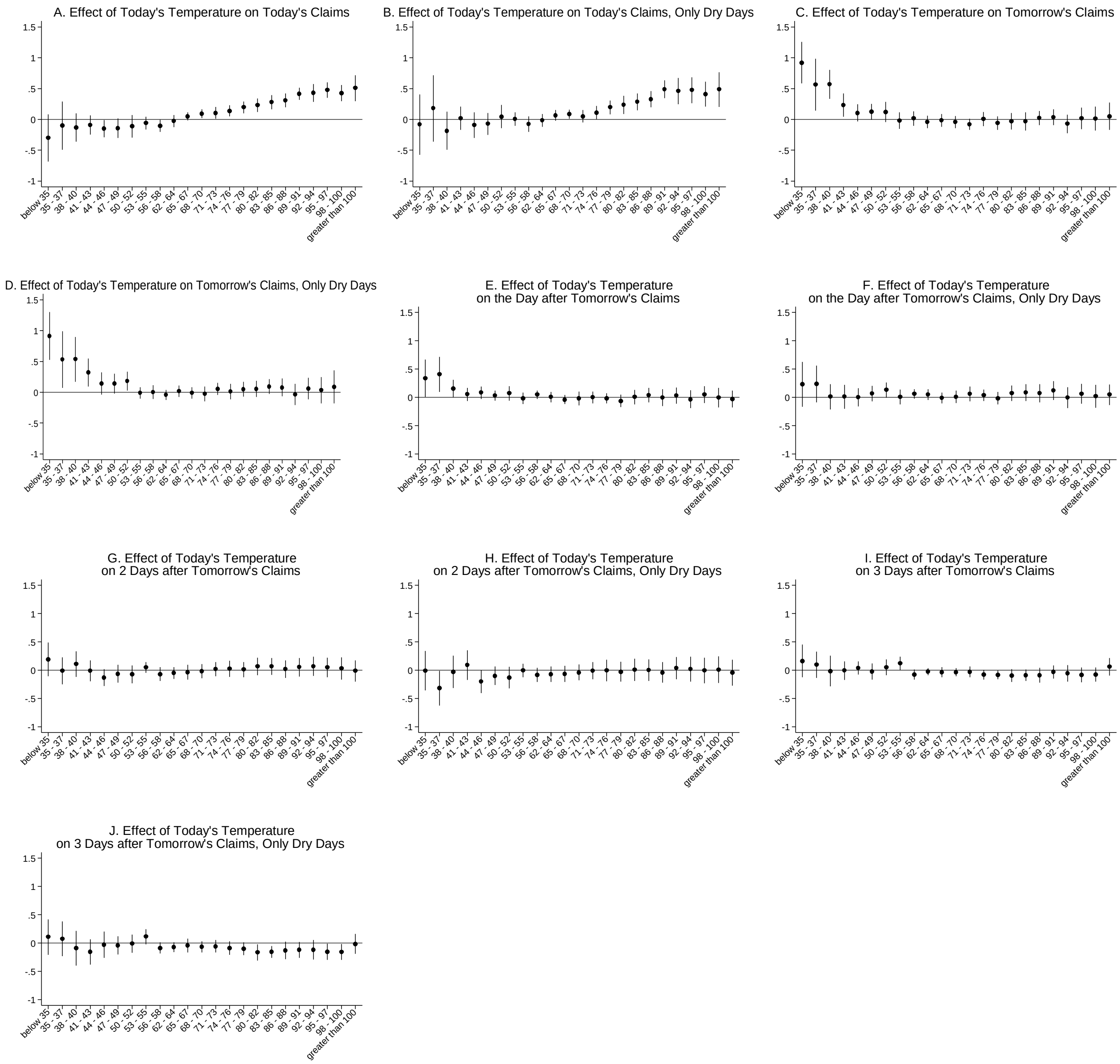

Figure 4: **The Effect of Temperature on Daily Claim Rates.** The underlying data come from 2006 to 2014 Texas WC claims. Each graph displays coefficient estimates on the temperature bins from a single regression. All estimates are relative to days with high temperatures of 59°F to 61°F. 95-percent confidence intervals calculated using standard errors clustered at the MSA level are displayed along with the estimates. All regressions control for day fixed effects, year-month-MSA fixed effects, and high temperature and precipitation indicator variables for each of the preceding five days and proceeding four days. Regressions that include days with precipitation also control for the day's precipitation. The mean number of claims per 100,000 workers when temperatures are 59°F to 61°F for each panel 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, and J: 4.5. The sample contains 154,968 MSA-days and 124,964 MSA-days without precipitation. The regressions are weighted using the number of workers in an MSA during the month of the observation from LAUS data.

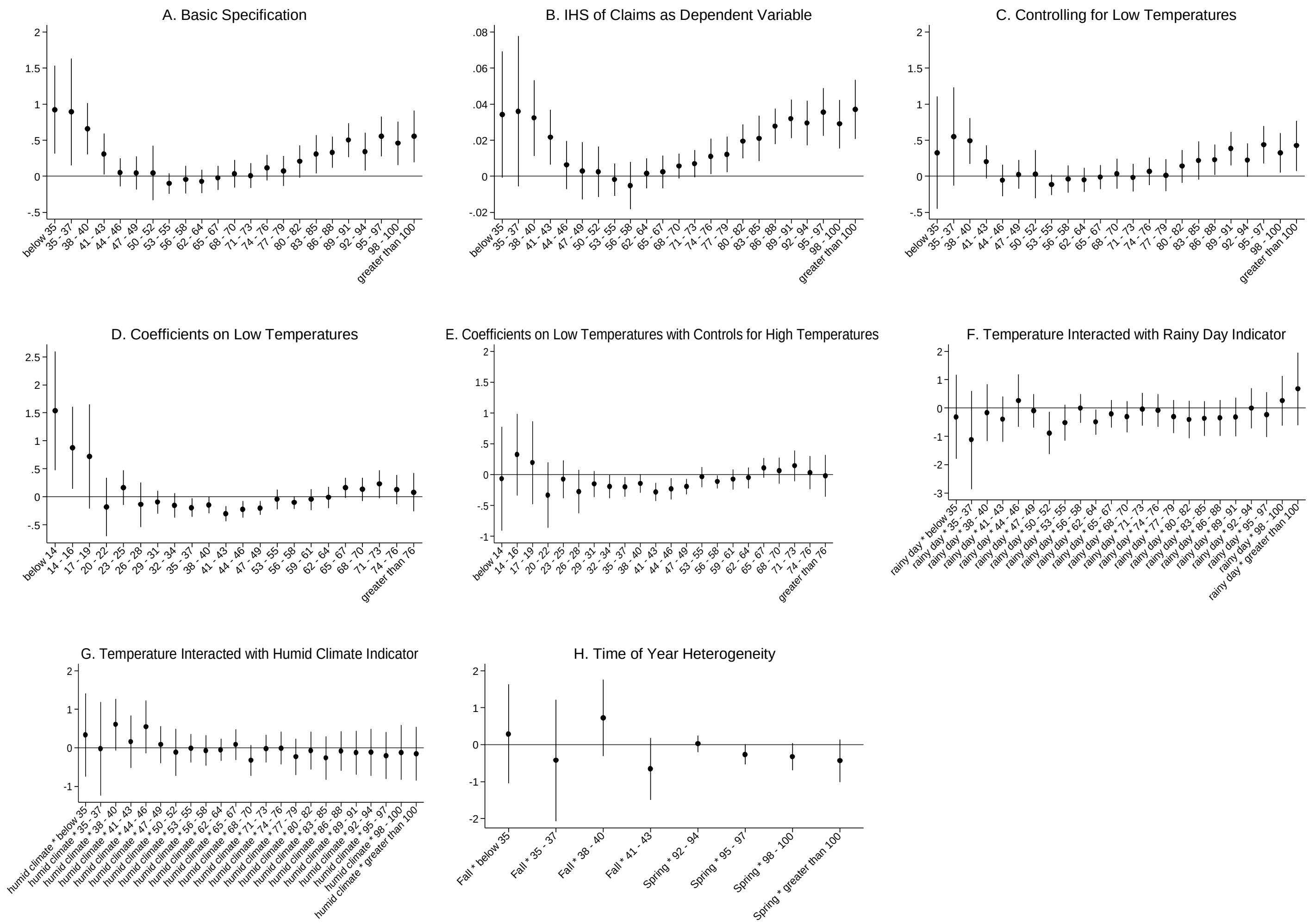

Figure 5: **The Effect of Temperature on Three-Day Claim Rates.** The underlying data come from 2006 to 2014 Texas WC claims. Each graph displays coefficient estimates on the temperature bins from a single regression. All estimates are relative to days with high temperatures of 59°F to 61°F. 95-percent confidence intervals calculated using standard errors clustered at the MSA level are displayed along with the estimates. All regressions control for day fixed effects, year-month-MSA fixed effects, precipitation indicator variables, and high temperature and precipitation indicator variables for the preceding three days and proceeding two days. The mean three-day claim rate per 100,000 workers when temperatures are 59°F to 61°F is 15.8. The sample contains 154,968 MSA-days. The regressions are weighted using the number of workers in an MSA during the month of the observation from LAUS data.

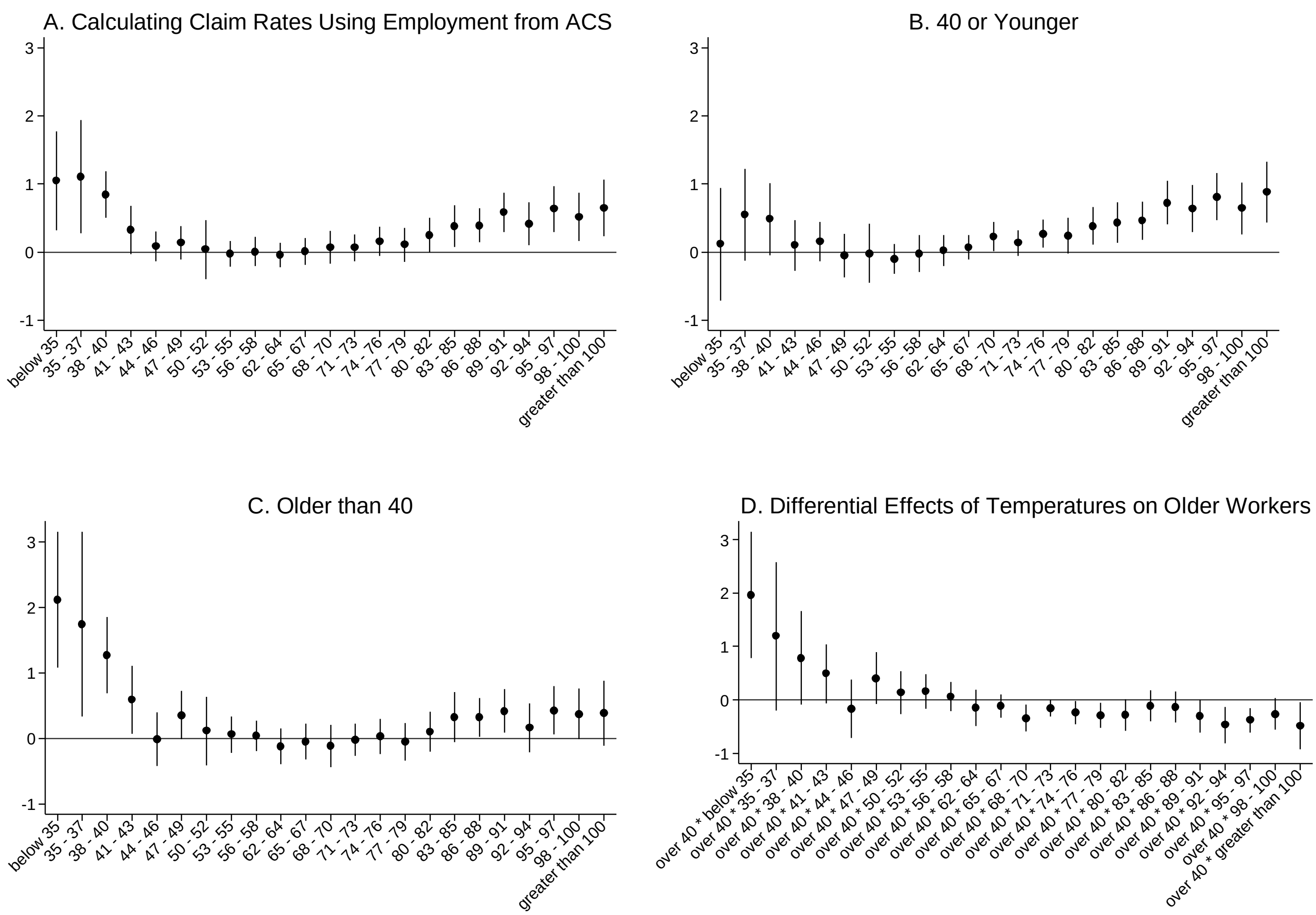

Figure 6: **The Effect of Temperature on Three-Day Claim Rates, Heterogeneity by Age.** The underlying data come from 2006 to 2014 Texas WC claims. Each graph displays coefficient estimates on the temperature bins from a single regression. All estimates are relative to days with high temperatures of 59°F to 61°F. 95-percent confidence intervals calculated using standard errors clustered at the MSA level are displayed along with the estimates. All regressions control for day fixed effects, year-month-MSA fixed effects, precipitation indicator variables, and high temperature and precipitation indicator variables for the preceding three days and proceeding two days. The regression in graph D also controls for interactions of being an observation from the over-40 sample. The mean three-day claim rate per 100,000 workers when temperatures are 59°F to 61°F for each graph is as follows: A and D: 16.2, B: 15.4, C: 17.3. The sample in graphs A, B and C contains 62,614 MSA-days. The sample in graph D contains 125,228 MSA-days. The regressions are weighted using the number of workers in an MSA during the year of the observation estimated from ACS data.

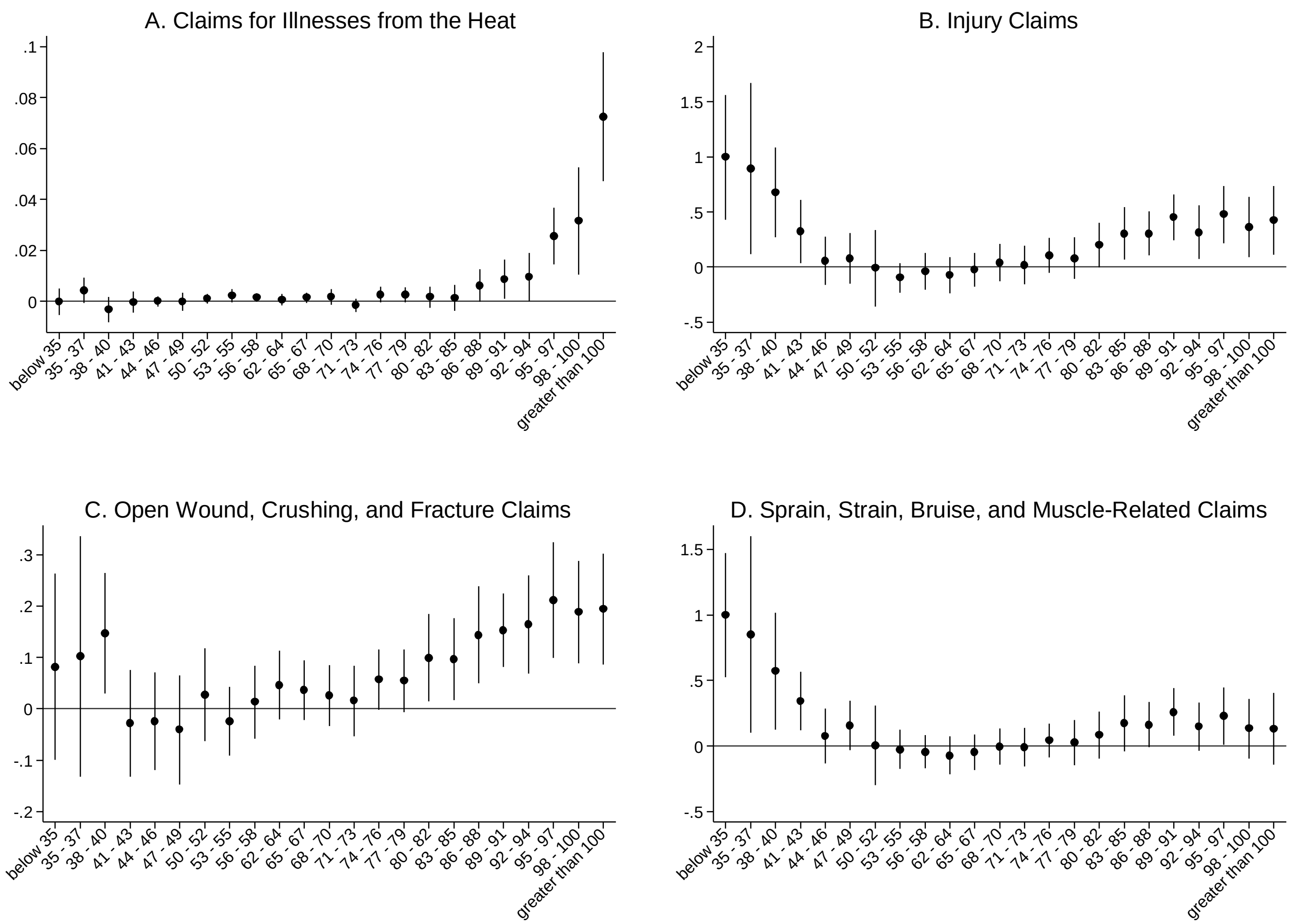

Figure 7: **The Effect of Temperature on Three-Day Claim Rates for Different Types of Claims.** The underlying data come from 2006 to 2014 Texas WC claims. Each graph displays coefficient estimates on the temperature bins from a single regression. All estimates are relative to days with high temperatures of 59°F to 61°F. 95-percent confidence intervals calculated using standard errors clustered at the MSA level are displayed along with the estimates. All regressions control for day fixed effects, year-month-MSA fixed effects, precipitation indicator variables, and high temperature and precipitation indicator variables for the preceding three days and proceeding two days. The mean three-day claim rate per 100,000 workers when temperatures are 59°F to 61°F for each graph is as follows: A: 0.0, B: 14.6, C: 3.6, and D: 10.6. The sample contains 154,968 MSA-days. The regressions are weighted using the number of workers in an MSA during the month of the observation from LAUS data.

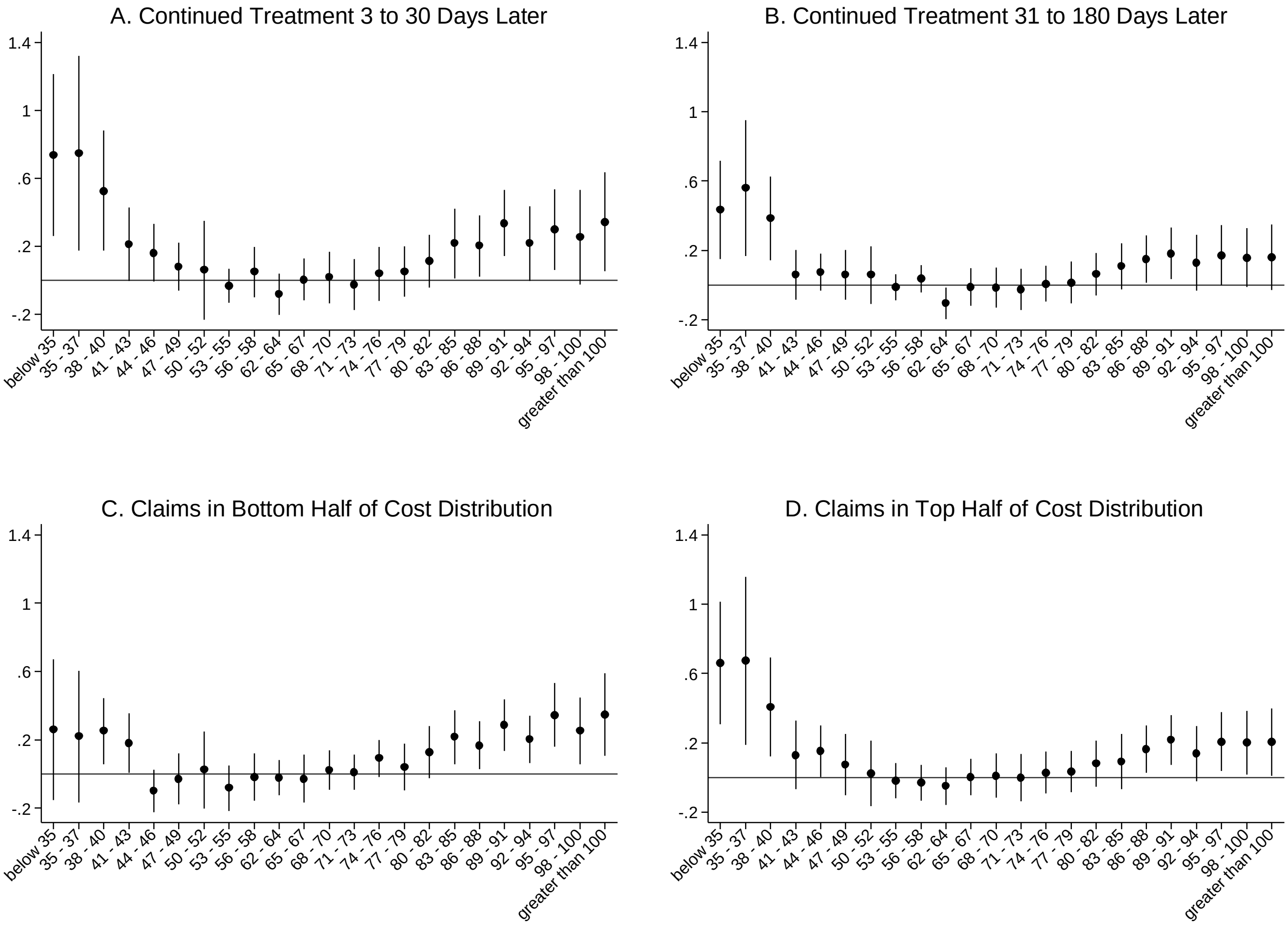

Figure 8: **The Effect of Temperature on Medical Costs and Later Treatment.** The underlying data come from 2006 to 2014 Texas WC claims. Each graph displays coefficient estimates on the temperature bins from a single regression. All estimates are relative to days with high temperatures of 59°F to 61°F. 95-percent confidence intervals calculated using standard errors clustered at the MSA level are displayed along with the estimates. All regressions control for day fixed effects, year-month-MSA fixed effects, precipitation indicator variables, and high temperature and precipitation indicator variables for the preceding three days and proceeding two days. The mean three-day claim rate per 100,000 workers when temperatures are 59°F to 61°F for each graph is as follows: A: 11.6, B: 6.2, C: 8.9, and D: 8.8. The sample contains 154,968 MSA-days. The regressions are weighted using the number of workers in an MSA during the month of the observation from LAUS data.

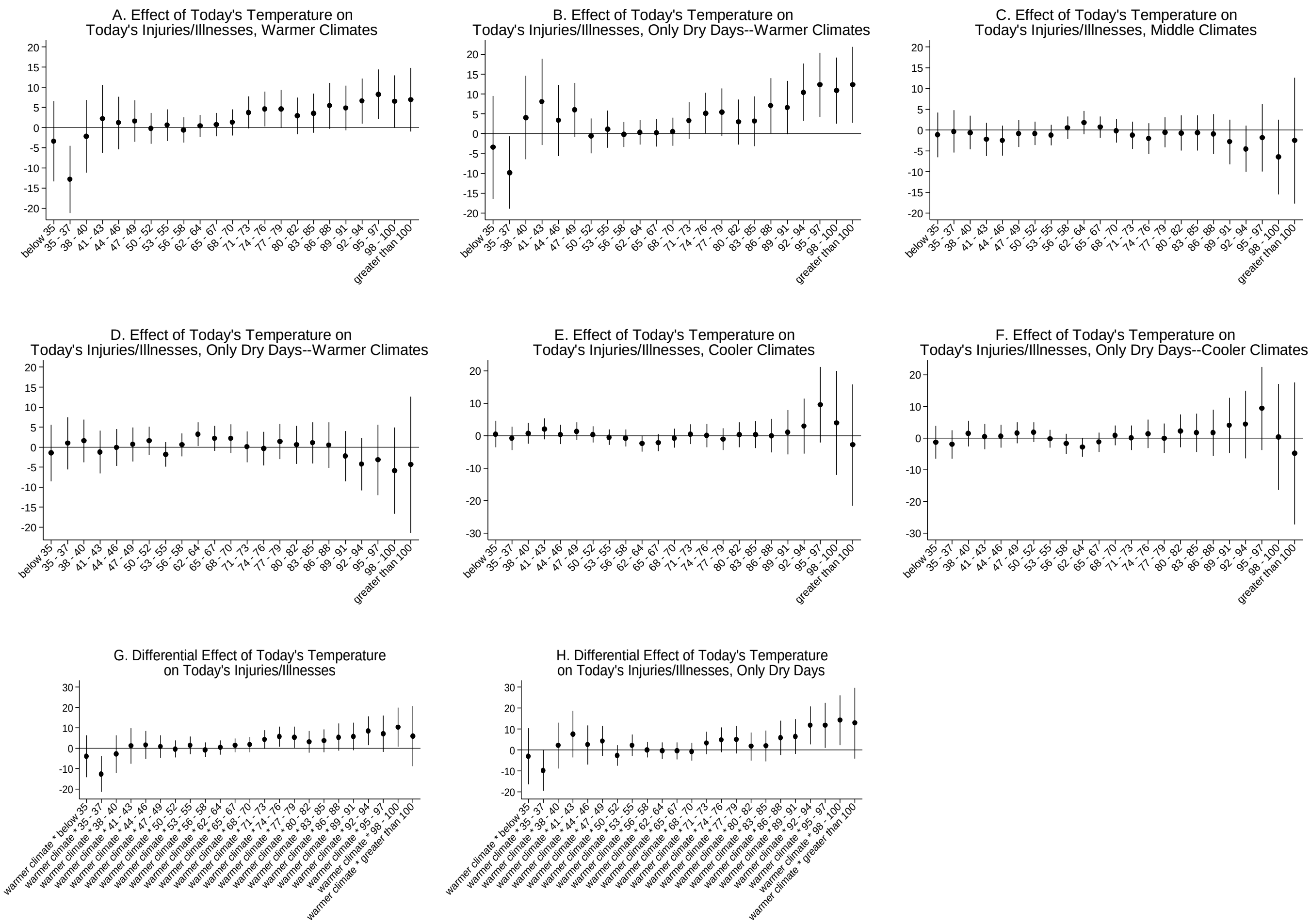

Figure 9: **The Effect of Temperature on Injuries in Mining Data.** The underlying data come from the 2006 to 2014 MSHA injury logs. Each graph displays coefficient estimates on the temperature bins from a single regression. All estimates are relative to days with high temperatures of 59°F to 61°F. 95-percent confidence intervals calculated using standard errors clustered at the site level are displayed along with the estimates. All regressions control for day fixed effects, year-month-site fixed effects, precipitation indicator variables, and high temperature and precipitation indicator variables for the preceding three days and proceeding two days. The means of injuries per 100,000 workers when temperatures are 59°F to 61°F are as follows: A: 10.34, B: 10.94, C: 10.90, D: 10.06, E: 10.08, F: 8.99, G: 10.47, and H: 9.90. The sample contains 2,615,672 site-days and 1,820,433 site-days without rain.

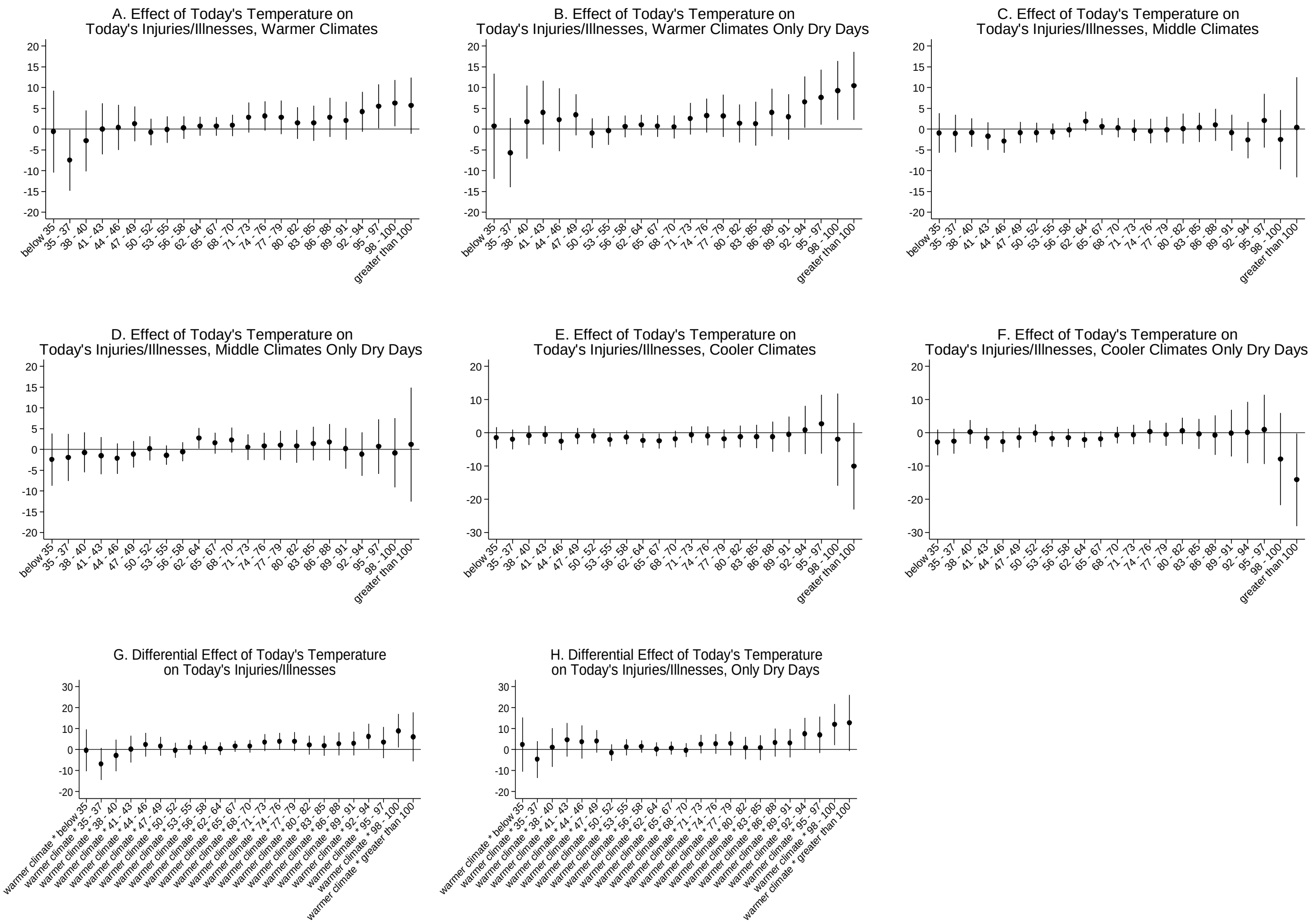

Figure 10: **The Effect of Temperature on Time-Loss Injuries in Mining Data.** The underlying data come from the 2006 to 2014 MSHA injury logs. Each graph displays coefficient estimates on the temperature bins from a single regression. All estimates are relative to days with high temperatures of 59°F to 61°F. 95-percent confidence intervals calculated using standard errors clustered at the site level are displayed along with the estimates. All regressions control for day fixed effects, year-month-site fixed effects, precipitation indicator variables, and high temperature and precipitation indicator variables for the preceding three days and proceeding two days. The means of injuries per 100,000 workers when temperatures are 50°F to 64°F are as follows: A: 6.99, B: 7.25, C: 7.32, D: 7.00, E: 6.76, F: 5.57, G: 7.07, and H: 6.55. The sample contains 2,615,672 site-days and 1,820,433 site-days without rain.

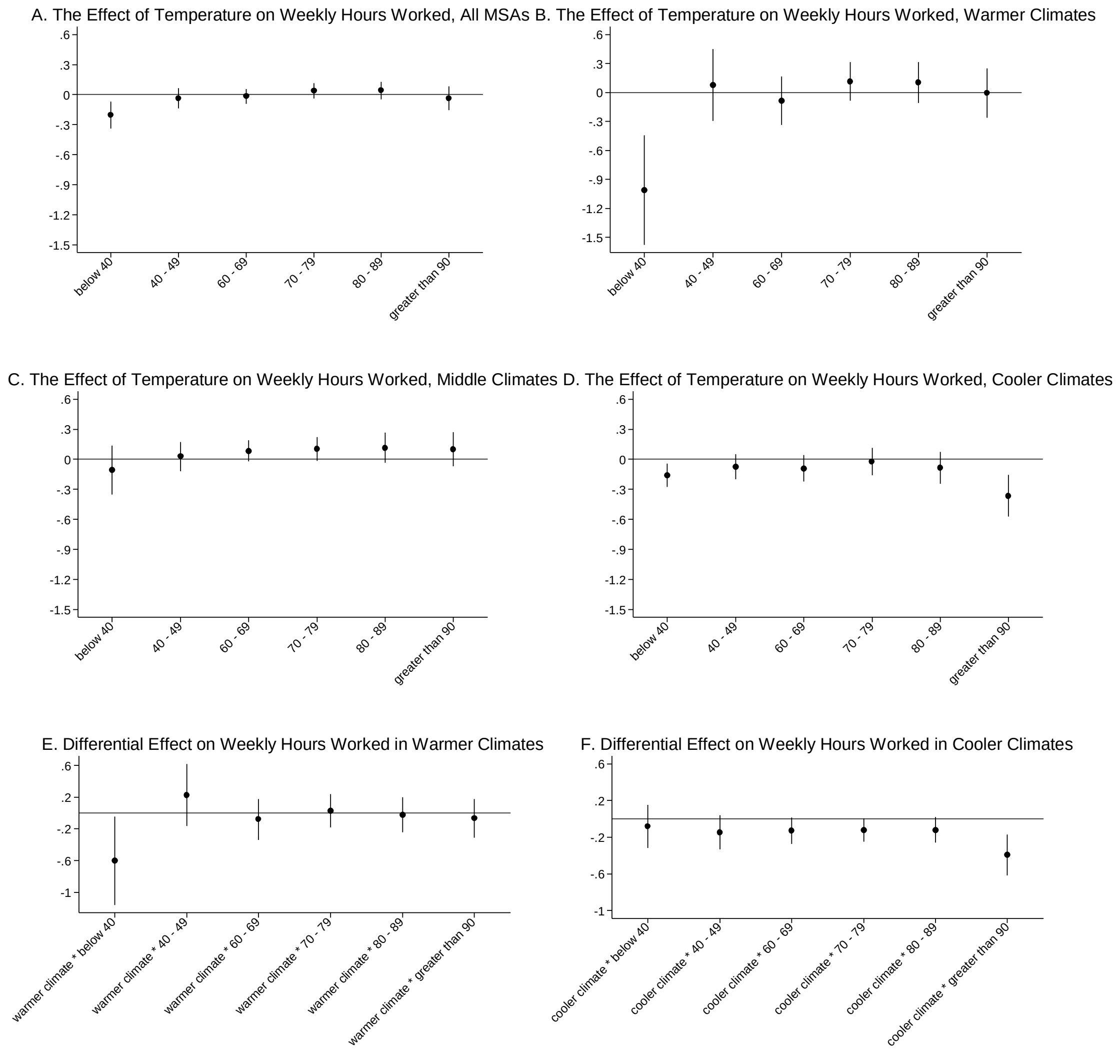

Figure 11: **The Effect of Temperature on Hours Worked for Workers Exposed to Outdoor Temperatures More than Once per Week.** The data come from the 2006 to 2014 basic monthly CPS. Each graph displays coefficient estimates on the temperature bins from a single regression. All estimates are relative to weeks with high temperatures of 50°F to 59°F each day. 95-percent confidence intervals calculated using standard errors clustered at the MSA level are displayed along with the estimates. All regressions control for MSA fixed effects, year-month fixed effects, the number of days in the week with precipitation, and the individual's race, sex, age, education, usual hours worked, occupation, and industry. The means of hours worked when temperatures are 50°F to 59°F all week are as follows: A, E, and F: 39.1, B: 38.7, C: 39.0, and D: 39.2. The sample sizes for each graph are as follows: A, E, and F: 325,395, B: 65,758, C: 145,549, and D: 114,088.

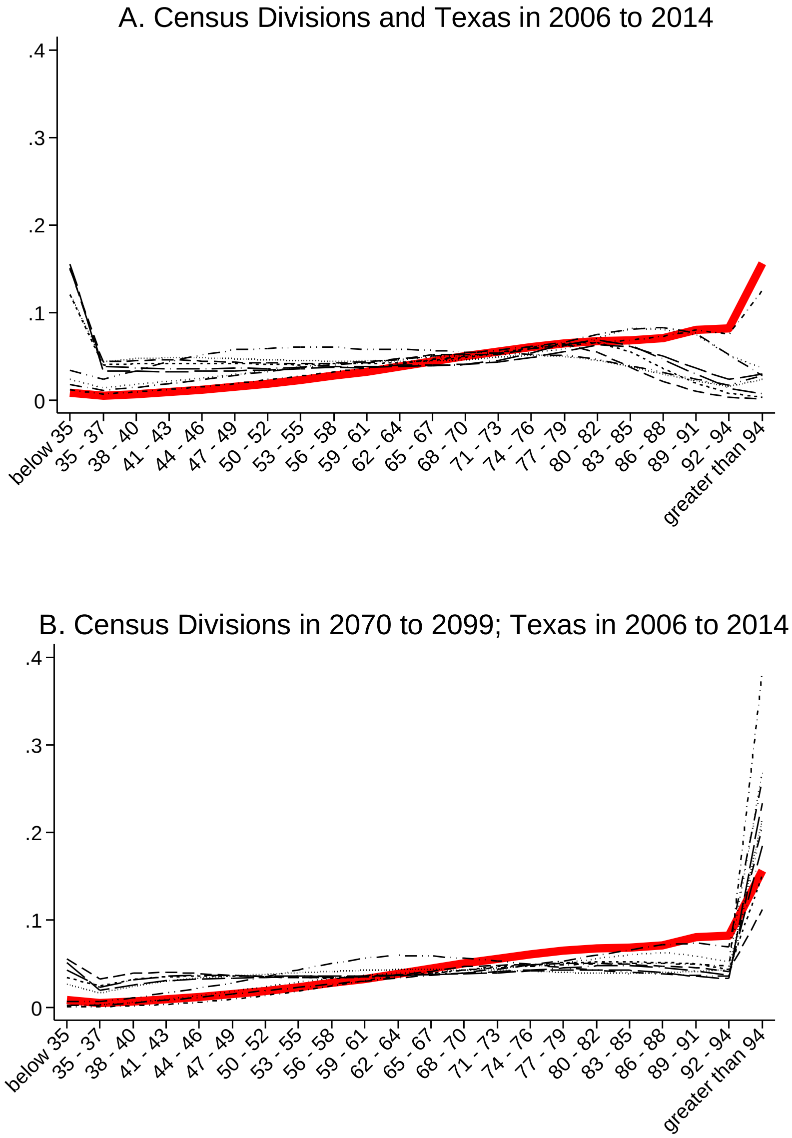

Figure 12: **Temperature Distributions of Texas and Census Divisions.** The thick red line in both graphs represents the distribution of daily high temperatures of Texas from 2006 to 2014. Graph A also displays the distribution of daily high temperatures for each Census region from 2006 to 2014, while 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.

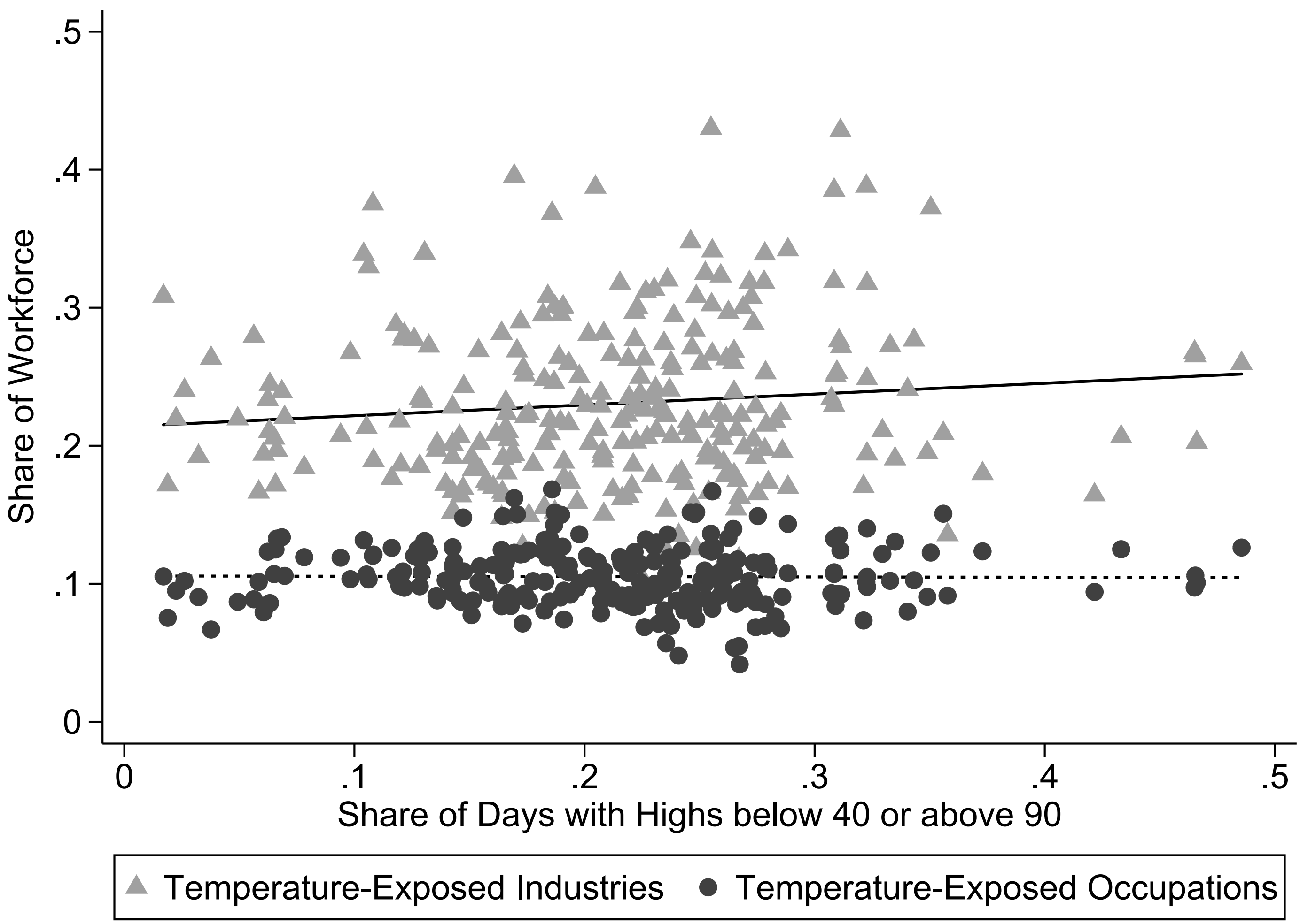

Figure 13: **Correlation between MSAs' Share of Days with Dangerous Temperatures and Share of Workforce in Temperature-Exposed Jobs.** The share of dangerous days is from 2006 to 2014. The industry shares come from the 2014 ACS. The occupation shares come from the 2014 ACS and the O*NET.

Appendices

A Appendix: Estimates Corresponding to Figures

Table A.1: Estimates from Figure 4

	A	B	C	D	E	F	G	H	I	J
below 35	-0.302	-0.085	0.921***	0.913***	0.337**	0.231	0.192	-0.008	0.163	0.106
	(0.192)	(0.246)	(0.168)	(0.195)	(0.164)	(0.197)	(0.149)	(0.174)	(0.145)	(0.157)
35 - 37	-0.101	0.179	0.562***	0.529**	0.406**	0.237	-0.012	-0.318**	0.097	0.074
	(0.195)	(0.269)	(0.211)	(0.230)	(0.154)	(0.163)	(0.119)	(0.153)	(0.116)	(0.154)
38 - 40	-0.130	-0.183	0.567***	0.534***	0.158**	0.012	0.109	-0.028	-0.016	-0.091
	(0.116)	(0.154)	(0.118)	(0.182)	(0.078)	(0.112)	(0.114)	(0.143)	(0.136)	(0.155)
41 - 43	-0.091	0.018	0.232**	0.320***	0.052	0.011	-0.011	0.090	-0.008	-0.157
	(0.077)	(0.094)	(0.094)	(0.113)	(0.059)	(0.106)	(0.092)	(0.130)	(0.083)	(0.113)
44 - 46	-0.150**	-0.094	0.105	0.141	0.083	0.002	-0.132*	-0.200*	0.040	-0.028
	(0.069)	(0.103)	(0.069)	(0.090)	(0.055)	(0.081)	(0.075)	(0.102)	(0.059)	(0.117)
47 - 49	-0.142*	-0.073	0.124*	0.141*	0.032	0.066	-0.062	-0.099	-0.023	-0.039
	(0.080)	(0.090)	(0.064)	(0.080)	(0.045)	(0.069)	(0.080)	(0.082)	(0.071)	(0.080)
50 - 52	-0.111	0.046	0.120	0.183**	0.071	0.130*	-0.073	-0.130	0.050	-0.010
	(0.092)	(0.094)	(0.081)	(0.077)	(0.063)	(0.067)	(0.078)	(0.097)	(0.070)	(0.080)
53 - 55	-0.060	0.005	-0.021	-0.013	-0.018	0.008	0.048	-0.003	0.120**	0.112*
	(0.052)	(0.054)	(0.067)	(0.046)	(0.050)	(0.065)	(0.048)	(0.060)	(0.060)	(0.067)
56 - 58	-0.103**	-0.076	0.016	0.000	0.046	0.060	-0.068	-0.083	-0.078*	-0.087*
	(0.049)	(0.062)	(0.059)	(0.056)	(0.038)	(0.042)	(0.061)	(0.063)	(0.045)	(0.050)
62 - 64	-0.029	-0.016	-0.043	-0.041	0.005	0.049	-0.048	-0.069	-0.026	-0.073
	(0.050)	(0.052)	(0.051)	(0.041)	(0.046)	(0.048)	(0.053)	(0.069)	(0.031)	(0.044)
65 - 67	0.049	0.064	-0.017	0.016	-0.039	-0.009	-0.035	-0.065	-0.033	-0.043
	(0.032)	(0.044)	(0.052)	(0.047)	(0.041)	(0.048)	(0.066)	(0.072)	(0.044)	(0.062)
68 - 70	0.094**	0.087**	-0.042	-0.010	-0.019	0.009	-0.016	-0.039	-0.032	-0.066
	(0.035)	(0.037)	(0.049)	(0.047)	(0.060)	(0.055)	(0.062)	(0.071)	(0.036)	(0.049)
71 - 73	0.107**	0.052	-0.079*	-0.027	-0.001	0.060	0.020	-0.008	-0.028	-0.057
	(0.048)	(0.051)	(0.045)	(0.059)	(0.052)	(0.065)	(0.063)	(0.075)	(0.047)	(0.055)
74 - 76	0.139***	0.108**	0.005	0.054	-0.018	0.037	0.026	-0.005	-0.079*	-0.089
	(0.045)	(0.054)	(0.058)	(0.048)	(0.045)	(0.049)	(0.072)	(0.097)	(0.044)	(0.059)
77 - 79	0.195***	0.196***	-0.058	0.011	-0.062	-0.015	0.011	-0.026	-0.083**	-0.099*
	(0.048)	(0.056)	(0.055)	(0.063)	(0.055)	(0.056)	(0.067)	(0.089)	(0.038)	(0.057)
80 - 82	0.230***	0.234***	-0.031	0.050	0.005	0.074	0.067	0.008	-0.094	-0.167**
	(0.054)	(0.074)	(0.068)	(0.060)	(0.063)	(0.069)	(0.077)	(0.098)	(0.057)	(0.071)
83 - 85	0.277***	0.286***	-0.034	0.057	0.040	0.083	0.065	-0.000	-0.088*	-0.155***
	(0.057)	(0.069)	(0.074)	(0.065)	(0.064)	(0.075)	(0.075)	(0.096)	(0.050)	(0.052)
86 - 88	0.309***	0.329***	0.023	0.093	-0.004	0.072	0.021	-0.040	-0.089	-0.133*
	(0.057)	(0.067)	(0.057)	(0.061)	(0.075)	(0.081)	(0.077)	(0.091)	(0.066)	(0.078)
89 - 91	0.414***	0.489***	0.035	0.079	0.032	0.120	0.052	0.039	-0.032	-0.120*
	(0.049)	(0.073)	(0.065)	(0.072)	(0.072)	(0.083)	(0.082)	(0.098)	(0.058)	(0.071)
92 - 94	0.429***	0.458***	-0.073	-0.037	-0.033	-0.006	0.069	0.019	-0.054	-0.116
	(0.072)	(0.106)	(0.075)	(0.087)	(0.078)	(0.093)	(0.085)	(0.110)	(0.074)	(0.086)
95 - 97	0.477***	0.473***	0.016	0.061	0.047	0.062	0.050	-0.006	-0.082	-0.154**
	(0.063)	(0.105)	(0.087)	(0.088)	(0.075)	(0.087)	(0.086)	(0.113)	(0.067)	(0.072)
98 - 100	0.426***	0.411***	0.014	0.032	-0.005	0.021	0.032	0.010	-0.078	-0.160**
	(0.065)	(0.100)	(0.096)	(0.107)	(0.086)	(0.101)	(0.098)	(0.118)	(0.063)	(0.070)
greater than 100	0.507***	0.484***	0.050	0.088	-0.029	0.046	-0.014	-0.043	0.059	-0.016
	(0.105)	(0.140)	(0.111)	(0.134)	(0.075)	(0.090)	(0.093)	(0.115)	(0.078)	(0.088)

Notes: These are the corresponding estimates from Figure 4.

Table A.2: Estimates from Figure 5, Graphs A - C and F - H

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

Notes: These are the corresponding estimates from Figure 5, graphs A - C and F - H. Column F displays interactions between the temperature bins and a rainy day indicator. Column G displays interactions between the temperature bins and an indicator for the MSA being in a humid climate. Column H displays interactions between select temperature bins and the season of the year.

Table A.3: Estimates from Figure 5, Graphs D and E

	D	E
below 14	1.536***	-0.070
	(0.532)	(0.422)
14 - 16	0.874**	0.324
	(0.367)	(0.333)
17 - 19	0.722	0.189
	(0.466)	(0.336)
20 - 22	-0.181	-0.332
	(0.261)	(0.266)
23 - 25	0.164	-0.077
	(0.155)	(0.153)
26 - 28	-0.139	-0.276
	(0.199)	(0.177)
29 - 31	-0.096	-0.154
	(0.101)	(0.107)
32 - 34	-0.152	-0.195**
	(0.111)	(0.095)
35 - 37	-0.191**	-0.198**
	(0.084)	(0.081)
38 - 40	-0.146*	-0.145*
	(0.074)	(0.074)
41 - 43	-0.300***	-0.285***
	(0.068)	(0.074)
44 - 46	-0.224***	-0.229***
	(0.075)	(0.086)
47 - 49	-0.199***	-0.195***
	(0.062)	(0.062)
53 - 55	-0.047	-0.041
	(0.087)	(0.082)
56 - 58	-0.102*	-0.117**
	(0.056)	(0.053)
59 - 61	-0.049	-0.080
	(0.093)	(0.083)
62 - 64	-0.011	-0.054
	(0.094)	(0.086)
65 - 67	0.164*	0.108
	(0.090)	(0.081)
68 - 70	0.136	0.062
	(0.104)	(0.107)
71 - 73	0.225*	0.143
	(0.126)	(0.125)
74 - 76	0.129	0.032
	(0.132)	(0.135)
greater than 76	0.082	-0.021
	(0.172)	(0.170)

Notes: These estimates of the effect of daily low temperatures correspond to the estimates from Figure 5, graphs D and E.

Table A.4: Estimates from Figure 6

	A	B	C	D
below 35	1.045***	0.118	2.114***	1.969***
	(0.352)	(0.403)	(0.505)	(0.577)
35 - 37	1.106**	0.546	1.743**	1.191*
	(0.406)	(0.328)	(0.688)	(0.677)
38 - 40	0.847***	0.483*	1.271***	0.786*
	(0.166)	(0.256)	(0.284)	(0.426)
41 - 43	0.328*	0.100	0.590**	0.490*
	(0.172)	(0.181)	(0.251)	(0.269)
44 - 46	0.082	0.156	-0.010	-0.167
	(0.108)	(0.141)	(0.197)	(0.266)
47 - 49	0.140	-0.050	0.355*	0.405*
	(0.120)	(0.157)	(0.179)	(0.237)
50 - 52	0.039	-0.019	0.115	0.134
	(0.211)	(0.211)	(0.255)	(0.196)
53 - 55	-0.025	-0.100	0.060	0.160
	(0.091)	(0.105)	(0.136)	(0.157)
56 - 58	0.007	-0.021	0.040	0.062
	(0.105)	(0.131)	(0.114)	(0.132)
62 - 64	-0.041	0.025	-0.120	-0.145
	(0.088)	(0.111)	(0.131)	(0.166)
65 - 67	0.013	0.071	-0.046	-0.116
	(0.096)	(0.088)	(0.132)	(0.106)
68 - 70	0.069	0.227**	-0.114	-0.341***
	(0.117)	(0.105)	(0.157)	(0.121)
71 - 73	0.063	0.133	-0.021	-0.154*
	(0.097)	(0.092)	(0.119)	(0.078)
74 - 76	0.158	0.270**	0.032	-0.237**
	(0.103)	(0.100)	(0.132)	(0.106)
77 - 79	0.107	0.244*	-0.049	-0.293**
	(0.120)	(0.127)	(0.139)	(0.114)
80 - 82	0.251*	0.384***	0.100	-0.284*
	(0.122)	(0.135)	(0.149)	(0.143)
83 - 85	0.384**	0.436***	0.328*	-0.107
	(0.149)	(0.144)	(0.185)	(0.141)
86 - 88	0.392***	0.458***	0.322**	-0.135
	(0.122)	(0.137)	(0.145)	(0.143)
89 - 91	0.583***	0.726***	0.421**	-0.305*
	(0.139)	(0.154)	(0.162)	(0.150)
92 - 94	0.417**	0.637***	0.164	-0.472***
	(0.154)	(0.169)	(0.180)	(0.167)
95 - 97	0.633***	0.813***	0.429**	-0.383***
	(0.165)	(0.169)	(0.178)	(0.111)
98 - 100	0.514***	0.640***	0.374*	-0.265*
	(0.173)	(0.185)	(0.189)	(0.144)
greater than 100	0.647***	0.876***	0.387	-0.489**
	(0.202)	(0.218)	(0.241)	(0.215)

Notes: These are the corresponding estimates from Figure 6. Column D displays interactions between the temperature bins and an indicator for the observation being for workers over age 40.

Table A.5: Estimates from Figure 7

	A	B	C	D
below 35	-0.000	0.996***	0.082	0.999***
	(0.003)	(0.283)	(0.091)	(0.237)
35 - 37	0.004*	0.892**	0.103	0.853**
	(0.002)	(0.389)	(0.117)	(0.376)
38 - 40	-0.003	0.676***	0.147**	0.571**
	(0.003)	(0.204)	(0.059)	(0.223)
41 - 43	-0.000	0.323**	-0.028	0.342***
	(0.002)	(0.144)	(0.052)	(0.112)
44 - 46	-0.000	0.059	-0.024	0.077
	(0.001)	(0.110)	(0.048)	(0.105)
47 - 49	-0.000	0.079	-0.041	0.159*
	(0.002)	(0.115)	(0.053)	(0.094)
50 - 52	0.001	-0.010	0.028	0.006
	(0.001)	(0.173)	(0.045)	(0.152)
53 - 55	0.002	-0.097	-0.024	-0.025
	(0.001)	(0.067)	(0.033)	(0.075)
56 - 58	0.001*	-0.039	0.013	-0.043
	(0.001)	(0.084)	(0.036)	(0.064)
62 - 64	0.001	-0.074	0.047	-0.071
	(0.001)	(0.082)	(0.033)	(0.073)
65 - 67	0.001	-0.027	0.036	-0.047
	(0.001)	(0.077)	(0.029)	(0.069)
68 - 70	0.002	0.041	0.026	-0.005
	(0.002)	(0.085)	(0.030)	(0.069)
71 - 73	-0.002	0.018	0.015	-0.007
	(0.001)	(0.088)	(0.035)	(0.074)
74 - 76	0.003*	0.107	0.057*	0.044
	(0.002)	(0.081)	(0.030)	(0.065)
77 - 79	0.003*	0.082	0.054*	0.027
	(0.002)	(0.095)	(0.030)	(0.086)
80 - 82	0.002	0.197*	0.100**	0.083
	(0.002)	(0.101)	(0.043)	(0.090)
83 - 85	0.001	0.305**	0.096**	0.174
	(0.003)	(0.118)	(0.040)	(0.108)
86 - 88	0.006*	0.305***	0.144***	0.164*
	(0.003)	(0.100)	(0.047)	(0.087)
89 - 91	0.009**	0.450***	0.153***	0.260***
	(0.004)	(0.105)	(0.036)	(0.090)
92 - 94	0.010**	0.316**	0.164***	0.149
	(0.005)	(0.122)	(0.048)	(0.092)
95 - 97	0.026***	0.476***	0.212***	0.229**
	(0.006)	(0.129)	(0.056)	(0.109)
98 - 100	0.032***	0.363**	0.188***	0.133
	(0.011)	(0.137)	(0.050)	(0.115)
greater than 100	0.072***	0.425***	0.194***	0.132
	(0.013)	(0.156)	(0.054)	(0.137)

Notes: These are the corresponding estimates from Figure 7.

Table A.6: Estimates from Figure 8

	A	B	C	D
below 35	0.736***	0.434***	0.260	0.662***
	(0.238)	(0.142)	(0.206)	(0.177)
35 - 37	0.747**	0.558***	0.219	0.673***
	(0.287)	(0.196)	(0.193)	(0.242)
38 - 40	0.525***	0.384***	0.251**	0.406***
	(0.177)	(0.120)	(0.097)	(0.142)
41 - 43	0.210*	0.058	0.182**	0.129
	(0.108)	(0.072)	(0.087)	(0.099)
44 - 46	0.161*	0.074	-0.099	0.152**
	(0.086)	(0.053)	(0.062)	(0.075)
47 - 49	0.078	0.059	-0.029	0.074
	(0.071)	(0.071)	(0.075)	(0.088)
50 - 52	0.058	0.057	0.024	0.023
	(0.146)	(0.083)	(0.113)	(0.094)
53 - 55	-0.035	-0.013	-0.083	-0.019
	(0.050)	(0.038)	(0.067)	(0.050)
56 - 58	0.048	0.037	-0.017	-0.029
	(0.074)	(0.040)	(0.069)	(0.052)
62 - 64	-0.084	-0.105**	-0.022	-0.050
	(0.061)	(0.045)	(0.052)	(0.055)
65 - 67	0.003	-0.010	-0.026	0.003
	(0.062)	(0.054)	(0.070)	(0.053)
68 - 70	0.015	-0.014	0.023	0.011
	(0.076)	(0.058)	(0.057)	(0.064)
71 - 73	-0.026	-0.024	0.011	0.000
	(0.075)	(0.059)	(0.052)	(0.068)
74 - 76	0.037	0.008	0.091*	0.029
	(0.079)	(0.051)	(0.054)	(0.060)
77 - 79	0.050	0.014	0.041	0.034
	(0.073)	(0.061)	(0.068)	(0.060)
80 - 82	0.112	0.063	0.127*	0.079
	(0.078)	(0.061)	(0.076)	(0.067)
83 - 85	0.215**	0.108	0.215***	0.091
	(0.103)	(0.066)	(0.079)	(0.079)
86 - 88	0.201**	0.150**	0.168**	0.165**
	(0.091)	(0.068)	(0.070)	(0.068)
89 - 91	0.335***	0.183**	0.286***	0.215***
	(0.097)	(0.074)	(0.076)	(0.072)
92 - 94	0.216*	0.129	0.203***	0.139*
	(0.110)	(0.081)	(0.070)	(0.080)
95 - 97	0.297**	0.171*	0.346***	0.207**
	(0.119)	(0.087)	(0.093)	(0.085)
98 - 100	0.252*	0.157*	0.253**	0.202**
	(0.139)	(0.085)	(0.097)	(0.092)
greater than 100	0.343**	0.160*	0.349***	0.205**
	(0.147)	(0.094)	(0.121)	(0.097)

Notes: These are the corresponding estimates from Figure 8.

Table A.7: Estimates from Figure 9

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

Notes: These are the corresponding estimates from Figure 9. Columns G and H display interactions between the temperature bins and a warmer climate indicator.

Table A.8: Estimates from Figure 10

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

Notes: These are the corresponding estimates from Figure 10. Columns G and H display interactions between the temperature bins and a warmer climate indicator.

Table A.9: Estimates from Figure 11

	A	B	C	D	E	F
below 40	-0.185***	-1.011***	-0.107	-0.160***	-0.602**	-0.083
	(0.066)	(0.283)	(0.124)	(0.059)	(0.282)	(0.119)
40 - 49	-0.020	0.079	0.029	-0.073	0.228	-0.147
	(0.050)	(0.186)	(0.073)	(0.063)	(0.199)	(0.094)
60 - 69	-0.014	-0.086	0.084	-0.091	-0.081	-0.129*
	(0.039)	(0.126)	(0.053)	(0.066)	(0.130)	(0.074)
70-79	0.047	0.115	0.103*	-0.024	0.027	-0.121*
	(0.039)	(0.100)	(0.060)	(0.068)	(0.107)	(0.065)
80-89	0.038	0.104	0.115	-0.085	-0.021	-0.121*
	(0.049)	(0.105)	(0.076)	(0.080)	(0.113)	(0.071)
greater than 90	-0.045	-0.005	0.103	-0.364***	-0.068	-0.392***
	(0.063)	(0.127)	(0.086)	(0.106)	(0.124)	(0.113)

Notes: These are the corresponding estimates from Figure 11. 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.

B Appendix: The Effect of Temperature on Injury Rates by Day for Mining Analysis

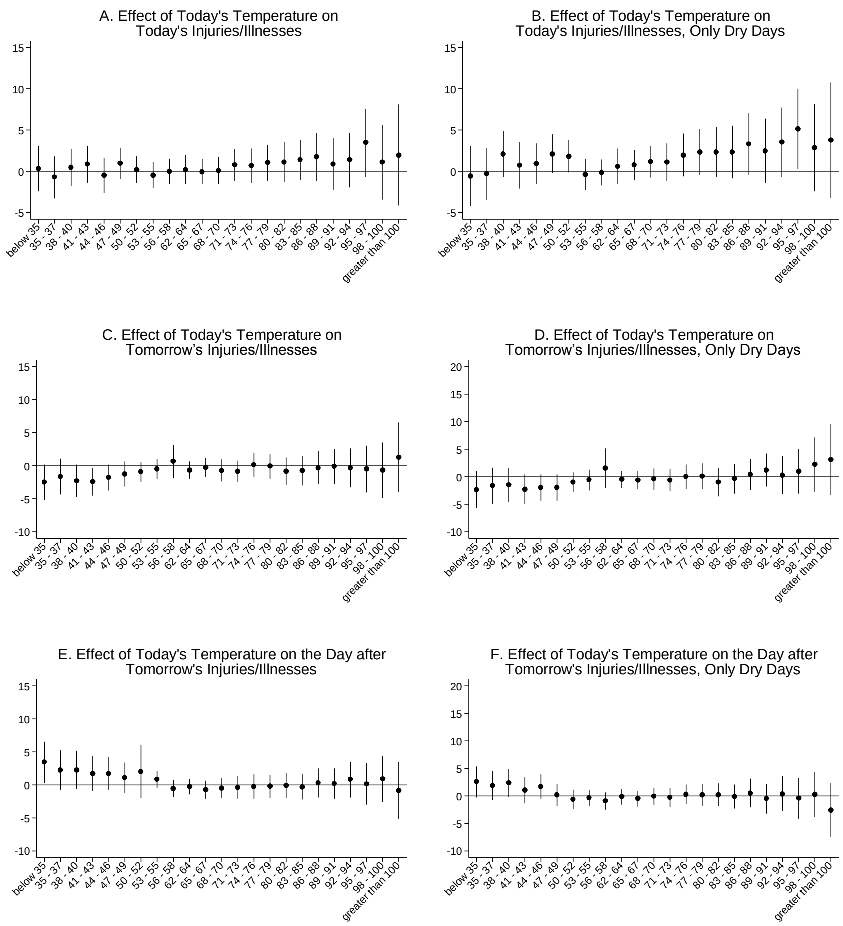

Figure B.1: **The Effect of Temperature on Injuries in Mining Data.** The underlying data come from the 2006 to 2014 MSHA injury logs. Each graph displays coefficient estimates on the temperature bins from a single regression. All estimates are relative to days with high temperatures of 59°F to 61°F. 95-percent confidence intervals calculated using standard errors clustered at the site level are displayed along with the estimates. All regressions control for day fixed effects, year-month-mine fixed effects, precipitation indicator variables, and high temperature and precipitation indicator variables for the preceding three days and proceeding two days. The means of injuries per 100,000 workers when temperatures are 59°F to 61°F are as follows: A: 10.47, B: 9.90, C: 9.30, D: 9.07, E: 7.45, and F: 7.60. The sample contains 2,615,672 site-days and 1,820,433 site-days without rain.