NETWORK
LISER

Discussion Paper Series

IZA DP No. 18592

April 2026

Climate Change and Workplace Injury

Qifan Fu
University of Osaka

Masaru Sasaki
University of Osaka and IZA@LISER

IZA@LISER NETWORK
ISSN: 2365-9793

IZA DP No. 18592 April 2026

Climate Change and Workplace Injury

Abstract

This study comprehensively assesses the effects of exposure to temperature extremes on workplace health, safety, and economic outcomes. Using Japanese prefecture-level data on work-related injuries and fatalities (2014–2019) combined with weather records, we estimate that higher temperatures significantly increase work-related injuries and their associated social costs. When exposed to temperature extremes, workers neither reduce their working hours nor exit the labor force. Furthermore, testing the compensating wage differential model reveals minimal wage increases for exposure to temperature extremes. These findings highlight the need for effective policies to mitigate the adverse effects of temperature extremes in the workplace.

JEL classification

J28, J31

Keywords

extreme temperatures, defensive investment, work-related injuries, climate change adaptation, compensatory wage differentials

Corresponding author

Qifan Fu

u670245b@ecs.osaka-u.ac.jp

1 Introduction

Global warming is likely to significantly alter the climate environment within a relatively short timeframe (Houghton (2009); Nordhaus and Boyer (2003)). According to Romanello et al. (2025), climate change negatively impacted global labor productivity in 2024, reducing working hours by 640 billion and causing an estimated income loss of USD 1.09 trillion. While reducing greenhouse gas emissions is a high priority, the understanding of how societies adapt to climate change remains limited. This knowledge gap presents challenges in accurately estimating climate-related costs and designing effective risk-mitigation strategies. Costello et al. (2009) and (Campbell-Lendrum et al. (2009)) emphasize that identifying adaptation opportunities to reduce the human health costs of climate change should be recognized as a global research priority for the 21st century.

Beyond health impacts, temperature extremes impose widespread negative effects, including reduced labor productivity (Zhang et al. (2018); Burke et al. (2015); Carleton and Hsiang (2016)), impaired learning among children (Graff Zivin and Neidell (2014)), and increased overall mortality rates (Botzen et al. (2019); Karlsson and Ziebarth (2018)). Building on these findings, a growing body of research has examined the potential effects of temperature extremes on workplace safety (Varghese et al. (2018)) [1].

Japan's average annual temperature in 2024 reached its highest level since record-keeping began in 1898. According to the Japan Meteorological Agency, the 2024 average temperature deviated from the historical norm by +1.48 degrees Celsius ($°C$), exceeding the previous record of $+1.29°C$ set in 2023. More broadly, Japan's average annual temperature has increased by $1.30°C$ per century, with extremely high temperatures occurring more frequently between 1901 and 2022. Consequently, assessing the impacts of climate extremes on health, human capital, and welfare has become increasingly critical (Schlenker and Roberts (2009); Hsiang et al. (2013)).

[1] Dillender (2021) systematically assessed the relationship between temperature and workplace injuries for the first time using data from Texas, USA.

Therefore, this study comprehensively assesses the effects of temperature exposure on workplace health and safety in Japan, expanding current estimates of the economic costs associated with extreme temperatures. We address three key aspects of this issue.

First, we compile and analyze a Japanese prefecture-level dataset spanning 2014 to 2019, detailing work-related fatalities and injuries requiring at least four days of absence. By combining this dataset with daily weather records aggregated at the monthly prefecture level, we estimate the impact of higher temperature exposure on workplace safety, measured by the number of work-related injuries and fatalities.

Second, we account for potential endogenous bias arising from workers' behavioral responses to temperature extremes. To address this concern, we estimate the effect of high temperature exposure on average hours worked and prefecture-level employment. This approach reveals that failing to incorporate defensive investments—such as proactive measures to mitigate heat exposure—may underestimate the true effect of exposure to high temperatures on occupational hazards. We hypothesize that, in the absence of such defensive investments, workers may reduce their working hours, shift to jobs offering more favorable working conditions, or exit the labor force entirely to avoid unsafe workplace environments.

Finally, we examine the effect of high-temperature exposure on average prefecture-level wages using monthly data from the Basic Survey on Wage Structure published by Japan ' s Ministry of Health, Labour and Welfare (MHLW). Specifically, we test Rosen ' s (1986) compensating wage differential hypothesis, which posits that firms may offer higher wages to compensate workers for the extreme-temperature risks. Additionally, we calculate the incremental costs firms incur when providing wage compensation due to this hazard.

Our analysis yields three key findings. First, exposure to temperature extremes adversely affects workers' health conditions and human capital. Our estimates indicate that each additional day with a maximum daily temperature exceeding $35°C$ increases monthly work-related injuries by 3.145-–3.968 at the prefecture level, totaling approximately 148-–186 cases nationwide. This translates to an estimated nationwide economic cost of JPY 51,505,184–

64,729,488 (USD 367,894–462,353) [2]. Similarly, each additional day with a maximum daily temperature of $30°C$ or higher but below $35°C$ increases monthly work-related injuries by 0.531—0.806 at the prefecture level, aggregating approximately 25—38 cases nationwide, imposing an estimated national cost of JPY 8,700,200–3,224,304 (USD 62,144–94,459).

Interestingly, the relationship between the number of days with maximum ambient temperatures and the risk of work-related injuries is not monotonically positive but U-shaped. This relationship pattern emerges clearly when plotting the estimated temperature coefficients against daily maximum temperature intervals.

When analyzing work-related fatalities as the dependent variable, we find that exposure to extreme temperatures correlates with increased fatality risk. However, the statistical significance is weaker, and the magnitude of the effects is smaller compared to the analysis using work-related injuries as the dependent variable. This discrepancy likely stems from the limited number of recorded fatalities and substantial missing data in the fatality records.

Furthermore, the U-shaped relationship between maximum temperature days and work-related injury risk persists across selected industries. Notably, this pattern is more pronounced in industries dominated by outdoor occupations compared to those primarily involving indoor work.

Second, when testing the hypothesis that workers decrease their labor supply in the absence of defensive investments, we find that workers exposed to temperature extremes neither exit the labor force nor significantly reduce their working hours. This result holds even after controlling for prefecture, month, year, and other fixed effects. Consequently, we conclude that workers do not necessarily adjust their labor supply, implying that they instead rely on purchasing defensive goods to mitigate heat exposure. Thus, our estimated impact does not accurately reflect the true biological effect of temperature extremes on occupational injury and fatality rates.

[2] In 2023, the USD/JPY exchange rate moved between roughly JPY 127 and 152 per U.S. dollar. Therefore, for the purpose of this study, we take the average and convert at an exchange rate of JPY 140 per U.S. dollar.

Finally, examining the compensating wage differential model reveals that each additional day exceeding $35°C$ increases monthly earnings by just 0.51% (JPY 1,623 (USD 11.6) for regular workers). Similarly, each additional day between $30°C$ and $35°C$ yields a mere 0.06% increase in monthly earnings (JPY 191 (USD 1.4) for regular workers). However, the statistical significance diminishes after controlling for prefecture, month, year, and other fixed effects. These findings suggest that the compensation for temperature-induced hazards is negligible.

This study makes two distinct contributions to the existing literature. First, we expand the research on the use of micro-level data to estimate marginal losses from climate change. While previous studies have investigated 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)), and cognitive performance (Graff Zivin et al. (2018)), our study—along with recent work by Dillender (2021) and Park et al. (2021)—is among the first to assess the potential impact of temperature on workplace safety. Furthermore, we enhance the external validity of our findings by leveraging nationwide weather records, which have not been utilized in prior studies on this topic[3].

Second, we contribute to the literature valuing the social costs of temperature extremes. Prior research has primarily examined the relationship between high temperatures and income (Deryugina and Hsiang (2014); Garg et al. (2020)) or economic output (Dell et al. (2009)), both across countries and within specific regions (Cattaneo and Peri (2016); Heal and Park (2013)). By contrast, our work quantifies the specific costs of absenteeism and fatalities resulting from temperature-induced occupational accidents. Additionally, we contribute to the literature on compensating wage differentials by analyzing wage responses to prolonged exposure to temperature extremes. These findings align with those of Lavetti

[3]Park et al. (2021) used administrative data on workplace injuries from the California Department of Workers' Compensation to examine the relationship between temperature and workplace injuries, finding that lower-income workers may be disproportionately affected. However, the broader applicability of this conclusion, and that of Dillender (2021) remains unexplored.

(2020)[4].

The remainder of the paper is organized as follows. Section 2 presents the conceptual framework, including a physiological model linking temperature extremes to workplace health. Section 3 outlines the data sources and summary statistics. Section 4 details the econometric specifications and estimation results. Section 5 explores the implications of the compensating wage differentials model. Finally, Section 6 offers concluding remarks.

2 Conceptual Framework

2.1 Relationship between Temperature and Health

In extreme temperature environments, the human body relies on neural, endocrine, and physiological mechanisms to thermoregulate and maintain its internal temperature within an acceptable range. Thermoregulation primarily involves sweat gland secretion, skin vasodilation, respiratory regulation, and neuromodulation (Tansey and Johnson (2015); Romanovsky (2018)). For instance, at high temperatures, the skin's vasculature dilates, enlarging the surface area for heat dissipation, thereby facilitating heat-loss from the body. The nervous system plays a crucial role by monitoring changes in body temperature and regulating physiological functions, such as sweat gland activity and vasoconstriction, via neurotransmitter signals (González-Alonso (2012)). However, exposure to temperatures outside the normal range or prolonged exposure to extreme temperature conditions poses serious risks to human health (Patz et al. (2005); Lim et al. (2008)).

The direct relationship between temperature and human health is well-documented. For example, prolonged exposure to extreme environments can increase cardiovascular risks, such as ischemic heart disease, by altering blood pressure and heart rate (Huynen et al.

[4]However, the findings are inconsistent with those of Kim and Lim (2017), who used data from the Korean Working Conditions Survey to show higher wages for workers in the non-heat exposure group. Nonetheless, the empirical literature has widely tested and debated the compensating wage differentials hypothesis (Gertler et al. (2005); Lavetti and Schmutte (2016)).

(2001); Basu and Ostro (2008)). High temperatures also correlate with increased prevalence of respiratory and chronic diseases (Basu (2009); Kovats and Hajat (2008)). Recent studies further provide growing evidence that high temperatures significantly impact overall mortality (Gosling et al. (2009); Deschênes and Greenstone (2011)).

Hot environments can also impair human performance in both work and sports (González-Alonso et al. (1999); Graff Zivin et al. (2018)). For instance, elevated temperatures can degrade cognitive functions, adversely influencing decision-making and its outcomes (Pilcher et al. (2002); Hancock and Vasmatzidis (2003); Cheema and Patrick (2012); Heyes and Saberian (2019)). Overall, extreme temperature conditions impact work efficiency and safety by affecting both physiological and cognitive aspects. These mechanisms motivate our formal model decomposing observed injury-temperature relationships.

2.2 Conceptual Framework

We develop a conceptual model to formalize these ideas and guide the empirical analysis. We assume that a worker's risk of injury by temperature extremes at the workplace or during commuting, $I(t, a)$, depends positively on exposure time to temperature extremes t and negatively on defensive investments a. Defensive measures that mitigate heat exposure, such as installing air conditioning and using fan-equipped work outfits, can be adopted under prolonged exposure to extreme temperatures.

A representative worker solves a utility-maximization problem $\max_{x,l,a} U(x, l, I)$ subject to the budget constraint $w(T - l - f(I)) \geq x + pa$, where x denotes a bundle of consumption goods and services normalized to price 1, T total length of time available, l leisure time, w the wage per unit of time, $f(I)$ the length of time absent from work due to a work-related injury caused by exposure to temperature extremes, and p the price for purchasing defensive goods that protect health from temperature extremes [5]. The representative worker chooses

[5] In this conceptual framework, we assume that an increase in defensive investments mitigates the risk of work-related injury $I(.)$ directly and thereby affects leisure time l, which differs from the logic of compensating wage differentials (Rosen (1986)). In the compensating wage differential model, employers compensate

the optimal defensive investment level a^*.

Following Park et al. (2021) and Deschenes et al. (2017), the relationship between work-related injury risk and temperature can be expressed as:

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

Eq(1) decomposes the total derivative of work-related injury risk with respect to exposure to extreme temperatures (total effect) into the partial derivative in exposure time (biological effect) and the product of the partial derivative in defensive investments, $\frac{\partial I}{\partial a}$, and the partial derivative of defensive investments in exposure time, $\frac{\partial a}{\partial t}$ (defensive effect). We assume that defensive investments reduce work-related injury risk ($\frac{\partial I}{\partial a} < 0$). We then investigate whether workers increase self-protective investments as the number of days with extreme temperatures rises. When this condition holds, the inequality $\frac{\partial I}{\partial a} < 0$ implies that the defensive effect—the second term on the right-hand side of Eq(1)—is negative.

Most existing studies (e.g., Bui et al. (2024)) focus on the total effect, $\frac{dI}{dt}$, that is, the impact of ambient temperature on overall work-related injury risk, rather than on the biological effect ($\frac{\partial I}{\partial t}$). Empirically isolating the biological effect of temperature extremes on injury risk requires controlling for variations in workers' defensive investment decisions, which remains challenging in many settings. A focus solely on the total effect, $\frac{dI}{dt}$, can therefore substantially underestimate the biological effect of ambient temperature on work-related injury risk if workers actively adopt defensive measures against heat. This decomposition guides our empirical strategy distinguishing total from biological effects.

As another channel for reducing exposure to extreme temperatures, workers may adjust labor supply by optimally cutting working hours, or in extreme cases, quitting their jobs. However, flexible adjustment of working hours often remains impractical or infeasible as a

employees for worse working conditions (Lavetti (2023)), implying a trade-off between $I(.)$ and the offered wages. To focus on optimal defensive investments in protecting health from temperature extremes, we simplify the model by treating the wage as exogenous. Lately, we teat the wage endogenous and explore the validity of the compensating wage differential model.

response to heat exposure. When workers do not choose this option, they continue to work in jobs involving prolonged exposure to extreme temperatures and instead rely on defensive goods. This behavioral assumption underpins our later empirical design, where we estimate the employment equation to test for such adjustments.

3 Data and Summary Statistics

Work-related Accidents—This study uses monthly prefecture-level data on work-related injuries collected by the Japanese MHLW from 2014 to 2019. According to the Labour Standards Act and the Occupational Safety and Health Regulations, employers must report worker-related injuries requiring at least four days of leave immediately, and those requiring shorter leave every quarter, to the nearest Labor Standard Inspection Office[6]. This compulsory reporting yields a more comprehensive and reliable description of workplace safety risk than many publicly available datasets provide.

To assess the robustness of our results over a longer period, we also employ data on work-related fatalities from 2007 to 2019. These data are released monthly at the prefecture level by MHLW, although some months contain missing values, which makes the fatality series less reliable than the injury series. Additionally, we exclude prefectures severely damaged by the Great East Japan Earthquake in 2011, because numerous work-related injuries in those areas arose from the earthquake and tsunami rather than from extreme temperatures.

Temperatures—We collected daily maximum temperature and average precipitation data released by the Japan Meteorological Agency. Given that prefectures typically contain multiple meteorological stations, we use the average of the station-level maximum temperature and precipitation within each prefecture. As the work-related injury data are monthly, we count, for each month and prefecture, the number of days falling into each temperature range based on daily maximum temperatures. Considering the nonlinear effects of temperature, we

[6]Employers are required to participate in the Industrial Accident Compensation Insurance System, which provides benefits to employees who are injured or become ill during work or while commuting and supports their social reintegration. In principle, the employer bears the insurance premium.

divide daily temperatures into 5-degree Celsius intervals, forming nine temperature ranges from below $0°C$ to above $35°C$: (1) below $0°C$, (2) $0°C$ to below $5°C$, (3) $5°C$ to below $10°C$, (4) $10°C$ to below $15°C$, (5) $15°C$ to below $20°C$, (6) $20°C$ to below$25°C$, (7) $25°C$ to below $30°C$, (8) $30°C$ to below $35°C$, and (9) above $35°C$.

Employment, Wages, Hours—The primary identification concern stems from endogenous worker movements across industries or prefectures to avoid uncomfortable workplaces created by extreme temperatures. To mitigate this bias (i.e., the influence of other potential variables affecting workplace injuries), we construct a monthly prefecture-level dataset from the Basic Survey on Wage Structure conducted by MHLW, spanning from 2007 to 2019. This dataset includes prefectural data on hours worked per week, overtime hours, wages, and days of attendance per week. We merge these labor-market data with the work-related injury and meteorological data by prefecture and year-month to estimate the impact of temperature on workplace injuries.

Summary Statistics—Table 1 presents summary statistics for various variables, including temperature, work-related injuries and fatalities, and labor outcomes at the prefecture level. Across all sample periods, the number of days with maximum daily temperatures from $20°C$ to below $25°C$ is the largest among all temperature intervals, whereas days with temperatures below $0°C$ or above $35°C$—considered extreme—occur much less frequently. Figure 1 illustrates the distribution of yearly average days across all temperature intervals. The table also summarizes work-related injuries by industry, using MHLW classifications, with particular focus on manufacturing, construction, and transportation. Work-related injuries and fatalities concentrate heavily in these three industries.

4 Temperature and Work-Related Injuries

4.1 Econometric Specification

This subsection presents the empirical specification of the temperature response function. Identification relies on random variations in temperature intervals defined in the previous section at the provincial-level. The econometric specification is as follows:

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

where Y_{imt} denotes the number of work-related injuries in prefecture i, month m, and year t. This specification also includes a full set of prefecture-monthly fixed effects (θ_{im}) and year-monthly fixed effects (δ_{mt}). The prefecture-month fixed effects are included to account for seasonal fluctuations in the number of work-related injuries, while controlling for time-invariant, unobserved factors that affect work-related injury rates across prefectures and months. These fixed effects capture regional differences in seasonal employment patterns, including variations in agricultural harvest seasons. Additionally, year-month fixed effects are incorporated to control for macroeconomic shocks and broader macroeconomic trends over the sample period.

The primary variables of interest in this study are the daily average temperature $Temp_{imtj}$—measured by prefectures, months, and years—defined as the number of days when the daily maximum temperature falls within one of nine temperature intervals. In this specification, one interval serves as the reference category, allowing the model to capture the additional effect of temperature within interval j relative to the reference interval. We use $20°C$ to below $25°C$ as the reference interval, which contains the largest number of days on with maximum daily temperature. The actual temperature distribution for each prefecture-month pair naturally varies across years, and therefore, is treated as an exogenous variable, forming the basis for estimating temperature response function parameters (β_j). The parameters show the total effect, that is, the sum of the biological and defensive effects. Meanwhile, X includes control variables, such as precipitation and other region-specific labor-related variables(e.g., labor force participation and working hours), to account for potential effects on the outcome variable.

4.2 Results

Table 2 presents the main results of Equation 2. The table reports the coefficients for various daily temperature intervals, using the 20 to below $25°C$ range as the reference interval. Each coefficient captures the estimated impact of an additional day in temperature interval j on monthly prefecture-level work-related injuries, relative to an additional day in the 20 to below $25°C$ interval. The results are displayed in columns 1–4, which differ in terms of specifications that control for various fixed effects and employment outcomes by prefecture. Due to space limitations, only statistically significant coefficients for the daily temperature intervals appear in the table.

Across all columns of Table 2, an additional day with a maximum daily temperature exceeding $35°C$ increases monthly work-related injuries by 3.145–3.968 cases at the prefecture level (approximately 148–186 cases nationwide calculated by multiplying by 47 prefectures), at the 1% level of significance. Similarly, an additional day with a maximum daily temperature from $30°C$ to below $35°C$ increases monthly work-related injuries by 0.531–0.806 cases at the prefecture level (approximately 25–38 cases nationwide). Importantly, these results remain consistent and robust even after controlling for various fixed effects and employment outcomes at the prefecture level.

According to MHLW data, injured workers (at the workplace or while commuting) take an average of 41 days of leave. Under the Workers' Accident Compensation Insurance system, an injured worker receives 80% of their monthly earnings as compensation. The Basic Survey on Wage Structure reports average 2023 monthly earnings for regular workers at JPY 318,300 (USD 2,274). The total compensation cost per injured worker can thus be calculated as $\left(\frac{41}{30}\right) \times 318,300 \times 0.8 =$ JPY 348,008(USD 2,486).

Applying these estimates from Table 2, each additional day exceeding $35°C$ generates nationwide compensation costs of JPY 51,505,184–64,729,488 (USD 367,894–462,353). Similarly, each additional day from $30°C$ to below $35°C$ imposes nationwide costs of JPY 8,700,200–13,224,304 (USD 62,144–94,459).

Figure 2 plots the column 4 coefficients from Table 2 with 95% confidence intervals. The figure illustrates that the risk of work-related injuries peaks at temperatures exceeding $35°C$. Exposure to cold temperatures also elevates risk: an additional day with a maximum daily temperature below $0°C$ increases monthly work-related injuries by 2.4 cases at the prefecture level (approximately 113 cases nationwide), at the 5% level of significance. This U-shaped relationship between the maximum temperature days and injury risk aligns with findings from previous studies of temperature effects on mortality (Deschenes (2014); Barreca et al. (2016)) and workplace injuries Dillender (2019).

4.3 Robustness Test

To assess the robustness of the results presented in the previous section, we re-estimate Equation 2 using daily *minimum* temperatures (instead of daily *maximum* temperatures) as the independent variable. Minimum temperature distributions differ markedly: days with minimum temperatures exceeding $25°C$ become rare, whereas days with minimum temperatures below $0°C$ increase proportionally. Unlike the approach in the previous section, we utilize the minimum temperature interval from $10°C$ to below $15°C$ as the reference category.

Table 3 presents the estimated results, where daily minimum temperature is used as the independent variable. As columns 1–4 show, days falling within extreme temperature intervals continue to significantly affect the incidence of prefecture-level work-related injuries. An additional day with a daily minimum temperature exceeding $25°C$ increases prefecture-level work-related injuries by 1.570–2.336 cases (approximately 74–110 cases nationwide), compared to the reference interval, at the 1% level of significance, generating nationwide costs of JPY 25,752,592—38,280,880 (USD 183,947–273,435). Similarly, an additional day with a daily minimum temperature below -5°C increases monthly prefecture-level work-related injuries by 2.085–2.963 cases (approximately 98–139 cases nationwide), at the 1% level of significance, generating additional nationwide costs of JPY 34,104,784–48,373,112 (USD 243,606–345,522) [7].

4.4 Work-related Fatalities

Longer exposure to extreme temperatures (t) produces more severe worker outcomes. In this subsection, we replace work-related injuries with work-related fatalities as the dependent variable in Equation 2. Unlike injury data, fatality data are available for a broader time span, as summarized in Table 1, but contain many zero values. Therefore, we estimate using the logarithmic transformation of fatality count ($log(deaths + 0.01)$).

Table 4 reports temperature effects on fatality risk using monthly prefecture-level data from 2007 to 2019. As column 4 shows (which excludes potentially noisy data of 2011), an additional day with a daily maximum temperature from 30°C to below 35°C increases prefecture-level fatalities by 0.038 cases (1.786 cases nationwide), at the 5% level of significance. The estimated temperature effects on fatalities are notably smaller and less precisely estimated than effects on injuries. Furthermore, temperatures exceeding 35°C show positive but insignificant effects on fatalities. These patterns likely reflect sparse fatality data and substantial missing observations.

4.5 Defensive Investments

As argued in Section 2, the estimated results from Eq(2) reflect the total temperature effect on the risk of work-related injuries or fatalities, capturing both biological and defensive effects. Consequently, these estimates likely underestimate the pure biological effect of tem-

[7]Consistent with the results in the previous section, the estimates demonstrate a significant U-shaped relationship between minimum temperature days and work-related injury risk.

perature on work-related injury risk. Although empirically distinguishing between biological and defensive effects is challenging, we can test whether workers adopt defensive behaviors against prolonged extreme-temperature exposure. Recall from Eq(1) that the defensive effect is expressed as the product of the partial derivative of the risk of work-related injuries with respect to defensive investments, $\frac{\partial I}{\partial a}$, and the partial derivative of defensive investments with respect to peripheral temperatures, $\frac{\partial a}{\partial t}$. In this subsection, we investigate whether workers adopt defensive behaviors to avoid extreme temperature exposure at the workplace.

The most effective defense against extreme temperatures—particularly those working outdoors—involves purchasing protective equipment to minimize exposure to such conditions. In the absence of such measures, workers may reduce working hours or quit entirely. Both responses predict lower labor supply under extreme temperatures when defensive investments are unavailable. Firms often invest in workplace adaptations to enable to continued work under extreme temperatures. For example, they may install air conditioning systems for indoor workers during periods of high temperatures or heating systems during low temperatures, allowing comfortable task performance despite adverse weather conditions. These investments reduce workers' need to cut hours or exit jobs when exposed to temperature extremes.

To test the hypothesis that higher temperatures reduce labor supply, we apply the fixed-effects framework from Equation 2, replacing the dependent variable (number of work-related injuries) with prefecture-level employee counts and average monthly hours worked. The estimated results are presented in Tables 5 and 6, respectively.

Columns 1–4 of Table 5 show no statistically significant effect of temperature intervals on employee counts. Overall, these findings suggest that extreme temperatures do not necessarily prompt workers to exit the labor force.

Table 6 presents the effects of temperature intervals on prefecture-level average monthly hours worked. Results show that an additional day with a daily temperature from $0°C$ to below $5°C$ reduces prefecture-level average monthly hours worked, after controlling for prefecture and year-month fixed effects, at the 1% level of significance (column 1). This effect persists even when the precipitation fixed effect is included in the specification, but weakens to the marginal level of significance (column 2). These findings align with Graff Zivin and Neidell (2014), who examined temperature effects on the allocation of time to work and leisure in the U.S. and found that workers in temperature-sensitive industries cut working hours by up to one hour when daily maximum temperatures exceed $85°F$.

However, prefecture-month fixed effects and employment controls eliminate temperature effects on average monthly hours worked, as shown in columns 3 and 4 of Table 6. Combined with Table 5, these fully specified results suggest that workers neither exit the labor force nor significantly reduce their working hours under extreme temperatures.

Therefore, workers exposed to extreme temperatures likely purchase defensive goods rather than adjust labor supply. *Sen-i News* (2024/11/05), a newspaper specializing in the textile industry, reports fan-equipped workwear shipments exceeding JPY 20 billion (USD 143 million) in 2024 ’ s record heat, up from approximately JPY 17.5 billion (USD 125 million) in 2014 [8] Furthermore, Yano Research Institute Ltd., a private economic and business research organization, projects commercial air conditioning shipments growing from JPY 483 billion (USD 3,450 million) in 2023 to JPY 567 billion (USD 4,050 million) by 2030 [9] This gradual expansion in market size may reflect worsening workplace conditions caused by prolonged exposure to extreme temperatures [10].

One approach to measuring defensive investments is to use electricity costs as a proxy for electricity consumption (Deschenes (2022)), as air conditioning and other defensive equipment typically increase power usage. However, this proxy has its limitations because factory electricity costs are often affected by production capacity and order volumes, which obscures the portion attributable to defensive investments. Consequently, we treat the estimated impacts of extreme temperatures on work-related injuries and fatalities as the total effect that

[8] See $https://www.sen-i-news.co.jp/seninews/view/?article = 406498$. (Japanese)

[9] See $https://www.yano.co.jp/press-release/show/press_id/3658$.(Japanese)

[10] As before, we will use the same exchange rate of JPY 140 per U.S. dollar for conversion in this paragraph.

combines biological and defensive components. Notably, the nationwide compensation costs per injured worker reported in Section 4.2 are therefore likely underestimated and should be interpreted as a lower bound.

4.6 Heterogeneity Across Industries

Previous analyses assume uniform temperature effects across industries. However, this assumption does not hold in many cases. For instance, workers in industries with predominantly outdoor occupations experience longer exposure times and therefore are more sensitive to temperature extremes than those in industries with primarily indoor occupations. As discussed in Section 2, high temperatures impair human physiological health and decision making. Consequently, in industries where workers are exposed to extreme temperatures due to outdoor work, the adverse health effects of high temperatures are likely to be more severe. In this subsection, using MHLW industry classification, we estimate Equation 2 separately for six selected industries: Manufacturing, Transportation, Construction, Commerce, Education, and Services.

Using the same specification from column 4 of Table 2, Figure 3 presents the results illustrating the impact of days within specific temperature ranges on work-related injuries by industries. All industries exhibit U-shaped relationships consistent with Figure 2: temperature extremes (the ends of the horizontal axis) positively correlate with work-related injuries. Figures 3a (Manufacturing), 3b (Transportation), and 3c (Construction) show particularly strong effects from high temperatures. For instance, in the transportation industry—dominated by outdoor work—an additional day with temperatures exceeding $35°C$ increases monthly work-related injuries by 1.37 cases at the prefecture level (approximately 64 cases nationwide), at the 5% level of significance. Conversely, Figures 3d (Commerce), 3e (Education), and 3f (Services), which represent predominantly indoor industries, show insignificant temperature effects on the work-related injuries.

5 Extreme Temperatures and Wages

5.1 Compensating Wage Differentials

Labor economics theory posits that workers demand higher wages to compensate for non-monetary costs associated with certain jobs (e.g., occupational hazards, poor working conditions), and in response to these demands, firms provide additional wages. Since Rosen's seminal work in 1986, which laid the foundation for the compensating wage differential model, extensive theoretical and empirical research has examined compensating wage differentials. Workers with identical productivity but heterogeneous risk preferences concerning work-related injuries, sort into occupations balancing wages against injury risk.

As discussed in Section 2, a representative worker ’ s utility level is determined by three factors: consumption goods and services bundle, leisure time, and work-related injury risk. Here, we adopt an alternative utility framework that focuses on two factors: wage and work-related injury risk. Recall that the risk of work-related injuries is positively correlated with exposure to temperature extremes and negatively correlated with defensive measures against such extremes. For simplicity, we fix defensive investments a, assuming prohibitively high costs for firms to improve workplace safety. The utility function can then be expressed as $U(w, I(t))$, where w represents the wage, and I and t denote work-related injury risk and exposure to temperature extremes, respectively.

Based on utility function properties, worker indifference curves are convex and upward sloping: higher injury risk requires higher wages to maintain utility levels. Therefore, risk-averse workers tend to avoid working in firms that are more vulnerable to temperature extremes and demand greater wage compensation.

Conversely, firms' iso-profit curves are concave and upward sloping. Higher injury risk necessitates higher wages, with compensation depending on the firm's technological capacity to create safer and more secure workplaces. Firms unable to cost-effectively improve safety instead pay compensating differentials.

The market-equilibrium difference curve, which represents the relationship between the equilibrium wage and the risk of work-related injuries, is upward sloping. Here, the equilibrium wage is defined as the wage at which workers' indifference curves are tangent to firm iso-profit curves for each specific level of work-related injury risk. Based on this, we hypothesize that prolonged exposure to temperature extremes, which increases work-related injury risk, leads to higher wages.

5.2 Results

To test whether workers receive compensating differentials for temperature extremes, we estimate Equation 2 with the logarithm of monthly earnings (Japanese Yen) as the dependent variable. Table 7 reports estimated results.

Column 1, which controls only for prefecture and year-month fixed effects, shows that an additional day with a maximum daily temperature exceeding $35°C$ increases monthly earnings by 0.51%, at the 1% level of significance. An additional day with a maximum daily temperature from 30° to below $35°C$ increases monthly earnings by 0.06%, at the marginal level of significance. Column 2, which adds precipitation controls, yields nearly identical estimates (0.50% and 0.06%), although the 30°–$35°C$ effect weakens to marginal significance.

Recall that the average monthly earnings for regular workers in 2023 are estimated at JPY 318,300. Based on column 1 results, each additional day with a maximum daily temperature exceeding $35°C$ increases the monthly earnings for a regular worker by JPY 1,623 (USD 11.6). Similarly, each additional day with a maximum daily temperature from 30° to below $35°C$ increases monthly earnings per regular worker by merely JPY 191 (USD 1.4). Thus, the compensation for temperature hazards appears minimal.

Further controlling for prefecture-month fixed effects, employment variables, and average hours worked renders all the coefficients of temperature intervals statistically insignificant.

This aligns with Dell et al. (2009) and Deryugina and Hsiang (2014)[11]. Prefecture-specific seasonal industry patterns, rather than temperature extremes, likely drive differences in the monthly earnings across prefectures.

6 Concluding Remarks and Discussions

Prolonged exposure to temperature extremes imposes substantial costs on individuals and society. With extreme weather events expected to increase, understanding climate change impacts on workplace health and safety grows increasingly critical —not only due to lost productivity from work-related injuries or fatalities but also because of mounting workers ' accident insurance burdens (Wang et al. (2017); Beniston et al. (2007); Seneviratne et al. (2021)).

Our findings indicate that exposure to temperature extremes adversely impacts workers' health and human capital, particularly in outdoor-dominated industries. From a welfare perspective, work-related injuries generate direct medical costs and reduce expected lifetime earnings (Krause et al. (2001)). Furthermore, work-related fatalities risk plunging families into poverty. MHLW reports 764,558 nationwide work-related injuries and fatalities in 2022—a record low, yet substantial.

These results suggest that governments should allocate greater resources to improving workplace safety, particularly where benefits outweigh escalating social costs of temperature extremes [12].

References

Barreca, A., Clay, K., Deschênes, O., Greenstone, M., and Shapiro, J. S. (2015). Convergence in adaptation to climate change: Evidence from high temperatures and mortality, 1900–2004. *American Economic Review*, 105(5):247–251.

[11] We obtain negative coefficients of temperature intervals in Table 7, although they are not statistically significant. These results are broadly similar to Hübler et al. (2008), who find that high temperatures reduce labor productivity, and thus wages.

[12] Most studies confirm that air conditioning installation effectively mitigates heat-related damage(Barreca et al. (2015); Park et al. (2020)).

Barreca, A., Clay, K., Deschenes, O., Greenstone, M., and Shapiro, J. S. (2016). Adapting to climate change: The remarkable decline in the US temperature-mortality relationship over the twentieth century. *Journal of Political Economy*, 124(1):105–159.

Basu, R. (2009). High ambient temperature and mortality: a review of epidemiologic studies from 2001 to 2008. *Environmental Health*, 8:1–13.

Basu, R. and Ostro, B. D. (2008). A multicounty analysis identifying the populations vulnerable to mortality associated with high ambient temperature in california. *American Journal of Epidemiology*, 168(6):632–637.

Beniston, M., Stephenson, D. B., Christensen, O. B., Ferro, C. A., Frei, C., Goyette, S., Halsnaes, K., Holt, T., Jylhä, K., Koffi, B., et al. (2007). Future extreme events in european climate: an exploration of regional climate model projections. *Climatic Change*, 81:71–95.

Botzen, W. W., Deschenes, O., and Sanders, M. (2019). The economic impacts of natural disasters: A review of models and empirical studies. *Review of Environmental Economics and Policy*, 13(2):167–188.

Bui, T.-H., Bui, H.-P., and Pham, T. M.-A. (2024). Effects of temperature on job insecurity: Evidence from Australia. *Economic Analysis and Policy*, 82:264–276.

Burke, M., Dykema, J., Lobell, D. B., Miguel, E., and Satyanath, S. (2015). Incorporating climate uncertainty into estimates of climate change impacts. *Review of Economics and Statistics*, 97(2):461–471.

Campbell-Lendrum, D., Bertollini, R., Neira, M., Ebi, K., and McMichael, A. (2009). Health and climate change: a roadmap for applied research. *The Lancet*, 373(9676):1663–1665.

Carleton, T. A. and Hsiang, S. M. (2016). Social and economic impacts of climate. *Science*, 353(6304):aad9837.

Cattaneo, C. and Peri, G. (2016). The migration response to increasing temperatures. *Journal of Development Economics*, 122:127–146.

Cheema, A. and Patrick, V. M. (2012). Influence of warm versus cool temperatures on consumer choice: A resource depletion account. *Journal of Marketing Research*, 49(6):984–995.

Costello, A., Abbas, M., Allen, A., Ball, S., Bell, S., Bellamy, R., Friel, S., Groce, N., Johnson, A., Kett, M., et al. (2009). Managing the health effects of climate change: Lancet and University College London Institute for Global Health Commission. *The Lancet*, 373(9676):1693–1733.

Dell, M., Jones, B. F., and Olken, B. A. (2009). Temperature and income: reconciling new cross-sectional and panel estimates. *American Economic Review*, 99(2):198–204.

Dell, M., Jones, B. F., and Olken, B. A. (2014). What do we learn from the weather? the new climate-economy literature. *Journal of Economic Literature*, 52(3):740–798.

Deryugina, T. and Hsiang, S. M. (2014). Does the environment still matter? Daily temperature and income in the United States. *NBER Working Paper, No.20750*.

Deschenes, O. (2014). Temperature, human health, and adaptation: A review of the empirical literature. *Energy Economics*, 46:606–619.

Deschenes, O. (2022). The impact of climate change on mortality in the United States: Benefits and costs of adaptation. *Canadian Journal of Economics/Revue canadienne d'économique*, 55(3):1227–1249.

Deschênes, O. and Greenstone, M. (2011). Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US. *American Economic Journal: Applied Economics*, 3(4):152–185.

Deschenes, O., Greenstone, M., and Shapiro, J. S. (2017). Defensive investments and the demand for air quality: Evidence from the NOx budget program. *American Economic Review*, 107(10):2958–2989.

Dillender, M. (2021). Climate change and occupational health: Are there limits to our ability to adapt? *Journal of Human Resources*, 56(1):184–224.

Dillender, M. O. (2019). Climate change and occupational health: Can we adapt? *Employment Research Newsletter*, 26(4):1.

Finger, R. and Lehmann, N. (2012). Modeling the sensitivity of outdoor recreation activities to climate change. *Climate Research*, 51(3):229–236.

Garg, T., Jagnani, M., and Taraz, V. (2020). Temperature and human capital in India. *Journal of the Association of Environmental and Resource Economists*, 7(6):1113–1150.

Gertler, P., Shah, M., and Bertozzi, S. M. (2005). Risky business: the market for unprotected commercial sex. *Journal of Political Economy*, 113(3):518–550.

González-Alonso, J. (2012). Human thermoregulation and the cardiovascular system. *Experimental Physiology*, 97(3):340–346.

González-Alonso, J., Teller, C., Andersen, S. L., Jensen, F. B., Hyldig, T., and Nielsen, B. (1999). Influence of body temperature on the development of fatigue during prolonged exercise in the heat. *Journal of Applied Physiology*, 86(3):1032–1039.

Gosling, S. N., Lowe, J. A., McGregor, G. R., Pelling, M., and Malamud, B. D. (2009). Associations between elevated atmospheric temperature and human mortality: a critical review of the literature. *Climatic Change*, 92:299–341.

Graff Zivin, J., Hsiang, S. M., and Neidell, M. (2018). Temperature and human capital in the short and long run. *Journal of the Association of Environmental and Resource Economists*, 5(1):77–105.

Graff Zivin, J. and Neidell, M. (2014). Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics*, 32(1):1–26.

Hancock, P. A. and Vasmatzidis, I. (2003). Effects of heat stress on cognitive performance: the current state of knowledge. *International Journal of Hyperthermia*, 19(3):355–372.

Heal, G. and Park, J. (2013). Feeling the heat: Temperature, physiology & the wealth of nations. Technical report.

Heyes, A. and Saberian, S. (2019). Temperature and decisions: evidence from 207,000 court cases. *American Economic Journal: Applied Economics*, 11(2):238–265.

Houghton, J. (2009). *Global warming: the complete briefing*. Cambridge university press.

Hsiang, S., Kopp, R., Jina, A., Rising, J., Delgado, M., Mohan, S., Rasmussen, D. J., Muir-Wood, R., Wilson, P., Oppenheimer, M., et al. (2017). Estimating economic damage from climate change in the United States. *Science*, 356(6345):1362–1369.

Hsiang, S. M., Burke, M., and Miguel, E. (2013). Quantifying the influence of climate on human conflict. *Science*, 341(6151):1235367.

Hübler, M., Klepper, G., and Peterson, S. (2008). Costs of climate change: the effects of rising temperatures on health and productivity in Germany. *Ecological Economics*, 68(1-2):381–393.

Huynen, M. M., Martens, P., Schram, D., Weijenberg, M., and Kunst, A. K. (2001). The impact of heat waves and cold spells on mortality rates in the Dutch population. *Envi-*

ronmental Health Perspect, 109(5):463–470.

Karlsson, M. and Ziebarth, N. R. (2018). Population health effects and health-related costs of extreme temperatures: Comprehensive evidence from Germany. *Journal of Environmental Economics and Management*, 91:93–117.

Kim, D. and Lim, U. (2017). Wage differentials between heat-exposure risk and no heat-exposure risk groups. *International Journal of Environmental Research and Public Health*, 14(7):685–702.

Kovats, R. S. and Hajat, S. (2008). Heat stress and public health: a critical review. *Annual Review of Public Health*, 29:41–55.

Krause, N., Frank, J. W., Dasinger, L. K., Sullivan, T. J., and Sinclair, S. J. (2001). Determinants of duration of disability and return-to-work after work-related injury and illness: Challenges for future research. *American Journal of Industrial Medicine*, 40(4):464–484.

Lavetti, K. (2020). The estimation of compensating wage differentials: Lessons from the Deadliest Catch. *Journal of Business & Economic Statistics*, 38(1):165–182.

Lavetti, K. (2023). Compensating wage differentials in labor markets: Empirical challenges and applications. *Journal of Economic Perspectives*, 37(3):189–212.

Lavetti, K. and Schmutte, I. M. (2016). Estimating compensating wage differentials with endogenous job mobility.

Lim, C. L., Byrne, C., and Lee, J. K. (2008). Human thermoregulation and measurement of body temperature in exercise and clinical settings. *Annals Academy of Medicine Singapore*, 37(4):347–353.

Nordhaus, W. D. and Boyer, J. (2003). *Warming the world: economic models of global warming*. MIT press.

Park, J., Pankratz, N., and Behrer, A. (2021). Temperature, workplace safety, and labor market inequality. *IZA DP No.14560*.

Park, R. J., Goodman, J., Hurwitz, M., and Smith, J. (2020). Heat and learning. *American Economic Journal: Economic Policy*, 12(2):306–39.

Patz, J. A., Campbell-Lendrum, D., Holloway, T., and Foley, J. A. (2005). Impact of regional climate change on human health. *Nature*, 438(7066):310–317.

Pilcher, J. J., Nadler, E., and Busch, C. (2002). Effects of hot and cold temperature exposure on performance: a meta-analytic review. *Ergonomics*, 45(10):682–698.

Romanello, M., Walawender, M., Hsu, S.-C., Moskeland, A., Palmerio-Silva, Y., Scamman, D., and et al. (2025). The 2025 report of the Lancet Countdown on health and climate change: climate change action offers a lifeline. *The Lancet*, 406(10521):2804–2857.

Romanovsky, A. A. (2018). The thermoregulation system and how it works. *Handbook of Clinical Neurology*, 156:3–43.

Rosen, S. (1986). The theory of equalizing differences. *Handbook of Labor Economics*, 1:641–692.

Schlenker, W. and Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to US crop yields under climate change. *Proceedings of the National Academy of sciences*, 106(37):15594–15598.

Seneviratne, S. I., Zhang, X., Adnan, M., Badi, W., Dereczynski, C., Luca, A. D., Ghosh, S., Iskandar, I., Kossin, J., Lewis, S., et al. (2021). Weather and climate extreme events in a changing climate. *IPCC Sixth Assessment Report, Ch.11*.

Tansey, E. A. and Johnson, C. D. (2015). Recent advances in thermoregulation. *Advances*

in Physiology Education, 39(3):139–148.
Varghese, B. M., Hansen, A., Bi, P., and Pisaniello, D. (2018). Are workers at risk of occupational injuries due to heat exposure? a comprehensive literature review. *Safety Science*, 110, Part A:380–392.
Wang, X., Jiang, D., and Lang, X. (2017). Future extreme climate changes linked to global warming intensity. *Science Bulletin*, 62(24):1673–1680.
Watts, N., Amann, M., Arnell, N., Ayeb-Karlsson, S., Belesova, K., Berry, H., Bouley, T., Boykoff, M., Byass, P., Cai, W., et al. (2018). The 2018 report of the Lancet Countdown on health and climate change: shaping the health of nations for centuries to come. *The Lancet*, 392(10163):2479–2514.
Zhang, P., Deschenes, O., Meng, K., and Zhang, J. (2018). Temperature effects on productivity and factor reallocation: Evidence from a half million Chinese manufacturing plants. *Journal of Environmental Economics and Management*, 88:1–17.

Table 1: Summary Statistics

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 monthly data on work-related injuries and fatalities by prefecture, as collected by the Ministry of Health, Labour and Welfare (MHLW), with daily maximum temperature and average precipitation data published by the Japan Meteorological Agency for the period from 2014 to 2019. We calculated the number of days in each month falling within specific temperature ranges and derived their means and standard deviations.

Table 2: Work-Related Injuries and 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: Each coefficient represents the estimated impact of an additional day within a given temperature range on the number of work-related injuries at the prefecture level, relative to the impact of an additional day within the 20–25°C interval. It is noted that insignificant temperature ranges are not shown but are included as controls in all estimates. Heteroskedasticity robust standard errors are clustered by prefecture and year-month and are presented in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 3: Work-Related 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: Each coefficient represents the estimated impact of an additional day within a given temperature range on the number of work-related injuries at the prefecture level, relative to the impact of an additional day within the 10–15°C interval. It is noted that insignificant temperature ranges are not shown but are included as controls in all estimates. Heteroskedasticity robust standard errors are clustered by prefecture and year-month and are presented in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 4: Work-Related Fatalities and Temperature - Daily Maximum Temperature

	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: Each coefficient represents the estimated impact of an additional day within a given temperature range on the number of work-related fatalities at the prefecture level, relative to the impact of an additional day within the 20–25°C interval. It is noted that insignificant temperature ranges are not shown but are included as controls in all estimates. Column 4 reports the result obtained after excluding the potentially noisy data from 2011. Heteroskedasticity robust standard errors are clustered by prefecture and year-month and presented in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 5: Employment (x 1000) and Daily Maximum Temperature

	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: Each coefficient represents the estimated impact of an additional day within a given temperature range on the number of employees at the prefecture level, relative to the impact of an additional day within the 20–25°C interval. It is noted that insignificant temperature ranges are not shown but are included as controls in all estimates. Heteroskedasticity robust standard errors are clustered by prefecture and year-month and are presented in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 6: Average Monthly Hours worked and Daily Maximum Temperature

	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: Each coefficient represents the estimated impact of an additional day within a given temperature range on the average monthly hours worked at the prefecture level, relative to the impact of an additional day within the 20–25°C interval. It is noted that insignificant temperature ranges are not shown but are included as controls in all estimates. Heteroskedasticity robust standard errors are clustered by prefecture and year-month and are presented in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 7: Monthly Earning and Daily Maximum Temperature

	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: Each coefficient represents the estimated impact of an additional day within a given temperature range on the logarithm of monthly earning (Japanese yen) at the prefecture level, relative to the impact of an additional day within the 20–25°C interval. It is noted that insignificant temperature ranges are not shown but are included as controls in all estimates. Heteroskedasticity robust standard errors are clustered by preference 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.

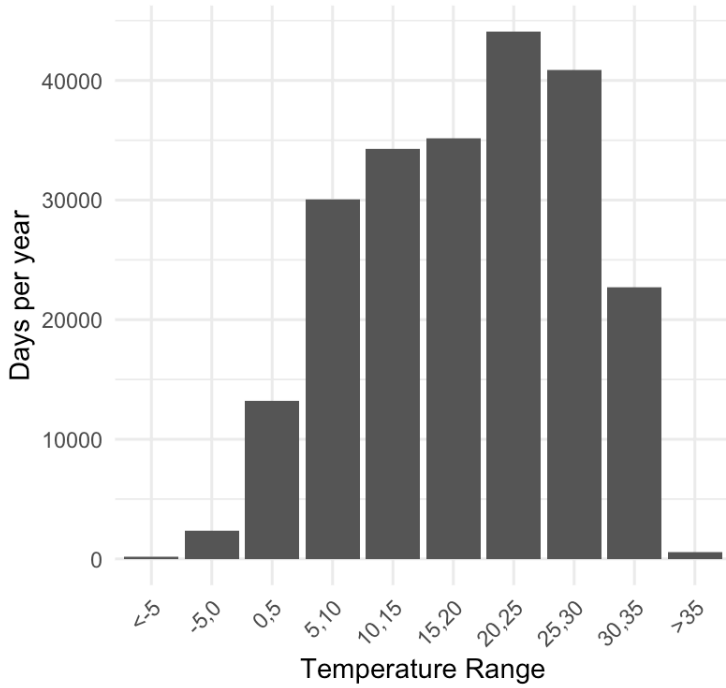


Figure 1: Annual distribution of daily maximum temperature

Notes: Figure 1 shows the annual distribution of daily maximum temperatures (°C) for the period 2007 to 2019.

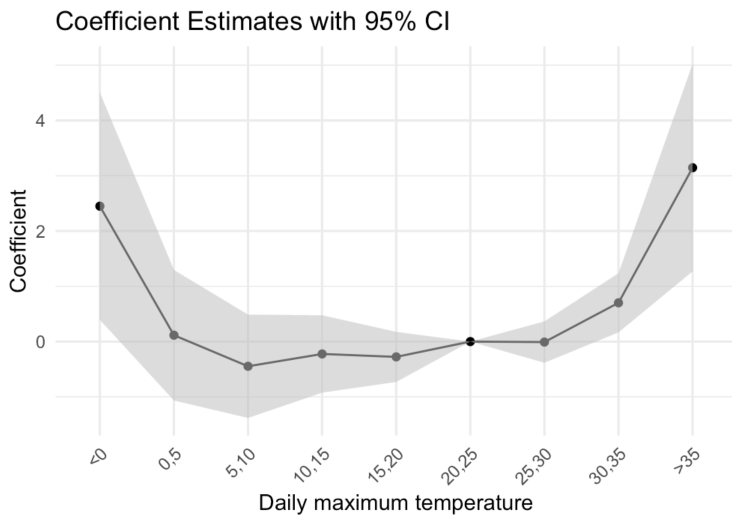
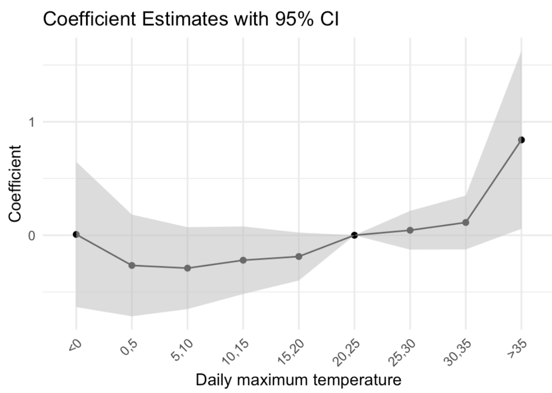


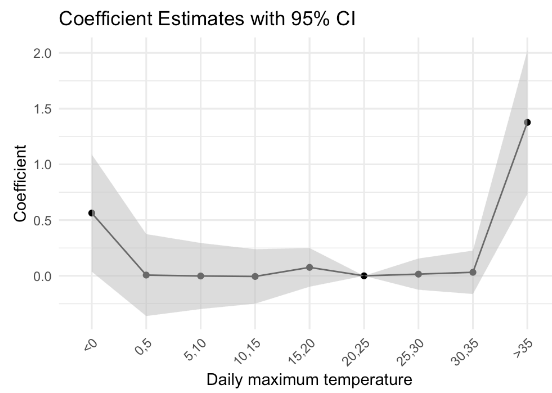
Figure 2: Estimated temperature-injuries relationship

Notes: Figure 2 plots the temperature response function for monthly work-related injuries, obtained by fitting Equation 2. (estimates of coefficients for all variables in column 4 of Table 2). The core explanatory variable indicates the number of days in a month within a certain temperature range. The coefficients can be interpreted as the increase in injury incidence associated with one additional day in the current temperature range, relative to the reference category. The reference category is the temperature interval with daily maximum temperatures from 20 to below $25°C$. Heteroskedasticity-robust standard errors, clustered by prefecture and year-month, underpin the 95% confidence intervals shown in gray.

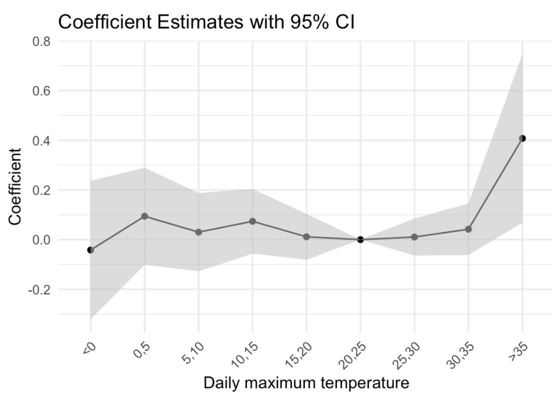
Figure 3: Estimated temperature-injuries relationship: by industry



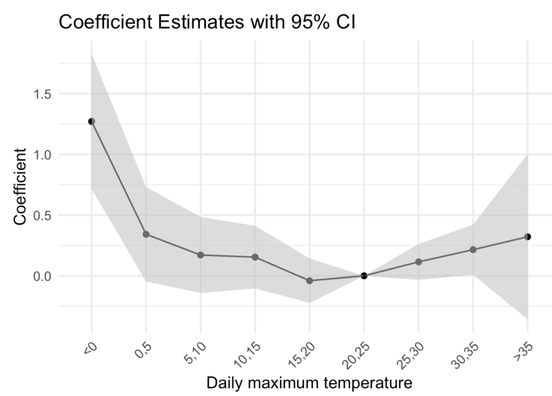
(a) Manufacturing (Cls=1)



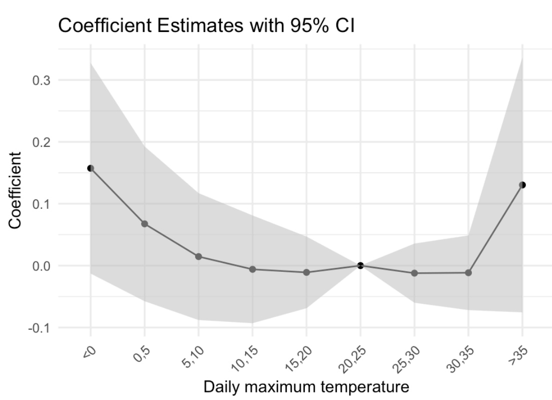
(b) Transportation (Cls=4)



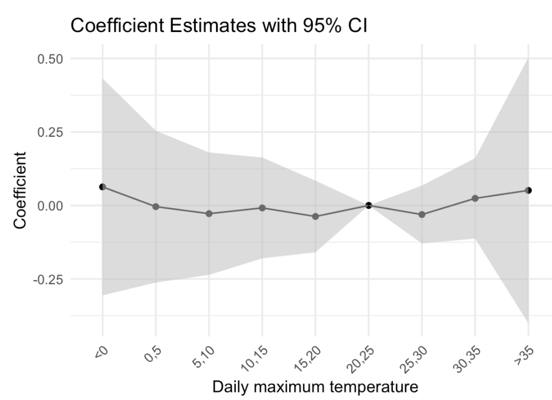
(c) Construction (Cls=3)



(d) Commercial (Cls=8)



(e) Education (Cls=12)



(f) Service (Cls=14)

Notes: Figure 3 plots industry-specific temperature response functions for monthly work-related injuries, estimated using Equation 2. Industry classifications are based on MHLW's Industry Classification Standards. The reference category is the temperature interval with daily maximum temperatures from 20 to below 25°C. Heteroskedasticity-robust standard errors, clustered by prefecture and year-month, underpin the 95% confidence intervals shown in gray.

Appendix A. All Temperature Intervals

In the Appendix, Tables 9 and 10 report full coefficient estimates for all temperature intervals omitted from Tables 2 and 3. Non-extreme temperature intervals show few significant effects on injury risk. Figure 2 reveals an inverted U-shape pattern across all coefficients. This finding differs from the results in Park et al. (2021), likely because their analysis uses injury data from a single region, whereas our estimates are based on nationwide prefecture-level data, offering greater external validity.

Coincidentally, the inverted U-shaped relationship we find between temperature and workplace injuries remains largely consistent with the findings of Barreca et al. (2016) and Barreca et al. (2015). Barreca et al. (2015) focuses on temperature and mortality, using data on the number of mortalities from all regions of the United States as the dependent variable.

Table 9: Worked-Realted Injuries and Daily Maximum Temperature - Supplement for Table 2

	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: It included both significant and insignificant coefficients in contrast with the estimation results for Table 2 showing only significant coefficients. *p<0.1; **p<0.05; ***p<0.01.

Table 10: Work-Related Injuries and Daily Minimum Temperature - Supplement for Table 3

	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: It included both significant and insignificant coefficients in contrast with the estimation results for Table 3 showing only significant coefficients. *p<0.1; **p<0.05; ***p<0.01.