Heat Stress: Ambient Temperature and Workplace Accidents in the US*

Lucy Page† and Stephen Sheppard‡

April 6, 2019

Abstract

Combining records for 71,225 severe accidents from the Occupational Safety and Health Administration with a panel of county-level weather data for 1990 to 2010, we find that heat shocks significantly increase accident rates across the United States, while cold shocks significantly reduce them. We find that heat shocks increase accidents both in plausibly temperature-sensitive industries, like construction and agriculture, and among industries that are not obviously sensitive to weather. While we find suggestive evidence of short-term adaptation to heat shocks over summer months, we find no evidence that the impacts of heat shocks have fallen over our 21-year panel.

*We would like to thank Ben Olken and Rohini Pande for helpful advice and comments, and D. J. Rasmussen for guidance on access and use of temperature forecast data for US counties. Any errors are of course the sole responsibility of the authors.

†MIT Department of Economics

‡Williams College Department of Economics, 24 Hopkins Hall Drive, Williamstown, MA 01267

1 Introduction

A growing literature in economics finds that temperature stress reduces productivity, focusing especially on the hot weather extremes growing more common under climate change (Hsiang, 2010; Dell, Jones, and Olken, 2012; Jones and Olken, 2010). This work suggests that output falls both at temperature highs and lows: Burke, Hsiang, and Miguel (2015) 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. Productivity is vulnerable to temperature even in the US, where Deryugina and Hsiang (2014) find that average daily productivity falls linearly by about 1.7% for each 1°C increase in daily average temperature above 15°C. See Heal and Park (2016) for a review of the growing literature on temperature and productivity.

The impacts of high temperature on output may arise in part through temperature's effects on individual workers. Graff Zivin and Neidell (2014), for instance, use county-level data from the American Time Use Survey to show that people spend significantly less time working in industries that are plausibly exposed to weather, like agriculture, forestry, mining, construction, and utilities, when it is hot. The impacts of temperature on worker safety could be another key mechanism through which temperature reduces economic output. As temperatures rise under a changing climate, more frequent extreme heat might threaten laborers working outside in industries like construction, utility services, forestry, and agriculture. At the same time, milder winters might reduce these risks. Changes in accident rates due to climate change could impose substantial costs: the National Institute for Occupational Safety and Health (NIOSH) (2017) finds that a total of 42,380 fatal occupational injuries cost the United States more than $44 billion between 2003 and 2010 in medical expenses and lost future earnings.

In this paper, we investigate the impact of temperature on the rate of workplace accidents in a panel of counties across the United States from 1990 through 2010. This work adds to a small literature providing early evidence that temperature extremes, and especially hot weather, increase the risk of workplace accidents (Osborne et al., 1922; Ramsey and Burford, 1983; Fogleman et al., 2005). In Adelaide, Australia, Xiang et al. (2014a) find that the number of daily injury compensation claims increases weakly with temperature at temperatures below 100°F, but then falls by 1.4% with each 1°C increase in daily maximum temperature above that threshold. Xiang et al. (2014b) also find that heat waves, which they define as three or more consecutive days with daily maximum temperature over 95°F, increase compensation claims in outdoor industries by 6.2%. Adam-Poupart et al. (2015) conduct similar analysis in 16 health administration regions of Quebec, finding 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.

Our paper builds on this literature in key ways. Drawing on the growing climate-economy literature, we use a suite of geographic and temporal fixed effects to identify the causal impacts of short-term, plausibly exogenous local variation in weather (Dell et al., 2014). Our panel covers nearly all counties of the contiguous United States, lending our results substantially greater external validity than the existing region- or city-specific studies in public health. Next, like other work on climate impacts in economics, we estimate the impacts of temperature using a series of temperature bins, improving on the rigid functional form restrictions of previous research in public health. Finally, we provide the first preliminary exploration of the role of adaptation in the relationship between temperature and accidents.

We use a balanced daily panel of weather, accident, and employment data for 3,093 counties across the contiguous United States from 1990 to 2010. These data include records for 71,225 occupational injuries and fatalities reported to the Occupational Safety and Health Administration (OSHA), daily temperature and precipitation data from the North America Land Data Assimilation System (NLDAS), and monthly employment data from the Bureau of Labor Statistics (BLS) Quarterly Census of Employment and Wages.

We find that heat shocks significantly increase accident rates, while cold shocks significantly reduce them. Accident rate rises monotonically with high temperature extremes, ranging from an increase of 4.0% on days with maximum temperature between 70°and 75°F to an increase of 41.0% on days with maximum temperature over 105°F, both relative to a day with maximum temperature between 65°and 70°F. In contrast, accident rate falls monotonically with decreasing temperature at low temperature extremes: these impacts range from a drop in accident rates of 4.5% on days with maximum temperature between 55 and 60°F to a drop of 37.0% on days between 5 and 10°F, again relative to a day with maximum temperature between 65°and 70°F. Crucially, we find that heat shocks increase accidents both in a set of plausibly temperature-sensitive industries, like construction and agriculture, and in indoor industries like hospitals and schools. These results add to a growing literature, led by Cachon et al. (2012), showing that temperature impacts even production processes that are ostensibly insulated to the impacts of weather.

A key question for the climate-economy literature is the extent to which the short-run impacts of weather map into the long-run impacts of climate change, or a gradual shift in the distribution of weather outcomes (Dell et al., 2014). In particular, adaptation to the risks of working in hot weather could reduce these long-run impacts. On the other hand, intensification, where longer stretches of hot weather under a warmer climate have more severe impacts than isolated heat shocks, could increase them. We explore the impact of temperature over time after controlling for differential temperature impacts by region, finding no evidence of long-run adaptation. Making the simplifying assumption that our short-term estimates will hold as climate change progresses, we use climate data compiled by Rasmussen, Meinshausen, and Kopp (2016) to project that the US will suffer 134,518 additional severe workplace accidents per year by 2099 under business as usual emissions, relative to a high-abatement climate scenario.

The rest of the paper is organized as follows: Section 2 reviews the relationship between temperature and workplace safety, Section 3 describes our data. Section 4 presents our empirical strategy, and Section 5 presents our primary results. Section 6 documents preliminary results on adaptation, and Section 7 concludes.

2 Temperature and workplace safety

Research on temperature, health, and cognition suggests that the physiological impacts of temperature on the human body could have direct implications for worker safety (Heal and Park, 2016). First, heat stress or cold stress can be debilitating or even fatal. In extreme heat, 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 and Rosenberg, 2010). The BLS estimates that heat exposure led to 37 work-related deaths and 2,830 nonfatal illnesses in 2015 (BLS 2017). While less studied, cold stress poses similar risks. In cold environments, the body shifts blood flow from its extremities to its core in order to maintain a sufficiently high core temperature, exposing the skin and extremities to rapid cooling and increasing the risk of frostbite. Prolonged cold stress can lead to hypothermia, with symptoms ultimately progressing to cardiac failure, respiratory failure, and death (Stocks et al., 2004).

Besides causing explicitly temperature-related illnesses like heat or cold stress, extreme temperatures may increase the risk of workplace accidents more broadly. Many intermediate symptoms of heat and cold stress, like dizziness, confusion, and loss of dexterity, could increase accident risk (Jackson and Rosenberg, 2010). Furthermore, a large lab-based literature in physiology finds that exposure to hot and cold temperatures impairs various measures of cognitive function that link directly to accident risk, like coordination, vigilance, reaction time, and mental performance (Seppanen et al., 2006; Hancock and Vasmatzidis, 2003; Ramsey and Kwon, 1992). For example, Epstein et al. (1980) report that study participants' proportion of errors when shooting at a square target on a video screen increased from 7.9%, to 15.9%, and then to 16.6% between 70°F, 86°F, and 95°F, respectively.

Based on these mechanisms, we might hypothesize a U-shaped curve between temperature and accident risk, with the risk of workplace accidents rising both at high and low temperatures. But even if accident *risk per unit of work* charts a U-shaped curve with respect to temperature, adaptation to temperature may alter even the short-run impacts of temperature that we observe (Behrer and Park, 2017). First, adaptation may be physiological. The human body acclimatizes to hot weather by sweating earlier, in higher volumes, and with lower electrolyte concentration, allowing workers to function with a lower core temperature and reduced heart rate (NIOSH, 2013). The average body can acclimatize to most hot conditions over one to two weeks (Lind and Bass, 1963, WHO, 1969). Acclimatization to cold is less rapid and has been the subject of less extensive study, but research suggests that workers may adapt to consistently cold temperatures over similar timescales by improving core insulation or metabolic heat production (Kaciuba-Uscilko et al, 1989; Castellani and Young, 2016).

Besides physically acclimatizing, workers or employers may make protective investments and behavioral changes to adapt to temperature extremes across a range of timescales. In the short-run, workers could take breaks for rest and water, and employers could provide areas for rest and recovery, provide cooling protective clothing, or reschedule strenuous jobs to cooler times (Jackson and Rosenberg, 2010). As noted above, Graff Zivin and Neidell (2014) find that workers reduce labor supply in certain outdoor industries at high temperatures. At longer timescales, other forms of economic adaptation to extreme temperatures would become available, like migration to cooler areas and the development of new worker safety technologies or regulations. While perhaps costly in other ways, these adaptive responses could help to avert some of the safety risks of extreme temperature, bending down the arms of the curve between temperature and observed accident rates even in the short-run.

We might expect the impacts of temperature to be largest in industries where workers are directly exposed to weather, like construction and agriculture. However, some previous research on temperature impacts has found that temperature matters even in industries that we might expect to be fully insulated to weather. For example, Cachon, Gallino, and Olivares (2012) find that plant-level automobile production in the US falls by 8.75% on weeks with six or seven days with maximum temperature over 90°F. Even in indoor industries, workers might be more prone to accident due to heat exposure on their way to and from work, for example, or due to inadequate air conditioning. We will first explore the impact of temperature on accidents across all industries and then explore differences in impacts between temperature-sensitive and other industries.

3 Data

3.1 Accident Data

We collect data on workplace accidents from the Occupational Safety and Health Administration's (OSHA) Enforcement Inspection and Accident Investigation Data. Employers have been required to report severe workplace accidents to OSHA since 1971, after the agency was established under the Occupational Safety and Health Act of 1970. While regulations first required employers only to report fatalities and accidents that hospitalized at least five employees, these regulations have grown more stringent over time. Employers have been required to report accidents that hospitalized at least three workers since 1994 and have been required to report all work-related inpatient hospitalizations, amputations, and losses of an eye since 2015 (US DOL, 1996 and 2014).

A total of 93,683 unique accidents were reported to OSHA from the contiguous United States between 1972 and 2013. The number of accidents reported each year varies widely over that period, but it is not clearly tied to these changes in reporting regulations. Accidents are first recorded in large volumes in the OSHA data in the mid-1980s and drop off in recent years due to a backlog

Figure 1: 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.

in accident investigation and processing. We also see a sudden increase in the volume of accidents reported to OSHA in 1990.[1] We will 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 and which accounts for 79.5% of all reported accidents. Our analysis will control for any national trends in total accident reporting. Next, we restrict to private sector accidents to bypass variation in OSHA's coverage of public sector employees by state. Finally, we restrict our sample to the contiguous United States, excluding Alaska, Hawaii, and any other U.S. territories. In total, our balanced panel includes 71,225 private-sector accidents in the contiguous US between 1990 and 2010. About 49.0% of these accidents are fatalities. These severe accidents are rare: the average county has just 1.10 OSHA-reported accidents each year. Reporting to OSHA varies across states, and our accident reports are heavily concentrated in California, which accounts for 38.6% of accidents in our sample. We test that our analysis is robust to excluding California.

[1]This increase in accident reporting in 1990 may be tied to a transfer of record-keeping requirements from BLS to OSHA in that year. A Memorandum of Understanding dated July 11, 1990 delegated responsibility for administration of accident record-keeping to OSHA.

3.2 Weather Data

Our weather outcomes of interest are maximum daily temperature and daily precipitation. We use daily data from the North America Land Data Assimilation System (NLDAS), a collaborative project between NOAA, NASA, Princeton University, and the University of Washington. NLDAS provides a record of county-level daily weather across North America from 1979 to 2011, with measures including maximum temperature, heat index, and total precipitation. The NLDAS data provides a balanced panel of weather data from January 1, 1990 through December 31, 2010 for 3,109 counties in the contiguous United States.

Physiology research suggests that heat index, a measure of apparent temperature that incorporates humidity, is a better measure of temperature exposure than dry temperature. However, we focus on results using maximum temperature in order to generate estimates compatible with future temperature projections under climate change. We run sensitivity analysis using heat index.

3.3 Employment Data

Finally, we use county-level employment data from the Quarterly Census of Employment and Wages (QCEW), a cooperative program between the BLS and the State Employment Security Agencies (SESAs) that produces monthly employment data by industry and by county for the entire United States. To match our accident data, we restrict to private sector employment. The QCEW suppresses data whenever it may reveal employment data for particular firms; we approximate missing county-specific employment by linearly interpolating between non-missing data wherever possible. This interpolation accounts for about 0.2% of our final employment data. While our primary analysis explores the impacts of temperature among all private-sector accidents reported to OSHA, we will also explore any differential impact of temperature in plausibly temperature-sensitive (TS) industries. Appendix section 1.2 describes our method for estimating TS employment by county.

In total, our final sample includes a balanced panel of 21 years of total private employment and weather data for 3,093 counties. Counties in our balanced panel account for 99.9% of the private-sector accidents reported to OSHA between 1990 and 2010.

4 Econometric Strategy

We use temporal and geographic fixed effects to identify the causal impact of short-term, plausibly exogenous variation in weather on the rate of workplace accidents across the United States. We model workplace accident count as a Poisson-distributed random variable, estimating variants of the following model:

$$E[\text{accidents}_{it}] = \exp(ln(z_{im}) + \sum_{j=1}^{23} \beta_j \ \text{tmax}_{itj} + \sum_{k=1}^{12} \lambda_k \ \text{prcp}_{itk} + \alpha_i + \gamma_y + \theta_m + \nu_d) \tag{1}$$

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. Here, we include temperature-sensitive employment in county i in month m (z_{im}) as the Poisson "exposure" variable, setting its coefficient to 1. Taking the natural log of our simplified model then yields the following:

$$ln(\text{accidents}_{it}) = ln(z_{it}) + x_{it}'\beta \iff ln(\text{accidents}_{it}) - ln(z_{it}) = x_{it}'\beta \tag{2}$$

$$\iff ln\left(\frac{\text{accidents}_{it}}{z_{it}}\right) = x_{it}'\beta \tag{3}$$

While our immediate outcome variable is the number of temperature-sensitive accidents in county i on day t, we effectively estimate the impact of temperature on accident rate per recorded worker.

We regress accident rate on a series of 23 five-degree bins for maximum temperature on day t, $tmax_j$ for j in $\{1, 2, 3, \ . \ . \ . \ 23\}$, ranging from maximum temperature below 0°F and maximum temperature between 0 and 5°F to daily maximum temperature above 105°F. In all regressions, we omit the temperature bin corresponding to daily maximum temperature between 65°and 70°F, which physiology research suggests may be ideal working conditions (Hancock and Vasmatzidis, 2003; Ramsey and Kown, 1992; Pilcher et al., 2002). Each β_i gives the incidence rate ratio of accidents on a day with maximum temperature in bin i relative to a day with maximum temperature between 65°and 70°F. We control for precipitation using a similar set of indicator bins.[2]

Next, we control for a suite of temporal and geographic fixed effects, allowing us to isolate the impacts of plausibly exogenous local weather variation. Our primary specification includes

[2] In particular, we control for a dummy variable indicating zero precipitation, eleven bins split at 10-percentile intervals from the 10th through 90th percentiles of the distribution of non-zero precipitation in our sample, and a bin indicating precipitation above the 95th percentile of this distribution.

county fixed effects, α_i, year fixed effects, γ_y, month fixed effects, θ_m, and day-of-week fixed effects, ν_d. Therefore, we exploit county-specific variation in weather and accident rates about long-term county averages after controlling for national averages by year and for seasonal cycles. Altogether, this fixed effect structure allows us to plausibly estimate the causal effects of short-term weather variation. We cluster standard errors at the county level throughout our analysis to account for potential auto-correlation in county errors.

This empirical strategy improves on past research on temperature and accidents by using some of the methodological innovations of the recent climate-economy literature in economics. First, while past work has assumed either a linear or single-splined piecewise linear relationship between temperature and accidents, our specification only assumes that the impact of temperature is constant within these 5-degree ranges (Adam-Poupart et al., 2015; Xiang et al., 2014a, 2014b). Next, our panel fixed effect structure allows us to analyze a broader geographic study area than does recent public health research on temperature and accidents, which focuses on particular cities or sub-country regions (Adam-Poupart et al., 2015; Xiang et al., 2014a, 2014b). Our analysis covers the contiguous United States, which allows us to make use of greater variation in weather and improves the external validity of our estimates (Deschênes, 2014).

Our empirical strategy also draws from recent public health research on temperature and accidents in key ways. While much of the climate-economy literature uses OLS regression, we use the Poisson count model common to the public health literature. Next, like this literature, we analyze daily accident counts (Xiang et al., 2014a, 2014b; Adam-Poupart et al., 2015). In contrast, most economic analyses of the impacts of climate change use annual or monthly data on economic outcomes (Deschênes, 2014). In studies of temperature and mortality, this longer exposure window helps to prevent confounding by harvesting, or the accelerated death of those already nearing death due to chronic conditions. To the extent that accidents occur randomly within a population of workers and not among a subset of workers that were "due" for an accident, harvesting is unlikely to be relevant to the incidence of workplace accidents. Daily-level analysis allows us to more closely capture the immediate relationship between temperature and accident risk today.

In summary, we present the first analysis of accident incidence and temperature to make use of a broad geographic 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.

5 Estimates

We present the results of our primary Poisson regression in graphical form in Figure 2 and in column 2 of Table A1 in the Appendix. Coefficients on temperature bins give ratios of accident rates relative to a day with maximum temperature between 65°and 70°F, our omitted category. We find that accident rates are closely tied to ambient temperature. First, accident rates rise monotonically with temperature for all temperature bins above 65°to 70°F, spiking up sharply at maximum daily temperature over 100°F. Days with maximum temperature between 90°and 95°F have 9.9% more accidents, days between 95°and 100°F have 13.4% more accidents, days between 100°and 105°F have 29.3% more accidents, and days with maximum temperature over 105°F have 41.0% more accidents, all relative to days with maximum temperature between 65°and 70°F.

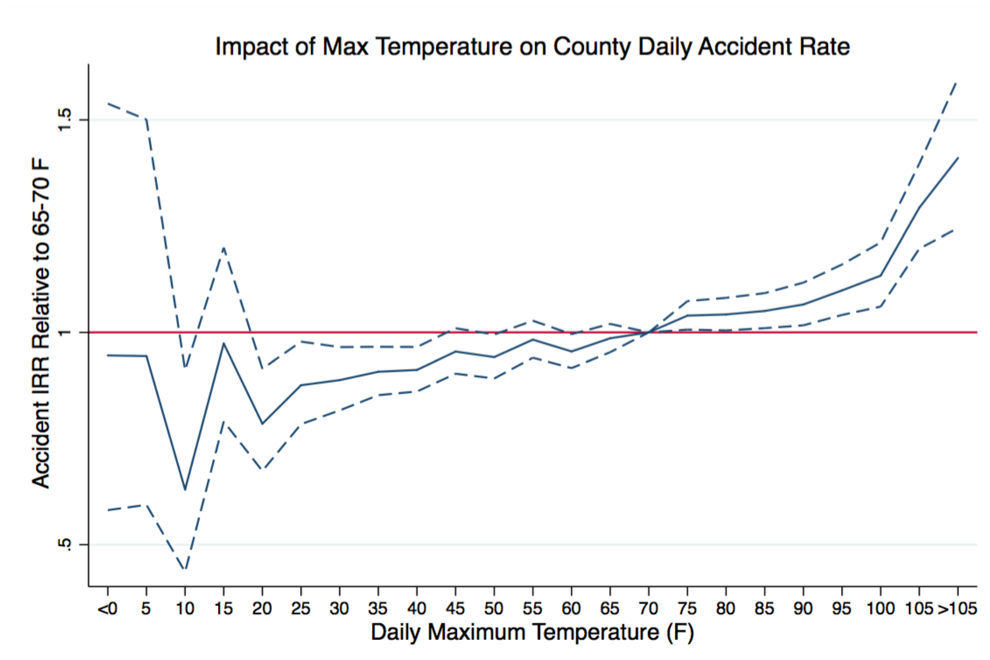


Figure 2: Poisson estimates of the impact of daily maximum temperature on daily private accident rate. Coefficients give incident rate ratios relative to maximum temperature between 65°and 70°F. Regression includes a balanced panel of 2,807 counties; the remaining counties in our full panel of 3,093 counties are dropped from the regression because they reported no accidents to OSHA between 1990 and 2010. Dashed lines give 95% confidence intervals. See Appendix Table A1 column 2 for the regression coefficients.

In contrast, we find that cold days significantly reduce accident rates; these coefficients largely decrease monotonically with colder temperatures before losing precision at very low temperatures. We estimate that days with maximum temperature between 35°and 40°F have 8.8% fewer accidents, days between 20 and 25°F have 12.4% fewer accidents, days between 15 and 20°F have 21.5% fewer accidents, and days with maximum temperature between 5 and 10°F have 37.0% fewer accidents, all relative to a day with maximum temperature between 65°and 70°F.

Table A1 in the Appendix presents a series of robustness checks to these primary results, where our primary results are given in column 2. In particular, our results are robust to using any available data rather than restricting to a balanced panel by county, to controlling for region-specific seasonal cycles with region-month fixed effects, to measuring heat exposure with maximum daily heat index, and to excluding California, which accounts for almost 40% of accidents in our sample.

It is important to note that these estimates are net of any protective behaviors that workers or their employers have historically taken in response to temperature shocks. These adaptive behaviors may account for the drop in accident rates at low temperatures, while physiology research predicts that accident risk would rise at both high and low temperature extremes. For example, if industries typically operating in winter more flexibly allow for postponement of work to better weather conditions than those operating in summer, we could expect to see that cold temperatures have smaller impacts on accident rate than do hot temperatures, or that accident rates even fall on particularly cold days. Previous studies have found similar decreases in accident rates at temperature extremes, which they attribute to a reduction in work volume or protective measures taken under those conditions (Xiang et al., 2014a). We more closely explore the role of adaptation in Section 6 below.

So far, we have estimated these impacts in the full sample of private-sector accidents reported to OSHA. But do these temperature impacts hold across all industries, or are they driven by industries where workers are directly exposed to weather? We now estimate our model separately in a sample of "temperature-sensitive" (TS) industries and non-TS industries. We loosely base this classification on Graff Zivin and Neidell's (2014) set of "at-risk" industries, defining TS industries as agriculture, forestry, and fishing; construction; manufacturing; transportation, communications, electric, gas, and sanitary services; oil and gas extraction; and other miscellaneous outdoor services. (See Tables A2 and A3 in the Appendix for our full list of TS industry codes.) Our set of non-TS accidents then includes accidents associated with retail, restaurants, schools, and hospitals, for example. We have been deliberately over-inclusive in identifying TS industries to limit misclassification into the non-TS category. In total, we classify about 90% of the private-sector accidents in our sample as TS.

Figure 3 plots our estimates for the impact of temperature in TS and non-TS industries. We focus only on the impacts of high temperature, since our estimates for low temperature bins are highly imprecise in our small sample of non-TS accidents. We present our full set of estimates in Table A4 in the Appendix. In columns 2 and 4, we check that our results are robust to excluding counties where QCEW data suppression has severely limited data on TS employment. (See Appendix section 1.2 for details on how we estimate TS employment.)

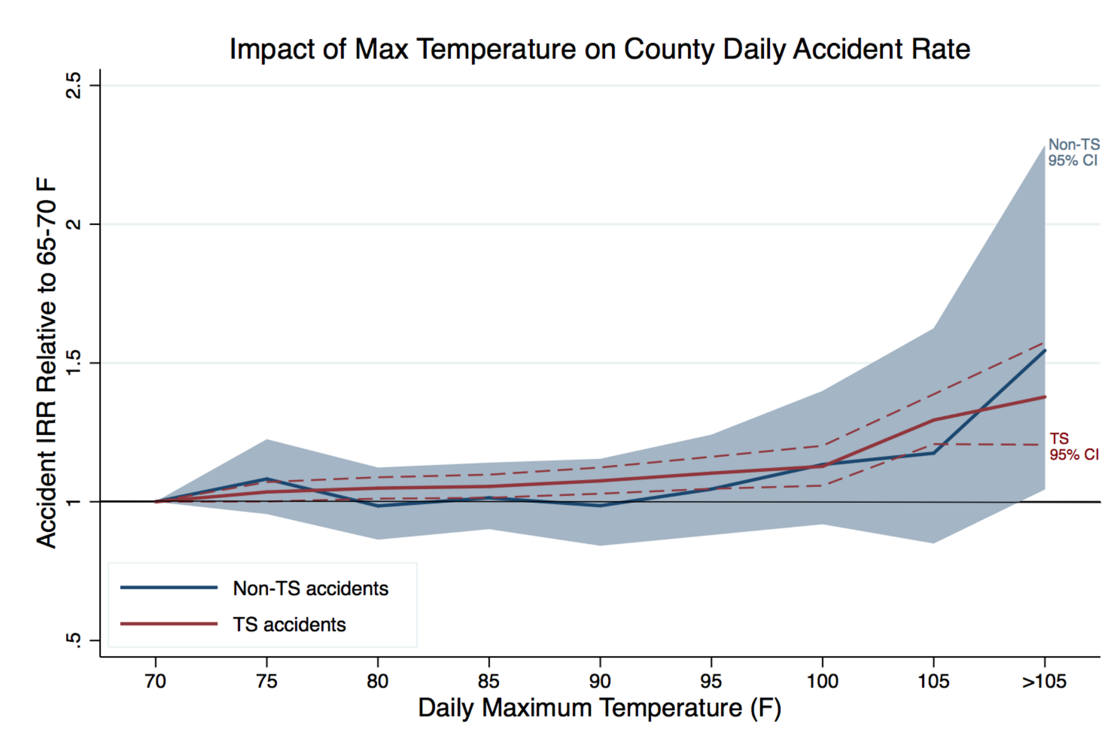


Figure 3: Poisson estimates of the impact of daily maximum temperature on daily accident rate in temperature-sensitive (TS) industries and non-TS industries. Coefficients give incident rate ratios relative to maximum temperature between 65°and 70°F. The TS regression includes 2,789 counties, while the non-TS regression includes 1,014 counties. This gap arises because the regression mechanically drops any county with no (non-)TS accident in 1990 through 2010 from the (non-)TS regression. The red dashed lines give 95% confidence intervals for TS industries, while the blue shaded region gives 95% confidence intervals for non-TS industries. See Appendix Tables A2 and A3 for our full list of TS industries and see Appendix Table A4 for these regression coefficients. Columns 2 and 4 of Table A4 restrict to county-months without substantial missing employment data, while we estimate these results in our full sample.

We find that heat shocks increase accident risk even in our conservative set of non-TS industries. Our estimates are less precisely estimated in the much smaller sample of non-TS industries, but our point estimates are similar across TS and non-TS industries. In particular, days with maximum temperature between 90°and 95°F raise accident rates by 4.5% in non-TS industries and 10.3% in TS industries, days between 95°and 100°F raise accident rates by 13.4% in non-TS industries and 12.7%

in TS industries, days between 100 and 105°F raise accident rates by 17.5% in non-TS industries and 29.4% in TS industries, and days with maximum temperature over 105°F raise accident rates by a full 54.5% in non-TS industries, while increasing accidents by 37.8% in TS industries. These impacts only become statistically significant in non-TS industries at temperatures over 105°F. Our point estimates for the impacts of cold temperatures in non-TS industries are irregular and statistically insignificant.

Thus, we find that heat shocks increase accidents even in indoor industries like retail and healthcare, not just in industries where workers are directly exposed to weather. This work adds to a growing body of literature, led by Cachon et al. (2012), that finds that temperature impacts even those production processes that are not obviously vulnerable to weather. Here, workers in indoor industries might still be prone to workplace accidents due to heat exposure overnight, during a commute, or because workplace cooling systems are insufficient.

6 Exploring Long-Run Adaptation

Altogether, our results suggest that we might expect to see more workplace accidents as extremely hot days become more frequent and cold days become less frequent under climate change. However, future adaptation will play a key role in dictating how our short-run estimates map into the long-run impacts of climate change on workplace safety.[3] This adaptation could take many forms. In the short term, workers or employers could reduce the risks associated with heat shocks by postponing work to cooler hours or scheduling additional breaks. Workers may also physically acclimatize to consistently hotter or colder weather. In the long term, we might see the development of new worker safety regulations or additional investments in protective technologies. In this section, we document preliminary exploration of the role of long-term adaptation in the impacts of temperature on worker safety.

We investigate the prevalence of long-run adaptation in our data by exploring how the impacts of heat shocks change over the course of our twenty-year panel, splitting our full panel into four

[3] While adaptation would likely lessen the long-run impacts of climate change relative to the short-run impacts we've estimated, any *intensification* could increase them. Intensification would occur if longer stretches of hot weather under a changed climate have more severe impacts than isolated heat shocks (Dell, Jones, and Olken, 2014). In this setting, for example, companies might lose the flexibility to postpone work to cooler days if an increasing share of the summer is extremely hot.

periods: 1990-1994, 1995-1999, 2000-2004, and 2005-2010. At first pass, we might simply be interested in how the impact of heat shocks changes across these periods. However, any such changes might just be driven by changes in the geographic incidence of heat shocks. For example, the impacts of heat shocks might rise over time if heat shocks increasingly occur in historically cold areas, which may be less adapted to heat risks. Thus, we estimate a model that assesses changes in the impact of temperature across time while also controlling for differential impacts of temperature across counties. In particular, we allow for differential impacts of temperature across historically hot, medium, and cool counties, which we define by terciles of the distribution for average number of days per year over 90°F from 1990 through 2000. We estimate the following model:

$$\begin{aligned} E[\text{accidents}_{it}] = &\exp(ln(z_{im}) + \sum_{p=1}^{4}\sum_{j=1}^{12}\beta_{jp}\ \text{tmax}_{itj} * \text{period}_p \\ &+ \sum_{g=1}^{3}\sum_{j=1}^{12}\beta_{jg}\ \text{tmax}_{itj} * \text{county group}_g + \sum_{k=1}^{12}\lambda_k\ \text{prcp}_{itk} + \alpha_i + \gamma_y + \theta_m + \nu_d) \end{aligned} \tag{4}$$

where, as before, 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. Here, we separately include interactions between temperature bins and dummies both for period and county group. Note that this specification constrains adaptation over time to be constant across the US. Instead of using the 23 five-degree temperature bins that we use throughout the rest of our analysis, we estimate this model using a set of 12 ten-degree temperature bins ranging from denoting maximum temperature below 0°F and maximum temperature between 0 and 10°F to maximum temperature over 100°F. OSHA-reported accidents are sufficiently rare that we cannot estimate standard errors in a model with the full set of interactions and five-degree temperature bins. We present our results in Table 1, and we plot the impacts of temperature in the historically hottest tercile of counties in Figure 4. We give the parallel figures for the coolest and middle terciles in Figures 1 and 2 in the Appendix.[4]

[4] Note that while the level of the temperature impacts vary across these groups, our Poisson model constrains the multiplicative changes in these coefficients across time for a given temperature bin to be constant across the county groups. Thus, we can visually assess adaptation over time by plotting temperature impacts across time periods for only a single county group.

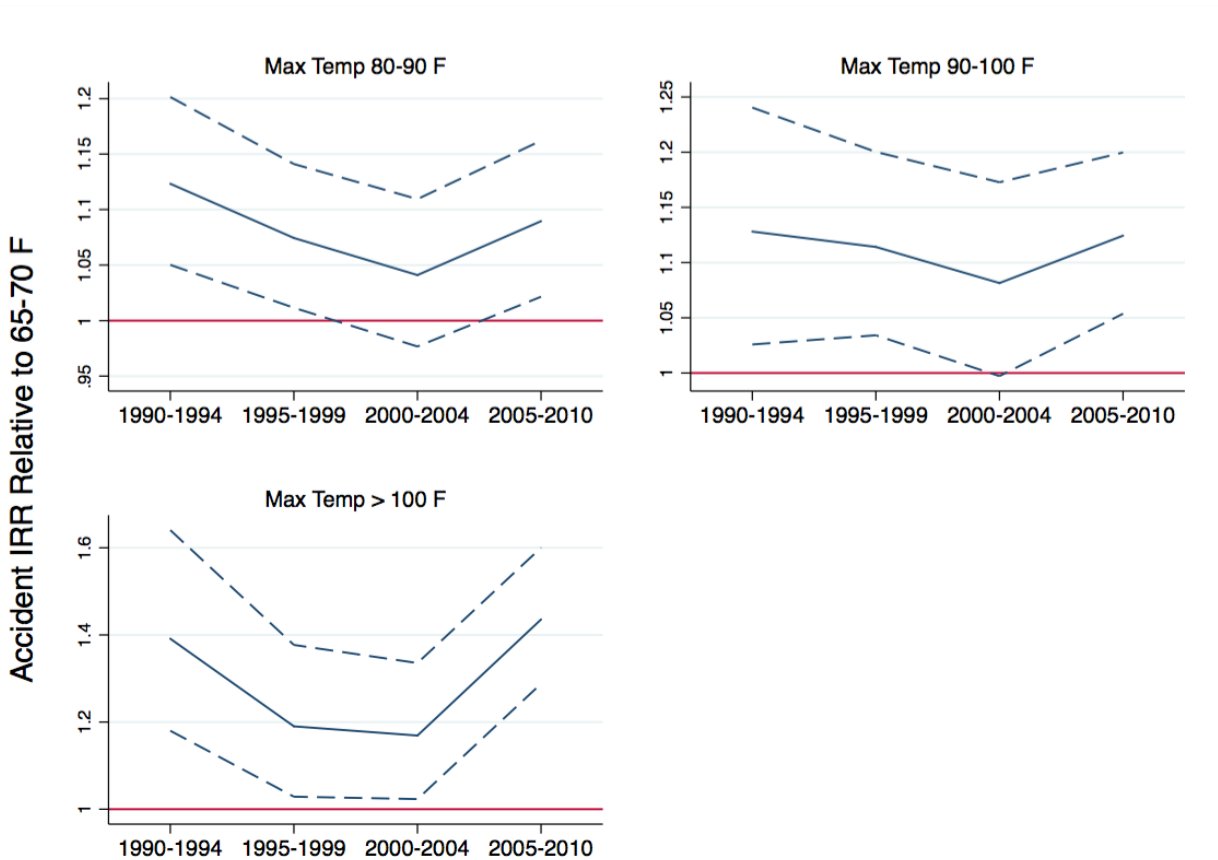
Table 1: Temperature impacts by yearblock and region

		Private Accident IRR			
		1990-1994	1995-1999	2000-2004	2005-2010
80-90 F	Interaction		0.956	0.927	0.970
			(0.17)	(0.10)	(0.46)
	Cool	1.101	1.053	1.020	1.067
		(0.01)	(0.14)	(0.60)	(0.07)
	Medium	1.092	1.045	1.012	1.059
		(0.04)	(0.24)	(0.73)	(0.08)
	Hot	1.123	1.074	1.041	1.090
		(0.00)	(0.02)	(0.22)	(0.01)
90-100 F	Interaction		0.988	0.959	0.997
			(0.82)	(0.46)	(0.95)
	Cool	1.254	1.239	1.203	1.250
		(0.01)	(0.01)	(0.01)	(0.00)
	Medium	1.116	1.102	1.070	1.112
		(0.07)	(0.05)	(0.11)	(0.02)
	Hot	1.128	1.114	1.081	1.124
		(0.01)	(0.00)	(0.06)	(0.00)
$\geq$ 100 F	Interaction		0.855	0.840	1.032
			(0.08)	(0.16)	(0.77)
	Cool	1.231	1.053	1.034	1.270
		(0.73)	(0.93)	(0.96)	(0.69)
	Medium	1.752	1.499	1.472	1.808
		(0.00)	(0.01)	(0.01)	(0.00)
	Hot	1.391	1.190	1.169	1.435
		(0.00)	(0.02)	(0.02)	(0.00)

Note: P-values derived from robust standard errors are given in parentheses. "Interaction" coefficients measure the differential effect of temperature in that year block relative to 1990-1994. "Cool" refers to the first (coolest) tercile of the county-level distribution for average annual number of days above 90°F between 1990 and 2000, "Medium" refers to the second tercile, and "Hot" refers to the third (hottest) tercile. Rows labeled with "Cool," "Medium," or "Hot" give the estimated full effect of a day in that temperature bin and time period on accident rate in that county group.

We find no evidence that the impacts of temperature have fallen over time due to adaptation. The time period interaction terms given in Table 1, all of which are multiplicative IRRs relative to 1990-1994, are not statistically significant, and Figure 4 shows no clear trend downwards in any of the top three temperature bins. In interpreting these time trends, it is important to keep in mind that they might in part reflect falling measurement error over time. While the total volume of accidents reported to OSHA has remained relatively constant from 1990-2010 (see Figure 1), the

Figure 4: Impacts of heat shocks over time in the historically hottest tercile of counties



Note: Estimated incident rate ratios of the four highest 10-degree temperature bins relative to days with maximum temperature between 60°and 70°F, plotted over time. These coefficients give estimated temperature impacts in counties in the third tercile of the county-level distribution of average number of days with max temperature over 90°F per year from 1990 through 2000. The dashed lines mark 95% confidence intervals.

quality of accident reporting may have risen over time, making accidents more accurately matched to particular dates and counties in the later years of our panel. Then, it is possible that attenuation bias in our estimates in early time period could obscure actual adaptation.

Besides evaluating how the impacts of temperature have changed over time, this specification allows us to explore how heat risks vary across counties with different historical climates. We might expect historically hot counties to be better adapted to heat shocks, and thus to see smaller temperature impacts among the highest bins. We see some limited evidence of this in Table 1, where, again, we explore the impacts of temperature across terciles of the county-level distribution for average number of days over 90°F per year from 1990 through 2010 (labelled "Cool," "Medium," and "Hot.") Here, note that we have constrained the relative impacts of temperature between county groups to remain constant across time periods.

While days with maximum temperature between 80 and 90°F have similar impacts across these county groups, our point estimates suggest that days between 90 and 100°F have impacts about twice as large in historically cool counties as in historically medium or hot counties. Next, while the impact of days over 100°F is imprecisely estimated in cool counties, those extremely hot days have impacts that are almost twice as high in historically medium counties as in historically hot counties. While the differential IRRs of heat shocks in hot or medium counties relative to cool counties are not statistically significant, they provide some suggestive evidence of adaptation; namely, our coefficients suggest that extreme heat shocks may have less impact in historically hotter places.

7 Conclusions

Using plausibly exogenous day-to-day fluctuations in temperature, we estimate the impact of temperature on workplace accident rates in a daily panel of 2945 counties in the United States from 1990 through 2010. We find that while cold shocks reduce accident rates, heat shocks substantially increase them. The impacts of heat shocks rise monotonically with temperature, with heat increasing accident rates by up to 38.6% at maximum temperature over 105°F, relative to a day between 65°and 70°F. Heat shocks are not just costly in obviously temperature-sensitive industries like construction and agriculture, but also in a conservative set of industries like schools, hospitals, and restaurants. We find no evidence that the impacts of heat shocks have fallen over our 21-year panel.

Under the possibly naive assumption that no further adaptation will occur, our estimates suggest that climate change may substantially increase the rate of workplace accidents in the US. To assess the possible magnitude of these impacts, we pair our model predictions with climate projections produced by Rasmussen, Meinshausen, and Kopp (2016). We find that the US will suffer 134,518 additional severe workplace injuries per year by 2099 under a scenario in which CO_2-equivalent concentrations rise above 1200 ppm, relative to a scenario in which concentrations remain below 450 ppm. The impact varies widely across US counties and regions, with the largest predicted increases in the South Atlantic and West South Central census regions. We predict smaller impacts in the Pacific, New England, and North Atlantic. Using estimates from Leigh (2011), we estimate that this increase in injuries could cost the US economy more than \$3.6 billion per year by 2099, valued at 2019 prices. We present details of these calculations and a map of estimated impacts in the Appendix.

It is important to note that these estimates of climate impacts are highly uncertain. In particular, our estimates of the short-term impact of temperature on accident incidence might diverge from the long-term impacts of climate change on accident incidence through a combination of adaptation, or the process by which economic actors develop behavioral mechanisms, policies, or technologies that reduce the impacts of temperature shifts, and intensification, where shifts in weather patterns associated with climate change produce larger damages than those revealed by transient, short-term weather fluctuations. While these long-run shifts may yet occur, we find no evidence that the impact of temperature changed significantly between 1990 and 2010.

Our work adds to a growing literature estimating the impacts of weather variation on economic outcomes ranging from mortality rates to human capital formation (Deschênes and Greenstone, 2011; Graff Zivin, Hsiang, and Neidell, 2018). These studies have helped to identify the crucial links between climate, labor productivity, and health. Subject to the uncertainties identified above, our analysis suggests that changes in worker safety may be another such link. If so, future research on the impacts of temperature on accident rate may prove salient both to climate and worker safety and productivity.

8 References

Adam-Poupart, Ariane, Audrey Smargiassi, Marc-Antoine Busque, Patrice Duguay, Michel Fournier, Joseph Zayed, and France Labreche. 2014. "Summer Outdoor Temperature and Occupational Heat-Related Illnesses in Quebec (Canada)." *Environmental Research* 134: 339-344.

Bureau of Labor Statistics (BLS). 2017. "Work Injuries in the Heat in 2017." https://www.bls.gov/opub/ted/2017/injuries-in-the-heat-in-2015.htm

Behrer, A. Patrick and Jisung Park. 2017. 'Will We Adapt? Temperature, Labor and Adaptation to Climate Change". https://www.dropbox.com/s/tx6bbvnhxkthylt/paper_will_we_adapt_park_behrer.pdf?dl=0

Burke, Marshall, Solomon Hsiang, and Edward Miguel. 2015. "Global Non-linear Effect of Temperature on Economic Production." *Nature* 527: 235-239.

Cachon, Gerard P., Santiago Gallino, and Marcelo Olivares. 2012. "Severe Weather and Automobile Assembly Productivity." Columbia Business School Research Paper No. 12/37.

Deryugina, Tatyana and Solomon Hsiang. "Does the Environment Still Matter? Daily Temperature and Income in the United States." (2014). NBER Working Paper No. 20750.

Deschênes, Olivier. 2014. "Temperature, Human Health, and Adaptation: A Review of the Empirical Literature." *Energy Economics* 46: 606-619.

Deschênes, Olivier and Michael Greenstone. 2011. "Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US." *American Economic Journal: Applied Economics* 3, no. 4: 152-185.

Epstein, Y., G. Keren, J. Moisseiev, O. Gasko, and S. Yachin. 1980. "Psychomotor Deterioration During Exposure to Heat." *Aviation, Space and Environmental Medicine* 51, no. 6: 607-610.

Dell, Melissa, Jones, Benjamin F., and Benjamin A. Olken. 2012. "Temperature Shocks and Economic Growth: Evidence from the Last Half Century." *American Economic Journal: Macroeconomics* 4, no. 3: 66-95.

Dell, Melissa, Jones, Benjamin F., and Benjamin A. Olken. 2014. "What Do We Learn From the Weather? The New Climate-Economy Literature." *Journal of Economic Literature* 52, no. 3: 740-798.

Fogleman, Maxwell, Layla Fakhrazadeh, and Thomas E. Bernard. 2005. "The Relationship Between Outdoor Thermal Conditions and Acute Injury in an Aluminum Smelter." *International Journal of Industrial Ergonomics* 35, no. 1 (2005): 47-55.

Graff Zivin, Joshua, Solomon Hsiang, and Matthew Neidell. Temperature and Human Capital in the Short and Long Run. 2018 *Journal of the Association of Environmental and Resource Economists* 5, no. 1: 77-105.

Graff Zivin, Joshua and Matthew Neidell. 2014. "Temperature and the Allocation of Time: Implications for Climate Change." *Journal of Labor Economics* 32, no. 1: 1-26.

Hancock, P.A. and I. Vasmatzidis. 2003. "Effects of Heat Stress on Cognitive Performance: the Current State of Knowledge." *International Journal of Hyperthermia* 19, no. 3: 355-372.

Heal, Geoffrey and Jisung Park. 2016. "Temperature Stress and the Direct Impact of Climate Change: A Review of an Emerging Literature." *Review of Environmental Economics and Policy* 10, no. 2: 347-362

Hsiang, Solomon M. 2010. Temperature and Cyclones Strongly Associated with Economic Production in the Caribbean and Central America. *Proceedings of the National Academy of Sciences of the United States of America* 107, no. 35: 15367-15372.

Hsiang, Solomon M., Robert Kopp, Amir Jina, James Rising, Michael Delgado, Shashank Mohan, D.J. Rasmussen, Robert Muir-Wood, Paul Wilson, Michael Oppenheimer, Kate Larsen, and Trevor Houser. 2017. "Estimating Economic Damages From Climate Change in the United States." *Science* 356, no. 6345: 1362-1369.

Jackson, Larry L. and Howard R. Rosenberg. 2010. "Preventing Heat-Related Illness Among Agricultural Workers." *Journal of Agromedicine* 15, no. 3: 200-215.

Jones, Benjamin F. and Benjamin A. Olken. 2010. "Climate Shocks and Exports." *American Economic Review* 100, no. 2: 454-459.

Kjellstrom, Tord, Ingvar Holmer, and Bruno Lemke. 2009. "Workplace Heat Stress, Health and Productivity–An Increasing Challenge for Low and Middle-Income Countries During Climate Change." *Global Health Action* 2. Published online. doi: 10.3402/gha.v2i0.2047.

Kjellstrom, Tord, Sabine Gabrysch, Bruno Lemke, and Keith Dear. 2009. "The 'Hothaps' Programme for Assessing Climate Change Impacts on Occupational Health and Productivity: an Invitation to Carry Out Field Studies." *Global Health Action* 2. Published online. doi: 10.3402/gha.v2i0.2082.

Leigh, J. Paul. 2011. "Economic Burden of Occupational Injury and Illness in the United States." *The Milbank Quarterly* 89, no. 4: 728-772.

Lind, A.R. and Bass, D.E. 1963. "Optimal Exposure Time for Development of Acclimatization to Heat." *Proceedings of American Societies for Experimental Biology* 22: 704-708.

Lucas, Rebekah A., Yoram Epstein, and Tord Kjellstrom. 2014. "Excessive Occupational Heat Exposure: a Significant Ergonomic Challenge and Health Risk for Current and Future Workers." *Extreme Physiology and Medicine* 23, no. 3: 14.

National Climatic Data Center. 1981, updated monthly. "Daily Meteorological Data for U.S. Cooperative Stations from NCDC TD3200." Research Data Archive at the National Center for Atmospheric Research, Computational and Information Systems Laboratory. http://rda.ucar.edu/datasets/ds510.0/ (accessed August 1, 2015).

National Institute for Occupational Safety and Health (NIOSH). 2017. "Economic Burden of Occupational Fatal Injuries in the United States Based on the Census of Fatal Occupational Injuries, 2003-2010. NIOSH Dataset SD-1002-2017-0." https://www.cdc.gov/niosh/data/datasets/sd-1002-2017-0/default.html (accessed January 5, 2019).

CDC Wonder Database. 2012. "North America Land Data Assimilation System (NLDAS) Daily Air Temperatures and Heat Index (1979-2011)." https://wonder.cdc.gov/nasa-nldas.html (accessed December 7, 2015).

Occupational Safety and Health Administration (OSHA). April 7, 2010, updated daily. "OSHA Enforcement Inspection and Accident Investigation Data." United States Department of Labor. https://enforcedata.dol.gov/homePage.php (accessed August 5, 2015).

Osborne, Ethel E., Horace M. Vernon, and Bernand Muscio. 1922. "The Influence of Temperature and Other Conditions on the Frequency of Industrial Accidents." In *Two Contributions to the Study of Accident Causation.* London: H.M. Stationery Office.

Pilcher, June J., Eric Nadler, and Caroline Busch. 2002. "Effects of Hot and Cold Temperature Exposure on Performance: a Meta-Analytic Review." *Ergonomics* 45, no. 10: 682-698.

Ramsey, Jerry D., and Charles L. Burford. 1983. "Effects of Workplace Thermal Conditions on Safe Work Behavior." *Journal of Safety Research* 14, no. 3: 105-114.

Ramsey, Jerry D. and Yeong G. Kwon. 1992. "Recommended Alert Limits for Perceptual Motor Loss in Hot Environments." *International Journal of Industrial Ergonomics* 9, no. 3: 245-257.

Rasmussen, D. J. and Meinshausen, Malte and Kopp, Robert E. 2016. "Probability-Weighted Ensembles of U.S. County-Level Climate Projections for Climate Risk Analysis." *Journal of Applied Meteorology and Climatology* 55, no. 10: 2301-2322.

Seppanen, Olli, William J. Fisk, and Quanhong Lei-Gomez. 2006. "Effect of Temperature on Task Performance in Office Environment." LBNL-60946. Lawrence Berkeley National Laboratory, Berkeley, CA.

Stocks, Jodie M., Nigel A.S. Taylor, Michael J. Tipton, and John E. Greenlead. 2004. "Human Physiological Responses to Cold Exposure." *Aviation, Space, and Environmental Medicine* 75, no. 5: 444-457.

U.S. Department of Labor (U.S. DOL). 1996. "Occupational Injury and Illness Recording and Reporting Requirements." 29 CFR Parts 1904 and 1952. Federal Registry # 61:4029-4067. Washington D.C.: U.S. Government Printing Office.

U.S. Department of Labor (U.S. DOL). 2014. "Occupational Injury and Illness Recording and Reporting Requirements. NAICS Update and Reporting Revisions." 29 CFR Part 1904. Federal Registry # 79: 56129-56188. (2014). Washington, D.C.: U.S. Government Printing Office.

World Health Organization (WHO). 1969. "Health Factors Involved in Working Under Conditions of Heat Stress: Report of a WHO Scientific Group." Geneva: World Health Organization.

Xiang, Jianjun, Peng Bi, Dino Pisaniello, and Alana Hansen. 2014. "The Impact of Heatwaves on Workers? Health and Safety in Adelaide, South Australia." *Environmental Research* 133: 90-95.

Xiang, Jianjun, Peng Bi, Dino Pisaniello, Alana Hansen, and Thomas Sullivan. 2014. "Association Between High Temperature and Work-Related Injuries in Adelaide, South Australia, 2001-2010." *Occupational and Environmental Medicine* 71, no. 4: 246-252.

Appendix: Heat Stress: Ambient Temperature and Workplace Accidents in the US

Table A1: Primary robustness checks

	(1)	(2)	(3)	(4)	(5)
		Private Accident IRR			
	Unbalanced	Balanced Full			Excluding CA
Max temp $<$ 0 F	0.942	0.946	0.972	0.941	0.927
	(0.23)	(0.23)	(0.24)	(0.23)	(0.23)
0-5 F	0.941	0.944	0.970	0.941	0.945
	(0.22)	(0.22)	(0.23)	(0.22)	(0.22)
5-10 F	0.628	0.630	0.646	0.628	0.635
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)
10-15 F	0.971	0.974	0.997	0.971	0.983
	(0.10)	(0.10)	(0.11)	(0.10)	(0.11)
15-20 F	0.788	0.785	0.801	0.783	0.798
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
20-25 F	0.874	0.876	0.890	0.874	0.889
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
25-30 F	0.890	0.888	0.900	0.886	0.900
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
30-35 F	0.908	0.907	0.919	0.906	0.925
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
35-40 F	0.912	0.912	0.920	0.911	0.922
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
40-45 F	0.955	0.955	0.962	0.955	0.984
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
45-50 F	0.944	0.942	0.946	0.942	0.971
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)
50-55 F	0.983	0.983	0.984	0.982	1.010
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
55-60 F	0.955	0.955	0.956	0.955	0.954
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
60-65 F	0.987	0.986	0.985	0.986	0.997
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
70-75 F	1.039	1.040	1.041	1.033	1.015
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
75-80 F	1.042	1.042	1.044	1.049	1.026
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
80-85 F	1.051	1.050	1.051	1.046	1.057
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
85-90 F	1.066	1.066	1.061	1.070	1.095
	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)
90-95 F	1.099	1.099	1.094	1.089	1.117
	(0.03)	(0.03)	(0.03)	(0.02)	(0.04)
95-100 F	1.134	1.134	1.135	1.171	1.224
	(0.04)	(0.04)	(0.04)	(0.03)	(0.05)
100-105 F	1.293	1.293	1.304	1.242	1.417
	(0.05)	(0.05)	(0.05)	(0.04)	(0.08)
Max temp $\geq$ 105 F	1.410	1.410	1.434	1.417	1.585
	(0.09)	(0.09)	(0.09)	(0.06)	(0.19)
Balanced		✓	✓	✓	✓
Uses heat index				✓	
Standard FE	✓	✓		✓	✓
+ Region month FE			✓		
Nr. observations	21594330	21529690	21529690	21529690	21084830
Nr. counties	2817	2807	2807	2807	2749

Note: Robust standard errors are given in parentheses.

1 Temperature-Sensitive (TS) Accidents and Employment

1.1 Identifying TS industries

In this section, we outline our procedure for identifying temperature-sensitive TS accidents and employment. First, Tables A2 and A3 list the industry codes that we classify as TS. The BLS Quarterly Census of Employment and Wages (QCEW) categorizes industries by Standard Industrial Classification (SIC) Codes throuhg 2000, after which it classifies them by North American Industry Classification System (NAICS) codes, so we identify industries under both coding systems. OSHA accident data categories accidents by SIC codes.

Table A2: TS Standard Industrial Classification (SIC) codes

Temperature-Sensitive Industry	**SIC Code**
SIC Divisions	
Agriculture, Forestry, and Fishing	Division A
Mining	Division B
Construction	Division C
Manufacturing	Division D
Transportation, Communications, Electric, Gas, and Sanitary Services	Division E
Wholesale Trade	Division F
SIC Major Groups (2-digit codes)	
Automotive Dealers and Gasoline Service Stations	Division G, Major Group 55
Automotive Repair, Services, and Parking	Division I, Major Group 75
Miscellaneous Repair Services	Division I, Major Group 76
SIC 4-Digit Codes	
Lumber and Other Building Materials Dealers	Division G, 5211
Retail Nurseries, Lawn and Garden Supply Stores	Division G, 5261
Sporting and Recreational Camps	Division I, 7032
Recreational Vehicle Parks and Campsites	Division I, 7033
Other Building Cleaning and Maintenance Services	Division I, 7349
Heavy Construction Equipment Rental and Leasing	Division I, 7353
Public Golf Courses	Division I, 7992
Amusement Parks	Division I, 7996
Membership Sports and Recreation Clubs	Division I, 7997
Police Protection	Division J, 9221
Fire Protection	Division J, 9224

Table A3: TS North American Industry Classification System (NAICS) codes

Temperature-Sensitive Industry	**NAICS Code**
NAICS Sectors	
Agriculture, Forestry, Fishing, and Hunting	Sector 11
Mining, Quarrying, and Oil and Gas Extraction	Sector 21
Utilities	Sector 22
Construction	Sector 23
Manufacturing	Sector 31-33
Wholesale Trade	Sector 42
Transportation and Warehousing	Sector 48-49
NAICS Subsectors	
Motor Vehicle and Parts Dealers	Subsector 441
Building Material and Garden Supply Stores	Subsector 444
Gasoline Stations	Subsector 447
Waste Management and Remediation Services	Subsector 562
Repair and Maintenance	Subsector 811
NAICS Industry Groups	
Machinery and Equipment Rental and Leasing	Industry Group 5324
Services to Buildings and Dwellings	Industry Group 5617
Other Amusement and Recreation Industries	Industry Group 7139
RV Parks and Recreational Camps	Industry Group 7212
NAICS Industries	
Amusement and Theme Parks	NAICS Industry 71311
Police Protection	NAICS Industry 92212
Fire Protection	NAICS Industry 92216

1.2 Calculating TS employment

We collect monthly employment data, broken down by county and SIC code, from the BLS Quarterly Census of Employment and Wages (QCEW). Extensive county-level data suppression within the QCEW prevents us from directly calculating TS employment as the simple sum of employment across TS industries. Instead, we undertake the following process:

- Given county A and TS industry B in month C, we calculate the share of county A's private employment that is in industry B for month C separately for all years from 1990 through 2010 for which data is available.
- We then average this proportion across all years, generating estimates for the average proportion of county A's total private employment that is in industry B in month C.
- Then, we sum these average proportions over all TS industries to generate a measure of the average share of total private employment in county A in month C that is in TS industries.
- Finally, we estimate TS employment in county A, month C, year D by multiplying total private employment for that county-year-month by the TS employment ratio for county A in month C.

Note that this method creates a single value for the share of private employment in TS industries for each county-month in our data, assuming that the total proportion of county-level employment in TS industries stays constant from 1990 through 2010. Then, all variation in our measure of TS employment comes from variation in total private employment.

While this method reduces missing data by pooling data from any years in which it is available, many counties are still missing estimates of the proportion of employment in a subset of TS industries due to QCEW data suppression. Then, we estimate TS employment using only the subset of industries for which data are available. To identify counties where our TS employment measures are based on incomplete data, we create a simple quality index. For the years 1990 through 2010, we construct the index as follows:

- For a county with employment data for every temperature-sensitive industry at some point in our sample period, this index takes the value of 0.
- We add 1 to a county's index for each TS SIC Division with no available employment data
- We add 0.1 to a county's index for each TS SIC Major Group (2-digit code) with no available employment data.
- We add 0.01 to a county's index for each TS SIC 4-digit code with no available employment data

We create a parallel index based on NAICS codes for the years 2001 through 2010, and finally we average these two indices by county to generate a single measure of data quality for TS employment. When we separately estimate the impact of temperature in TS and non-TS industries in section **??**, we verify that our results are robust to excluding counties with an index greater than 1, i.e. those that are on average missing data for more than one TS industry division. These results appear in Table **??** below.

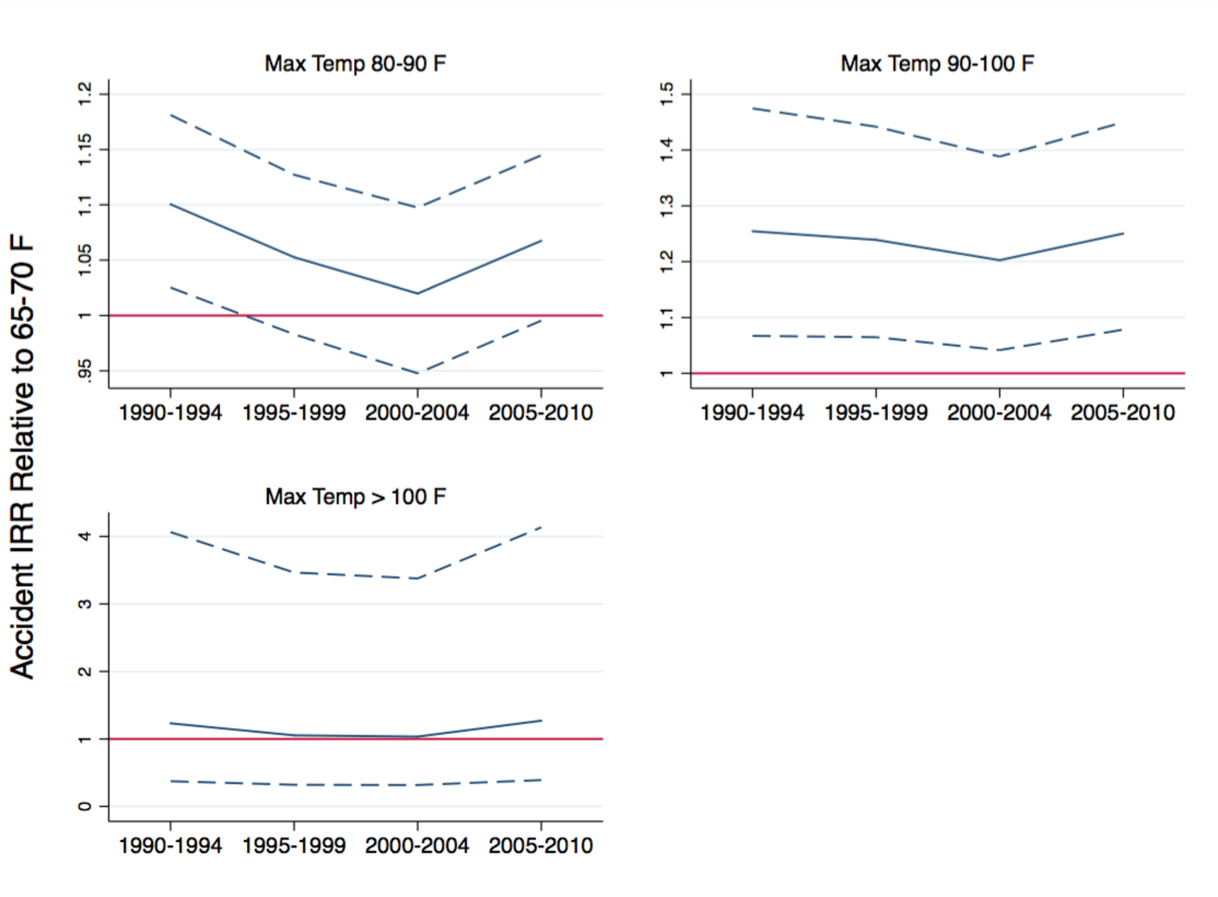
Table A4: Primary regressions with TS and non-TS accidents

	(1)	(2)	(3)	(4)
	Private Accident IRR			
	Non-TS Accidents		TS Accidents	
Max temp < 0 F	2.705	3.551	0.821	0.765
	(1.50)	(2.00)	(0.24)	(0.29)
0-5 F	1.736	1.471	0.892	0.849
	(1.01)	(1.05)	(0.21)	(0.25)
5-10 F	1.098	1.373	0.598	0.587
	(0.56)	(0.71)	(0.12)	(0.14)
10-15 F	1.561	1.880	0.935	0.934
	(0.47)	(0.56)	(0.11)	(0.12)
15-20 F	1.478	1.340	0.734	0.714
	(0.30)	(0.29)	(0.06)	(0.07)
20-25 F	1.093	1.007	0.864	0.846
	(0.19)	(0.17)	(0.05)	(0.06)
25-30 F	0.991	1.015	0.885	0.859
	(0.13)	(0.14)	(0.04)	(0.04)
30-35 F	1.006	0.977	0.904	0.916
	(0.10)	(0.10)	(0.03)	(0.03)
35-40 F	0.887	0.852	0.918	0.912
	(0.08)	(0.08)	(0.03)	(0.03)
40-45 F	0.978	0.991	0.956	0.958
	(0.09)	(0.09)	(0.03)	(0.03)
45-50 F	0.909	0.911	0.948	0.944
	(0.07)	(0.07)	(0.03)	(0.03)
50-55 F	0.942	0.932	0.988	0.984
	(0.05)	(0.05)	(0.02)	(0.02)
55-60 F	0.871	0.876	0.966	0.965
	(0.06)	(0.06)	(0.02)	(0.02)
60-65 F	0.961	0.946	0.990	0.992
	(0.07)	(0.06)	(0.02)	(0.02)
70-75 F	1.082	1.069	1.035	1.031
	(0.07)	(0.07)	(0.02)	(0.02)
75-80 F	0.985	0.986	1.049	1.053
	(0.07)	(0.07)	(0.02)	(0.02)
80-85 F	1.014	1.011	1.055	1.052
	(0.06)	(0.06)	(0.02)	(0.02)
85-90 F	0.986	0.988	1.075	1.083
	(0.08)	(0.08)	(0.02)	(0.03)
90-95 F	1.045	1.053	1.103	1.110
	(0.09)	(0.10)	(0.03)	(0.03)
95-100 F	1.134	1.155	1.127	1.133
	(0.12)	(0.13)	(0.04)	(0.04)
100-105 F	1.175	1.187	1.294	1.307
	(0.19)	(0.20)	(0.05)	(0.05)
Max temp $\geq$ 105 F	1.545	1.577	1.378	1.382
	(0.31)	(0.32)	(0.09)	(0.10)
Quality restricted		✓		✓
Standard FE	✓	✓	✓	✓
Nr. observations	7777380	6180041	21391630	15878368
Nr. counties	1014	826	2789	2179

Note: Robust standard errors are given in parentheses. Columns 2 and 4 restrict to county-months without substantial missing data for TS employment. We describe this "quality restricted" sample in Appendix Section 1.2 above. The variation in sample size between the TS and non-TS regressions arises because the regression mechanically drops any county with no (non-)TS accident in 1990 through 2010 from the (non-)TS regression.

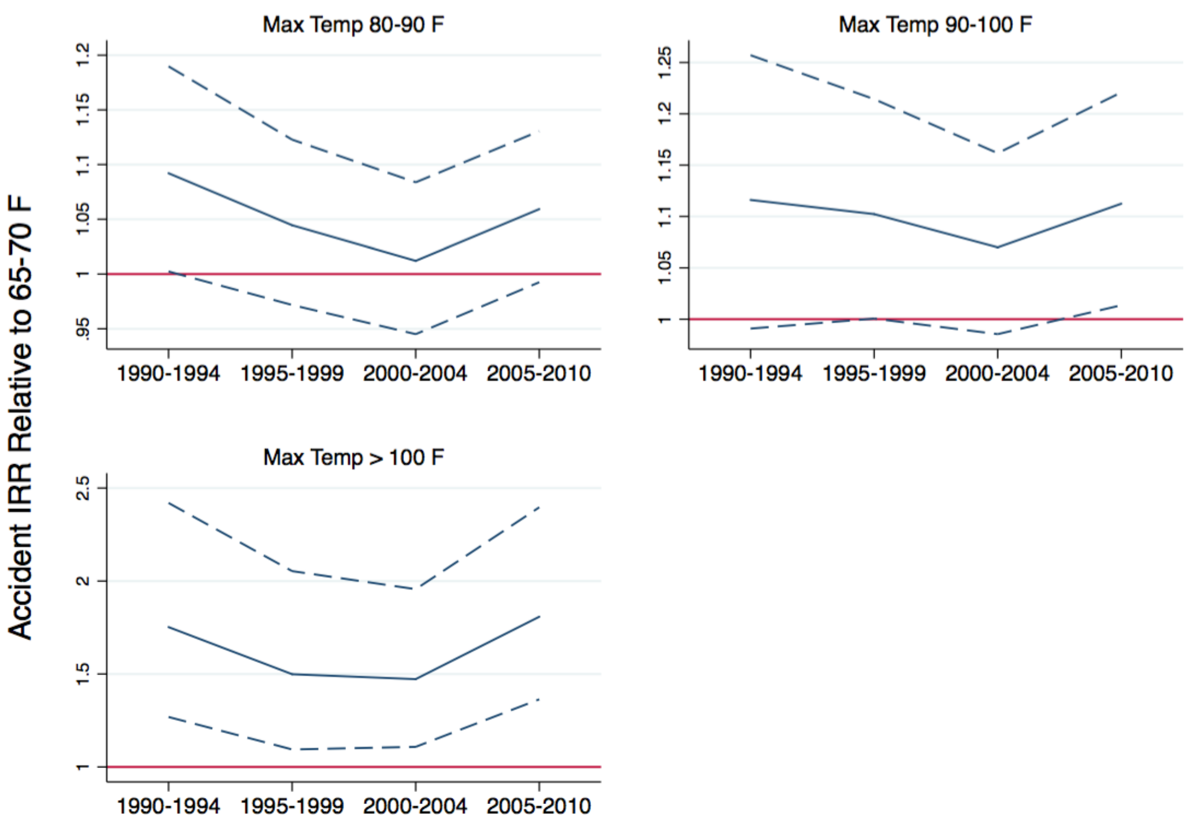
2 Long-run adaptation results

Figure 1: Impacts of heat shocks over time in the historically coolest tercile of counties



Note: Estimated incident rate ratios of the four highest 10-degree temperature bins relative to days with maximum temperature between 60°and 70°F, plotted over time. These coefficients give estimated temperature impacts in counties in the third tercile of the county-level distribution of average number of days with max temperature over 90°F per year from 1990 through 2000. The dashed lines mark 95% confidence intervals.

Figure 2: Impacts of heat shocks over time in the historically middle tercile of counties



Note: Estimated incident rate ratios of the four highest 10-degree temperature bins relative to days with maximum temperature between 60°and 70°F, plotted over time. These coefficients give estimated temperature impacts in counties in the second tercile of the county-level distribution of average number of days with max temperature over 90°F per year from 1990 through 2000. The dashed lines mark 95% confidence intervals.

3 Projecting workplace accidents under climate change

Our model estimates can be used to infer the increase in occupational injuries that might be expected with climate change in the coming decades. To make these inferences we utilize the Monte-Carlo simulations of global climate outcomes over the coming century imputed to the US county-level that have been undertaken and discussed more fully by Rasmussen, Meinshausen, and Kopp (2016).

Rasmussen, *et al.* produce temperature forecasts for US counties that are based on four IPCC Relative Concentration Pathways (RCP). These are different assumed levels of *radiative forcing* or energy input minus energy output for the entire planet. The scenarios are identified by the watts per meter^2 increase in radiative forcing relative to the year 1750. We undertake a comparison between the RCP 8.5, a 'baseline' scenario in which CO_2 equivalent concentrations rises to 1313 ppm by the end of this century, and RCP 2.6 as a 'mitigation' scenario in which CO_2 equivalent concentrations are held below 475 ppm. Rasmussen, *et al.* develop dual approaches to estimating the maximum temperature in US counties under these (and other) scenarios. We make use of their Monte Carlo simulations of the two scenarios.

Their Monte-Carlo simulations provide county level temperatures for each percentile of global mean temperature under each scenario. We take these data and calculate, for each county and day, the median temperature obtained in these simulations. We use this as a predicted future temperature for each US county and calculate the appropriate indicator variable for the temperature range for each day.

In addition to the indicator for temperature range, we need to make some assumptions about future values of precipitation and total private employment. In order to focus attention on the effects of future temperature change, and because forecasting future changes in employment is well beyond the scope of this study, we take the mean value of private sector employment for each county over the period 2001-2010, and assume that will prevail in the future.

Although there are forecasts available of future precipitation levels, these remain even more uncertain than the temperature forecasts. Therefore, again to focus attention on the expected future changes in ambient temperatures, we assume each county experiences a daily precipitation amount that is the mean of that recorded in our sample from 2001 through 2010.

Using these data, we estimate our core model whose results are presented above and then use the estimated parameters to predict the number of accidents for each day and each county for future days. We summarize in Table A5 the associated increase in workplace accidents for the entire year 2099.

Table A5 presents the estimated impact by US Census districts and presents a total for the 49 contiguous jurisdictions in the continental United States. The first column identifies the geographic area. The second column, labeled 'Increased Accidents' provides the sum over all counties in the jurisdiction and all days in 2099 of the predicted accidents under RCP 8.5 median temperature minus predicted accidents under RCP 2.6 median temperature.

The predicted increase in accidents, being based on our analysis of workplace accidents involving injuries reported to OSHA, represent only a fraction of the total number of workplace injuries. This under-reporting of workplace injuries arises from variation in state-level and regional practices in reporting these mishaps, as well as OSHA regulations themselves that may only require reporting of accidents that involve several workers.

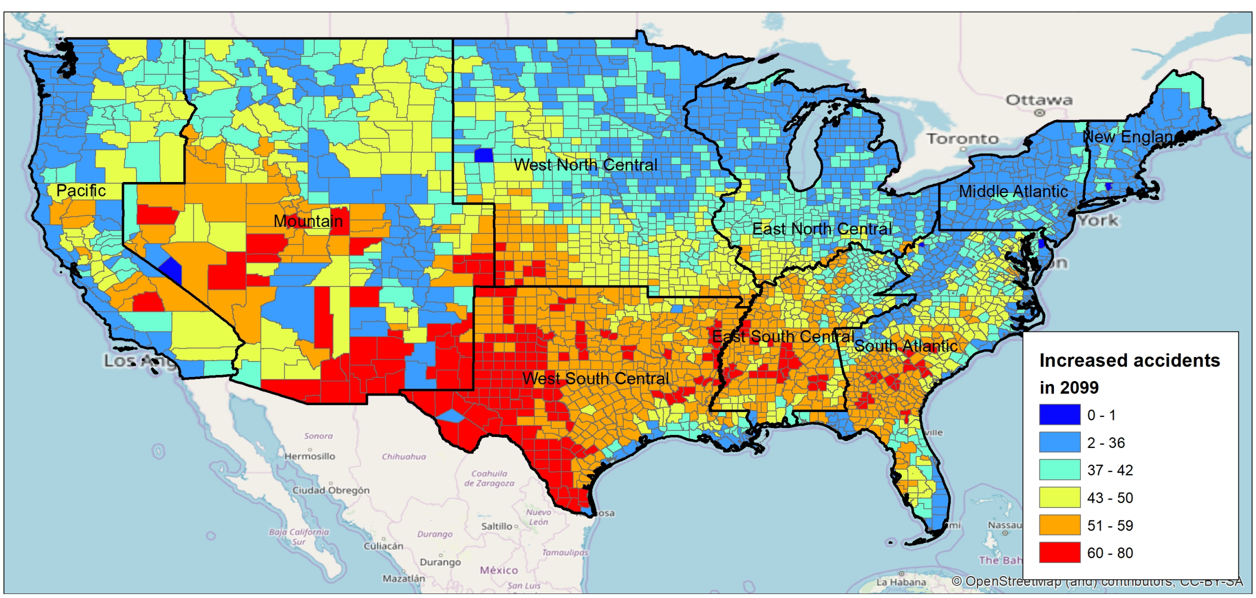
Obtaining an estimate of the extent of under-reporting in each county is probably impossible, but we can obtain an idea by comparing the number of fatalities resulting from workplace accidents reported to OSHA and the more complete data on fatalities generated by workplace injuries collected by the Bureau of Labor Statistics and the Census of Fatal Occupational Injuries. These

Table A5: Predicted increase in accidents in 2099

Region	Increased Accidents	Scaled Accidents	Private Employment	Increase per Employment	Cost
New England	686	2,071	5,707,723	363	$56,096,163
North Atlantic	1,667	5,029	14,820,070	339	$136,234,310
East North Central	5,325	16,068	17,057,635	942	$435,283,384
West North Central	8,306	25,065	8,028,194	3,122	$678,991,367
South Atlantic	8,409	25,374	20,225,760	1,255	$687,388,104
East South Central	5,895	17,789	5,954,958	2,987	$481,904,829
West South Central	8,607	25,971	11,909,701	2,181	$703,550,114
Mountain	4,166	12,570	7,645,967	1,644	$340,510,465
Pacific	1,518	4,581	16,173,030	283	$124,106,151
Total	44,579	134,518	107,523,038	1,251	$3,644,064,890

data indicate that from 2003 to 2010 there were 42,577 fatalities due to workplace injury in our 49 sample geographies. During the same period, our OSHA data record 14,110 fatalities resulting from reported injuries. Using this ratio as a conservative estimate of the fraction of total workplace injuries that are reported in our data suggests that the true number of workplace injuries is larger than our reported number by a factor of approximately 3.018. The third column labeled 'Scaled Accidents' reports the difference in accidents in the two RCP scenarios, scaled by this factor. Figure 3 presents a map of the US with counties colored according to this scaled estimated increase in workplace injuries.

Figure 3: Predicted increase in accidents in US Counties, 2099



Note: Derived from difference between median temperature at county level under IPCC RCP 8.5 (baseline) and RCP 2.6 (aggressive abatement), scaled to account for OSHA under-reporting.

It should be noted that the map presented in Figure 3 reveals a very different pattern than mapping the predicted increase in temperature. The largest absolute increases in temperature are generally predicted to be in the northern portions of the Mountain and West North Central districts. Much of this increase, however, still leaves the local area with relatively moderate temperatures where the risk of workplace accident is not highly elevated. The estimated increase in workplace accidents illustrated in the map takes into account the non-linear relationship between temperature range and accident risk, plus the number of local workers who are exposed to this risk.

As indicated in column four of Table A5, the total employment varies considerably across regions (and implicitly across counties). Column five of Table A5 shows the estimated increase in workplace accidents per million private sector workers. As shown, this varies from low levels of increased risk in New England, the North Atlantic and Pacific regions to high increased risk in the East South Central, and West North Central regions.

Finally, to provide an estimate of the burden that this increase in workplace accidents might place on the US economy, we use the estimated costs of workplace accidents provide in Leigh (2011). Updating those estimates to 2019 prices and applying the cost to the scaled estimated accidents produces the figures presented in the final column of Table A5. The total cost to the US economy is estimated to be over \$3.6 billion per year in 2099.