Heat Stress: the impact of ambient temperature on occupational injuries in the US

Lucy Page and Stephen Sheppard

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Abstract

Work-related injuries in the US generate annual costs exceeding $250 billion, with approximately one third of these costs coming from the direct health care expenses of dealing with the injuries and the remainder coming from the impacts on economic productivity associated with accidental injury. Beyond these costs, considerable expenses and efforts are devoted to avoiding injuries, and monitoring workplaces for compliance with safety rules.

There are many factors that can increase the probability of workplace accidents, as well as a variety of regulations and regulatory agencies designed to reduce or limit these factors and to monitor compliance with regulations by employers. Of course there are some factors that even the most well-intentioned employers can not control, or that may not be easy to regulate at the local or even the national level. In this paper we investigate one of these factors: the ambient temperature within which work takes place. Clinical and empirical evidence such as that presented in Colquhoun (1969), Chiles (1958) or Azer, McNall & Leung (1972) indicates that high temperatures and heat stress diminish mental alertness, vigilance and ability to perform complex tasks.

In a recent paper, Deschênes & Greenstone (2011) documented the potential impact of climate change on mortality in the US. Their research indicates that between 2010 and 2099, increased temperature could be expected to increase annual mortality rates in the US by about 3%, with about half of the heat-related deaths occurring in the South Atlantic and West South Central regions of the US.

We investigate the impact of increased temperature on occupational injuries in heat-sensitive industries in the US, providing what appear to be the first available estimates of the impact of increased ambient temperatures on workplace injuries. Using some approximations from climate models we provide estimates of the potential economic cost of climate change caused by this previously undiscussed mechanism.

1 Introduction

Climate change is expected to have a wide range of impacts around the world, from changing the incidence and geographic range of vector- and water-borne diseases in Africa to affecting the tourism industry by propelling tourists to higher altitudes and latitudes. To maximize economic efficiency, policies aimed at reducing greenhouse gas emissions should equate the marginal costs and benefits of these reductions; to do so, they should rely on a comprehensive understanding of the extensive and varied impacts of climate change. Unfortunately, a complete treatment of these impacts is extremely difficult; not only can we not pinpoint all of the multitude of possible effects of a changing climate, but projections of possible impacts rely on climate models that remain uncertain. The most useful research seeks to inform policy design with as much information on the impacts of climate change as is possible.

Currently, an active economic literature is working to estimate the impacts of climate change on a range of economic outcomes. So far, this work has estimated the effect of climate change on health, through deaths from air quality, deaths from extreme temperature, loss of labor productivity, and damages from water quality; on infrastructure, like bridges, roads, urban drainage, and coastal property; on the demand and supply of electricity; on water resources, through inland flooding, drought, and water shortages; on agriculture and forestry; and on ecosystem services, through coral reefs, shellfish, freshwater fish, wildfire, and carbon storage. A simple summary is available in Environmental Protection Agency (2015). Despite these efforts, large gaps in our knowledge remain. Climate change will affect all sectors of the global economy, as well as ecosystems and other non-market assets that are difficult to quantify, and many of these sectors have been studied only partially, if at all. In this paper, we add to this literature through an examination of the potential impacts of climate change on the incidence of workplace accidents in temperature-sensitive industries in the United States. To date, no studies have estimated the national impacts of climate change on worker safety, although Adam-Poupart, Smargiassi, Busque, Duguay, Fournier, Zayed & Labreche (2014) have evaluated the relationship between temperature and accident incidence in Quebec. Other studies by Xiang, Bi, Pisaniello & Hansen (2014*b*) and Xiang, Bi, Pisaniello, Hansen & Sullivan (2014) provide comparable estimates for Adelaide, Australia.

The occupational health effects of increased accident risk could be a significant impact of climate change in the United States and around the world. As temperatures rise around the country under a changing climate, one might expect that more frequent extreme temperature highs would pose a risk to laborers working outside in industries like construction, utility services, forestry, and agriculture. At the same time, milder winters might reduce these risks. Workplace injuries impose a significant cost on the United States economy, so even a modest change in the incidence of these accidents could be economically significant. Biddle & Keane (2011) found that fatal occupational injuries in the United States were associated with a total cost of over $53 billion between 1992 and 2002. This is about $6.4 billion per year at current prices. This figure is generated by an average of about 6,125 fatal occupational accidents each year. These costs are both direct and indirect, including medical expenses, lost production, and lost future wages. Leigh (2011) finds that fatal and nonfatal occupational injuries and illnesses in the US inflicted total costs of about $250 billion in 2007, with about $192 billion of this cost associated with accidents. Thus, any changes in the risk of accidents could have important economic impacts.

In this paper we investigate the impact of temperature on the incidence of workplace accidents in a panel of counties across the United States from 1990 through 2010, focusing on industries where workers are plausibly exposed to outdoor temperatures, like construction, agriculture, forestry, and utilities servicing. This analysis draws both from the recent body of work on the impacts of climate change and from this work in public health. Like Dell, Jones & Olken (2014) and much of the recent research on climate impacts, we use a suite of geographic and temporal fixed effects to identify the impacts of short-term, plausibly exogenous local variation in weather. This identification strategy allows robust causal inference of the impacts of temperature. Like other research on climate impacts, we estimate this relationship across the contiguous United States and using a series of ten-degree temperature bins, improving on the city-specific analysis and strict functional form restrictions of previous public health research in this area. However, we also draw from the public health literature by looking closely at the daily impact of temperature on accident incidence and by using Poisson regression, which is ideal for modeling the arrival of random events, like workplace accidents.

We present the first analysis (of which we are aware) that examines the relationship between accident incidence and ambient temperature. Our analysis makes use of a broad geographic spatial scale and flexibly models the impacts of temperature, while retaining a framework of daily-level Poisson analysis that is well-suited to analysis of accident counts. We conduct this analysis using a panel of weather, accident, and employment data for a panel of daily-level data for about 2,500 counties across the contiguous United States from 1990 to 2010. This dataset includes records for 71,218 occupational injuries and fatalities reported to the Occupational Safety and Health Administration (OSHA), daily-level temperature and precipitation data measured by the National Weather Service cooperative station network and from the North America Land Data Assimilation System, and monthly-level employment data from the Bureau of Labor Statistics Quarterly Census of Employment and Wages.

We find a statistically significant relationship between daily maximum temperature and accident rate, where accident rate rises at high temperature extremes and falls at low temperature extremes. At high temperatures, we find that accident rate increases by 8.2% on days with maximum temperature between 90°and 100°F and by 30.0% on days with maximum temperature over 100°F, both relative to a day with maximum temperature between 60°and 70°F. At low temperatures, accident rate falls by 21.0% on days with maximum temperature between 10°and 20°F and by 30.1% on days with maximum temperature between 0°and 10°F, both relative to a day with maximum temperature between 60°and 70°F. These impacts are heterogeneous across the United States, but this variation does not appear to be systematically related to historical climate conditions. Next, it appears that both extremely high temperatures on the preceding day and temperature spikes today increase accident rate today. It is important to note that our estimates for the impacts of temperature incorporate both the impact of temperature on the risk of accidents for a given duration and intensity of work and behavioral changes in response to temperature, or adaptation.

We take preliminary steps to project these results into estimates of the impacts of climate change associated with changes in the incidence of workplace accidents. Based on estimates for the short-run impacts of temperature, we project that climate change may cause between about 33,600 and 102,400 additional accidents in temperature-sensitive industries per year between 2070 and 2099. These additional accidents could pose costs of between $750 million and $2.30 billion per year between 2070 and 2099. It is important to interpret these results with caution. Our analysis identifies the impacts of weather fluctuations on accident incidence, where we can think of weather as a particular draw from a climate distribution. The impacts of these short-run fluctuations in weather are not necessarily analogous to the impacts of climate change on worker safety, where climate change occurs gradually over a long timescale. In particular, the estimates may overstate the impacts of climate change if adaptation occurs in the long-run, perhaps through the development of new worker safety technologies or regulations. On the other hand, our estimates may understate the impacts of climate change if these impacts are characterized by intensification, where prolonged periods of heat have more drastic impacts on accident rate than are revealed in the impacts of transient weather fluctuations as suggested in Dell et al. (2014).

The rest of the paper is organized as follows: section 2 reviews relevant literature on the relationship between temperature and occupational safety. Section 3 describes our data sources and reports summary statistics, and Section 4 outlines our econometric strategy and presents the primary results. Section 5 gives some extensions of this analysis, identifies some possible directions for future research and presents concluding remarks.

2 Previous research

Prior research relevant for our analysis has appeared in the public health, medical, industrial engineering and economics literature. It is therefore helpful to provide a more comprehensive overview of previous research, including estimates of both economic, physiological and behavioral responses to ambient temperature changes.

2.1 Climate Change and Industry

There are several studies that have examined the relationship between ambient temperature and industrial output, mostly in the context of developing countries. For example, Hsiang (2010) estimates the impacts of temperature and cyclones on output in Caribbean countries between 1970 and 2006. Using plausibly exogenous local year-to-year fluctuations in weather for 28 countries, he finds that unusually hot periods significantly reduce output, with losses of about 2.4% of nonagricultural output per 1°C increase. These impacts are driven by productivity losses in mining and utilities, wholesale, retail, restaurants, and hotels, and other service-related industries.

Similarly, Dell, Jones & Olken (2012) and Jones & Olken (2010) estimate the impacts of temperature on aggregate output in a global sample. Dell et al. (2012) use data from 125 countries between 1950 and

2003. They find that increases in average temperature reduce value added by 2% per increase of 1°C in poor countries. Jones & Olken (2010) use international trade data including exports to the US and to the wider world. They find that warming of 1°C reduces the growth in exports from poor countries by about 2.4%.

While these studies find that temperature significantly impacts output in developing countries, Dell et al. (2012) do not find evidence that this relationship holds in wealthy countries. Burke, Hsiang & Miguel (2015) address this by accounting for non-linearities in the impacts of temperature on aggregate macroeconomic productivity. They find that country-level aggregate production is smooth, non-linear, and concave with respect to temperature for all countries, with a maximum at 13°C. This relationship appears to be consistent since 1960 and across agricultural and non-agricultural production in both rich and poor countries, suggesting that economic activity depends on climate in all countries, regardless of level of development. Deryugina & Hsiang (2014) explicitly investigate the possibility that wealth protects countries from the adverse of impacts of temperature by estimating the impact of daily temperature on annual income in United States counties between 1969 and 2011. They find that the average productivity of individual days falls roughly linearly by about 1.7% for each 1°C in daily average temperature above 15°C, with this impact remaining consistent across their study period.

Cachon, Gallino & Olivares (2012) supplement these estimates with a detailed study of the impacts of weather on plant-level output in the automobile industry in the United States. They find that production does not fall significantly in weeks with one day with maximum temperature over 90°F or with between two and five days with maximum temperature over 90°F, production falls by 8.75% on weeks with six or seven days with maximum temperature over 90°F. This result is particularly interesting in that it identifies negative impacts of outdoor temperature in an industry where work is indoors and likely to be air-conditioned. These impacts might arise because indoor air-conditioning is insufficient when it is extremely hot outside, because exposure to temperature outside of work reduces employees' at-work productivity, or because of other disruptions to production outside the plant interior. Thus the impacts of temperature may extend beyond those industries that are obviously sensitive to weather conditions.

A recent study by Zivin & Neidell (2014) looks at the impact of temperature on the allocation of time to labor. The authors use a panel of county-level data from 2003 through 2006 from the American Time

Use Survey to estimate how temperature impacts the amount of time spent working in industries where workers are plausibly exposed to weather during work. Overall, they find that time spent working in these temperature-sensitive industries falls significantly at high temperature extremes, with labor supply falling by about an hour per day on days with maximum temperatures over 100°F relative to a day with maximum temperature between 76 and 80°F. The authors do not find that temperature significantly reduces time spent working in indoor industries other than manufacturing.

2.2 Temperature and Accidents

Despite rapid growth of research on the impacts of climate change, no studies have as yet estimated the potential risks that climate change may pose to worker safety. Impacts of temperature on accident incidence could be one mechanism through which temperature reduces aggregate economic output as found in the studies cited above. These impacts may partially arise through the physiological impacts of temperature on the human body.

Working under high temperatures may put workers at risk of heat stress, which is defined as exposure to excess heat from the combination of one's own metabolism and environmental sources. If heat stress is extended, the loss of plasma and electrolytes from continuous sweating and changes in blood circulation can overwhelm the body's thermo-regulatory systems, allowing core body temperature to rise and compromising the cardiovascular and central nervous systems. Jackson & Rosenberg (2010) observe that the symptoms of heat stress can range from discomfort (heat rash, heat syncope, heat cramps, heat exhaustion, or heat stroke) to death.

While there are no government-mandated standards for workplace thermal conditions, the National Institute for Occupational Safety and Health (NIOSH) periodically publishes recommended standards for temperature exposure. Recent research has shown that heat exposure has historically posed a significant threat to worker safety. Luber, Sanchez & Conklin (2006) report that between 1999 and 2003 there were a total of 3,442 deaths in the US due to exposure to excessive heat, an average of 688 per year.

While most research on work in extreme temperature has focused on the risks of working in extremely hot conditions, Workers may also be at risk in very cold environments. In particular, workers exposed to extreme cold may be at risk of cold stress. Stocks, Taylor, Tipton & Greenlead (2004) note that as hypothermia becomes more severe, its symptoms can progress from goose bumps and shivering to cardiac and respiratory failure, and ultimately to death.

There is reason to believe that extreme temperatures in either direction might impact the rate of occupational accidents. While heat and cold stress can be the primary cause of workplace mortality or morbidity, their symptoms also likely make workers more susceptible to accidents. Even with heat illness of low severity, workers are likely to grow dizzy or faint. Jackson & Rosenberg (2010) note that as heat illness progresses, victims may exhibit fatigue, nausea, lack of coordination, and confusion, all of which would impair their ability to work safely. Similarly, Occupational Health Clinics for Ontario Workers Inc. (2005) notes that workers suffering from cold stress may become sluggish, confused, and unable to use their hands properly, again increasing accident risk.

Mackworth (1948), Fraser (1957), Pepler (1960), Bell, Provins & Hiorns (1964), Azer et al. (1972) and Fine & Kobrick (1978) all provide evidence that workers may experience impaired measures of cognitive function that link directly to accident risk like coordination, vigilance, reaction time, and mental performance even before serious symptoms of heat or cold stress appear.

Epstein, Keren, Moisseiev, Gasko & Yachin (1980) report that when study participants were asked to shoot at a square target on a video screen at 70°F, 86°F, and 95°F, their proportion of error increased from 7.9% to 15.9%, and then to 16.6% between those temperatures. Similarly, Wyon, Wyon & Norin (1996) find that the proportion of signals missed by drivers increases by 50% and reaction time increases by 22% between 70 and 80°F.

Some studies[1] have produced conflicting estimates regarding cognitive impacts, but several meta-analyses have found consistent negative associations between heat exposure and task performance after accounting for studies' measures of heat exposure and task type, as noted in Hancock & Vasmatzidis (2003). Ramsey & Kwon (1992) review 150 studies and find that performance of tasks requiring more demanding perceptual motor skills, like vigilance and coordination, is impaired at high temperatures. Pilcher, Nadler & Busch (2002) undertake a meta-analysis of task performance studies and find that exposure to hot and cold temperatures impairs performance of attention- and perception-based, mathematical, and reaction

[1] See for example (Chiles 1958), (Pepler 1960), (Colquhoun 1969), (Grether, Harris, Mohr, Nixon, Ohlbaum, Sommer, Thaler & Veghte 1971), (Ramsey, Dayal & Ghahramani 1975), (Ramsey & Pai 1975) and (Lewis, Meese, Kok, Wentzel & Wyon 1983)

time-based tasks, with the worst performance above 90°F and below 50°F. Similarly, Seppänen, Fisk & Faulkner (2003) find that productivity in various cognitive tasks falls by about 2% for each increase of 1°C at temperatures above 25°C.

In turn, these physiological effects may translate into increasingly risky worker behavior. Ramsey & Burford (1983) observe worker behavior at a metal products manufacturing plant and a foundry, and develop a measure for risky behavior called the Unsafe Behavior Index (UBI). Using a quadratic model and controlling for workers' metabolic workload, job risk group and the observation's time of day and day of the week, they find a statistically significant U-shaped relationship between thermal exposure and unsafe work behavior. Unsafe behavior is lowest between about 63°F and 73°F, but increases roughly proportionally both at high and low temperatures.

Even if the risk of accidents for a given amount of work follows this U-shape, however, the observed relationship between temperature and the incidence of accidents could be altered by adaptation. In this context, we can think of adaptation as processes or decisions that help reduce the negative impacts of short- or long-run shifts in temperature. This adaptation could be physiological or economic. Physiological adaptation describes the process by which human bodies physically acclimatize to adverse weather conditions, and economic adaptation describes actions and behavior changes that economic actors take to reduce the negative impacts of temperature shocks on accident incidence.

Research in physiology suggests that workers can adjust fairly quickly to adverse temperature environments, creating a mechanism for physiological adaptation that could significantly reduce the impacts of temperatures on the risk of workplace accidents. Workers can typically achieve acclimatization with daily heat exposure over one to two weeks, though the speed of this process depends on worker age and health.

This process of acclimatization, which has been well-documented by Lind & Bass (1963) and World Health Organization (1969), *inter alia*, would likely reduce the risk of both heat illness and accidents among workers that are consistently exposed to high ambient temperatures. Kaciuba-Uscilko (1989) suggests that physiological adaptation to cold temperatures is less rapid but that nevertheless workers would likely show a similar capacity to adapt. If so, these physiological adaptive mechanisms might reduce the impact of temperature on accident incidence.

In contrast to physiological adaptation, economic adaptation to the impacts of temperature can occur at a wide range of timescales. Jackson & Rosenberg (2010), for example, outline a range of protective behaviors for both employees and employers including modifying work assignments in response to weather, providing shaded rest stations, creating heat acclimation plans, and taking frequent breaks of adequate duration. Studies such as Zivin & Neidell (2014) have found some evidence that workers adjust time spent working in response to temperature, with workers in certain outdoor industries allocating about an hour less to labor on days with maximum temperature over 100°F relative to days with maximum temperature between 76°F and 80°F.

At longer timescales, other forms of economic adaptation to extreme temperatures would become possible. Even if accident *risk* is represented by a U-shaped curve with respect to temperature, these physiological and economic adaptive behaviors might alter the shape of the relationship between temperature and the *incidence* of accidents, both in the short- and long-term. We would expect to see that short-term behavioral adaptations would reduce the impacts of temperature on accident risk. They would lessen the increase in accident incidence at temperature extremes implied by the increase in accident risk per unit of work at those temperatures. Even in the short term we might expect to see a dampened U-shaped relationship between temperature and the incidence of workplace accidents, or even the inverted U-shaped relationship found by Xiang, Bi, Pisaniello & Hansen (2014*a*). While these long-term adaptation possibilities may not show up in our estimates of the short-term impacts of temperature, extrapolating these short-term estimates to the long-term changes in accident incidence that we would expect to see under climate change would require considering the extent to which adaptation will reduce these impacts.

Some studies actually provide estimates of the association between temperature and the incidence of occupational accidents. These studies have identified a variety of nonlinear relationships between temperature and accidents, ranging from reversed U-shaped curves, where accidents become less frequent at extreme temperatures, to U-shaped curves, where accidents become more frequent at extreme temperatures. Xiang, Bi, Pisaniello & Hansen (2014*a*) note that this divergence appears to be largely explained by studies' inclusion or exclusion of "denominator data," where the denominator is a measure of work volume or output that can be used to calculate a rate of accidents per unit of work. They note that while adaptive behaviors may "result in the unexpected decline in the number of work-related injuries," the association between temperature and accidents tends to be U-shaped when "denominator information is available for calculating work-related injury rates". In other words, this denominator data partially captures the extent of short-term adaptation to temperature through reduction of units worked.

The earliest quantitative study of the relationship between temperature exposure and occupational accidents was Osborne, Vernon & Muscio (1922). The study examines the frequency of accidents in three British munitions factories, and seeks to address broad differences in work volume or duration by controlling for shift type and verifying that employment and output remain relatively constant over the year. The study finds that the frequency of accidents is lowest between 65 and 69°F. The rate of accidents increases at temperatures below 65°F, and increases between 65 to 69°F and 70 to 74°F, and then again between 70 to 74°F and temperatures over 75°F. The only exception to this steady U-shaped curve is a dip in accident frequency below 49°F, which the authors attribute to adaptive behavior, suggesting that work may slow or cease altogether at those temperatures.

Powell (1971) undertakes a study of the causes of 2,367 accidents in four different industrial workshops between 1966 and 1969. In each of the four facilities, the frequency of accidents that occur over a spread of temperature ranges is calculated, and simple t-tests are used to determine whether the mean temperature at which accidents occur in each facility is significantly different from the mean temperature over the study period. They find significant relationships in two of the four shops, with an increase in the frequency of accidents at temperatures below about 68°F. They find no increase of accidents at high temperatures, which they attribute to "the noticeable slackening of work done in hot weather." They do not collect data on work volume at these facilities, so their estimates of the impact of temperature on accident frequency are influenced by the impact of temperature on work duration and intensity.

In a study of safety records at a Midwestern aluminum smelting plant, Fogleman, Fakhrazadeh & Bernard (2005) adjusts the methodology of these earlier investigations by incorporating detailed data on person-hours worked at the facility. This denominator data allows them to evaluate the impact of temperature on the number of accidents for a given amount of work, more cleanly measuring changes in accident risk. The study uses an outdoor heat index based on temperature and humidity as a surrogate for heat conditions inside the open plant and uses Poisson regression to evaluate the effect of categories of this heat index on the ratio of incidents to person-time after controlling for age and work location. They find significantly elevated odds ratios for accidents for an outdoor heat index both at temperatures below 20°F (-7°C) and at temperatures above 90°F (32°C), though this increase is much larger in magnitude at low temperatures.

Because Fogleman et al. (2005) uses a measure of accident frequency adjusted for work volume, the estimates are unique in the literature on temperature and accidents in that they are able to estimate the impact of temperature on the risk of accidents for a given amount of work, rather than simply estimating the impact of temperature on the number of accidents that take place.

Morabito, Cecchi, Crisci, Modesti & Orlandini (2006) aims to evaluate the effect of temperature on occupational safety at the level of cities and regions. While these studies may be more widely relevant than the facility-specific design of earlier work, this broader spatial scale also makes it increasingly difficult to identify meaningful denominator data. The study explores the effect of high daily ambient temperature on summer hospitalizations for work accidents at six hospitals in Tuscany, Italy between 1998 and 2003. Overall, the study finds a reversed U-shape relationship between AT and hospitalizations for workplace accidents, with the highest accident rates occurring between about 76°F and 82°F, representing high, but not extreme, apparent temperature. This reduction in accident incidence at extreme temperatures is attributed to behavioral changes that actually reduce accident incidence below that at moderately high temperatures, despite the plausible increase in the risk of accidents for a given volume of work at very hot temperatures.

The analysis presented in Xiang, Bi, Pisaniello & Hansen (2014*b*) and Xiang, Bi, Pisaniello, Hansen & Sullivan (2014) examine the association between high temperature and workplace accidents in Adelaide, Australia using workers' compensation data. The first paper estimates the association between daily maximum temperature and injury counts on weekdays from 2001 to 2010 using a negative binomial model. The estimation allows for nonlinearity in the relationship between temperature and work-related injury. The study separately accounts for "indoor" and "outdoor" industries, where outdoor industries include agriculture, forestry, fishing, construction, electricity, gas, and water services. Overall they find that an increase of 1.8°F (1°C) is associated with a 0.2% increase in the number of daily injury claims at temperatures below 100°F, but that the number of daily injury claims decreases by 1.4% with an increase in daily maximum temperature of 1.8°F (1°C) at temperatures above 100°F (37.7°C). Thus, the relationship between daily maximum temperature and worker compensation claims takes a reversed U-shape. The reduction in injuries at extremely high temperatures is attributed to protective measures. No such decrease in injuries is observed for workers in "electricity, gas, and water" industries at extreme temperatures, potentially because workers in those industries must ensure the continuous supply of utilities despite extreme conditions, and are therefore unable to make behavioral adjustments.

Xiang, Bi, Pisaniello, Hansen & Sullivan (2014) investigate the impact of heat waves on workers' compensation claims, again in Adelaide, Australia between 2001 and 2010. For the study a *heat wave* is defined as a period of at least three consecutive days with daily maximum temperature over 95°F. Other aspects of the analysis are similar to Xiang, Bi, Pisaniello & Hansen (2014*b*). They find that while heatwave conditions do not significantly increase worker safety claims among all workers, claims within outdoor industries increase by 6.2% during heatwaves.

Adam-Poupart et al. (2014) follow a similar methodology in their analysis of the association between heat-related occupational injury compensations and exposure to summer maximum daily temperatures in each of the 16 health regions of Quebec for the years 1998 through 2010. Like Xiang, Bi, Pisaniello & Hansen (2014*b*) and Xiang, Bi, Pisaniello, Hansen & Sullivan (2014), the authors estimate the association between daily compensation counts and daily hourly maximum temperature using a generalized linear model with negative binomial regression. They also include a similar suite of controls, but impose a linear relationship between daily maximum temperature and heat-related compensation counts. In analyzing each of the health regions of Quebec, this analysis is the first to examine the impact of temperature on accidents across different working populations. The analysis includes the log of monthly working population in each health region to adjust for the sizes of these worker pools. Overall, the authors find that an increase of 1°C in daily maximum temperature is associated with a 42% increase in the count of daily heat-related occupational injury compensations in Quebec.

To date, all substantive work on the impacts of temperature on worker safety has focused on North America, Europe, and Australia. However, climate change may pose particular risks to workers in low- and middle-income countries. Kjellstrom, Holmer & Lemke (2009) argue that the impacts of temperature on accident incidence could be particularly severe due to limited access to air-conditioning, the prevalence of output-based payment systems that discourage protective behavior in favor of high productivity, and industrial structures centered around outdoor industries like agriculture, forestry, or mining. For example, Tawatsupa, Yiengprugsawa, Kjellstrom, Berecki-Gisolf, Seubsman & Sleight (2013) have found that heat stress is significantly associated with occupational injuries in Thailand, though the study is limited in that it relies on qualitative measures of heat exposure and occupational injuries reported by participants in the 2005 Thai Cohort Study.

3 Data

3.1 Weather Data

We use daily-level weather data generated from raw data drawn from the National Climatic Data Center (NCDC) Summary of the Day Data files (TD-3200). These files contain daily weather observations from stations in the National Weather Service (NWS) cooperative station network across the United States. While most of these stations are operated by private volunteers, they include NWS principal climatological stations and stations operated by employees of other federal agencies such as the Federal Aviation Administration and the National Park Service. About 8,000 stations in this cooperative network are currently active, but about 23,000 stations have been active since the network's formation in the mid 1900s.[2] Our primary data elements of interest are daily maximum temperature, minimum temperature, and precipitation.

To ensure the accuracy of these weather readings, we use weather data from stations selected using a rule modeled after that used by Deschênes & Greenstone (2011), who use the same weather data. First, we ensure the quality of weather data by only including data for a given year from stations that provide measurements for maximum temperature and precipitation for each day of that year. Over 10,000 weather stations meet this selection criterion for at least one year between 1984 and 2010, and an average of 4,407 stations meet this selection rule in a given year in that range. While Deschênes & Greenstone (2011) only use weather data from stations at elevations below 7000 feet to reflect the weather conditions experienced by most residents of a county, we seek to better accomplish this goal by using stations located in census tracts that had population density of over 100 people per square km in 2004. Indeed, a rule based on station elevation only loosely identifies the areas where people live, and such a rule potentially places far more restrictions on stations in mountainous areas of the country, like Wyoming and Montana, than on stations in areas like the Midwest.

[2] The earliest data collection began in 1854, but most stations in operation now began operating in or after 1948.

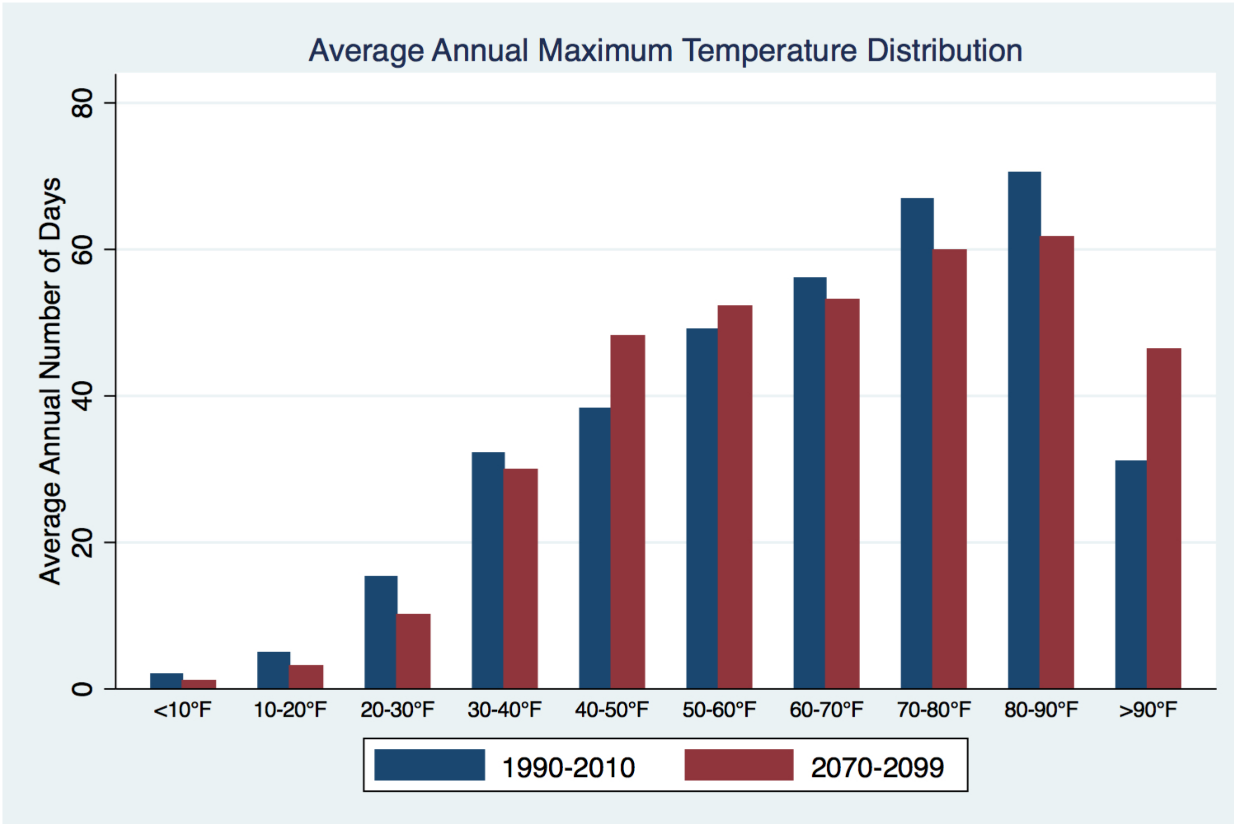

Figure 1: Historical and forecast distribution of daily maximum temperature across ten temperature bins. Bars for 1990-2010 represent the average number of days in each temperature bin per year for a county in our sample. Bars for 2070-2099 represent the average number of days in each temperature bin per year in a county under the Hadley 3 climate model under the highest warming scenario (A1).

A total of 3,322 stations meet our final selection rule for at least one year between 1984 and 2010, and an average of 1,632 stations meet this rule for a given year in that range. We then produce county-level weather data by taking an inverse-distance weighted average of the data from all remaining stations within 200 km of the centroid of each county. While this does result in some cases where our data for a county's weather conditions is drawn entirely from data from stations outside of that county, it does smooth out irregularities caused by tremendous differences in the size of counties across the US, and provides for inclusion of more counties in the analysis. Inverse-distancing weighting allows us to approximate weather in counties without stations while also privileging the readings from within-county stations for those counties with functioning weather stations within their borders.

We then merge these weather data with additional daily data on temperature from the North America Land Data Assimilation System (NLDAS). NLDAS is a collaborative project between NOAA, NASA, Princeton University, and the University of Washington that has produced a record of county-level daily maximum temperature and heat index across North America from 1979 to 2011. Heat index is a measure of apparent temperature that incorporates humidity, and which therefore may be a better measure of temperature exposure than are dry temperature measurements. NLDAS calculates heat index for days with temperatures at or above 80°F according to the following formula, where HI is heat index, T is ambient dry bulb temperature, and RH is relative humidity:

$$\begin{aligned} HI = -42.379 + 2.049 \cdot T \; + \; 10.14333127 \cdot RH \; - \; 0.22475541 \cdot T \cdot RH \; - \\ 0.00683783 \cdot T^2 \; - \; 0.05481717 \cdot RH^2 \; + \; 0.00000199 \cdot T^2 \cdot RH^2 \end{aligned} \tag{1}$$

We then merge this NLDAS maximum temperature and heat index data with data on maximum temperature and precipitation from the NCDC Summary of the Day datafiles. These data sources are in close agreement when both are available; NLDAS and NCDC data on maximum temperature have a correlation coefficient of 0.9561. In some cases, only NLDAS temperature data is available for a particular county-year combination. Then, since NLDAS data does not include a measure of precipitation, we assign daily precipitation as the simple average of available precipitation data from neighboring counties. Figure 1 presents the distribution of the average number of days with maximum temperatures in each range for our sample of counties (blue bars) and predicted for the future using the Hadley 3 climate model (dark red bars).

We restrict our sample to the contiguous United States, excluding Alaska, Hawaii, and any other U.S. territories. The contiguous United States contains 3,108 county equivalents. Using the two sources for weather data described, all 3,108 counties have daily weather data for at least one year between 1989 and 2010, and 2,840 counties have daily weather data for every year between 1989 and 2010. About 92% of accidents reported to OSHA during our study period can be matched to these weather data. Summary statistics for selected temperature data in each Census division[3] are presented in Table 1.

[3]Census divisions are defined in the usual way: New England (CT, ME, MA, NH, RI, VT); Middle Atlantic (NJ, NY, PA); East North Central (IN, IL, MI, OH, WI); West North Central (IA, KS, MN, MO, NE, ND, SD); South Atlantic (DE, DC, FL, GA, MD, NC, SC, VA, WV); East South Central (AL, KY, MS, TN); West South Central (AR, LA, OK, TX); Mountain (AZ, CO, ID, NM, MT, UT, NV, WY); Pacific (CA, OR, WA)

Table 1: Temperature Summary Statistics

Census Division	Avg Daily Max Temp (°F)	Avg # Days with Max Temp < 10°F	Avg # Days with Max Temp < 20°F	Avg # Days with Max Temp > 90°F	Avg # Days with Max Temp > 100°F
All	64.53	2.005	7.045	30.477	3.637
New England	54.172	2.156	9.296	3.389	0.305
Middle Atlantic	56.476	1.04	7.705	2.506	0.006
E.N. Central	58.196	2.292	10.936	8.714	0.328
W.N. Central	60.042	6.818	19.336	30.866	4.067
South Atlantic	69.425	0.045	0.526	25.759	0.553
E.S. Central	69.023	0.114	0.663	25.023	0.988
W.S. Central	75.953	0.034	0.252	83.137	14.623
Mountain	57.875	1.867	7.745	20.053	1.969
Pacific	61.774	0.578	3.132	22.27	4.721

Note: All figures *per annum* and by county. Averages calculated first by county and then averaged across counties in our sample.

3.2 Accident Data

Our data for occupational accidents comes from the Occupational Safety and Health Administration's Enforcement Inspection and Accident Investigation Data. Since the Occupational Safety and Health Administration (OSHA) was formed with the passage of the Occupational Safety and Health Act of 1970, employers have been required to report certain workplace incidents to OSHA. The first accident reporting requirements were instituted by a bill passed in July 1971. This bill, 36 FR 12612, required that employers report all workplace fatalities and accidents resulting in the hospitalization of five or more employees to OSHA within 48 hours of the incident. In 1994, these regulations were expanded to require that employers report accidents resulting in the hospitalization of only three workers and that employers make these reports within eight hours of learning of the incident. These regulations were strengthened again in 2015 to require that employers report to OSHA all work-related fatalities within 8 hours of the event, and report all work-related inpatient hospitalizations of one or more employees, all work-related amputations, and all work-related losses of an eye within 24 hours of the event. Figure 2 shows the number of reported accidents since passage of the legislation.

A total of 93,566 accidents were reported to OSHA from the contiguous United States between 1970 and 2013. There is significant variation in the number of accidents reported each year over that period, but

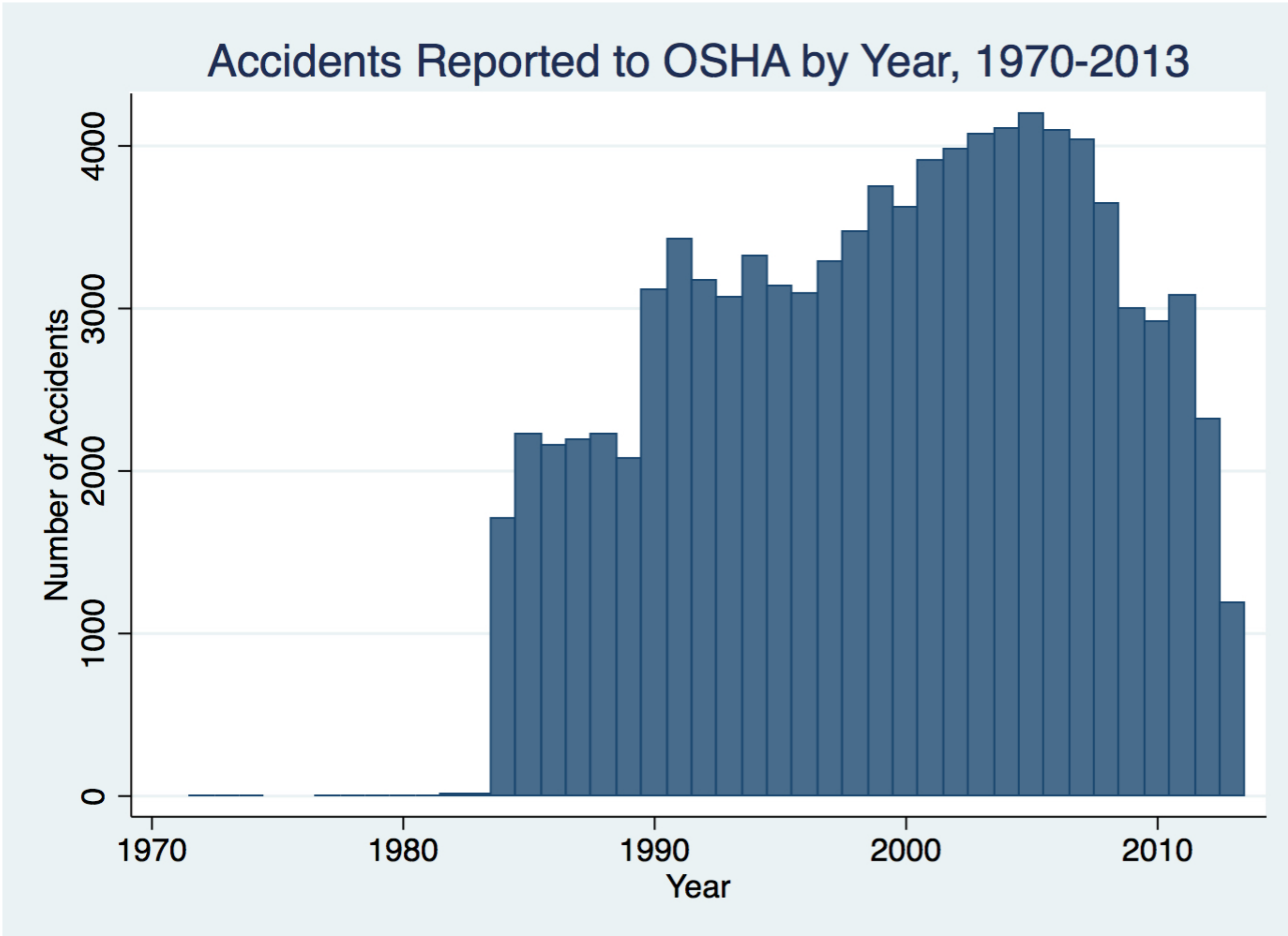

Figure 2: Total number of fatal and nonfatal accidents reported to the Occupational Safety and Health Administration (OSHA) by year. Figures are based on OSHA's Enforcement Inspection and Accident Investigation Data.

it is not clearly tied to the changes in reporting regulations. Accidents were first reported in large volume in the mid-1980s.[4]

OSHA's records for occupational accidents also drop off in recent years due to a backlog in accident investigation and processing, since accident investigation cases must pass through a review process before being reported to the public. While OSHA states that this backlog of cases currently extends back to August 2013, the marked fall in the number of accidents following 2010 suggests that some cases from 2011 and 2012 may also currently be unreported (DOL Data Enforcement). We also see a sudden increase in the volume of accidents reported to OSHA in 1990, which does not correspond to a change in accident

[4]Current OSHA employees are not able to offer an explanation for the near absence of reports recorded for the first ten years after passage of the enabling legislation.

reporting requirements.[5]

In order to avoid questions raised by these unexplained changes in accident reporting over time, we restrict our analysis to the years 1990 through 2010, a range in which there are no abrupt shifts in the volume of accidents reported each year. About 79.5% of accidents reported to OSHA occurred in this period. In the estimates we also control for changes in the volume of accidents reported to OSHA with year fixed effects.

OSHA's accident records are not a complete record of workplace injuries and deaths in the United States. Not only do these records include only the more severe accidents, but they include only those accidents that occur in certain industries and among certain groups of workers. While OSHA has ultimately responsibility for the safety and health of all employees in the United States, its jurisdiction is limited in several respects. OSHA covers almost all private sector employees in all 50 states, Washington D.C., and other U.S. jurisdictions, but its coverage of public sector employees varies across the United States. Over 95% of the accidents reported to OSHA between 1970 and 2013 occurred in the private sector. Twenty-two states and territories have an OSHA-approved program, and such programs are are required to be at least as strict as the Federal law. For these states the plans cover state and local government employees in addition to private sector employees. In addition to these twenty-two states, Connecticut, Illinois, Maine, New Jersey, New York, and the Virgin Islands have OSHA-approved plans that specifically cover public sector employees. In other states, public sector employees are not protected under OSHA, and accidents concerning them may not be reported to OSHA.

In order to bypass uncertainty in coverage of public-sector employees by state, we limit our analysis to accidents involving private-sector employees. Besides excluding public-sector employees in a number of states, OSHA does not cover self-employed workers, the immediate relatives of farm employers, or domestic workers. In addition to this limited coverage of public sector employees, the self-employed, and family farm workers, OSHA's purview over certain industries is limited. Based on communication with OSHA and our best analysis of available resources on OSHA's jurisdiction, OSHA's accident records do not include accidents related to the defense industry, accidents related to mining, accidents related to aviation besides

[5] Again, OSHA's Office of Health Enforcement could not provide an explanation. We hypothesize that this increase in accident reporting in 1990 may be tied to a transfer of recordkeeping requirements from BLS to OSHA in that year. A Memorandum of Understanding dated July 11, 1990 delegated responsibility for administration of accident recordkeeping to OSHA, while leaving BLS responsible for conducting the Annual Survey Of Occupational Injuries And Illnesses.

those involving ground crews or other airport-based labor, trucking accidents except those in off-highway loading and unloading, accidents involving Department of Energy contractors, fishing accidents except those at shipyards or near the coast, motor vehicle accidents on public streets or highways unless in a construction work zone, and accidents that occurred on a commercial or public transportation system.

Furthermore, employers likely do not report all accidents to OSHA. The report of the Committee on Education and Labor (2008) notes that employers have strong incentives to under-report workplace accidents and illnesses, since businesses with fewer accident reports are more likely to receive government contracts, are less likely to receive OSHA inspections, and have lower workers' compensation insurance premiums. Thus, the Committee on Education and Labor (2008) finds that workers report that their employers actively discourage or intimidate them from reporting injuries and illnesses.

Several studies have attempted to estimate the rate of underreporting to OSHA, focusing primarily on underreporting to the Survey of Occupational Injuries and Illnesses (SOII). The SOII is an annual program administered by OSHA and the Bureau of Labor Statistics that uses detailed accident and illness logs from a sample of establishments around the country to estimate nation-wide accident incidence, so it is distinct from the incident-specific reporting of severe accidents to OSHA that is supposed to be required of all businesses. However, rates of underreporting of accidents to the SOII likely reflect the rate of compliance with these incident-specific reporting requirements.

Careful evaluation of the SOII suggest that the rate of underreporting may be high. Rosenman, Kalush, Gardiner, Reeves & Luo (2006) analyze Michigan worker compensation and BLS data for 1999 through 2001, finding that between 60% and 69% of injuries and illnesses went unreported to the BLS during that period. Similarly, Wuellner & Bonauto (2014) find that 90% of firms in Washington State either willfully or accidentally failed to fully comply with OSHA's record-keeping requirements in 2008. While some failed to meet the required reporting time frame or did not report all eligible incidents, 12% of the establishments surveyed failed to even keep an OSHA accident log. Finally, Dong, Fujimoto, Ringen, Stafford, Platner, Gittleman & Wang (2011) estimate that small construction establishments reported only 25% of severe injuries among Hispanic workers and 60% of severe injuries among white workers nationally between 1992 and 2006.

Thus, accidents reported to OSHA make up only a portion of all accidents that occur each year, both because they exclude those occurring among large groups of public sector employees and in a number of risky industries and due to likely noncompliance with reporting requirements.

It is possible to obtain a rough estimate of how the volume of accidents reported to OSHA compares to the total volume of workplace accidents that occur each year using data on workplace fatalities from the Census of Fatal Occupational Injuries (CFOI) available from the Bureau of Labor Statistics. CFOI combines federal and state-level data to create reliable counts of occupational fatalities. These national fatality counts include all industries and both public and private-sector workers, including workers covered under OSHA, those covered under other federal or state agencies, and those workers outside the scope of regulatory coverage. Besides collecting data on standard paid employees, CFOI monitors fatalities among volunteers, self-employed or unpaid family workers, laborers on small farms, and undocumented workers performing the same duty as paid employees. Furthermore, the CFOI is less susceptible to concerns of underreporting. While the CFOI is based partially on employers' reports of fatalities to OSHA, CFOI also verifies the accuracy of workplace fatality statistics using death certificates, workers' compensation records, news reports, and reports to other Federal and State agencies

CFOI fatality counts should theoretically provide a complete measure of workplace fatalities in the United States, and we can get a sense for the completeness of OSHA's accident records by comparing its total fatality counts to those reported under CFOI. Across the years 1992 to 2010, OSHA's records include an average of 29.9% of the workplace fatalities recorded by CFOI. This reporting rate ranges from a low of 25.2% in 1993 to a high of 35.1% in 2005. Therefore due to the combination of underreporting by employers and limitations in OSHA's coverage, OSHA's fatality records include slightly less than one third of the total occupational fatalities occurring in the US. Morantz (2014) argues that since fatalities are easily detectable, it is likely that they are reported at higher rates than are non-fatal injuries. For this reason we might expect the ratio of non-fatal injuries reported to OSHA to the total volume of non-fatal workplace injuries to be even lower.

Despite these limitations, OSHA's accident records remain the best available source of data on accident incidence because of their geographic and temporal granularity. Other sources of accident data, like CFOI, provide aggregate accident counts, but do not disclose data on specific accidents. In particular, CFOI's most detailed accident data give annual accident counts by Metropolitan Statistical Area. In contrast, OSHA's accident records provide specific data on each accident, including the street address of the accident site, the Standard Industrial Classification (SIC) code of the associated industry, and the date of the accident. This geographic and temporal specificity allows us to match particular accidents with a close measure of the weather conditions in which they occurred, which is essential for the issue being investigated. While CFOI's data on occupational fatalities are more complete and likely to be somewhat more accurate than OSHA's accident records, using annual accident totals would likely obscure information on the contemporaneous relationship between temperature and accident incidence that could be revealed in analysis at the daily level. For these reasons, we proceed with OSHA's records of occupational accidents.

Table 2: Accident Summary Statistics

Census Division	Average # Accidents per County	Average # Fatalities per County	Average # TS Accidents per County	Average # Accidents per Million	Average # TS Accidents per Million
All	1.071	0.531	0.890	12.830	10.944
New England	1.945	1.134	1.546	13.971	11.105
Middle Atlantic	1.423	1.200	1.196	5.934	5.066
E.N. Central	0.706	0.520	0.604	7.493	6.438
W.N. Central	0.244	0.182	0.195	11.412	8.753
South Atlantic	0.809	0.585	0.690	9.784	8.434
E. S. Central	0.361	0.329	0.314	8.271	7.431
W. S. Central	0.560	0.539	0.480	17.864	16.240
Mountain	0.674	0.421	0.560	15.210	13.162
Pacific	12.547	1.666	10.255	53.620	45.434

Note: All figures *per annum* and by county. Averages calculated first by county and then averaged across counties in our sample.

Table 2 presents summary statistics on the numbers of accidents per county and per million persons in our sample, for US Census division. These records include a wide range of information on each accident and the resulting workplace inspection, including accident location, an SIC code for the associated industry, and the accident date. Using the SIC code associated with each accident, we classify each accident by whether it is associated with a "temperature-sensitive" industry and whether it is a fatality or a nonfatal hospitalization.

Broadly speaking, we define temperature-sensitive industries as agriculture, forestry, and fishing; construction; manufacturing; transportation, communications, electric, gas, and sanitary services; oil and gas extraction, and other miscellaneous outdoor services, like amusement park operation and police and fire protection. In general, we model these classifications on the designations of industries at "high risk" of temperature exposure used in Zivin & Neidell (2014). Our list of temperature-sensitive industries is a combination of broad SIC divisions, like Division A, Agriculture, and a set of 2- and 4-digit SIC coded industries. See Page (2016) for a complete list of SIC codes associated with temperature-sensitive industries.

Our definition of "temperature-sensitive" accidents is not limited to accidents that are directly attributed to heat stress, but rather includes all accidents in temperature-sensitive industries. This classification reflects the body of research in physiology that suggests that extreme temperature may impair measures of cognitive function like coordination, reaction time, and vigilance. Extreme temperatures could affect the risk of all workplace accidents in outdoor industries, not just the incidence of heat stress or heat illness.

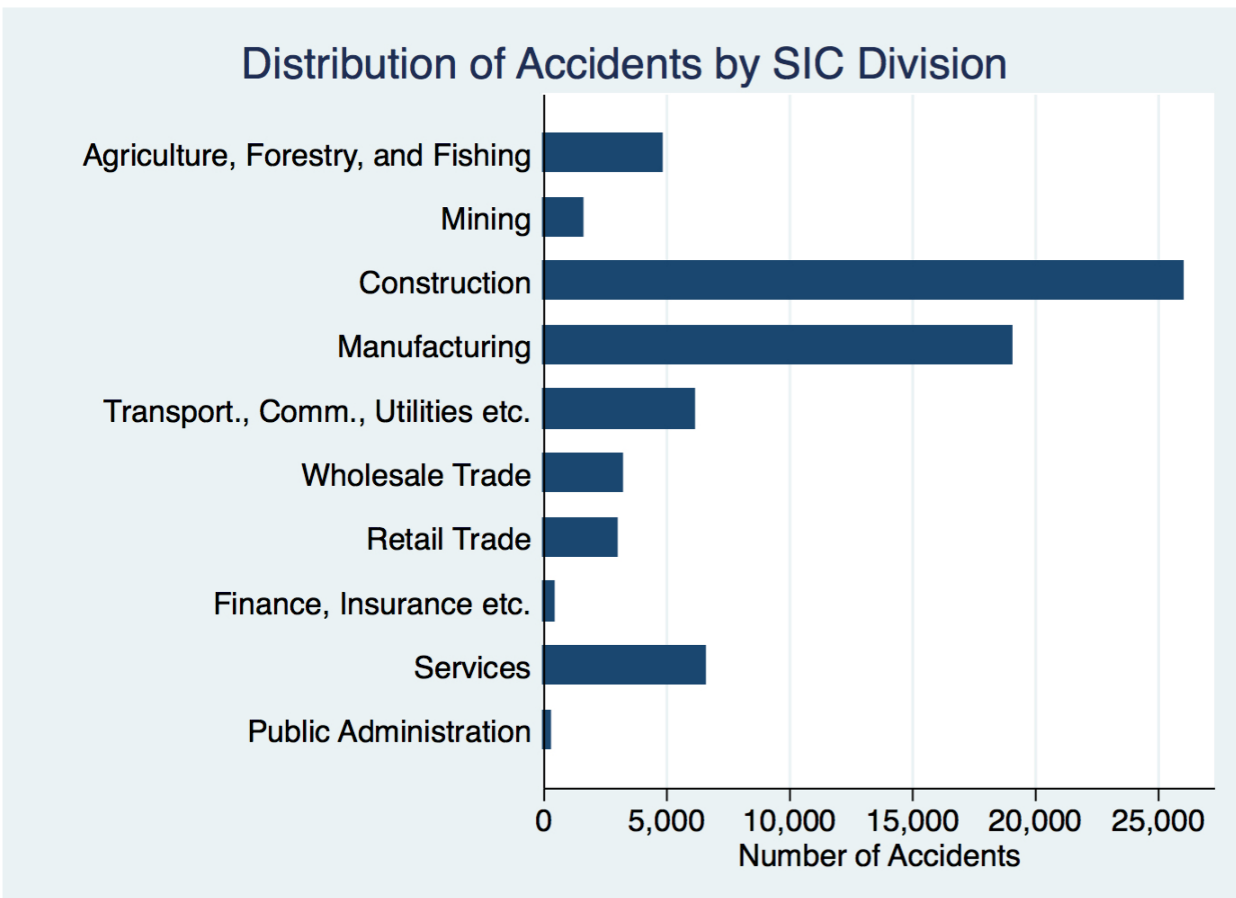

Figure 3: Number of accidents in our sample by associated industry division. Our data include a total of 71,218 private-sector accidents reported to OSHA between 1990 and 2010 in the contiguous United States. We classify accidents into divisions under the Standard Industrial Classification (SIC) system.

Restricting attention to OSHA-reported accidents involving workers in the private sector and occurring between 1990 and 2010, our analysis is based on records for 71,218 accidents. In Figures 3, 4, and

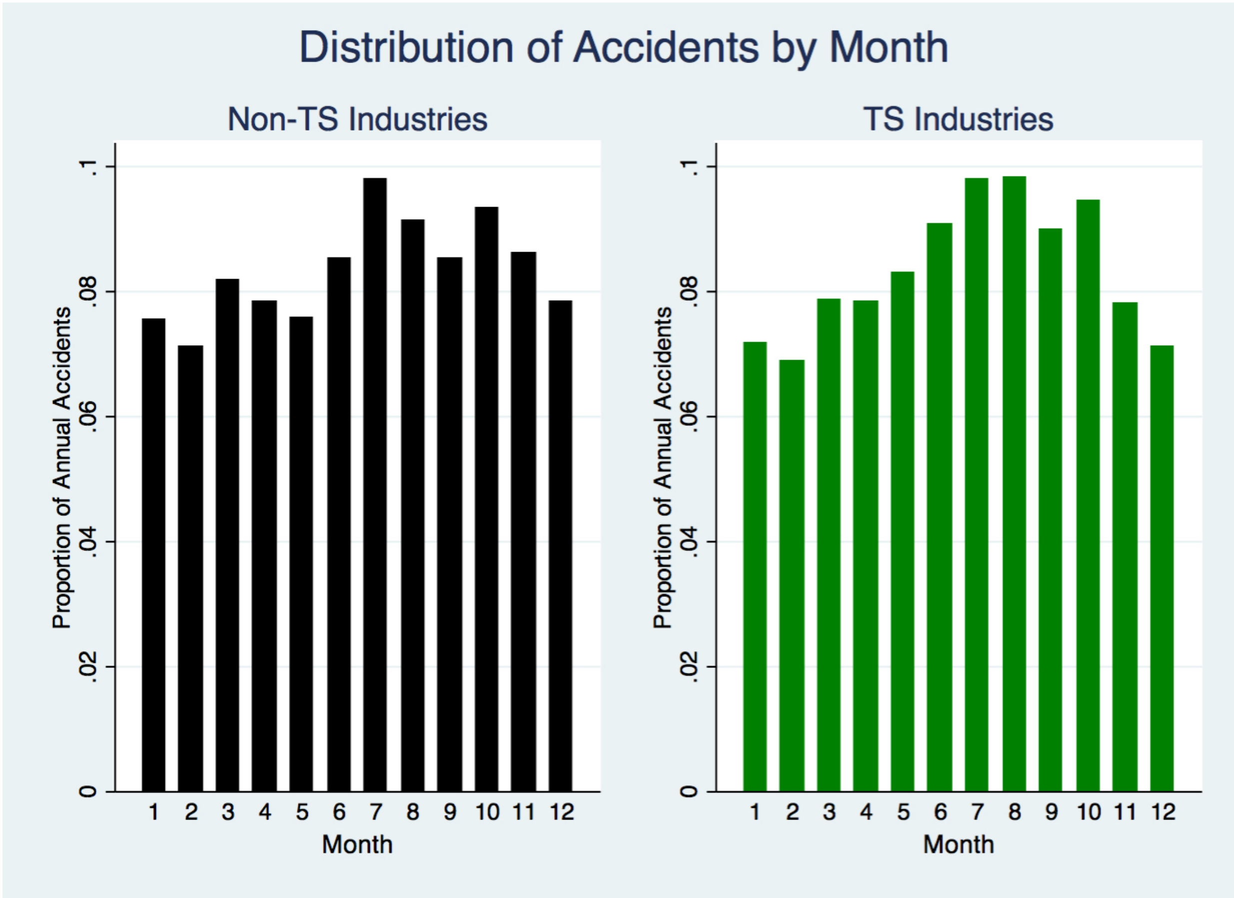

Figure 4: Distribution of accidents in our sample by month in which they occur. Our data includes a total of 71,218 private-sector accidents reported to OSHA between 1990 and 2010 in the contiguous United States. We present seasonal distributions separately for non-temperature-sensitive (non-TS) industries and temperature-sensitive (TS) industries. See the Appendix for a complete list of temperature-sensitive industries.

2fig:region, we explore the distribution of these accidents across industries, seasons, and regions.

Figure 3 decomposes this collection of accidents by SIC division. About 86.2% of accidents occurred in what we classify as temperature-sensitive industries. This distribution of accidents across industries depends on OSHA's coverage of certain industries. For example, since OSHA does not cover accidents in most mining sectors, the volume of accidents reported in mining only includes accidents in oil and gas extraction. Figure 4 shows the distribution of accidents in our sample across months.

The bars in Figure 5 show the distribution of accidents in our sample across U.S. census divisions. We see that a large proportion of the accidents in our sample occurred in the Pacific U.S. census division. Most of this large number of accidents appears to come from California, which accounts for about 38.6% of the accidents in our sample. While California is a large state with high levels of employment in temperature

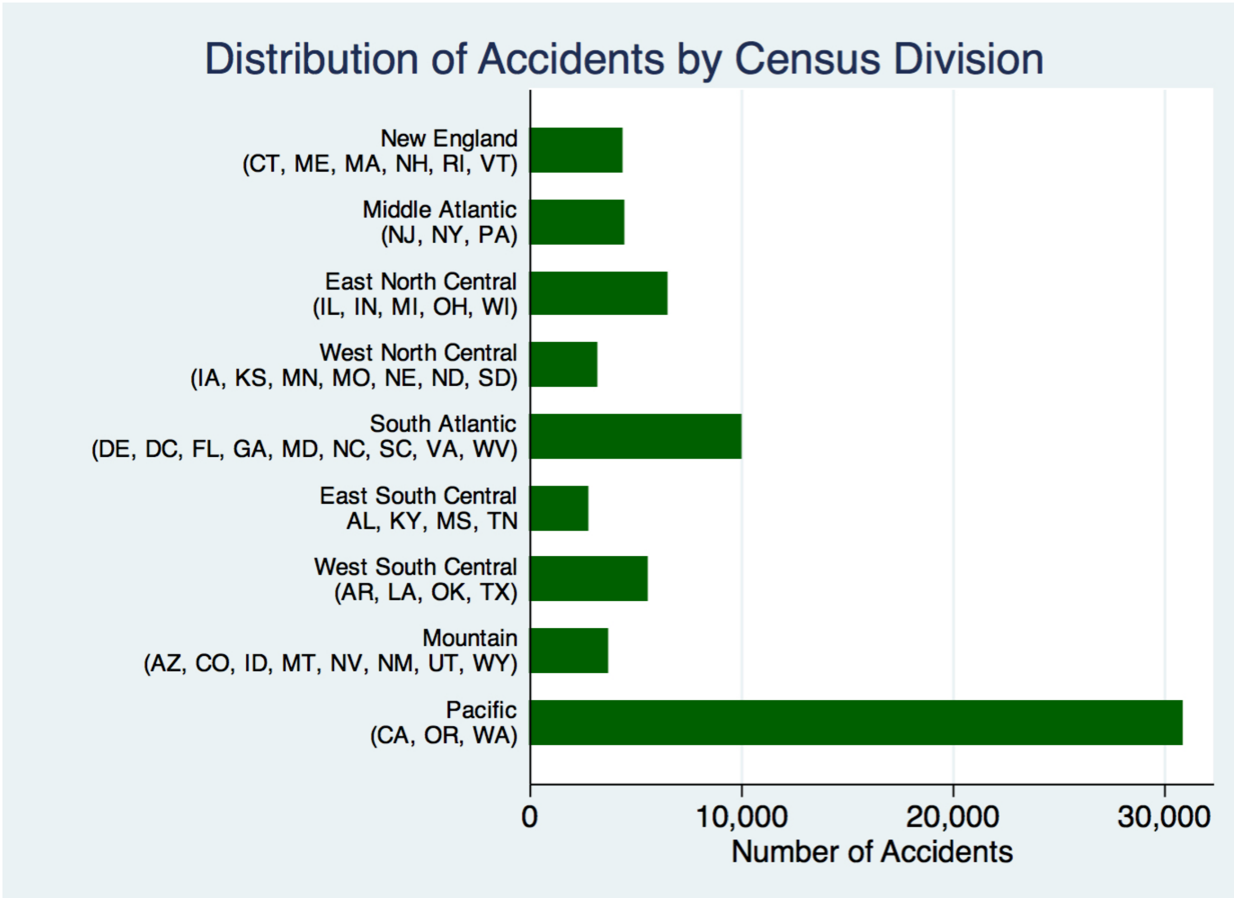

Figure 5: Distribution of accidents in our sample by Census Division in which they occur. Our data includes a total of 71,218 private-sector accidents reported to OSHA between 1990 and 2010 in the contiguous United States. States included in each Census Division are given in parentheses above.

sensitive industries such as agriculture and construction, the difference may also relate to differences in regulations for accident reporting across regions.

As mentioned above, twenty-two states including California have an OSHA-approved state program for ensuring worker safety, and as noted above these are required to be at least as comprehensive as the Federal OSHA program but may in fact be more strict.[6] In addition to differences in regulations on accident reporting, regions of the country vary in their norms for compliance with these regulations. According to an OSHA representative, the huge number of accidents reported from California is a product of both strict reporting requirements and widespread compliance with those requirements.

One approach for checking to see if the variation in accident incidence across the United States reflects

[6]According to OSHA's Directorate of Cooperative and State Programs, there are no unified resources on differences across state OSHA regulations. In the future we hope to identify relevant differences in accident reporting requirements through careful examination of the text of state regulations.

variation in accident reporting across regions, rather than true differences in accident incidence, is to compare the proportion of accidents in our sample that occurred in each census division with the proportion of fatalities tabulated in CFOI that occurred in the same region. CFOI tabulates all workplace fatalities, with little concern of underreporting, so it should allow us to compare the true incidence of accidents across regions. Such a comparison suggests that the large number of accidents from the Pacific census division in our sample primarily reflects a difference in accident reporting norms or regulations, rather than a difference in accident incidence or risk. For further details see Page (2016).

Since we control for time-invariant characteristics that impact accident reporting, including reporting regulations and norms, industrial composition, and labor force size, with county fixed effects, such difference in norms or regulations should not be a problem for our estimation. We combine the records for the 71,218 accidents in our sample with weather data, generating daily counts of all accidents and accidents in temperature-sensitive industries by county from 1990 to 2010.

We use data on total employment to control for levels of worker activity that may vary as a short-term adaptation to fluctuations in ambient temperature. Our data on employment comes from the Quarterly Census of Employment and Wages (QCEW), which is a cooperative program between the Bureau of Labor Statistics and the State Employment Security Agencies (SESAs). The QCEW monitors employment and wage information for workers covered under state unemployment insurance laws and federal workers covered under the Unemployment Compensation for Federal Employees program. Unfortunately data suppression of QCEW county-level employment totals in detailed industry groups makes it impossible to construct the "denominator data" as we describe in Section 2, measuring county-level exposure to accident risk.

Instead, we have developed a new method of estimating temperature-sensitive employment that pulls industry-specific data from any years in which it is available. Given county A and a particular temperature-sensitive industry, we identify all of the years for which data on employment in that county and in that industry is available. For each such year, we calculate the proportion of total employment falling in that industry, and then average this proportion across all years for which we have data on that industry in that county. For each temperature-sensitive industry, we use all available data to calculate the average proportion of employment in that industry over total employment for each county. Then we sum these proportions over all temperature-sensitive industries to generate a measure of the average proportion of total employment in a county found in temperature-sensitive industries over our study period, 1989 to 2010. This employment ratio takes an average value of 0.419 in our sample. Figure 6 shows the average employment share in each Census Division over our sample period.

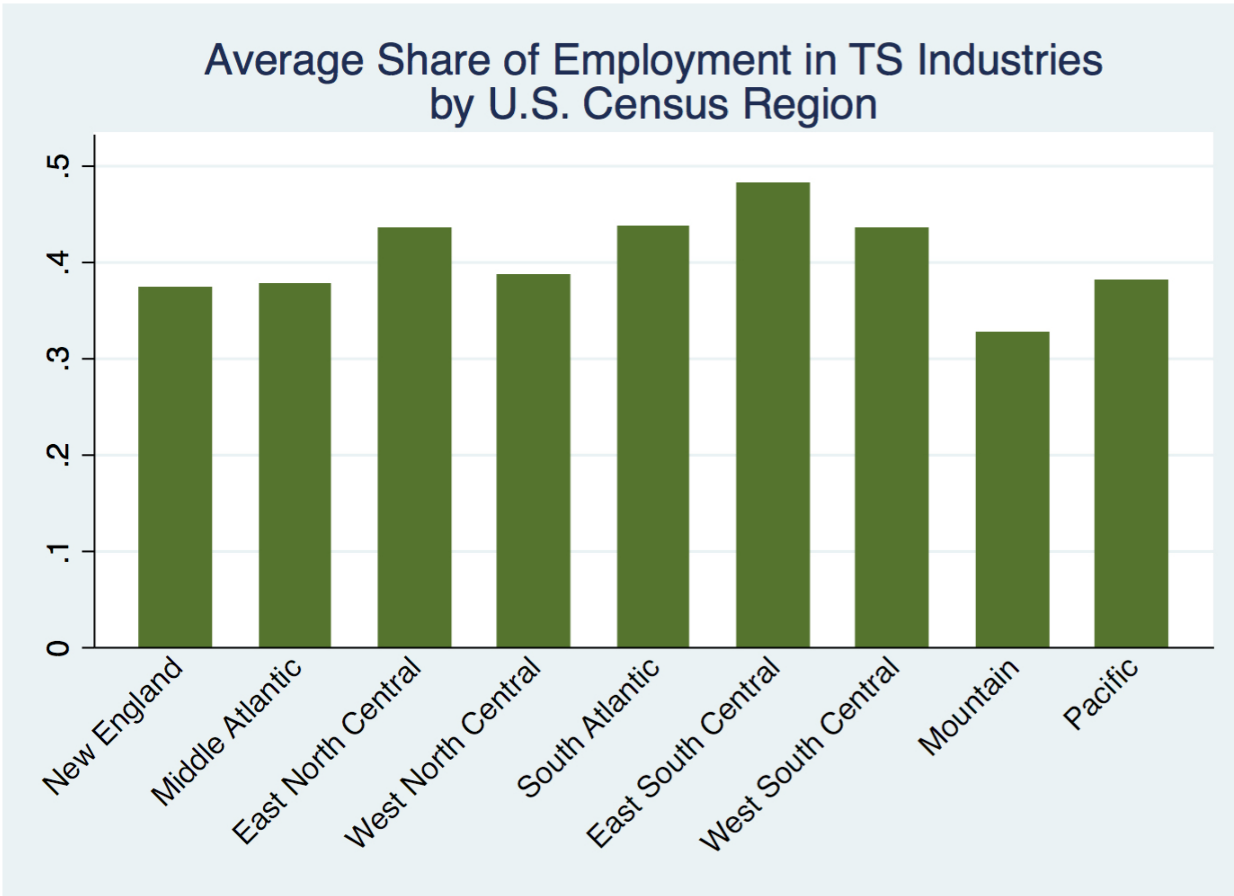

Figure 6: Average share of employment in temperature-sensitive industries by U.S. Census Division. This ratio gives the average proportion of employment in a county that is in temperature-sensitive industries. While we calculate this employment ratio separately by month in analysis, here we average across months to generate an average annual employment ratio. See text for a more detailed description of how we generate data on employment ratio.

We then are able to generate estimates of temperature-sensitive employment by month for each county by multiplying total employment in a county, which is almost never undisclosed, by this ratio of temperature-sensitive employment to total employment. It is important to note that this method of generating data on temperature-sensitive employment assumes that local industrial structure stays constant between 1989 and 2010, even if employment totals are changing. In particular, we assume that the total proportion of county-level employment based in temperature-sensitive industries stays constant over our study period.[7]

[7]We also construct an indicator of data quality that reflects the number of industries and time periods that had to be

4 Estimates

4.1 Impacts of temperature on accidents: OLS estimates

Our estimation strategy draws from the growing economic literature on the impacts of climate change and from previous work in public health on the impacts of temperature on accident incidence introduced in section 2. Our simplest models use a set of temporal and geographic fixed effects to identify the impact of short-term, plausibly exogenous variation in weather on the incidence of occupational accidents similar to the approach used in Dell et al. (2014). We estimate parameters to fit variations of the following equation:

$$accidents_{it} \;=\; \sum_{j=1}^{12} \beta_j \; tmax_{itj} + \sum_{k=1}^{13} \lambda_k \; prcp_{itk} + \alpha_i + \gamma_y + \theta_{r*m} + \nu_d + \epsilon_{it} \tag{2}$$

where i denotes county, t denotes calendar day, y denotes year, r denotes U.S. census region, m denotes month, and d denotes day of week. We regress the temperature-sensitive industry accident count in county i on day t on a series of twelve 10-degree bins for maximum temperature on day t, each denoted by $tmax_j$ for j in $\{1, 2, 3, \; . \; . \; . \; 12\}$.

The coefficients on these temperature indicator variables are of primary interest. These bins range from daily maximum temperature below 0°F to daily maximum temperature above 100°F. Thus, a day with maximum temperature of 92°F will take a value of 1 for $tmax_{11}$, the temperature bin for maximum temperature between 90 and 100°F, while all other temperature bin indicators will take the value 0. Using these temperature bins allows us to nonlinear relationships between temperature and accidents. In all regressions, we omit the temperature bin corresponding to daily maximum temperature between 60 and 70°F, which physiology research suggests may be ideal working conditions. This strategy allows us to estimate the change in the incidence of accidents on a day with maximum temperature in some range relative to a day with maximum temperature between 60 and 70 °F.

We control for precipitation using a similar set of indicator bins. In addition to variables for precipitation and temperature, we also control for a suite of temporal and geographic fixed effects. These include county fixed effects, α_i, year fixed effects, γ_y, region-by-month fixed effects, θ_{r*m}, and day-of-week fixed effects,

approximated as described above, and exclude about 4.5% of the observations if this indicator suggests that the data are of poor quality,

ν_d. The inclusion of county fixed effects controls for time-invariant county characteristics that could impact accident rates and correlate with climate, and year fixed effects control for nation-wide average temperatures and accident counts.

In this panel fixed effect structure, these estimates reflect the impact of short-term local temperature fluctuations within a county on daily accident incidence. It is plausible that this variation in weather is exogenous with respect to unobserved determinants of accident incidence, so estimation of our primary regression equation 2 will give unbiased estimates of the causal impact of each temperature bin on accident rate.

The most likely exceptions to this assumption are temporal dependence within counties and cross-sectional dependence across counties. First, temperature today may correlate with temperature on recent days, which may also impact the volume of work done, and thus the incidence of accidents, today, creating cross-sectional dependence. Next, temperature is likely correlated across nearby counties on any given day. These and related issues are discussed in Page (2016).

While much of the climate-economy literature uses a standard OLS regression framework, we also examine the Poisson regression framework common to public health analysis and arguably appropriate in this case because the data being analyzed are count data. This form of analysis allows us to estimate the relative risk of accidents associated with different temperature conditions, and it is a more suitable framework for analysis of accident incidence. In doing so, we present the first analysis of accident incidence and temperature to make use of a broad geographic spatial scale and to flexibly model the impacts of temperature, while retaining a framework of daily-level Poisson analysis that is well-suited to analysis of accident counts.

Because the central variables of interest are the estimated parameters associated with the temperature bins, we present the results diagrammatically in Figure 7 showing the estimated impact for each temperature along with 5% and 95% confidence intervals. These are obtained from the model specified in equation 2, regressing daily accident count in a county on the twelve 10-degree bins for daily maximum temperature, with precipitation controls, and the fixed effects discussed above.

The coefficients for the temperature bins are generally significant at low and high temperatures, and they trace out an interesting U-shaped relationship between temperature and accident count. Recall that

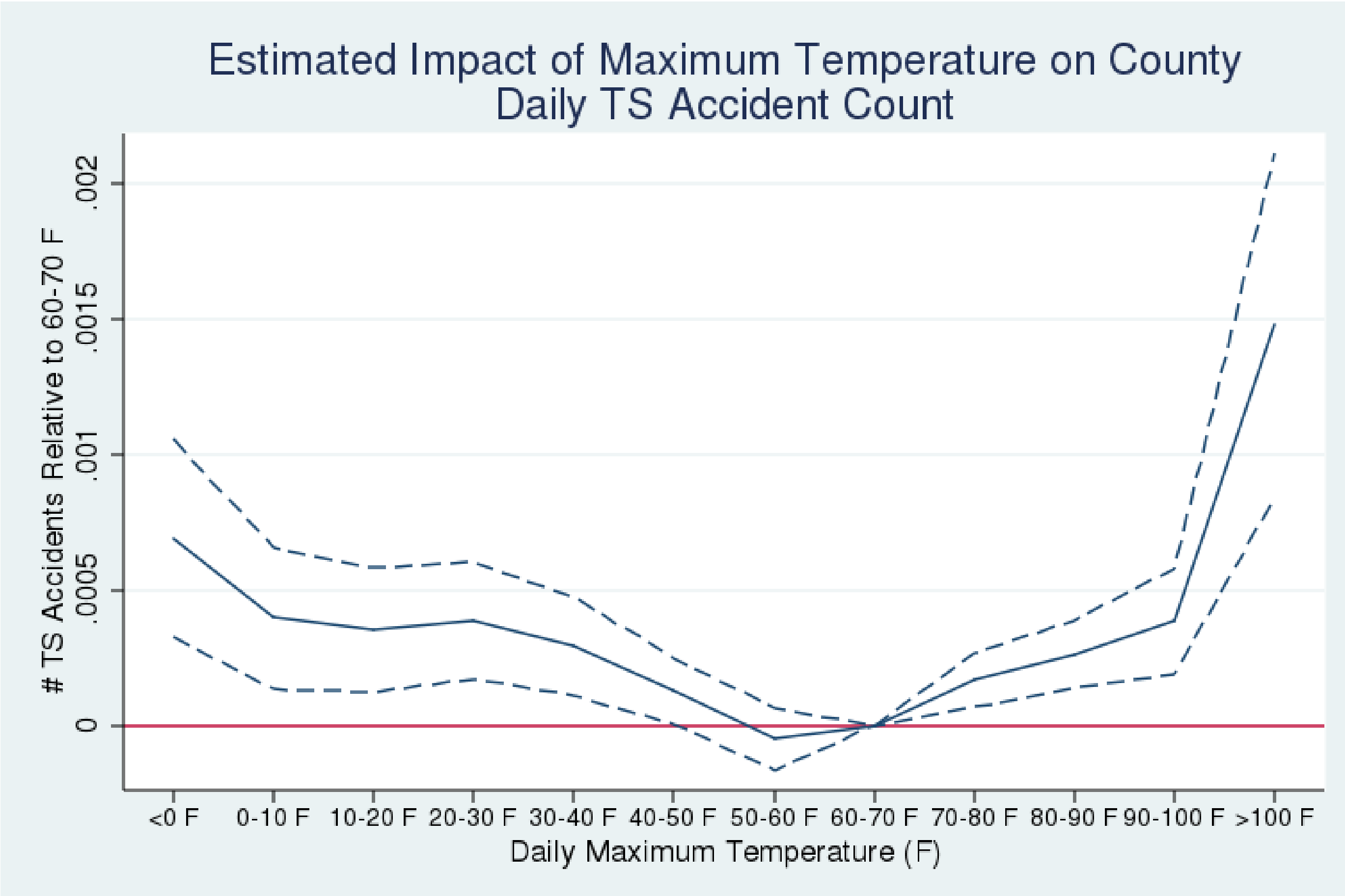

Figure 7: OLS estimates of the impact of daily maximum temperature and county daily accident count in temperature-sensitive industries. N=23,614,877. Dashed lines give the 95% confidence interval. While this graph interpolates between coefficients at 10°F intervals, our regression assumes that temperature impacts are constant within 10°ranges. Regression includes precipitation bins and county, year, region-by-month, and day-of-week fixed effects.

in this regression and throughout our analysis, we omit the bin for maximum temperature between 60 and 70 °F, so coefficients on temperature bins give the number of additional accidents in temperature-sensitive industries in a county on a day with maximum temperature in that bin relative to the a day with maximum temperature with maximum temperature between 60 and 70 °F.

Thus, we see that days with maximum temperature in all temperature bins above 70°F and all temperature bins below 50°F are associated with significantly more accidents than days with maximum temperature between 60 and 70°F, where the magnitude of this increase rises as temperatures become more extreme. For example, a day with maximum temperature over 100°F is associated with an additional 0.00144 accidents in temperature-sensitive industries per county on that day, and a day with maximum temperature below

0°F is associated with an additional 0.000691 accidents in temperature-sensitive industries per county on that day, all relative to a day with maximum temperature between 60 and 70°F.

This OLS regression suggests that very hot and very cold days significantly increase the incidence of accidents in temperature-sensitive industries, with the magnitude of this increase rising as temperatures become more extreme. While these coefficients appear to be quite small in magnitude, they are large relative to the mean number of accidents per county per day. Our data only includes particularly severe accidents resulting in worker hospitalization or death, so they are rare events. On average, counties in our sample have an average of about 0.00250 OSHA-reported accidents per day, so an additional 0.00144 accidents on days with maximum temperature over 100°F is about a 57.6% increase over mean accident incidence. If each of the 3108 county-equivalents in the contiguous United States were to experience an additional day with maximum temperature over 100°F instead of a day with maximum temperature between 60 and 70°F, we would expect to see about 4.5 additional severe nonfatal or fatal accidents reported to OSHA on that day.

4.2 Accounting for Employment

As discussed in section 2, an important form of adaptation when confronted with temperature extremes is to try to avoid working when such extremes occur. Accounting for this requires some sort of control for the level of employment in temperature sensitive industries. As a first pass at controlling for the role of employment volume in our results, we add a variable to our primary OLS regression for the level of temperature-sensitive employment in each county. The upper graph in Figure 8 gives the results from our primary OLS regression, and the lower graph presents the results of this regression with the addition of a control for temperature-sensitive employment.

In the lower graph, then, the coefficients on temperature bins give the impact of days in each temperature category on accident count after removing the impacts of variation in the level of temperature-sensitive employment. We see that the coefficients on the temperature bins are largely robust to this addition, though they change slightly in magnitude. Thus, it appears that the impacts of temperature on accident count that we observe are not driven by monthly-level variation in employment. In the absence of daily-level employment data, we cannot investigate the possibility that temperature impacts are driven by within-month employment changes, which could be relevant for industries staffed by day laborers and would provide a better measure of the impacts of this form of adaptation.

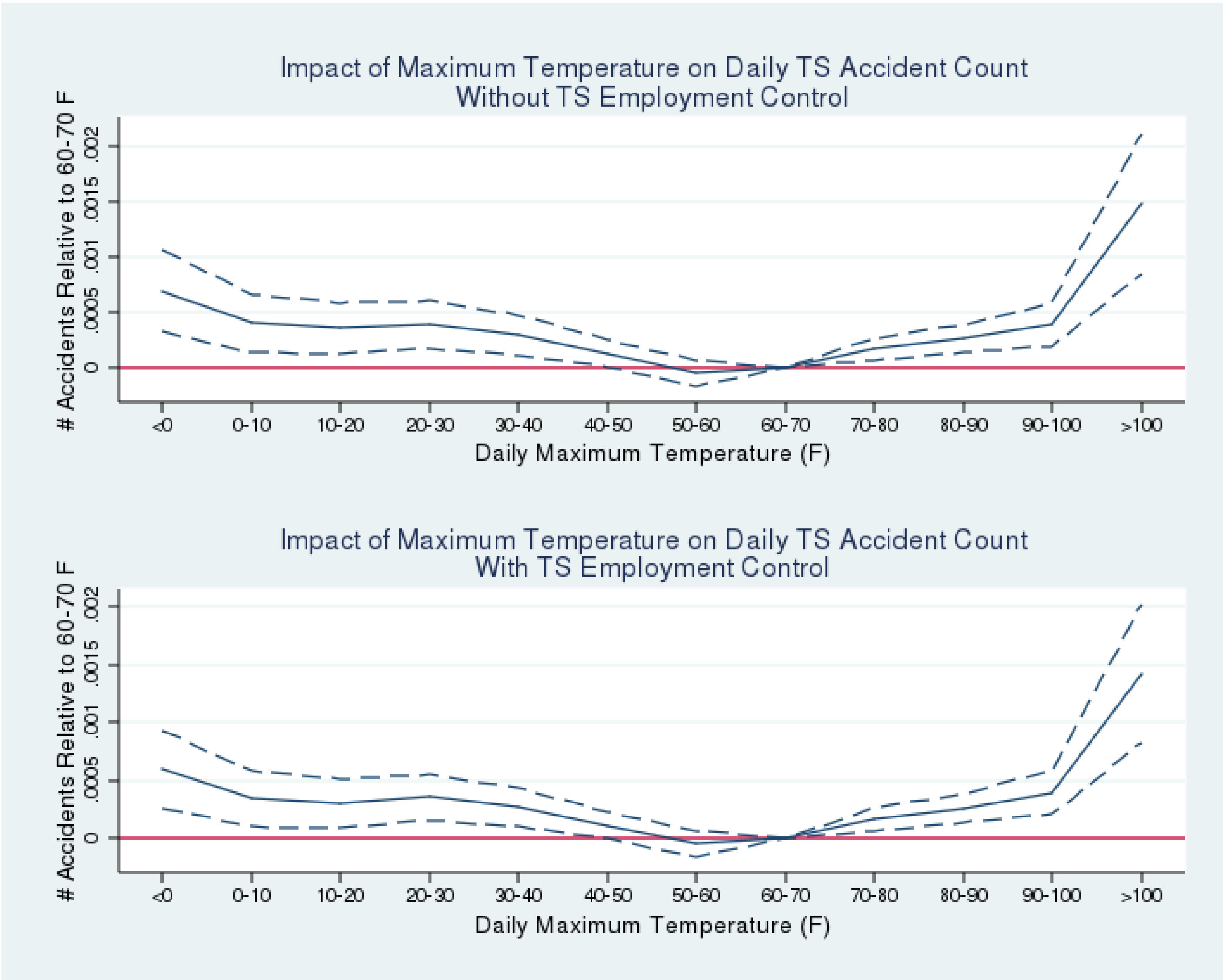

Figure 8: OLS estimates of the impact of daily maximum temperature on county-level daily accident count in temperature-sensitive industries, both with and without a linear control for temperature-sensitive employment. Coefficients give the number of additional accidents relative to a day with maximum temperature between 60 and 70°F. N=23,527,479 in both regressions. Dashed lines give the 95% confidence interval. While this graph interpolates between coefficients at 10°F intervals, our regression assumes that temperature impacts are constant within 10°ranges. Regression includes precipitation bins and county, year, region-by-month, and day-of-week fixed effects.

To further explore this issue, we estimate the impact of temperature on the rate of accidents by county, where we calculate this rate first as accidents over total employment by county and then as accidents over temperature-sensitive employment by county. Theoretically, we might expect the impact of temperature

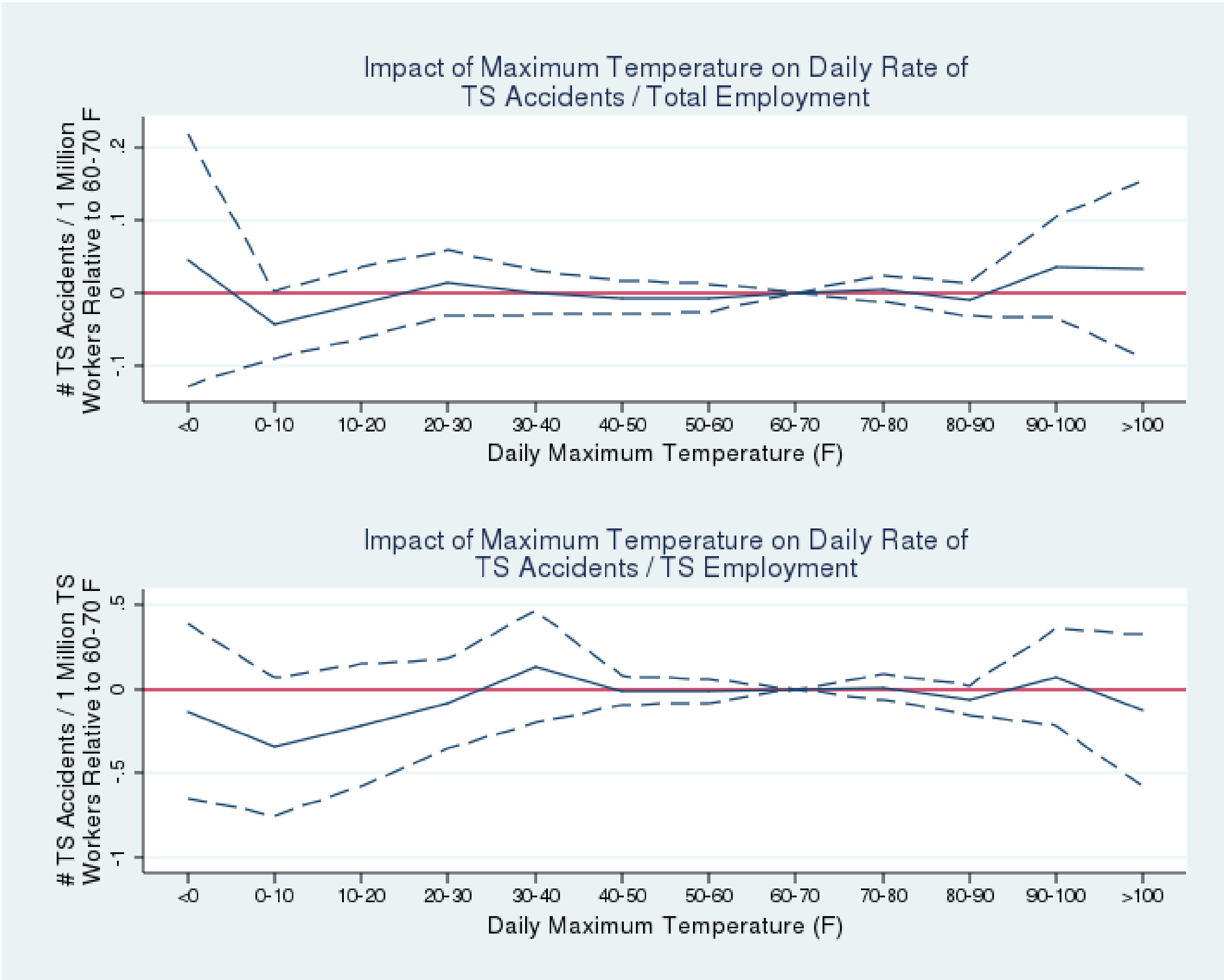

Figure 9: OLS estimates of the impacts of daily maximum temperature on the rate of temperature-sensitive accidents over total employment and on the rate of temperature-sensitive accidents over temperature-sensitive employment at the county level. Coefficients give change in accident rate relative to a day with maximum temperature between 60 and 70°F. Dashed lines give the 95% confidence interval. While this graph interpolates between coefficients at 10°F intervals, our regression assumes that temperature impacts are constant within 10°ranges. Regression includes precipitation bins and county, year, region-by-month, and day-of-week fixed effects.

on accident rate to be constant across counties of different sizes, while we would expect the impact on accident count to rise with county size. In Figure 9, we present the results of regressing dependent variables of temperature-sensitive accidents over total employment and temperature-sensitive accidents over temperature-sensitive employment, respectively, on the set of independent variables from our primary OLS regression. In these regressions, the coefficients on the temperature bins become largely insignificant, and many of them have opposite sign to the corresponding coefficients in Figure 7.

Why does the impact of temperature disappear when we use an accident *rate* as our dependent variable in an OLS regression? It may be because the relationship we are seeing between temperature and accidents is actually explained by the relationship between temperature and employment. Perhaps increases in the number of accidents at extreme temperatures are actually just the result of an increase in the number of people working at more extreme temperatures, after controlling for seasonal cycles. Our regression in the lower graph of Figure 8 suggests that this explanation does not hold, since our estimates of the impacts of temperature bins on accident count survive the addition of a control for temperature-sensitive employment.

One way to explore this possibility is by regressing the natural log of monthly employment in a county on our temperature bin variables; we perform this regression using both temperature-sensitive and total employment as our dependent variable. We run these regression at the monthly level, redefining each temperature bin variable as the number of days in each temperature bin in a month. We then control for precipitation with the same percentile-based bin variables that we employ in our primary regressions, and include county, year, and region-by-month fixed effects. The results of this regression for temperature-sensitive employment are presented graphically in Figure 10.

Here, we see that both monthly total and temperature-sensitive employment appear to decrease with an additional day in any temperature bin in a month, relative to a day with maximum temperature between 60 and 70°F. While these coefficients are small in magnitude–an additional day with maximum temperature over 100°F is associated with a decrease of 0.107% in temperature-sensitive employment, for example–they are broadly significant and increase in magnitude as temperature becomes more extreme. Thus, these results suggest that the impact of temperature on the level of employment is not explaining the increase in accident counts at extreme temperatures, since accident count increases even as employment decreases at extreme temperatures. In fact, these results suggest that our estimates for the impact of temperature on accidents may actually understate the impact of temperature on the risk of workplace accidents.

These regressions of employment on temperature do not capture any impacts of temperature on industrial composition, so it is possible that changes in industrial composition that correlate with temperature might actually give rise to our findings that temperature increases the incidence of occupational accidents.

Despite shortcomings of a simple OLS with fixed-effects approach to estimation, we do see evidence of

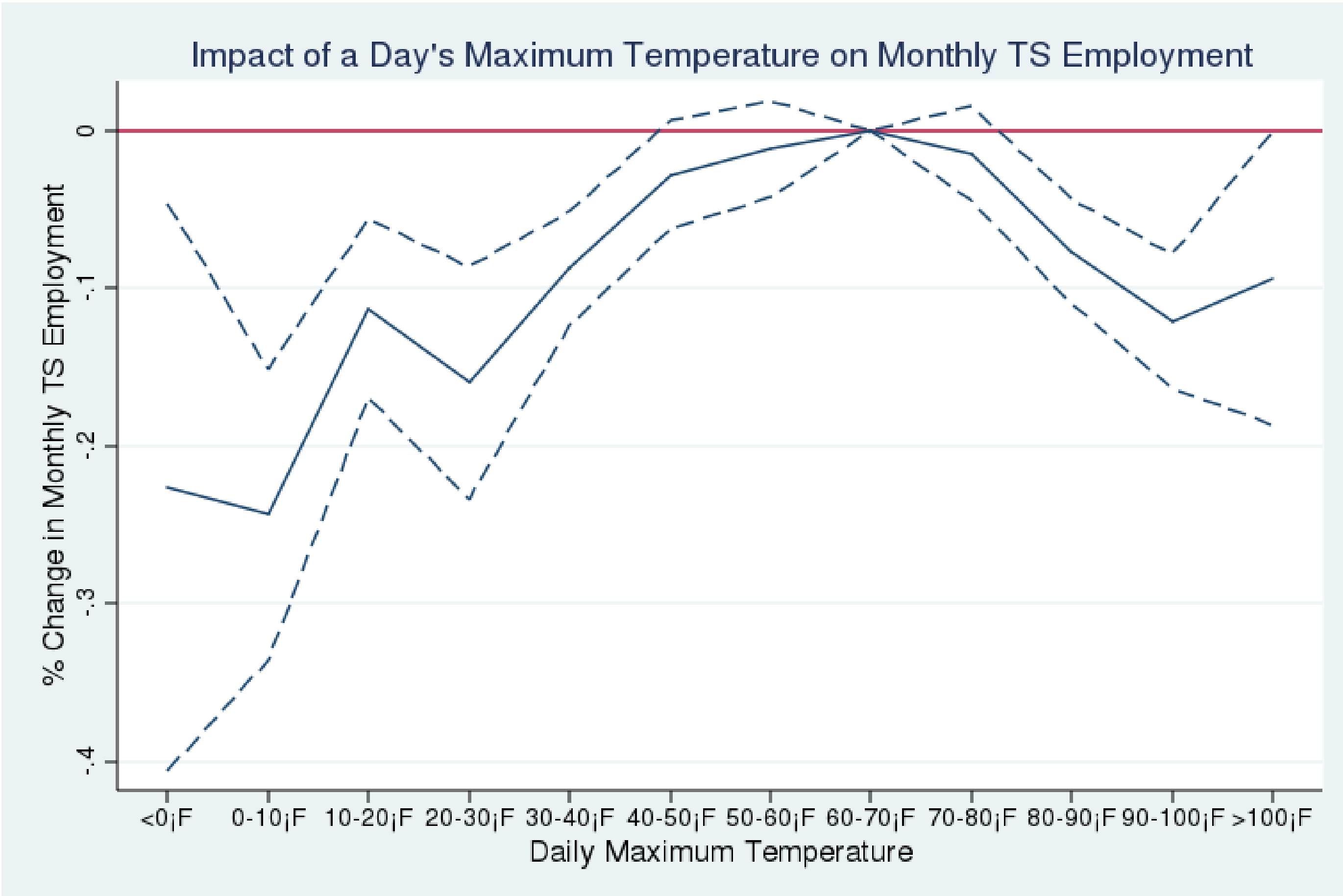

Figure 10: OLS estimates of the impact of a day's maximum temperature on county-level monthly employment in temperature-sensitive industries. Coefficients give the % change in employment level from replacing a day in a month with maximum temperature between 60 and 70°F with a day in another temperature bin. N=773,001 in both regressions. Dashed lines give the 95% confidence interval. While this graph interpolates between coefficients at 10°F intervals, our regression assumes that temperature impacts are constant within 10°ranges. Regression includes precipitation bins and county, year, and region-by-month fixed effects.

increase in total numbers of accidents to ambient temperature. Furthermore, the effects we are seeing do not seem to be related to some unexplained increase in employment during times of extreme temperature. The OLS analysis does not, however, appear to be well-suited for estimation of the sensitivity of accident rates to temperature. For this, we will turn to the more appropriate Poisson model, which is well-suited to analysis of count data.

4.3 The Poisson Model

A random variable Y takes a Poisson distribution with rate or intensity parameter $\mu > 0$ if it takes integer values $y = 0, 1, 2, ...$ with probability given by

$$Pr(Y = y) = \frac{e^{-\mu}\mu^y}{y!}, \quad y = 0, 1, 2, 3, ... \tag{3}$$

Then, we have that $E(Y) = \mu$ and $Var(Y) = \mu$, so the model is intrinsically heteroskedastic.

We can think of the univariate Poisson distribution as describing the number of occurrences of the event y over a fixed time window. We suppose that events occur randomly in time such that the probability of at least one occurrence of the event in a given time interval is proportional to the length of the interval, the probability of more than one event occurrences in a very small time period is negligible, and the number of occurrences of the event in disjoint time intervals are mutually independent (Rodríguez, 2007). Then, we can describe the probability distribution of the number of event occurrences in a fixed time interval as a Poisson distribution with mean $\mu = \lambda t$, where λ gives that rate of event occurrences per unit of time and t gives the length of the time interval. Thus, Poisson estimation is commonly used for analysis of "Poisson processes," like the arrivals of cars to an intersection, the number of bomb strikes in particular areas, or counts of radioactive disintegrations as discussed in Rodríguez (2007).

One particularly useful feature of the Poisson distribution is that the sum of independent Poisson random variables is also Poisson. In particular, say that we have a group of n individuals with identical covariate values, let Y_i give the number of events experienced by individual i, and let Y give the number of events experienced by the full group of n individuals. Then, assuming that these individuals are independent, if $Y_i \sim P(\mu)$ for $i = 1, 2, ..., n$, then $Y \sim P(n\mu)$. That is, the group total Y is Poisson with mean $n\mu$, so we will estimate the same likelihood function if we work with individual or group counts as noted in Rodríguez (2007).

In the Poisson model, we model the exponential mean parameterization as

$$E[y_i|x_i] = \mu_i = \exp(x_i'\beta) = \exp(\beta_1 + \beta_2 x_{2i} + ... + \beta_k x_{ki}). \tag{4}$$

Based on this specification, μ is restricted to positive values. Here, the exponentiated regression coefficient $\exp(\beta_{\mathrm{j}})$ gives the multiplicative effect of the j-th predictor on the mean, so increasing x_j by one unit multiplies the mean by $\exp(\beta_j)$.

We estimate a panel Poisson regression of daily accident count in a county on the same suite of explanatory variables that we used in our OLS analysis presented above. That is, we regress accident count on twelve 10-degree bins for daily maximum temperature, precipitation controls, and year, region-by-month, day-of-week, and county fixed effects. Our basic model is:

$$E[\text{accidents}_{it}|x_{it}] = \exp(\sum_{j=1}^{12} \beta_j \ \text{tmax}_{itj} + \sum_{k=1}^{13} \lambda_k \ \text{prcp}_{itk} + \alpha_i + \gamma_y + \theta_{r*m} + \nu_d + \epsilon_{it}) \tag{5}$$

where subscripts are defined analogous to those in equation 2. As in our OLS analysis, we omit the indicator variable for maximum temperature between 60 and 70°F. We make one key modification to this Poisson model in that we account for temperature-sensitive employment by county as an "exposure" variable in the Poisson model. In general, an exposure variable measures the volume of opportunities for an event to occur, where we expect the volume of events to increase proportionally with this exposure variable. For example, we would expect to see twice as many accidents among twice as many workers, all else equal. If we refer to this variable for temperature-sensitive employment as z, we estimate $E[\text{accidents}_{i,t}|x_{it}, z] = z \exp(x'_{it}\beta) = \exp(lnz + x'_{it}\beta)$. If we take the natural log of this expression, we get

$$\begin{gathered} ln(\text{accidents}_{it}) = ln(z_{it}) + x'_{it}\beta \iff ln(\text{accidents}_{it}) - ln(z_{it}) = x'_{it}\beta \iff \\ ln\left(\frac{\text{accidents}_{it}}{z_{it}}\right) = x'_{it}\beta \end{gathered} \tag{6}$$

Thus, the coefficient on $ln(z)$ is constrained to be 1, allowing us to effectively estimate the impact of our independent variables on accident rate. Then, we could rewrite our primary Poisson model as

$$E[\text{accidents}_{it}|x_{it}] = \exp(ln(z_{it}) + \sum_{j=1}^{12} \beta_j \ \text{tmax}_{itj} + \sum_{k=1}^{13} \lambda_k \ \text{prcp}_{itk} + \alpha_i + \gamma_y + \theta_{r*m} + \nu_d + \epsilon_{it}) \tag{7}$$

Estimates of this model are presented in Figure 11. As in our primary OLS analysis, we cluster standard errors at the county level. Here, coefficients on temperature bins give incident rate ratios, or the ratio of

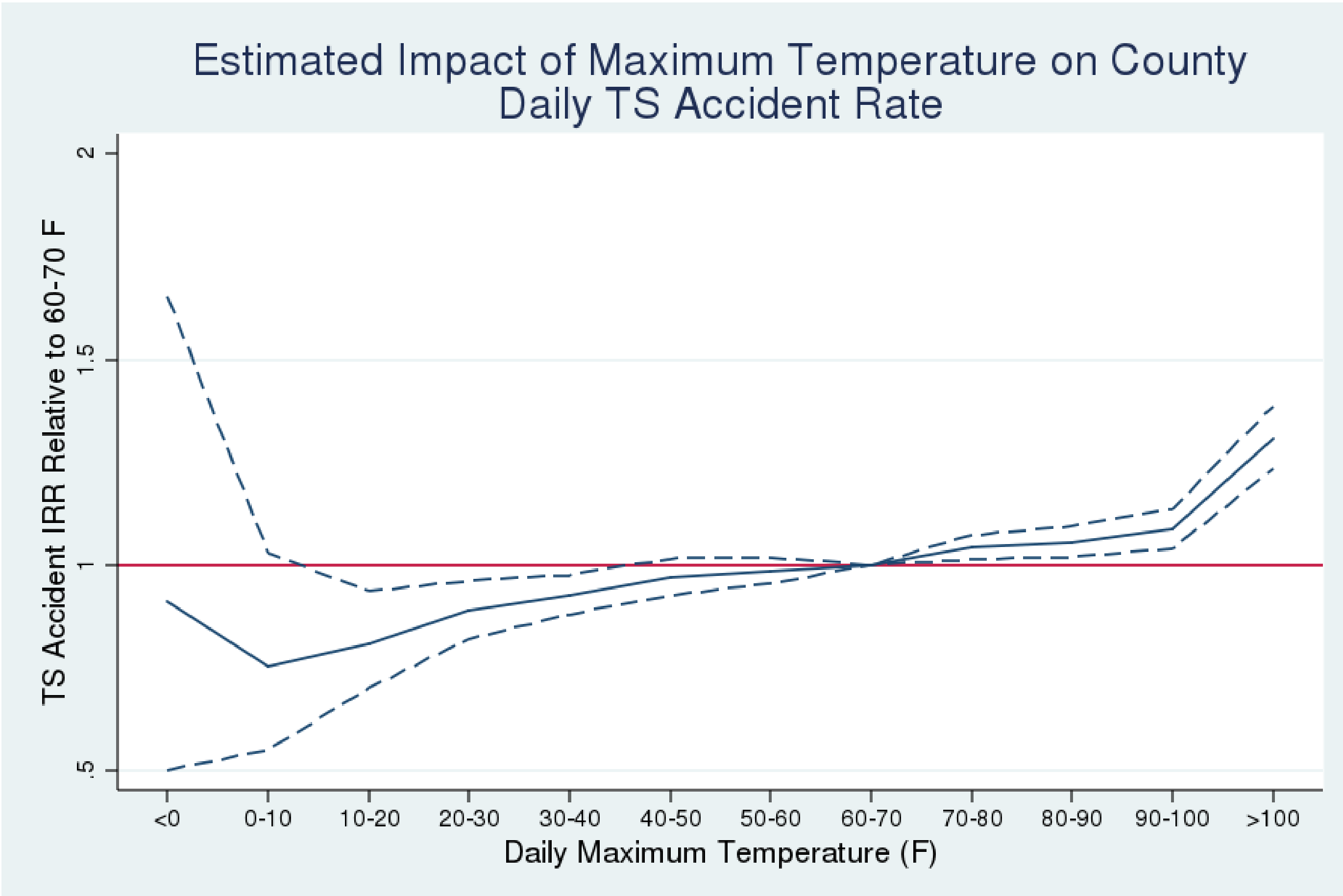

Figure 11: Poisson estimates of the impact of daily maximum temperature on the daily rate of accidents in temperature-sensitive industries. Coefficients give incident rate ratios relative to maximum temperature between 60 and 70°F. N=20,955,316. Dashed lines give the 95% confidence interval. While this graph interpolates between coefficients at 10°F intervals, our regression assumes that temperature impacts are constant within 10°ranges. Regression includes precipitation bins and county, year, and region-by-month fixed effects.

the rate of accidents on a day with maximum temperature in that range over the rate of accidents on a day with maximum temperature between 60 and 70°F, our omitted category. For example, the coefficient of 1.038 on the indicator variable for maximum temperature between 70 and 80°F means that days with maximum temperature in that range have 3.8% more accidents than do days with maximum temperature between 60 and 70°F.

As in our primary OLS analysis, we see that hot days are associated with significantly higher accident rates. In particular, days with maximum temperature between 70 and 80°F have 3.8% more accidents, days with maximum temperature between 80 and 90°F have 5.2% more accidents, days with maximum temperature between 90 and 100°F have 8.2% more accidents, and days with maximum temperature over 100°F have 30.0% more accidents, all relative to days with maximum temperature between 60 and 70°F. Thus, this impact appears to be nonlinear, increasing slowly with rising temperature before spiking up at extremely high temperatures.

These results are qualitatively similar to our OLS estimates of the impact of high temperature on accident count, where we also see nonlinear increases in accident count associated with very hot days. These results are also of comparable magnitude. For example, our OLS analysis suggests that days with maximum temperature over 100°F have about 0.00146 additional accidents relative to days with maximum temperature between 60 and 70°F. Since days with maximum temperature have an average of 0.00288 accidents in our sample, this represents an increase of about 50.7% in accident incidence. This estimate is roughly similar to our corresponding Poisson estimate, 30.0%. Similarly, while our OLS regression estimates that days with maximum temperature between 90 and 100°F have about 12.4% more accidents than days between 60 and 70°F, our corresponding Poisson estimate is 8.2%.

However, our Poisson estimates for the impact of low temperatures on accident incidence differ sharply from those of our OLS analysis. In particular, while our OLS regressions estimated that very cold days are associated with significantly more accidents than days with maximum temperature between 60 and 70°F, our Poisson analysis suggests that cold days tend to have no significant impact on accident incidence or significantly reduced accident incidence. That is, we estimate that days with maximum temperature between 30 and 40°F have 7.0% fewer accidents, days with maximum temperature between 20 and 30°F have 10.6% fewer accidents, days with maximum temperature between 10 and 20°F have 21.0% fewer accidents, and days with maximum temperature between 0 and 10°F have 30.1% fewer accidents, all relative to a day with maximum temperature between 60 and 70°F. Since Poisson analysis better accounts for the discreteness and nonlinearities of count data, it is likely that these results are more accurate than those of our OLS analysis.

Overall, then, our results suggest that while particularly cold days are associated with reduced accident incidence in temperature-sensitive industries, hot days are associated with high accident incidence. These impacts become more pronounced as temperature becomes more extreme, rising to a 30.0% increase in accident counts on days with maximum temperature between 100°F and to a 30.1% reduction in accident counts on days with maximum temperature between 0 and 10°F, both relative to days with maximum temperature between 60 and 70°F. Since we are identifying these impacts from presumably exogenous local variation in weather, which we isolate with a collection of seasonal, temporal, and geographic fixed effects, we can plausibly interpret these coefficients as the causal impact of temperature on accident incidence. Thus, these results suggest that we might expect to see more accidents in temperature-sensitive industries as extremely hot days become more frequent and cold days become less frequent under climate change.

Why might we see that the incidence of accidents rises at high temperatures but falls at low temperatures? Recall that the impact of temperature on accident rate is a combination of the impact of temperature on the risk of accidents for a given volume of work and the impact of temperature on the volume and type of work being performed. The relevant literature discussed in section 2 has identified a series of physiological mechanisms by which the risk of accidents for a given type and duration of work would rise both at very high and very low temperatures. For example, research in physiology has found that performance of attention- and perception-based, mathematical, and reaction time-based tasks are impaired both at high and low temperature extremes. However, if high temperatures increase accident risk by more than do low temperatures, the same level of behavioral adaptation might reduce the accident rate below baseline at low temperatures while failing to adapt away elevated accident rates in hot conditions.

On the other hand, perhaps behavioral adaptation is more effective or possible at low temperatures than at high temperatures. Behavioral adaptations might be sufficient to actually reduce the risk of accidents below that at more temperate conditions in very cold weather, while failing to adapt away elevated accident risk in hot weather. For example, workers can add more layers than they can remove, and while removing layers might mean removing protective gear, additional clothing could protect workers from injury. Next, industries typically operating in winter might allow for postponement of work to better weather conditions, while those industries operating in the summer might be less flexible; then, we could expect to see that cold temperatures have smaller impacts on accident rate than do hot temperatures, or that accident incidence even falls on particularly cold days. Previous studies have found similar decreases in accident incidence at temperature extremes, which they attribute to a reduction in work volume or protective measures taken under those conditions.

5 Conclusions

In this paper we have considered the potential impact of changes in ambient air temperature on the incidence of occupational accidents among a set of "temperature-sensitive industries," like construction, agriculture, forestry, manufacturing, and utilities servicing. Research in physiology suggests that extreme temperature make workers more tired and impair cognitive functions like coordination, vigilance, and reaction time, thereby increasing their risk of accidents when working in extreme temperature conditions. Thus, we might expect to see increased incidence of workplace accidents as temperatures rise under climate change. At the same time, behavior responses to extreme temperatures might reduce this impact if, for example, workers postpone work to cooler conditions or take additional rest breaks. We estimate the short-term impact of temperature on accident incidence with daily data for a panel of over 2000 counties in the United States between 1990 and 2010. Using a suite of seasonal, temporal, and geographic fixed effects, we are able to isolate the impacts of plausibly exogenous day-to-day fluctuations in temperature. Our preferred estimates rely on Poisson regression, and provide the accident incident rate ratios (IRR) for a series of twelve ten-degree F bins for daily maximum temperature ranging from maximum temperature below 0°F to maximum temperature above 100°F.

Overall, we find that significantly more accidents occur at high temperature extremes and that fewer accidents occur at low temperature extremes. This relationship is nonlinear, spiking sharply upwards at the highest temperature extremes. At high temperatures, these impacts range from 3.8% more accidents on days with maximum temperature between 70 and 80°F to 30.0% more accidents on days with maximum temperature over 100°F, both relative to a day with maximum temperature between 60 and 70°F. At low temperatures, these impacts range from 7.0% fewer accidents on days with maximum temperature between 30 and 40°F to 30.1% fewer accidents on days with maximum temperature between 0 and 10°F, both relative to a day with maximum temperature between 60 and 70°F.

As the climate changes, hot days are projected to become increasingly frequent and cold days increasingly infrequent. The estimates we obtain imply that climate change will increase the incidence of occupational accidents in the United States. How large do we expect these impacts to be? Using climate projection data derived from the A1F1 scenario in the Hadley 3 climate model discussed in Deschênes & Greenstone (2011), we can project percentage changes in accident rate averaged across the years 2070 through 2099. Using these rates it appears that we should expect an average of between 22 and 67 additional fatal occupational accidents in temperature-sensitive industries each year between 2070 and 2099. Using estimates from Leigh (2011) for the ratio of fatal to nonfatal accidents in 2007, we would expect an average of between 33,600 and 102,400 addition nonfatal accidents between 2070 and 2099. This implies that these fatal and non-fatal additional accidents could impose average annual costs of between $750 million and $2.30 billion between 2070 and 2099.

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