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Research paper

Unsafe temperatures, unsafe jobs: The impact of weather conditions on work-related injuries[☆]

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ABSTRACT

We estimate the impact of temperatures on work-related accident rates in Italy by using daily data on weather conditions matched to administrative daily data on work-related accidents. The identification strategy of the causal effect relies on the plausible exogeneity of short-term daily temperature variations in a given spatial unit. We find that both high and cold temperatures impair occupational health by increasing workplace injury rates. The positive effect of warmer weather conditions on work-related accident rates is larger for men and for workplace injuries. Older workers and jobs in the service sector are instead affected less. Colder temperatures lead to a substantial increase in commuting accidents, especially on rainy days.

1. Introduction

In the past decade, global warming has given rise to a rapidly growing body of scientific literature interested in the impact of weather conditions on several economic and health outcomes (see e.g. Dell et al., 2014; Deschênes, 2014). About the former, recent evidence relates to labor productivity (Neidell, 2017; Adhvaryu et al., 2020; Somanathan et al., 2021; Picchio and van Ours, 2024), well-being (Noelke et al., 2016; Frijters et al., 2020), and allocation of time (Connolly, 2018; Garg et al., 2020). As for the latter, the outcome variable has usually consisted of mortality rate (see e.g. Deschênes and Moretti, 2009; Deschênes and Greenstone, 2011; Adélaïde et al., 2022; Liao et al., 2023; Helo Sarmiento, 2023), low birth weight (Deschênes et al., 2009; Cil and Kim, 2022), and hospitalization rate (see e.g. Piver et al., 1999; Schwartz et al., 2004; White, 2017; Masiero et al., 2022; Rizmie et al., 2022).

A limited number of studies have instead investigated the relation between changing climatic conditions and occupational health, although exposure to excessive heat limits workers' physical functions and capabilities, thereby increasing the risk of injury (ILO,

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2019). The recent comprehensive meta-analysis in Fatima et al. (2021) is based on 22 studies, most of which: (i) analyze the association between temperature and workplace safety and health in particular local areas and/or sectors; (ii) are time-trend analyses, "impairing the possibility to make any causal inference from the study results" (Bonafede et al., 2016). Nevertheless, understanding the causal effect of rising temperatures on workplace health and safety is important for policymakers, not only in regard to designing effective public health policies but also from the economic perspective, given the costs caused by work-related injuries and illnesses and their importance for labor productivity. Our paper contributes to this strand of the literature by estimating the causal effect of temperatures on work-related injuries in Italy in the period 2008–2021.

Only four studies have analyzed the causal effect of temperatures on work-related injuries: Marinaccio et al. (2019), Dillender (2021), Park et al. (2021), and Ireland et al. (2023) relied on plausibly exogenous short-term variations of temperatures in a given spatial unit, so that their estimates were not driven by potential endogenous changes in labor inputs (Park et al., 2021). The results for Texas in Dillender (2021) indicated that both high and low temperatures increased injury rates and that high temperatures had more severe adverse effects in warmer climates. Using data on workplace accidents in California, Park et al. (2021) found that hotter temperatures increased the likelihood of injury on the job in both indoor and outdoor settings, whereas they found no evidence for significant impacts of extreme cold temperature. Their results also suggested that temperature exposure increased labor market inequality, because lower-wage or younger workers experienced greater injury rates, and that there are adaptation potentials because the effect of temperature on work-related injuries fell over time. Ireland et al. (2023) provided evidence of adverse impacts of high temperatures on claims for the Australian state of Victoria in the period 1985–2020, with the greatest effect in the last 5 years, despite considerable economic and heat-related policy changes. The epidemiological study by Marinaccio et al. (2019) estimated, for each Italian province from 2006 to 2010, the association between temperatures and the number of injuries, relying on the variation of local temperatures from the average local temperature across the same day of the week of the same month. Although they added also covariates for special days of the year, like influenza peaks or holidays, they did not fully control for calendar date fixed effects and other daily climatic conditions, which may be correlated with temperatures and the risk of injury.

One of the main problems in studying the effect of weather conditions on work-related accidents is obtaining granular data on both accidents and weather conditions, so as to relate the weather conditions experienced by workers on a particular day and in a given local area with the work-related accidents which occurred on that same day and in that same area (Dillender, 2021). We were able to solve this problem by matching daily data on work-related accidents from the *Istituto Nazionale per l'Assicurazione contro gli Infortuni sul Lavoro* (INAIL), which is the Italian national workers compensation authority for work-related accidents, with daily meteorological data from Copernicus, the European Union's Earth Observation Programme. The former dataset contains information about the Italian province in which the work-related accident took place; the latter dataset reports the meteorological conditions with gridded fields at a spacing of $0.25° \times 0.25°$ in regular latitude/longitude coordinates (Cornes et al., 2018). We matched the meteorological data with provincial accident rates by using the latitude and longitude of the provincial capital. With the resulting matched dataset, we estimated the impact of local temperatures on local accident rates using fixed effects estimators. As in Dillender (2021), in our benchmark model we employed month-year-province fixed effects and calendar-date fixed effects, so that we relied on the plausible exogeneity of short-term variations in daily local temperatures.

Our results complement those set out in the aforementioned literature. Dillender (2021) and Park et al. (2021) limited their studies to two states of the US, Texas and California, respectively, whereas Ireland et al. (2023) focused on the Australian state of Victoria. Therefore, their results cannot be easily generalized to a country with different labor market institutions, economy, climate, and demographic structure. In this paper, we estimate the effect of temperatures on work-related accident rates in Italy, which represents an interesting case study for various reasons. First, Italy is particularly vulnerable to climate change, since it is predicted to suffer greatly from increases in temperatures and from the modification of rainfall patterns. According to the 2019 Global Climate Risk Index (Eckstein et al., 2021), which summarizes fatalities and the losses in terms of GDP, Italy ranked 35th in the world, and 6th among the OECD countries. The forecasts in Spano et al. (2020) predicted that in Italy average temperatures will rise by 2 °C in the period 2021–2050 and by 5 °C by the end of the century, relative to the period 1981–2010. Second, because of both the seas surrounding a large part of the country and the mostly mountainous hinterland, the Italian climate is highly diverse. It ranges from the Mediterranean climate of the coastal areas to the humid subtropical and oceanic climate of the inland northern and central regions. With respect to the aforementioned studies, this allows us to rely on a wider distribution of temperatures, and to assess their effects in areas with different climate and with colder days than those generally experienced in Victoria, Texas and California. Third, in terms of rates of both fatal and non-fatal accidents at work, Italy is characterized by a high incidence: in 2019 it was above the median among the EU-27 countries.[1] Fourth, since the Italian population is ageing quite rapidly, and the health of the elderly is more exposed to heat stress (Levi et al., 2018), the consequences in terms of public health and labor market issues are amplified because more workers in Italy are at greater risk of heat stress and potentially more severely affected than in other countries. Lastly, Italy is characterized by marked economic and social inequalities among regions. Prior research has found that the burden of rising temperatures will fall more on workers in sectors more exposed to heat and living in warmer regions (Connolly, 2018). Hence, this raises questions about the impact of climate change on inequalities that in Italy are particularly significant. Understanding how the climate change may affect occupational safety is important for obtaining a more complete picture of the health effects and costs of climate change.

With respect to Marinaccio et al. (2019), who studied Italy in the period 2006–2010, our contribution extends in several directions. First, we focused on more recent years and on a much longer time window. The past decade is interesting, because it was characterized by a surge in temperatures: the last seven years were globally the warmest on record.[2] Second, we tackled the

[1] See the figures reported in the Eurostat Statistics Explained on Accidents at Work Statistics on https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Accidents_at_work_statistics (last accessed on May 10th, 2024).

[2] See https://climate.copernicus.eu/esotc/2021/globe-in-2021 (last accessed on May 10th, 2024).

issue of the identification of the causal effect of temperatures on work-related injuries more thoroughly: we used multiway high dimensional fixed effects, both at the level of calendar dates and for each interaction among local area, month, and year; and we added further controls for daily climate conditions. Third, we also examined commuting accidents in order to isolate the importance of extreme weather conditions on the risk faced by workers while going to work. Finally, we delved into the issues of adaptation, acclimation, and changing inequalities. Adaptation, i.e. how people may adapt by modifying their behaviors or by investing to avoid negative consequences, and acclimation have not yet been investigated in Italy. Inequalities may be exacerbated by climate change, especially the North and South divide, for example if different geographical areas are differently affected by rising temperatures. To answer these questions, we estimated the heat-sensitivity of workplace injuries in different geographical and climatic zones, and we used a battery of tests to account for the presence of cumulative effects of previous days' temperatures.

This article is organized as follows. Section 2 illustrates our data sources and provides summary statistics on the sample used in the empirical analysis. Section 3 presents the econometric model and the strategy used to identify the effect of temperatures on work-related accidents. Section 4 reports and discusses the main findings. Section 5 concludes and draws policy implications.

2. Data and sample

We conducted the empirical analysis by merging different data sources. We gathered meteorological data from Copernicus, the European Union's Earth Observation Programme. More specifically, we used the E-OBS, a daily gridded land-only observational dataset over Europe.[3] We downloaded meteorological data with a horizontal grid resolution of 0.25° on daily temperature (average, maximum and minimum),[4] precipitation amount, and wind speed from 1 January 2008 until 31 December 2021.

We obtained data on work-related accidents, which are defined as incidents caused by a rapid and harmful action, from INAIL.[5] Employers must report to INAIL work-related accidents, both workplace and commuting accidents, causing injuries which cannot be healed within three days and within 48 h of receiving the corresponding medical certificate. Independently on the time elapsed between the accident and the notification deadline, employers must declare the accident date, which is the information we used to compute daily accident rates at the provincial level. Therefore, the INAIL dataset contains all declared work-related injuries – both at the workplace and while commuting – that caused more than three days of absence from work.[6] After dropping accidents involving persons younger than 16, we collapsed the number of accidents by province and day over the observed time window and divided it by the number of people at work in that year derived from the National Institute of Statistics (Istat).[7] We therefore computed daily provincial accident rates per 100,000 workers. We also derived the same statistics by gender, sector, age, severity of the injury measured by the number of days of absence of the injured worker, and by whether the accident occurred at the workplace or while commuting.

We matched the daily meteorological data with daily provincial accident rates by using the latitude and longitude of the provincial capital. Hence, we used the meteorological conditions in the 0.25° × 0.25° latitude/longitude square where the provincial capital is located as an approximation of the conditions in the whole province.[8] Some provinces, especially those in the centre of Italy which go from the coast to the Apennines or the largest ones, like Sassari or Bolzano, are characterized by heterogeneity in terms of temperatures, with colder temperatures on the mountains.[9] This may generate measurement error because we used temperatures of the 27.8 square kilometres where the provincial capital is located, attenuating the estimated effects of temperature on injury rates. However, this potential problem is reduced by two facts. First, population and employment activities are not uniformly distributed over provinces but are more densely present in capital provinces. Although the surface of provincial capitals amount to only 6.8% of the Italian territory, about 30% of the population and 40% of private employees live and work, respectively, in provincial capitals.[10] Second, as clarified in Section 3, our identification strategy relies on the deviation of the daily temperature from the average temperature in the same month and province. This short-term deviation is likely to be more uniformly distributed in a given province than the daily temperature because of the strong spatial correlation of climatic events.

After matching the two main data sources, we removed the days of national public holidays in Italy and those days in summer and during the Christmas period when workers are typically not at work.[11] The final sample was made up of 480,294 observations, coming from 106 provinces observed for a maximum of 4624 days.

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[3] For more details see https://cds.climate.copernicus.eu/cdsapp#!/dataset/insitu-gridded-observations-europe?tab=overview (last accessed on May 10th, 2024).

[4] Daily mean, maximum, and minimum temperatures are dry bulb temperatures and measured 2 meters above ground level.

[5] See https://dati.inail.it/opendata/default/Daticadenzasemestrale/index.html (last accessed on May 10th, 2024). Further information on the INAIL data is provided in the final appendix.

[6] Although employers are not obliged to report work-related injuries which can be healed within 3 days, in the administrative data some of these events are present. We excluded them because they were likely to be a nonrandom sample of the underlying population of less severe injuries.

[7] Yearly provincial time series on employment by gender and sector are downloadable from http://dati.istat.it/ (last accessed on May 10th, 2024). We cannot fully take into account the potential impact of temperatures on labor supply, since daily employment data are not available.

[8] A 0.25° × 0.25° latitude/longitude square corresponds approximately to 27.8 square kilometres.

[9] The average surface area of Italian provinces is about 2,800 square kilometres, spanning from those larger than 7,000 square kilometres (e.g., Sassari and Bolzano) to those smaller than 400 square kilometres (e.g., Prato and Trieste).

[10] These figures refer to 2015 and come from Atlante Statistico dei Comuni (Istat, https://asc.istat.it/ASC/asc.html, last accessed May 15th, 2024).

[11] We removed 25/04, 01/05, 02/06, 01/11, 08/12, and the time span from 23/12 to 06/01 and from 08/08 to 22/08. On those days, the accident rates decreased artificially because the number of people actually at work diminished. Furthermore, these periods are likely to have been affected by an important variation in the employment distribution, with workers mostly concentrated in sectors like tourism.

Descriptive statistics on work-related accident rates are set out in Fig. A.1 and Table A.1, while Table A.2 reports the daily average temperature over the 24 h after collapsing the data by province and date. On average, the daily provincial accident rate was about 5.6 per 100,000 workers. The fatal accident rate was 1.1 per million workers. These figures diminish to 4.8 and 0.8 if we focus only on workplace accidents. The workplace accident rate was higher for men: it was 5.8 per 100,000 workers for men compared to 3.4 for women. The gender difference was particularly large in terms of fatal workplace accident rates, with the male one (1.28 per million) being almost twelve times higher than the female one (0.11 per million). Approximately 1.5 workplace accidents per 100,000 workers induced an absence from work of more than 30 days. Finally, the highest workplace accident rates are registered in the manufacturing sector.

Like Dillender (2021), we used the deviation in daily temperature from the average temperature in the corresponding month-year-province, conditional on calendar-date fixed effects, to identify the causal effect of temperatures on accidents.[12] Hence, our identification strategy is not compounded by seasonal variation in work-related accidents and thus enabled us to avoid spurious correlation between temperatures and injuries. Indeed, over the seasons and across provinces, the kind of job activities performed may vary as the weather conditions change. For example, during the summer season the workforce may be more concentrated in a set of job activities connected to the tourist industry. Consequently, the work-related accident rate may change, and this may happen at the same time in which the temperatures rise, resulting in a spurious correlation. However, we did not identify responses to gradual and systemic changes in temperatures as predicted by the scientific literature on climate change, and our results may have low external validity for processes like global warming (Dell et al., 2014). We exploit short-run temporal weather variation to identify the temperature effect, whereas long-run effects of climate change may not be necessarily similar. They may be larger due to intensification and accumulation effects. Or, they may be smaller due to, for example, behavioral or technological adaptation. Although imperfect, our results may be nonetheless useful to assess channels through which a changing climate may alter employment quality, sustainability of the social insurance system and labor productivity under existing conditions.

3. Econometric model

In the last few years, there has been a rapid growth of the empirical literature that uses data from non-experimental settings to study how weather conditions affect economic outcomes (Dell et al., 2014). In this framework, the most convincing strategy with which to identify the causal effect is based on longitudinal high-frequency data and on short-term variation over time of the weather outcome within a given spatial entity. By exploiting this (plausibly) exogenous variation in weather variables, it is possible to identify the impact of temperatures on outcomes like work-related injuries.

Operationally, we estimated the following linear model

$$y_{it} = f(temp_{it}; \boldsymbol{\beta}) + \boldsymbol{\alpha}\mathbf{x}_{it} + \delta_t + \gamma_{im} + \varepsilon_{it}, \tag{1}$$

where $i = 1, \dots, 106$ indexes the 106 provinces and $t = 1, \dots, 4624$ refers to the different calendar dates in our observed time window; y_{it} is the measure for the work-related accident rates; δ_t is the calendar-date fixed effects; γ_{im} is the month-year-province fixed effects; $f(temp_{it}; \boldsymbol{\beta})$ is a step function of the daily average temperature and $\boldsymbol{\beta}$ is the parameter vector associated with the linear combination of indicators of temperature intervals; $\mathbf{x}_{it}$ is a $1 \times K$ vector of other weather characteristics which are likely to be correlated with both the daily temperature and to the risk of accident; finally, ε_{it} is the idiosyncratic error term. We weighted each regression by the provincial employment during the year of the observation.

Calendar-date fixed effects δ_t control for daily shocks common at national level and they flexibly capture the national trend in temperatures over time. They are therefore able to purge from estimates the fact that work-related accident rates may vary over particular days of the week, different months of the year, and different years. For example, they account for possible greater absenteeism on “bridging days” (Böheim and Leoni, 2020) or on Mondays and Fridays (Vahtera et al., 2001), which may be correlated to the weather and, at the same time, may affect the accident rate, because absenteeism artificially reduces it.

Month-year-province fixed effects γ_{im} capture possible different patterns of labor market conditions and the business cycle across provinces. They enabled us to base the identification strategy on the exogeneity of daily temperature deviation from the month-year average temperature in the corresponding province.

In order not to impose too strict parametric restrictions on $f(temp_{it}; \boldsymbol{\beta})$, we opted for a step function to map the relation between daily average temperatures and work-related accident rates. More precisely, we divided the support of daily average temperatures among equally sized bins of two Celsius degrees, apart from a first bin for daily temperatures below 0 °C, and a last one for those above 28 °C. We chose the (10,12]° C bin as the reference point, and the corresponding indicator variable was excluded from the set of regressors entering Eq. (1).[13]

The vector $\mathbf{x}_{it}$ contained the constant term, a dummy for dry days (i.e. days with no precipitation), precipitation amount, wind speed, and their quadratic and cubic polynomials.

Finally, the idiosyncratic error term may be correlated within both calendar date t and province i. The former correlation may be due to the fact that, when there are anomalous heat or cold waves on particular days, they often affect large areas, generating spatial correlation across observations (provinces) on those anomalous days. Moreover, spatial correlation in temperature shocks very likely affects our climate gridded dataset because it was obtained by spatial interpolation from station data (Hsiang, 2016). In

[12] Fig. A.2 graphically clarifies this identification source.

[13] This is an innocuous normalization without loss of generality.

regard to the latter correlation, each local area has its own features in terms of geography, climate, infrastructures, employment, and production structure. We therefore suspected that observations were not independent over time within a province. Hence, when estimating the variance–covariance matrix, we used the two-way cluster variance estimator proposed by Cameron et al. (2011), with clusters at provincial and calendar date levels. The number of clusters was sufficiently large in both dimensions, since in our sample we had 106 provinces and 4624 calendar dates. This estimator is robust to heteroskedasticity, within-province serial correlation and cross-sectional spatial correlation.

4. Estimation results

4.1. Main findings

Our main findings are reported in Figs. 1–10, which display the estimated coefficients of each temperature bin, along with their 95% confidence intervals. The full set of estimation results are instead reported in the Appendix.

Panel (a) of Fig. 1 shows that the work-related injury rate increases with both cold and warm temperatures, as in Dillender (2021). A daily average temperature lower than 0 °C (of 0-2 °C) significantly increases the work-related accident rate by 0.727 (0.378) per 100,000 workers, relative to a day with an average temperature of 10-12 °C. With respect to the average work-related accident rate with a temperature of 10-12 °C, this is an approximately 13.3% (6.9%) increase. The lowest work-related accident rate is registered when daily average temperatures are between 4 and 6 °C. When they are above 16 °C, we detected a significant and increasing positive impact of temperatures on the injury rate. When the daily average temperatures are above 28 °C, the injury rate per 100,000 workers is 0.426 points higher than the reference (10-12 °C). This effect is about 7.8% of the average work-related accident rate with a temperature of 10-12 °C. Panel (b) of Fig. 1 reports the impact of temperatures on the fatal accident rate. It shows that warmer temperatures result in higher fatal injury rates. With a daily average temperature above 28 °C, the fatal injury rate per 100,000 workers is higher than that at the reference (10-12 °C) by 0.004 points, which is 40% of the average at the reference (0.010).

Several mechanisms may explain these findings. On the one hand, hotter temperatures create greater risks of physiological traumas like heat stroke, exhaustion and respiratory failure. On the other hand, colder temperatures may cause low energy, muscle strains and falls. More in general, the effect of extreme temperatures on occupational health may operate through different channels, such as workers' lower reaction capacities, cognitive performance and concentration (Graff Zivin et al., 2018); compromised decision-making abilities (Heyes and Saberian, 2019); higher physical and mental stress (Heal and Park, 2016); perceived fatigue and energy outlays (Deschênes and Greenstone, 2011); increased costs of safety investments for both workers and firms (Park et al., 2021); or just because some jobs become more dangerous amid extreme weather conditions.

Panels (c) to (f) display estimates of the effects distinguishing between workplace accidents and commuting injuries. Hot temperatures only impacted on workplace injuries, while cold temperatures are particularly significant for commuting accidents.

The former effect is such that a day with average temperature above 28 °C increases the workplace accident rate by 10% relative to the baseline mean during days in the 10-12 °C range.[14] The effect of hot temperatures may be due to a higher risk of injuries caused by exposure to heat, especially in outdoor workplaces like construction sites (Marinaccio et al., 2019), or in industries which do not provide adequate air-conditioning systems. Furthermore, not all jobs can benefit from climate control, and high temperatures may affect workers' decision-making and impair their cognitive capacities and performances even indoors (Park et al., 2020; Park, 2022).

As regards the effect on commuting accidents, a day with average temperature below 0 °C increases the commuting accident rate by more than 60% compared to 10-12 °C. We speculate that extremely low temperatures may strongly affect safety because of dangerous road conditions due, for example, to slipperiness caused by frost and/or rain. To highlight these possible mechanisms, Fig. 2 shows the estimation results after splitting the sample between dry days and days with precipitations. As in Dillender (2021), the temperature effect on the workplace accident rate is not influenced by rain because the profile of the relation on dry days is very similar to the one on rainy days. The impact of extremely cold temperatures on commuting accidents becomes much more important on rainy days, probably due to the combined effect of frost and rain; when it is rainy and the temperatures are below 0 °C, the commuting accident rate per 100,000 workers is 0.810 points higher than the rate on a rainy day with 10-12 °C (+ 93%).

4.2. Effect heterogeneity

We now focus only on workplace accidents, and we delve further into the issue of effect heterogeneity by exploring whether the effect of extreme temperatures on workplace injuries differs by sector, gender, age, and injury severity. Since sectors are characterized by different production technologies, employees in them may be differently exposed to ambient temperatures, or they may work in environments which are differently equipped and equippable with systems for climate control. Similarly, gender differences and segregation in occupations and industries are still important (Blau and Kahn, 2017), and they may imply that men

[14] The magnitude of this effect is similar to, if not larger than, those in Dillender (2021), Park et al. (2021) and Ireland et al. (2023). Dillender (2021) found that a day with maximum temperatures in the 86-88° F (30-31.1 °C) range or above 100° F (37.8 °C) increased the injury claim rate by, respectively, 5.2% and 8.2%, relative to a day with a high temperature of 59-61° F (15-16.1 °C). Park et al. (2021) found that a day with maximum temperatures between 85-90° F (29.4-32.2 °C) or 100-105° F (37.8–40.6 °C) increases injuries, respectively, by 4.8% and 6.6% relative to 60-65° F (15.6–18.3 °C). Ireland et al. (2023) found that a day with maximum temperatures in the 33-36 °C range rises the claim rate by 6.2% compared to 18-21 °C.

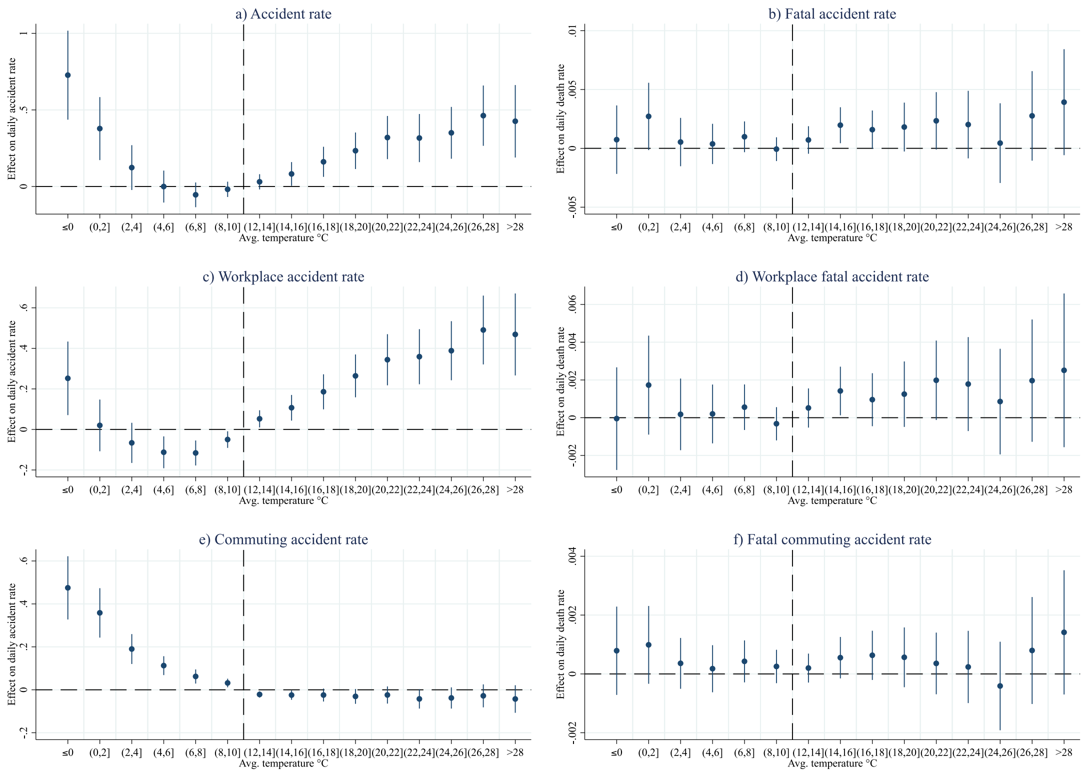

Fig. 1. Effect of today's average temperature on today's accident rates, disaggregated by workplace and commuting accidents.
Notes: The vertical segments are 95% confidence intervals. The vertical dashed lines indicate the reference category (10, 12]° C, whose coefficient is normalized to zero. Each regression is weighted by the provincial employment during the year of the observation. The average of the dependent variable, daily (fatal) injury rates per 100,000 workers, at 10 °C to 12 °C for each graph is as follows: (a) 5.451; (b) 0.010; (c) 4.671; (d) 0.008; (e) 0.780; (f) 0.002.

and women are employed in workplaces which are differently affected by ambient temperatures. Moreover, the temperature gradient may vary with age. Older workers may be at a greater risk of heat stress because the ability to regulate body temperature decreases with age (Blatteis, 2011). However, older workers are more experienced with safety practices and they may be more able to adjust their working habits to cope with heat, for instance by paying more attention to conserving energies and having strategic rest. Finally, we checked whether the impact of ambient temperatures is confined to mild workplace accidents or also involves more serious injuries. By doing so, we enriched the analysis reported in the previous subsection, which already provided evidence in terms of fatal injuries.

To understand if the type of industry in which workers are employed plays a significant role, we estimated Eq. (1) separately for the primary, secondary, and tertiary sectors. Fig. 3 displays the estimates for each sector. Extremely hot temperatures similarly affect the workplace accident rate in all sectors. When the temperature is above 28 °C, the magnitude of this effect is the largest in manufacturing in absolute terms, with an increase of about 0.664 accidents per 100,000 workers with respect to the reference temperature bin (+ 11.1%) and in agriculture in relative terms, with an increase of 0.271 accidents per 100,000 workers (+ 26.5%). Extremely cold temperatures are relevant only in the service sector.[15] When the temperature is below 0 °C, the injury rate per 100,000 workers is 0.303 higher than when the temperature is 10-12 °C (+ 6.9%).

Fig. 4 reports the effect of temperatures on both accident and fatal accident rates by gender. Like Marinaccio et al. (2019), we found that extremely cold temperatures (below 0 °C) are especially important for women. Compared to the average workplace accident rate at 10-12 °C, below 0 °C the female accident rate increases by 6.9%, while the male one rises by 4.7%. By contrast, the male workplace accident rate is more sensitive to heat and, when the temperature is above 28 °C, the injury rate per 100,000 workers is almost 0.700 points higher than at 10-12 °C.[16] These gender differences in our findings are in line with those reported by Park et al. (2021) and they may be due to the fact that men are more likely to be employed in outdoor jobs, like construction

[15] When testing if the coefficients for temperatures below 0 °C (above 28 °C) are different between sectors, we got a p-value equal to 0.043 (0.051).

[16] When above 28 °C, the injury rate increased by 12.6% for men and 5.3% for women with respect to the workplace accident rate at the reference temperature bin. The gender differences in the coefficients of temperature bins were significant at the 1% statistical level for all the bins starting from 16-18 °C and up to 'above 28 °C'.

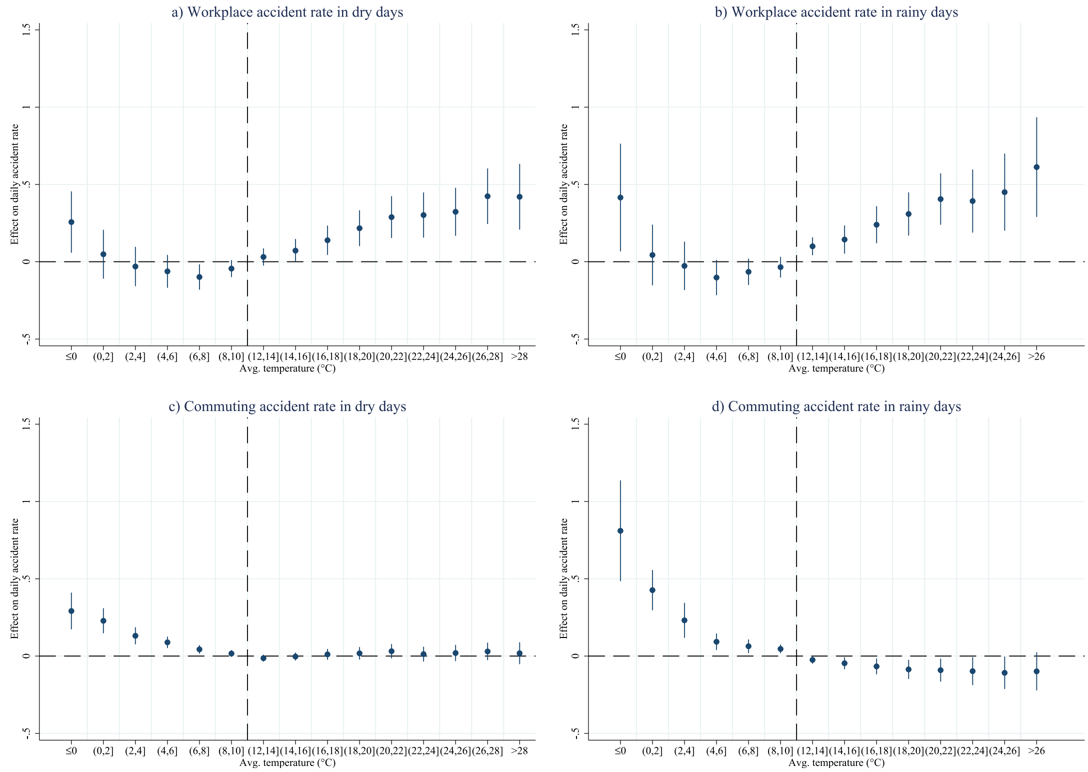

Fig. 2. Effect of today's average temperature on today's accident rates, workplace and commuting accidents in dry and rainy days.
Notes: The vertical segments are 95% confidence intervals. The vertical dashed lines indicate the reference category (10, 12]° C, whose coefficient is normalized to zero. Each regression is weighted by the provincial employment during the year of the observation. The average of the dependent variable, daily injury rates per 100,000 workers, at 10 °C to 12 °C for each graph is as follows: (a) 4.684; (b) 4.651; (c) 0.726; (d) 0.868.

or transport, or physically demanding industrial jobs, which are more likely to cause trauma due to heat stress. Indeed, in 2016 male employees corresponded to 73% of total employment in manufacturing, 91% in the construction sector, 78% in transportation sector, 74% in agriculture, and 83% in mining and quarrying (Labour Force Survey, Eurostat). To dig further into this issue, we estimated the equation for the workplace accident rate by gender and sector. Figure OA.3 in the online appendix shows that hot temperatures have a negative effect on workplace safety for male employees especially in manufacturing, whereas the increase in workplace accidents for females is detected in the service sector only, i.e. the sector in which women are employed the most.

Next, we estimated the effects of temperatures by worker's age after splitting accidents by injured workers' age in three categories: younger (16–29), middle-aged (30–54), and older workers (55–64). Istat does not release provincial employment time series by age. Hence, in computing the injury rates for each category, we used the total provincial employment as the denominator. This means that the plot of the estimated coefficients reported in Fig. 5 should not be read and interpreted in levels, but only in relative deviation from the reference temperature bin. In terms of fatalities, we did not detect age heterogeneity. In terms of non-fatal injury rates, temperatures below 0 °C increased workplace accident rates for middle-aged and older workers very similarly (+ 6.7% and + 8.3%, respectively) but not for young people, as in Dillender (2021). When temperatures were above 28 °C, the injury rate grew significantly with respect to the reference temperature by about 11%–12% for younger and middle-aged workers. The effect on older workers is instead not significant and close to zero (+ 2.5%). These findings are similar to those in Park et al. (2021). A potential explanation may be job tenure which is related to workplace safety behavior, contract type (Picchio and van Ours, 2017), bargaining power and job tasks. Younger workers have lower experience of safety practices at the workplace, have less bargaining power, for instance because they are more likely to be employed with temporary contracts and to be assigned to dangerous and physical exhausting tasks. These contracts and tasks may also be more sensitive to ambient temperatures. Senior workers, because of their greater workplace experience, may be less likely to undertake unforeseen dangerous actions, may be more able to adjust their working habits to cope with heat, for example by paying more attention to conserving energies and having strategic rest, and may be more likely to have stepped to different job tasks, which are less affected by ambient temperatures.

Finally, to check whether the severity of injuries is sensitive to cold and warm ambient temperatures, Fig. 6 presents the results by the severity of the injuries measured by the number of days of absence from work caused by the workplace accident. Severe (less than 30 days of absence from work) and not-severe (more than 30 days of absence from work) injury rates display similar profiles of the temperature effect. Major accidents are much less affected by under-reporting because they are more difficult to

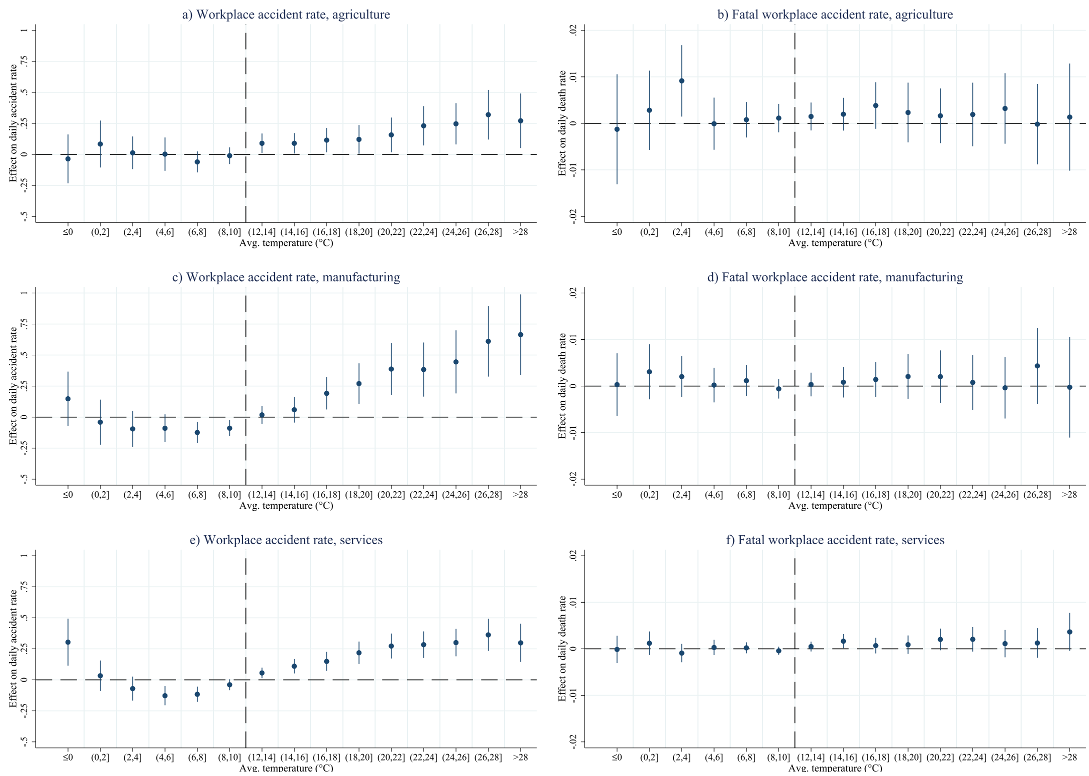

Fig. 3. Effect of today's average temperature on today's accident rates, workplace accidents by sector.
Notes: The vertical segments are 95% confidence intervals. The vertical dashed lines indicate the reference category (10, 12]° C, whose coefficient is normalized to zero. Each regression is weighted by the provincial employment by sector during the year of the observation. The average of the dependent variable, daily (fatal) injury rates per 100,000 workers, at 10 °C to 12 °C for each graph is as follows: (a) 1.021; (b) 0.002; (c) 5.997; (d) 0.012; (e) 4.371; (f) 0.006. Equality tests of the temperature profiles yielded the following *p*-values when compared pairwise: (a) vs (c) 0.003; (a) vs (e) 0.001; (c) vs (e) 0.005; (b) vs (d) 0.371; (b) vs (f) 0.218; (d) vs (f) 0.494.

hide or ignore (Picchio and van Ours, 2017; Bellés-Obrero et al., 2021). Hence, finding similar temperature profiles for minor and major workplace accidents is reassuring about eventual biases stemming from under-reporting behavior and its eventual endogeneity with respect to climatic conditions. Severe injuries were especially sensitive to colder temperatures. Below 0 °C, the rate of severe injuries was 8.1% larger than the one at 10-12 °C; the same effect amounted to 3.9% for minor injuries. Moreover, at 0-2 °C, the rate of severe injuries was still significantly higher (+ 3.9%) that the one at 10-12 °C, whereas for minor injuries the accident rate was in line with the one at the reference temperature. Minor injuries were also more impacted by heat: temperatures above 28 °C significantly increased the rate of minor (major) injuries by 0.367 (0.102) points per 100,000 workers, that is a 11.5% (6.9%) rise with respect to the average injury rate at 10-12 °C.[17]

4.3. Quantification of the effect of rising temperatures

Our estimates suggest that the impact of temperatures on the accident rate is nonlinear, with both cold and warm temperatures creating a higher risk of injuries. Therefore, it is not straightforward to quantify what our findings imply in terms of the impact of rising temperatures on the number of injured workers. To gain a clearer idea about the effect of rising temperatures on work-related accidents, we predicted accident rates both using actual temperatures and after increasing them by two degrees Celsius, which is the expected increase in average temperatures in Italy for the period 2021–2050 (Spano et al., 2020).

Table 1 reports the predicted impact on the daily accident rate and the number of accidents per year at the national level induced by an increase of two degrees Celsius when using 2014 as the reference year, which is the intermediate year of our time window. Moreover, hot temperatures are not only harmful for workers but also costly for firms because workplace accidents reduce labor productivity. In the last column of Table 1, we show the nationwide yearly impact on lost days.[18] An increase by 2 °C in daily

[17] When testing if the coefficients for temperatures above 28 °C (below 0 °C and 0-2 °C) are different between minor and major injuries, we got a *p*-value equal to 0.0002 (0.003).

[18] The full set of estimates of the effect of daily average temperatures on lost days rates per 100,000 workers is available from the authors upon request.

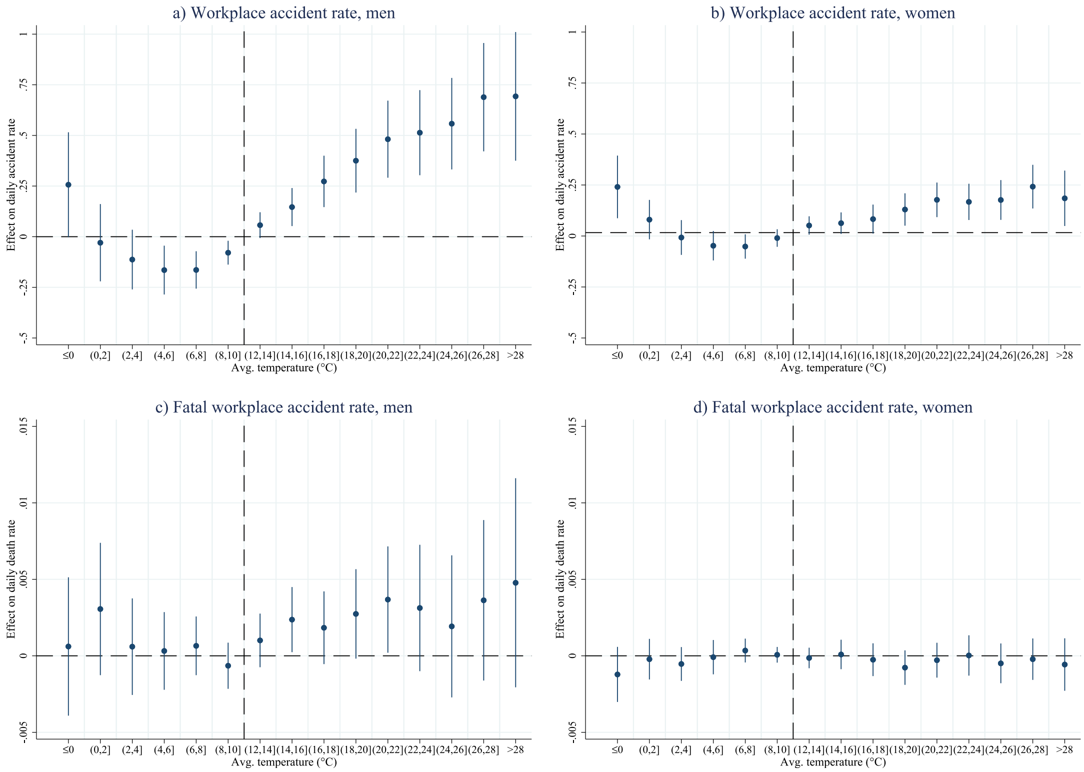

Fig. 4. Effect of today's average temperature on today's accident rates, workplace accidents by gender.
Notes: The vertical segments are 95% confidence intervals. The vertical dashed lines indicate the reference category (10, 12]° C, whose coefficient is normalized to zero. Each regression is weighted by the provincial employment by gender during the year of the observation. The average of the dependent variable, daily (fatal) injury rates per 100,000 workers, at 10 °C to 12 °C for each graph is as follows: (a) 5.514; (b) 3.474; (c) 0.012; (d) 0.002. Equality tests of the temperature profiles yielded the following *p*-values when compared pairwise: (a) vs (b) 0.021; (c) vs (d) 0.045.

temperatures would translate, *ceteris paribus*, into a significant yearly increase of about 6800 work-related accidents and almost 232,000 lost working days. Workplace and commuting accidents would be asymmetrically affected, with a decrease of about 2000 commuting accidents and an increase of approximately 8,850 workplace accidents, which translate into 263,000 yearly lost days. Focusing on the number of yearly work-related accidents by sector, our estimates predict an increase of about 9000 workplace injuries per year in manufacturing, while the days lost in manufacturing industries will be more than twice as many as those in the other sectors. Finally, the impact is markedly different in magnitude between genders, with an yearly increase of about 3800 workplace accidents for women and of almost 13,000 workplace accidents for men, accounting for more than 450,000 days off work.

4.4. Adaptation, accumulation, acclimation

The significance of the policy implications of our findings in light of climate change depends on whether firms and workers can adapt to changes in temperatures over time (Kahn, 2016; Park et al., 2021). The adaptation hypothesis suggests that the dangerous effect of warmer (colder) temperatures should be smaller in warmer (colder) climates. People who live in historically warmer regions should be more used to coping with extremely hot temperatures than people who live in historically colder areas. However, possible limits to adaptation may be not only physical, but also endogenous to workers and firms' investments in new technologies (Park et al., 2021): inefficient ventilation and temperature control in the workplace and the lack of mandatory safety regulations are likely to exacerbate the harmful impact of hot temperatures on workplace safety and labor productivity. Thus, to adapt to a changing climate, firms may aim to reduce workers' injuries and the related loss of productivity by installing air conditioning at the workplace or by allowing a greater flexibility in working hours through mandatory pauses during the hottest hours, a reduction of working time or greater turnover during the day. For example, shifting outdoor activities to cooler times of the day may be particularly helpful for outdoor workers, who are directly exposed to heat-related stress and have fewer options to adapt to extreme temperatures. Investigating whether adaptive behavior is at work is closely relevant to assessing the importance that climate change and global warming may have in the long run (Kahn, 2016; Connolly, 2018).

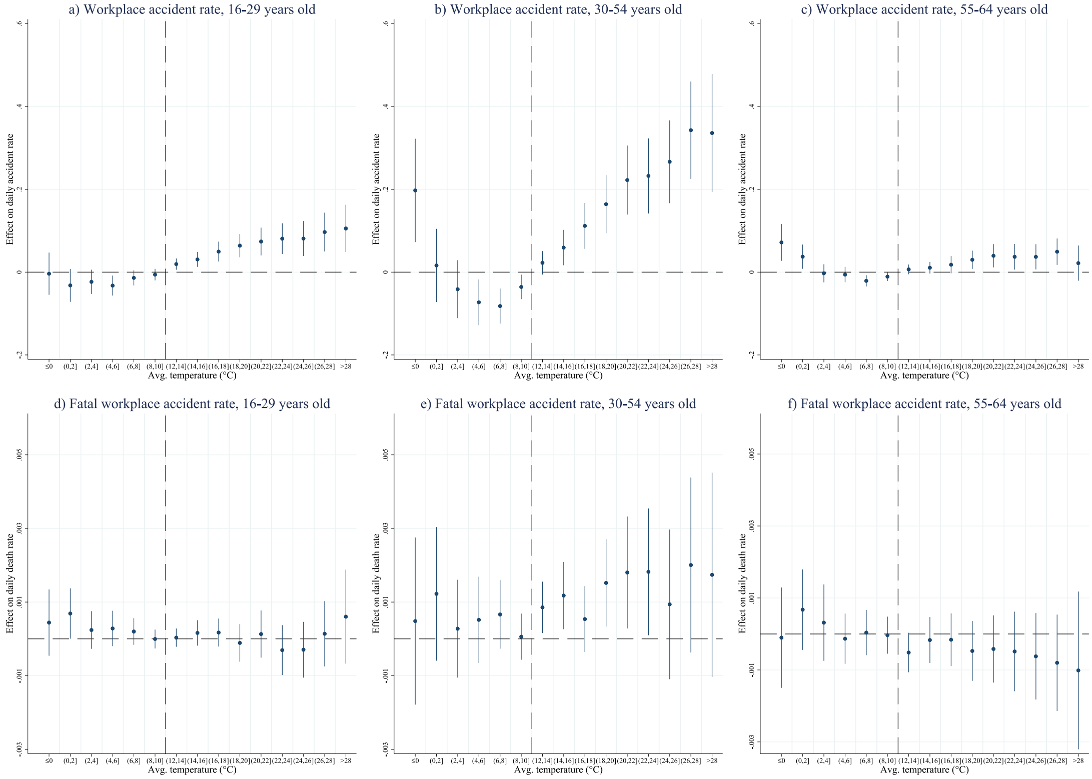

Fig. 5. Effect of today's average temperature on today's accidents, workplace accidents by age.
Notes: The vertical segments are 95% confidence intervals. The vertical dashed lines indicate the reference category (10, 12]° C, whose coefficient is normalized to zero. Each regression is weighted by the provincial employment during the year of the observation. The average of the dependent variable, daily (fatal) injury rates per 100,000 workers, at 10 °C to 12 °C for each graph is as follows: (a) 0.8971 ; (b) 2.9405; (c) 0.8604; (d) 0.0006; (e) 0.0040; (f) 0.0027.

Table 1
Prediction of the effect of a 2 °C increase in daily average temperatures with respect to 2014 temperatures.

Increase induced by +2 °C in:	Daily accident rate	Yearly accidents nationwide	Daily fatal accident rate	Yearly deaths nationwide	Yearly lost days nationwide
Work-related accidents	0.03849***	6812.191***	0.00015	26.437	232,187.300***
	(0.01043)	(1788.679)	(0.00019)	(33.093)	(65,799.010)
Workplace accidents	0.05182***	8852.090***	0.00014	23.894	263,224.700***
	(0.00880)	(1516.659)	(0.00017)	(29.249)	(58,698.570)
Commuting accidents	−0.01333***	−2039.899***	0.00000	2.543	−28,562.15
	(0.00357)	(592.567)	(0.00009)	(15.592)	(28,232.740)
Workplace accidents, agriculture	0.03067***	2745.350***	−0.00006	4.417	125,898.500**
	(0.00985)	(886.382)	(0.00047)	(43.550)	(55,600.900)
Workplace accidents, manufacturing	0.06066***	8829.452***	0.00002	3.902	322,118.200***
	(0.01451)	(2103.738)	(0.00040)	(58.347)	(97,690.760)
Workplace accidents, services	0.04045***	7300.289***	0.00017	29.213	181,158.900***
	(0.00694)	(1282.337)	(0.00017)	(30.693)	(56,994.900)
Workplace accidents, men	0.07532***	12,618.080***	0.00028	46.987	450,135.000***
	(0.01394)	(2344.214)	(0.00028)	(47.468)	(84,399.480)
Workplace accidents, women	0.02238***	3864.910***	0.00003	−5.881	10,278.920
	(0.00570)	(1009.467)	(0.00007)	(12.734)	(55,916.520)

The figures reported in this table were estimated by: (i) computing in each province the difference between the predicted accident rates using the actual 2014 temperatures and the predicted accident rates after adding 2 °C to the daily average temperatures; (ii) averaging over the 2014 sample. The nationwide yearly figures were obtained by multiplying the result of steps (i) and (ii) by the 2014 employment, the 107 provinces, and the 330 days of 2014. Standard errors are in parentheses, are robust to heteroskedasticity, within-province serial correlation and cross-sectional spatial correlation, and were estimated using the delta method.

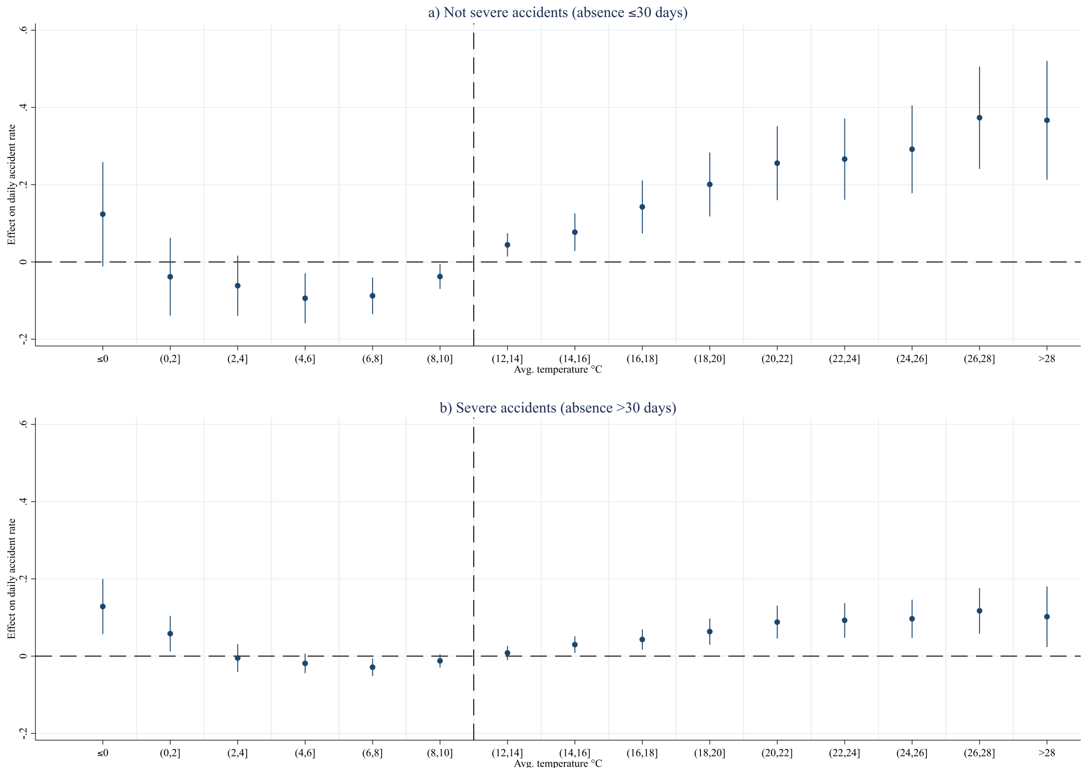

Fig. 6. Effect of today's average temperature on today's accident rates, workplace accidents by severity.
Notes: The vertical segments are 95% confidence intervals. The vertical dashed lines indicate the reference category (10, 12]° C, whose coefficient is normalized to zero. Each regression is weighted by the provincial employment during the year of the observation. The average of the dependent variable, daily injury rates per 100,000 workers, at 10 °C to 12 °C for each graph is as follows: (a) 3.1915; (b) 1.4797. The equality test of the temperature profiles yielded a *p*-value equal to 0.001.

To assess if the adaptation hypothesis is at work in Italy, we performed several empirical exercises. First, to check if Italian workers and firms have been able to adapt to changes in climate conditions over time, we estimated the effect by allowing it to be different over time, as in Park et al. (2021). We interacted each temperature dummy with two-year period dummies. In the case of adaptation, the impact of temperatures on workplace accidents should decrease over time. The 7 graphs in Fig. 7 do not reveal a clear time trend indicating a detrimental effect of hot temperatures. However, formal statistical tests for time heterogeneity of the temperature effects pointed out that we cannot reject the null hypothesis that the temperature effects have been constant over time. The conclusion from formal tests and the visual non-monotonic trend in the heat-sensitivity of the injuries over time may reveal limits to adaptation.

Second, we split the provinces of our sample between those in the Centre-North and those in the South. The North and South of Italy are characterized by conspicuous differences in many socio-economic features and in climate. Questioning this dimension of heterogeneity may provide important evidence in terms of the capacity to adapt to extreme temperatures in different climates. Furthermore, it may help to understand whether climate change may exacerbate geographical inequalities, for example, if extremely hot temperatures have a stronger effect in the South than in the rest of the country. Fig. 8 shows the temperature effect on the workplace accident rate. Graphs (a) and (b) focus on all the workplace injuries in the Centre-North and in the South, respectively. Graphs (c) and (d) report the effect of temperature on the fatal injury rate. On comparing graph (a) with graph (b), we realized that the U-shaped relationship between temperatures and workplace accident rates detected at national level is driven by the Centre-North and is almost nonexistent in the South. In terms of the North-South economic divide, this finding suggests that climate change should not exacerbate the economic gap between the North and the South of the country when it comes to workplace injuries with their productivity, economic, and health costs. In terms of adaptation, if one considers the Centre-North as a climate area colder than the South, our findings contrast with those of Dillender (2021) for the US, because we found that in Italy extremely warm temperatures more strongly impacted the workplace injury rate in the provinces of supposedly colder climate. However, our attribution of the colder/warmer climate label to the geographical Centre-North and South may be too rough an approximation of the real climatic features of the two macro-regions and may conceal significant climatic heterogeneity within the two macro-areas.

Third, to obtain a classification of provinces that was more consistent with their actual climate, we followed Fatima et al. (2021) and used the Köppen–Geiger climate classification (Beck et al., 2018). We distinguished Italian provinces into three different climatic

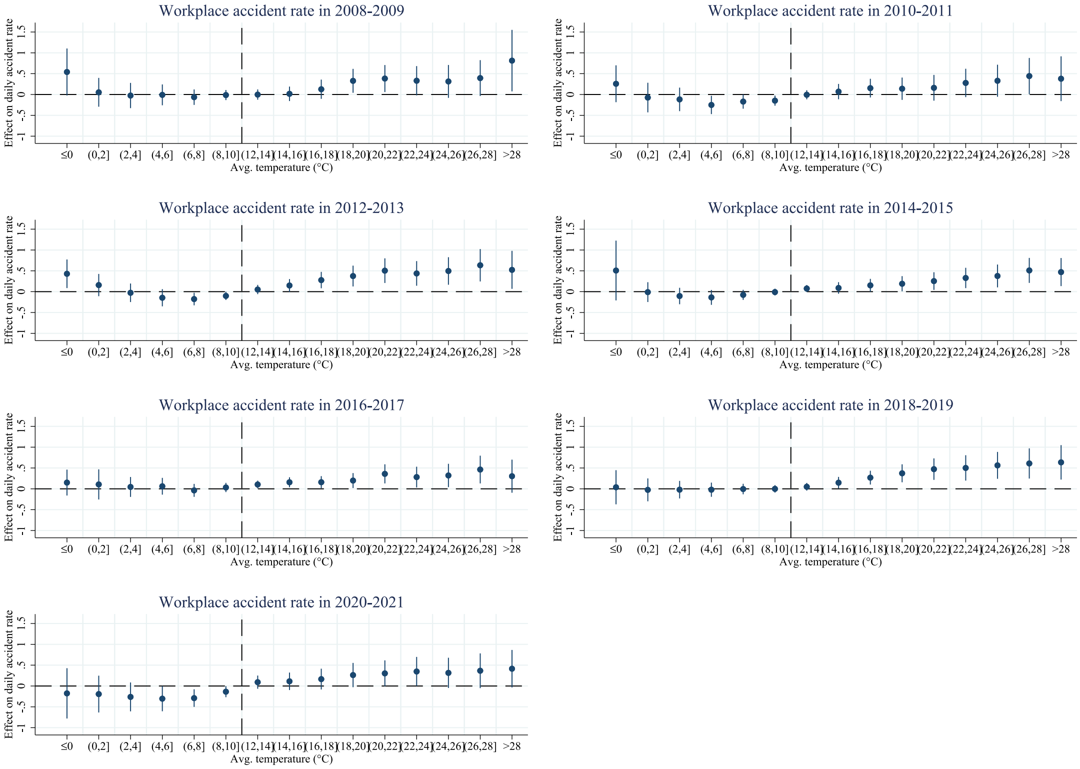

Fig. 7. Effect of today's average temperature on today's workplace accident rates over time.
Notes: The vertical segments are 95% confidence intervals. The vertical dashed lines indicate the reference category (10, 12]° C, whose coefficient is normalized to zero. The estimates are weighted by provincial employment.

zones: oceanic, humid subtropical, and hot Mediterranean. Fig. 9 shows the effect of temperature by climatic area. On the one hand, we found that extremely low temperatures increase the injury rate only in humid subtropical climates and reduce it in oceanic climates, supporting the adaptation hypothesis. On the other hand, we found statistically significant evidence that extremely hot temperatures play a role in the warmest and most humid climates, i.e. in hot Mediterranean and humid subtropical climates, a finding which does not confirm the adaptation hypothesis. As in Dillender (2021), we obtained evidence more in line with avoidance behavior where warmer temperatures are rarer, rather than acclimation as a mitigating factor of extreme temperatures.

Fourth, to check if the relationship between temperatures and occupational health accumulates over time, for example because the accumulation may operate by increasingly affecting fatigue and workers' concentration, we allowed the effect of temperatures up to 3 days previously to affect workplace injury rates at time t. Like Helo Sarmiento (2023), we estimated the following equation:

$$y_{it} = \sum_{l=0}^{3} f(temp_{it-l}; \boldsymbol{\beta}_l) + \boldsymbol{\alpha}\mathbf{x}_{it} + \delta_t + \gamma_{im} + \varepsilon_{it}, \tag{2}$$

where $\boldsymbol{\beta}_0$ is the effect of today's average temperature on today's accident rates, while the cumulative effect derives from summing all of the estimated coefficients of each temperature bin up to three days before today. Table B.2 in the appendix displays the estimated parameters of the contemporaneous and lagged step functions, along with the cumulative effects, i.e. the effect of having 4 days in a row with a given temperature bin with respect to the reference temperature bin. For the workplace accident rate, the temperature on the previous day especially matters, whereas the lags of order 2 and 3 are not statistically significant. The cumulative effect of hot days is significant: the impact of a series of days with warm temperatures on the workplace injury rate is about one third bigger than that of the baseline model.

To further investigate the issue of acclimation, we studied the heat-sensitivity of workplace injuries to exposure to temperature on previous days as in Sexton et al. (2022). We interacted the binary indicators of the step function of today's daily temperature with the difference between the temperature today and the average temperature in the preceding week. As a further test, we replaced

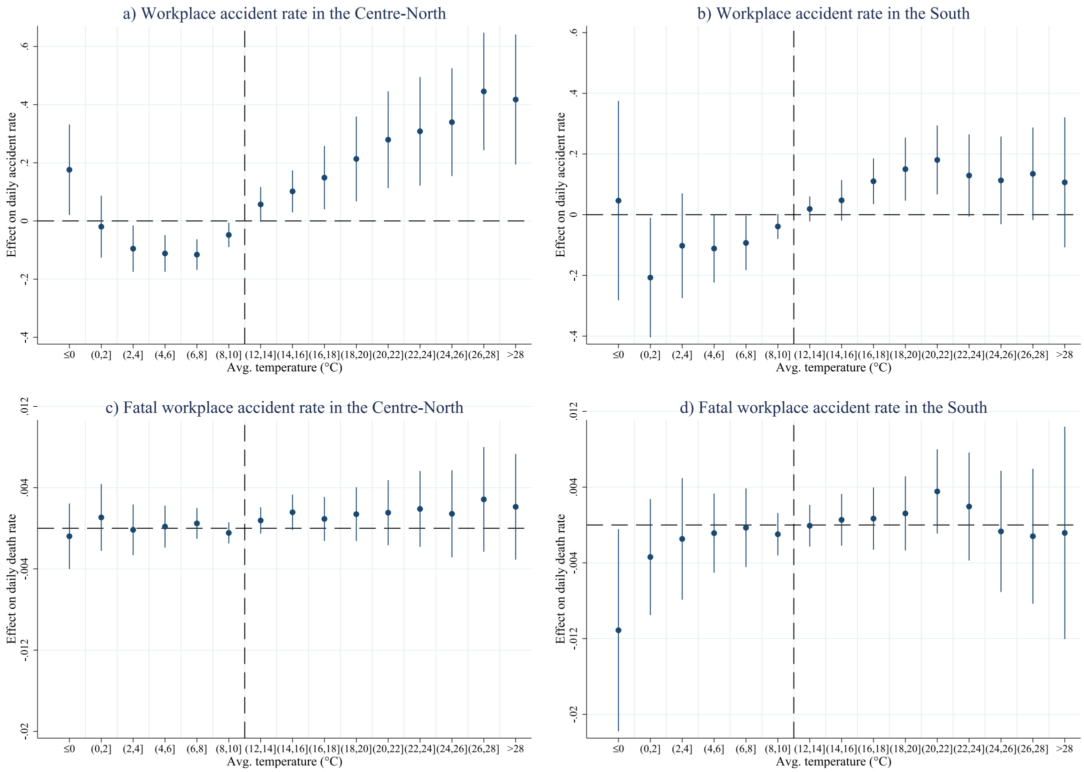

Fig. 8. Effect of today's average temperature on today's accident rates, workplace accidents by geographical area.
Notes: The vertical segments are 95% confidence intervals. The vertical dashed lines indicate the reference category (10, 12]° C, whose coefficient is normalized to zero. Each regression is weighted by the provincial employment during the year of the observation. The average of the dependent variable, daily (fatal) injury rates per 100,000 workers, at 10 °C to 12 °C for each graph is as follows: (a) 5.0920; (b) 3.6917; (c) 0.0072; (d) 0.0093. Equality tests of the temperature profiles yielded the following *p*-values when compared pairwise: (a) vs (b) 0.070; (c) vs (d) 0.498.

such a difference with the number of days above 22 °C in the previous week.[19] In case of habituation, we would expect a positive sign of the interactions for the hottest bins: the warmer the previous week compared to today, i.e. the smaller the difference from the average temperature of the previous week, the lower the workplace injury rate. Table B.3 reports the estimated coefficients of the interaction terms. In all the models, they are jointly not significant. However, for the workplace accident rate, some of the bins for hot temperatures interacted with the difference between current temperature and the average temperature in the preceding week are negative and significant at the 5% level. This means that previous days' heat makes today's high temperature more damaging for workers. This is in favor of accumulation of the effect, as in the previous empirical exercise, rather than acclimation.

4.5. Heat, fatigue and sleep quality

Direct exposure to excessive heat may increase the risk of workplace injury because heat reduces workers' physical and cognitive functions and capabilities. However, the direct and immediate effect may not be the only one. In the previous subsection, we detected evidence in favor of accumulation of the effect, with a series of hot days reinforcing the direct and contemporaneous effect of same-day temperatures. Another indirect effect may arise from poor sleep quality (Ireland et al., 2023): temperatures disturb sleep (Mullins and White, 2019), which in turn may affect day-time physical and mental performance.

In order to provide evidence about the indirect effect coming from night-time temperatures and disentangle it from the one induced by day-time conditions, we modified the baseline model by replacing the average temperature with both minimum and maximum temperatures. Minimum temperatures approximate the temperatures experienced overnight, because minimum

[19] We also included among the set of regressors either the difference between the temperature at time t and the average temperature in the preceding week or the number of days above 22 °C in the previous week.

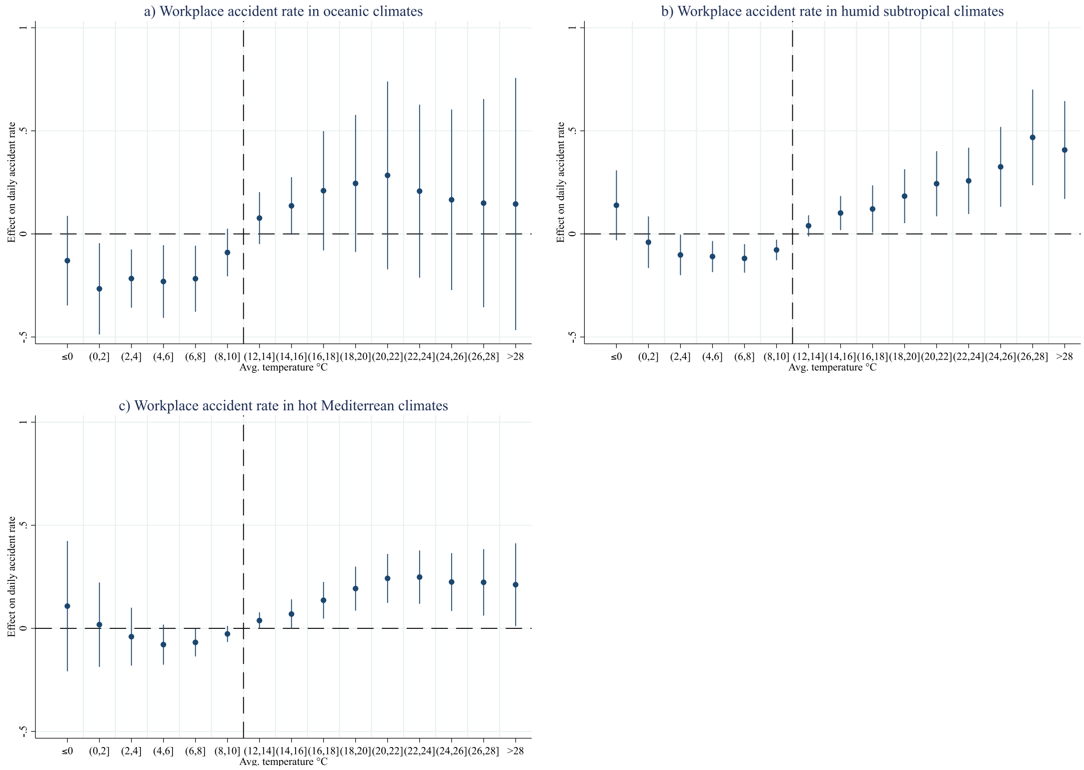

Fig. 9. Effect of today's average temperature on today's accident rates, workplace accidents by climatic area.
Notes: The vertical segments are 95% confidence intervals. The vertical dashed lines indicate the reference category (10, 12]° C, whose coefficient is normalized to zero. Each regression is weighted by the provincial employment during the year of the observation. The average of the dependent variable, daily injury rates per 100,000 workers, at 10 °C to 12 °C for each graph is as follows: (a) 5.4734; (b) 5.4382; (c) 3.7334. Equality tests of the temperature profiles yielded the following *p*-values when compared pairwise: (a) vs (b) 0.030; (b) vs (c) 0.045; (a) vs (c) 0.239.

temperatures are almost always registered in the first hours of the morning, whereas the latter approximate the conditions experienced in the daytime, since maximum temperatures are generally recorded in the first hours of the afternoon.

Fig. 10 shows the effects of maximum and minimum temperatures on workplace injury rates (graphs a and b) and workplace fatal injury rates (graphs c and d). We found that the primary mechanism of the relationship between heat and workplace injuries is the temperature during the day. Nevertheless, minimum temperatures play a role that is by no means irrelevant and, in some cases, very close to the one of maximum temperatures. In terms of fatal injury rate, for which so far we have never detected a temperature effect, graph d shows that when the minimum temperature is above 24 °C, the same-day fatal injury rate increases by 0.005 points, with respect to the reference temperature bin. Compared to the average fatal injury rate at 10-12 °C, this is a 64% increase.

By running this exercise, we cannot claim that the minimum temperature effect is purely induced by poor sleep quality. In fact, it may be due in part to the impact of heat on workplace accidents for night shift workers. Moreover, detailed information about air conditioning penetration in residential buildings is not available.[20] Therefore, we cannot further explore this problem, for example, by looking at sleep quality as a mediator channel of the detected temperature effects.

4.6. Sensitivity analysis

To assess the robustness of our findings, we performed several sensitivity checks. The corresponding estimation results are set out in the online appendix. First, we followed Dillender (2021) and controlled for weather conditions on the days surrounding the calendar date of observation. Thus, we included in the vector of covariates $\mathbf{x}_{it}$ the average temperature, amount of precipitation,

[20] Information on air conditioning penetration in residential buildings is collected by Istat in the survey on Households' Energy Consumption (*Consumi energetici delle famiglie*). However, this survey is available only in 2013 and 2021 and the penetration of air conditioning in residential buildings is made available disaggregated at the regional level.

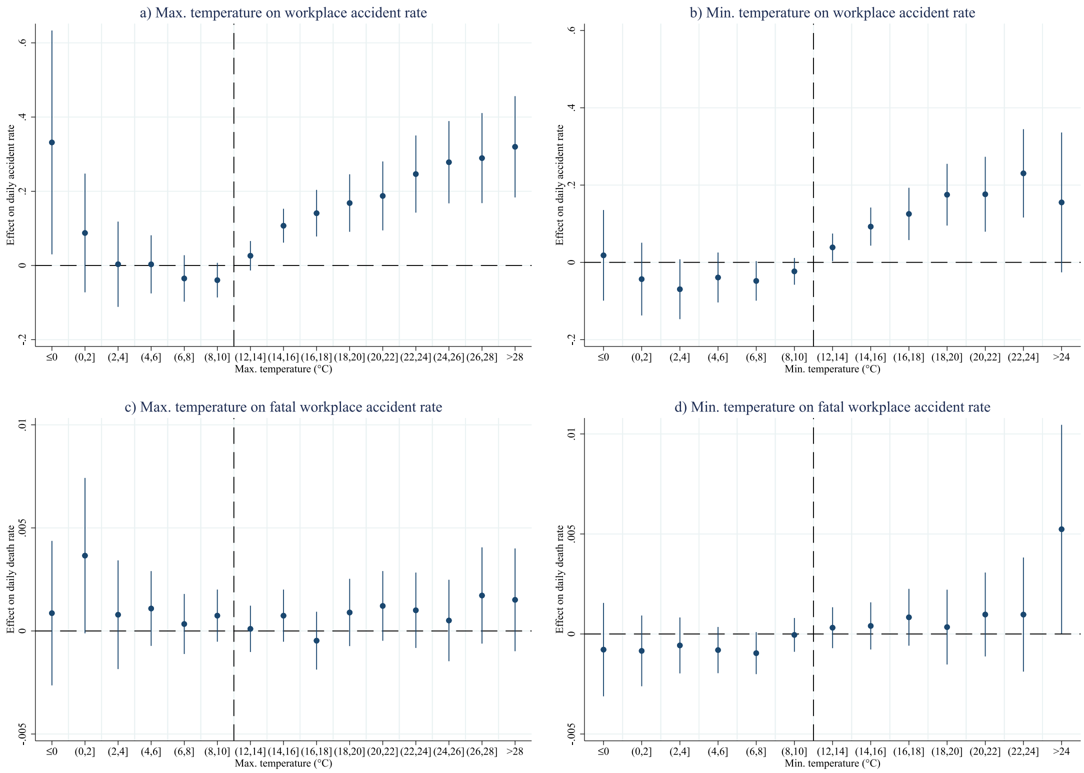

Fig. 10. Effect of today's maximum and minimum temperatures on today's workplace accident rates.
Notes: The vertical segments are 95% confidence intervals. The vertical dashed lines indicate the reference category (10, 12]° C, whose coefficient is normalized to zero. Each regression is weighted by the provincial employment during the year of the observation. The average of the dependent variable, daily (fatal) injury rates per 100,000 workers, at 10 °C to 12 °C for each graph is as follows: (a) 4.9143; (b) 4.6782; (c) 0.0072; (d) 0.0082.

and wind speed on the previous three days and on the following three days. The results are shown in Table OA.10. They are very similar to the baseline estimates.

Second, we tested if using a different set of fixed effects, and therefore a different local variation of the daily temperatures as plausibly exogenous identifying information, might lead to different findings. We replaced fixed effects defined by the triple interaction among province, month, and year with fixed effects defined by the interaction between province and day of the year. Hence, in this sensitivity analysis, we exploited the variation of the provincial temperature on a given day of the year from the 2008–2021 average temperature registered in the same province and on the same day of the year. Table OA.11 shows that the effects of hot temperatures on workplace accident rates are even greater than those of our baseline model.

Third, we replicated the empirical analysis using a different weather data source. Auffhammer et al. (2013) pointed out that, when relying on deviations from averages to identify the impact of weather variables on economic outcomes, robustness analysis should be performed using more than one data source. Many gridded weather data sets are constructed based on observed weather conditions acquired from weather stations located with an irregular distribution and density in space. Then, through interpolation techniques, irregular distributed station data are converted into regular (gridded) distributed data. During this process, idiosyncratic measurement errors may arise, leading to attenuation biases (Fisher et al., 2012). We gathered further climatic data from the JRC MARS Meteorological database of the Agri4Cast project,[21] which contains meteorological observations on a daily basis from weather stations interpolated on a 25 × 25 km grid. The results shown in Table OA.12 are very similar to those obtained when using Copernicus data.

[21] For more information on the JRC MARS Meteorological database, see https://agri4cast.jrc.ec.europa.eu/dataportal/index.aspx (last accessed on May 10th, 2024).

Fourth, we replaced temperature bins with equally sized bins for the Heat Index (HI) calculated as in Blazejczyk et al. (2012), which combines air temperature and relative humidity to determine a measure of the temperature perceived by the human body.[22] Table OA.13 reports these estimation results, which confirm previous findings from our benchmark specifications.

Fifth, to check whether our estimates were mixing seasonal differences with temperature shocks, for example because jobs may be heterogeneous over seasons, we replicated the main estimates using only the warmest months, i.e., from May until October. The results are reported in Table OA.14, and the effects of the warmest temperature bins are very similar to the baseline estimates.

Sixth, as well as through the Italian COVID-19 lockdown (March-May 2020), the pandemic may have interacted with the impact of temperatures in the subsequent months, because of fewer people at the workplace due to sick leaves, quarantine, or smart working. We therefore replicated our main estimates after removing the 2020–2021 period. The results reported in Table OA.15 are in line with the main findings.

Seventh, we assessed the robustness of our findings by switching from the average daily temperature to the maximum daily temperature. The results are reported in Table OA.16, and they lead to the same conclusions as those obtained using average daily temperatures.

Eighth, we checked the robustness of our standard errors to alternative clustering methods. In our benchmark model, the estimation of the variance–covariance matrix was robust to heteroskedasticity, within-province serial correlation and cross-sectional spatial correlation because we used the two-way cluster variance estimator proposed by Cameron et al. (2011), with clusters at provincial and calendar date levels. Table OA.17 in the online appendix displays the main estimation results with standard errors clustered by month and province in brackets, as in Park et al. (2021), and standard errors clustered only by province in braces, as in Dillender (2021) and Ireland et al. (2023). We found that our two-way clustering and Park et al.'s (2021) two-way clustering delivered very similar standard errors: for higher (lower) temperatures our standard errors were slightly more (less) conservative, but there was no impact on the statistical significance level. Clustering only on the basis of the local area for within-province serial correlation would have instead produced much more precise standard errors, in some cases more than 40% smaller. This suggests that ignoring spatial correlation in temperature shocks, which is very likely with granular data about climatic exposure, may more easily lead to a type I error.

Finally, we replicated the main empirical analysis by using the Poisson quasi-maximum likelihood estimator, as in Park et al. (2021) and Ireland et al. (2023). This is a robustness check of the parametric specification of the model. Table OA.18 reports the estimated parameters. It shows temperature profiles very similar to those in Fig. 1. The coefficients of the temperature intervals, if multiplied by 100, can be directly interpreted as the percentage change in the outcome variable with respect to the reference daily temperature (10-12 °C). These percentage impacts are of the same magnitude of those mentioned in Section 4.1. For example, a day above 28 °C leads to an increase of about 7.2% in the workplace accident rate relative to the reference mean of days in the 10-12 °C range.

5. Conclusions

Although economists' interest in global warming has significantly increased in recent years, understanding the causal implications of climate change for health and economic outcomes is a major challenge (Connolly, 2018). Nevertheless, it is of utmost importance to highlight its impact in terms of occupational safety and economic costs, especially in light of a predicted continuous increase in temperatures. Recent evidence converges in underlying the harmful impact of high temperatures on workplace safety, but at the same time providing scant insights and mixed results on possible adaptation mechanisms.

In this article, we have contributed to this growing body of literature by estimating the causal effect of ambient temperatures on work-related accident rates in Italy during the period 2008–2021. Different from previous studies, this paper relied on a more heterogeneous context in terms of economic development, climate, and local labor market characteristics like the Italian one, and on a wider distribution of temperatures which allowed us to estimate also the negative effects of colder days more effectively than studies from the US (Dillender, 2021; Park et al., 2021) and Australia (Ireland et al., 2023). Furthermore, this also makes our results on the effects of weather conditions on workplace safety more likely to be generalized to several contexts.

We matched daily meteorological data with daily information on work-related injuries. Exploiting an identification strategy based on short-term variations in local daily temperatures, we obtained evidence that work-related accident rates increase with both cold and warm temperatures. On the one hand, hot temperatures are significantly harmful in terms of workplace injuries, especially for men, in agriculture and manufacturing, and for young and middle aged workers. On the other hand, extremely cold temperatures increase the commuting accident rate, especially during rainy days. We quantified the economic importance of our results by predicting the variation in the number of injuries and lost work days induced by a 2 °C increase in daily average temperatures. We found that a 2 °C rise in daily average temperatures generates an increase in the number of lost work days, especially for men and in the manufacturing sector (respectively +450,000 and +322,000 lost days per year at national level).

As a further contribution, we performed a broad battery of tests to investigate whether workers and firms adapted to increasingly warmer temperatures, whether the heat effects accumulated over time, and whether increasing temperatures could have exacerbated North-South economic inequalities in Italy. We did not find evidence for a decreasing trend over time in the heat-sensitivity of the injury rate. Moreover, when splitting provinces into climatic areas, we found that hotter temperatures play a role in warmer and more humid climates, a finding which does not support the hypothesis that acclimation has been a mitigating factor of extreme

[22] The HI corresponds to the daily temperature when the latter is below 20 °C.

temperatures. When analyzing the presence of cumulative effects, we found that a series of hot days exacerbates the impact on workplace accident rates. The temperature effects are stronger in the Centre-North of Italy and almost absent in the South, suggesting that climate change should not exacerbate the economic gap between the North and the South of the country, at least in terms of workplace injuries and their associated productivity, economic, and health costs.

Although our analysis provides compelling evidence on the relationship between temperatures and work-related injuries, we cannot shed light on the consequences of such a relationship on the reactions of firms and workers in terms of profit-maximizing strategies and changes in labor supply, respectively (see e.g. Huang et al., 2020). Nonetheless, our results are policy relevant as countries around the world continue to experience increasing temperatures with detrimental effects on labor productivity and workers' health. Given the difficulties in adapting to rising temperatures, our findings highlight the importance of monitoring policies aimed at safeguarding workplace safety and containing both healthcare costs and productivity losses.

Declaration of competing interest

None.

Data availability

Data will be made available on request.

Appendix A. Data and summary statistics

INAIL is the Italian national agency monitoring work-related illness and injury and managing the mandatory insurance scheme against work-related accidents. The INAIL data do not include accidents involving some special categories of workers, like firemen, policemen, servicemen and journalists, because they are covered by other insurers. The workforce covered by INAIL is about 75%–80% of total employment. For example, in 2018 (2021), INAIL covered 16,893 (17,101) thousand workers out of 22,333 (21,849) thousands, i.e. 75.6% (78.3%).[23] The INAIL data provide information like the day of the accident, the Italian province in which the accident took place, some information on the injured person (like gender and age), some administrative and health features of the injury and degree of impairment, some firm characteristics (like sector), and if the accident was at the workplace or while commuting. Thus, this dataset makes it possible to distinguish between accidents involving or not involving a means of transport. In this paper we have used the term 'workplace accident' to refer to those accidents which are strictly work-related, i.e. which did not happen while the worker is commuting. Among the 'workplace accidents', therefore, we included both those involving a means of transport and those not involving one. About 95% of the workplace accidents did not involve a means of transport. With the term 'commuting accident' we refer to injuries that happen while workers are commuting from home to the workplace or vice versa, and are compensated as if they occurred at the workplace. After matching the meteorological data with provincial accident rates by using the latitude and longitude of the provincial capital, the final sample was made up of 480,294 observations, coming from 106 provinces observed for a maximum of 4624 days.[24]

Table A.1 shows descriptive statistics of work-related accident rates after collapsing the data by province, and Fig. A.1 depicts the variability of the accident rates and fatal accident rates across Italian provinces during the observed time-window.

Table A.2 reports descriptive statistics about the daily average temperature over the 24 h after the data have been collapsed by province and date.[25] The mean of the daily average temperature is about 14.5 °C. After splitting its support among 16 (almost) equally spaced bins, the mode is the interval (12 °C, 14 °C], in which 9.3% of the observations lie. Fewer than 5% of the observations corresponds to a daily average temperature higher than 26 °C.

Fig. A.2 graphically clarifies the identification source, focusing on both the whole sample (Fig. A.2(a)) and four selected provinces, the most populated ones, in a particular month of our time window (Fig. A.2(b)).

Appendix B. Further estimation results

See Tables B.1–B.4.

Appendix C. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jebo.2024.06.016.

[23] The number of workers covered by INAIL comes from https://bancadatistatisticaoas.inail.it/analytics/saw.dll?Dashboard. Total employment comes from the Labour Force Survey (Eurostat).

[24] We could not use data for the province of Brindisi, because information about the wind speed was missing. Moreover, the meteorological data were not available on all the days of the observed time window for the following provinces: Matera, Catanzaro, Reggio di Calabria, Trapani, Palermo, Messina, Agrigento, Caltanisetta, Enna, Catania, Ragusa, Siracusa, and Vibo Valentia. They had between 3913 and 4623 daily observations instead of 4624. Finally, the INAIL data for the province of Sud Sardegna are only available from 2013 (2972 daily records).

[25] For 3098 observations, the average daily temperature was either below the minimum temperature or above the maximum temperature. In these cases, we replaced the original value with the midpoint between the maximum and minimum daily temperature.

Table A.1
Summary statistics of the daily provincial accident rates (per 100,000 workers).

Rates per 100,000 workers	Average	Std. Dev.	Min.	Max.
(a) Overall accident rates				
Accident rate	5.6338	3.7273	0.0000	95.4481
Deadly accident rate	0.0106	0.0802	0.0000	9.5422
(b) Accident rates at the workplace or in commuting				
Accident rate in commuting	0.8449	0.9422	0.0000	65.8059
Accident rate at the workplace	4.7889	3.2322	0.0000	76.9326
Deadly accident rate in commuting	0.0027	0.0367	0.0000	6.6251
Deadly accident rate at the workplace	0.0079	0.0709	0.0000	9.5422
(c) Workplace accident rates by gender				
Workplace accident rate for men	5.8129	4.3557	0.0000	91.5783
Workplace accident rate for women	3.3524	2.8908	0.0000	107.2784
Deadly workplace accident rate for men	0.0128	0.1153	0.0000	9.1709
Deadly workplace accident rate for women	0.0011	0.0430	0.0000	13.1449
(d) Workplace accident rates by seriousness of the consequences				
Severe workplace accident rate[(a)]	1.4881	1.2339	0.0000	42.8736
Not severe workplace accident rate	3.3008	2.4355	0.0000	46.7318
(e) Workplace accident rates by sector				
Workplace accident rate in agriculture	1.0503	5.7589	0.0000	1,785.7140
Workplace accident rate in manufacturing	6.3672	5.6239	0.0000	115.3403
Workplace accident rate in services	4.3637	3.0382	0.0000	93.5793
Deadly workplace accident rate in agriculture	0.0033	0.3165	0.0000	934.5794
Deadly workplace accident rate in manufacturing	0.0120	0.1674	0.0000	45.7875
Deadly workplace accident rate in services	0.0063	0.0768	0.0000	13.7781
(f) Workplace accident rates by age				
Workplace accident rate for younger workers (16-29)	0.9165	0.9105	0.0000	24.8412
Workplace accident rate for middle-aged workers (30-54)	3.0433	2.2414	0.0000	60.0837
Workplace accident rate for older workers (55-64)	0.8496	0.8211	0.0000	22.2338
Deadly workplace accident rate for younger workers (16-29)	0.0008	0.0216	0.0000	3.7833
Deadly workplace accident rate for middle-aged workers (30-54)	0.0045	0.0529	0.0000	7.8072
Deadly workplace accident rate for older workers (55-64)	0.0022	0.0353	0.0000	4.5179
# of observations				480,294
# of days				4624
# of provinces				106

Notes: Summary statistics are weighed by the provincial employment (total, by gender, by sector, and by gender).
[(a)] We defined as "severe" those accidents which caused a number of days of absence from work equal to or more than 30.

Table A.2
Summary statistics of daily average temperatures collapsed by province and day.

	Mean	Std. Dev	Min.	Max.
Daily average temperature	14.5143	7.2898	−18.9500	35.6200
Fraction of days below 0 °C	0.0160	0.1255	0.0000	1.0000
Fraction of days (0, 2]°C	0.0255	0.1578	0.0000	1.0000
Fraction of days (2, 4]°C	0.0415	0.1995	0.0000	1.0000
Fraction of days (4, 6]°C	0.0556	0.2292	0.0000	1.0000
Fraction of days (6, 8]°C	0.0685	0.2525	0.0000	1.0000
Fraction of days (8, 10]°C	0.0836	0.2768	0.0000	1.0000
Fraction of days (10, 12]°C	0.0924	0.2896	0.0000	1.0000
Fraction of days (12, 14]°C	0.0931	0.2906	0.0000	1.0000
Fraction of days (14, 16]°C	0.0903	0.2867	0.0000	1.0000
Fraction of days (16, 18]°C	0.0858	0.2801	0.0000	1.0000
Fraction of days (18, 20]°C	0.0812	0.2732	0.0000	1.0000
Fraction of days (20, 22]°C	0.0796	0.2707	0.0000	1.0000
Fraction of days (22, 24]°C	0.0769	0.2665	0.0000	1.0000
Fraction of days (24, 26]°C	0.0641	0.2449	0.0000	1.0000
Fraction of days (26, 28]°C	0.0343	0.1819	0.0000	1.0000
Fraction of days above 28 °C	0.0114	0.1061	0.0000	1.0000
# of observations				480,294

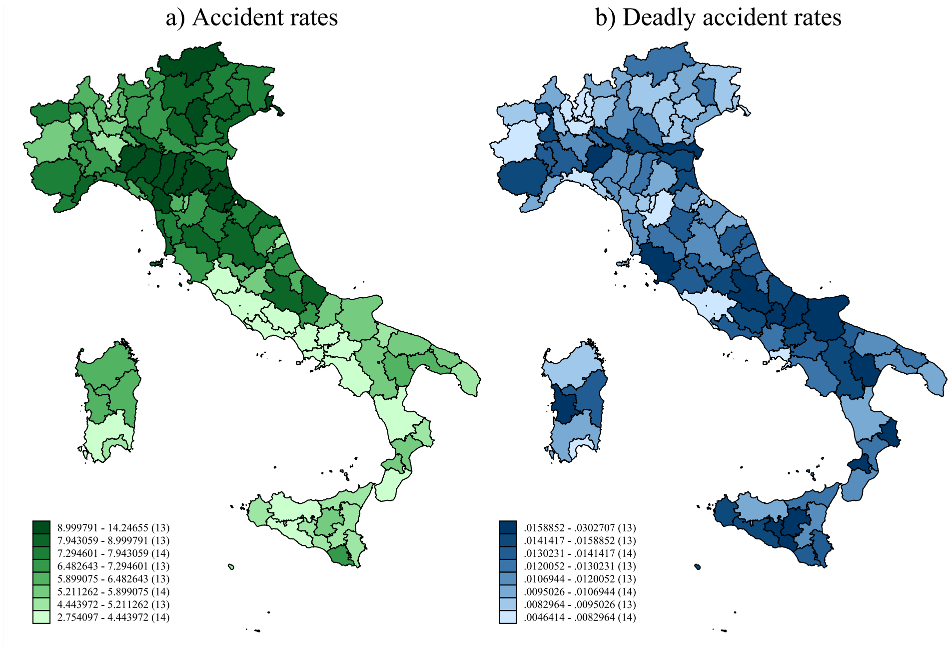

Fig. A.1. Work related daily accident rates per 100,000 workers averaged over 2008–2021.

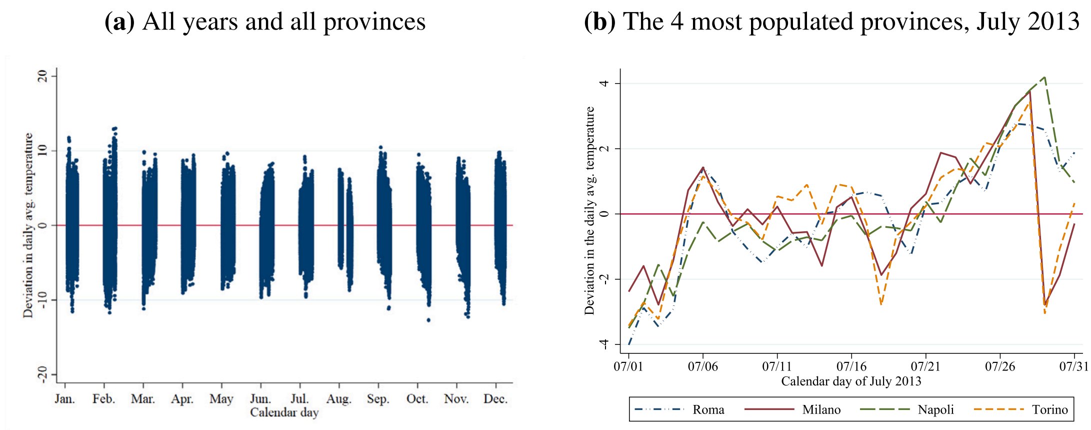

Fig. A.2. Deviation in the daily temperature from the average temperature in the corresponding month-year-province.

Table B.1
Estimation results of the main model used to draw Fig. 1.

	Accident rate (1)	Workplace accident rate (2)	Commuting accident rate (3)	Fatal accident rate (4)	Fatal workplace accident rate (5)	Fatal commuting accident rate (6)
Temperature - Reference: (10, 12]°C						
≤0 °C	0.72679***	0.25208***	0.47471***	0.00074	−0.00005	0.00079
	(0.14650)	(0.09155)	(0.07425)	(0.00147)	(0.00137)	(0.00076)
(0, 2]°C	0.37796***	0.01980	0.35817***	0.00271*	0.00173	0.00099
	(0.10372)	(0.06432)	(0.05803)	(0.00144)	(0.00132)	(0.00067)
(2, 4]°C	0.12337*	−0.06640	0.18977***	0.00053	0.00018	0.00036
	(0.07381)	(0.04995)	(0.03512)	(0.00104)	(0.00096)	(0.00044)
(4, 6]°C	−0.00042	−0.11285***	0.11243***	0.00037	0.00020	0.00018
	(0.05258)	(0.03961)	(0.02217)	(0.00086)	(0.00079)	(0.00040)
(6, 8]°C	−0.05428	−0.11622***	0.06194***	0.00098	0.00056	0.00043
	(0.04074)	(0.03107)	(0.01663)	(0.00066)	(0.00061)	(0.00036)
(8, 10]°C	−0.01841	−0.05008**	0.03167***	−0.00007	−0.00032	0.00025
	(0.02520)	(0.02069)	(0.01006)	(0.00051)	(0.00044)	(0.00029)
(12, 14]°C	0.03056	0.05234**	−0.02179***	0.00071	0.00051	0.00020
	(0.02510)	(0.02133)	(0.00730)	(0.00059)	(0.00052)	(0.00025)
(14, 16]°C	0.08198**	0.10678***	−0.02479**	0.00197**	0.00142**	0.00055
	(0.03910)	(0.03190)	(0.01096)	(0.00077)	(0.00065)	(0.00036)
(16, 18]°C	0.16112***	0.18564***	−0.02452	0.00158*	0.00095	0.00063
	(0.04951)	(0.04359)	(0.01515)	(0.00082)	(0.00071)	(0.00042)
(18, 20]°C	0.23336***	0.26420***	−0.03084*	0.00181*	0.00125	0.00056
	(0.06017)	(0.05330)	(0.01738)	(0.00105)	(0.00087)	(0.00051)
(20, 22]°C	0.31957***	0.34385***	−0.02428	0.00234*	0.00198*	0.00036
	(0.07106)	(0.06363)	(0.02011)	(0.00123)	(0.00106)	(0.00053)
(22, 24]°C	0.31633***	0.35887***	−0.04253*	0.00202	0.00178	0.00024
	(0.07922)	(0.06852)	(0.02267)	(0.00145)	(0.00126)	(0.00062)
(24, 26]°C	0.35030***	0.38837***	−0.03806	0.00044	0.00085	−0.00041
	(0.08535)	(0.07348)	(0.02494)	(0.00171)	(0.00141)	(0.00076)
(26, 28]°C	0.46235***	0.49059***	−0.02824	0.00276	0.00196	0.00080
	(0.09929)	(0.08558)	(0.02693)	(0.00192)	(0.00163)	(0.00092)
>28 °C	0.42580***	0.46872***	−0.04291	0.00392*	0.00251	0.00141
	(0.11926)	(0.10197)	(0.03237)	(0.00227)	(0.00205)	(0.00106)
Dry day	−0.00068	0.01835	−0.01903**	−0.00001	−0.00002	0.00001
	(0.01839)	(0.01348)	(0.00849)	(0.00049)	(0.00040)	(0.00025)
Precipitation (mm)	0.00797***	−0.00199	0.00996***	−0.00006	−0.00002	−0.00004
	(0.00288)	(0.00224)	(0.00134)	(0.00009)	(0.00006)	(0.00006)
Precipitation^2	−0.00842	0.00366	−0.01207***	0.00029	0.00016	0.00013
	(0.00675)	(0.00595)	(0.00309)	(0.00028)	(0.00017)	(0.00019)
Precipitation^3	−0.00084	−0.00576**	0.00493**	0.00001	−0.00007	0.00008
	(0.00311)	(0.00283)	(0.00213)	(0.00016)	(0.00009)	(0.00012)
Wind speed (m/s)	−0.00497	−0.02863	0.02365	0.00038	−0.00041	0.00079*
	(0.03159)	(0.02827)	(0.01709)	(0.00106)	(0.00085)	(0.00043)
Wind speed^2	0.22210	0.72560	−0.50351	−0.01305	0.00628	−0.01933*
	(0.77962)	(0.76802)	(0.38325)	(0.02562)	(0.02032)	(0.01027)
Wind speed^3	−0.38188	−3.57537	3.1935	0.02917	−0.06725	0.09642
	(5.38715)	(5.64600)	(2.56967)	(0.16249)	(0.13953)	(0.05816)
# of observations	480,294	480,294	480,294	480,294	480,294	480,294
# of calendar dates	4624	4624	4624	4624	4624	4624
# of provinces	106	106	106	106	106	106
Adj. R-Square	0.72087	0.70710	0.37854	0.00767	0.00655	0.00571

* p-value <0.10, ** p-value <0.05, *** p-value <0.01. Two-way clustered standard errors are in parenthesis; clusters are at the level of calendar dates and of provinces. All the models contain calendar date fixed effects and month-year-province fixed effects. Each regression is weighted by the provincial employment during the year of the observation.

Table B.2
Lagged effects and cumulative effect of temperature on workplace accident rate.

	Workplace accident rate					Fatal workplace accident rate				
	Current β_0	Lag 1 β_1	Lag 2 β_2	Lag 3 β_3	Cumulative $\sum_{l=0}^{3}\beta_l$	Current β_0	Lag 1 β_1	Lag 2 β_2	Lag 3 β_3	Cumulative $\sum_{l=0}^{3}\beta_l$
Temperature - Reference: (10, 12]°C										
≤0 °C	0.14119*	0.13130	0.04218	0.15901*	0.47368***	−0.00044	0.00241	−0.00313	0.00025	−0.00092
	(0.08451)	(0.09268)	(0.08555)	(0.08887)	(0.14785)	(0.00154)	(0.002)	(0.00205)	(0.00183)	(0.00195)
(0, 2]°C	−0.01481	0.03241	0.00416	−0.01128	0.01049	0.00111	0.00201	−0.00135	0.00029	0.00206
	(0.06604)	(0.06959)	(0.06798)	(0.06381)	(0.09304)	(0.00144)	(0.00151)	(0.00143)	(0.00132)	(0.00166)
(2, 4]°C	−0.06699	−0.01659	−0.00950	−0.00633	−0.09941	−0.00038	0.00128	0.0002	−0.00044	0.00066
	(0.0531)	(0.05793)	(0.05139)	(0.05377)	(0.07436)	(0.00107)	(0.00129)	(0.00131)	(0.00098)	(0.00141)
(4, 6]°C	−0.10851**	0.01286	−0.01123	−0.03061	−0.13749**	−0.00024	0.00117	−0.00014	−0.00114	−0.00035
	(0.04302)	(0.04653)	(0.04094)	(0.0419)	(0.06117)	(0.00087)	(0.00091)	(0.00105)	(0.00085)	(0.00125)
(6, 8]°C	−0.10876***	−0.00258	−0.00521	0.00099	−0.11556**	0.0004	0.00036	0.00019	−0.0006	0.00035
	(0.03319)	(0.03388)	(0.03024)	(0.0344)	(0.05450)	(0.00067)	(0.00075)	(0.00086)	(0.00072)	(0.00105)
(8, 10]°C	−0.04174*	−0.00935	−0.00868	0.02928	−0.03049	−0.00031	0.00012	−0.00046	−0.00036	−0.00102
	(0.02155)	(0.02169)	(0.01935)	(0.02319)	(0.03376)	(0.00044)	(0.00055)	(0.00054)	(0.00058)	(0.00085)
(12, 14]°C	0.03742*	0.04430**	0.01195	−0.03699*	0.05667	0.00039	0.00058	−0.00026	−0.0004	0.00031
	(0.02151)	(0.02108)	(0.0202)	(0.02223)	(0.03510)	(0.00053)	(0.00047)	(0.00061)	(0.00065)	(0.00104)
(14, 16]°C	0.07909**	0.07640**	0.01305	−0.06886*	0.09968**	0.00132*	0.00075	−0.00087	−0.00127	−0.00008
	(0.03361)	(0.03119)	(0.02974)	(0.03576)	(0.04898)	(0.0007)	(0.00067)	(0.00074)	(0.00077)	(0.00107)
(16, 18]°C	0.15338***	0.08211**	0.01862	−0.07214*	0.18198***	0.00101	0.00051	−0.0004	−0.00166*	−0.00054
	(0.04569)	(0.03885)	(0.03775)	(0.0386)	(0.06134)	(0.00078)	(0.00099)	(0.00096)	(0.00092)	(0.00132)
(18, 20]°C	0.22287***	0.11091**	0.00978	−0.05776	0.28580***	0.00144	−0.00004	0.0005	−0.00219*	−0.00029
	(0.05691)	(0.04676)	(0.04396)	(0.04733)	(0.06852)	(0.00099)	(0.00117)	(0.00107)	(0.00113)	(0.00163)
(20, 22]°C	0.29274***	0.11659**	0.01772	−0.04677	0.38029***	0.00228**	−0.00049	0.00065	−0.00272**	−0.00027
	(0.0691)	(0.05295)	(0.04924)	(0.05295)	(0.07799)	(0.00115)	(0.00133)	(0.00129)	(0.0013)	(0.00186)
(22, 24]°C	0.29474***	0.12893**	0.04261	−0.05942	0.40686***	0.00202	−0.00043	0.00133	−0.00333**	−0.00041
	(0.07519)	(0.05788)	(0.0563)	(0.05834)	(0.08453)	(0.00144)	(0.00139)	(0.00135)	(0.00139)	(0.00192)
(24, 26]°C	0.30133***	0.18288***	0.06839	−0.06858	0.48402***	0.00083	0.00011	0.00081	−0.00309**	−0.00134
	(0.07784)	(0.06445)	(0.06367)	(0.063)	(0.09660)	(0.0016)	(0.00157)	(0.00154)	(0.00149)	(0.00218)
(26, 28]°C	0.39275***	0.19427***	0.06795	−0.06807	0.58690***	0.00174	0.00012	0.00062	−0.00232	0.00015
	(0.08671)	(0.07247)	(0.07619)	(0.07157)	(0.11719)	(0.00181)	(0.00184)	(0.00178)	(0.00154)	(0.00236)
>28 °C	0.38700***	0.18980**	0.01860	−0.05207	0.54334***	0.00107	0.00297	0.00173	−0.00367*	0.00210
	(0.11333)	(0.09176)	(0.09082)	(0.08488)	(0.12548)	(0.00222)	(0.00244)	(0.00251)	(0.00205)	(0.00345)
Joint significance test $\beta_1 = \beta_2 = \beta_3 = 0$, p-value			0.0998					0.0204		
Joint significance test $\beta_2 = \beta_3 = 0$, p-value			0.4958					0.0990		
Joint significance test $\beta_1 = 0$, p-value			0.0747					0.7286		
# of observations			480,294					480,294		
# of calendar dates			4624					4624		
# of provinces			106					106		
Adj. R-Square			0.7072					0.0065		

* p-value <0.10, ** p-value <0.05, *** p-value <0.01. Two-way clustered standard errors are in parenthesis; clusters are at the level of calendar dates and of provinces. The model contain calendar date fixed effects, month-year-province fixed effects, a dummy for dry days, precipitation amount, wind speed, and their quadratic and cubic polynomials. The full set of estimation results are available from the authors upon request. Each regression is weighted by the provincial employment during the year of the observation. The standard errors of the cumulative effects in the last column are estimated by the delta method.

Table B.3
Interactions among temperature bins and either the difference from the average temperature of the previous week or the number of days above 22 °C in the previous week.

	Interaction with the difference from the average temperature of the previous week		Interaction with the number of days above 22 °C in the previous week	
	Workplace 1 accident rate (1)	Fatal workplace accident rate (2)	Workplace accident rate (3)	Fatal workplace accident rate (4)
Temperature - Reference: (10, 12]°C				
≤0 °C	0.00999	−0.00066*	−0.04987	−0.00134
	(0.02593)	(0.00037)	(0.05215)	(0.00111)
(0, 2]°C	0.01545	−0.00034	−0.01505	−0.00132
	(0.01852)	(0.00036)	(0.03141)	(0.00079)
(2, 4]°C	0.01199	−0.00007	−0.04350*	−0.00134*
	(0.01501)	(0.00031)	(0.02315)	(0.00071)
(4, 6]°C	0.00472	0.00002	−0.03001	−0.00110
	(0.01275)	(0.00028)	(0.02354)	(0.00075)
(6, 8]°C	0.00936	0.00007	−0.01526	−0.00048
	(0.01141)	(0.00021)	(0.02119)	(0.00076)
(8, 10]°C	−0.00341	−0.00029	−0.01016	−0.00043
	(0.00753)	(0.00020)	(0.01856)	(0.00080)
(12, 14]°C	−0.00401	0.00007	−0.00399	−0.00098
	(0.00797)	(0.00022)	(0.02326)	(0.00078)
(14, 16]°C	−0.01489	0.00017	0.02178	−0.00141*
	(0.01148)	(0.00026)	(0.03413)	(0.00072)
(16, 18]°C	−0.01322	0.00014	0.04650	−0.00084
	(0.01218)	(0.00024)	(0.03536)	(0.00076)
(18, 20]°C	−0.02179*	−0.00022	0.04193	−0.00045
	(0.01270)	(0.00029)	(0.03634)	(0.00076)
(20, 22]°C	−0.03236**	−0.00016	0.04437	−0.00050
	(0.01449)	(0.00033)	(0.03673)	(0.00072)
(22, 24]°C	−0.03641**	0.00031	0.04482	−0.00093
	(0.01526)	(0.00033)	(0.03709)	(0.00072)
(24, 26]°C	−0.04154**	−0.00003	0.04159	−0.00054
	(0.01728)	(0.00039)	(0.03828)	(0.00077)
(26, 28]°C	−0.01942	−0.00030	0.00943	−0.00055
	(0.01950)	(0.00055)	(0.04146)	(0.00100)
>28 °C	−0.04244	0.00201	0.06549	−0.00109
	(0.02897)	(0.00141)	(0.06335)	(0.00202)
Difference from average temperature of previous week	0.00917	0.00012		
	(0.01043)	(0.00019)		
Number of days above 22 °C previous week			−0.02250	0.00070
			(0.03611)	(0.00075)
Joint significance test of interactions, *p*-value	0.3971	0.1938	0.4363	0.0899
# of observations	411,755	411,755	480,294	480,294
# of calendar dates	3966	3966	4624	4624
# of provinces	106	106	106	106
Adj. R-Square	0.70719	0.0068362	0.70712	0.0065433

* *p*-value <0.10, ** *p*-value <0.05, *** *p*-value <0.01. Two-way clustered standard errors are in parenthesis; clusters are at the level of calendar dates and of provinces. All the models contain temperature bins, calendar date fixed effects, month-year-province fixed effects, a dummy for dry days, precipitation amount, wind speed, and their quadratic and cubic polynomials. The full set of estimation results are available from the authors upon request. Each regression is weighted by the provincial employment during the year of the observation.

Table B.4
Estimation results with maximum and minimum temperatures used to draw Fig. 10.

	Workplace accident rate (1)		Workplace fatal accident rate (2)	
	Impact of max. temperature	Impact of min. temperature	Impact of max. temperature	Impact of min. temperature
Maximum/minimum temperature - Reference: (10, 12]°C				
≤0 °C	0.33165**	0.01823	0.00086	−0.00078
	(0.15215)	(0.05916)	(0.00177)	(0.00118)
(0, 2]°C	0.08764	−0.04327	0.00365*	−0.00084
	(0.08071)	(0.04746)	(0.00190)	(0.00089)
(2, 4]°C	0.00335	−0.06947*	0.00079	−0.00057
	(0.05797)	(0.03907)	(0.00133)	(0.00071)
(4, 6]°C	0.00304	−0.03906	0.00109	−0.00080
	(0.03953)	(0.03260)	(0.00092)	(0.00058)
(6, 8]°C	−0.03494	−0.04794*	0.00034	−0.00096*
	(0.03159)	(0.02582)	(0.00073)	(0.00053)
(8, 10]°C	−0.03953*	−0.02322	0.00074	−0.00005
	(0.02353)	(0.01745)	(0.00064)	(0.00043)
(12, 14]°C	0.02619	0.03884**	0.00010	0.00031
	(0.02003)	(0.01806)	(0.00057)	(0.00052)
(14, 16]°C	0.10717***	0.09259***	0.00074	0.00040
	(0.02303)	(0.02488)	(0.00064)	(0.00059)
(16, 18]°C	0.14096***	0.12537***	−0.00047	0.00083
	(0.03170)	(0.03413)	(0.00071)	(0.00072)
(18, 20]°C	0.16832***	0.17510***	0.00090	0.00034
	(0.03910)	(0.04025)	(0.00082)	(0.00094)
(20, 22]°C	0.18751***	0.17631***	0.00122	0.00097
	(0.04685)	(0.04888)	(0.00085)	(0.00106)
(22, 24]°C	0.24643***	0.23038***	0.00100	0.00097
	(0.05244)	(0.05763)	(0.00092)	(0.00144)
(24, 26]°C (>24 °C)	0.27838***	0.15522*	0.00051	0.00524**
	(0.05593)	(0.09125)	(0.00100)	(0.00263)
(26, 28]°C	0.28941***	–	0.00172	–
	(0.06123)		(0.00118)	
>28 °C	0.31992***	–	0.00151	–
	(0.06882)		(0.00126)	
Precipitation (mm)		−0.00157		−0.00002
		(0.00224)		(0.00006)
Precipitation^2		0.00315		0.00016
		(0.00593)		(0.00017)
Precipitation^3		−0.00563**		−0.00007
		(0.00282)		(0.00009)
Wind speed (m/s)		−0.03281		−0.00035
		(0.02824)		(0.00086)
Wind speed^2		0.82239		0.00450
		(0.76082)		(0.02059)
Wind speed^3		−4.05999		−0.05484
		(5.57496)		(0.14177)
# of observations	480,294		480,294	
# of calendar dates	4624		4624	
# of provinces	106		106	
Adj. R-Square	0.70707		0.00655	

* p-value <0.10, ** p-value <0.05, *** p-value <0.01. Two-way clustered standard errors are in parenthesis; clusters are at the level of calendar dates and of provinces. All the models contain calendar date fixed effects and month-year-province fixed effects. Each regression is weighted by the provincial employment during the year of the observation.

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