INPS
Istituto Nazionale Previdenza Sociale

giugno 2025 – numero 97

WorkINPS *Papers*

The impact of weather on worker absences in Italy

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ISSN 2532 -8565

In copertina: uno storico "Punto cliente" a Tuscania
INPS, Direzione generale, Archivio storico

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The impact of weather on worker absences in Italy

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The impact of weather on worker absences in Italy

L'impatto delle condizioni metereologiche sulle assenze dei lavoratori in Italia

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Abstract

This research aims to assess the impact of weather on worker absences in Italy. Using a database merging employer-employee data from the National Institute for Social Security (INPS) and climate data from the European Centre for Medium-Range Weather Forecasts (ECMWF), during the period 2009 and 2018, we estimate econometric models for panel data with fixed effects. The dependent variable is a measure of the salary share workers received from INPS due to absences exceeding 7 days, a proxy both for worker absence length and for the related public expenses. Weather variables (temperatures, precipitations, wind) are used as explanatory variables, along with control variables.

The results show that longer absences, and more costly ones for INPS, were caused by extremely low temperatures. Though, extremely high temperatures, while less impactful at the margin, are more frequent and have a larger impact in a subsample of older workers. Linear probability and logit estimates, moreover, show that lower temperatures do not affect the frequency of absences.

Questa ricerca mira a valutare l'impatto delle condizioni meteorologiche sulle assenze dei lavoratori in Italia. Utilizzando un database che combina dati datore di lavoro-dipendente dell'Istituto Nazionale della Previdenza Sociale (INPS) e dati climatici del Centro Europeo per le Previsioni Meteorologiche a Medio Termine (ECMWF) per il periodo 2009-2018, stimiamo modelli econometrici per dati panel con effetti fissi.
La variabile dipendente è una misura della quota di stipendio ricevuta dai lavoratori dall'INPS a causa di assenze superiori ai 7 giorni, che funge da proxy sia per la durata delle assenze sia per i relativi costi pubblici. Le variabili meteorologiche (temperature, precipitazioni, vento) vengono utilizzate come variabili esplicative, insieme ad altre variabili di controllo.
I risultati mostrano che le assenze più lunghe e più costose per l'INPS sono state causate da temperature estremamente basse. Tuttavia, le temperature estremamente alte, pur avendo un impatto marginalmente inferiore, si verificano con maggiore frequenza e hanno un effetto più significativo in un sottocampione di lavoratori più anziani. Inoltre, le stime con probabilità lineare e logit indicano che le temperature più basse non influenzano la frequenza delle assenze.

Keywords: Labor Market, Extreme Temperature, Climate Change, Panel.

Parole chiave: Mercato del lavoro, Temperature estreme, Cambiamento climatico, Panel.

JEL Code: J22, J22, I38

Ringraziamenti:
La realizzazione del presente articolo è stata possibile grazie alle sponsorizzazioni e le erogazioni liberali a favore del programma 'VisitINPS Scholars'.
The findings and conclusions expressed are solely those of the author and do not represent the views of INPS.

1. Introduction

Climate change increasingly affects our daily lives. Among its many documented impacts, as summarized in studies such as Dell (2014), Hsiang (2016), Auffhammer (2018), Carleton & Hsiang (2016), and Cianconi et al. (2020), higher temperatures can negatively affect working careers. Previous research has tested hypotheses about the relationship between rising temperatures and labour inputs at both the aggregate and business levels, concerning issues such as worked hours and productivity. Climate-related shocks to worker performance can trigger cascading effects, undermining the economic and social stability of the labour force (Kjellstrom et al., 2009). Damage functions within integrated assessment models now account for the labour productivity consequences of climate change at the microeconomic level (e.g., Lamperti et al., 2018, 2020).

Worker performance can be directly affected by illness and injuries or indirectly by extreme climatic events that disrupt productive facilities and supply chains. For example, floods and intense heat waves, especially when accompanied by high humidity, can lead to health issues such as cardiovascular problems and malnutrition (Schulte et al., 2016). Similarly, heavy rain can increase the prevalence of intestinal diseases (Jagai et al., 2015; McKinnon et al., 2016). Evidence suggests that extreme temperatures impair worker performance, reduce attention spans, and increase the risk of accidents (Filomena and Picchio, 2024; Picchio and Van Ours, 2024). This is particularly true for outdoor workers or those exposed to chemicals (Cianconi et al., 2020; Levy and Roelofs, 2019), but not only for them: the National Institute for Insurance against Accidents at Work (INAIL 2018) highlighted that workplace microclimates affect worker safety, emphasizing the importance of incorporating these factors when assessing and mitigating occupational risks.

Over the long term, climate-related work interruptions can significantly harm careers. Severe health effects may force career breaks, reduce opportunities for promotions or salary increases (Hoey et al., 2023), and ultimately lower average income levels over the life cycle (Huang et al., 2020; Burzyński et al., 2021).

This paper investigates the impact of climate on worker absences and on the associated cost that the social security agency must pay for them. Using panel data models, we analyze employer-employee data from the National Institute for Social Security (INPS) merged with weather data from the European Centre for Medium-Range Weather Forecasts (ECMWF).

The dependent variable measures worker absences as the fraction of monthly wages paid by INPS for justified absences longer than seven days, which may arise from illness, injury, childcare, or redundancy payments. The main explanatory variables include temperatures, wind, and precipitation in the municipality where the workplace is located. Control variables, such as gender, nationality, qualification, sector of activity, and commuting status (i.e., whether the residence and workplace municipalities differ), account for heterogeneity among workers and occupations. Panel data models with fixed effects allow to control for unobserved individual-level characteristics.

This study contributes to the empirical literature on climate change and labor markets, which typically adopts one of two approaches: projecting future impacts (via integrated assessment models) or estimating existing effects (climate econometrics). Our research falls within the latter category, addressing the issue of worker absences, which has been seldom explored in the previous literature. The few papers dealing with worker interruptions have focused on work-related injuries and accidents (see Marinaccio et al. 2019, Dillender 2021, Park et al. 2021, Ireland et al. 2023, Filomena and Picchio 2024), while perhaps the only one dealing with a broader range of absence reasons is Somanathan et al. (2021), who explored absences and temperatures in Indian manufacturing. Unlike Somanathan et al. (2021), whose dataset was limited to the manufacturing sector, our dataset from INPS covers the tertiary sector too and represents over 70% of Italian employees. Filomena and Picchio (2024) and Marinaccio et al. (2019) relied on INAIL data to study work related injuries in Italy, while our study includes a wider range of absences, can proxy for their length, and can quantify expenditure by the social security agency related to absences. These may be seen as advantages that compensate for the lower time granularity of our analysis (monthly frequency INPS data vs. daily frequency of INAIL-based studies). Further existing studies have focused on topics related to labour supply, such as labor productivity (Dasgupta et al., 2021), time allocation (Garg et al., 2020), and employment reallocation due to climate shocks (Acharya et al., 2023).

Our findings reveal that extreme temperatures lead to longer worker absences, resulting in higher expenditures for INPS. Back-of-the-envelope calculations suggest that 10 additional days with temperatures below -15°C (and 10 fewer days with milder weather) increase INPS costs by €77.14 per month per average-wage worker, holding other factors constant. Similarly, 10 extra days with temperatures between -15°C and 0°C raise costs by €21.94 per month per worker.

Our results are robust to alternative temperature bin specifications. Checks on workers that have changed sector during the sample period dispel suspected biases due to avoidance behaviors. Sub-sample analyses show that older workers (over 50 years of age) are more vulnerable to very high temperatures, and that the estimated effects of warmer temperatures are larger if the sample is restricted to the summer months. Moreover, while finding stronger impacts when temperatures are very low was unexpected, linear probability and logit model estimations suggest that lower temperatures affect the duration of absences, but not their frequency. The impact of high temperatures is smaller in magnitude but more widespread geographically, and their frequency is expected to increase due to climate change.

The paper is structured as follows: Section 2 reviews the related literature. Section 3 describes the dataset and presents summary statistics. Section 4 outlines the econometric models. Section 5 discusses the results, and Section 6 concludes.

2. Previous literature

2.1 Why worker absences matter

Why study worker absences? The existing literature provides multiple perspectives on their relevance, encompassing the viewpoints of workers, employers, and taxpayers.

For individual workers, absences, particularly longer ones, can entail significant costs. These include foregone income, persistently reduced physical and/or cognitive abilities, disrupted knowledge accumulation, and loss of workplace-specific information. Income loss during work interruptions is the most immediate and visible consequence. In most developed countries, including Italy, workers on health-related leave are shielded by social protection systems, receiving full or partial income replacement, typically funded by public labor insurance agencies (Maclean et al., 2020). However, such safety nets do not fully mitigate the broader consequences of absences.

Long-term absences can impede career progression, reducing opportunities for promotions and higher earnings. For example, workers competing within an organization for career advancement may lose valuable informational advantages during prolonged absences, leading to asymmetries vis-à-vis their colleagues. This can weaken their bargaining power with respect to employers. Moreover, absences disrupt the process of on-the-job learning, which is typically cumulative and vital for skill development and career growth (Spurk et al., 2019). The resulting gap in productivity compared to peers can hamper competitiveness, affecting long-term earnings potential[1]. Evidence suggests that employees on extended sick leave face reduced chances of returning to work, exacerbating these effects (D'Amato and Zijlstra, 2010). While statistical associations support these conjectures, causal relationships between health-related absences and career outcomes remain an open research question (Chadi and Goerke, 2018).

For employers, absent workers represent a reduction in labor input, compelling firms to resort to temporary hires or overtime, which incurs additional costs. Firms also risk losing the skills embodied in absent employees, necessitating investments in training replacements. Absences can sometimes reflect opportunistic behavior by employees. For instance, absences on favorable weather days may signal a misalignment between workers' and employers' interests. While some evidence, such as Shi and Skuterud (2015) for Canada, supports this view, other

[1]Although not specifically related to the goals of the present article, there is ample evidence of how pregnancy and childbearing can slow down a woman's career (see Baum II 2003, Dahl et al. 2016 among others).

studies, including Böheim and Leoni (2020) for Austria, find no such inflation in absence rates on bridging days. [2]

From taxpayers' perspectives, absences are relevant due to their economic and fiscal implications. As mentioned, public labor insurance agencies in some regulatory systems cover income during sick leave. Beyond direct costs, absences can slow down productivity and increase public healthcare expenses while eroding the tax base. Union bargaining power can also play a role, with some evidence suggesting a trade-off between wages and the extent of sick pay (Goerke, 2017).

2.2 Determinants of absences, with a focus on climate-related ones

A recent paper by Filomena and Picchio (2024) uses Italian INAIL data on work-related accident rates (i.e. accidents per 100,000 workers by province, including workplace and commuting accidents) and Copernicus weather data between 2008 and 2021 included. Both injury and weather data are observed daily. Their fixed-effects model, which includes 15 temperature bins, wind speed, precipitation amount, and control variables, shows that both extreme heat and cold affect injury rates, with notable differences across temperature intervals, sectors, and worker categories. Their findings align with previous studies, such as Marinaccio et al. (2019), which also used INAIL data on work-related injuries for a shorter, preceding period (2006-2010), focusing on accident counts, and excluding road accidents that occurred to workers while commuting. Through Distributed Lag Non-Linear Models (DLNM) and a meta-analysis, Marinaccio et al. found significant links between extreme temperatures and occupational injury risks in Italy. Evidence from other countries includes Dillender (2021), who analyzed workplace injuries in Texas using a fixed-effects model with temperature and rainfall as explanatory variables, incorporating data on the exact dates of medical treatments from 2006 and 2014. Park et al. (2021) examined workplace injuries between 2001 to 2018 in the U.S., using information on the date of injury and applying a fixed-effects model with binned temperature and precipitation as independent variables. Ireland et al. (2023) used data on workers in the Australian state of Victoria, incorporating information on the exact day of absence between 1985 and 2020. They estimated a fixed-effects model with maximum

[2] Employer-employee dynamics, shaped by contractual terms and bargaining power, also influence absence behaviors. For instance, private-sector employers often detect and address opportunistic behavior more effectively than public-sector employers (Biscardo et al., 2019). Workers with a history of opportunistic absences may transition to less-demanding public-sector jobs (Ehlert and García-Morán, 2022). In contrast, incentive programs have shown promise in reducing absenteeism in both sectors (Eskildsen et al., 2021).

temperature and precipitation as dependent variables, confirming that extreme temperatures increase injury rates.

Our study differs from the reviewed ones in several respects. First, it considers, as dependent variable, a proxy for the length of worker absences, whereas previous works focused on the number of work-related injuries or on injury rates. Secondly, it includes Those previous studies did not include, absences due to other, potentially climate-related reasons, such as sickness of the worker, sickness of family members, and occupational difficulties faced by employers (redundancy programme "Cassa Integrazione Guadagni"), that are available in the INPS dataset but not in the INAIL one. Climate conditions can influence these absences either directly, through health impacts like heat stress, or indirectly, by affecting family members or employer operations. Opportunistic absences, such as those motivated by favorable weather, also deserve consideration but are not declared. Additionally, papers using INAIL data do not provide information on the additional costs borne by taxpayers.

Perhaps the only previous paper analyzing absences in general – including but not limited to accidents – is Somanathan et al. (2021) who analyzed the impact of extreme temperatures on worker productivity and absenteeism in the Indian manufacturing sector. The data were collected on a daily basis over a 15-year period (1998–2009), providing a detailed analysis of the effects of daily temperature variations on productivity and absenteeism. The study employs a fixed-effects model that includes temperature bins for estimation. The findings indicate that, in the absence of air conditioning, worker productivity decreases on particularly hot days. Moreover, both current and past high temperatures increase absenteeism, even in air-conditioned workplaces.

It is worth remarking, following Filomena and Picchio (2024, p. 852), that evidence based on a country's data is not easily generalizable, as it may convey country-specific labour regulations and climate risk exposure. Further caveats are in order before comparing evidence about countries at different stages of development. In fact, a substantial body of research explores climate-related determinants of worker absences in developing economies (Jessoe et al., 2018; Somanathan et al., 2021; Gupta & Somanathan, 2023). In these settings, limited resources constrain adaptation strategies, and climate-sensitive sectors like agriculture dominate. Evidence shows that adverse weather events often lead to job changes, migration, and pressures on healthcare systems (Flatø et al., 2017; Acevedo, 2015). Workers may compensate for income losses by increasing work hours in unaffected sectors or reallocating their labor to less-exposed jobs (Huang et al., 2020; Branco & Féres, 2021).

Studies about developing countries still warn about limitations in adaptation capacity; for instance, Somanathan et al. (2021) demonstrates that extreme temperatures reduce worker productivity and increase absences even in workplaces with air conditioning. Moreover, elevated temperatures are linked to greater workplace injuries and accidents (Kreshpaj et al., 2022).

Climate-related impacts extend beyond workplaces. Weather conditions in residential municipalities or during commuting also influence absences. Studies such as Belloc et al. (2022) underscore the importance of commuting-related exposure, while Wiese et al. (2024) highlight the broader implications of commuting quality on worker well-being.

3. Data

The analysis leverages an employer-employee dataset provided by INPS, focusing on private-sector, non-agricultural workers. This dataset covers employees, who constitute more than 70% of Italy's labor market (see Di Porto et al., 2021, for a previous, related use of this dataset).

The INPS dataset offers monthly observations about various employee-related variables, such as wages and absences[3]. Labor market data are hereby matched with monthly weather variables ensuring temporal alignment[4].

The sample collected for use in the econometric analysis includes only workers who experienced during the study period at least one absence lasting seven days or more. Such absences are remunerated by INPS rather than the employer.

By focusing solely on workers with at least one absence, the analysis examines the intensive margin effects of weather variation. This means that the study does not investigate whether a worker is absent or present but rather assesses the severity of absences. Since the INPS dataset lacks information on the duration of each absence, we use the percentage of monthly wages not paid by employers due to absences (and instead covered by INPS) as a proxy for absence length. This metric also facilitates the estimation of taxpayer costs associated with absences.

To analyze the relationship between weather and labor market outcomes, meteorological data, including temperature, wind speed, and precipitation, are integrated into the dataset. These weather variables are sourced from the European Center for Medium-Range Weather Forecasts (ECMWF) as part of the Copernicus Climate Change Service.

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[3] It was obtained by combining the labor market dataset and the personal data of the workers.

[4] Climate data in this paper are monthly aggregates of daily data (further details in the weather data section).

The sample covers the period from 2009 to 2018. The selection of this timeframe is driven by several considerations: data from 2009 onward are chosen to minimize missing values of the dependent variable; 2018 was the latest year for which meteorological data were available. Additionally, excluding the COVID-19 pandemic years (2020–2022) avoids potential distortions due to atypical labor market and health conditions.

Table 1 contains the definitions of all variables used in the analysis.

Table 1: Variables and their definitions (2009-2018).

Variables	**Definitions**
Credit difference percentage	The credit percentage (based on theoretical wage) received by the worker due to a justified absence exceeding seven days or because he\she is receiving redundancy pay.
Temperatures_max	The average maximum monthly temperature recorded in each municipality.
Temperatures_min	The average minimum monthly temperature recorded in each municipality.
Temperatures_avg	The average monthly temperature recorded in each municipality.
Wind speed	The average monthly wind speed recorded in each municipality.
Precipitation	Total monthly rainfall recorded in each municipality.
Exposed sectors	A dummy equal to one if the sector in which the employee works is a sector exposed to climate risk (see Table A.2 in the Appendix).
Exposed qualification	A dummy equal to 1 if the qualification of the employee is blue-collar worker.
Commuter	A dummy equal to one if the employee does not work in the municipality of residence.
Nationality	A dummy equal to one if the employee has Italian nationality.
Gender	A dummy equal to one if the employee is male.
Age	The age in numerical value, obtained by subtracting the year of birth from the current year in the dataset.
Paid days	The number of monthly working days per contract, not including deduction of the number of days for illness.
Temperature bins	Number of days within a given temperature range in a month.

Source: Own elaboration on INPS and ECMWF datasets.

The subsequent sections provide detailed descriptions of the employees data (Section 3.1) and weather data (Section 3.2) used in the study.

3.1 Employees Data

Table 2 presents descriptive statistics on the variables concerning employees, focusing exclusively on workers who experienced at least one absence lasting longer than 7 days during the sample period, i.e., the sampled workers. Let us recall that the INPS dataset exclusively covers employees, excluding business owners and managers[5].

The average age of workers in the dataset is approximately 42 years, with an average service length of about 22 years. These figures exhibit an upward trend over time, partly because the dataset tracks the same workers over multiple years and possibly due to a decline in the number of young people entering the labor market and an increase in the retirement age.

Approximately 66% of the workers in the sample are classified as blue-collar workers, while the remaining 34% are white-collar workers. Foreign workers constitute about 10% of the sample, predominantly originating from Morocco, China, Romania, and Albania. These statistics align with the Ministry of Labor and Social Policy's XI Annual Report on Foreigners in the Italian Labor Market (2021). Women are 57% of workers in the sample. Controlling for nationality and gender is useful, as previous evidence showed that foreign workers and females tend to experience longer sick leaves[6] (see also Di Porto et al., 2021).

It is well established in the climate econometrics literature that not all sectors are equally vulnerable to climate risks, because of higher exposure of assets to extreme climate events or because tasks are performed outdoors. Therefore, examining the sectoral composition of the sampled workers is essential. In our analysis, we include a dummy variable that equals one if the occupation can be considered climate sensitive, namely if they require tasks performed outdoors (Habibi et al., 2024). The full list of these sectors is provided in Appendix Table A.1.

The dataset also allows for the identification of the reasons behind worker absences, particularly those potentially linked to climate change. Illness and injuries may be directly attributed to weather events, although INPS does not report the exact reason for such health issues. Childcare absences are also relevant, as adverse weather conditions can impact children's health, prompting parents to take leave to care for them. Additionally, absences indirectly related to climate include employers' use of redundancy funds, which may occur when extreme weather events damage business assets or disrupt commercial channels, forcing firms to temporarily

[5] As they are not classified as employees under Italian labor market definitions (ISTAT, 2013).

[6] https://www.integrazionemigranti.gov.it/AnteprimaPDF.aspx?id=2877

reduce employment levels.[7] These reasons collectively account for approximately 85% of the total absences recorded in the dataset[8].

Statistics indicate that the longest periods of absence tend to occur at the ages of 30 and 55. The peak in absences for workers aged 55 might relate to inclusion in the redundancy program, which is more likely for workers aged 50 and above than for younger employees (cf. the 2018 INPS Annual Report).

The average theoretical monthly wage in the dataset is approximately €1,672. The Credit Difference variable represents the amount of wage paid by INPS to workers during justified absences exceeding seven days, or when workers receive redundancy pay. For unpaid absences, when workers are not entitled to INPS payments (e.g. absences less than 8 days long), the variable is set to 0. Given the duration of an absence, the credit difference is generally higher for workers with higher salaries, as it reflects the daily wage multiplied by the length of the absence.

To facilitate comparisons of earnings losses among workers with varying salary levels and to obtain a proxy for absence duration, a "credit difference percentage" variable was calculated as the ratio of the credit difference to the theoretical wage. On average, the credit difference amounts to €463 per month, representing approximately 30% of the theoretical wage. This percentage serves as a proxy for the length of work interruptions.

Table 2: Descriptive statistics on labor market variables[9].

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Years in service	21.87	11.09	0	49
Age	42.36	9.74	15	64
Credit difference	463.53	437.79	0	1870
Theoretical wage	1672.44	545.08	0	3152
Credit difference, %	30.26	28.83	0	100
Paid days	21.66	6.57	1	31
Exposed sectors	0.17	0.38	0	1

[7] Though, it is only since 2023 that in Italy employers can motivate their application for redundancy funds by citing climate events.

[8] The other types of absence concern absence due to disability, leave for various reasons (including maternity, paternity or victim of violence), donations (including blood or marrow). We will run estimates including also these absences, which are less obviously related to climate conditions, but will also narrow the focus on only the ones potentially due to weather (injuries, illness, childcare, redundancy fund).

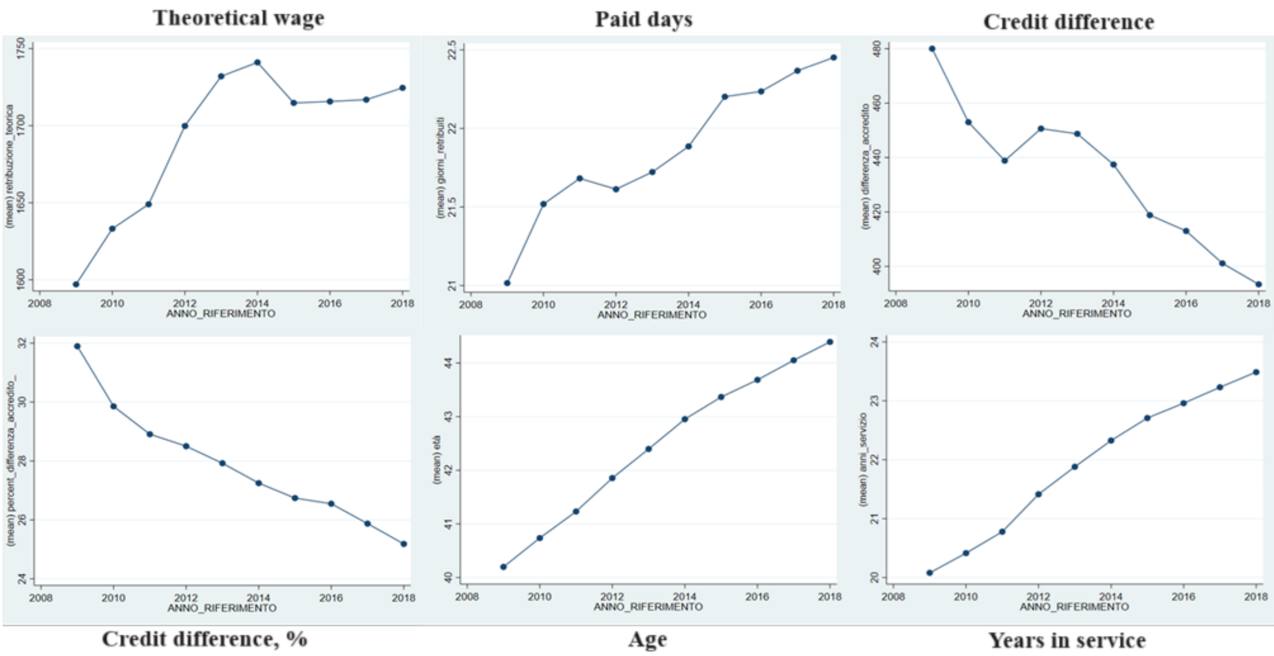
[9] Number of observations: 101,518,123.

Exposed qualification	0.65	0.47	0	1
Commuter	0.64	0.47	0	1
Nationality	0.89	0.30	0	1
Gender	0.57	0.49	0	1

Source: INPS dataset, employees and non-agricultural workers, monthly data, years 2009-2018.

Figure 1 illustrates the time series of the workforce variables (mean values). Until 2015, the average salary showed a rising trend, stabilizing afterward. Over the study period, the average number of working days lost due to absences increased by about one and a half days. Meanwhile, the credit difference variable and its percentage exhibit a declining trend, while the average age and years of service of workers rise steadily each year.

Figure 1: Time series of the workforce variables (mean values), from 2009 to 2018.



Source: own processing INPS data, employees and non-agricultural workers, monthly data, years 2009-2018.

3.2. Weather Data

This study considers temperatures, wind speed, and precipitation as the weather variables of interest. The data, sourced from the European Centre for Medium-Range Weather Forecasts (ECMWF), are recorded daily and include information on daily minimum, average, and maximum temperatures. To merge the weather dataset and the workforce dataset, which is available at a monthly frequency, we calculated monthly averages and other statistical measures of the weather variables for use in the econometric analysis.

The weather data fall under the category of assimilation data, derived through a sophisticated process that combines various meteorological parameters from direct measurements, such as those from weather stations, radiosondes, and sensors. This assimilation process is based on advanced atmospheric physics models, generating consistent historical datasets on a regular grid[10]. These reanalysis datasets have been publicly available since 1965 and are produced at two spatial resolutions: monthly data with a 5x5 km grid and daily data with a 17x17 km grid[11]. More detailed information about the weather variables is provided as follows.

Temperatures. Extreme temperatures, both high and low, can impact workers' productivity and well-being. High temperatures can lead to heat stress, dehydration, heat-related illnesses, cardiovascular strain, and long-term health effects, while low temperatures can cause cold stress and reduced dexterity. The optimal temperature range for human comfort is 18–24°C (Ryan et al., 2014). Unfortunately, lack of humidity data did not allow to compute wet-bulb temperatures (Yang et al., 2021).

During the study period, the average monthly minimum and maximum temperatures were 9.8°C and 19°C, respectively, with substantial variation. The lowest recorded average monthly minimum temperature was -17.7°C (February 2018, Lombardy), while the highest recorded average monthly maximum temperature was 37.3°C (August 2017, Sicily). The regions with the highest monthly average temperatures were Sicily (21.9°C) and Sardinia (21.3°C), while the lowest monthly average temperatures were recorded in Val d'Aosta (1.9°C).

For use in the econometric analysis, we count the number of days in each month when maximum daily temperatures fell within given bins (see below for more details).

Precipitation. Climate change alters precipitation patterns, increasing the intensity and frequency of extreme rainfall events, which may cause floods and other disasters. High precipitation can hinder commuters and outdoor workers, while low precipitation can indicate prolonged dry periods. Rainfall also influences how workers perceive temperatures (Neog, 2022; Ireland et al., 2023).

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[10] https://climate.copernicus.eu/climate-datasets

[11] The decision to use monthly-averaged daily data instead of monthly data has been informed by an analysis of the trade-offs induced by the different spatial resolution of the monthly and daily data provided by ECMWF. Consider that while the daily data are coarser in spatial terms, their higher frequency allows computing further monthly statistics, such as the standard deviation of temperatures, which may be useful for robustness exercises. Indeed, climate variability may be as threatening as changes in the weather variables levels.

The average precipitation is 72.39 mm (Calculated by averaging the total rainfall across different municipalities), with a standard deviation of 61.98 mm. The minimum recorded value is 0 mm, while the maximum reaches 785.4 mm. Both rainfall and snowfall are included linearly in our econometric models.

Wind Speed. Wind speed significantly affects outdoor workers, altering their perceived temperature and increasing physical demands. Strong winds can cause discomfort, safety hazards, and increased risks of accidents, particularly for those in construction or other outdoor industries (Huang et al., 2020). Wind can also exacerbate noise, blow dust and debris, and require greater physical effort from workers (INAIL, 2018; Lemke and Kjellstrom, 2012). The average wind speed in the sample is 2.39 m/s, with a standard deviation of 0.95 m/s. The minimum recorded wind speed is 0.45 m/s, while the maximum reaches 10.45 m/s. Wind speed is included linearly in our econometric specifications.

Table 3: Descriptive statistics on weather variables[12].

Variable	Mean	Std. Dev.	Min	Max
Temperature, monthly max (°C)	19.01	7.86	-6.16	37.39
Temperature, monthly min (°C)	9.86	6.65	-17.75	26.16
Temperature, monthly average (°C)	14.43	7.18	-11.1	30
Wind speed (m/s)	2.39	0.95	0.45	10.45
Precipitation (mm)	72.39	61.98	0	785.4

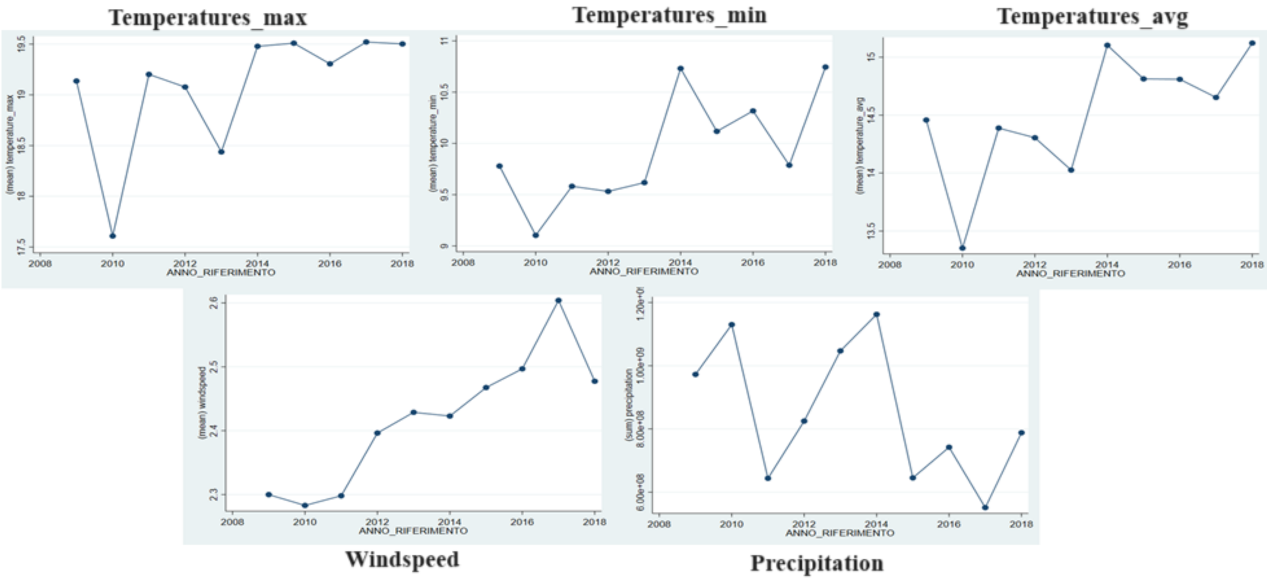
Source: own elaboration on ECMWF *dataset.*

Figure 2 highlights the climatic trends observed during the period. A notable increase in both minimum and maximum temperatures occurred in 2014. Precipitation levels fluctuated significantly, with peaks in 2010 and 2014, while the highest daily precipitation value was recorded in 2016. A general increase in wind speed was observed, except in 2018.

[12] Number of observations 101,518,123.

This graphical analysis confirms the impact of climate change, as evidenced by rising temperatures, increased droughts, and the higher frequency of extreme weather events (Fiorillo et al., 2018).

Figure 2: trend of the most important climatic variables, from 2009 to 2018.



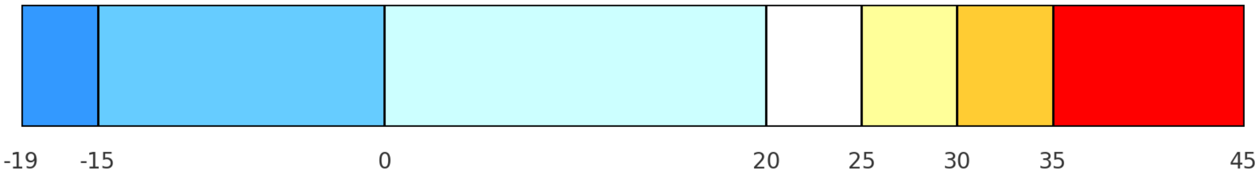
Source: own elaboration on ECMWF *dataset.*

4. Methodology

The econometric estimates were conducted using a dataset that combines the INPS data on workers and the ECMWF data on weather conditions, yielding a total of 101,518,123 observations spanning the years from 2009 to 2018. The data frequency is monthly. The dataset is structured as an unbalanced panel because workers are only included in months when they were absent from work. On average, the dataset includes over 10,000 individuals per year.

To evaluate the impact of extreme temperatures on worker absences, maximum recorded temperatures at the monthly frequency were divided into temperature bins. This methodology aligns with approaches used in the literature (e.g., Somanathan et al., 2021; Filomena and Picchio, 2024). The binning strategy was performed to allow for non-linear dependencies of absences on temperatures and to isolate the effects of extreme temperatures. The division into 7 bins was used in the primary specification, representing a compromise between granularity and degrees of freedom; the bins were the following: [-19, -15],]-15,0],]0,20],]20,25],]25,30],]30,35],]35,45] (see Fig. 3). In the study by Somanathan et al. (2021), the temperature bins are defined in different ways depending on the specification of the econometric model. In the base model, the temperature bins are as follows: (0,19], (19,21], (21,23], (23,25], (25,27], (27,29], (29,31], (31,33], (33,35], (35,50]. In other specifications, the temperature bins are defined as: (0,20], (20,25], (25,30], (30,35], (35,50].

Figure 3: Division into temperature bins.



Source: own elaboration.

The primary model used for the analysis is (Eq 1):

$$Y_{it} = \alpha_i + \beta_t + X_{it}\gamma + \sum_{n=1}^{7} B_{itn}\,\delta_n + P_{it}\mu + W_{it}\eta + \epsilon_{it} \quad (1)$$

In this model, Y_{it} represents the dependent variable, which is the "credit difference percentage" for worker i in month t, measured on a scale from 0 to 100. The term B_{itn} represents the number of days when temperatures belonged to the n-th temperature bin, in worker i's workplace municipality. Hence, $\sum_{n=1}^{7} B_{itn}$ is equal to the number of days in month t. To prevent collinearity, we exclude the central bins (the 4th in the 7-bin case).

P_{it} indicates the total precipitation in month t for the municipality where worker i is employed, and W_{it} represents the average wind speed during the same period in the same municipality. X_{it} is a vector of control variables that includes the following: exposed sectors (e.g., construction, transport, distribution, shipping), exposed qualification, commuter[13], and paid days. The terms α_i and β_t correspond to firm-level and time (month and year) fixed effects, respectively. β_t is a unique numerical identifier assigned to each month in the dataset, continuing sequentially across years. It helps capture changes over time, such as seasonality or trends, without directly depending on the specific year or month label. Finally, the parameters in the model are denoted by δ, η, μ, γ.

Each parameter δ_n quantifies the expected change in the dependent variable Y_{it} (the percentage credit difference) in response to an additional day in a specific temperature bin, while holding

[13] The inclusion of the commuting variable provides a proxy for individuals' additional exposure to external climate conditions.

all other variables in the model constant. Since each temperature bin corresponds to a specific range of degrees Celsius, the model identifies the differential impact of temperature on Y_{it}, allowing the identification of critical temperature ranges, such as extremely low or high temperatures.The gross marginal effect of an additional day in a temperature bin is captured by coefficient δ_n, associated with temperature bins B_{itn}. The net effect arising from one more day in a temperature bin and one day less in another temperature bin is defined as $\delta_n - \delta_m$, where bins m and n can be adjacent (i.e. m = n + 1, m = n -1) or not.

The Hausman test (available upon request) supports the use of the fixed effects model, consistent with prior studies in the literature. The estimator applies robust standard errors (Angrist and Pischke, 2009). These robust standard errors use Huber-White corrections, making them resistant to heteroskedasticity.

Although the dataset does not include detailed diagnoses for health-related absences or information about the actual reasons pushing employers to use redundancy funds, individual fixed effects help mitigate these limitations. These effects account for time-invariant factors such as chronic health conditions and firm-specific vulnerabilities to climate events and/or to market competition.

The coefficients linked to temperature, wind, and precipitation may reveal the causal effects of climate, provided these variables can be considered exogenous. While a few studies have evaluated the potential endogeneity of climate variables (e.g., Branco and Féres, 2021; Jessoe et al., 2018), there is general acknowledgment that mutual influences exist. Climate exercises impacts on the labor market, yet human-generated emissions (produced through labor) also affect climate (Pretis, 2021). For example, fewer absences could result in higher output, leading to greater GHG emissions at the firm level. Despite this, much of the literature treats climate variables as exogenous, assuming variations in these variables are unexpected from the worker's perspective (e.g., Garg et al., 2020; Branco and Féres, 2021).

Hereby we argue that while sudden climate shocks can disrupt the activities of many workers, individual working hours and outputs contribute only minimally to global GHG emissions, therefore the link with local climate change is highly indirect.

We are more concerned about sources of endogeneity arising from worker behaviours (Garg et al., 2020). For instance, workers may engage in avoidance behaviors, such as switching to less exposed sectors or jobs (He et al., 2021; Di Porto et al., 2021). Some workers might relocate closer to their workplace and avoid commuting to minimize exposure to adverse weather or viral spread.[14] Our dataset shows that very few workers change sectors or qualifications.

Finally, we account for the possibility that temperature effects may vary by season. For instance, an increase in winter temperatures is likely less harmful to health than a similar rise during peak summer weeks. To capture these seasonal differences, we extend the model by interacting with temperature bins two seasonal dummies: one for winter and another for summer. The extended model specifications are as follows (see Eq 2-3):

$$Y_{it} = \alpha_i + \beta_t + X_{it}\gamma + (\sum_{n=1}^{7} B_{itn} * \delta_n) * Winter + P_{it}\mu + W_{it}\eta + \epsilon_{it} \tag{2}$$

$$Y_{it} = \alpha_i + \beta_t + X_{it}\gamma + (\sum_{n=1}^{7} B_{itn} * \delta_n) * Summer + P_{it}\mu + W_{it}\eta + \epsilon_{it} \tag{3}$$

The variables remain the same as in the first specification, except for the addition of the seasonal dummies. The variable "Winter" equals 1 during December, January, and February, while "Summer" equals 1 during June, July, and August.

5. Results

5.1 Baseline specification

The estimates from Eqs. 1, 2, and 3 are summarized in Table 4 and organized as follows: In Column (1), the dependent variable is the percentage credit difference considering all types of absences, analyzed across seven temperature bins. Column (2) narrows the focus to climate-related absences only[15]. Column (3) returns to the percentage credit difference for all absences but isolates the winter effect, while Column (4) highlights the summer effect. All estimations rely on two-way fixed effects (FE) models.

The results confirm that climate significantly impacts worker absences. Table 4 shows that extreme temperatures lead to longer worker absences. Similarly, increases in wind speed and precipitation also result in higher absenteeism. These findings remain consistent across all model specifications.

When considering all types of absences (Column 1), the impact of temperature on worker absences appears milder, except for bin 1 (temperatures below -15°C). However, when focusing

[14] Employer policies may matter, too, as companies may adapt their organizational frameworks to climate change, i.e. to comply with updated regulations on workplace microclimates.

[15] Absences due to illness, injuries, childcare, and redundancy fund.

solely on climate-related absences (Column 2), the coefficients are larger, indicating a stronger relationship between extreme weather and absences.

In winter (Column 3), lower temperatures, specifically bins 1 and 2, exert a significant effect on worker absences. Conversely, in summer (Column 4), the effect becomes more pronounced at the highest temperature bins.

Table 4: Panel two-way FE regression of percentage credit difference on climate variables and controls, for Italian workers between 2009 and 2018[16].

Dep.var.: Y_it	***(1)***	***(2)***	***(3)***	***(4)***
	All absences	***Climate rel. abs.***	***All abs., winter***	***All abs., summer***
temp.Bin1_it	*0.6112****	*0.4509****	*0.5784****	−
temp.Bin2_it	*0.0967****	*0.1244****	*0.223****	−
temp.Bin3_it	*−0.0002*	*−0.0054****	*0.0614****	*0.0347****
temp.Bin5_it	*0.0062****	*0.0122****	*−0.573****	*0.0346****
temp.Bin6_it	*0.0231****	*0.034****	*11.7589*	*0.0361****
temp.Bin7_it	*0.0080****	*0.0297****	−	*0.0524****
precipitation_it	*0.0008****	*0.0011****	*0.0008****	*0.0009****
windspeed_it	*0.0596****	*0.0456****	*0.0608****	*0.0585****
Exposed qualification	*0.1718****	*−0.385****	*0.1715****	*0.172****
Exposed sector	*−2.7743****	*−2.2291****	*−2.7741****	*−2.7744****
Commuter dummy	*−0.1799****	*−0.2696****	*−0.1801****	*−0.1799****
Worker FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N. obs.	*99,605,222*	*99,605,222*	*99,605,222*	*99,605,222*

[16] The coefficients have been truncated to four decimal places.

**p<0.10; **p<0.05; ***p<0.01*

Source: own processing of INPS data, employees and non-agricultural workers, monthly dataset, years 2009-2018. Column (1) utilizes as dependent variable the percentage credit difference based on all types of absences; column (2) restricts absences to climate-related ones; column (3) and (4) use the percentage credit difference based on all types of absences as the dependent variable, but focuses on isolating respectively the winter effect and the summer effect.

The coefficients for temp Bin6 and temp Bin7 (representing days with high temperatures) are statistically significant and positive across all specifications (except in winter), indicating a strong impact on the rate of absences. For temp Bin6, an additional day in this temperature range is associated with an increase of between 0.0231% and 0.0361% in absences, depending on the specification. For temp Bin7, the effect is even more pronounced considering summer: a strongly positive and significant impact with coefficient reaching 0.0524%. These results align with the hypothesis that both very high and very low temperatures can increase physical discomfort, reduce productivity, and encourage absenteeism, particularly in sectors or roles requiring outdoor work or physical efforts.

The coefficients in column (2) imply that one more day with temperatures falling below -15°C leads to an additional cost of € 5.52[17] per month for INPS for a worker whose wage is equal to the sample average, holding all other variables constant. The impact decreases when considering bin2, i.e. temperatures in the range [-15, 0]°C. In this case, the monthly cost borne by INPS for an average worker is €2.18. The increase in cost is less pronounced for very high temperatures. One more day with temperatures above 35°C results in an additional monthly cost to public finances of approximately €0.29 on average for each additional worker absence, and this cost increases during the summer period (see Table A.2 in the Appendix).

The calculated costs may seem small. Yet, it is worth considering that climate change may cause an increase in days with extreme temperatures, both very high or very low; if so, the costs

[17] The theoretical wage is €1690,44 on average. Since the coefficient for the bin with temperatures below -15°C is *0.4509475*, one additional day in that bin results in an increase of *0.4509475*% in the monthly credit difference percentage, which translates to *0.4509475* (the dependent variable is measured on a scale from 0 to 100). Multiplying *0.004509475* by €1690,44 yields €7,62. This is the monthly cost to INPS for an "average" worker due to one extra day with particularly low temperatures, considering all other factors. For completeness, we need to subtract the savings resulting from one extra day with temperatures above -15°C, which means one less day with lower temperatures. For example, if there's one less day in the [-15, 0]°C interval (estimated coefficient 0.12), we need to calculate 0.0012 * €1,690.44 = €2,10. Subtracting this from the previously estimated €7,62 gives us €5.52.

for INPS may be rising in the future. In fact, assuming that climate change will elongate the tails of the temperature distribution in the future, if there are 10 more days with temperatures between -15 and 0 °C, and 10 less in the 0, 20 °C interval, the average cost for INPS for a single worker would increase by €21.94 assuming that all other variables remain constant, including worker behavior and the level of adaptation of companies. Additionally, it is worth noting that for 10 more days with very high temperatures, between 30 and 35 °C, instead of days with milder temperatures (between 0 and 20 °C), INPS costs would increase by €6.66.

It also looks surprising that the marginal effects are higher for the coldest temperatures. In this respect, assessing the overall impact on the INPS budget requires measuring the number of days when temperatures fall within the upper tail of the distribution and the number of workers whose workplace is exposed to such temperature shocks.

Considering control variables, we find positive coefficients for exposed qualifications, negative for exposed sectors and for commuters. The result about exposed qualifications was rather expected, whereas it is more intriguing that workers in more climate-exposed sectors tend to display lower credit differences percentages, ceteris paribus, i.e. have shorter absences. Several factors may contribute to this pattern, including workplace closures during extreme weather conditions, or a relatively low bargaining power by workers in sectors where tasks are performed outdoors, as constructions. We will discuss more about these conjectures in the concluding section.

The negative coefficient associated with the commuter dummy indicates that the worker residing outside the municipality where they work tend to take shorter absence periods. This could be due to several factors, including avoidance behaviors, where workers deliberately choose to live in areas with better temperatures rather than in municipalities with more extreme climates. Moreover, the analysis does not control for the distance to work, some workers may reside in nearby municipalities that offer better environmental conditions, even though they are still close to their workplace.

Some coefficients, particularly that of temp Bin1 and temp Bin2, are exceptionally high. This could be due to different motivations. It is essential to verify whether the inclusion of such extreme values skews the overall results. Variation in the geographical or sectoral distribution of workers might contribute to such high values. The binning of temperature data might cause spurious correlations, especially in extreme bins with relatively few observed days actually really low temperature are less frequent. Robustness checks including sectoral dummies and a different split into temperature (see section 5.2) help to address these problems.

Sample selection could represent a significant issue. Since the study relies on INPS data, certain worker groups may be underrepresented or excluded. Self-employed are not included but may react differently to climate shocks, potentially reducing or adjusting their working hours. Seasonal workers may contribute to the observed effects during summer months. Moreover, the effect of temperature might vary significantly across regions or sectors (northern vs. southern Italy) due to differing climatic conditions and economic structures.

5.2. Robustness checks

Useful information regarding the frequency of climate-related worker absences can be achieved by estimating a binary dependent variable model. Indeed, absence lengths may be distorted if workers reduce them to avoid negative effects on their work careers. We estimate a linear probability model (col. 5 in Table 5) and a logit model (col. 6), using a binary dependent variable that takes the value of one for climate-related absences (illness, injury, childcare, redundancy) and zero otherwise.

The estimates of Table 5 show that worker absences increase in frequency with rising temperatures. It is important to note that the estimates for the first temperature bin lack statistical significance, unlike in previous estimates where the length of the absence is considered. Hence, very low temperatures affect the duration but not the frequency of potentially climate-related absences[18].

[18] Credit difference percentage is a proxy of absence duration.

Table 5: Panel FE regressions of workers absences on climate variables: linear probability model (col. 5) and logit (col. 6).

Dep.var.: Y_it	***(5)***	***(6)***
temp.Bin1_it	−0.0023	−0.0028
temp.Bin2_it	0.0007***	0.0014***
temp.Bin3_it	−0.00012***	0.00006***
temp.Bin5_it	0.00013***	0.00008***
temp.Bin6_it	0.0002***	0.0002***
temp.Bin7_it	0.0003***	0.0004***
precipitation_it	0.000006***	0.00001***
windspeed_it	−0.0009678***	−0.0011474***
Exposed qualification	*Yes*	*Yes*
Exposed sector	*Yes*	*Yes*
Commuter dummy	*Yes*	*Yes*
Worker FE	*Yes*	*Yes*
Time FE	*Yes*	*Yes*
N. obs.	*99,605,222*	*99,605,222*

**p<0.10; **p<0.05; ***p<0.01*

Source: own processing of INPS data, employees and non-agricultural workers, monthly dataset, years 2009-2018.

The main findings have been confirmed through various robustness checks.

When comparing estimates for workers aged over and under 50, we observe a notable pattern: absences increase in the highest temperature bin exclusively for workers over 50. Conversely, for low temperatures, the effect is more pronounced among workers under 50 (see Table 6, columns 7 and 8).

We also examined lagged climate variables to address potential simultaneity issues. Since our weather data are averaged monthly, absence durations and weather conditions could appear correlated even if an absence occurs before an extreme climatic event, such as a heat wave, within the same month. In such cases, the estimated correlation would capture only part of the full causal effect. Lagging the weather variables can help mitigate this issue, as absences occurring early in a month might depend on weather conditions from the end of the previous month. However, as shown in Table 6 (column 9), this specification reveals no significant increase in absences as temperatures rise. This implies that the time lag between a weather event and its impact on absences is short.

The main results are also robust to alternative binning (5 or 16 bins; see Tables A.3 and A.4 in the Appendix) defined using different approaches, including quantile distribution and two-degree interval bin. Furthermore, the impact of extreme weather conditions on worker absences remains consistent even when incorporating fixed effects for regions and cities, while accounting for seasonality and exposure to specific sectors.

Table 6: Panel regression with FE. Dependent variable: credit difference percentage. Col. 7: only workers aged less than 50 years. Col. 8: only workers aged 50 and more. Col. 9: full sample, using 1-month lagged weather explanatory variables.

Dep. var.: Y_it	**(7)**	**(8)**	**(9)**
	All abs.; workers aged < 50 years	**All abs.; workers aged 50+**	**All abs., all workers, 1-month lagged weather variables**
temp.Bin1_it	0.5906***	0.5779*	-0.5321**
temp.Bin2_it	0.0961***	0.0955***	0.0464***
temp.Bin3_it	-0.0008	0.0013	-0.0126***
temp.Bin5_it	0.0026***	0.0149***	-0.0058***
temp.Bin6_it	0.0212***	0.0304***	-0.0133***
temp.Bin7_it	0.0020	0.02101***	-0.0111***
precipitation_it	0.0008***	0.00105***	-0.0004***
windspeed_it	0.0856***	-0.00501	0.0846***
Exposed qualification	Yes	Yes	Yes
Exposed sector	Yes	Yes	Yes
Commuter dummy	Yes	Yes	Yes
Worker FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
N. obs.	73,005,870	23,300,597	57,175,508

*p<0.10; **p<0.05; ***p<0.01

Source: own processing of INPS data, employees and non-agricultural workers, monthly dataset, years 2009-2018.

6. Conclusion

This paper aimed to estimate the impact of climate on employee absences in Italy. Previous literature has highlighted that climate can have a negative impact on workers as it may cause absences, thereby causing income losses and a slowdown in working careers. Using monthly data from the INPS database for employees and weather data from ECMWF, a monthly-frequency panel dataset was constructed, covering a time of 10 years, from 2009 to 2018. An empirical analysis was performed using an econometric model with two-way fixed effects.

The results of our regressions reveal a significant relationship between weather variables and a proxy for the length of absences, given by the percentage of wages accredited by INPS to the worker due to absences longer than 7 days. Specifically, very high or very low temperatures, as well an increase of rainfall and of wind speed, lead to an increase in the duration of worker absences. As wage during absences is paid by INPS, this is resulting in higher public expenditure. It was estimated that 10 more days with temperatures between -15 and 0 °C, instead of 10 days with milder temperatures, has increased the average cost for INPS by €21.94 per worker, using the sample average salary as a reference and if all other variables remain constant. Additionally, it is found that for 10 more days with high temperatures, between 30 and 35 °C, instead of 10 days with milder temperatures, INPS costs would increase by €6.66 ceteris paribus for a worker with an average wage. Before interpreting the estimates causally, we preliminarily verify that cross-sector job changes are quite rare and not related to climate, hence biases due to avoidance behaviors do not seem likely; and we control for the commuter status of workers and for fixed effects. Though, the lack of short-term weather variation in our sample, due to the monthly frequency of INPS data, recommends caution and calls for further research efforts.

Finding larger marginal effects from very cold temperature may sound odd in times of global warming. However, it should be noted that high temperatures occur more frequently and affect a larger geographical area in Italy. This must be considered when calculating the overall impact on workers and public finances.

The estimates have been repeated on subsamples including only the warmest and coldest months, as well as splitting the sample by age (under 50 vs. over 50). As expected, absences are more sensitive to the top temperature bins in the warmest months. Older workers suffer more from very high temperatures than from the lowest ones.

The results remain overall significant when measuring absence frequency through a binary variable and estimating linear probability and logit models, but interestingly, the coefficients associated to temperatures below -15 °C lose significance. Hence, absences due to colder temperatures are more costly because they are longer, although they are not more frequent.

The results of this study have important policy implications and underline the need for targeted interventions on specific demographic subgroups, for workers most exposed to climate risk and for the elderly. Workers in exposed sectors experience shorter absences, which could highlight the contractual weakness of workers in those sectors (who may go to work even if mildly ill to avoid losing their jobs) or testify to the effectiveness of preventive and adaptation measures, assumed by employers or imposed by law. In the former case, estimates of the effects of climate on absences underestimate the actual effects on health, and therefore it is necessary to provide certain categories of workers with better assistance in bargaining; in the latter, it means that regulations work and should not be dismantled, despite pressures by climate skeptics on public opinion.

Furthermore, the results show that commuters do not experience longer absences, although one may expect them to be more exposed to weather. In this case, too, the reasons could be multiple, for example those who live close to their workplace may underestimate the climate risks; alternatively, workers may have chosen carefully where to live to reduce exposure. In the former case, awareness campaigns for non-commuting workers would be needed. Future research will need data to verify these conjectures.

The next steps in this research endeavor may focus on the impact of climate on each type of absence, thereby expanding upon work done e.g. by Filomena and Picchio (2024) on injuries. Whether redundancy placement is related to climate requires a rather complex analysis of indirect and second-order effects, which should trace the consequences of a given extreme weather event for the financial sustainability of a firm, and therefore for its labor demand and its need for public support. Further extensions of the analysis may as well consider measures of climate perception based on the characteristics of the tasks performed by workers.

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Appendix.

Table A.1: Contracts exposed to climate change[19].

Aqueducts	Collective Labor Agreements (CCNL) for employees of private aqueduct companies.
Aqueducts	CCNL for employees of municipal gas companies and municipal aqueduct companies.
Aerophotogrammetry	CCNL for employees of companies in the sector.
Air Agencies, Insurance,	CCNL for employees of recommended maritime agencies, airlines, and public maritime mediators.

[19] The INPS dataset does not contain contracts relating to agricultural workers, specifically there are no types of workers whose employers are obliged to report their wages on a quarterly basis. For all agricultural companies subjected to UNIEMENS on a monthly basis, they are present in the INPS dataset.

Equestrian, and Maritime	
Air Agencies, Insurance, Equestrian, and Maritime	CCNL for employees of equestrian agencies.
Agriculture	CCNL for agricultural employees.
Agriculture	CCNL for agricultural workers and flower growers.
Agriculture	CCNL for employees of agricultural cooperatives.
Food	CCNL for employees of cooperative companies for the processing of agricultural and livestock products and food processing.
Food	CCNL for employees of municipal milk companies.
Farmers and Livestock Consortia	CCNL for employees of livestock breeder organizations and consortia and zootechnical entities.
Woods and Forests	CCNL for employees in forestry and forest industries.
Woods and Forests	CCNL for employees of small and medium-sized companies in the sector.
Agricultural and Reclamation Consortia	CCNL for employees of agricultural consortia.
Agricultural and Reclamation Consortia	CCNL for employees of reclamation and land improvement consortia.
Agricultural and Reclamation Consortia	CCNL for workers engaged in hydraulic-forestry and hydraulicagricultural works carried out directly by reclamation consortia.
Credit	CCNL for executive managers and professional areas personnel of cooperative credit banks, rural and artisanal banks - FEDERCASSE (from 08/2018).
Construction	CCNL for employees of construction companies and related industries - ANCE (from 02/2019).
Construction	CCNL for employees of small construction companies and related industries CONFAPI ANIEM.
Construction	CCNL for employees of production and work cooperatives in construction and related activities.
Construction	CCNL for employees of artisanal enterprises and small and mediumsized industrial enterprises in construction and related fields – CONFARTIGIANATO, CNA, CASARTIGIANI, CLAAI.
Stone	CCNL for employees of companies engaged in the excavation and processing of stone materials.
Stone	CCNL for employees in small and medium-sized industries in the sector.
Wood and Furniture	CCNL for employees of companies in the wood, furniture, furniture, excavation, and stone materials processing sectors - CNA, CONFARTIGIANATO, CASARTIGIANI, CLAAI.
Urban Hygiene and Environmental Sanitation	CCNL companies and environmental service providers – FISE ASSOAMBIENTE.

Urban Hygiene and Environmental Sanitation	CCNL for cleaning companies and integrated/multiservice companies ANIP CONFINDUSTRIA, LEGACOOP PRODUZIONE E SERVIZI, CONFCOOPERATIVE FEDERLAVORO E SERVIZI, AGCI SERVIZI, UNIONSERVIZI CONFAPI.
Fruit and Citrus	CCNL for employees of fruit and citrus companies.
Maritime Fishing	CCNL for employees in maritime fishing.
Ports	CCNL for employees of companies operating mechanical means, employees of companies attending port operations, general warehouses, and silos; for employees attending port companies.
Stables – Racetracks	CCNL for employees of racing companies and employees of tote operators and racetrack entrances.
Stables – Racetracks	CCNL for employees of racehorse stables.
Stables – Racetracks	CCNL for equestrian artisans employed by trotting stables.
Food	CCNL for employees of artisanal enterprises and non-artisanal enterprises with up to 15 employees in the food sector and for employees of baking companies – CNA, CONFARTIGIANATO, CASARTIGIANI, CLAAI.
Institutes – Private Surveillance , Consortia Commerce	Firefighting surveillance cooperatives Flower processing and trade
Construction	CCNL for artisanal companies and small industrial enterprises in the construction and related industries – CNAI, UNAPI.
Maritime Fishing	CCNL for non-embarked personnel employed by cooperatives operating in maritime fishing, mariculture, aquaculture, and valley culture activities - ACGI AGRITAL, FEDERCOOPESCA CONFCOOPERATIVE, LEGACOOP Agroalimentare Fishing Department.
Agriculture	CCNL for subcontractors in agriculture.
Urban Hygiene and Environmental Sanitation	CCNL for public and private environmental services companies – UTILITALIA, CISAMBIENTE, LEGACOOP PRODUZIONE E SERVIZI, AGCI SERVIZI, CONFCOOPERATIVE LAVORO E SERVIZI.
Stables – Racetracks	Racetracks: freelance professionals.
Construction	Construction CCNL CONFIMI
Wood and Furniture	CCNL CONFIMI WOOD COMPANY for employees of small and medium-sized wood, cork, furniture, furniture, and forest industry companies.
Stone	CCNL ANIEM for employees of small and medium-sized excavation and stone materials processing industries.
Agriculture	CCNL for cooperative companies in the agricultural sector FEDERTERZIARIO, CONFIMEA, C.F.C., UGL, UGL AGRICULTURAL AND FORESTRY, UGL FEDERATION AGROALIMENTARE
Fishing	CCNL for those employed on boats of fishing cooperatives FEDERTERZIARIO, CONFIMEA, C.F.C., UGL AGROALIMENTARE, and UGL
Agriculture	CCNL for employees in the agriculture, fishing, and agri-food sectors cooperative sector and associated forms of business SISTEMA IMPRESA – SISTEMA COOP CONFSAL
Agriculture	CCNL FOR.ITALY, A.I.C., F.AGRI, ASSO.TEC F.AGRI. ENTREPRENEURS & COMPANIES - FAMAR for employees of agriculture-related companies and activities.

Fishing	CCNL FOR.ITALY, A.I.C., F.AGRI, ASSO.TEC F.AGRI. ENTREPRENEURS & COMPANIES - FAMAR for employees of fishing-related companies and activities.
Agriculture	CCNL FOR.ITALY, A.I.C., F.AGRI, ASSO.TEC F.AGRI. ENTREPRENEURS & COMPANIES - FAMAR for employees of agri-food-related companies and activities.
Agriculture	CCNL first sector: agriculture-livestock-forestry CONFIMI NORD INDUSTRIALE FASPI and CONFAEL FAL SNALP.
Construction	CCNL for employees of artisanal construction companies and small and medium-sized industrial construction companies - FEDERTERZIARIO
Construction	CCNL for employees of companies engaged in the excavation and processing of stone materials - FEDERTERZIARIO
Construction	CCNL employees of artisanal construction companies and related artisanal companies - FAPI, CESAC.
Agriculture	CCNL for employees of companies in the agri-food, agricultural, and fishing sectors - FAPI, CESAC.
Fishing	CCNL for employees and members of professional fishing cooperatives and companies operating in the fishing and fish farming sector - UNCI
Construction	CCNL for workers in artisanal construction companies and small industrial construction companies - UNIMPRESA.
Fishing	CCNL for workers of companies in the fishing, aquaculture, and mariculture sectors - UNIMPRESA, CIDEC.
Food	CCNL small and medium-sized companies in the food sector - FEDARCOM, UNITERZIARIO, UNIPMI.

Source: INPS.

Table A.2: INPS cost related to transitions among temperature bins.

one more day with temperature in the interval…	one day less with temperature in the interval…						
	[-19, -15]	]-15,0]	]0,20]	]20,25]	]25,30]	]30,35]	]35,45]
[-19, -15]	0	5.519848	0.091321	7.622997	7.416287	7.047938	7.119751
]-15,0]	-5.51985	0	2.19447	2.103149	1.896439	1.52809	1.599903
]0,20]	-7.71432	-2.19447	0	-0.09132	-0.29803	-0.66638	-0.59457
]20,25]	-7.623	-2.10315	0.091321	0	-0.20671	-0.57506	-0.50325
]25,30]	-7.41629	-1.89644	0.298031	0.20671	0	-0.36835	-0.29654
]30,35]	-7.04794	-1.52809	0.66638	0.575059	0.368349	0	0.071813
]35,45]	-7.11975	-1.5999	0.594567	0.503246	0.296535	-0.07181	0

Source: own processing of INPS data, employees and non-agricultural workers, monthly dataset, years 2009-2018.

The division into 5 bins (see Table A.3) was based on the quantiles of the temperature distribution to ensure a balanced representation of the different temperature ranges. The estimation with 5 bins uses the following temperature intervals: [-19,11[, [11,16[, [16,21],]21,27],]27,45]. The division into 16 bins (see Table A.3) was carried out to create smaller temperature intervals, following the methodology of Filomena and Picchio (2024). For the 16-bin case, the intervals are: [-19,0[,]0,2],]2,4],]4,6],]6,8],]8,10],]10,12],]12,14],]14,16],]16,18],]18,20],]20,22],]22,24],]24,26],]26,28],]28,45].

The use of different binning strategies is crucial for validating the reliability of the results. Specifically, to capture nonlinear effects: Dividing the data into smaller intervals (16 bins) allows the model to better capture potential nonlinear relationships between temperature and absenteeism. Larger bins (5 bins) might obscure nuanced effects within broader temperature ranges, but it allows us to understand the overall effect of high and low temperatures by dividing the intervals equally. By comparing results across different binning approaches, we can assess whether the findings are robust to changes in the granularity of temperature intervals. This helps ensure that the results are not driven by arbitrary choices in bin definitions. Following the methodology of Filomena and Picchio (2024) ensures consistency with previous studies, enhancing the comparability of findings and providing a benchmark for interpreting results. Smaller intervals (16 bins) allow for a more detailed understanding of the temperature thresholds at which absenteeism increases, which can inform targeted climate adaptation policies. By demonstrating consistent results across both the 5-bin and 16-bin specifications, this robustness check strengthens the credibility and interpretability of the study conclusions.

Table A.3: Panel regression with FE and dependent variable credit difference percentage, 5 bins.

Dep.var.: Y_it	Abs.(10)
temp.Bin1_it	0.0035***
temp.Bin2_it	-0.0005
temp.Bin4_it	0.0035***
temp.Bin5_it	0.0239***
precipitation_it	0.0007***
windspeed_it	0.0587***
Exposed qualification	Yes
Exposed sector	Yes
Commuter dummy	Yes
Worker FE	Yes
Time FE	Yes
N. obs.	99,605,222

*p<0.10; **p<0.05; ***p<0.01

Source: own processing of INPS data, employees and non-agricultural workers, monthly dataset, years 2009-2018.

Table A.4: Panel regression with FE and dependent variable credit difference percentage, 16 bins.

Dep.var.: Y_it	Abs.(11)	ClimateAbs.(12)
temp.Bin1_it	0.0884***	0.1142***
temp.Bin2_it	0.0511***	0.0537***
temp.Bin3_it	-0.0041*	-0.0088***

temp.Bin4_it	0.0018	-0.0015
temp.Bin5_it	-0.0070***	-0.0031*
temp.Bin6_it	0.00007	-0.0171***
temp.Bin8_it	0.0205***	0.0163***
temp.Bin9_it	-0.0167***	-0.0140***
temp.Bin10_it	-0.0085***	-0.0103***
temp.Bin11_it	0.0023	-0.0012
temp.Bin12_it	-0.0028*	0.0018
temp.Bin13_it	0.0025	0.0048***
temp.Bin14_it	-0.0120***	-0.0041**
temp.Bin15_it	0.0009	0.0087***
temp.Bin16_it	0.0133***	0.0286***
precipitation_it	0.0008***	0.0011***
windspeed_it	0.0712***	0.0518***
Exposed qualification	Yes	Yes
Exposed sector	Yes	Yes
Commuter dummy	Yes	Yes
Worker FE	Yes	Yes
Time FE	Yes	Yes
N. obs.	99,605,222	99,605,222

**p<0.10; **p<0.05; ***p<0.01*

Source: own processing of INPS data, employees and non-agricultural workers, monthly dataset, years 2009-2018.