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Heat and work-related injuries: How temperature measurement affects outcomes

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Abstract

Climate change is producing significant transformations in the labor market, intensifying inequalities due to its heterogeneous effects. This paper proposes an empirical analysis for Italy on the causal relationship between high temperatures and work-related injuries, at the provincial and daily levels, for the period 2014-2022, by exploiting within-country local variation. Our analysis is the first to compare the estimated effects of heat on injuries at the workplace using, besides air temperature, two other meteorological indicators that are comprehensive human heat stress indexes not applied yet in economics: the wet-bulb globe temperature (WBGT) and the universal thermal climate index (UTCI). Our findings confirm that higher temperatures significantly increase the risk of work-related injuries, with coefficients rising across temperature thresholds and varying by indicator and worker characteristics. The study finds that results vary depending on the temperature indicator used, with greater sensitivity observed at moderate-risk temperatures rather than extremes, where indicators align more closely. Our findings suggest the need for advanced climatic metrics and detailed analyses to better assess heat stress effects on workplace safety, particularly in climate-vulnerable regions like Italy.

Keywords: Climate Change, Temperatures, Work-related injuries, Occupational health & safety.
JEL: Q54, Q51, J28, J80, I18.

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1 Introduction

Over the last decades, the impact of global warming has emerged as a critical area of inquiry in economic research (Burke et al., 2023a; Moore et al., 2024; Dell et al., 2012). This growing body of literature reflects an increasing awareness of the pervasive and multifaceted impacts of climate change on economic systems, extending from the micro-level behaviours of individuals (Hoffmann and Rud, 2024) and firms (Zhang et al., 2018), to macroeconomic outcomes at the national and global scales (Bilal and Känzig, 2024; Byrne and Vitenu-Sackey, 2024).

Undoubtedly, a significant portion of these impacts manifests itself through the adverse consequences that high temperatures exert on health. A well-established literature, indeed, shows that climate change and extreme temperatures are risk factors for population health, a threat projected to intensify as the climate continues to warm (Amoadu et al., 2023; Gifford et al., 2019). Moreover, the distribution of these impacts is strongly uneven with certain groups of individuals subject to a higher risk of heat-related morbidity and mortality than others (Yardley et al., 2011).

Among these health-related effects, the relationship between temperatures and work-related injuries represents a crucial research topic. According to the International Labour Organization, 2.41 billion workers worldwide are exposed to excessive heat each year (ILO, 2024a,b). The worsening of working conditions due to global warming has been particularly pronounced in Europe (Eurofond, 2024). Between 2000 and 2020, the share of work-related accidents associated with high temperatures increased by 16.4%, while workers' exposure to excessive heat, both outdoors and indoors, rose by 17.3%, a figure nearly double the global average (ILO, 2024b). The effect of extreme temperatures on worker safety, directly and indirectly, impacts on their health and productivity (Guo et al., 2014), causing GDP losses (Lai et al., 2023), and affecting public health and social security systems (Gould et al., 2024). Empirical evidence shows that the incidence of such injuries due to heat has experienced a dramatic rise globally (Fatima et al., 2021), thereby highlighting the urgency for mitigation strategies aimed at addressing the impact of environmental risk factors on occupational health and safety.

The primary objective of the present paper is to empirically investigate the relationship between heat and work-related injuries. Our study is the first to employ an advanced set of heat stress indicators, including the Wet Bulb Globe Temperature (WBGT) and the Universal Thermal Climate Index (UTCI), which provide a more accurate assessment of climatic variables compared to standard air temperature. Complementing the latter with the WBGT and UTCI indicators enables a more comprehensive evaluation of the impact of heat stress on workplace accidents.

Despite the critical importance of this topic, the body of empirical evidence in this field remains limited.[1] The empirical study by Dillender (2021), using data from Texas over the period 2006-2014, shows that work accidents increase significantly on days of extreme heat, with the effects being particularly pronounced among men and workers with lower levels of education. Park et al. (2021) exploits administrative data encompassing the entire universe of work-related injuries in California from 2001 to 2018 showing that the risk of high-temperature-related injuries is higher for men, young workers and workers with lower incomes. Contrarily, using an extensive dataset from the state of Victoria, Australia, span-

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[1] A number of studies provide evidence in other fields of research. For example, epidemiological studies use occupational injuries as health outcomes to evaluate the effects of exposure to extreme temperatures. See Fatima et al. (2021) for a systematic review.

ning the period 1985–2020, Ireland et al. (2023) find that within manual occupations, women, older workers, and individuals with higher average earnings are more likely to face increased risks of work-related injuries due to heat stress. Concerning the Italian context, Marinaccio et al. (2019) estimate the impact of temperatures on work-related injuries for the period 2006–2010, while Filomena and Picchio (2024) extend the analysis to the period 2008–2021, employing causal inference methods. These studies confirm the positive relationship between high temperatures and workplace injuries, highlighting the greater vulnerability of men compared to women.

Our research contributes to this body of literature by providing new evidence on the impact of temperature on work-related injuries, with a particular focus on workers' physical labor capacity under climate-induced strain (Havenith et al., 2024; Gao et al., 2018; Parsons, 2014). A consistent body of interdisciplinary research (ranging from physiology to public health and climate) emphasizes that the surface air temperature indicator may fail to effectively capture the complex nature of actual climatic variations offering limited value in analyzing the impact of climate on workplace heat stress. To accurately assess the impact of heat on human performance, safety, and health, it is essential to consider four key climatic parameters: temperature, humidity, wind, and radiation (Havenith et al., 2024). Furthermore, projections indicate that the average exposure to extreme humid-heat days is likely to increase more significantly than exposure to extreme dry-heat days, underscoring the importance of exploring this climate dimension (Fan et al., 2024).

At the same time, the literature advocates for the use of more accurate and comprehensive human biometeorological parameters to assess the connection between external climate conditions and human well-being (Gao et al., 2018; Havenith et al., 2024; Zare et al., 2019), yet much of the economic literature relies predominantly on variations in surface air temperature (temperature measured at 2 meters above ground) as the primary predictor. This simplification neglects the complex interactions within the multidimensional climate space, potentially leading to underestimation or overestimation of the economic consequences of heat stress on workers.[2]

To fill this gap, we adopt two new metrics that integrate standard surface air temperature: WBGT and UTCI. WBGT is an experimental index extensively utilized across various research domains including e.g., occupational and public health, sports science, and climate studies (Heo et al., 2019; Lemke and Kjellstrom, 2012; Lucas et al., 2014). This index provides a measure of perceived heat and physiological responses during extreme heat events. Moreover, WBGT is an International Standards Organization (ISO) approved metric to measure the effect of heat on the human body, both in indoor and outdoor environments, during an eight-hour workday and is used in health and safety recommendations for workers exposed to heat (Brimicombe et al., 2023; ISO, 2017; Jacklitsch et al., 2016). The introduction of this indicator is aimed at capturing a ”feels like” temperature that, together with humidity, takes into account solar exposure, acclimatization, clothing, and metabolic heat production.

On the other hand, UTCI represents the state-of-the-art temperature index in biometeorological research and it is mainly used for estimating heat stress in outdoor environments, with a primary focus on promoting public health (Zare et al., 2019). It is a multivariate parameter designed to integrate the human physiology and thermal regulation model with a clothing model (Di Napoli et al., 2020; Gao et al., 2018). Grounded in human physiolog-

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[2] For literature reviews on studies relating temperature to economic outcomes, see Dell et al. (2014) and Picchio and van Ours (2024).

ical responses, UTCI outperforms other climate indicators in predicting thermal perception and comfort (Havenith et al., 2024), making it the most reliable index for assessing thermal sensation beyond standard air temperature. This characteristic makes the UTCI indicator particularly interesting for the present research because it can be adopted to capture also indoor conditions –a relevant feature as far as the service sector is concerned (e.g., office and desk tasks). While such workers experience low physical work intensity, they may still suffer from heat-related impacts due to mental fatigue and physiological strain. Supporting this, Vatani et al. (2016) highlights that UTCI is well-suited for environments with low air velocity and humidity, such as indoor workspaces.[3]

We analyze the Italian labor market over the period 2014-2022 and carry out heterogeneity analyses that can help to highlight vulnerable groups among the working population. To estimate the relationship between high temperature and work-related injuries, we collect administrative data on the universe of work-related injuries provided by the National Institute for Insurance against Accidents at Work (INAIL) archive of insurance compensation claims for accidents. Secondly, we combine this information, at the province level (NUTS3), with climate variables, from Copernicus, the European Union's Earth Observation Programme. This source allowed us to retrieve data on UTCI and climate variables such as air temperature, rain, wind speed and humidity to calculate WBGT. Finally, we exploit the ISO heat stress categories to classify the temperature spectrum into four bins: "$<$ 23 °C", "[23–25) °C", "[25–28) °C", "$\geq$ 28 °C" (ISO, 2017).

We identify through a Poisson model the causal impact of temperature on injuries by exploiting the deviations of the daily temperature recorded in the provincial capital from the average of that temperature at the province-month level (Ireland et al., 2023; Filomena and Picchio, 2024). Our findings confirm previous evidence that heat has a positive impact on workplace accidents. This relationship holds not only for standard air temperature measures but also for the alternative heat stress indices introduced in this study. Our contribution extends beyond existing research by highlighting key differences in how these metrics capture the effects of temperature on occupational injuries. Specifically, we find that WBGT and standard air temperature follow a similar pattern, with WBGT generally yielding more conservative estimates. In contrast, UTCI produces lower coefficients, with statistically significant effects emerging primarily at higher temperature thresholds.

Regarding the magnitude of effects, WBGT coefficients range from 1.6% to 6.6%, increasing from the 23–25°C bin to the +28°C bin. Air temperature coefficients are slightly higher, ranging from 2.7% to 8.5%. In contrast, UTCI coefficients remain more stable but lower, spanning 1% to 3.9%. These estimates imply that on days with temperatures exceeding 28°C, the increase in daily workplace accidents at the provincial level is 3.9%, 6.6%, or 8.5%, depending on the temperature indicator used (UTC, WBGT and air temperature, respectively). Furthermore, heat stress increases the risk of work-related injuries across demographic groups, but the effect varies by age, gender and nationality. Furthermore, we observe variability of the estimates across economic sectors.

The contributions of the paper are manifold. The study is the first to employ an innovative set of heat stress indicators, enabling a more precise estimation of climatic variables compared

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[3] The UTCI indicator shares certain limitations with WBGT when applied to workers wearing protective clothing. Since UTCI relies on a clothing insulation model based on the behavior of urban residents, it requires further refinement to accurately assess heat stress for individuals using specialized safety attire (Gao et al., 2018). Despite these limitations, UTCI remains a robust tool due to its physiological basis and superior performance in predicting heat-induced reductions in physical work capacity (Havenith et al., 2024).

to relying on standard air temperature alone. Moreover, it facilitates a comparative analysis of the estimated effects of heat on workplace injuries. Second, we carry out heterogeneity analyses that can help to identify the most vulnerable groups among working populations. Indeed, we consider individual risk factors such as gender and age, and differently from the existing literature, we also distinguish between native and foreign workers. With respect to previous studies on this topic, we also provide a more granular decomposition of the economic sectors. In addition, we differentiate our analysis by the severity of injuries, distinguishing between fatal, severe, and non-severe accidents. This allows us to investigate the potential bias introduced by underreporting, particularly for moderate and minor injuries, whereas severe and fatal accidents are almost always documented (Antonelli et al., 2024).

The remainder of the paper is organized as follows: Section 2 presents the data whereas Section 3 illustrates the estimation method; Section 4 reports the results of the econometric analysis; Section 5 concludes and suggests some policy implications of our findings.

2 Data

2.1 Work-related injuries data

To conduct our analysis, we relied on administrative data on workplace accidents collected by INAIL. According to national regulations, an accident is defined as any injury occurring during work, caused by a violent event, that results in the death of the individual or partially/fully impairs their work capacity (Presidential Decree n.1124/1965). Additionally, workplace accidents include not only incidents caused by external factors but also those resulting from the worker's own fault.

By law, according to Presidential Decree No. 1124/1965, and for insurance purposes, employers are required to report workplace accidents to INAIL, regardless of whether they occur at the workplace or *in itinere*, provided that the resulting injuries require more than three days for recovery. For statistical purposes, even accidents requiring only one day of absence must be reported to INAIL (Law 19/2017). Consequently, the INAIL dataset contains data on the universe of workplace accidents. Regardless of when it has been reported, employers are required to declare the exact date of the accident. This requirement ensures the accuracy of temporal records, allowing us to observe the number of workplace accidents at the provincial (NUTS3) and daily levels over the period from 2014 to 2022.

Moreover, the INAIL dataset provides information on various aspects related to the accident: the worker's characteristics (anonymous worker identifier, age, gender, nationality, province); the employer's characteristics (employer identifier, economic sector); and the characteristics of the accident (date, province, severity of the accident including fatalities, workplace or *in itinere* accident, number of work-days lost). The final dataset covers more than 5.7 million events with an average of 637,803 injury-related claims per year. However, we reduced the dataset by almost 30% by excluding non-compensable injuries.[4]

Next, we focused on events that concern subjects with at least 16 years and, following Picchio and van Ours (2024), we excluded bank holidays like 25/04, 01/05, 02/06, 01/11, 08/12 and the period from 23/12 to 06/01 and 08/08 to 22/08. On these days, the reported injuries are artificially reduced as the number of people actually working is lower and more

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[4] INAIL verifies if the injury is claimable and provides information on whether the injury is compensable or not.

concentrated in specific sectors, such as tourism. We also deleted observations where the economic sector of the firm is not available. We eventually obtained a dataset of 3 million events.

2.2 Meteorological data

Meteorological data are obtained from Copernicus, the European Union's Earth Observation Programme. The primary dataset used in this study is E-OBS, which provides daily meteorological variables with gridded fields at a spatial resolution of 0.25° × 0.25° in regular latitude/longitude coordinates, covering the period from 1950 to the present. The dataset provides information on average, maximum and minimum air temperature (Celsius degrees, °C), wind speed in meters per second (m/s), total precipitation (millimeters of rain), and relative humidity (RH) [5]. Following the American College of Sports Medicine (1987) measurement –which incorporates air temperature ($airtemp$) and vapour pressure as a proxy for humidity– we exploited this dataset to compose the WBGT index. [6] Specifically, we converted relative humidity into vapour pressure ($vapourpressure$, hPa) (Chen et al., 2019):

$$\text{vapourpressure} = \frac{\text{RH}}{100} \times 6.105 \times \exp\left(\frac{17.27 \times \text{airtemp}}{\text{airtemp} + 237.7}\right) \tag{1}$$

Then, we calculated the WBGT index according to the equation suggested by American College of Sports Medicine (1987):

$$\text{WBGT} = 0.567 \times \text{airtemp} + 0.393 \times \text{vapourpressure} + 3.94 \tag{2}$$

Moreover, we employed the ERA5-HEAT (HumanthErmAlcomforT) dataset –derived from the ERA5 hourly global gridded reanalysis data by the European Centre for Medium-Range Weather Forecasts (ECMWF)–(Hersbach et al., 2020) to measure the UTCI (Di Napoli et al., 2020). This dataset provides a gridded time series of the UTCI index, from 1979 to the present. Each time series consists of spatial grids at 0.25°x 0.25° resolution with hourly intervals, which are subsequently aggregated by taking the daily average. [7].

The literature and relevant policy measures have identified 6 occupational heat stress categories associated with the WBGT level, from 23 °C to 33 °C (Brimicombe et al., 2023; ISO, 2017) In this analysis, we applied the WBGT classification to all indexes as it is widely applied in the field of workplace safety, and thus it allows us to assess how these categories would apply to the other indicators. Table 1 displays the WBGT heat stress categories. Using the risk categories defined by international standards highlights how different indicators affect the evaluation of occupational heat stress. Finally, we collapsed temperature levels above 28 °C in one bin, similarly to Filomena and Picchio (2024).[8]

To examine the relationship between different temperature indicators, Figure 1 presents the average daily temperature for each month based on the three metrics used in this study:

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[5] Daily mean relative humidity is measured near the surface at a height of 2 meters.

[6] It is worth noting that, even if this method is widely applied in literature, in some contexts it may have a large bias (Brimicombe et al., 2023; Chen et al., 2019; Kong and Huber, 2022).

[7] Data are publicly and freely available for download at the Climate Data Store which has been developed as part of the Copernicus Climate Change Service (C3S) at ECMWF. See https://cds.climate.copernicus.eu/ (last accessed February 2025).

[8] As can be observed in Table A.1, which shows the average daily temperature in each bin for all the years considered in our study, the number of days with temperatures above 28 °C is extremely low.

Table 1: Heat-related work stress categories

WBGT (°C)	Maximum recommended workload	Approximate work/rest cycles (minutes)	Category
> 33	Rest	Rest	5
30–33	Light	15/45	4
28–30	Moderate	30/30	3
25–28	Heavy	30/15	2
23–25	Very heavy	45/15	1
< 23	No recommendation	No recommendation	0

Source: (Brimicombe et al., 2023; ISO, 2017).

air temperature, WBGT, and UTCI. Two key patterns emerge from this comparison. First, WBGT is closely related to air temperature, as it is a linear combination of air temperature and vapor pressure (i.e., humidity) (American College of Sports Medicine, 1987; Brimicombe et al., 2023). Notably, WBGT tends to produce higher temperature values during the winter months, which may indicate a potential bias in air temperature measurements, particularly in colder seasons. his pattern can be attributed to the fact that WBGT was specifically designed for screening heat stress, outlining safe heat thresholds for workers and providing precautional recommendations on the duration and intensity of work for workplace safety (Brimicombe et al., 2023). In contrast, UTCI exhibits a more complex relationship with air temperature, as it is a comprehensive bioclimatic index designed to evaluate the physiological comfort of the human body under specific meteorological conditions (Bröde et al., 2012). Unlike air temperature and WBGT, UTCI accounts for additional factors such as wind speed and solar radiation, integrated with a clothing model, which collectively influences the body's physiological responses to thermal environments. The UTCI equivalent temperature is defined as the air temperature in a reference environment that would produce the same physiological strain value as the actual combination of meteorological variables, including wind, radiation, humidity, and air temperature (Jendritzky et al., 2012). For instance, if the UTCI value is 30°C, it implies that the body perceives the thermal environment as if it were exposed to a temperature of 30°C, even if the actual air temperature is significantly lower. This explains why UTCI generally registers higher values than air temperature, particularly during warm and humid months, while displaying lower values during colder periods. As a result, UTCI tends to converge with WBGT during the hottest months of the year but diverges significantly in winter, reflecting its broader capacity to account for thermal comfort and physiological stress across different climatic conditions.

2.3 Descriptive statistics

In order to conduct the analysis, we matched the meteorological data with daily provincial accidents by using the latitude and longitude of the provincial capital. We ended up with a sample corresponding to roughly 257,000 observations for 107 provinces.[9] In this section, we show some descriptive statistics for the matched sample.

Table 2 reports insights into the accident rates categorized by total, fatal, severe, non-severe, native, foreign, male, and female statistics, focusing on both daily and yearly figures.

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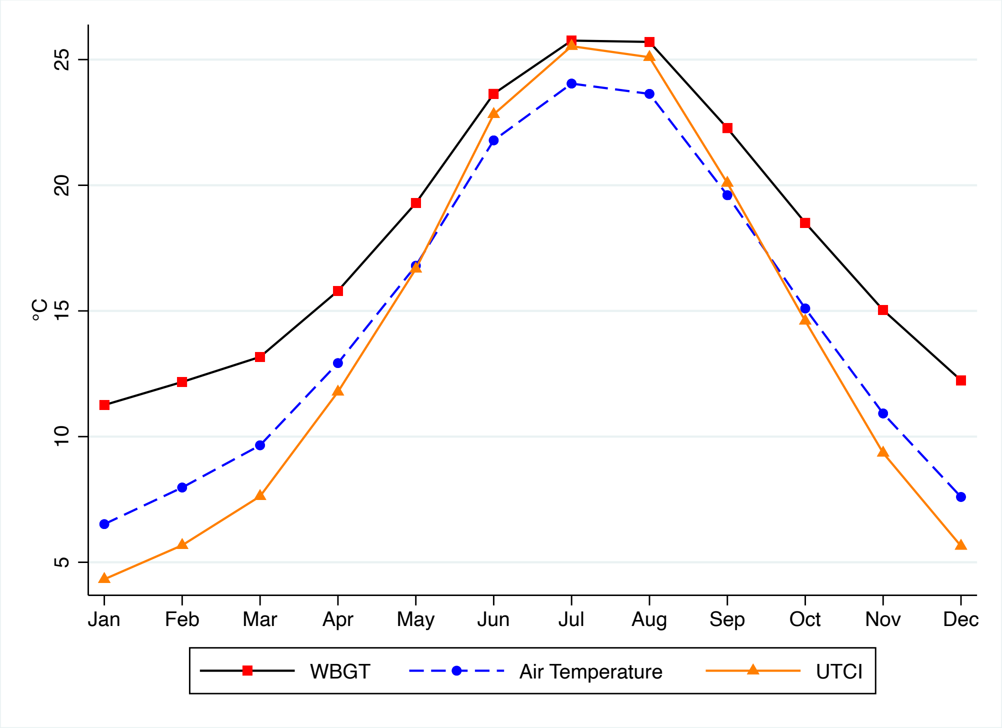
[9] We focused on positive temperatures for each indicator for two reasons. First, in Italy temperatures rarely drop below 0°C and, second, WBGT is designed to assess heat stress and we need comparable results for each indicator (Ireland et al., 2023; Brimicombe et al., 2023).

Figure 1: Average daily temperature - all years



First, the total accident rate confirms that workplace injuries represent a significant concern at the provincial level, with 8.83 accidents per day. Notably, non-severe accidents account for the majority of reported incidents (6.08 daily, 1,630 yearly), while severe accidents occur at a lower frequency (2.74 daily, 731 yearly). Fatal accidents, though relatively rare (0.02 daily rate), still result in an average of 4.46 cases per year per province, underscoring the persistent risk of extreme workplace injuries.

Natives account for the majority of incidents, with a daily rate of 7.29, compared to 1.54 for foreigners. Men exhibit a higher daily rate of 6.26, whereas women report a rate of 2.57. Yearly accident rates display a similar pattern, with a total rate of 2,361 and a fatal accident rate of 4.46. Natives again represent the majority, with an annual rate of 1,949, while foreigners report 412 incidents per year. Men show a significantly higher yearly rate of 1,674 compared to 687 for women.

In Table 2, we also represent the distribution of the daily provincial accident rate by sector. In Agriculture, we register an accident rate of 0.76 which corresponds to 204 accidents per year. In addition, we calculate the accident rate for Industry, and it amounts to 3.17, which takes the yearly count of events at 848. Then, we separated the Service sector into four branches of activities: the highest level of accidents on a daily basis is registered in the Public Administration, education, and health activities branch (1.71), then we have the case of ICT, financial, real estate, professionals and logistics (1.57) and the lowest rates are registered for Trade, travel and rental agencies, support services and accommodation (1.34) and Other services, activities of extraterritorial bodies and activities of households as employers (0.19), respectively.

Table 2 provides an overview of workplace accident rates across different age groups too. Daily accident rates show that individuals aged 30–54 experience the highest rate (5.55) followed by individuals aged 55+ (1.87) and individuals aged 15–29 (1.41). Yearly accident

Table 2: Provincial Workplace Accident Rates (Daily and Yearly)

Category	Daily Accident Rate	Yearly Accident Rate
Total	8.83	2361
Fatal	0.02	4.46
Severe	2.74	731
Non Severe	6.08	1630
Natives	7.29	1949
Foreigners	1.54	412
Men	6.26	1674
Women	2.57	687
Individuals 15–29	1.41	378.01
Individuals 30–54	5.55	1482
Individuals 55+	1.87	500.65
Agriculture	0.76	204.48
Industry	3.17	848.29
Trade	1.34	358.33
ICT	1.57	419.07
Public	1.71	456.92
Other Services	0.19	51.60

Notes: Rates are based on provincial data and represent daily and yearly figures. ”Trade” stands for ”Trade - Accommodation - Rent - Travel Agencies and Support Service Activities”; ”ICT” stands for ”ICT, financial, real estate, professionals and logistics”; ”Public” stands for ”Public administration - education - health activities”. ”Other activities” stands for ”Other services activities - Activities of extraterritorial bodies - Activities of households as employers”. Confidence intervals are calculated at the 95% level using province-clustered standard errors where applicable.

rates follow a similar trend with the 30–54 age group showing the highest figure of 1,482.47 while the 55+ group and the 15–29 group register rates of 500.65 and 378.01, respectively.

Regarding geographical differences, we report the distribution of yearly workplace accidents across the territory in Figure A.1. The accidents are concentrated in the North of Italy, reflecting the firm distribution that characterizes the Italian industrial structure (ISTAT, 2021). The highest number of accidents are registered in the province of Milan and Rome (painted in black). However, high levels of accidents are also registered in the most populated areas of the South of Italy.

3 Empirical strategy

Once we assembled our data, we estimated the impact of temperatures on accident rates at the local level using fixed effects estimators and controlling for concurrent environmental factors. As in Filomena and Picchio (2024), in our model, we implemented month-year-province fixed effects and calendar-date fixed effects so that we exploited plausibly exogenous daily variation in the provincial capital temperature over time to characterize the causal relationship between temperatures and workplace accidents.

Our methodology follows the approach used in the articles by Ireland et al. (2023) and Filomena and Picchio (2024). This method is based on the following Poisson regression:

$$\ln(accidents_{it}) = f(Temp_{it}; \beta) + \alpha \mathbf{X}_{it} + \delta_t + \eta_{im} + \varepsilon_{it} \tag{3}$$

Moving to the conditional mean of the dependent variable, the model can be easily exponentiated, and this allows for the coefficients to be interpreted as incidence rate ratios, i.e., the rate at which the events (the accidents) occur, at the daily level in our case. This allows us to gain a more punctual interpretation of the coefficients, especially with categorical variables (Wooldridge, 2010). The conditional mean of the dependent variable is given by equation (4):

$$E[accidents_{it} \mid \mathbf{X}] = \exp\Big(f(\mathrm{Temp}_{it}; \boldsymbol{\beta}) + \alpha \mathbf{X}_{it} + \delta_t + \eta_{im}\Big), \tag{4}$$

In this equation, i and t indicate, respectively, the province (107 in total) and the date of the analyzed period. The variable y_{it} represents the number of workplace accidents, while $f(Temp_{it})$ is a function that allows us to observe the non-linear effect of the temperature index on workplace accidents by dividing the index values into intervals corresponding to the risk categories: "< 23 °C", "[23–25) °C", "[25–28) °C", "≥ 28 °C". β is the parameter vector associated to the temperature bins.

As mentioned, a contribution of this paper is to perform the analysis using multiple temperature indicators. Thus, $f(Temp_{it})$ will be air temperature, WBGT, or UTCI, alternatively, and for each outcome, we will show three different estimates with respect to the different indicators. Additionally, $\mathbf{X}_{it}$ is a vector of other meteorological variables, such as a linear, quadratic, and cubic polynomial for wind speed and precipitations. Calendar-date fixed effects δ_t are included to control for seasonal variations of accidents, while η_{im} represents fixed effects for month-year and province, included to account for structural differences in accident rates between provinces and local economic cycles due, for instance, to the seasonal trend of temperature and labor supply (and its composition).

Controlling for fixed effects of province-year-month allows us to identify the causal effect of temperature on workplace injuries through the exogenous variation of daily temperature from its average at the province-month level, as climate-economics literature suggests (Hsiang, 2016). In this way, we can also mitigate potential measurement errors in the relationship between temperature (in the provincial capital) and accidents, which might occur anywhere in the province. Indeed, while the temperature of the provincial capital may not be directly linked to an accident occurring elsewhere in the province (as the capital's temperature could differ from that of the accident's location), it is more plausible that the daily deviation of the capital's temperature from its monthly average is more uniformly distributed across the territory, thus providing a more precise measure of its connection to the accident occurring in the provincial territory (Filomena and Picchio, 2024; Dillender, 2021). [10] To further account for this strong spatial correlation of climatic events, standard errors are clustered at the provincial level.

Finally, our estimates are conducted across different configurations of the outcome: accidents by the severity of injuries (fatal, severe, nonsevere), by worker nationality, gender, age, and by economic sector.

4 Results

In this section, we present the results of our analysis. The estimated coefficients for the various air temperature indicators –namely air temperature, WBGT, and UTCI– are represented

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[10] On the exogeneity of this procedure using the three temperature indicators, please refer to Figure A.2 in the Appendix A.

graphically, illustrating the outcomes of the estimations of equation (4). [11].

As reported in Section 3, our strategy relies on a non-linear representation of the temperature, categorized into four bins. Throughout the paper, the bin related to temperatures below 23 °C is chosen as a benchmark for the interpretation of the other coefficients. Moreover, we report the coefficients as incidence rate ratios, stemming from the exponential version of the Poisson model in equation (4) and comment the coefficients as percentage changes from the reference temperature bin.[12] Throughout this section, we will refer to each temperature indicator as a separate model as mentioned in Section 3.

4.1 Main results

Figure 2 reports the estimates of the impact of temperature on daily accidents. We can observe that heat exerts a positive effect on daily accidents, especially for days with temperatures above 28 °C, regardless of how it is measured. Focusing on each indicator, WBGT and air temperature are statistically significant across all temperature bins, yielding the highest coefficients. In contrast, UTCI is positive and significant only for temperatures above 25 °C.

In terms of magnitude, the coefficients for WBGT range from 1.6% (23-25 °C bin) to 6.6% (+28 °C bin), while air temperature coefficients increase from of 2.7% to 8.5% when we move from the lowest bin (23-25 °C) to the highest (+28 °C). It is worth noting that the UTCI coefficients are more stable across the different temperature bins and, at the same time, significantly lower compared to those of air temperature.[13] The range of UTCI coefficients varies between 1% (25-28 °C bin) and 3.9% (+28 °C bin).

Overall, air temperature and WBGT lead to similar results. An exception regards the 25-28 °C bin in which WBGT is significantly higher than air temperature – a pattern confirmed in almost all estimates throughout the study.

Overall, these coefficients imply that an additional day with temperatures above 28 °C leads to an increase in daily accidents of 3.9%, 6.6%, and 8.5%, for the UTCI, WBGT, and air temperature indicator, respectively. Intuitively, using as a baseline the average provincial daily count of accidents for days with temperatures below 23°C—approximately 8.8 accidents per day, regardless of the temperature indicator—if we were in the summer with an average daily temperature of 23–25°C, the monthly accident count would increase from 264 in the baseline scenario to 268 (+1.6%) under the WBGT model and to 271 (+2.7%) under the air temperature model. In contrast, the UTCI model would indicate no significant difference on average.

At first glance, work-related injuries appear to be substantially driven by extreme heat days. More to the point, the estimated magnitude of this effect varies depending on the

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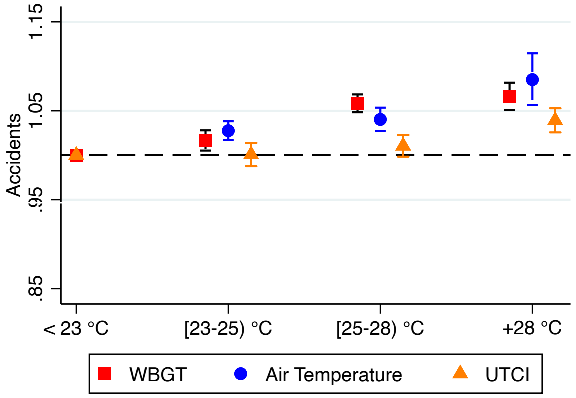
[11] Appendix A provides the corresponding tables for all the regressions presented graphically in the main text.

[12] From equation (4), we obtained the incidence rate ratios for a specific bin, that is the effect on the outcome of a daily temperature in a specific bin, e.g., 23-25 °C, with respect to the benchmark, i.e., days with temperatures below 23 °C. The incidence rate ratio is given by: $\frac{\exp\left(\beta_{23-25}\right)}{\exp\left(\beta_{<23}\right)} = \exp\left(\beta_{23-25}\right)$, holding everything else constant and withdrawing the intercept, for the ease of exposition. The proportional change of it is given by $\exp\left(\beta_{23-25}\right) - 1$ and this leads to the percentage change, $(\exp(\beta_{23-25}) - 1) * 100$, that we will report for each outcome in the discussion of the results (Wooldridge, 2010). Of course, these formulas can be adapted to each model and to each bin we consider.

[13] In Table A.5, we report the results of z-tests where we compare the coefficients of temperature bins ([23-25)°C, [25-28)°C, and +28°C) across our three thermal indices in a pairwise fashion.

chosen measure of temperature. Among the indicators, UTCI provides the most conservative estimate, yielding significantly lower coefficients than both WBGT and standard air temperature measurements. This suggests that incorporating meteorological factors such as humidity, wind speed, solar angle, and radiation, together with individuals' adaptive responses to elevated temperatures, which are modeled through clothing adjustments that regulate evapotranspiration, leads to a reduction of the size of the estimated effect. As a result, UTCI provides a more moderate assessment of the impact of heat on work-related injuries. This heterogeneity underscores the importance of employing multiple indices when assessing heat-related accident risk, as the results of equation (4) vary significantly depending on the chosen indicator.

Figure 2: Effect of temperature on daily workplace accidents



Notes: Effect of temperature on daily workplace accidents. The coefficients are exponentiated following the estimation of equation (4). Confidence intervals are at the 95% level and they derive from province-clustered standard errors.

4.2 Temperature, mortality and the severity of accidents

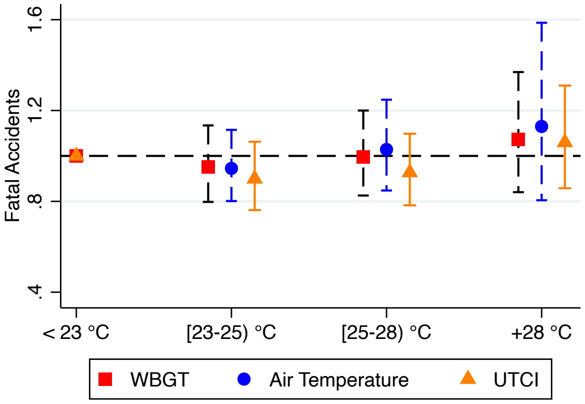
In Figure 3, we explore whether heat exerts an impact on fatal accidents. In contrast to the previous case, when the model is restricted to this specific type of event we observe no significant impact for any of the indicators used –as observed in related studies like Filomena and Picchio (2024). This could be explained by the fact that fatal accidents are low-probability extreme events that are likely driven primarily by deficiencies in firm-level occupational safety measures, such as the lack of personal protective equipment or the obsolescence of machinery at the plant level.

However, when examining the relationship by injury severity –where accidents are defined as severe when they require more than 30 days of recovery– Figure 4 reveals a pattern consistent with that observed in Figure 2.

The highest coefficients are obtained from the models using standard air temperature and WBGT. The UTCI model produces the lowest estimates that are statistically significant only for the +28 °C temperature bin. The magnitudes of the coefficients across the three models are consistent with those obtained for the total number of accidents, as presented in Figure2.

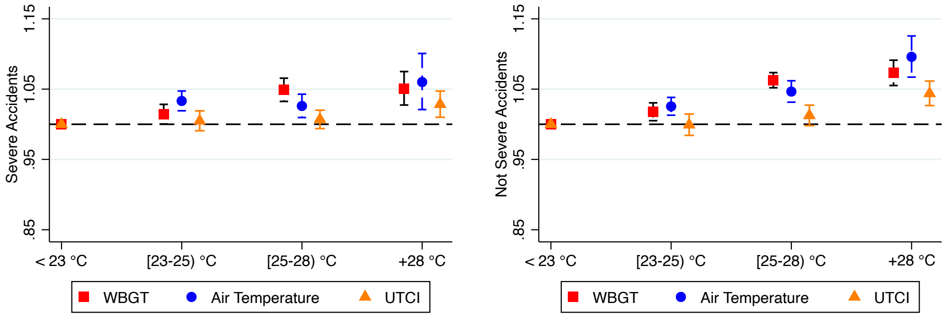
Interestingly, Figure 4 shows that the coefficients of each single indicator are higher for the case of non-severe accidents (right panel). The difference emerges particularly in the

Figure 3: Effect of temperature on fatal daily workplace accidents



Notes: Effect of temperature on fatal daily workplace accidents. The coefficients are exponentiated following the estimation of equation (4). Confidence intervals are at the 95% level and they derive from province-clustered standard errors.

Figure 4: Effect of temperature on daily workplace accidents by severity.



Notes: Effect of temperature on severe daily workplace accidents (left panel), and on non-severe daily workplace accidents (right panel). The coefficients are exponentiated following the estimation of equation (4). Confidence intervals are at the 95% level and they derive from province-clustered standard errors.

case of days with 28 °C. In the hottest days, for the case of severe (non-severe) injuries, we observe an increase in workplace accidents by 5% (7.3%), 6% (9.6%) 2.8% (4.3%) for the WBGT, air temperature and UTCI indicators respectively. Overall, the similar pattern observed between the two types of accidents provides a useful indication that underreporting does not bias our results and is not endogenous to climatic conditions (Picchio and van Ours, 2024). This is because severe accidents are more difficult to underreport, making it less likely that reporting behavior systematically varies with heat (Antonelli et al., 2024).

The results of these tests, as in the case of total accidents, highlight the importance of analyzing multiple indicators, particularly when considering adaptation policies for scenarios involving moderate temperatures. This is crucial given that the three indicators yield positive results with differences in their magnitude.

4.3 Heterogeneity by nationality and gender

In Figure 5, we report the coefficients for the three models across two dimensions: worker nationality and gender.

Examining the top of the figure, which distinguishes between natives and foreigners, we observe that the effects of heat are consistent with those in our baseline analysis (Figure 2). The estimated effects remain positive across all cases, with the highest coefficients observed for WBGT and air temperature, particularly in the temperature bin above 28°C. In contrast, UTCI yields the lowest coefficients compared to the other two indicators.

Another interesting feature that is common to the three models is that the coefficients related to foreign workers are greater than the ones related to natives. This phenomenon could be explained by the different composition of the occupation of migrants and natives. Indeed, the majority of non-native workers are migrants employed in physically intensive occupations, in sectors like agriculture, construction, accommodation, and tourism, and they are also the ones potentially more exposed to the risk of workplace accidents and heat stress (Ministero del Lavoro, 2023). This could also be related to the different tasks migrants perform with respect to natives: the former could be less educated and trained and also younger when compared to natives As a consequence, migrants carry out riskier tasks (Alacevich and Nicodemo, 2024) and are less capable of adapting their work routines to environmental conditions (Picchio and van Ours, 2017).

In terms of magnitude, for lower-risk days —defined as those with temperatures between 23–25°C— no significant difference emerges between natives and foreigners. However, as temperatures rise, particularly above 28°C, notable variability is observed across groups and indicators. Specifically, WBGT coefficients range from 1.7% to 5.7% for natives and from 1.4% to 7.8% for foreigners. Air temperature exhibits a similar pattern, though its coefficients are generally higher for both the 23–25°C and +28°C bins. Lastly, UTCI yields statistically significant coefficients from 25°C onwards, with estimates of approximately 1% for both groups in the 25–28°C range, while, for foreigners, the coefficient reaches 5.4% on days exceeding 28°C.[14]

In the lower section of Figure 5, we analyze the effects of temperature across the three models by gender. The results show that, overall, the effects remain positive, with a more pronounced impact on days with temperatures exceeding 28°C. The behavior of the coefficients is consistent with previous findings: WBGT and air temperature yield the highest estimates, while UTCI produces the lowest coefficients, which is statistically significant only at temperatures above 28°C. Another noteworthy aspect of these results is that, on lower-risk days, the magnitude of the coefficients is comparable across genders. However, at temperatures exceeding 25°C, the effects are slightly more pronounced for male individuals, regardless of the indicator used. The estimated coefficients for WBGT range from 1.8% (23-25°C) to 6.4% (+28°C) for women and from 1.5% to 6.6% for men. For air temperature, the coefficients vary between 1.9% and 5.4% for women and between 3% and 9.6% for men. Regarding UTCI, no significant effect is observed for temperatures in the 23–25°C bin, while the estimated impact reaches 1% in the 25–28°C bin and 4% in the +28°C one. In addition, the coefficients for the UTCI are lower and only statistically significant for women at the highest temperature bin.

Table A.5 provides insights into the significance difference between the three indicators

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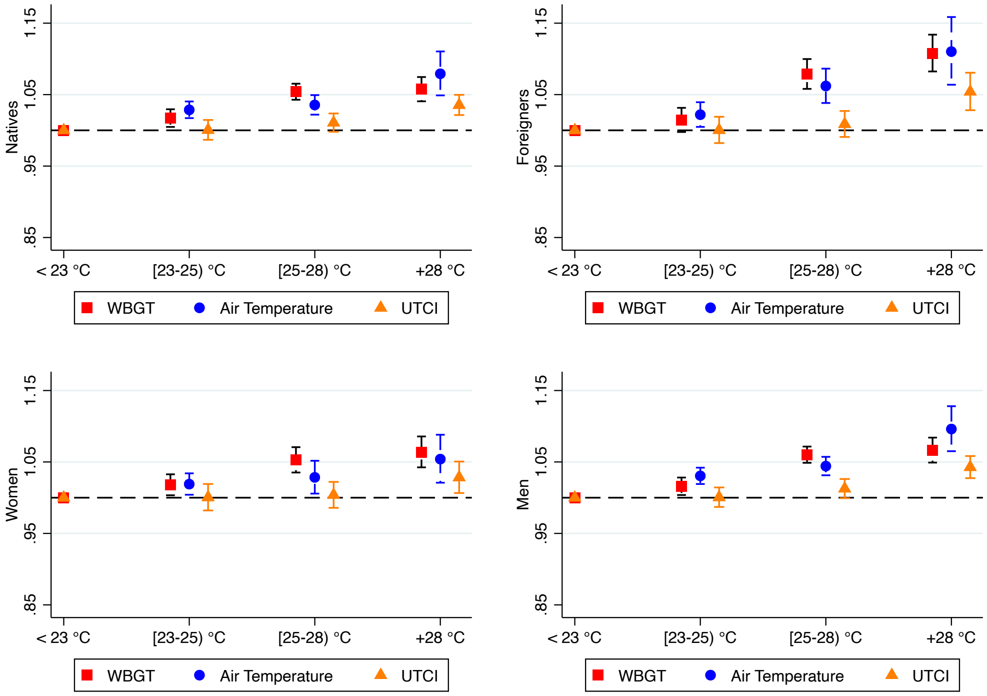
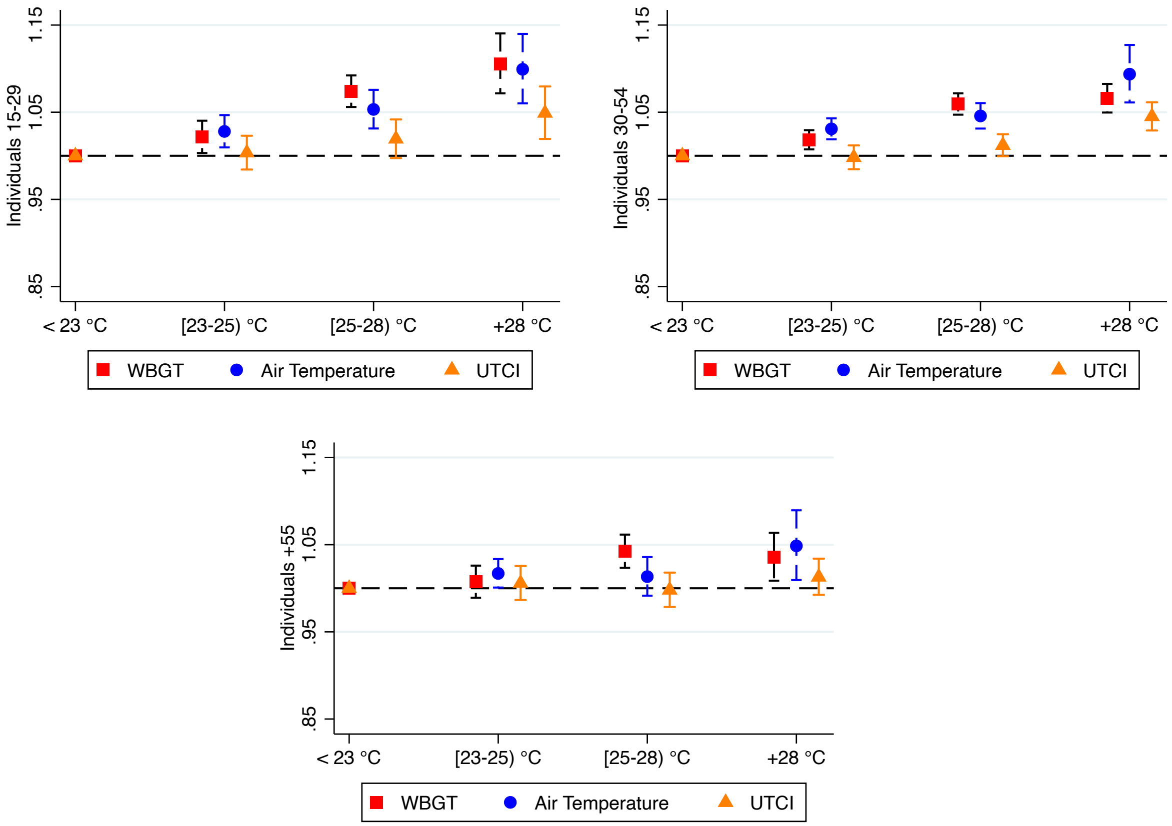
[14] We report the results of the z-tests in Table A.5. As in the previous cases, the comparison between models yields significant results, particularly for temperatures above 25°C, especially when the UTCI model is included in the comparison.

Figure 5: Effect of temperature on daily workplace accidents by nationality and gender



Notes: Effect of temperature on daily workplace accidents on natives (top-left). Effect of temperature on daily workplace accidents on foreigners (top-right). Effect of temperature on daily workplace accidents on women (bottom-left). Effect of temperature on daily workplace accidents on men (bottom-right). The coefficients are exponentiated following the estimation of equation (4). Confidence intervals are at the 95% level and they derive from province-clustered standard errors.

Figure 6: Effect of temperature on daily workplace accidents by age



Notes: Effect of temperature on daily workplace accidents on 15-29-year-old individuals (top-left). Effect of temperature on daily workplace accidents on 30-54-year-old individuals (top-right). Effect of temperature on daily workplace accidents on +55 years old individuals (bottom). The coefficients are exponentiated following the estimation of equation (4). Confidence intervals are at the 95% level and they derive from province-clustered standard errors.

when we distinguish work-related injuries by gender. Overall, women generally show weaker differences across indices than men. Furthermore, these differences are higher and statistically significant, especially for intermediate temperatures. This stresses the policy relevance of the analysis of multiple indicators to evaluate workplace accident risk related to heat stress.

A final remark concerns the overall lower effect observed for women, which aligns with existing evidence on work-related injuries in Italy (Razzolini et al., 2014). This finding is consistent with prior research showing that tasks with higher occupational risks are typically performed by men (Ireland et al., 2023; Park et al., 2021). However, it is noteworthy that, according to the WBGT metric, no substantial gender gap in heat-induced workplace accidents emerges. This unexpected result raises important concerns regarding the adequacy of workplace safety measures for female workers.

4.4 Heterogeneity by age

Another important aspect of the relationship between temperature and workplace injuries is the role of age. It is well established that the body's thermoregulatory capacity changes with age, influencing individuals' physiological responses to heat stress. However, differences in workplace experience and task allocation across age groups may also play a pivotal role in shaping injury risks, as workers of different ages may be assigned to distinct roles and carry out different tasks within the same company (Ireland et al., 2023). These factors contribute to potential variations in vulnerability to heat-related injuries across age groups.

Figure 6 presents the estimates of the three models (i.e. WBGT, standard air temperature, and UTCI), examining the number of daily accidents across three age categories. Consistent with the previous cases, the coefficients are positive and increase with temperature. Furthermore, the UTCI model systematically yields the lowest coefficients compared to WBGT and air temperature, reinforcing the pattern observed in earlier results.

The most interesting aspect of Figure 6 is how the coefficients vary across age groups. While for temperatures between 23°C and 25°C, the three models yield similar estimates across age groups, a distinct pattern emerges for temperatures above 25°C. In this case, younger individuals experience the highest effect of heat stress, whereas the impact of temperature is weaker for individuals over 55, regardless of the indicator used. However, the effect remains positive, particularly at extreme temperatures. In between, individuals aged 30–54 exhibit coefficient values that fall between those observed for the youngest and oldest workers.

This insight suggests that younger individuals, presumably with less work experience and bargaining power, perform tasks that are more exposed to climatic conditions (Euosha, 2009; Picchio and van Ours, 2017). More experienced workers may have developed the ability to adapt to extreme temperatures at the workplace, for instance, by requesting modifications to their duties. Consequently, older individuals, due to their seniority, may have greater bargaining power to negotiate working conditions, particularly when supported by employment contracts that offer them stronger protections compared to younger workers.[15]

4.5 Heterogeneity by sector

In Figure 7 and 8, following NACEs classification, we report the coefficients for the three estimated models (equation (4)) by macro-sector: Agriculture, Industry, Services. [16]

The analysis aims to investigate the heterogeneity of temperature impacts across sectors, taking into account the nature of the activities involved. Of course, in some sectors (e.g. construction and agriculture or some manufacturing industries such as petrochemical, steel, glass, and textile factories) the working environment is potentially hazardous because of the direct exposure of workers to high temperatures or the demanding physical activity (Varghese et al., 2018). However, several studies suggest that workers carrying out cognitive tasks may be more adversely affected by heat than those in physically intensive jobs when considering factors such as mental and emotional state as well as cognitive performance (Picchio and van Ours, 2024; Zander and Mathew, 2019; Dell et al., 2014). This channel may have significant implications for workplace injuries, as heat-induced concentration lapses and impaired decision-making can increase the risk of accidents. It is also important to note

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[15] To complement the evidence already presented, we report in Table A.9 the results of the z-tests for the three age groups considered in Figure 6. The findings indicate that differences between the models estimated using the three thermal indices are most pronounced for individuals aged 15–29 and 30–54. In contrast, for individuals aged 55 and older, significant differences emerge only in the case of intermediate temperatures. This suggests that the older age group exhibits lower sensitivity to thermal indices compared to younger individuals, reinforcing the argument that experienced workers may have greater adaptive capacity in response to extreme temperatures.

[16] Industry consists of: mining and quarrying, manufacture, electricity, gas, steam and air conditioning supply, water supply, sewerage, waste management and remediation activities, and construction activities.

that firms operating in different industries have varying capacities to implement mitigation strategies for heat stress. That is, some sectors may be characterized by the possibility of installing air conditioning systems or adopting other technological solutions to reduce workers' exposure to high temperatures, whereas other sectors, particularly those involving outdoor or physically demanding tasks, may face greater constraints in adapting to extreme heat conditions (Dillender, 2021; Picchio and van Ours, 2024).

Related to these points, the service sector contributes to a large proportion of total employment in advanced countries, thus it is crucial to assess the impact of heat stress on work-related injuries in this sector (Burke et al., 2023b). In general, workers in Services are less likely to experience heat stress due to the lower physical effort required. Consequently, studies on occupational injuries often overlook this sector (see, e.g., (Marinaccio et al., 2025)). However, certain service occupations, such as those in tourism, may be particularly affected by heat (ILO, 2019). Furthermore, it is also important to examine whether and how different temperature indicators capture mental exhaustion due to heat in office and desk-based tasks. Given this heterogeneity within service occupations, we argue that this sector warrants further investigation. For all these reasons, we disaggregated the service sector into four branches: (i) Trade, travel and rental agencies, support services, and accommodation; (ii) ICT, financial, real estate, professional services, and logistics; (iii) Public administration, education, and health; and (iv) Other services.[17] This disaggregation allows us to identify specific activities that may be more exposed to heat stress.

Figure 7 reports the results across sectors. We observe that temperature exerts a positive effect on daily accidents in each sector, and irrespectively of the temperature indicator used. The top-left panel of Figure 7 reports the estimates of the three indicators for the agricultural sector. Overall, the coefficients are positive and increase with temperature. However, the standard air temperature coefficient is not significant for high temperatures. Instead, both WBGT and UTCI are positive and significant in all temperature bins. In particular, when using WBGT the effect on work accidents is 4.6% for the 23-25°C bin, 8.5% for the 25-28 °C bin and 6.5% for days with temperatures above 28 °C. As for standard air temperature, the estimated coefficients are between 3% for 23-25°C and 4.1% for 25-28°C. The same pattern is observed for the UTCI indicator, i.e., the UTCI coefficients span from 2.4% for the 23-25°C bin to 4.3% for the +28°C bin. Notably, when accidents in the agricultural sector are concerned, standard air temperature fails to capture the positive impact of heat on work accidents on days with temperatures higher than 28°C –the most prevalent days when agricultural work activities are carried out. In addition, this set of estimates is also interesting in that the UTCI temperature exhibits comparable coefficients with the other two models. This could be coherent with the literature stressing that UTCI is more suited to measure heat stress in outdoor contexts (Gao et al., 2018).

The right panel of Figure 7 reports the estimates for the three models for the industry sector. The coefficients of standard air temperature increase as far as temperature grows. However, the estimated coefficients for WBGT and UTCI (in their respective models) follow a different pattern. As for the former, the coefficient is not statistically different from zero in the 23-25°C bin, whereas it is positive and significant in the top two temperature bins. The UCTI coefficients instead are positive and significant only in the +28°C bin. That is, a day with an average temperature higher than 28°C leads to an increase in daily accidents of

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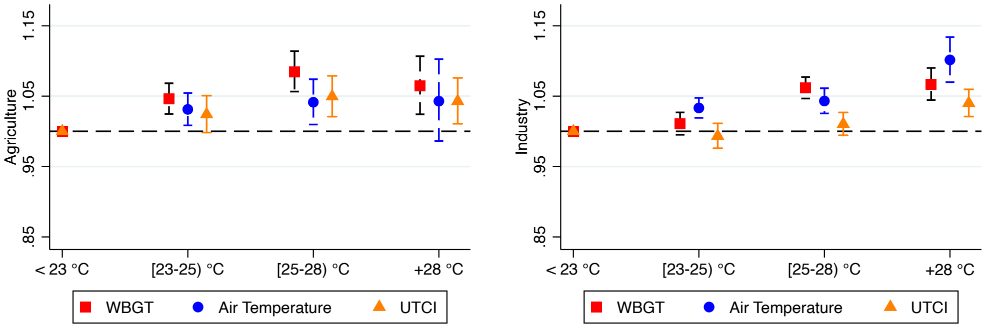
[17] Other services consists of: arts, entertainment and recreation, other services activities, activities of households as employers; undifferentiated goods - and services - producing activities of households for own use, activities of extraterritorial organizations and bodies.

Figure 7: Effect of temperature on daily workplace accidents by sector



Notes: Effect of temperature on daily workplace accidents on agriculture(left). Effect of temperature on daily workplace accidents on industry (right). The coefficients are exponentiated following the estimation of equation (4). Confidence intervals are at the 95% level and they derive from province-clustered standard errors.

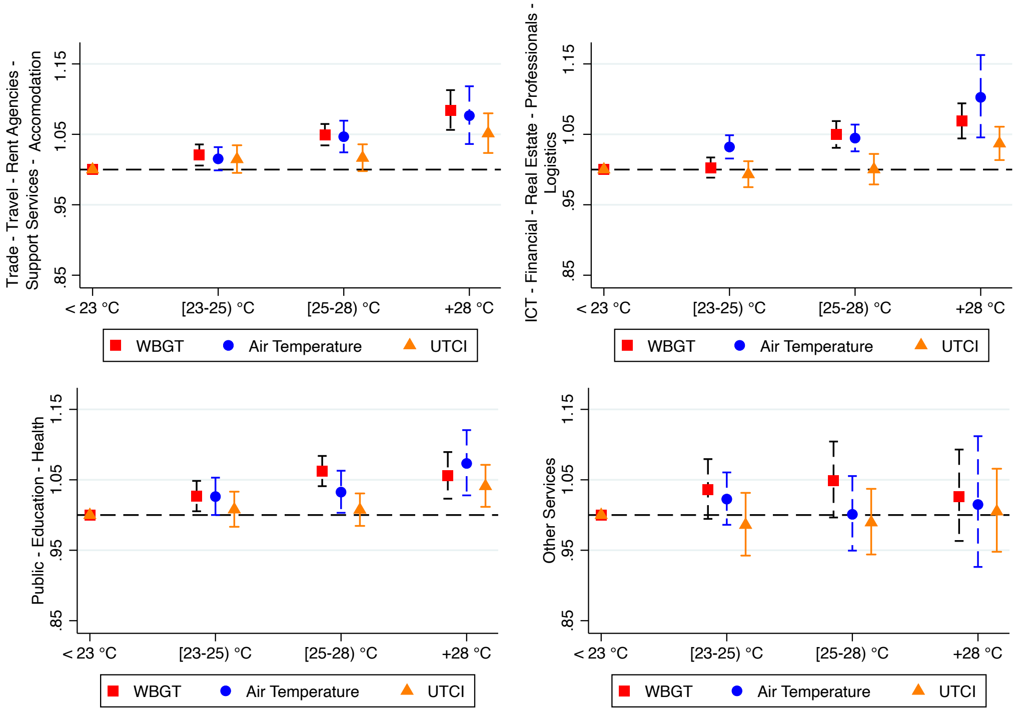
6.7% (WGBT), 10% (stadard air temperature), or 4% (UTCI).

In the top-left panel of Figure 8, we present an initial set of estimates for a sub-sample of activities within the service sector concerning Trade, travel and rental agencies, support services, and accommodation. The coefficients are positive and increase with temperature. Indeed, WBGT model coefficients range between 2% and 8%, while the stardard air temperature model provides coefficients that range between 1.5% and 7.6%. Also in this case the UTCI model shows lower coefficients as they span 1.5% to 5%.

The top-right panel of Figure 8 reports estimates for a different subsample of activities in the service sector related to ICT, financial, real estate, professional services, and logistics. The estimates for the three models are similar to the ones registered in the top-left panel of Figure 8. However, a significant difference emerges between the two cases: in the latter graph, UTCI coefficients are slightly lower and this could be related to the fact that a greater share of the activities considered in this case are usually carried out indoors, differently from the ones in the top-left panel of Figure 8, e.g. Trade, travel and rental agencies, support services, and accommodation. This could be coherent with the estimates obtained for accidents in the agricultural sector and with the fact that UTCI was originally designed to measure outdoor thermal discomfort (Gao et al., 2018). In addition, as UTCI is a metric that also captures thermal perceptions, the lower values of UTCI in the ICT branch of service activities may also suggest that Italian firms are widely using heat adaptation tools that prevent injuries related to heat illness in indoor work environments.

On the bottom left panel of Figure 8, we report the estimates for the Public-education-health sector, where we observe that the coefficients increase with temperature, regardless of the indicator used. In addition, the UTCI indicator provides the lowest coefficients while air temperature is almost in line with WBGT in terms of magnitude. In the bottom right panel of Figure 8, we report the estimates for work accidents that occurr in the Other services brunch. In this case, the estimates are not statistically significant, which could be attributed to several factors. A lower provincial accident rate may reduce the precision of the estimates, while the presence of informal employment could lead to underreporting of workplace injuries. Additionally, the specific nature of the activities within this sector, such as those carried out by extraterritorial bodies, may contribute to distinct injury patterns. The interplay of these factors suggests that workplace injuries in this sector may follow different dynamics compared to those observed in the other sectors analyzed above.

Figure 8: Effect of temperature on daily workplace accidents by sector: Services



Notes: Effect of temperature on daily workplace accidents on Trade - Travel and Rent Agencies - support services - accommodation (top-left). Effect of temperature on daily workplace accidents on ICT - financial - real estate - professionals - logistics (top-right). Effect of temperature on daily workplace accidents on Public - Education - Health (bottom-left). Effect of temperature on other service activities (bottom-right). The coefficients are exponentiated following the estimation of equation (4). Confidence intervals are at the 95% level and they derive from province-clustered standard errors.

5 Conclusion

Using a set of temperature indicators that capture different dimensions of climate, the present study analyzed the impact of heat on work-related injuries in Italy over the period 2014–2022. By employing multiple measures of heat exposure, we were able to account for both direct thermal effects and broader climatic conditions that influence occupational risks.

Our findings show a significant increase in the risk of work-related injuries as temperatures rise, with the magnitude of the effect varying across different temperature thresholds and indicators. Moreover, the analysis reveals distinct patterns of vulnerability, showing that exposure to heat stress is not uniform across the workforce. Differences emerge based on gender, and age confirming the results obtained in other studies (Picchio and van Ours, 2024). In addition, the present paper corroborates these findings by investigating the heterogeneity across detailed economic sectors and workers' nationality, underscoring the importance of considering these factors when designing policies to mitigate the impact of high temperatures on occupational safety.

Our results highlight the importance of employing multiple indicators to measure heat stress, as suggested in other disciplines. By integrating different temperature indices, our approach identifies the idiosyncratic characteristics of each measure, providing a more nuanced understanding of the relationship between heat and workplace injuries.

First, when using a climatic indicator that accounts for humidity and other meteorological factors that directly affect workers' physiological responses –such as WBGT– our estimates are generally consistent with those derived from air temperature alone, although some differences emerge. This suggests that WBGT, by incorporating additional weather-related stressors, captures a more pronounced effect of heat on occupational risks, especially between 25-28 °C.

On the other hand, when employing an indicator that not only reflects climatic conditions but also integrates an evapotranspiration-based model to account for adaptation mechanisms (i.e., UTCI) the effect of heat on workplace accidents appears to manifest primarily at higher temperature thresholds. It could be likely due to its ability to account for adaptive responses such as clothing insulation and humidity regulation. Overall, the results demonstrate sensitivity to the choice of indicator, with no single measure systematically providing a more conservative estimate of accident risk. The variability of the estimates further suggests that sensitivity to temperature variations is particularly pronounced at moderate-risk temperature levels, which occur more frequently than extreme temperatures—where different indicators tend to converge.

These findings highlight the necessity of adopting a multidimensional approach to measuring heat stress, as different indicators provide complementary insights into how temperature affects occupational risks.

Considering future scenarios of climate change and the expected increase of magnitude, intensity and frequency of extreme heat, the definition of more accurate policies and safety regulations to reduce the exposure to high temperatures of vulnerable groups of workers is becoming a critical issue to tackle worker safety and disparities in the labor market. In this regard, this paper provides valuable information to regulators and policy-makers relating to occupational heat stress management and worker protection. Our findings show that managing safety risks requires a framework that integrates different climate metrics for tailoring daily practices to different worksite risks caused by high temperatures.

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Appendix

A Additional tables and figures

Table A.1: Descriptive statistics of temperature metrics

	Mean	Standard Deviation
a) WBGT:		
Daily average	18.55	5.66
Fraction of days < 23 °C	0.739	0.439
Fraction of days [23–25) °C	0.103	0.304
Fraction of days [25–28) °C	0.117	0.322
Fraction of days ≥ 28 °C	0.040	0.197
b) Air temperature:		
Daily average	15.53	6.72
Fraction of days < 23 °C	0.834	0.372
Fraction of days [23–25) °C	0.081	0.273
Fraction of days [25–28) °C	0.070	0.256
Fraction of days ≥ 28 °C	0.014	0.119
c) UTCI:		
Daily average	15.08	8.10
Fraction of days < 23 °C	0.790	0.407
Fraction of days [23–25) °C	0.070	0.256
Fraction of days [25–28) °C	0.091	0.288
Fraction of days ≥ 28 °C	0.048	0.213

Notes: WBGT refers to Wet Bulb Globe Temperature. Air temperature is measured in degrees Celsius, and UTCI stands for Universal Thermal Climate Index. The table summarizes daily averages and the fraction of days within specified temperature ranges, along with their standard deviations.

Figure A.1: Average accidents by province-year (2014-2022).

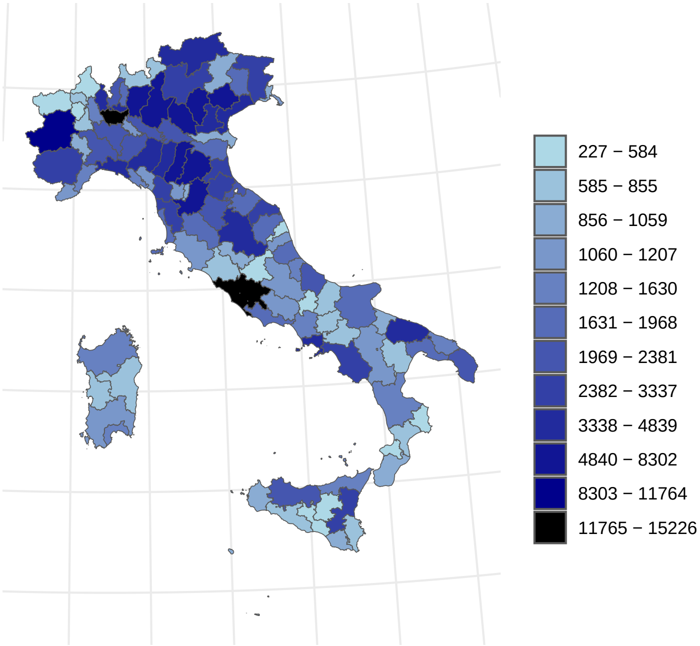
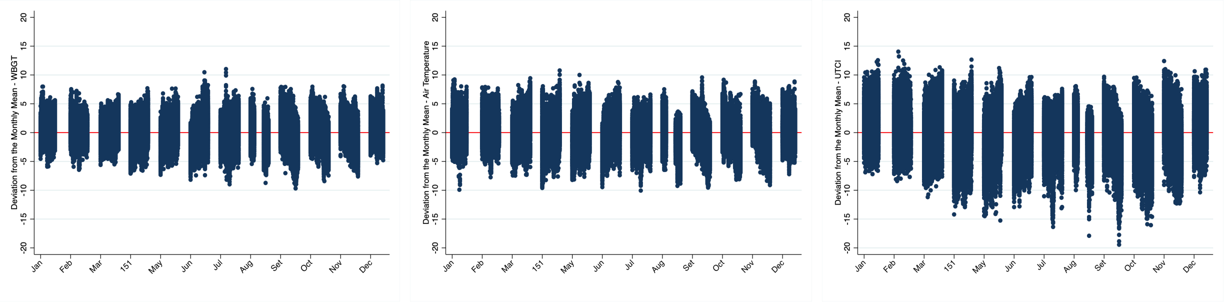


Figure A.2: Comparison of deviation from the monthly mean for WBGT, air temperature, and UTCI (all years).



(a) WBGT

(b) Air Temperature

(c) UTCI

Table A.2: Effects of air temperature on daily accidents at the provincial level

VARIABLES	(1) Accidents	(2) Fatal Accidents	(3) Severe Accidents	(4) Non-Severe Accidents	(5) Natives	(6) Foreigners	(7) Women	(8) Men
[23 – 25) °C	1.0276***	0.9451	1.0332***	1.0255***	1.0287***	1.0219**	1.0190**	1.0305***
	(0.0054)	(0.0796)	(0.0072)	(0.0065)	(0.0059)	(0.0088)	(0.0076)	(0.0058)
[25 – 28) °C	1.0402***	1.0284	1.0260***	1.0466***	1.0355***	1.0620***	1.0285**	1.0442***
	(0.0067)	(0.1014)	(0.0085)	(0.0078)	(0.0070)	(0.0123)	(0.0117)	(0.0066)
+28 °C	1.0850***	1.1299	1.0601***	1.0960***	1.0792***	1.1102***	1.0540***	1.0961***
	(0.0149)	(0.1956)	(0.0204)	(0.0149)	(0.0157)	(0.0242)	(0.0171)	(0.0160)
Rain	0.9956***	0.9858**	0.9949***	0.9960***	0.9959***	0.9944***	0.9995	0.9942***
	(0.0006)	(0.0070)	(0.0009)	(0.0005)	(0.0006)	(0.0009)	(0.0009)	(0.0006)
Rain^2	1.0001***	1.0002	1.0001***	1.0001***	1.0001***	1.0001***	1.0000	1.0001***
	(0.0000)	(0.0003)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Rain^3	1.0000***	1.0000	1.0000***	1.0000***	1.0000***	1.0000**	1.0000*	1.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Wind	1.0317***	0.7657*	1.0329**	1.0320**	1.0315***	1.0292	1.0254*	1.0358**
	(0.0115)	(0.1215)	(0.0138)	(0.0131)	(0.0113)	(0.0182)	(0.0141)	(0.0152)
Wind^2	0.9941**	1.0667	0.9942*	0.9939**	0.9939**	0.9961	0.9938*	0.9939*
	(0.0026)	(0.0449)	(0.0031)	(0.0030)	(0.0025)	(0.0050)	(0.0036)	(0.0032)
Wind^3	1.0003*	0.9959	1.0003	1.0004*	1.0003**	1.0002	1.0004*	1.0003
	(0.0002)	(0.0032)	(0.0002)	(0.0002)	(0.0002)	(0.0004)	(0.0002)	(0.0002)
Observations	257,301	257,301	257,301	257,301	257,301	257,301	257,301	257,301
Month-Year-Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean	8.83	0.02	2.74	6.08	7.29	1.54	2.57	6.26
P-value (Wald test for the bins)	0	0.5096	0.1606	0	0.0007	0	0.0891	0

Notes: estimates of equation (4) with standard errors clustered at the provincial level. All the models contain year-month-province and calendar date FEs. The last row of the table reports the p-values for the Wald test performed to test the equality of the coefficients related to each bin within the models. The null hypothesis is the equality of the coefficients.
*** p<0.01, ** p<0.05, * p<0.1

Table A.3: Effect of WBGT temperature on daily accidents at the provincial level

VARIABLES	(1) Accidents	(2) Fatal Accidents	(3) Severe Accidents	(4) Non-Severe Accidents	(5) Natives	(6) Foreigners	(7) Women	(8) Men
[23 – 25) °C	1.0165***	0.9511	1.0143**	1.0177***	1.0171***	1.0144*	1.0179**	1.0159**
	(0.0058)	(0.0855)	(0.0071)	(0.0065)	(0.0063)	(0.0086)	(0.0075)	(0.0062)
[25 – 28) °C	1.0583***	0.9954	1.0489***	1.0627***	1.0540***	1.0787***	1.0528***	1.0601***
	(0.0051)	(0.0949)	(0.0084)	(0.0055)	(0.0057)	(0.0107)	(0.0091)	(0.0058)
+28 °C	1.0660***	1.0728	1.0509***	1.0730***	1.0575***	1.1078***	1.0639***	1.0665***
	(0.0079)	(0.1335)	(0.0122)	(0.0092)	(0.0087)	(0.0131)	(0.0110)	(0.0089)
Wind	1.0320***	0.7664*	1.0333**	1.0322**	1.0317***	1.0294	1.0258*	1.0359**
	(0.0115)	(0.1218)	(0.0138)	(0.0131)	(0.0113)	(0.0181)	(0.0140)	(0.0152)
Rain	0.9954***	0.9859**	0.9947***	0.9957***	0.9957***	0.9941***	0.9994	0.9939***
	(0.0005)	(0.0071)	(0.0009)	(0.0005)	(0.0006)	(0.0009)	(0.0009)	(0.0006)
Rain^2	1.0001***	1.0002	1.0001***	1.0001***	1.0001***	1.0001***	1.0000	1.0001***
	(0.0000)	(0.0003)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Rain^3	1.0000***	1.0000	1.0000***	1.0000***	1.0000***	1.0000**	1.0000*	1.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Wind^2	0.9941**	1.0664	0.9941*	0.9939**	0.9939**	0.9961	0.9938*	0.9939*
	(0.0026)	(0.0449)	(0.0030)	(0.0030)	(0.0025)	(0.0050)	(0.0035)	(0.0032)
Wind^3	1.0003*	0.9959	1.0003	1.0004*	1.0003**	1.0002	1.0004*	1.0003
	(0.0002)	(0.0032)	(0.0002)	(0.0002)	(0.0002)	(0.0004)	(0.0002)	(0.0002)
Observations	257,301	257,301	257,301	257,301	257,301	257,301	257,301	257,301
Month-Year-Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean	8.83	0.02	2.74	6.08	7.29	1.54	2.57	6.26
P-value (Wald test for the bins)	0	0.5630	0.0003	0	0	0	0	0

Notes: estimates of equation (4) with standard errors clustered at the provincial level. All the models contain year-month-province and calendar date FEs. The last row of the table reports the p-values for the Wald test performed to test the equality of the coefficients related to each bin within the models. The null hypothesis is the equality of the coefficients.
*** p<0.01, ** p<0.05, * p<0.1

Table A.4: Effect of UTCI temperature on daily accidents at the provincial level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Accidents	Fatal Accidents	Severe Accidents	Non-Severe Accidents	Natives	Foreigners	Women	Men
[23 – 25) °C	1.0007	0.8995	1.0048	0.9993	1.0005	1.0004	1.0005	1.0006
	(0.0067)	(0.0765)	(0.0072)	(0.0077)	(0.0071)	(0.0094)	(0.0095)	(0.0070)
[25 – 28) °C	1.0105*	0.9270	1.0069	1.0126*	1.0107*	1.0087	1.0038	1.0127*
	(0.0062)	(0.0800)	(0.0067)	(0.0074)	(0.0065)	(0.0093)	(0.0093)	(0.0068)
+28 °C	1.0391***	1.0600	1.0284***	1.0439***	1.0354***	1.0541***	1.0283**	1.0427***
	(0.0069)	(0.1145)	(0.0095)	(0.0089)	(0.0072)	(0.0134)	(0.0112)	(0.0079)
Wind	1.0321***	0.7670*	1.0332**	1.0324**	1.0318***	1.0297	1.0256*	1.0362**
	(0.0117)	(0.1214)	(0.0138)	(0.0132)	(0.0114)	(0.0184)	(0.0141)	(0.0153)
Rain	0.9954***	0.9855**	0.9947***	0.9958***	0.9957***	0.9941***	0.9994	0.9939***
	(0.0006)	(0.0071)	(0.0009)	(0.0005)	(0.0006)	(0.0009)	(0.0009)	(0.0006)
Rain^2	1.0001***	1.0003	1.0001***	1.0001***	1.0001***	1.0001***	1.0000	1.0001***
	(0.0000)	(0.0003)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Rain^3	1.0000***	1.0000	1.0000***	1.0000***	1.0000***	1.0000**	1.0000*	1.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Wind^2	0.9941**	1.0659	0.9942*	0.9939**	0.9939**	0.9960	0.9938*	0.9939*
	(0.0026)	(0.0448)	(0.0031)	(0.0030)	(0.0025)	(0.0050)	(0.0035)	(0.0032)
Wind^3	1.0003*	0.9959	1.0003	1.0004*	1.0003**	1.0002	1.0004*	1.0003
	(0.0002)	(0.0032)	(0.0002)	(0.0002)	(0.0002)	(0.0004)	(0.0002)	(0.0002)
Constant	11.8590***	0.0968***			9.5629***	2.6870***	4.0289***	8.1552***
	(0.1775)	(0.0166)			(0.1388)	(0.0558)	(0.0636)	(0.1575)
Observations	257,301	257,301	257,301	257,301	257,301	257,301	257,301	257,301
Month-Year-Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean	8.83	0.02	2.74	6.08	7.29	1.54	2.57	6.26
P-value (Wald test for the bins)	0	0.2569	0.0391	0	0	0	0.0216	0

Notes: estimates of equation (4) with standard errors clustered at the provincial level. All the models contain year-month-province and calendar date FEs. The last row of the table reports the p-values for the Wald test performed to test the equality of the coefficients related to each bin within the models. The null hypothesis is the equality of the coefficients.
*** p<0.01, ** p<0.05, * p<0.1

Table A.5: Pairwise z-tests for differences in temperature bins across indicators

Bin	Accidents	Fatal Accidents	Severe Accidents	Not-Severe Accidents	Natives	Foreigners	Women	Men
[23-25) °C								
Temp vs WBGT	1.40	-0.06	1.87*	0.85	1.34	0.61	0.10	1.71*
Temp vs UTCI	3.12***	0.41	2.60***	2.95***	3.03***	1.67*	1.51	3.27***
WBGT vs UTCI	1.78*	0.45	0.94	1.83*	1.74*	1.09	1.43	1.63*
[25-28) °C								
Temp vs WBGT	-2.15**	0.24	-1.69*	-1.88*	-2.05**	-1.01	-1.63*	-1.80*
Temp vs UTCI	3.25***	0.79	1.78*	3.17***	2.59***	3.47***	1.66*	3.32***
WBGT vs UTCI	5.89***	0.55	3.95***	5.39***	4.95***	4.95***	3.79***	5.24***
+28 °C								
Temp vs WBGT	1.14	0.24	0.39	2.11**	1.32	0.85	-0.48	1.63*
Temp vs UTCI	2.83***	0.31	1.42	3.04***	2.57**	2.05**	1.27	3.04***
WBGT vs UTCI	2.55**	0.072	1.46	2.27**	1.96**	2.87***	2.25**	1.98**

Notes: Z-tests comparing coefficients of equation (4) across temperature indicators for each bin. The null hypothesis is that coefficients are equal.
*** p<0.01, ** p<0.05, * p<0.1

Table A.6: Effect of air temperature and weather variables on various age groups

VARIABLES	(1) Individuals 15-29	(2) Individuals 30-54	(3) Individuals +55
[23 – 25) °C	1.0280***	1.0309***	1.0170**
	(0.0095)	(0.0061)	(0.0083)
[25 – 28) °C	1.0533***	1.0458***	1.0134
	(0.0113)	(0.0074)	(0.0113)
+28 °C	1.0993***	1.0937***	1.0487**
	(0.0203)	(0.0168)	(0.0204)
Rain	0.9956***	0.9957***	0.9956***
	(0.0009)	(0.0007)	(0.0008)
Rain^2	1.0001***	1.0001***	1.0001***
	(0.0000)	(0.0000)	(0.0000)
Rain^3	1.0000***	1.0000**	1.0000***
	(0.0000)	(0.0000)	(0.0000)
Wind	1.0130	1.0361***	1.0310**
	(0.0141)	(0.0130)	(0.0150)
Wind^2	0.9988	0.9934**	0.9933**
	(0.0037)	(0.0029)	(0.0031)
Wind^3	1.0000	1.0004*	1.0003*
	(0.0003)	(0.0002)	(0.0002)
Observations	257,301	257,301	257,301
Month-Year-Province FE	Yes	Yes	Yes
Calendar Date FE	Yes	Yes	Yes
Mean	1.41	5.55	1.87
P-value (Wald test for the bins)	0	0.0001	0.1557

Notes: Estimates of equation (4) with standard errors clustered at the provincial level. All the models contain year-month-province and calendar
date FEs.
*** p<0.01, ** p<0.05, * p<0.1

Table A.7: Effect of WBGT and weather variables on various age groups

VARIABLES	(1) Individuals 15-29	(2) Individuals 30-54	(3) Individuals +55
[23 − 25) °C	1.0215**	1.0183***	1.0074
	(0.0094)	(0.0056)	(0.0094)
[25 − 28) °C	1.0740***	1.0594***	1.0423***
	(0.0093)	(0.0063)	(0.0097)
+28 °C	1.1056***	1.0659***	1.0358***
	(0.0175)	(0.0084)	(0.0140)
Rain	0.9953***	0.9954***	0.9955***
	(0.0008)	(0.0007)	(0.0008)
Rain^2	1.0001***	1.0001***	1.0001***
	(0.0000)	(0.0000)	(0.0000)
Rain^3	1.0000***	1.0000***	1.0000***
	(0.0000)	(0.0000)	(0.0000)
Wind	1.0136	1.0363***	1.0311**
	(0.0141)	(0.0131)	(0.0150)
Wind^2	0.9988	0.9934**	0.9933**
	(0.0037)	(0.0029)	(0.0031)
Wind^3	1.0000	1.0004*	1.0003*
	(0.0003)	(0.0002)	(0.0002)
Observations	257,301	257,301	257,301
Month-Year-Province FE	Yes	Yes	Yes
Calendar Date FE	Yes	Yes	Yes
Mean	1.41	5.55	1.87
P-value (Wald test for the bins)	0	0.0001	0.0013

Notes: estimates of equation (4) with standard errors clustered at the provincial level. All the models contain year-month-province and calendar
date FEs.
*** p<0.01, ** p<0.05, * p<0.1

Table A.8: Effect of UTCI and weather variables on various age groups

VARIABLES	(1) Individuals 15-29	(2) Individuals 30-54	(3) Individuals +55
$[23-25)$ °C	1.0034	0.9982	1.0058
	(0.0099)	(0.0070)	(0.0099)
$[25-28)$ °C	1.0193*	1.0121*	0.9980
	(0.0113)	(0.0064)	(0.0101)
+28 °C	1.0490***	1.0451***	1.0130
	(0.0154)	(0.0083)	(0.0106)
Rain	0.9953***	0.9954***	0.9954***
	(0.0008)	(0.0008)	(0.0008)
Rain^2	1.0001***	1.0001***	1.0001***
	(0.0000)	(0.0000)	(0.0000)
Rain^3	1.0000***	1.0000**	1.0000***
	(0.0000)	(0.0000)	(0.0000)
Wind	1.0136	1.0366***	1.0309**
	(0.0142)	(0.0131)	(0.0151)
Wind^2	0.9988	0.9934**	0.9933**
	(0.0037)	(0.0030)	(0.0031)
Wind^3	1.0000	1.0004*	1.0003*
	(0.0003)	(0.0002)	(0.0002)
Observations	257,301	257,301	257,301
Month-Year-Province FE	Yes	Yes	Yes
Calendar Date FE	Yes	Yes	Yes
Mean	1.41	5.55	1.87
P-value (Wald test for the bins)	0.0013	0	0.3857

Notes: Estimates of equation (4) with standard errors clustered at the provincial level. All the models contain year-month-province and calendar
date FEs.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.9: Pairwise z-tests for differences in temperature bins across age groups

Bin	Individuals 15-29	Individuals 30-54	Individuals +55
[23-25) °C			
Temp vs WBGT	0.48	1.51*	0.77
Temp vs UTCI	1.80	3.48***	0.86
WBGT vs UTCI	1.33	2.25**	0.11
[25-28) °C			
Temp vs WBGT	-1.42	-1.41	1.95*
Temp vs UTCI	2.13**	3.42***	1.02
WBGT vs UTCI	3.72***	5.25***	3.17***
+28 °C			
Temp vs WBGT	-0.24	2.13**	0.52
Temp vs UTCI	1.98**	2.63***	1.56
WBGT vs UTCI	2.43**	1.76*	1.30

Notes: Z-tests comparing the coefficients of equation (4) across temperature indicators for each bin. The null hypothesis is that the coefficients are equal.
Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.10: Effect of air temperature on daily accidents at the provincial level by sector

VARIABLES	(1) Agriculture	(2) Industry	(3) Trade	(4) ICT	(5) Public	(6) Other Services
$[23-25)$ °C	1.0312***	1.0333***	1.0152*	1.0321***	1.0262**	1.0226
	(0.0118)	(0.0072)	(0.0084)	(0.0084)	(0.0135)	(0.0190)
$[25-28)$ °C	1.0414**	1.0432***	1.0467***	1.0447***	1.0326**	1.0010
	(0.0164)	(0.0091)	(0.0115)	(0.0097)	(0.0152)	(0.0270)
+28 °C	1.0429	1.1015***	1.0765***	1.1026***	1.0732***	1.0149
	(0.0296)	(0.0163)	(0.0209)	(0.0298)	(0.0236)	(0.0473)
Rain	0.9865***	0.9930***	0.9997	1.0001	0.9972**	0.9993
	(0.0012)	(0.0008)	(0.0011)	(0.0011)	(0.0012)	(0.0021)
Rain^2	1.0002***	1.0001***	1.0000	1.0000	1.0001*	0.9999
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Rain^3	1.0000***	1.0000**	1.0000	1.0000	1.0000*	1.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Wind	1.0279	1.0421**	1.0232	1.0531***	0.9994	1.0122
	(0.0206)	(0.0195)	(0.0155)	(0.0210)	(0.0186)	(0.0469)
Wind^2	0.9962	0.9946	0.9960	0.9899**	0.9963	0.9953
	(0.0044)	(0.0041)	(0.0040)	(0.0042)	(0.0048)	(0.0120)
Wind^3	1.0001	1.0002	1.0002	1.0007***	1.0003	1.0005
	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0008)
Observations	257,301	257,301	257,301	257,301	257,301	257,301
Month-Year-Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean	0.76	3.17	1.34	1.57	1.71	0.19
P-value (Wald test for the bins)	0.7609	0	0.0002	0.0093	0.1159	0.5739

Notes: estimates of equation (4) with standard errors clustered at the provincial level. All the models contain year-month-province and calendar date FEs. The last row of the table reports the p-values for the Wald test performed to test the equality of the coefficients related to each bin within the models. The null hypothesis is the equality of the coefficients.
For the ease of exposition, the column are named after the first sector we report in each panel of Figure 7 (column 1-2) and Figure 8 (column 3-6).
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.11: Effect of WBGT temperature on daily accidents at the provincial level

	(1) Agriculture	(2) Industry	(3) Trade	(4) ICT	(5) Public	(6) Other Services
VARIABLES						
$[23-25)$ °C	1.0463***	1.0109	1.0206***	1.0027	1.0267**	1.0361*
	(0.0111)	(0.0081)	(0.0076)	(0.0073)	(0.0110)	(0.0217)
$[25-28)$ °C	1.0849***	1.0618***	1.0494***	1.0497***	1.0622***	1.0490*
	(0.0147)	(0.0078)	(0.0077)	(0.0097)	(0.0110)	(0.0275)
+28 °C	1.0647***	1.0671***	1.0842***	1.0688***	1.0558***	1.0260
	(0.0211)	(0.0116)	(0.0144)	(0.0127)	(0.0169)	(0.0331)
Rain	0.9863***	0.9927***	0.9994	0.9998	0.9970**	0.9992
	(0.0012)	(0.0008)	(0.0010)	(0.0010)	(0.0012)	(0.0021)
Rain^2	1.0002***	1.0001***	1.0000	1.0000	1.0001*	0.9999
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Rain^3	1.0000***	1.0000**	1.0000	1.0000	1.0000*	1.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Wind	1.0285	1.0421**	1.0237	1.0530**	0.9997	1.0131
	(0.0205)	(0.0195)	(0.0155)	(0.0212)	(0.0185)	(0.0469)
Wind^2	0.9962	0.9946	0.9959	0.9899**	0.9963	0.9951
	(0.0044)	(0.0041)	(0.0040)	(0.0042)	(0.0048)	(0.0120)
Wind^3	1.0001	1.0002	1.0002	1.0007***	1.0003	1.0005
	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0008)
Observations	257,301	257,301	257,301	257,301	257,301	257,301
Month-Year-Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean	0.76	3.17	1.34	1.57	1.71	0.19
P-value (Wald test for the bins)	0.0007	0	0	0	0.0078	0.6415

Notes: Notes: estimates of equation (4) with standard errors clustered at the provincial level. All the models contain year-month-province and calendar date FEs. The last row of the table reports the p-values for the Wald test performed to test the equality of the coefficients related to each bin within the models. The null hypothesis is the equality of the coefficients.
For the ease of exposition, the column are named after the first sector we report in each panel of Figure 7 (column 1-2) and Figure 8 (column 3-6).
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.12: Effect of UTCI temperature on daily accidents at the provincial level

VARIABLES	(1) Agriculture	(2) Industry	(3) Trade	(4) ICT	(5) Public	(6) Other Services
[23 – 25) °C	1.0242*	0.9935	1.0147	0.9933	1.0079	0.9859
	(0.0134)	(0.0090)	(0.0100)	(0.0094)	(0.0127)	(0.0227)
[25 – 28) °C	1.0495***	1.0105	1.0167*	1.0003	1.0073	0.9895
	(0.0148)	(0.0083)	(0.0097)	(0.0110)	(0.0118)	(0.0238)
+28 °C	1.0429***	1.0402***	1.0513***	1.0369***	1.0410***	1.0050
	(0.0166)	(0.0098)	(0.0144)	(0.0121)	(0.0152)	(0.0301)
Rain	0.9865***	0.9927***	0.9995	0.9997	0.9971**	0.9991
	(0.0012)	(0.0008)	(0.0011)	(0.0011)	(0.0012)	(0.0021)
Rain^2	1.0002***	1.0001***	1.0000	1.0000	1.0001*	1.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Rain^3	1.0000***	1.0000**	1.0000	1.0000	1.0000*	1.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Wind	1.0290	1.0424**	1.0240	1.0531**	0.9997	1.0124
	(0.0206)	(0.0196)	(0.0153)	(0.0212)	(0.0186)	(0.0467)
Wind^2	0.9962	0.9946	0.9960	0.9898**	0.9964	0.9951
	(0.0044)	(0.0041)	(0.0040)	(0.0042)	(0.0048)	(0.0120)
Wind^3	1.0001	1.0002	1.0002	1.0007***	1.0003	1.0005
	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0008)
Observations	257,301	257,301	257,301	257,301	257,301	257,301
Month-Year-Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean	0.76	3.17	1.34	1.57	1.71	0.19
P-value (Wald test for the bins)	0	0.0926	0	0.0022	0.0122	0.7331

Notes: estimates of equation (4) with standard errors clustered at the provincial level. All the models contain year-month-province and calendar date FEs. The last row of the table reports the p-values for the Wald test performed to test the equality of the coefficients related to each bin within the models. The null hypothesis is the equality of the coefficients.
For the ease of exposition, the column are named after the first sector we report in each panel of Figure 7 (column 1-2) and Figure 8 (column 3-6).
*** p<0.01, ** p<0.05, * p<0.1

Table A.13: Pairwise z-tests for differences in temperature bins across sectors

Bin	Agriculture	Industry	Trade	ICT	Public	Other Services
[23-25) °C						
Temp vs WBGT	-0.93	2.06**	-0.47	2.63***	-0.02	-0.47
Temp vs UTCI	0.40	3.42***	0.04	3.05***	0.99	1.24
WBGT vs UTCI	1.27	1.44	0.47	0.78	1.11	1.6
[25-28) °C						
Temp vs WBGT	-1.97**	-1.54	-0.2	-0.37	-1.57	-1.25
Temp vs UTCI	-0.37	2.65***	1.99**	3.01***	1.31	0.32
WBGT vs UTCI	1.68*	4.49***	2.62***	3.36***	3.41***	1.65
+28 °C						
Temp vs WBGT	-0.60	1.72**	-0.33	1.05	0.60	-0.19
Temp vs UTCI	0.00	3.26***	0.99	2.09**	1.16	0.18
WBGT vs UTCI	0.82	1.77*	1.61*	1.83*	0.65	0.47

Notes: Z-tests comparing the coefficients of equation (4) across temperature indicators for each bin. The null hypothesis is that coefficients are equal.
*** p<0.01, ** p<0.05, * p<0.1