Climate Change and Workplace injury

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November 13, 2024

Abstract

We explore the impact of temperature on workplace injuries and its welfare consequences using Japanese workplace injury claims data from 2007-2019. We find both higher and lower temperatures significantly increase workplace injuries, and this effect is more pronounced in outdoor environments. Workers also do not make defensive investments in temperature extremes, such as reducing labor hours. We also find no significant association between wages and temperature at the national level, suggesting that the potential welfare implications of extreme temperatures may have been overlooked.

Keywords:extreme temperatures, defensive investment, workplace injuries, climate change adaptation, compensatory wage differentials.

JEL Codes: J28, J31

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1 Introduction

Global warming is poised to significantly alter the climate environment within a relatively short period (Houghton [2009]; Nordhaus and Boyer [2003]). Despite the high priority placed on reducing greenhouse gas emissions, there is limited knowledge about how societies are adapting to climate change. This gap creates challenges in reliably estimating the costs associated with climate change and developing effective solutions to mitigate its risks. According to Costello et al. [2009], identifying adaptation opportunities that can reduce the human health costs of climate change is a global research priority for the 21st century (Campbell-Lendrum et al. [2009]).

In addition to health effects, extreme temperatures lead to a range of other negative impacts, including reducing worker productivity (Zhang et al. [2018]; Burke et al. [2015]; Carleton and Hsiang [2016]), making learning difficult for children (Graff Zivin and Neidell [2014]), and increasing overall mortality rates (Botzen et al. [2019]; Karlsson and Ziebarth [2018]). A growing body of research[1] is now focusing on the potential impact of extreme weather on workplace safety (Varghese et al. [2018]). According to the Japan Meteorological Agency (JMA), the average annual temperature anomaly for Japan in 2022 was $+0.60°C$, the fourth highest since records began in 1898. Japan's average annual temperature has risen by 1.30°C per century, with extreme high temperatures becoming more frequent over the 1901-2022 period. Therefore, measuring the impacts of climate extremes on health, human capital, and welfare is increasingly important(Schlenker and Roberts [2009]; Hsiang et al. [2013]).

In this paper, we provide the most comprehensive assessment to data of the impact of temperature on workplace health and safety, expanding estimates of temperature-induced welfare consequences. There are three things to be considered. First, we compile and analyze a new dataset of work-induced fatalities and injuries resulting in more than four days of leave

[1] Dillender [2021] used data from the U.S. state of Texas to provide the first systematic assessment of the relationship between temperature and workplace injuries.

in Japan's prefecture from 2014 to 2019. Combined with daily weather data aggregated to the monthly level, this dataset allows for an updated and nuanced estimation of the temperature-injury relationship. Second, considering the potential endogenous effect of temperature on labor supply, we empirically estimate the temperature fluctuation-employment relationship using monthly data on the labor force population and regional average labor hours in Japan. Finally, we estimate the effect of temperature fluctuations on wages using monthly prefectural data on average wages in Japan. Utilizing the compensating wage differentials framework, the wage response function to extreme temperatures enables us to calculate workers' willingness to pay in response to temperature shocks. We also link the injury rate and the willingness-to-pay valuation of economic loss estimates to determine the magnitude of external costs associated with temperature shocks.

We find two main findings. First, we find that the occurrence of days with extreme temperatures has a positive impact on workplace injuries. Specifically, a hot day with temperatures between 30-35$°C$ leads to an increase of approximately 0.7 injuries per day during the month compared to a day with temperatures between 20-25$°C$. Furthermore, a day with temperatures above 35$°C$ results in an increase of 3.1 injuries per day. Our causality identification relies on the premise that idiosyncratic changes in daily temperatures within a given panel of months by prefectural are plausibly exogenous, ensuring that the observed impact on workplace injuries is not driven by underlying endogenous changes in the labor force.

To elucidate our empirical strategy, we describe a simple temperature-workplace injury model. Our model suggests that the effect of temperature on the risk of workplace injuries will be underestimated if workers' defensive investments (e.g., proactively reducing exposure time to extreme temperatures) are not considered. Based on this premise, we further estimate the effect of temperature on labor force participation and labor hours. We find that while extreme temperatures seem to reduce hours to work, this effect nearly disappears when controlling for year-month fixed effects and area fixed effects, and further controlling for time-area interaction fixed effects. The likely explanation is the presence of region-specific seasonal variations in labor time that are not captured when only controlling for time and region.

We also find that the risk of workplace injuries is more sensitive to extreme temperature exposure for outdoor workers than for indoor workers. For instance, in manufacturing, a one-day increase in the number of days with temperatures above $35°C$ leads to a 0.9 unit increase in workplace injuries, while in transportation, this effect increases to about 1.67 times[2]. We hypothesize that outdoor jobs or jobs with higher underlying safety risks (e.g., working at heights, over-the-road truck drivers) exhibit higher sensitivity to temperature extremes. Conversely, in industries such as education and services, where exposure to extreme temperatures is less likely, neither high nor low temperatures have a significant effect on the risk of injury.

Our second finding centers around workers' willingness to pay for ambient temperatures. We find that high temperatures are generally associated with lower wages on a national scale, with an increase in the number of days above $35°C$ leading to a 0.05% wage loss. However, after further controlling for data from regions with high output in industries with significant exposure to temperature extremes, such as industrial manufacturing, high temperatures exhibit a positive impact on wages. Specifically, in regions with high manufacturing output, a $35°C$ day can increase average regional wages by 0.007%, and days with temperatures between 30-$35°C$ are associated with a 0.19% increase in wages. Under the compensating differentials hypothesis, the wage response function to temperature provides an indication of workers' utility evaluations of extreme temperatures. This enables us to assess the welfare consequences of extreme temperatures, revealing that workers' willingness to pay, as reflected in wage adjustments, is higher than the cost of air conditioning investments.

This paper contributes to a variety of literatures. First, we extend the literature on the

[2]In our conceptual model, the effects of extreme temperatures on work safety can be conveyed through direct physiological thermal injuries, as well as impairments to attention and performance (Graff Zivin et al. [2018]; Heyes and Saberian [2019])

use of micro-variables to estimate marginal losses from climate change. Previous studies have estimated the causal effects of temperature on health (Watts et al. [2018]; Hsiang et al. [2017]; Dell et al. [2014]), labor supply (Finger and Lehmann [2012]; Graff Zivin and Neidell [2014]), learning and cognitive performance (Graff Zivin et al. [2018]). With the exception of Dillender [2021] and Park et al. [2021], we provide the first assessment of the potential impact of temperature on workplace safety and, in particular, extend the external validity of our findings by using nationwide weather data for the first time[3].

Secondly, we also add to the literature on income loss due to high temperatures. Previous work has focused on the assessment of the relationship between high temperatures and income (Deryugina and Hsiang [2014]; Garg et al. [2020]), and between high temperatures and output (Dell et al. [2009]), both internationally and within countries (Cattaneo and Peri [2016]; Heal and Park [2013]). Our contribution is to measure workers' willingness to pay for comfortable temperature environments based on a wage response function to temperature, with the inclusion of industry information. Our conclusions[4] are consistent with Lavetti [2020].

The remainder of the paper is organized as follows. Section 2 introduces the conceptual framework in which we review the physiological relationships that link temperature to health and the mechanisms that link the moderators of the temperature-work injury relationship. Section 3 describes the data sources and reports summary statistics. Section 4 describes the econometric models used to study the temperature-injury headcount relationship and the results of fitting these models. Section 5 reports the results of empirical measures of the temperature-wage relationship. Section 6 presents conclusions.

[3]Park et al. [2021] used administrative data on workplace injuries from the California Department of Workers' Compensation (DWC) to validate the temperature-injury relationship and found that lower-income workers may be more impacted. However, whether this conclusion holds on a larger scale remains unexplored by existing studies, including those by Dillender [2021] and Park et al. [2021].

[4]However, inconsistent with Kim and Lim [2017], who used data from the Korean Working Conditions Survey, the empirical results suggest higher wages for the no heat exposure risk group. But the compensating differentials hypothesis is tested in most of the existing empirical literature (Gertler et al. [2005]; Lavetti and Schmutte [2016]).

2 Conceptual Framework

2.1 The Temperature-Workplace Injuries Relationship

In extreme temperature environments, the human body thermoregulates through neural, endocrine, and physiological mechanisms to maintain its temperature within an acceptable range. This thermoregulatory process primarily involves sweat gland secretion, skin vasodilation, respiratory regulation, neuromodulation, and other mechanisms (Tansey and Johnson [2015]; Romanovsky [2018]). For example, at high temperatures, skin vasculature dilates, increasing the surface area over which heat is dissipated, thus facilitating the loss of body heat. The nervous system monitors changes in body temperature and regulates physiological functions such as sweat gland secretion and vasoconstriction through neurotransmitter signals (González-Alonso [2012]). However, exposure to temperatures outside the normal range or prolonged exposure to extreme temperatures can jeopardize human health (Patz et al. [2005]; Lim et al. [2008]).

The direct link between temperature and human health is well documented. For instance, prolonged exposure to extreme environments can induce cardiovascular risks such as ischemic heart disease through changes in blood pressure and heart rate (Huynen et al. [2001]; Basu and Ostro [2008]). There is also an association between high temperatures and respiratory and chronic diseases (Basu [2009]; Kovats and Hajat [2008]). Recently, growing evidence indicates that high temperatures significantly affect overall mortality (Gosling et al. [2009]; Deschênes and Greenstone [2011]).

Hot environments also negatively affect human performance in work and sports (González-Alonso et al. [1999]; Graff Zivin et al. [2018]). For example, there is evidence that elevated temperatures can impair cognitive abilities (Pilcher et al. [2002]; Hancock and Vasmatzidis [2003]) and negatively impact both the process and outcome of decision-making (Cheema and Patrick [2012]; Heyes and Saberian [2019]). In summary, extreme temperature environments can affect work efficiency and safety on both physiological and cognitive levels.

2.2 Conceptual Framework

We develop a conceptual model to explain our ideas and guide the empirical analysis. It is assumed that a worker's risk of injury at work $I(t, a)$, depends on the exposure time to temperature extremes t, and defensive behavior a. Defensive behaviors can be taken either before or after exposure to heat (including avoidance and mitigation activities). Referring to Park et al. [2021] and Deschenes et al. [2017]'s model, the relationship between injury risk and temperature can be expressed as:

$$\frac{dI}{dt} = \frac{\partial I}{\partial t} + (\frac{\partial I}{\partial a}\frac{\partial a}{\partial t}) \tag{1}$$

. Assume that defensive behavior reduces the risk of injury and that workers' willingness to behave defensively increases as the number of days with extreme temperatures rises. This equation shows that the relationship between the partial derivative of injury and exposure to extreme temperatures is equal to the total derivative plus the product of the partial derivative of injury risk on defensive behavior and the partial derivative of defensive behavior on temperature. In contrast, most of the existing research (e.g., Bui et al. [2024]) has focused only on $\frac{dI}{dt}$ which means the effect of ambient temperature on the total outcome variable, rather than $\frac{\partial I}{\partial t}$. As Eq 1 shows, the total derivative is an underestimate of the required partial derivative. In this case, focusing only on the full derivative would significantly underestimate the effect of ambient temperature on the risk of workplace injury.

In Eq 1, the optimal defensive behavior a^* is given by the maximization condition of the worker's utility function $\max_{x,l,a} U(x, l, I)$. People's utility can be determined by a good x normalized to price 1, leisure l, and the risk of injury I. The utility[5] is determined by a budget constraint: $w(T - l - f(I)) \geq x + pa$, where w is the wage per unit of time, $f(I)$

[5] In this conceptual framework, we have assumed that changes in defense investment affect only leisure l and the risk of injury. Whereas, according to the idea of compensating wage differentials (Rosen [1986]), employers tend to compensate workers for worse working conditions (Lavetti [2023]), which makes $I(.)$ may in fact be related to wages. It can make the model extraordinarily complex, and to deal with this potential effect, we discuss it in the following section.

is the amount of time off from work due to an injury, and the defensive behavior at price p. In practice, however, the choice of defensive behavior against extreme temperatures is more sparse. Intuitively, we can assume that workers can reduce exposure time to mitigate negative effects (although workers may not be free to choose the appropriate labor hours). And, if a job is exposed to extreme temperatures for too long and the effects $\frac{\partial U}{\partial I}$ exceed a certain threshold, the worker may choose to quit or sacrifice wages for a better working environment (less exposure). This informs our later empirical design.

3 Data and Summary Statistics

Work-related Accidents.——This paper uses workplace injuries data (roudousaigai hassei zyoukyou) in Japan from 2014 to 2019. According to Industrial Accident Compensation Insurance Act, employers are required to report workers' injuries at work to the Ministry of Health, Labor and Welfare. This requirement enables us to provide a more comprehensive and reliable description of workplace safety risks compared to many publicly available datasets. To verify the reliability of the results over a longer time frame, this paper also uses data on work-related fatalities from 2007 to 2019. The fatalities data is published monthly, with some months containing missing values. The fatality dataset may have more noise than the injury data. Furthermore, due to significant fluctuations in the number of work-related injuries in certain prefectures caused by the Great East Japan Earthquake in 2011, data from the affected period have been excluded from the empirical analysis.

Weather.——We compiled daily maximum temperature and average precipitation data reported by the Japan Meteorological Agency. Given the varying numbers and locations of observation stations within each prefecture, we simplified our approach by using the average of the data reported by all observation stations within each prefectures. Using postal codes and dates, we merged the corresponding provincial work injury data with the meteorological data. Since the work injury data is on a monthly level, we calculated the number of days within each temperature range based on the daily maximum temperature data for each month. Considering the nonlinear effects of temperature, we divided the daily temperatures into 5-degree intervals, resulting in eight temperature ranges from below 0 degrees to above 35 degrees.

Employment, Wages, Hours.——The primary concern to identification stems from potential endogenous shifts of workers across industries or prefectures, as it is impractical to entirely discount the potential impact of temperature on working hours. To mitigate the influence of other potential variables affecting workplace injuries, we construct a dataset using monthly labor force data at the provincial level in Japan from monthly wage reports spanning from 2007 to 2019. This data includes information on hours worked per week, overtime hours, wages, and days of attendance per week. In this study, we integrate both of these datasets to assess the impact of temperature on workplace injuries.

Summary Statistics.——Table 1 presents the mean, standard deviation, and provincial representation of the main variables in our analysis. The distribution of days with maximum daily temperatures between 20 and 25 degrees Celsius is the highest across all time periods, with relatively fewer days below 0 degrees and above 35 degrees Celsius, which can be considered as extremes. Figure 1 illustrates the distribution of days across all temperature bands. Additionally, the table provides information on workplace injuries by industry, according to the standards of the Ministry of Health, Labor and Welfare of Japan. As per government reports, the table includes details on manufacturing, construction, and transportation industries, which account for the highest number of deaths and injuries.

4 Temperature and Injuries

4.1 Econometric Model

The following empirical model reports the estimated results of the temperature response function. The model is identified by presumed random temporal variation in weather distributions at the provincial-level. Specifically, we estimate models of the form:

$$Y_{imt} = \sum_j \beta_j \cdot Temp_{imtj} + \gamma \cdot X_{imt} + \delta_{mt} + \theta_{im} + u_{imt} \tag{2}$$

where Y_{imt} denotes the number of injuries in prefecture i, month m, and year t. The model also includes a full set of prefecture-month fixed effects (θ_{im}) and year-month fixed effects (δ_{mt}). prefecture-month fixed effects are used to absorb seasonal differences in the number of injuries, adjusting for permanent unobserved determinants of injury rates across prefectures and months. This accounts for fixed differences in seasonal employment between regions, such as regional variations in agricultural harvest seasons. Year-month fixed effects control for macro-level economic shocks and macroeconomic trends.

The primary variables of interest are the binned daily average temperature variables $Temp_{imtj}$ realized within each county-month-year, corresponding to the number of days with daily average temperatures falling within one of the nine bins, ranging from below 0 Celsius to above 30 Celsius in 5 Celsius increments. According to this specification, one bin serves as the reference temperature, capturing the additional temperature effect within bin j compared to the reference temperature. In this paper, the reference temperature is defined as the interval with the highest number of days, ranging from 20 to 25 degrees Celsius. The actual temperature distribution for each county-month pair naturally varies across years and is considered an exogenous variable, forming the basis for determining the temperature-response function parameters (β_j). X controls for potential influences on the outcome variable, including precipitation and other regional labor-related variables like labor force participation and working time.

4.2 Results

The main results of Equation 2 are presented in Table 2. The table reports the regression coefficients associated with daily temperature intervals, where the 20-25$°C$ range is the reference (omitted) category. That is, each coefficient measures the estimated impact on the number of workplace injuries in the area of an additional day in the temperature range j relative to the impact of an additional day in the 20-25°C range.

As shown in column 3, a day with a maximum daily temperature between 30 and 35°C leads to an increase in the count of injuries of 0.629 units (standard error = 0.301), controlling for year-month fixed effects and prefecture-month fixed effects in the specification. And a day when the temperature rises beyond 35°C can lead to an average increase in the number of injuries of 3.6, an effect that is statistically significant at the 5% level. Continuing to control for monthly regional employment and labor hour data on this specification does not substantially change the significance of these effects.

Figure 2 plots the estimated coefficients and their 95% confidence intervals for other temperature intervals not shown in Table 2. The chart shows that the risk of workplace injuries is highest at temperature extremes, especially in the temperature range above 35°C. By contrast, cold temperatures also lead to excess fatalities: replacing a day in the 20-25 degree range with a day below 0 degrees increases the number of workplace injuries by 2.4 and is also estimated to be statistically significant at the 5% level. We find that this U-shaped relationship of temperature on workplace injuries is surprisingly consistent with previous findings on temperature and mortality studies (Deschenes [2014]; Barreca et al. [2016]). Also this paper is consistent with the findings of Dillender [2019], who pioneered the discovery of the impact of extreme temperatures on workplace injuries.

To verify the robustness of the results in the previous section, we re-estimated the independent variables in Model 2 using the daily minimum temperature instead. We recounted the distribution of daily minimum temperatures and found that they are significantly different from the daily maximum temperatures, as shown in Figure 2. In this case, the number of days above 25°C is almost zero due to the minimum temperature, and similarly the number of days less than 0°C has expanded accordingly. Differently from the estimates in the previous section, we here use 10-15 degrees as the reference (omitted) category for the model.

Table 3 reports the new estimation results for Model 2 using daily minimum temperature as the independent variable. As shown in columns 1-4 of Table 3, the number of days in the extreme temperature range continues to have a significant effect on the number of injuries in the area after changing the independent variable. As shown in column 3, a day with a daily minimum temperature above 25°C increases the number of injuries by 2.038 units (standard error = 0.519) relative to the effect of an additional day in the 10-15°C range, an effect that is statistically significant at the 5% level. Similarly, the days below -5°C variable causes a higher number of injuries. In similar to the results in the previous section, the estimation results (number of days with minimum daily temperature and number of work injuries) continue to exhibit a significant U-shaped relationship even after fixing the specification with year-month fixed effects and prefecture-month fixed effects.

4.3 Work-related Fatalities

In the conceptual model, we assumed that the risk function for workplace injuries is expressed as $I(t, a)$, and it remains to be seen whether the risk of workplace injuries will translate further into more serious consequences when the exposure time t is sufficiently large. In this section, we replace the work place injuries with the risk of a fatality occurring in the dependent variable, and all other specifications refer to Model 2. Unlike the counts of injuries, data on fatalities are available in a longer time dimension. Data on the deaths are reported in Table 1, where we can see that unlike the counts of injuries, the deaths contain a large number of zero values. To cope with this, we have used the logarithmic form of the count of deaths for our estimates ($log(deaths + 0.01)$).

Table 4 reports the effect of temperature on fatality risk. The estimates are based on monthly work-related deaths in each region of Japan from 2007 through 2019. As shown in column 3, a day with a daily maximum temperature between 30 and 35°C increases the number of fatalities by 0.038 units (standard error = 0.015). The estimated effect of temperature on the risk of death is significantly smaller compared to the number of injuries.

And, in the temperature range above $35°C$, while exposure time still had a positive effect on fatality risk, it became statistically insignificant at the 5% level. We suggest that this may stem from the fact that the raw data on fatalities contain a large number of missing values, which, combined with the small number of days with extreme temperatures above 35 degrees, may make estimation difficult.

4.4 Defensive Investments

As we discussed in Chapter 2, the estimates from Model 2 respond to what may be the total derivative of temperature on injury risk. Focusing only on the total derivative and ignoring defense investment would lead to a false underestimate of the true estimate of temperature on injury. The key to estimation accuracy requires that we estimate the partial derivative of injury risk with respect to defensive behavior and the partial derivative of defensive behavior with respect to high temperatures whenever possible. In this section, we show a possible way to simulate workers' defensive behavior.

It is well known that the best defense against extreme temperatures is to reduce exposure time. This defensive investment comes with a cost, meaning the wage value of shorter labor hours. So a simple idea is to observe whether extreme temperatures have an endogenous effect on the labor supply of workers. Here, we use the same fixed-effects model as in equation 2, taking the average monthly hours worked in the region and the number of people employed in the region as the explained variable (assuming that laborers exposed to extreme temperatures are free to leave their jobs as they choose). Tables 5 and 6 present the results of the estimation of the response function of the number of days of extreme temperatures to endogenous changes in the labor force.

The results in Table 5 are not consistent with our hypothesis. The results from columns 1-4 show that the number of days in any temperature interval does not significantly affect the employed population. A day in an extreme weather interval, such as below 0 degrees, and a day in the 30 to 35 degree interval reduces the employed population but is not statistically significant at the 5% level. This may imply that the utility of extreme weather is not sufficient to keep workers out of the labor market.

To further verify whether workers would choose less costly defensive investments, such as reducing working hours rather than withdrawing from the labor market to hedge against potential injury risks. Table 6 reports the effect of extreme weather on the average monthly hours worked in the region. After controlling for provincial and year-month fixed effects, the results in columns 1 and 2 indicate that both days above 35 $°C$ and days below the 5$°C$ range interval have a negative impact on labor hours, and in particular the estimates of the variable for days with low temperatures of 0 to 5$°C$ are statistically significant at the 5 percent level. This situation is generally consistent with our hypothesis of defensive investment. After further controlling for regional month fixed effects, the effect of days in extreme temperature ranges on hours worked becomes less significant. The possible explanation is that certain regions may have specific seasonal industries, such as the planting and harvesting seasons in agriculture, and both of these activities have a significant effect on labor hours, but may not have been captured separately under the specifications in Columns 1 and 2. This result is similar to Graff Zivin and Neidell [2014], which analyzed temperature and the distribution of labor hours in the U.S. and found that while temperature does not have a significant effect on overall employment, workers in industries that are more affected by temperature reduce their labor supply when it is hot.

While the results in Columns 3 and 4 show no significant link between extreme weather and hours to work, it is still not possible to rule out the estimated impact of defensive investments. Consider that firms may have provided better defenses that allowed workers to continue working in extreme weather or even work longer hours. For example, providing air conditioning units in high temperatures or heating units in low temperatures allows workers to work efficiently despite extreme weather[6]. Under this assumption, there is still a

[6] Unlike data on the consumption of domestic air conditioners in the household sector, data on specialized air conditioners or other defensive investments used in companies or factories are almost impossible to obtain. Another possible solution is to use electricity costs as a proxy for electricity consumption (Deschenes [2022]), since air conditioning or other defense-oriented equipment increases power consumption, but this approach

high probability that our estimates of the impact of temperature on workplace injuries are underestimated.

4.5 Heterogeneity Across Occupations

All of the above estimates are based on the setup that all occupations are subject to the same risk function and defense investments. In reality, however, this is not the case in many situations. For example, outdoor occupations clearly have longer exposure times than indoor workers, and the group of outdoor workers should be more sensitive to temperature extremes. And as we discussed in Section 2, high temperatures can affect human physiological health and decision-making behavior. So in industries that require high levels of concentration and are more prone to workplace injuries, the impact of high temperatures should be higher by hypothesis. In this section, we have followed the Japanese Ministry of Health, Labor and Welfare's criteria for classifying occupations (work-related injuries) to examine the heterogeneity of the temperature response function for each occupation.

Following the specification in column 4 of Table 2 (controlling for month-prefecture and month-year fixed effects), the results of the effect of temperature on the risk of workplace injuries across occupations are presented in Figure 3.We can visualize that, regardless of the industry, as in Figure 2, the U-shaped effect of temperature persists, with extremes of temperature (at the ends of the horizontal coordinates) tending to have a positive effect on workplace injuries. Comparing the broad categories of indoor and outdoor, according to Figures a (Manufacturing), b (Transportation), and c (Construction), we can see that high temperatures have a much more significant impact on the risk of workplace injuries in outdoor industries. For example, in the transportation industry, a day with temperatures above $35°C$ can 1.37 units of workplace accidents (standard error = 0.328), which is statistically significant at the 5% level. In indoor industries, such as Figure d (commerce), e (education), and f (services), we find little significant relationship between temperatures and workplace

also has limitations. Due to the fact that, unlike the cost of electricity used in the home, the cost of electricity in factories is often also closely related to the capacity of the factory and the demand for orders.

injuries. In the merchant industry, a day with temperatures higher than $35°C$ raises the number of workplace injuries occurring by only 0.35 units, a value that is about 64% lower than the estimate for the outdoor industry.

A possible explanation for this is that indoor environments such as stores and hotels have more defensive investments (e.g., air conditioning) than factories, so that high temperatures may have much less of an impact on indoor work than on outdoor work. Moreover, due to the differences in job content, as opposed to the relative safety of indoor work, operating machinery in factories and driving trucks for transportation clearly demand more attention from workers. Thus the potential effect of high temperatures on attention and decision-making behavior is illustrated based on the results of the heterogeneity test.

5 Extreme Temperatures and Wages

5.1 Compensating Wage Differentials

One of the classic views in labor economics posits that in order to compensate for the non-monetary costs of a particular job (e.g., occupational hazards, poor working conditions, etc.) in the labor market, employers will offer additional wages to workers on their own initiative. This makes it possible to find willing workers even for jobs in bad conditions, while compensatory wage differentials reflect workers' evaluations of and preferences for working conditions.

In the previous discussions, we have shown that extreme temperatures significantly increase the risk of workplace injuries. This means that longer exposure to temperature extremes means worse working conditions (higher risk of workplace injuries). According to the idea of compensating wage differentials, workers' evaluation of the risk of workplace injuries can be reflected in differences in wages. In the labor market equilibrium setting, we argue that the compensating wage, i.e., the worker's valuation of extreme environments $\frac{\partial w}{\partial temp}$, should be equal to the worker's willingness to pay for a reduction in exposure time t to extreme temperatures. According to the utility model setup for workers in Section 2, the quantity of consumer goods that workers are willing to sacrifice to reduce t (i.e., willingness to pay) is equal to the increase in utility that they would receive to reduce t, divided by the marginal utility of the consumer good:

$$WTP = \frac{dU}{dt} / \frac{\partial U}{\partial x} \tag{3}$$

. The total change in the utility function with respect to exposure time t can be split into two parts the marginal effect of injury risk on utility multiplied by the marginal effect of exposure time on injury risk ($\frac{dU}{dt} = \frac{\partial U}{\partial I} * \frac{\partial I}{\partial t}$). And according to the first order condition for effect maximization, the marginal utility of the consumer good is $\frac{\partial U}{\partial x} = \lambda$. So the worker's willingness to pay for a reduction in exposure time can be expressed as:

$$\frac{\partial w}{\partial temp} = \frac{\frac{\partial U}{\partial I} \cdot \frac{\partial I}{\partial t}}{\lambda} \tag{4}$$

. This represents the amount of consumption that a worker is willing to sacrifice to reduce exposure per unit of time. This expression reflects the worker's preference for reducing the risk of injury and the extent to which exposure time affects the risk of injury. It is worth noting here that defensive behaviors a can also affect injury risk, and workers may make trade-offs between defensive behaviors and reduced exposure time. Situations such as voluntarily reducing hours to work[7], withdrawing from the labor market, changing jobs, etc. can be categorized under particular defensive strategies. In practice, workers may be constrained by work regimes that prevent them from freely adjusting their working hours, which can affect the realization of willingness to pay.

[7] If the worker chooses to voluntarily reduce his hours of work as his defense strategy, then the injury function $I(.)$ depends only on the exposure time t and the model will be greatly simplified.

5.2 Results

Table 7 reports the estimates of the response function of wages to changes in the days of extreme temperatures. Except for the first column, which controls only for prefecture and year-month fixed effects, the estimates under all the other specifications show that there is no significant link between wages and temperatures across regions at the national level. This may be due to the existence of region-specific seasonal differences in major industries that lead to differences in wages, rather than the effect of temperature.

After further controlling for prefecture-month fixed effects, the labor force population size of the region, and the control variables for average hours worked, each additional day of low temperatures above 30 degrees is instead associated with a wage loss of about 0.02%. This anomaly is broadly similar to the results verified in previous studies[8] (Dell et al. [2009]; Deryugina and Hsiang [2014]).

While the analysis above controls for prefecture-month interaction fixed effects, the data do not include information on industry. This means that there exists a heterogeneous effect of temperature on two regions with completely different industrial structures.The results in Section 4.5 suggest that temperature has a greater effect on workers who work outdoors, so it is natural to wonder whether this phenomenon would likewise hold for wages. Based on this hypothesis, we utilize manufacturing production data from the Japan Industrial Statistics Survey and screen out the 10 regions with the highest share of manufacturing as the experimental group and the rest as the control group to observe the response of wages to temperature across regions[9].

Table 8 shows the results of the subgroup regressions. Columns 1 and 2 are the low-

[8]Hübler et al. [2008] argues that high temperatures reduce labor productivity, which results in loss of wages for workers. However, in this paper, no direct evidence of a link between high temperatures and working hours was found.

[9]Selecting out regions with a high share of manufacturing may introduce additional omitted variable concerns, such as the fact that regions with high manufacturing tend to have higher infrastructure investment as well. The use of prefecture and month interaction fixed effects here allows for more precise control for those specific factors that vary over time within prefectures and can reduce this endogenous concern to some extent.

exposure risk group, i.e., the 38 regions with low manufacturing output. Columns 3 and 4 are the 10 districts with the highest manufacturing output value among all districts in Japan, which serve as the experimental group with high exposure to extreme temperatures. It is clear from Table 8 that there is a significant difference in the estimates between the two groups, with the regions with fewer outdoor jobs showing similar findings to those in Table 7 (i.e., extreme temperatures, especially high temperatures, are negatively correlated with wages). In contrast, the estimates of the response of wages to temperature in regions with the highest share of manufacturing are consistent with our hypothesis. We find that the number of days in extreme temperature intervals has a positive effect on wages in columns 3 and 4. And this effect remains significant at the 5% level even after controlling for prefecture-month fixed effects and control variables for precipitation. In the experimental group, an extra day in the 30 to 35 interval leads to a 0.19% increase in average wages. This implies that, unlike in low-exposure regions, extreme temperatures in regions with a large share of the outdoor industry seem to imply additional compensatory wages for employers[10].

5.3 Welfare Impacts

The measurements of the response function of workplace injuries to temperature in this paper allow us to estimate the welfare effects of policies to improve the working environment (e.g., subsidizing defensive investments in the outdoor work industry). According to the Ministry of Health, Labor and Welfare, 130,000 workplace injuries (resulting in more than four days of rest) occur annually across Japan, with an average of about 41 days of rest per injured worker. The benefit amount of the industrial accident compensation insurance is 80% of the monthly wage, so if we calculate based on the wage data in 2023 (310,000 yen/month)[11], a case of workplace injury will require $(41/30) * 310,000 * 80\%$ of the compensatory wage. According to the estimate in Table 2, reducing the number of days with temperatures above

[10] Similar to our findings, Lavetti [2020] uses data from the fishing industry and similarly verifies that wages are higher during periods of higher mortality risk.

[11] This data is derived from the average monthly wages in Basic Survey on Wage Structure provided by the Ministry of Health, Labor and Welfare of Japan.

$35°C$ for one day could reduce the occurrence of workplace injuries by an average of 3 cases per month per region. If this estimate is applied, measures to improve the work environment could reduce the incidence of workplace injuries by approximately $3*12*47$ cases. Converted into a payout, this equals a value of $1692 * 339,800$ in Japanese currency. This estimation process does not include other extreme temperature intervals, so the true welfare effect of measures to improve the work environment should be higher.

Similarly, we can use the compensating wage differential to represent workers' evaluations of the risk of injury. According to the estimates in Column 4 of Table 8, a one-day increase in the days in the 30-35$°C$ range leads to a simultaneous 0.19 percent increase in the average regional wage. The wage increase here can be characterized as a market valuation of heat risk. Based on the regional average population data of 1 million workers, then the welfare effect of increased defensive investment can be characterized as the value of $0.19\% * 310,000 * 12 * 1$ million yen. This valuation needs to be viewed with caution as the welfare effect in terms of wages may not be applicable in all regions of the country.

Given that no data on industrial air conditioners were obtained for this paper, it is not possible here to calculate the demand for investment in air conditioners to respond to high temperatures. Using only the data provided by the Japan Refrigeration and Air Conditioning Industry Association (JRAIA), there are approximately 750,000 industrial air conditioners sold in Japan each year, and it is assumed that 15% of these sales are actual demand to meet extreme temperatures. At a cost of about 200,000 yen per unit, the annual investment in air conditioners across Japan would be $15\% * 750,000 * 200,000$ yen-denominated costs. We can find that the welfare effect of the wage differential calculation is much larger than the increased defensive investment cost, but the payout for workplace injuries does not seem to be sufficient to support the investment cost. Here, however, is the underlying assumption that air-conditioning investments are effective in reducing the number of workplace injuries caused by extreme temperatures[12]. And the welfare returns on air conditioning investments

[12] In most of the literature, the addition of air conditioning has been validated as an effective way to reduce thermal damage(Barreca et al. [2015]; Park et al. [2020]).

are long-term.

6 Concluding Remarks and Discussions

Extreme temperatures can impose significant costs on individuals and societies that may not be directly detectable in everyday life. Understanding the impact of climate change on workplace safety is particularly important, not only because of the large population base of workers whose occupations are exposed to temperature extremes, but also because the frequency of extreme weather is likely to increase in the future (Wang et al. [2017]; Beniston et al. [2007]; Seneviratne et al. [2021]).

Our findings suggest that high temperatures are a significant workplace safety disadvantage, especially for workers in industries with high exposure potential. From a welfare perspective, workplace injuries incur significant direct medical costs and may reduce workers' expected future earnings (Krause et al. [2001]). According to Japan's Ministry of Health, Labor and Welfare, workplace injuries in 2022 have reached a sizeable 764,558 million yen across Japan. The results of this paper also imply that the government should increase the instruments to support this investment in workplace safety in cases where the benefits of defensive investments may outweigh the welfare consequences of extreme temperatures.

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Table 1: Mean Weather and Injuries Variables, 2007–2019

Statistic	N	Mean	St. Dev.	Min	Max
Weather (°C)					
Days above 30	6,862	3.39	7.01	0.00	31.00
Days [25,30]	6,862	5.93	7.23	0.00	30.00
Days [20,25]	6,862	6.04	7.02	0.00	29.00
Days [15,20]	6,862	4.44	5.63	0.00	25.00
Days [10,15]	6,862	4.43	5.96	0.00	29.00
Days [5,10]	6,862	4.04	6.30	0.00	28.00
Days [0,5]	6,862	1.84	4.51	0.00	29.00
Days below 0	6,862	0.35	2.05	0.00	31.00
Precipitation (mm)	6,862	159.55	115.71	0.50	1222.60
Injuries, Deaths					
Injuries-All	3,384	214.88	185.11	27.0	1085.0
Injuries-Transportation	3,381	29.53	32	1.00	186.00
Injuries-Manufacturing	3,384	47.78	36.98	3.00	206.00
Injuries-Construction	3,384	27.63	21.31	2.00	157.00
Deaths-All	6,862	1.79	2.41	0.00	54.00
Deaths-Construction	6,862	0.57	0.98	0.00	10.00
Deaths-Transportation	6,862	0.22	0.54	0.00	5.00
Labor Force					
Employment (1,000)	6,858	949.25	1193.27	167.60	8186.50
Working days (per week)	6,858	19.29	0.91	15.90	21.60
Wage (JPY)	6,858	295885.38	88030.46	203638.00	802422.00
Wage (Excluding bonuses)	6,858	244561.90	20289.01	200747.00	345648.00

Notes: We combined weather data and injury data for a prefectural panel of months from 2014 to 2019. Temperature information is counted as a count of the days in a month within a certain temperature range.

Table 2: Injuries and Temperature - Daily Maximum Temperature

	Dependent variable:			
	Injuries			
	(1)	(2)	(3)	(4)
Days above 35	3.755***	3.968***	3.619***	3.145***
	(0.919)	(0.940)	(1.090)	(0.957)
Days [30,35]	0.531**	0.806***	0.629**	0.701**
	(0.218)	(0.226)	(0.301)	(0.272)
Days [0,5]	1.104***	0.681**	0.138	0.115
	(0.263)	(0.278)	(0.619)	(0.602)
Days below 0	4.301***	3.850***	2.413**	2.449**
	(0.509)	(0.520)	(1.059)	(1.049)
Region FE	Y	Y	N	N
Year × Month FE	Y	Y	Y	Y
Precipitation	N	Y	Y	Y
Month × Region FE	N	N	Y	Y
Employment controls	N	N	N	Y
Time dimension	72	72	72	72
Observations	3,384	3,384	3,384	3,384

Notes: Table 2 presents estimates of the effect of temperature on the count of injury claims in Japan for the years 2014-2019. The core explanatory variable is an indicator of the number of days in a month with a certain range of temperatures. The coefficients can be interpreted as the increase in injury incidence associated with one additional day in the current temperature range, relative to the omitted category. The omitted category is the temperature bin with daily maximum temperatures between 20 and 25°C. In this table, non-significant temperature bands are not shown but are included as controls in all estimates. Heteroskedasticity robust standard errors are clustered by province and year-month and are presented in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 3: Injuries and Temperature - Daily Minimum Temperature

	Dependent variable:			
	Injuries			
	(1)	(2)	(3)	(4)
Days above 25	2.336***	2.297***	2.038***	1.570***
	(0.418)	(0.416)	(0.519)	(0.496)
Days [21,25]	0.966***	0.839***	0.023	0.030
	(0.233)	(0.233)	(0.360)	(0.344)
Days [-5,0]	-0.520**	-0.549**	0.567	0.725
	(0.252)	(0.251)	(0.482)	(0.460)
Days below -5	2.109***	2.085***	2.776***	2.963***
	(0.353)	(0.351)	(0.686)	(0.656)
Region FE	Y	Y	N	N
Year × Month FE	Y	Y	Y	Y
Precipitation	N	Y	Y	Y
Month × Region FE	N	N	Y	Y
Employment controls	N	N	N	Y
Time dimension	72	72	72	72
Observations	3,384	3,384	3,384	3,384

Notes: Table 3 presents estimates of the effect of temperature on the count of injury claims in Japan for the years 2014-2019. Distinguished from Table 2, the omitted category here is the temperature bin with daily minimum temperatures between 10-15°C. In this table, non-significant temperature bands are not shown but are included as controls in all estimates. Heteroskedasticity robust standard errors are clustered by province and year-month and are presented in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 4: Injuries and Temperature - Fatalities

	Dependent variable:			
	log (Deaths + 0.01)			
	(1)	(2)	(3)	(4)
Days above 35	0.0262	0.0325	0.0369	0.0316
	(0.0543)	(0.0542)	(0.0545)	(0.0560)
Days [30,35]	0.0302**	0.0375**	0.0383**	0.0348**
	(0.0152)	(0.0155)	(0.0156)	(0.0160)
Days [25,30]	0.0231**	0.0236**	0.0244**	0.0264**
	(0.0116)	(0.0116)	(0.0116)	(0.0120)
Region FE	Y	Y	Y	Y
Year × Month FE	Y	Y	Y	Y
Precipitation	N	Y	Y	Y
Employment controls	N	N	Y	Y
Time dimension	146	146	146	134
Observations	6,862	6,862	6,862	6,298

Notes: Table 4 presents estimates of the effect of temperature on the count of death claims in Japan for the years 2007-2019. The omitted category is the temperature bin with daily maximum temperatures between 20 and 25°C. In this table, non-significant temperature bands are not shown but are included as controls in all estimates. Column 4 and 5 report the specification of Eq. 2 with the potentially noisy 2011 data removed. Heteroskedasticity robust standard errors are clustered by province and year-month and presented in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 5: Temperature - Employment (x 1000)

	Dependent variable:			
	Employment			
	(1)	(2)	(3)	(4)
Days above 35	2.405	2.392	3.934	3.923
	(2.120)	(2.124)	(3.314)	(3.300)
Days [30,35]	-0.304	-0.322	-0.578	-0.572
	(0.596)	(0.616)	(1.002)	(0.998)
Days [0,5]	0.565	0.593	0.096	0.097
	(0.713)	(0.753)	(1.896)	(1.889)
Days below 0	-0.428	-0.399	-1.095	-1.325
	(1.053)	(1.084)	(2.707)	(2.700)
Region FE	Y	Y	N	N
Year × Month FE	Y	Y	Y	Y
Precipitation	N	Y	Y	Y
Month × Region FE	N	N	Y	Y
Employment controls	N	N	N	Y
Time dimension	72	72	72	72
Observations	3,384	3,384	3,384	3,384

Notes: Table 5 presents estimates of the impact of temperature on the employed population at the provincial level in Japan for 2014-2019. The omitted category is the temperature bin with daily maximum temperatures between 20 and 25°C. In this table, non-significant temperature bands are not shown but are included as controls in all estimates. Heteroskedasticity robust standard errors are clustered by province and year-month and are presented in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 6: Temperature - Hours worked

	Dependent variable:			
	Working hours			
	(1)	(2)	(3)	(4)
Days above 35	-0.019	-0.031	0.071	0.073
	(0.061)	(0.061)	(0.083)	(0.083)
Days [30,35]	0.013	-0.003	0.038	0.038
	(0.017)	(0.018)	(0.025)	(0.025)
Days [0,5]	-0.062***	-0.038*	-0.008	-0.008
	(0.016)	(0.021)	(0.047)	(0.047)
Days below 0	-0.041	-0.017	0.082	0.082
	(0.031)	(0.031)	(0.067)	(0.067)
Region FE	Y	Y	N	N
Year × Month FE	Y	Y	Y	Y
Precipitation	N	Y	Y	Y
Month × Region FE	N	N	Y	Y
Employment controls	N	N	N	Y
Time dimension	72	72	72	72
Observations	3,384	3,384	3,384	3,384

Notes: Table 6 presents estimates of the impact of temperature on the working hours at the provincial level in Japan for 2014-2019. The omitted category is the temperature bin with daily maximum temperatures between 20 and 25°C. In this table, non-significant temperature bands are not shown but are included as controls in all estimates. Heteroskedasticity robust standard errors are clustered by province and year-month and are presented in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 7: Temperature and Wage - Main

	Dependent variable:			
	log (Wage)			
	(1)	(2)	(3)	(4)
Days above 35	0.0051***	0.0050***	0.0003	-0.0005
	(0.0013)	(0.0013)	(0.0014)	(0.0013)
Days [30,35]	0.0006*	0.0006	0.00006	-0.0002
	(0.0003)	(0.0004)	(0.0004)	(0.0004)
Days [0,5]	-0.00002	0.00009	0.0001	0.0002
	(0.0004)	(0.0005)	(0.0008)	(0.0007)
Days below 0	0.0007	0.0009	0.0016	0.0011
	(0.0007)	(0.0007)	(0.0011)	(0.0011)
Region FE	Y	Y	N	N
Year × Month FE	Y	Y	Y	Y
Precipitation	N	Y	Y	Y
Month × Region FE	N	N	Y	Y
Employment controls	N	N	N	Y
Time dimension	72	72	72	72
Observations	3,384	3,384	3,384	3,384

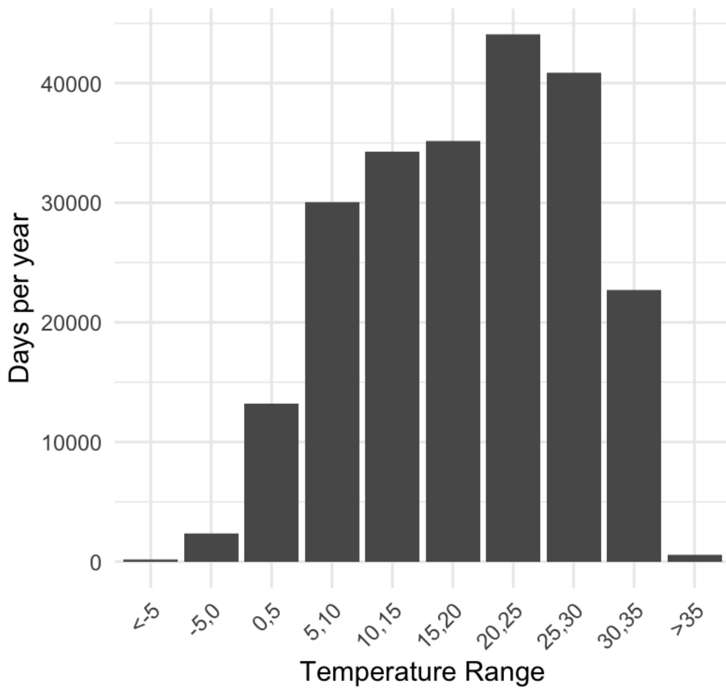
Notes: Table 7 presents estimates of the impact of temperature on per capita wages at the provincial level in Japan for 2014-2019. The omitted category is the temperature bin with daily maximum temperatures between 20 and 25°C. In this table, non-significant temperature bands are not shown but are included as controls in all estimates. Heteroskedasticity robust standard errors are clustered by province and year-month and are presented in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 8: Temperature and Wage - Industrial

	Dependent variable:			
	log (Wage)			
	(1)	(2)	(3)	(4)
Days above 35	-0.0001	-0.0001	-0.0002	0.00007
	(0.0020)	(0.0020)	(0.0016)	(0.0017)
Days [30,35]	-0.0005	-0.0005	0.0017^{*}	0.0019^{**}
	(0.0004)	(0.0004)	(0.0009)	(0.0009)
Days [0,5]	-0.0002	-0.0002	0.0007	0.0006
	(0.0008)	(0.0008)	(0.0019)	(0.0019)
Days below 0	0.0009	0.0009	0.0142	0.0143
	(0.0011)	(0.0012)	(0.0142)	(0.0142)
Region FE	N	N	N	N
Year × Month FE	Y	Y	Y	Y
Precipitation	N	Y	N	Y
Month × Region FE	Y	Y	Y	Y
Employment controls	Y	Y	Y	Y
Time dimension	72	72	72	72
Observations	2,736	2,736	648	648

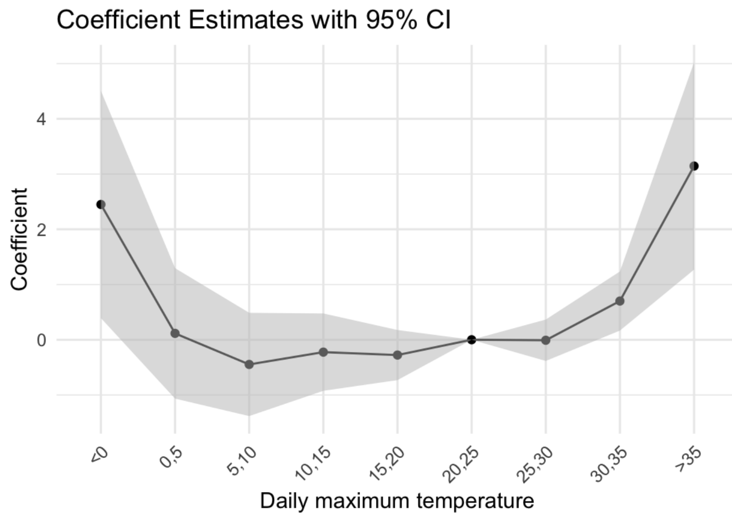
Notes: Table 8 Table 7 presents estimates of the impact of temperature on per capita wages at the provincial level in Japan for 2014-2019. Here, the sample ranges in columns 3 and 4 contain the 10 regions with the highest manufacturing output, and the estimates for the remaining regions are shown in columns 1 and 2. The omitted category is the temperature bin with daily maximum temperatures between 20 and 25°C. In this table, non-significant temperature bands are not shown but are included as controls in all estimates. Heteroskedasticity robust standard errors are clustered by province and year-month and are presented in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Figure 1: Annual distribution of daily maximum temperature



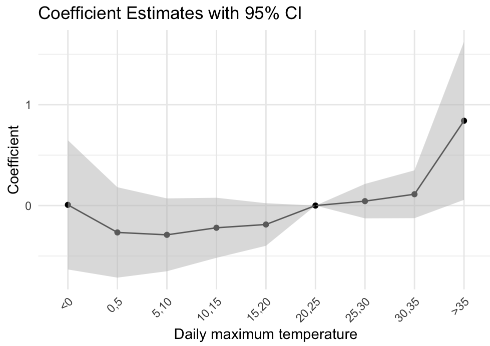
Notes: Figure 1 shows the annual distribution of daily maximum temperatures ($^{\circ}C$) for the period 2007 to 2019.

Figure 2: Estimated temperature-injuries relationship

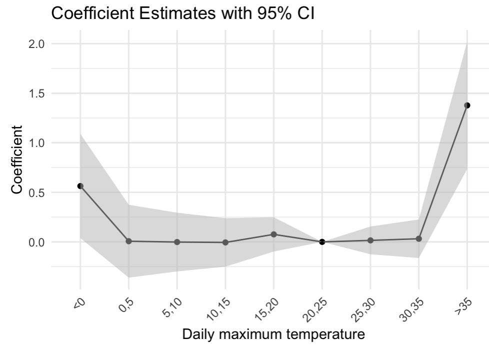


Notes: Figure 2 plots the response function between the number of monthly injuries and the daily maximum temperature, which was obtained by fitting equation 2. (Estimates of coefficients for all variables in Column 4 of Table 2). The core explanatory variable is an indicator of the number of days in a month with a certain range of temperatures. The coefficients can be interpreted as the increase in injury incidence associated with one additional day in the current temperature range, relative to the omitted category. The omitted category is the temperature bin with daily maximum temperatures between 20 and $25°C$. Heteroskedasticity robust standard errors by county and year and month, with 95% confidence intervals indicated by gray ranges.

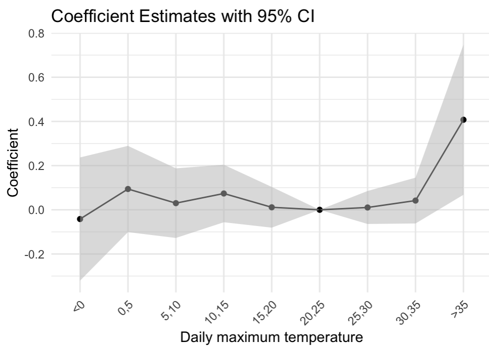
Figure 3: Estimated temperature-injuries relationship: by industry



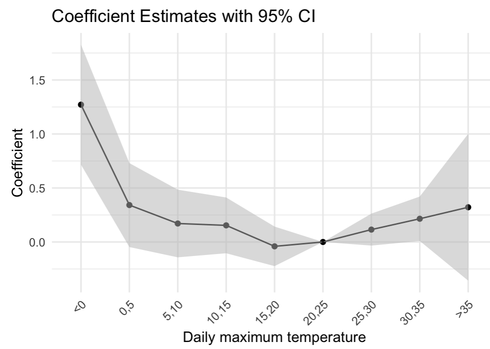
(a) Manufacturing (Classification=1)



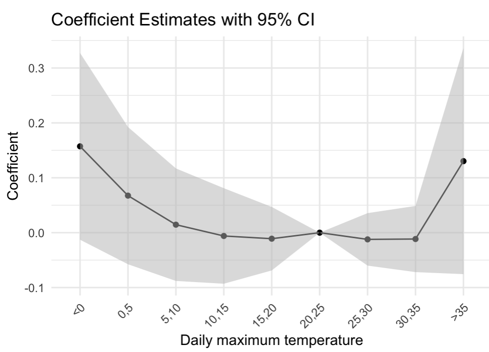
(b) Transportation (Classification=4)



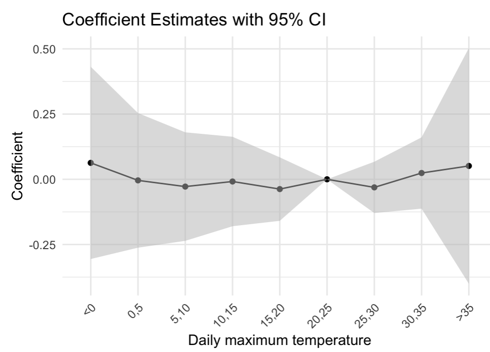
(c) Construction (Classification=3)



(d) Commercial (Classification=8)



(e) Education (Classification=12)



(f) Service (Classification=14)

Notes: Figure 3 plots the response function between the number of monthly injuries and the average daily temperature under different industries, which was obtained by fitting equation 2. The classification rules for industries are based on the Ministry of Health, Labor and Welfare's Industry Classification Standards for Labor Disasters. The omitted category is the temperature bin with daily maximum temperatures between 20 and 25°C. Heteroskedasticity robust standard errors by county and year and month, with 95% confidence intervals indicated by gray ranges.

Appendix A. All Temperature Bins

In the Appendix, we report coefficient estimates for all temperature bands in Table 2 and Table 3 that contain the remaining non-significant temperature intervals that have been omitted.

As can be seen in Table 9 and Table 10, there is almost no significant effect on injury risk in temperature intervals other than the extreme temperature intervals. And as shown in Figure 2, all coefficient estimates presumably exhibit an inverted U-shape. This finding is not strictly consistent with the results in Park et al. [2021]. This may be due to the fact that Park et al. [2021] only uses injury data from a single region, the estimates in this paper are based on data from individual prefectures across the country and are more externally valid. Coincidentally, the inverted U-shaped relationship we find between temperature and workplace injuries remains largely consistent with Barreca et al. [2016] and Barreca et al. [2015]'s conclusions. Barreca et al. [2015] focuses on temperature and mortality, and he uses data on the number of mortality from all regions of the United States as the dependent variable.

Table 9: Injuries and Temperature - Daily Maximum Temperature

	Dependent variable:			
	Injuries			
	(1)	(2)	(3)	(4)
Days above 35	3.755***	3.968***	3.619***	3.145***
	(0.919)	(0.940)	(1.090)	(0.957)
Days [30,35]	0.531**	0.806***	0.629**	0.701**
	(0.218)	(0.226)	(0.301)	(0.272)
Days [25,30]	-0.026	0.013	-0.038	-0.009
	(0.169)	(0.169)	(0.241)	(0.229)
Days [15,20]	-0.084	-0.249	-0.295	-0.277
	(0.179)	(0.182)	(0.298)	(0.284)
Days [10,15]	-0.273	-0.434**	-0.361	-0.224
	(0.199)	(0.201)	(0.420)	(0.400)
Days [5,10]	-0.120	-0.411*	-0.497	-0.447
	(0.236)	(0.244)	(0.510)	(0.486)
Days [0,5]	1.104***	0.681**	0.138	0.115
	(0.263)	(0.278)	(0.619)	(0.602)
Days below 0	4.301***	3.850***	2.413**	2.449**
	(0.509)	(0.520)	(1.059)	(1.049)
Region FE	Y	Y	N	N
Year × Month FE	Y	Y	Y	Y
Precipitation	N	Y	Y	Y
Month × Region FE	N	N	Y	Y
Employment controls	N	N	N	Y
Time dimension	72	72	72	72
Observations	3,384	3,384	3,384	3,384

Notes: Table 9 presents the estimation results for Table 2 including all coefficients that have been omitted. *p<0.1; **p<0.05; ***p<0.01.

Table 10: Injuries and Temperature - Daily Minimum Temperature

	Dependent variable:			
	Injuries			
	(1)	(2)	(3)	(4)
Days above 25	2.336***	2.297***	2.038***	1.570***
	(0.418)	(0.416)	(0.519)	(0.496)
Days [21,25]	0.966***	0.839***	0.023	0.030
	(0.233)	(0.233)	(0.360)	(0.344)
Days [15,20]	0.439***	0.384**	-0.026	-0.0667
	(0.167)	(0.166)	(0.246)	(0.235)
Days [5,10]	-0.296*	-0.302*	0.011	0.014
	(0.173)	(0.172)	(0.277)	(0.264)
Days [0,5]	-0.659***	-0.668***	0.060	0.138
	(0.187)	(0.186)	(0.374)	(0.358)
Days [-5,0]	-0.520**	-0.549**	0.567	0.725
	(0.252)	(0.251)	(0.482)	(0.460)
Days below -5	2.109***	2.085***	2.776***	2.963***
	(0.353)	(0.351)	(0.686)	(0.656)
Region FE	Y	Y	N	N
Year × Month FE	Y	Y	Y	Y
Precipitation	N	Y	Y	Y
Month × Region FE	N	N	Y	Y
Employment controls	N	N	N	Y
Time dimension	72	72	72	72
Observations	3,384	3,384	3,384	3,384

Notes: Table 10 presents the estimation results for Table 3 including all coefficients that have been omitted. *p<0.1; **p<0.05; ***p<0.01.