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Summary

This paper examines the impact of temperature shocks, measured by cold and heat waves, on labour market outcomes across 14 European countries. Using retrospective individual-level data from the Survey on Health, Ageing, and Retirement in Europe (SHARE) and daily climate data from the E-OBS dataset, we analyze the effect on wages and occupational transition. By leveraging plausibly exogenous weather shocks, we find that heat waves significantly reduce individual income, with losses accumulating over time. Moreover, our analysis documents that older individuals, those with severe health conditions, and workers in heat-exposed occupations experience particularly large income reductions. Losses are also more pronounced in Mediterranean and Eastern European countries, as well as in regions with less regulated wage-setting mechanisms. Additionally, our findings suggest that heat waves increase the likelihood of changing jobs and in particular to transition from heat-exposed to non-heat-exposed occupations. These results underscore the need for targeted policy interventions to mitigate economic losses and protect vulnerable workers in the face of increasing climate variability.

Keywords: Temperature, labour market, wages, occupational transition

JEL classification: Q54, J24, J30

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Hot Wages: How Do Heat Waves Change the Earnings Distribution?[*]

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December 24, 2024

Abstract

This paper examines the impact of temperature shocks, measured by cold and heat waves, on labour market outcomes across 14 European countries. Using retrospective individual-level data from the Survey on Health, Ageing, and Retirement in Europe (SHARE) and daily climate data from the E-OBS dataset, we analyze the effect on wages and occupational transition. By leveraging plausibly exogenous weather shocks, we find that heat waves significantly reduce individual income, with losses accumulating over time. Moreover, our analysis documents that older individuals, those with severe health conditions, and workers in heat-exposed occupations experience particularly large income reductions. Losses are also more pronounced in Mediterranean and Eastern European countries, as well as in regions with less regulated wage-setting mechanisms. Additionally, our findings suggest that heat waves increase the likelihood of changing jobs and in particular to transition from heat-exposed to non-heat-exposed occupations. These results underscore the need for targeted policy interventions to mitigate economic losses and protect vulnerable workers in the face of increasing climate variability.

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1 Introduction

An expanding body of research underscores the extensive effects of weather and climate on human society (Carleton and Hsiang, 2016). These impacts span across diverse areas, including agricultural losses, health costs, increased electricity consumption, and heightened risks of conflict and migration (Burke et al., 2015; Deryugina and Hsiang, 2014; Schlenker and Roberts, 2009; Barreca et al., 2016; Auffhammer, 2022). While early studies largely focused on the indirect aggregate economic costs, recent research has seen a growing emphasis on the direct effects of climate change on labour supply, productivity, human health, and human capital accumulation (Heal and Park, 2016), highlighting the first-order significance of these impacts. This evidence has documented that the impact of temperature on labour plays a crucial role in reducing production across key economic sectors (Cachon et al., 2012; Sudarshan and Tewari, 2014; Somanathan et al., 2021; Deryugina and Hsiang, 2014; Park, 2016). Indeed, even if each worker experiences a moderate reduction in labour supply or productivity, the aggregate effect is not negligible and can explain substantial losses in output, given that over 60% of prime-age adults globally are part of the workforce (Rode et al., 2022).

Our paper inserts itself into this body of research on the direct impacts of extreme temperatures by examining the effect on the European labour market over more than 60 years (1955-2018), leveraging individual longitudinal data. Our primary focus is on the consequences on individual income, but we also examine the probability of job transition. We use retrospective waves from the Survey on Health, Ageing, and Retirement in Europe (SHARE), which offers comprehensive data on individual job episodes and income across a wide range of occupations, including both self-employed individuals and wage employees. Daily weather data from the E-OBS dataset (Midões et al., 2024) is aggregated to the finest spatial units we are able to retrieve from SHARE, which correspond to an intermediate level between NUTS2 and NUTS3 regions, with further granularity in certain countries. To capture non-linearities in the temperature-income relationship, we utilize heat wave measures defined by both relative temperature thresholds (e.g., more than 2 consecutive days of maximum temperature exceeding the 95th percentile of the local temperature distribution) and absolute temperature thresholds (e.g., more than 2 consecutive days of maximum temperature above 30°C). By leveraging year-to-year random weather shocks — measured by the number of days in heat and cold waves — we estimate the effects on labour market outcomes.

First, we identify that exposure to high temperatures increases losses in income. On average, an additional day in a heat wave—defined as a period lasting more than two consecutive days with maximum temperatures exceeding either the 95th percentile or 30°C—reduces individual income by approximately 0.51% and 1.47%, respectively. These marginal effects translate to average income losses of \$14.85 and \$42.81. Moreover, we find that the effect of heatwaves is long-lasting and current income is influenced by past temperature shocks.

Second, we explore heterogeneity across various socioeconomic and labour market characteristics, enabling us to identify the most affected groups and gain insights into the mechanisms driving the observed results. Specifically, we find that the impact of extreme heat on income intensifies with workers' age and is more pronounced for individuals with severe health conditions. These groups are likely to experience significant declines in productivity or reductions in labour supply (absenteeism, hours worked) under heat stress due to their underlying physical vulnerabilities. The heterogeneity analysis by country of residence reveals that workers in the Mediterranean and Eastern European countries bear a disproportionate burden from temperature shocks. One possible explanation is the higher share of workers employed in outdoor occupations that are exposed to heat stress in these regions. Indeed, when examining the differential impacts for these occupations compared to others, we find a more pronounced negative effect on income. This impact is likely driven not only by greater exposure to extreme temperatures but also by the limited availability of protective measures and avoidance strategies for outdoor workers. These findings suggest that, even in countries with historically warmer climates, worker adaptation may be constrained (Park, 2016), particularly for those in outdoor occupations. Additionally, cross-country differences in the impact of temperature shocks may reflect variations in labour market structures. In support of this, we observe that workers in countries with less regulated wage systems such as Eastern Europe, experience more severe income losses due to temperature shocks.

Third, we further examine the impacts of heat waves on income by investigating whether these shocks have differential effects across the income distribution. Using unconditional quantile regression (Firpo et al., 2009), we find no substantial differences in the effect across most of the distribution. Significant differences appear only between the 5th and 70th-80th income percentiles when using relative temperature thresholds. While these results may suggest a potentially larger impact on lower-income groups, overall, we do not observe statistically significant trends across the distribution, with the magnitude of the effect being similar across most deciles.

Finally, we investigate the effects of heat waves on the likelihood of occupational transitions. The results indicate that heatwaves increase the probability of changing occupations, with the effects being long-lasting and partially delayed, as lagged exposure in years $t-1$ and $t-2$ significantly influences the current probability of transition. When examining heterogeneity across outdoor occupations with high exposure to heat stress, the findings suggest that individuals in these occupations are less likely to change jobs compared to other workers, potentially due to skill constraints. However, heat waves increase the likelihood for these workers to transition from heat-exposed to non-exposed occupations.

This paper contributes to the literature on the impact of weather shocks on income (Deryugina and Hsiang, 2014; Deryugina, 2017; Park, 2016; Colmer, 2021; Li and Pan, 2021; Oliveira et al., 2021). While prior studies have explored these effects at the county level

(Deryugina and Hsiang, 2014; Deryugina, 2017; Park, 2016) and firm level (Li and Pan, 2021), we add to this body of research by providing evidence at the individual level, as Oliveira et al. (2021) did for Brazil. Focusing on individual wages, we offer new insights across a large group of European countries over an extended time frame, encompassing employees and self-employed workers from diverse occupations both in agricultural and non-agricultural sectors.

Furthermore, we advance the understanding of the distributional effects of temperature on labour market outcomes. Previous research has demonstrated that temperature impacts are regressive, both across countries (Burke et al., 2015; Carleton and Hsiang, 2016; Heal and Park, 2016) and within them (Hsiang et al., 2017; Park et al., 2018). However, evidence on how these effects differ among various groups of workers remains limited. Studies suggest that poorer households are more likely to live in areas prone to severe climate events, while lower-income workers are disproportionately employed in jobs with higher exposure to heat stress (Park et al., 2018). Our study contributes by analyzing the effects of temperature along the income distribution, showing that the impact is not clearly distinguishable among deciles. Moreover, we deepen our investigation by examining heterogeneity across diverse sociodemographic characteristics and labour market conditions, including gender, age, education level, health status, geographical region, occupation type, and wage bargaining structures. This approach helps disentangle the mechanisms underlying wage reductions and provides evidence on the factors mediating the impact of temperature on labour market outcomes (Jessoe et al., 2018; Somanathan et al., 2021; Neidell et al., 2021; Acevedo et al., 2020). Our findings also contribute to the literature exploring the heterogeneity in the impact of temperature across heat-exposed and non-heat-exposed jobs. Consistent with prior research that observes more pronounced declines in labour productivity (Kjellstrom et al., 2009; Acevedo et al., 2020) and labour supply (Graff Zivin and Neidell, 2014; Neidell et al., 2021) within heat-exposed industries, we document larger income losses for workers employed in outdoor occupations at high risk of heat stress.

Previous research has shown that extreme heat can drive labour market adjustments through sectoral reallocation (Colmer, 2021; Liu et al., 2023; Jessoe et al., 2018; Xie, 2024; Lyu et al., 2024). We contribute to this literature by investigating the effects of heat waves on job transitions. While earlier studies primarily focus on sectoral reallocation, particularly from agricultural to non-agricultural sectors (Colmer, 2021; Liu et al., 2023; Lyu et al., 2024), our analysis broadens this evidence by estimating the probability of transitions between occupations. Specifically, we explore shifts from occupations at high risk of heat stress to those less exposed, identifying an increased likelihood of such transitions.

The remainder of the paper is structured as follows. Section 2 provides an overview of the study and examines the key mechanisms through which high temperatures may affect labour market outcomes. Section 3 introduces the data used in the analysis, with subsections detailing the SHARELIFE, weather, and NUTS and urbanization data, along with key descriptive statistics in Section 3.4. Section 4 outlines the empirical strategy. Section 5 presents the main findings. Section 5.1 focuses on the impact on income, while Section 5.2 explores heterogeneity in the effects across sociodemographic and labour market factors. Section 5.3 examines the distributional implications of these effects along the unconditional income distribution, and Section 5.4 analyzes the impact on the probability of job transition. Finally, Section 6 summarizes the results and discusses their broader implications.

2 Potential Mechanisms

High temperatures are consistently associated with declines in aggregate output at the regional and national levels (Dell et al., 2009; Hsiang, 2010; Dell et al., 2012; Park and Heal, 2013; Burke et al., 2015). While the direct effects of heat on individual labor outcomes may appear moderate, they are critical drivers of the broader economic impacts on output and growth (Carleton and Hsiang, 2016). This has drawn increasing attention to the mechanisms through which high temperatures affect economic activity. Extreme heat can reduce workers' productivity, influence labor supply decisions, lower work attendance, or prompt shifts to alternative employment types. Furthermore, it can negatively affect health and hinder human capital accumulation. The diversity of mechanisms underlying the relationship between temperature and labor poses substantial challenges in determining which channels are most significant and should be prioritized for adaptation strategies.

Productivity. Heat exposure reduces labor productivity by diminishing work intensity, primarily due to increased discomfort, fatigue, and impaired cognitive performance (Heal and Park, 2016). Empirical studies reveal a non-linear relationship between productivity and temperature shocks (Chen and Yang, 2019), with productivity declining as temperatures deviate from an optimal threshold of approximately 20°C (68°F) (Seppanen et al., 2006). For example, Cai et al. (2018) identify a U-shaped relationship between temperature and productivity in manual labor-intensive manufacturing tasks, where adverse effects are observed at both high and low temperatures.[1]

The negative effects of temperature are most pronounced in heat-exposed occupations with limited adaptive capacity (Kjellstrom et al., 2009), but they also extend to less physically demanding indoor settings, such as call centers in India (Niemelä et al., 2002). While earlier research primarily focused on labor productivity (Adhvaryu et al., 2020; Somanathan et al., 2021), more recent studies have expanded to examine the role of capital productivity in the temperature-output relationship. For instance, Zhang et al. (2018) find significant temperature-induced reductions in total factor productivity in Chinese manufacturing

[1]Similar U-shaped patterns are documented for other outcomes, such as mortality (Barreca et al., 2016) and electricity consumption (Auffhammer, 2022).

plants, with comparable losses in both labor- and capital-intensive firms. Similarly, Cachon et al. (2012) demonstrate substantial productivity losses in highly capital-intensive industries, such as automobile manufacturing, even within developed economies like the United States.

Heterogeneity in the effects of temperature on productivity is influenced by factors such as adaptive capacity, employment contract structures, and levels of supervision. Adaptation plays a crucial role in mitigating productivity losses, with evidence indicating smaller impacts in warmer countries where adaptive measures are more widespread (Chen and Yang, 2019). Contextual factors further shape the temperature-productivity relationship. For example, LoPalo (2023) analyze the effects of temperature on survey interviewers in developing countries and find that productivity losses are influenced by the degree of monitoring and supervision.

Labor Supply. Another potential response to heat exposure is a reduction in labor supply, either through shorter working hours or increased absenteeism (Graff Zivin and Neidell, 2014; Somanathan et al., 2021). Empirical evidence shows that when daily maximum temperatures exceed 30°C, workers in highly heat-exposed industries reduce their working hours by approximately 14%, equivalent to about one hour less of daily labor (Graff Zivin and Neidell, 2014; Neidell et al., 2021). This reduction is particularly pronounced toward the end of the workday, suggesting that heat-induced fatigue is a key driver. Additionally, in climate-exposed industries, workers may reduce their hours or increase absenteeism on particularly hot days to mitigate health risks (Neidell et al., 2021). The impact on health is likely to drive absenteeism not only on the day of exposure but also in the following days, as supported by evidence of significant lagged temperature effects, suggesting a delayed response (Somanathan et al., 2021). Recent estimates, encompassing approximately one-third of the world's population, reveal an inverse-U-shaped relationship between temperature and time worked (Rode et al., 2022). This pattern is particularly pronounced in heat-exposed industries such as agriculture, mining, construction, and manufacturing, but is notably absent among workers in less exposed occupations. Interestingly, this relationship exhibits remarkable stability across countries with varying income levels and climates.

However, the labour supply response to temperature may be influenced by contextual differences. Not all workers have access to effective protective measures, and the extent of the impact may depend on occupational exposure, local conditions, and workers' capacity to adapt. These factors highlight potential heterogeneity in the responses to temperature shocks (Graff Zivin and Neidell, 2014; Neidell et al., 2021; Kahn, 2016). Besides, some studies report a smaller or negligible role for labour supply reductions compared to productivity declines (Adhvaryu et al., 2020). In developing countries, for instance, the opportunity cost of not working is especially high due to low incomes. Many workers are paid only for hours worked, and staying home offers limited benefits, particularly given the low prevalence of residential adaptations (Sudarshan and Tewari, 2014). Absenteeism is particularly prevalent among workers with access to paid leave, highlighting the role of contractual structures in shaping labor supply responses (Somanathan et al., 2021). This is further supported by findings from manufacturing plants in China, where the widespread use of two-tier piece-rate contracts, which closely tie pay to hours worked, likely limits the impact of temperature on both labor inputs and labor supply responses (Zhang et al., 2018; Cai et al., 2018). Similarly, reductions in hours worked were not observed during the Great Recession, likely due to heightened job competition and constrained supply-side conditions (Neidell et al., 2021). These findings confirm that labor supply responses to extreme temperatures are highly context-dependent, influenced by factors such as job security and local economic conditions across sectors, occupations, and regions.

Finally, while climate-controlled environments can alleviate some of the direct effects of temperature on productivity, they are less effective at addressing absenteeism. Workers remain exposed to outdoor temperatures outside of work hours, underscoring the limits of workplace-specific adaptations (Somanathan et al., 2021).

Labor Reallocation and Employment. One potential response to weather shocks is the reallocation of labor across regions or sectors. Colmer (2021), examining the impact of temperature on labor in India, found evidence of labor reallocation within districts, with workers shifting from the agricultural sector to manufacturing and services. Notably, this reallocation is more pronounced for firms operating in flexible labor markets, highlighting the critical role of regulatory environments in facilitating adjustments to temperature shocks and mitigating potential losses.

Liu et al. (2023), also focusing on India, extend these findings by exploring the long-term effects of heat on labor reallocation and find that such reallocation remains constrained over time. Specifically, declines in agricultural productivity reduce farm income, which in turn lowers demand for non-agricultural goods and services, resulting in contractions in employment within these sectors. The demand for food is more rigid compared to other sectors, such as services, where wage workers may be more concentrated. This pattern is observed in Mexico, where Jessoe et al. (2018) found the impact of temperature exposure on employment in the non-agricultural sector. These effects are likely influenced by other factors, such as the presence of agricultural support programs, which can partially insulate farm incomes from climate shocks. Limited labor reallocation in response to heat shocks is also observed in other developing countries, such as Brazil. Xie (2024) report that extreme heat increases the probability of layoffs in Brazil's manufacturing sector, with routine manual labor occupations facing the highest risks. In China, evidence further suggests limited intersectoral reallocation, with the manufacturing sector unable to absorb employment from agriculture. The impact is notably more pronounced in contexts with less flexible labor markets (Lyu et al., 2024). In this context, a decline in labor share within the manufacturing sector is attributed to the substitution of labor with capital inputs, particularly affecting labor-intensive firms, those with tighter financing constraints, private firms, and those employing a higher proportion of informal and low-skill workers.

Health. Heat exposure can significantly impact health, with the most severe consequences including increased mortality, as extensively documented in the literature (Deschênes and Greenstone, 2011; Barreca et al., 2016; Deschenes, 2014; Burgess et al., 2014). Health, a critical component of human capital (Grossman, 1972) and early-life shocks may be particularly long-lasting (Currie and Almond, 2011). This is documented by evidence suggesting that weather shocks contribute to long-term reductions in individual labor market outcomes (Isen et al., 2017; Maccini and Yang, 2009). Thus, the temperature consequences on health represent a significant channel that, by shaping human capital accumulation, mediates the effects on labor market outcomes.

Beyond mortality and morbidity, heat exposure also increases the likelihood of workplace accidents, both in outdoor and indoor settings, highlighting the role of impaired cognitive function as a key mechanism (Park et al., 2021). Another pathway through which heat affects health and productivity is a reduction in sleep quality, which has been linked to temperature extremes (Drescher and Janzen, 2025). These findings underscore the multifaceted role of health in mediating the relationship between temperature and labor market outcomes, as diminished health can both directly and indirectly impair workers' productivity and economic well-being.

Wages The effects of high temperatures on productivity, labour supply, health, and labour reallocation also translate into significant consequences for wages. These wage adjustments, in turn, can influence other mechanisms, such as labour reallocation, and shape broader labour market dynamics. Empirical evidence underscores the substantial impact of high temperatures on wages across various contexts and scales. In the United States, Deryugina (2017) finds that an additional day with temperatures exceeding 30°C reduces average annual income at the county level by approximately $20 per person. Notably, this impact has persisted over the past four decades despite advancements in technology and adaptive strategies, highlighting the limited efficacy of current measures to mitigate these effects. Similarly, Park (2016) reports that payroll per capita declines during years of extreme heat, with colder counties experiencing larger impacts. This finding suggests that there is potential for adaptation to mitigate such losses. However, their analysis also reveals that adaptation remains incomplete, with significant costs associated with overcoming existing technological and economic constraints.

In the context of developing countries and emerging economies, evidence highlights the impact of temperature exposure on wages. Colmer (2021) show that in India, high temperatures reduce average daily wages at the district level, with agricultural workers experiencing the largest declines due to diminished labour demand. Manufacturing wages also decrease potentially reflecting labour reallocation into the sector, which depresses average wages. Similarly, Oliveira et al. (2021) document significant reductions in individual monthly wages in Brazil's formal, non-agricultural sector, underscoring the broader vulnerability of wage structures to temperature shocks.

Evidence from China reveals an inverted U-shaped relationship between temperature and firm-level labour wages, with extreme heat and cold both reducing earnings (Li and Pan, 2021). This effect is primarily driven by a decline in non-agricultural wages, linked to employment contraction. Losses are most pronounced in labour-intensive firms, firms with lower levels of technological adoption, and those employing less-educated workers. Moreover, temperature shocks exhibit long-lasting effects, with adverse impacts on current income depending also on shocks experienced in previous years. Finally, historically colder regions experience greater losses compared to warmer areas, suggesting that adaptation may play an important role.

In the long term, the overall impact of heat exposure may vary depending on the dynamics of local labour markets, particularly supply and demand factors. Wage adjustments may either capture the deteriorating working conditions caused by heat or serve as compensation for the additional burdens associated with heat-exposed jobs (Kahn, 2016). Indeed, the job disamenity of heat is far from negligible, with recent estimates suggesting significant economic costs (Rode et al., 2022). However, the evidence on industry-level responses remains limited, particularly regarding the role of contractual structures and labour market flexibility (Heal and Park, 2016). For instance, workers with long-term contracts may mitigate wage declines by adjusting labour supply or productivity, as their salaries are fixed in the short term. Conversely, self-employed workers, whose income directly depends on hours worked and productivity, may exhibit heightened vulnerability to heat shocks. By focusing on the average monthly salaries over a specific year, our analysis captures these broad wage effects while abstracting from short-term fluctuations that may occur across different days.

Other Channels. Beyond direct impacts on labor productivity, labor supply, and health, recent studies highlight additional channels through which temperature shocks affect economic outcomes. Chen and Yang (2019) show that lagged temperature impacts industrial output, identifying reductions in firm investment and increases in inventory levels as key mechanisms. Complementary evidence from Acevedo et al. (2020) indicates that temperature shocks reduce investment in both the short and long run. This reduction is driven by diminished resources available for investment, a lower rate of return on capital, and constrained savings and credit access. These constraints arise from income reductions that limit individuals' ability to save or increase their perception of investment risk, as consumption smoothing takes priority.

Moreover, temperature shocks influence labor market outcomes in less direct ways. Rising job insecurity—defined as the perceived stability of employment—has been linked to temperature shocks through their effects on mental health and increased energy poverty, as observed in Australia (Bui et al., 2024). Additionally, Chen et al. (2024) find that heatwaves negatively affect entrepreneurial activity. They attribute this to the broader adverse economic conditions induced by temperature shocks, including agricultural losses, slowed regional economic development, financial strain on governments, and discouraged business activities. Collectively, these findings underscore the wide-ranging economic implications of temperature shocks beyond immediate productivity effects.

3 Data

To empirically examine the impact of temperature on labor market outcomes, this paper employs retrospective data from the SHARELIFE survey, which provides detailed information on various aspects of individuals' working careers. This dataset offer the possibility of an analysis at the individual level across a broad set of European countries, spanning more than 60 years. The survey includes individuals aged 50 years and older from 14 European countries and provides detailed retrospective information on each job episode throughout their working lives. These data are linked to weather variables by matching individuals' places of residence during each job episode with corresponding temperature and precipitation data from the E-OBS dataset provided by Copernicus. The SHARELIFE data are recorded annually, with spatial granularity for residence locations varying by country. Specifically, this information is available at the NUTS1, NUTS2, or NUTS3 levels depending on the country[2]. To enhance spatial resolution, we incorporate additional data on the degree of urbanisation, subdividing each NUTS region at its finest available level into five urbanisation categories. Consequently, weather data are aggregated at the most detailed spatial resolution possible.

3.1 Labor Market and Socioeconomic Data from SHARELIFE

The SHARELIFE survey encompasses the retrospective modules of the third and seventh waves of the Survey on Health and Retirement in Europe (SHARE). The survey covers nearly 40,000 individuals residing in 14 European countries: Austria, Belgium, Czech Republic, Denmark, France, Germany, Greece, Italy, Poland, Portugal, Slovenia, Spain, Sweden, and Switzerland. These modules gather detailed information on respondents' work histories, including unemployment spells, wages, working hours (full-time or part-time), type of occupation (ISCO by 4-digit code) and type of employment (self-employed or employee). The retrospective nature of the survey implies that the information collected at one point in time refers to different periods in the respondents' lives, which can pose challenges

[2]NUTS1 for Belgium, France, and Germany; NUTS2 for Austria, Denmark, Greece, Hungary, Poland, Portugal, Spain, Sweden, and Switzerland; NUTS3 for the Czech Republic and Slovenia; and LAU1 for Luxembourg.

for the comparability of wage information. To address this issue, we manipulate the data following a procedure close to the one proposed by Trevisan et al. (2011).

All monetary information in SHARE is presented in nominal currencies. Most wage data is coded according to the ISO 4217 standard (e.g., “PLN – Polish zloty”). However, some observations use generic labels (e.g., “zloty”) or period-specific currencies (e.g., “Czechoslovak koruna, 1953–1992”). In the first step, we address these cases by assigning the appropriate ISO 4217 code when the currency can be clearly identified and the income information does not refer to a period before the availability of exchange rates and the Consumer Price Index (CPI). The second step converts all currencies into US dollars using exchange rates provided by the Bank of Italy. Observations with missing exchange rates, particularly those from before 1955, are thus excluded. For wages reported in euros prior to the euro’s adoption, we use the 1999 exchange rates. The third step adjusts for inflation and currency fluctuations over time by normalizing wages to 2010 US dollars using the CPI (2010 = 100) provided by the World Bank, or, where unavailable, by the OECD. Unlike Trevisan et al. (2011), we do not adjust for purchasing power parity (PPP), as country-fixed effects in our empirical models absorb cross-country differences in purchasing power. Wage data for Slovenia is retained only after 1991, following independence from Yugoslavia, due to the presence of outliers likely linked to political changes. Similarly, data for Poland before 1991 is excluded due to political instability and Soviet influence. Finally, we apply winsorization to the wage data to mitigate the impact of outliers, replacing extreme values with those at the 1st and 99th percentiles, first at the country level and then across the overall sample. Table A1 in Appendix A summarizes the data-cleaning process, detailing the steps and corresponding reductions in the number of observations for each monetary variable in the survey.

The survey classifies monetary information based on the timing within the job episode (e.g., first wage, last wage, current wage) and the source of income (self-employment vs. employment). This allows us to distinguish between initial income (or wage) for each job episode, final income (or wage) for the main job episode, and current income (or wage) if the respondent was still employed at the time of the interview. The survey differentiates between "income," which refers to self-employment earnings, and "wage," which pertains to earnings from employment. In our analysis, we aggregate all available monetary information, controlling for the source of earnings with a dummy variable for self-employment and employment, along with other labor market covariates. We then use "income" and "wage" interchangeably to refer to the labor earnings of each worker.

Occupations at the highest risk of heat illness include those with outdoor labor in hot climates, such as agriculture, construction, mining, and landscaping, as well as indoor workers in non-climate-controlled settings, like production workers. These individuals are vulnerable due to exposure to hot environments, labor-intensive tasks, and limited access to cooling resources, such as shade, air conditioning, and fans. The SHARELIFE modules provide detailed occupation information for each job episode, using the International Standard

Classification of Occupations (ISCO). Most occupations are classified with a 4-digit ISCO code, enabling a precise understanding of roles and tasks. This classification enables us to identify occupations at high risk for heat exposure, including both outdoor workers and indoor labor-intensive roles (e.g., production workers) in environments with significant heat sources (e.g., kitchens) or limited cooling systems (Gibb et al., 2024). We distinguished between outdoor and indoor occupations at risk of heat stress, such as firefighters, bakery workers, farmers, construction workers, miners, boiler room workers, and factory workers, in accordance with the National Institute for Occupational Safety and Health (NIOSH) guidelines. Table A3 in Appendix A provides the list of 4-digit ISCO occupations classified as heat-exposed, with 1 for outdoor and 2 for indoor occupations. Table A5 presents the number of observations by country with occupation exposure classifications.

In addition to comprehensive income data, SHARE offers extensive information on various aspects of individuals' lives. This includes respondents' health conditions reporting all the illnesses experienced during individuals' lives, socioeconomic and demographic characteristics, housing features, accommodation history, personal relationships, and childhood experiences. The availability of this diverse range of data enables us to control for both time-variant and time-invariant factors at the individual level.

3.2 Weather Data

Weather variables are sourced from the E-OBS data provided by Copernicus, which have been integrated with the SHARE survey in the SHARE-ENV dataset (Midões et al., 2024), a novel publicly accessible resource. The E-OBS dataset collects observational weather data across Europe on a daily gridded level (0.1° x 0.1°). These data are suitable for assessing the magnitude and frequency of weather extremes on a daily basis and its extensive temporal coverage allows for effective combination with the SHARE socio-economic data, which dates back to the early 1950s. A potential concern with the E-OBS dataset is that the grid information is derived through interpolation, which may introduce some measurement errors. However, given the spatial aggregation of weather variables at the granularity provided by SHARE — approximating a NUTS3 level through the creation of sub-NUTS areas using urbanization data — this potential bias is unlikely to have a meaningful impact on our results.

In our analysis, temperature is the primary weather variable of interest, while annual average precipitation serves as a control variable, particularly important in the absence of humidity data. We model temperature using measures of heat and cold waves, following the methodology proposed by Miller et al. (2021). Heat (cold) waves are defined as prolonged periods of thermal stress when the maximum (minimum) daily temperatures exceed (or fall below) the 95th (5th) percentiles of the 30-year moving average distribution of local temperature - at the sub-minimum NUTS level - for at least two consecutive days. Our metrics count the number of days experiencing heat or cold waves yearly.

This relative measure of heat waves captures temperature shocks relative to the local climate baseline, inherently accounting for the existing level of adaptation within each region. One advantage of this approach is its ability to reflect deviations from expected local climate conditions. This is particularly useful given our diverse set of countries with varying climates and adaptation levels. To complement this, we construct an alternative indicator based on absolute thresholds, defining heat waves as periods of at least two consecutive days during which maximum (minimum) temperatures exceed 30°C (or fall below -10°C). The advantage of this measure lies in its straightforward interpretation of the absolute magnitude of extreme temperatures. However, the frequency of temperatures above 30°C (or below -10°C) can vary substantially across countries, suggesting that individuals in different regions may be more or less familiar with, and thus adapted to, such temperature extremes.

Given the limitations of each approach, our analysis utilizes both relative and absolute heat wave measures. Additionally, we introduce a hybrid metric as a robustness check. This hybrid measure defines heat wave days as the minimum number of days identified by comparing the relative and absolute threshold approaches. It ensures that a minimum absolute threshold of 30°C (-10°C) for maximum (minimum) temperatures is applied, while also accounting for more extreme shocks in warmer regions where such temperatures are more common. In these regions, the minimum number of days is likely determined by the 95th percentile of the temperature distribution, which corresponds to thresholds exceeding 30°C.

For instance, Table A6 demonstrates that using absolute thresholds alone results in countries like Greece and Spain having disproportionately high average heat wave days compared to other regions. By contrast, the relative threshold approach produces more comparable counts across countries. The hybrid measure corrects for this discrepancy by ensuring a minimum absolute temperature threshold while capturing more extreme deviations in regions where such temperatures are less frequent.

Researchers have previously explored the socio-economic impacts of extreme temperatures, such as environmental attitudes and voting behavior, using heat wave metrics (Hoffmann et al., 2022). Heat and cold wave metrics offer the advantage of accounting not only for the occurrence of temperature shocks but also for the duration of thermal stress. Figure A1 in Appendix A illustrates the average number of days experiencing heat and cold waves, aggregated at the NUTS1, NUTS2, or NUTS3 level, depending on the data availability for each country.

3.3 NUTS and Urbanization Data

The SHARE dataset includes modules on accommodation where respondents provide detailed information on their living situations throughout their lives. Specifically, they report the geographic region at NUTS 1, 2, or 3 levels, depending on the country, and classify the area as "a big city," "suburbs or outskirts of a big city," "large town," "small town," or "rural area or village." For some countries, such as Slovenia and Czech Republic, data is available at the NUTS 3 level, while for others, like France, the spatial resolution is coarser, provided only at the NUTS 1 level.

To enhance the spatial disaggregation and thus rely on a more precise measure of temperature exposure, we leverage additional information on urbanization. Specifically, we divide each country-specific minimum NUTS level into five artificial sub-zones based on urban density, classifying areas from rural to highly dense urban. This categorization of each grid cell follows the criteria outlined in the DEGURBA Manual by the European Commission (2021). The mean daily temperature is then averaged among grid cells within each artificial sub-minimum NUTS area, thus representing the source of temperature exposure variation.

3.4 Descriptive Statistics

By combining climate variables with SHARELIFE data and focusing on individuals for whom income information is available, we obtained a sample of 42228 individuals across 16 countries, resulting in 129604 income records. This number decreases to 92583 when restricting the analysis to income data from countries where we can reconstruct temperature exposure. As shown in Table A4 in Appendix A, 16567 individuals have a single income record, while the majority have at least two, and over 35% of respondents provided more than three income records.

Table A2 in Appendix A presents key statistics for the monetary data, including the mean, standard deviation, and various percentiles, disaggregated by country of residence and occupation type (exposed vs. not exposed to heat stress risk). The median income is approximately $1501.91, while the mean income is around $2912.75. Mean income varies across countries and does not fully reflect the relative income ranking among the sampled countries. Importantly, differences in absolute income levels across countries are absorbed by location-fixed effects.

Table A5 in Appendix A presents the number of observations with available information on occupation type based on ISCO 4-digit classifications. Occupations are categorized into non-exposed, outdoor exposed, and indoor exposed to heat stress. On average, approximately 20% of workers are employed in outdoor occupations at risk of heat stress. This share is notably higher in Mediterranean countries such as Greece (33%) and Spain (28%), as well as in Eastern European countries like Poland (33%).

Table A6 presents the average number of days spent in heat and cold waves, calculated using both relative and absolute approaches. The yearly average percentage of days spent in heat waves is approximately 8% for absolute thresholds and nearly 9% for relative thresholds. However, the distribution across countries varies significantly, as discussed in Section

3.2. Specifically, when using relative thresholds, the shares are more consistent across countries, while absolute thresholds reveal greater variation. For instance, in Greece, the average percentage of days in heat waves is around 2% when defined by maximum temperatures exceeding the 95th percentile but increases to over 9% when using a 30°C threshold. This pattern is also evident in Figure A1, which shows the average number of days in heat and cold waves at the finest NUTS level available[3].

Finally, Tables A7 and A8 present the number of individuals by country of residence and by income decile, respectively, who were exposed at least once to heat or cold waves, defined both in relative and absolute terms, along with the average exposure experienced at the individual level.

4 Empirical Strategy

The empirical strategy leverages the longitudinal nature of the dataset by exploiting variability in exposure to plausibly random weather shocks at the location level (sub-minimum NUTS[4]), while controlling for location and individual fixed effects. Sub-minimum NUTS fixed effects account for the permanent component of climate as well as any time-invariant unobserved characteristics that could be correlated with temperature and the outcome, thereby reducing potential bias in the results (Hsiang, 2016).

We acknowledge that while this identification approach estimates the impact of weather shocks on income, it may not fully capture the effects of slower, long-term adjustments in climate. This limitation arises unless the assumption of marginal treatment comparability holds — i.e., if a marginal change in weather distribution has the same effect on income as an analogous marginal change in climate (Hsiang, 2016). This assumption is plausible in the absence of effective or limited adaptation.

We model the impact of temperature on our outcome of interest as follows:

$$Y_{ily} = \beta_j \sum_j T_{ily} + f(P_{ily}) + \gamma X_{ily} + \mu_i + \psi_c + \phi_l + \lambda_y + \epsilon_{ily} \tag{1}$$

where, given an individual i, residing in a location (sub-minimum NUTS) l, at year y, Y_{ily} is the income inverse hyperbolic sine transformation or a dummy variable indicating a transition to different occupations. $\sum_j T_{ly}$ is the temperature modelled by heat (HW) and cold wave (CW), as detailed in the section 3.2, where $j \in \{CW, HW\}$; $f(P_{sy})$ is a second-degree polynomial of precipitation used as a control variable; X_{ily} represents a rich set of individual constant or time-varying factors and includes both demographic and socioeconomic char-

[3]It is worth noting that the exposure data are more granular than what is depicted in the map, as each NUTS region is further divided into five sub-NUTS levels based on urbanization degree, as detailed in Section 3.3.

[4]This is the source of temperature variation across individuals.

acteristics, as well as labour market features and experience; μ_i, ψ_c, and λ_y represent individual, cohort (10-year generation) and location (sub-minimum NUTS) fixed effects, respectively. Specifically, ϕ_l controls for different climate and adaptation levels across locations. Given the extended time period covered in our analysis, we include cohort fixed effects, ψ_c, to control for generation-specific factors. In this way, we restrict the comparison, leveraging variations in exposure to temperature shocks among individuals within the same 10-year cohort, with shared labour market conditions and levels of adaptation.

Additionally, in our preferred specification, we include individual fixed effects μ_i controlling for potential unobserved time-invariant individual characteristics. Time-fixed effects λ_y are included in all specifications to account for potential shocks that are common across all units. We estimate an additional specification that includes individual-by-occupation fixed effects, ζ_{io}, to account for the potential self-selection of individuals into occupations. This approach controls for unobserved characteristics, preferences, or constraints that may jointly influence both occupational sorting and associated outcomes.

Finally, we test a model including temporal lags of temperature shocks at time $t-1$ and $t-2$ to detect potential delayed effects. This is relevant such as for some outcomes, these effects may dominate the contemporaneous ones (Anttila-Hughes and Hsiang, 2013; Deryugina, 2017). Standard errors are clustered at the sub-minimum NUTS level s because this level of spatial disaggregation determines the assignment of heat and cold wave exposure to individuals. The estimated coefficients β_{HW} and β_{CW} provide the causal impact of heat and cold waves, respectively, on the outcome of interest by leveraging quasi-random exogenous shocks in weather (Deschênes and Greenstone, 2007).

4.1 Unconditional Quantile Regression

We aim to investigate how extreme temperatures differentially affect the quantiles of the income distribution. To achieve this, we employ the framework proposed by Firpo et al. (2009), which enables us to estimate the impact of changes in regressors on a specific quantile, q^{th}, of the dependent variable's distribution. This approach involves regressing the Recentered Influence Function (RIF) — a transformation of the outcome variable — on covariates. The underlying idea is to assess how regressors influence the population shares below certain thresholds of the outcome, thereby allowing us to estimate the marginal effect on the cumulative distribution function (CDF) of income. In the second step, this effect on the CDF is inverted through a local linear approximation. Specifically, the marginal effect of each regressor on the share of the population above a given income cutoff is rescaled using the income's probability density at that cutoff level. This method works because regressing the RIF on covariates approximates how these covariates affect the unconditional distributional statistic of interest (Firpo et al., 2009)

4.2 Heterogeneity Analysis

Finally, we extend the main specification by including an interaction term to capture the heterogeneous effects of temperature on wages across different dimensions. This analysis provides further insight into the temperature-wage relationship, highlighting potential mechanisms through which temperature influences individual labour market outcomes.

Building on Equation 1, we interact the primary regressors $\sum_j T_{ily}$ with a dummy or categorical variable D_{ily} that denotes the belonging to a certain group, within a given dimension, based on personal or occupational characteristics. We examine individual features' heterogeneity across gender, age, health status, education, and geographic region. In addition, we consider occupation type and wage bargaining structure among countries for job characteristics. Specifically, we model this interaction as follows:

$$Y_{ily} = \beta_{1j} \sum_j T_{ily} + \delta_j \sum_j T_{ily} \times D_{g(il} + \eta D_{g(il)} + f(P_{ly}) + \gamma X_{ily} + \mu_i + \psi_c + \phi_l + \lambda_y + \epsilon_{ily} \quad (2)$$

where $D_{g(il)}$ is a categorical variable that indicates the dimension g characterizing either a group of individuals i or a locations l. The coefficients δ_j measure if there is a differential significant impact of the temperature effect on wages between the omitted group and an alternative group within a certain dimension.

5 Results

This section presents the results from the model estimations outlined in Section 4. The findings are structured as follows: Section 5.1 reports the results from the main model, assessing the impact of temperature on income. In Section 5.2, we explore heterogeneity in the effects across various sociodemographic groups and labour market dimensions. Section 5.3 discusses the results from the unconditional quantile regression, which examines differential impacts across the wage distribution. Finally, Section 5.4 investigates the effects of temperature on labour transitions between occupations.

5.1 The Effect of Temperature on Income

Table 1 presents the estimation results for income, expressed in 2010 base-year dollars, derived using Equation 1. The dependent variable is the inverse hyperbolic sine transformation of income and includes all job episodes and income records available in the sample. The identification strategy leverages plausibly exogenous weather shocks, occurring at the subminimum NUTS region level and over individuals' working lives. The model specification

Table 1: Temperature Impact on Income (All Job Episodes)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Days of CW (T_{MAX} < 5th perc)	-0.00544***	-0.00588***	-0.00506***	-0.00487***				
	(0.001)	(0.001)	(0.002)	(0.002)				
Days of HW (T_{MAX} > 95th perc)	-0.00640***	-0.00531***	-0.00518***	-0.00459***				
	(0.001)	(0.001)	(0.002)	(0.002)				
Days of CW (T_{MIN} < -10°C)					0.00189	0.00120	0.0000721	0.00188
					(0.001)	(0.001)	(0.002)	(0.002)
Days of HW (T_{MAX} > 30°C)					-0.0159***	-0.0145***	-0.0147***	-0.0134***
					(0.002)	(0.002)	(0.002)	(0.002)
Precipitation control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geo id, Generation,Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	No	No	Yes	Yes	No	No	Yes	Yes
Individual by Occupation (isco1) FE	No	No	No	Yes	No	No	No	Yes
Individuals	36684	17716	17716	17716	36684	17716	17716	17716
Observations	84028	59172	59172	50430	84028	59172	59172	50430
Adjusted R^2	0.275	0.277	0.510	0.543	0.278	0.280	0.513	0.546

Notes. The dependent variable is the inverse hyperbolic transformation of income expressed in dollars (base year 2010). Covariates: age and age squared by gender, level of education, cumulative days lost due to disability, books at age 10, rooms at age 10. Clustered standard errors at sub-minimum NUTS level in parentheses. * $(p < 0.10)$, ** $(p < 0.05)$, *** $(p < 0.01)$.

incorporates year, sub-minimum NUTS region, and generation fixed effects, as well as controls for precipitation, individual characteristics, and labour market conditions (Column 1). Column 2 presents the same regression as Column 1, but on the reduced sample of individuals with at least two income observations, for which individual fixed effects are applied in Column 3. Column 4 further accounts for occupational sorting by including individual-by-ISCO (1-digit) fixed effects. Columns 5 through 8 replicate the specifications from Columns 1 through 4, but use the alternative measure of heatwaves based on absolute temperature thresholds.

Table 1 reveals that heat waves have a statistically significant and negative impact on average monthly income. The magnitude of the effect diminishes slightly with the reduction in the sample and after incorporating more stringent individual and individual-by-ISCO fixed effects; however, the coefficient size remains consistent and relatively stable. Notably, the impact is more pronounced when absolute temperature thresholds are used compared to relative thresholds. This discrepancy is likely explained by the fact that, for several countries in our sample, heat waves defined by the 95th percentile may include days with lower temperatures compared to those defined by a maximum temperature exceeding 30°C. Relative thresholds have the advantage of capturing extremes specific to a given location, although they may correspond to temperatures that in other regions are not considered extreme. Conversely, absolute thresholds, while standardizing temperature extremes across locations, face limitations in representing shocks consistently across diverse countries due to varying frequencies of such days and differing levels of adaptation. To address these challenges, we test an alternative measure of heat waves that combines these two approaches.

Specifically, as anticipated in Section 3.2, we define shocks as the minimum number of heatwave days identified by both relative and absolute threshold approaches, while ensuring that the measure captures the most extreme days of exposure across countries, subject to a common minimum threshold of at least 30°C. Results for this hybrid approach are presented in Table A10 of Appendix B.

Our preferred specification, which includes individual fixed effects, indicates that an additional day within a heat wave lasting more than two consecutive days with maximum temperatures exceeding the 95th percentile of the local temperature distribution reduces average monthly income by approximately 0.51%. The income loss is larger when considering days with maximum temperatures exceeding 30°C, resulting in a decline of 1.47% (Table 1). When using the hybrid approach, the impact of heatwaves is even greater, reducing average income by 1.59% for each additional heatwave day (Table A10 of Appendix B).

The estimated marginal impact corresponds to an income loss of $14.85 when heatwaves are defined using relative temperature thresholds, and $42.81 when defined using absolute temperature thresholds. On average, individuals experience 8.04 heatwave days per year under relative temperature thresholds and approximately 8.9 heatwave days per year under absolute thresholds. With an average of 240 working days per year, this translates to roughly 0.44 and 0.48 heatwave working days per month, respectively. It follows that the average monthly income losses associated with relative heatwaves are approximately 0.22%, while the losses for absolute heatwaves are around 0.705%.

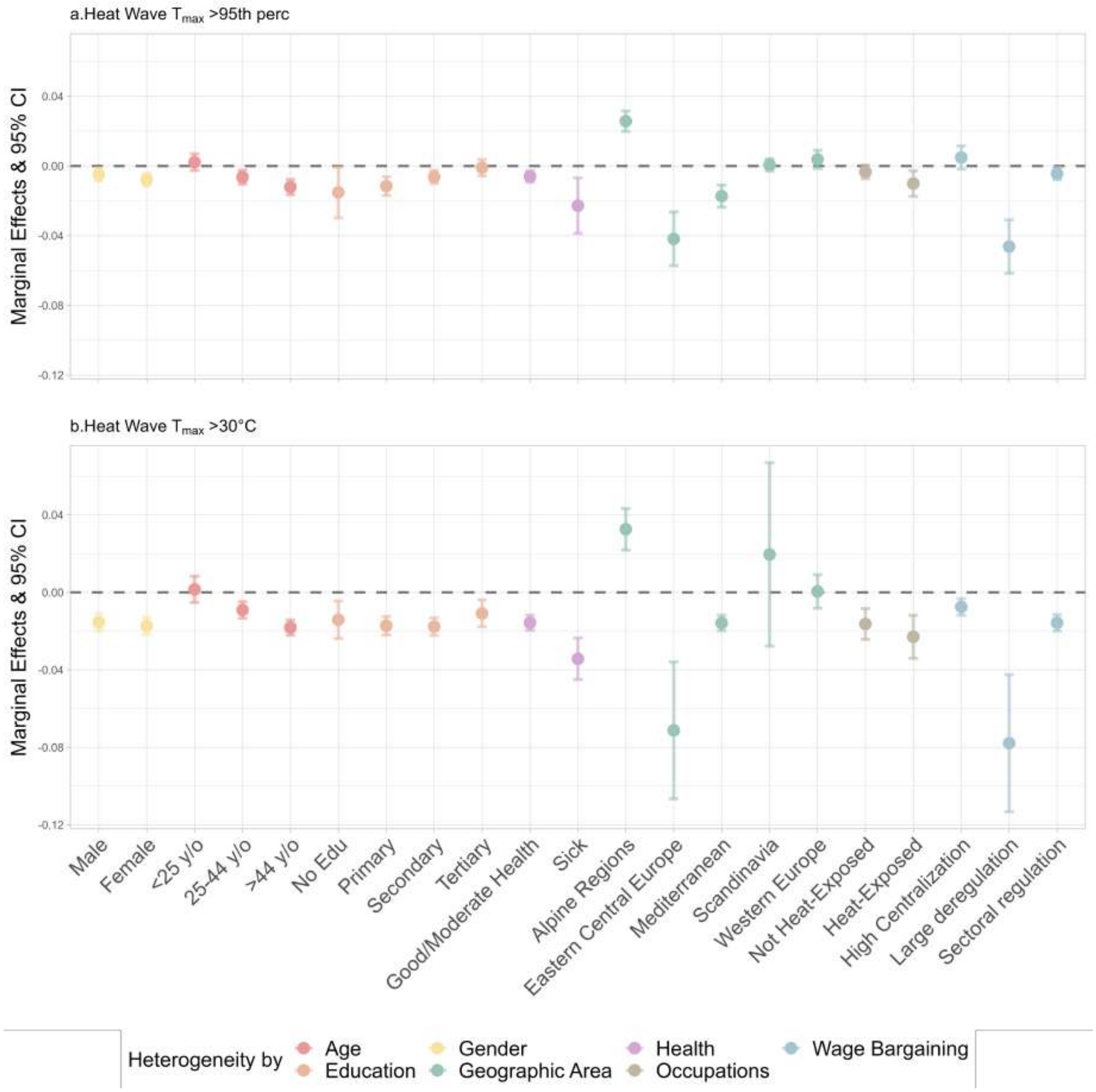
We also test a model that includes lagged heatwave effects for years $t-1$ and $t-2$. The corresponding findings, presented in Table A9 of Appendix B, highlight the persistence and delayed effects of temperature shocks, which accumulate over successive years. The impact increases significantly when accounting for the cumulative effect, resulting in an overall income loss of 1.09 percentage points with relative thresholds and 2.25 percentage points with absolute thresholds.

As robustness checks, we also present results incorporating additional controls. Table A11 in Appendix B reports estimates including indicators for individual by outdoor occupations at risk of heat stress fixed effects (Columns 1, 4, 7), to account for sorting into higher-risk occupations. We also include quadratic trends at the country level (Columns 2, 5, 8) and at the NUTS 1 level (Columns 4, 6, 9). Finally, the results remain robust when using a logarithmic transformation of income, rather than the inverse hyperbolic sine transformation. As shown in Tables A12, A13, and A14 of Appendix B, the findings consistently maintain their sign, statistical significance, and coefficient magnitudes.

5.2 Heterogeneous Impact of Temperature on Income

This section presents the findings from the heterogeneity analysis, offering insights into the differential impact of heat waves on income across demographic groups, geographic

Figure 1: Heterogenous Impact of Temperature on Income



Notes: The figure illustrates the marginal effects and associated 95% confidence intervals from the heterogeneity analysis across Gender, Age, Health, Education, Geographic Area, Occupation, and Wage Bargaining System. It shows the impact of an additional heatwave day for each sub-category within these groups. The top panel presents results for heatwaves defined as at least three consecutive days above the 95th percentile of the maximum temperature distribution, while the bottom panel shows results for heatwaves defined as at least three consecutive days with maximum temperatures exceeding 30°C. All estimates are based on a specification that includes individual fixed effects, with the outcome variable defined as the inverse hyperbolic sine transformation of income.

regions, and employment characteristics. These results contribute to disentangle the underlying mechanisms driving the aggregate effect.

Figure 1 summarizes the results of the heterogeneity analysis obtained from the estimation of Equation 2, displaying the marginal effects and the corresponding 95% confidence intervals for each group analyzed. Detailed results are provided in Appendix C: Table A16 reports findings by gender, age, and health status; Table A17 focuses on education and geographic area; and Table A18 presents outcomes by occupation type and wage bargaining system. Table A19 and Figure A2 present the results of the robustness check conducted using hybrid temperature thresholds.

Sociodemographic Dimensions Figure 1 and Table A16 reveal that the impact of heat increases with age: while it is nearly negligible for individuals younger than 25 years, it becomes pronounced for those aged 45 and older. For this group, an additional day of heat wave is associated with an income reduction of 1.42 and 1.97 percentage points, relative to younger individuals, when using relative and absolute temperature thresholds, respectively. Heterogeneity by health status compares individuals in the 99th percentile of the health loss distribution[5] with the rest of the population. Results show that income losses are significantly more pronounced for ill individuals, and this finding is robust across temperature threshold definitions. The use of the 99th percentile ensures the inclusion of individuals with effectively poor health conditions, as the distribution contains only zeros up to the 95th percentile. Table A20 of Appendix C also provides results using the 95th and 97th percentiles of the health loss distribution, showing that the findings remain robust for lower thresholds under both absolute and hybrid temperature definitions. This evidence suggests that the more substantial income losses may stem from greater declines in productivity or reductions in labour supply among individuals with underlying compromised physical conditions. These groups, such as the elderly and those in poor health, are more likely to experience heightened fatigue and physical stress when exposed to heat waves.

The results for gender and education are less robust across different definitions of heatwave thresholds. When considering relative temperature thresholds, we find that women experience greater income losses than men. These thresholds account for shocks relative to the local temperature distribution, reflecting the degree of local adaptation. This suggests a potential adaptation gap, with women facing disproportionately larger impacts. Table A17 in Appendix C provides detailed results for Education and Geographic Area of residence, corresponding to Figure 1. For education, individuals are classified by their highest level: no education, primary, secondary, or tertiary. Although no clear trend emerges, for relative heatwaves, individuals with tertiary education experience smaller income losses compared to those with no formal education. However, as for gender, these findings are not robust

[5]Health loss is measured as the number of days lost due to disability in a given year, capturing the severity of illnesses. This measure includes diseases potentially related to or susceptible to heat stress, such as angina or heart attack, other heart conditions, respiratory problems, asthma, allergies, stroke, meningitis, infectious diseases, and gynaecological issues.

when using absolute temperature thresholds.

Consistent results are identified for heterogeneity by area of residence (Table A17 in Appendix C). We distinguish five climatic regions: Alpine, Eastern Central Europe, Western Central Europe, the Mediterranean, and Scandinavia. The results reveal that the income impact of temperature is more pronounced in countries with hotter baseline climates, such as those in the Mediterranean. These substantial impacts may also stem from the higher proportion of outdoor workers in these regions, suggesting that adaptation opportunities are limited, likely due to insufficient protective measures for workers in exposed occupations who have few options to shield themselves from extreme heat. Similarly, Western Central Europe experiences significant income losses, likely influenced not only by the large number of outdoor workers but also by the prevailing wage-setting systems, as discussed in the following paragraph. When using absolute temperature thresholds, the confidence intervals for Scandinavia and Eastern Central Europe are notably wider. This reflects the lower frequency of heat shocks exceeding the 30°C threshold in these regions, which reduces the precision of the estimates. Overall, while macro-level studies have shown that the adverse effects of temperature on economic growth are predominantly observed in poorer countries (Dell et al., 2012) and that productivity losses are more pronounced in hotter climates (Burke et al., 2015; Park and Heal, 2013), our study complements this literature by providing micro-level evidence that temperature impacts are significant across diverse regions and may be stronger in already hot climates (Burke et al., 2015).

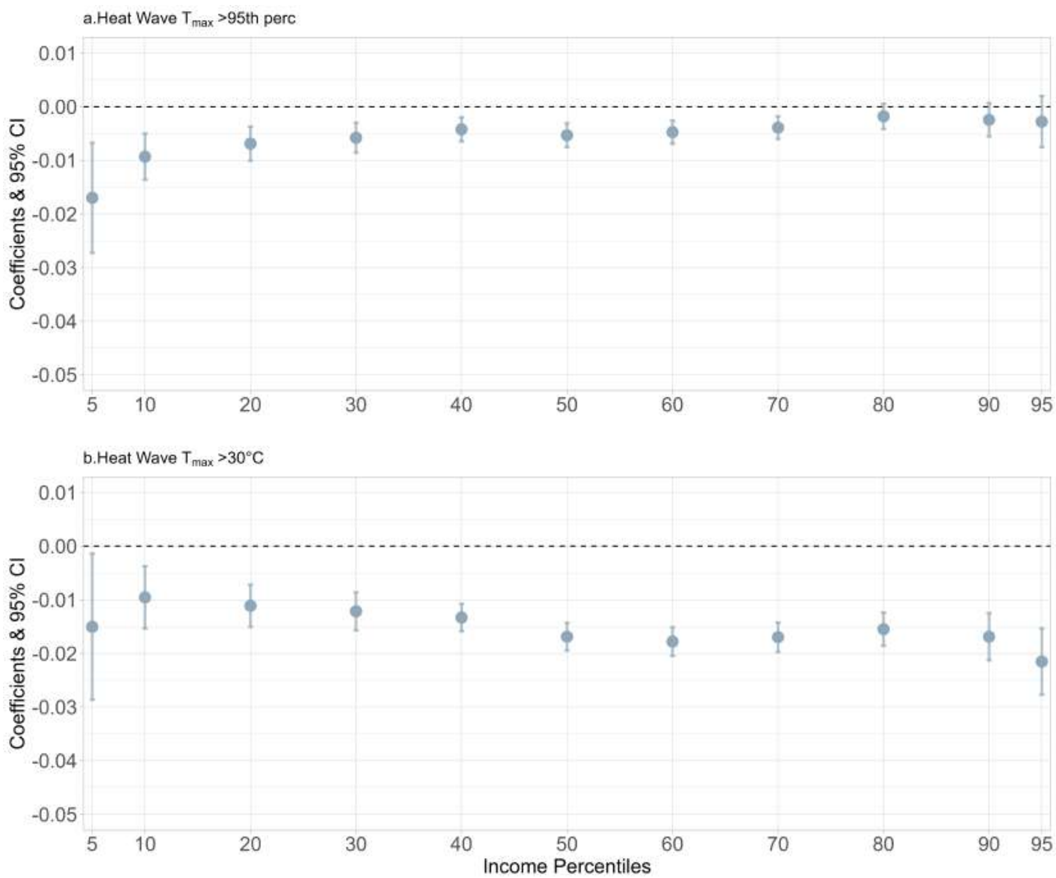
Labour Market Dimensions. Table A18 in Appendix C presents the results related to labour market heterogeneity. Specifically, we examine two dimensions: the type of occupation, distinguishing between jobs at risk of heat stress and those not at risk, and the wage bargaining system in place within the country. The findings indicate that individuals employed in outdoor occupations at risk of heat stress experience income losses that are 0.6 percentage points greater than those in other occupations for each additional heatwave day with temperatures exceeding the 95th percentile of the local distribution. These occupations typically involve greater physical effort, the observed gap may also reflect a more pronounced decline in productivity or labour supply among outdoor workers compared to those in other occupations. The observed gap is likely to reflect a more pronounced decline in productivity or labour supply among outdoor workers compared to those in other occupations. This is likely attributable to limitations in adaptive measures available to outdoor workers, such as restricted access to air conditioning or inflexible work schedules. Additionally, these occupations typically involve greater physical effort. These findings align with previous research that identifies environmentally susceptible industries, such as construction and mining, as more vulnerable to temperature shocks (Park, 2016; Graff Zivin and Neidell, 2014; Neidell et al., 2021; Kahn, 2016). It is important to acknowledge that the sample size is substantially reduced when conducting the heterogeneity analysis across occupations, due to the limited availability of data on ISCO occupation at the 4-digit level.

However, this result does not hold when heatwaves are defined using the absolute threshold of 30°C. These findings suggest that once the level of local adaptation is accounted for, outdoor workers are more vulnerable to the adverse effects of heat waves. This vulnerability is likely attributable to limitations in adaptive measures available to outdoor workers, such as restricted access to air conditioning or inflexible work schedules. Additionally, since these occupations typically involve greater physical effort, the observed gap may also reflect a more pronounced decline in productivity or labour supply among outdoor workers compared to those in other occupations. These findings align with previous research that identifies environmentally susceptible industries, such as construction and mining, as more vulnerable to temperature shocks (Park, 2016).

We further investigate the potential heterogeneity in the impact of temperature across countries with differing systems of wage determination. While the majority of European nations rely on labour union negotiations for wage-setting, the extent of wage coordination exhibits considerable variation (Bhuller et al., 2022; Du Caju et al., 2008). Over the past four decades, there has been a general trend toward greater decentralization in wage-setting systems; however, significant differences persist in bargaining structures and practices across countries. We classify these systems into three categories: highly centralized, sectorally regulated, and largely deregulated. The first category includes countries with centralized systems with a substantial role in government intervention in addition to sectoral and intersectoral agreements, such as Belgium, Slovenia, and Spain. The second category encompasses nations such as Austria, Denmark, France, Germany, Greece, Italy, Portugal, and Sweden, where wage-setting is predominantly regulated at the sectoral level with some firm-level coordination. Finally, the third group consists of countries with largely deregulated systems, exemplified by the Czech Republic and Poland, where wage bargaining is primarily decentralized. Table A18 in Appendix C presents the estimated income losses across countries with varying levels of wage coordination. For countries with highly centralized wage-setting mechanisms, the income loss estimate is not statistically significant when using relative temperature thresholds, and only modest when using absolute temperature thresholds. In contrast, for countries with sectorally regulated systems, the impact is negative and statistically significant, with the effect becoming notably more pronounced in countries with large-scale deregulated systems, such as Poland and the Czech Republic. Although the confidence intervals are wide, particularly for the absolute temperature thresholds, the estimated effects are clearly distinguishable from those in the other groups. These results suggest that more centralized wage-setting systems may mitigate the negative impact of temperature shocks on workers' incomes. In contrast, in countries where wage determination is decentralized and left to individual negotiations, temperature shocks appear to exert a more detrimental effect on income. Since the countries in the deregulated category overlap with those in the Western Central Europe group, the lower degree of worker protection likely is one of the primary mechanisms through which these countries experience greater temperature-related income losses.

5.3 Unconditional Quantile Regression

Figure 2: Impact of Temperature on Income



Notes: The figure illustrates the effect of an additional heatwave day across deciles of the unconditional income distribution. The top panel presents results for heatwaves defined as at least three consecutive days above the 95th percentile of the maximum temperature distribution, while the bottom panel depicts results for heatwaves defined as at least three consecutive days with maximum temperatures exceeding 30°C. All estimates are obtained from the specification without individual fixed effects.

Figure 2 summarizes the results of the temperature effect across the income distribution, using both relative and absolute measures of heatwaves. The analysis employs unconditional quantile regression to estimate the impact of temperature at specific income percentiles, offering insights into the distribution of income losses and their potential inequality implications. Both panels present the coefficients and 95% confidence intervals for the specification without individual fixed effects. Specifically, it shows the results of eleven separate regressions of equation 1, where the dependent variable is the RIF-Quantile transformation of each income decile. Each point on the figure represents the corresponding estimated coefficient, β, at that decile.

The detailed results are provided in Table A22 of Appendix D. Panel (a) reports the results for heatwaves defined using percentile thresholds, while Panel (b) presents estimates for days with maximum temperatures exceeding 30°C. The findings indicate that income losses are distributed relatively evenly across the income distribution, with no substantial differential effects across deciles. In Panel (a), a statistically significant difference is observed only between the 5th percentile and the 70th and 80th percentiles. Even if these findings may suggest a potentially disproportionate burden on the poorest individuals, the confidence intervals for estimates across most deciles largely overlap. Consequently, no definitive pattern emerges along the income distribution, with impacts of similar magnitude observed at both tails, particularly when absolute temperature thresholds are applied. Analogous findings are reported by Hultgren et al. (2022), who estimate the effect of temperature on agricultural yields across income deciles.

5.4 Impact of Temperature on Job Transitions

This section extends the analysis by examining complementary and alternative channels through which temperature affects workers, focusing on its impact on the probability of occupational transitions. The results are based on a linear probability model, estimated using Equation 1, where binary indicators represent each specific outcome as the dependent variable.

Table A24 in Appendix E presents the results on the impact of heat waves on the probability of changing occupation. The findings are consistent across all heat wave measures — relative, absolute, and hybrid thresholds — and indicate that heat waves increase the likelihood of changing occupation. Additionally, past heat wave shocks amplify this effect, consistent with the expectation that transitioning from one job to another often requires time. Specifically, an additional day of heat wave with temperatures exceeding the 95th percentile of the local temperature distribution increases the probability of changing occupation by approximately 0.009%. This effect rises to 0.021% when exposure from the previous two years is included. The corresponding cumulative effect, incorporating lagged exposures, is estimated to be a 0.0122% increase when using absolute temperature thresholds and a 0.0330% increase when using hybrid temperature thresholds. The heterogeneity analysis by occupation shows that individuals in outdoor heat-exposed occupations have a lower probability of changing occupations compared to other workers. This result may explained by the specific skill sets required in these occupations, which are more difficult to transfer or apply to other jobs. However, the sample size decreases significantly when analyzing heterogeneity across occupations due to the limited availability of detailed ISCO 4-digit occupational data.

We also construct a binary variable for individuals who transition from an occupation exposed to high heat stress risk to a non-exposed occupation. The related results are presented in Table A25 of Appendix E. The findings are highly consistent across specifications, both in terms of the sign and magnitude of the estimated effect. We find that heat waves increase the probability of transitioning from exposed to non-exposed occupations by 0.00357%, 0.0000457%, and 0.00465% when using relative, absolute, and hybrid heat wave measures, respectively, with the majority of the effect occurring with a delay. Specifically, our results show that the effect is primarily driven by exposure at time $t-2$.

It is important to note that even if workers in occupations exposed to high heat stress risk have a lower probability of changing occupations compared to those in non-exposed occupations in response to a heat wave, the likelihood of transitioning to jobs with lower exposure to heat stress increases. This finding highlights, on one hand, the constrained opportunities for workers in outdoor, heat-exposed occupations to change jobs following a shock. On the other hand, it suggests a plausible behavioural response among workers: those facing greater challenges due to direct exposure to temperature shocks opt to reduce their exposure by transitioning to less heat-intensive occupations. With the frequency of extreme temperatures expected to rise due to climate change, this trend implies a potential decrease in the labour supply for certain types of jobs. Consequently, there may be upward pressure on wages to compensate for the increasing job disamenities associated with rising temperatures (Park, 2016; Kahn, 2016).

6 Discussion and Conclusions

This paper investigates the impact of temperature shocks — specifically cold and heat waves — on individual labour market outcomes, focusing on income and job transitions. It uses retrospective data on job episodes from the Survey on Health, Ageing, and Retirement in Europe (SHARE), combined with daily weather data from the E-OBS dataset. The weather data is aggregated to the finest spatial units we are able to obtain from SHARE, which correspond to an intermediate level between NUTS2 and NUTS3 regions, with additional granularity in certain countries. We analyse data from approximately 40000 individuals across 14 European countries over a period of more than 60 years. By leveraging plausibly exogenous temperature shocks, we find that an additional day of a heat wave — defined as an event lasting more than two consecutive days with maximum temperatures exceeding either the 95th percentile of the local temperature distribution or 30°C — reduces personal monthly income by approximately 0.51% or 1.47%, respectively. The impact of heat waves is further amplified when considering lagged effects, indicating that previous shocks continue to affect current income, with economic losses accumulating over time.

To investigate the mechanisms behind income losses and explore the distributional effects, we examine heterogeneity across various sociodemographic characteristics and labour market dimensions, as well as potential differential impacts across the unconditional income distribution. We find that older individuals and those with severe health conditions are disproportionately affected, likely due to larger declines in productivity and labour supply. Workers in outdoor occupations at risk of heat stress also experience significantly larger income declines, driven by both greater exposure and constraints on their ability to protect or adapt. Geographically, the impact is more pronounced in Mediterranean and Eastern European countries, where outdoor workers are more prevalent. Additionally, countries with less regulated wage-setting mechanisms experience stronger effects, as workers in these contexts lack institutional protections. Unconditional quantile regressions reveal losses of comparable magnitude across income deciles, with no clear differential impacts, except at the 5th percentile compared to the 70th and 80th percentiles when using relative temperature thresholds for heatwaves. However, we do not identify a distinct trend along the income distribution.

Beyond income effects, temperature shocks also impact the probability of changing jobs. We find that even though workers in heat-exposed occupations have a lower probability of changing jobs compared to those in non-exposed occupations, the likelihood of transitioning to jobs with lower heat exposure increases. This suggests that while opportunities for job changes may be limited for those in outdoor heat-exposed roles, workers respond to temperature shocks by seeking occupations with lower risk of heat stress. With climate change expected to increase the frequency of extreme temperatures, this trend could lead to a reduced labor supply in certain jobs, potentially driving up wages to offset the growing job disamenities associated with higher temperatures.

This paper contributes to the literature on the impact of weather shocks on income by providing new evidence at the individual level, expanding on previous studies that mainly focused on county and firm-level effects. It offers a comprehensive analysis across multiple European countries, incorporating both employees and self-employed workers from diverse occupations. Our findings highlight the differentiated impacts of temperature shocks across demographic groups, labour market conditions, and income distributions, providing important insights for policymakers. Addressing these challenges will require targeted interventions to mitigate income losses, protect vulnerable workers, and prevent inequities exacerbated by exposure to extreme temperatures. Future research should focus on evaluating the effectiveness of adaptive strategies in reducing the impacts of rising temperature exposure on workers.

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Appendices

A Descriptive Statistics

Table A1: Income Data Cleaning and Sample Reduction Process

	Initial info	Decodable info	Exchange Rate	Consumer Price Index	Slovenia and Poland before 1991	Winsorizing (1st and 99th perc)
First Wage	143780	139082	101866	82569	72331	72331
Last Wage	28719	28044	25242	23493	22403	22403
First Income	6908	6784	5671	5303	4841	4841
Last Income	2245	2198	2077	2058	1997	1997
Current Wage	41699	18605	17753	17592	17592	17592
Current Income	29787	2283	2190	2149	2149	2149
Observations	253138	196996	154799	133164	129604	129604

Table A2: Summary Statistics - Income by Occupation and Country of Residence

	Observations	Mean	SD	p25	p50	p75	p95
By Occupation							
Not Exposed	36625	2888.70	9014.74	606.69	1429.78	2672.12	7036.52
Exposed	8722	2836.33	10748.89	514.59	1185.96	2271.70	6307.85
By Country							
Austria	7448	1299.23	3178.67	257.81	782.45	1699.25	3593.12
Belgium	4304	2705.35	6053.89	1497.00	2058.01	2803.51	4922.09
Czech Republic	3185	634.81	770.62	347.35	540.30	775.84	1332.75
Denmark	10438	3015.54	4654.57	1568.12	2572.23	3612.39	6484.37
France	8323	3791.06	12234.89	817.34	1495.78	2541.81	7689.16
Germany	5153	1992.65	2079.47	866.33	1544.89	2475.21	5116.89
Greece	3759	7161.40	20656.46	858.76	1746.96	3823.03	31883.20
Italy	9188	2667.28	5908.70	958.20	1625.35	2597.61	7368.90
Poland	3910	1967.44	12131.87	291.17	481.08	726.06	2218.94
Portugal	1943	3102.25	10329.23	467.19	939.89	2290.29	9651.52
Slovenia	1317	3090.50	9666.27	793.76	1137.10	1699.05	7040.96
Spain	5850	4619.13	16342.81	541.78	1248.95	2227.67	11733.45
Sweden	9887	3434.80	4840.14	1522.88	2426.00	3707.48	9473.40
Switzerland	9241	2876.10	4046.65	820.50	1912.67	3878.47	8204.96
Total	92583	2912.746	8662.64	655.59	1501.91	2757.723	7219.284

Table A3: Classification of Occupations at Risk of Heat Stress

ISCO-08	Definition ISCO-08	Heat-Exposed Occupation
310	Armed Forces Occupations, Other Ranks	1
1311	Agricultural and Forestry Production Managers	1
1312	Aquaculture and Fisheries Production Managers	1
1322	Mining Managers	1
1323	Construction Managers	1
2132	Farming, Forestry and Fisheries Advisers	1
2653	Dancers and Choreographers	2
2655	Actors	2
3117	Mining and metallurgical technicians	1
3121	Mining Supervisors	1
3123	Construction Supervisors	1
3131	Power Production Plant Operators	2
3132	Incinerator and Water Treatment Plant Operators	2
3133	Chemical Processing Plant Controllers	2
3134	Petroleum and Natural Gas Refining Plant Operators	1
3135	Metal Production Process Controllers	2
3142	Agricultural Technicians	1
3143	Forestry Technicians	1
3152	Ships' Deck Officers and Pilots	1
3421	Athletes and Sports Players	2
3422	Sports Coaches, Instructors and Officials	2
3434	Chefs	2
4323	Transport Clerks	1
4412	Mail Carriers and Sorting Clerks	1
5112	Transport Conductors	1
5113	Travel Guides	1
5120	Cooks	2
5131	Waiters	2
5141	Hairdressers	2
5151	Cleaning and Housekeeping Supervisors in Offices, Hotels and Other Establishments	2
5152	Domestic Housekeepers	2
5153	Building Caretakers	2
5165	Driving Instructors	1
5211	Stall and Market Salespersons	1
5212	Street Food Salespersons	1
5243	Door-to-door Salespersons	1
5246	Food Service Counter Attendants	2
5411	Fire Fighters	1
5412	Police Officers	1
5414	Security Guards	1
5419	Protective Services Workers Not Elsewhere Classified	1
6111	Field Crop and Vegetable Growers	1
6112	Tree and Shrub Crop Growers	1
6113	Gardeners, Horticultural and Nursery Growers	1
6114	Mixed Crop Growers	1
6121	Livestock and Dairy Producers	1
6122	Poultry Producers	2
6123	Apiarists and Sericulturists	1
6129	Animal Producers Not Elsewhere Classified	1
6130	Mixed Crop and Animal Producers	1

ISCO-08	Definition ISCO-08	Heat-Exposed Occupation
6210	Forestry and Related Workers	1
6221	Aquaculture Workers	1
6222	Inland and Coastal Waters Fishery Workers	1
6223	Deep-sea Fishery Workers	1
6224	Hunters and Trappers	1
6310	Subsistence Crop Farmers	1
6320	Subsistence Livestock Farmers	1
6330	Subsistence Mixed Crop and Livestock Farmers	1
6340	Subsistence Fishers, Hunters, Trappers and Gatherers	1
7111	House Builders	1
7112	Bricklayers and Related Workers	1
7113	Stonemasons, Stone Cutters, Splitters and Carvers	1
7114	Concrete Placers, Concrete Finishers and Related Workers	1
7115	Carpenters and Joiners	1
7119	Building Frame and Related Trades Workers Not Elsewhere Classified	1
7121	Roofers	1
7124	Insulation Workers	1
7126	Plumbers and Pipe Fitters	1
7127	Air Conditioning and Refrigeration Mechanics	1
7133	Building Structure Cleaners	1
7211	Metal Moulders and Coremakers	2
7212	Welders and Flame Cutters	2
7213	Sheet Metal Workers	2
7214	Structural Metal Preparers and Erectors	2
7215	Riggers and Cable Splicers	2
7221	Blacksmiths, Hammersmiths and Forging Press Workers	2
7223	Metal Working Machine Tool Setters and Operators	2
7224	Metal Polishers, Wheel Grinders and Tool Sharpeners	2
7231	Motor Vehicle Mechanics and Repairers	2
7232	Aircraft Engine Mechanics and Repairers	2
7233	Agricultural and Industrial Machinery Mechanics and Repairers	2
7314	Potters and Related Workers	2
7315	Glass Makers, Cutters, Grinders and Finishers	2
7411	Building and Related Electricians	2
7413	Electrical Line Installers and Repairers	1
7512	Bakers, Pastry-cooks and Confectionery Makers	2
7513	Dairy Products Makers	2
7535	Pelt Dressers, Tanners and Fellmongers	2
7542	Shotfirers and Blasters	1
7544	Fumigators and Other Pest and Weed Controllers	1
8111	Miners and Quarriers	1
8112	Mineral and Stone Processing Plant Operators	1
8113	Well Drillers and Borers and Related Workers	1
8114	Cement, Stone and Other Mineral Products Machine Operators	1
8121	Metal Processing Plant Operators	2
8122	Metal Finishing, Plating and Coating Machine Operators	2
8131	Chemical Products Plant and Machine Operators	2
8141	Rubber Products Machine Operators	2
8142	Plastic Products Machine Operators	2
8143	Paper Products Machine Operators	2
8157	Laundry Machine Operators	2
8171	Pulp and Papermaking Plant Operators	2
8181	Glass and Ceramics Plant Operators	2
8182	Steam Engine and Boiler Operators	2
8211	Mechanical Machinery Assemblers	2
8212	Electrical and Electronic Equipment Assemblers	2
8311	Locomotive Engine Drivers	1

ISCO-08	Definition ISCO-08	Heat-Exposed Occupation
8312	Railway Brake, Signal and Switch Operators	1
8322	Car, Taxi and Van Drivers	1
8331	Bus and Tram Drivers	1
8332	Heavy Truck and Lorry Drivers	1
8341	Mobile Farm and Forestry Plant Operators	1
8342	Earthmoving and Related Plant Operators	1
8343	Crane, hoist and related plant operators	1
8344	Lifting Truck Operators	1
8350	Ships' Deck Crews and Related Workers	1
9111	Domestic Cleaners and Helpers	2
9112	Cleaners and Helpers in Offices, Hotels and Other Establishments	2
9121	Hand Launderers and Pressers	1
9122	Vehicle Cleaners	1
9123	Window Cleaners	1
9129	Other Cleaning Workers	1
9211	Crop Farm Labourers	1
9212	Livestock Farm Labourers	1
9213	Mixed Crop and Livestock Farm Labourers	1
9214	Garden and Horticultural Labourers	1
9215	Forestry Labourers	1
9216	Fishery and Aquaculture Labourers	1
9311	Mining and Quarrying Labourers	1
9312	Civil Engineering Labourers	1
9313	Building Construction Labourers	1
9331	Hand and Pedal Vehicle Drivers	1
9332	Drivers of Animal-drawn Vehicles and Machinery	1
9333	Freight Handlers	1
9411	Fast Food Preparers	2
9412	Kitchen Helpers	2
9510	Street and Related Service Workers	1
9520	Street Vendors (excluding Food)	1
9611	Garbage and Recycling Collectors	1
9612	Refuse Sorters	1
9613	Sweepers and Related Labourers	1
9621	Messengers, Package Deliverers and Luggage Porters	1
9622	Odd Job Persons	1
9623	Meter Readers and Vending-machine Collectors	1
9629	Elementary Workers Not Elsewhere Classified	2

Table A4: Number of Income Information available at Individual Level

Income Info	Individuals (Frequency)	Percentage	Cumulative
1 Obs	16,567	39.2%	39.2%
2 Obs	10,621	25.2%	64.4%
3 Obs	7,090	16.8%	81.2%
4 Obs	3,753	8.9%	90.1%
5 Obs	1,898	4.5%	94.6%
6 Obs	1,097	2.6%	97.2%
7 Obs	542	1.3%	98.4%
8 Obs	325	0.8%	99.2%
9 Obs	178	0.4%	99.6%
10 Obs	79	0.2%	99.8%
$>$ 10 Obs	78	0.2%	100.0%
Total	42,228	100.0%	

Table A5: Observations by Type of Occupation and Country of Residence

Country of residence	**Occupations Exposed to Heat**						**Total**
	not exposed		**exposed (outdoor)**		**exposed (indoor)**		
	Freq.	Perc.	Freq.	Perc.	Freq.	Perc.	
Austria	3571	64.90%	1100	20.00%	831	15.10%	5502
Belgium	4796	72.60%	848	12.84%	963	14.57%	6607
Czech Republic	2003	67.84%	617	20.88%	334	11.29%	2954
Denmark	3939	75.68%	710	13.64%	555	10.67%	5204
France	2583	63.65%	799	19.68%	676	16.67%	4058
Germany	2486	68.05%	661	18.09%	507	13.87%	3654
Greece	500	52.52%	298	31.30%	154	16.18%	952
Italy	2472	60.08%	975	23.69%	668	16.23%	4115
Poland	3430	49.60%	2291	33.12%	1194	17.27%	6915
Portugal	1097	54.43%	514	25.51%	404	20.05%	2015
Slovenia	3491	61.53%	1258	22.17%	925	16.30%	5674
Spain	2912	53.63%	1526	28.09%	994	18.29%	5432
Sweden	4724	73.39%	864	13.43%	849	13.19%	6437
Switzerland	3043	72.12%	605	14.34%	572	13.54%	4220
Total	41050	64.38%	13069	20.50%	9629	15.11%	63748

Notes: The table displays the number of observations where information on both ISCO 4-digit codes and income is available, categorized by country of residence and exposure to heat. Percentages are calculated relative to the total observations for each country.

Table A6: Days of Cold and Heat Wave by Country of Residence

	T < -10°C			T < 5th perc			T > 30°C			T > 95th perc		
	N	Mean	Perc.	N	Mean	Perc.	N	Mean	Perc.	N	Mean	Perc.
Austria	218047	4.64	1.27%	218047	7.43	2.04%	218047	2.29	0.63%	218047	8.48	2.33%
Belgium	348748	0.95	0.26%	348748	9.21	2.53%	348748	0.63	0.17%	348748	6.66	1.83%
Czech Republic	90627	4.56	1.25%	90627	7.18	1.97%	90627	2.71	0.74%	90627	9.86	2.71%
Denmark	230198	1.03	0.28%	230198	7.68	2.11%	230198	0.04	0.01%	230198	9.37	2.57%
France	258742	0.41	0.11%	258742	5.84	1.60%	258742	2.94	0.81%	258742	8.10	2.23%
Germany	123165	1.65	0.45%	123165	7.27	2.00%	123165	1.57	0.43%	123165	8.90	2.44%
Greece	234691	0.02	0.01%	234691	6.71	1.84%	234691	34.68	9.53%	234691	7.88	2.16%
Hungary	389	5.91	1.62%	389	6.43	1.77%	389	4.44	1.22%	389	4.03	1.11%
Italy	319724	0.16	0.04%	319724	5.53	1.52%	319724	15.32	4.21%	319724	12.50	3.43%
Luxembourg	376	0.00	0.00%	376	0.00	0.00%	376	0.00	0.00%	376	0.00	0.00%
Poland	315927	8.31	2.28%	315927	6.41	1.76%	315927	1.04	0.29%	315927	7.34	2.02%
Portugal	75199	0.00	0.00%	75199	5.39	1.48%	75199	14.03	3.85%	75199	8.23	2.26%
Slovenia	219981	3.51	0.96%	219981	5.51	1.51%	219981	3.36	0.92%	219981	9.83	2.70%
Spain	325973	0.00	0.00%	325973	6.10	1.68%	325973	24.95	6.85%	325973	10.20	2.80%
Sweden	233423	15.42	4.24%	233423	5.34	1.47%	233423	0.14	0.04%	233423	9.63	2.65%
Switzerland	164031	2.24	0.62%	164031	7.87	2.16%	164031	0.83	0.23%	164031	7.19	1.98%
Total	3159241	3.08	0.85%	3159241	6.70	1.84%	3159241	8.04	2.21%	3159241	8.90	2.45%

Notes: The table presents the number of observations, the weighted means, and the percentages (calculated as mean divided by 365 days, multiplied by 100) for both absolute and relative measures of heat and cold waves, reported by country of residence.

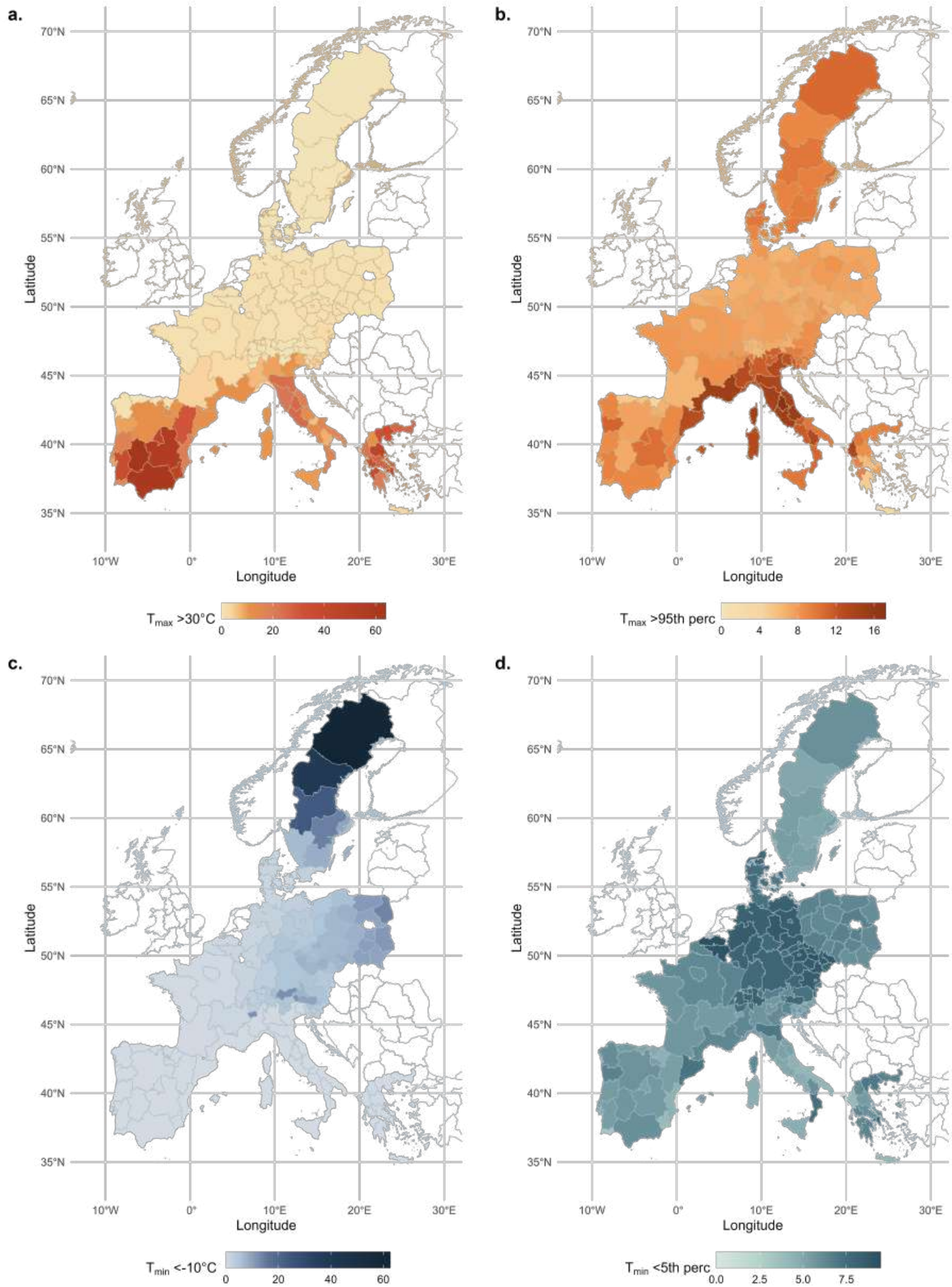


Figure A1: Average Number of Days in Heat and Cold Waves by Minimum NUTS Level

The table reports the average number of days spent in heat and cold waves at the minimum available NUTS level.

Table A7: Number of Individuals Exposed at least once to Heat or Cold Waves by Country of Residence

	T_{MAX} < -10°C			T_{MAX} < 5th perc			T_{MAX} > 30°C			T_{MAX} > 95th perc		
	Never	At Least Once	Mean	Never	At Least Once	Mean	Never	At Least Once	Never	Mean	At Least Once	Mean
Austria	0	2696	4.48	0	2696	7.38	80	2616	2.48	0	2696	8.56
Belgium	1	2913	0.92	0	2914	9.11	0	2914	0.64	0	2914	6.72
Czech Republic	0	2113	4.53	0	2113	7.21	0	2113	2.64	0	2113	9.82
Denmark	4	3240	1.01	0	3244	7.65	725	2519	0.04	0	3244	9.40
France	105	2973	0.41	0	3078	5.86	0	3078	3.04	0	3078	8.17
Germany	0	3053	1.68	0	3053	7.27	1	3052	1.57	0	3053	8.90
Greece	1485	463	0.02	0	1948	6.84	0	1948	34.78	0	1948	8.02
Hungary	58	231	6.04	83	206	5.91	75	214	4.54	72	217	3.95
Italy	1630	2067	0.16	0	3697	5.58	0	3697	15.64	0	3697	12.63
Luxembourg	252	0	0.00	252	0	0.00	252	0	0.00	252	0	0.00
Poland	0	2504	8.08	0	2504	6.40	0	2504	1.04	0	2504	7.35
Portugal	717	0	0.00	0	717	5.70	0	717	15.13	0	717	8.53
Slovenia	6	1000	3.41	0	1006	5.55	0	1006	3.58	0	1006	10.06
Spain	2275	274	0.00	0	2549	5.92	0	2549	26.90	0	2549	9.92
Sweden	0	3243	15.29	0	3243	5.33	358	2885	0.14	0	3243	9.65
Switzerland	0	2133	2.21	0	2133	7.87	26	2107	0.84	0	2133	7.29
Total	6533	28903	3.23	335	35101	6.70	1517	33919	6.86	324	35112	8.93

Table A8: Number of Individuals Exposed at least once to Heat or Cold Waves by Income Deciles

	T_{MAX} < -10°C			T_{MAX} < 5th perc			T_{MAX} > 30°C			T_{MAX} > 95th perc		
	Never	At Least Once	Mean	Never	At Least Once	Mean	Never	At Least Once	Never	Mean	At Least Once	Mean
1st decile	774	2895	4.40	108	3561	6.70	153	3516	6.17	108	3561	8.04
2nd decile	550	3118	4.45	76	3592	6.90	111	3557	5.22	76	3592	8.04
3rd decile	742	2927	3.52	65	3604	6.71	120	3549	7.23	65	3604	8.52
4th decile	783	2885	2.86	69	3599	6.61	136	3532	7.73	69	3599	8.76
5th decile	776	2893	2.62	81	3588	6.64	170	3499	7.66	81	3588	8.78
6th decile	676	2998	2.81	68	3606	6.77	200	3474	6.77	68	3606	8.74
7th decile	593	3069	3.25	73	3589	6.80	268	3394	6.12	73	3589	8.68
8th decile	530	3139	3.22	87	3582	6.86	295	3374	4.95	87	3582	8.60
9th decile	562	3106	3.37	83	3585	6.82	291	3377	5.37	83	3585	8.65
10th decile	1045	2623	3.19	98	3570	6.45	253	3415	9.83	98	3570	8.72
Total	7031	29653	3.37	808	35876	6.73	1997	34687	6.71	808	35876	8.55

B Temperature Impact on Income - Complementary Results

Table A9: Temperature Impact on Income (All Job Episodes) - Lags

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Days of CW (T_{MIN} < 5th perc)	-0.00387***	-0.00412***	-0.00334**	-0.00318*				
	(0.001)	(0.001)	(0.001)	(0.002)				
Days of HW (T_{MAX} > 95th perc)	-0.00620***	-0.00494***	-0.00444***	-0.00378**				
	(0.001)	(0.001)	(0.001)	(0.002)				
Days of CW (T_{MIN} < -10°C)					0.00276**	0.00203	0.000744	0.00279
					(0.001)	(0.001)	(0.002)	(0.002)
Days of HW (T_{MAX} > 30°C)					-0.0119***	-0.0107***	-0.00986***	-0.00863***
					(0.001)	(0.001)	(0.002)	(0.002)
Days of CW (T_{MIN} < 5th perc) at t-1	-0.00570***	-0.00596***	-0.00639***	-0.00693***				
	(0.001)	(0.001)	(0.002)	(0.002)				
Days of CW (T_{MIN} < 5th perc) at t-2	-0.00479***	-0.00520***	-0.00528***	-0.00461**				
	(0.002)	(0.002)	(0.002)	(0.002)				
Days of HW (T_{MAX} > 95th perc) at t-1	-0.00242**	-0.00266**	-0.00392***	-0.00406***				
	(0.001)	(0.001)	(0.001)	(0.001)				
Days of HW (T_{MAX} > 95th perc) at t-2	-0.00158	-0.00181	-0.00252*	-0.00291*				
	(0.001)	(0.001)	(0.001)	(0.001)				
Days of CW (T_{MIN} < -10°C) at t-1					-0.000378	-0.0000400	-0.000291	-0.000302
					(0.001)	(0.001)	(0.001)	(0.002)
Days of CW (T_{MIN} < -10°C) at t-2					-0.00122	-0.00125	-0.00000821	0.000449
					(0.002)	(0.002)	(0.002)	(0.002)
Days of HW (T_{MAX} > 30°C) at t-1					-0.00390***	-0.00384***	-0.00613***	-0.00544***
					(0.001)	(0.001)	(0.001)	(0.001)
Days of HW (T_{MAX} > 30°C) at t-2					-0.00679***	-0.00622***	-0.00653***	-0.00651***
					(0.001)	(0.002)	(0.001)	(0.002)
Marginal Effects								
Days of CW (T_{MIN} < 5th perc)	-0.0144***	-0.0153***	-0.0150***	-0.0147***				
	(0.003)	(0.003)	(0.003)	(0.004)				
Days of HW (T_{MAX} > 95th perc)	-0.0102***	-0.00941***	-0.0109***	-0.0108***				
	(0.002)	(0.002)	(0.003)	(0.003)				
Days of CW (T_{MIN} < -10°C)					0.00116	0.000746	0.000445	0.00294
					(0.002)	(0.002)	(0.003)	(0.003)
Days of HW (T_{MAX} > 30°C)					-0.0226***	-0.0208***	-0.0225***	-0.0206***
					(0.002)	(0.003)	(0.003)	(0.003)
Precipitation control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geo id, Generation,Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	No	No	Yes	Yes	No	No	Yes	Yes
Individual by Occupation (isco1) FE	No	No	No	Yes	No	No	No	Yes
Individuals	36443	17338	17587	17587	36443	17338	17587	17587
Observations	82389	57536	58337	49737	82389	57536	58337	49737
Adjusted R^2	0.278	0.280	0.511	0.545	0.281	0.282	0.514	0.547

Notes. The dependent variable is the inverse hyperbolic transformation of income expressed in dollars (base year 2010). Covariates: age and age squared by gender, level of education, cumulative days lost due to disability, books at age 10, rooms at age 10. Clustered standard errors at sub-minimum NUTS level in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table A10: Temperature Impact on Income (All Job Episodes) - Hybrid Thresholds

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Days of CW (T_{MAX} < -10°C or 5th perc., min)	-0.00743***	-0.00880***	-0.00801***	-0.00627*	-0.00572***	-0.00675***	-0.00584**	-0.00422
	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
Days of HW (T_{MAX} > 30°C or 95th perc., min)	-0.0196***	-0.0174***	-0.0159***	-0.0139***	-0.0155***	-0.0134***	-0.0111***	-0.00948***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
Days of CW (T_{MAX} < -10°C or 5th perc., min) at t-1					-0.00512**	-0.00570**	-0.00567**	-0.00718**
					(0.002)	(0.003)	(0.003)	(0.003)
Days of CW (T_{MAX} < -10°C or 5th perc., min) at t-2					-0.00756***	-0.00806***	-0.00703**	-0.00436
					(0.002)	(0.003)	(0.003)	(0.003)
Days of HW (T_{MAX} > 30°C or 95th perc., min) at t-1					-0.00610***	-0.00559***	-0.00817***	-0.00725***
					(0.002)	(0.002)	(0.002)	(0.002)
Days of HW (T_{MAX} > 30°C or 95th perc., min) at t-2					-0.00899***	-0.00834***	-0.00954***	-0.00909***
					(0.002)	(0.002)	(0.002)	(0.002)
Marginal Effects								
Days of CW (T_{MAX} < -10°C or 5th perc., min)					-0.0184***	-0.0205***	-0.0185***	-0.0158**
					(0.005)	(0.006)	(0.006)	(0.007)
Days of HW (T_{MAX} > 30°C or 95th perc., min)					-0.0306***	-0.0273***	-0.0289***	-0.0258***
					(0.004)	(0.004)	(0.005)	(0.005)
Precipitation control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geo id, Generation,Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	No	Yes	Yes	No	Yes	Yes	Yes	Yes
Individual by Occupation (isco1) FE	No	No	Yes	No	No	Yes	Yes	Yes
Individuals	37239	17338	17,974	17,974	37239	17338	17587	17587
Observations	85229	60006	60006	51152	82389	57536	58337	49737
Adjusted R^2	0.265	0.266	0.510	0.544	0.280	0.282	0.513	0.546

Notes. The dependent variable is the inverse hyperbolic transformation of income expressed in dollars (base year 2010). Covariates: squared Age, level of education, cumulative days lost due to disability, books at age 10, rooms at age 10. Clustered standard errors at location (sub-minimum NUTS) level in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table A11: Temperature Impact on Income (All Job Episodes)

	Outcome: IHS Income								
	Relative Thresholds			Absolute Thresholds			Hybrid Thresholds		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Days of CW (T_{MAX} < 5th perc)	-0.00364	-0.000220	0.000138						
	(0.002)	(0.001)	(0.001)						
Days of HW (T_{MAX} > 95th perc)	-0.00456**	-0.00445***	-0.00332***						
	(0.002)	(0.001)	(0.001)						
Days of CW (T_{MIN} < -10°C)				-0.000386	0.000683	0.00165			
				(0.003)	(0.002)	(0.002)			
Days of HW (T_{MAX} > 30°C)				-0.0163***	-0.00355**	-0.00155			
				(0.003)	(0.002)	(0.002)			
Days of CW (T_{MAX} < -10°C or 5th perc., min)							-0.00591*	0.00352*	0.00389*
							(0.004)	(0.002)	(0.002)
Days of HW (T_{MAX} > 30°C or 95th perc., min)							-0.0173***	-0.00579***	-0.00408**
							(0.004)	(0.002)	(0.002)
Precipitation control	Yes	Yes	Yes	Yes	Yes	Yes			
Location, Generation,Year FE	Yes	Yes	Yes	Yes	Yes	Yes			
Covariates	Yes	Yes	Yes	Yes	Yes	Yes			
Individual FE	No	Yes	Yes	No	Yes	Yes			
Individual by Outdoor Heat Exposed Occupation FE	Yes	No	No	Yes	No	No	Yes	No	No
Country Quadratic Trend	No	Yes	No	No	Yes	No	No	Yes	No
NUTS1 Quadratic Trend	No	No	Yes	No	No	Yes	No	No	Yes
Individuals	9928	20340	20107	19928	20340	20107	9928	20340	20107
Observations	29800	66115	65832	29800	66115	65832	29800	66115	65832
Adjusted R^2	0.505	0.554	0.543	0.502	0.555	0.543	0.504	0.554	0.543

Notes. The dependent variable is the inverse hyperbolic transformation of income expressed in dollars (base year 2010). Covariates: age and age squared by gender, level of education, cumulative days lost due to disability, books at age 10, rooms at age 10. Clustered standard errors at sub-minimum NUTS level in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table A12: Temperature Impact on Income (All Job Episodes)- Log Transformation

	Outcome: Log-Income					
	(1)	(2)	(3)	(4)	(5)	(6)
Days of CW (T_{MAX} > 95th perc)	-0.00517***	-0.00599***	-0.00513**			
	(0.001)	(0.002)	(0.002)			
Days of HW (T_{MAX} > 95th perc)	-0.00690***	-0.00708***	-0.00530***			
	(0.001)	(0.002)	(0.002)			
Days of CW (T_{MIN} < -5°C)				0.00195	-0.000505	0.00205
				(0.001)	(0.002)	(0.002)
Days of HW (T_{MAX} > 30°C)				-0.0159***	-0.0167***	-0.0139***
				(0.002)	(0.002)	(0.002)
Precipitation control	Yes	Yes	Yes	Yes	Yes	Yes
Location, Generation,Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	No	Yes	Yes	No	Yes	Yes
Individual by Occupation (isco1) FE	No	No	Yes	No	No	Yes
Individuals	36684	21149	17716	36684	21149	17716
Observations	84028	68490	50430	84028	68490	50430
Adjusted R^2	0.195	0.489	0.564	0.197	0.491	0.565

Notes. The dependent variable is the inverse hyperbolic transformation of income expressed in dollars (base year 2010). Covariates: squared Age, level of education, cumulative days lost due to disability, books at age 10, rooms at age 10. Clustered standard errors at location (sub-minimum NUTS) level in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table A13: Temperature Impact on Income (All Job Episodes) - Log Transformation, Lags

	Outcome: Log-Income					
	(1)	(2)	(3)	(4)	(5)	(6)
Days of CW (T_{MIN} < 5th perc)	-0.00391***	-0.00422**	-0.00365*			
	(0.001)	(0.002)	(0.002)			
Days of HW (T_{MAX} > 95th perc)	-0.00676***	-0.00624***	-0.00449***			
	(0.001)	(0.002)	(0.002)			
Days of CW (T_{MIN} < -10°C)				0.00283**	0.000181	0.00281
				(0.001)	(0.002)	(0.002)
Days of HW (T_{MAX} > 30°C)				-0.0122***	-0.0115***	-0.00921***
				(0.002)	(0.002)	(0.002)
Days of CW (T_{MIN} < 5th perc) at t-1	-0.00494***	-0.00606***	-0.00613***			
	(0.001)	(0.002)	(0.002)			
Days of CW (T_{MIN} < 5th perc) at t-2	-0.00361**	-0.00526***	-0.00403*			
	(0.002)	(0.002)	(0.002)			
Days of HW (T_{MAX} > 95th perc) at t-1	-0.00208*	-0.00356**	-0.00402**			
	(0.001)	(0.001)	(0.002)			
Days of HW (T_{MAX} > 95th perc) at t-2	-0.00141	-0.00371**	-0.00259			
	(0.001)	(0.002)	(0.002)			
Days of CW (T_{MIN} < -10°C) at t-1				-0.000738	-0.000498	-0.000269
				(0.002)	(0.002)	(0.002)
Days of CW (T_{MIN} < -10°C) at t-2				-0.00110	-0.000690	0.000422
				(0.002)	(0.002)	(0.002)
Days of HW (T_{MAX} > 30°C) at t-1				-0.00291**	-0.00527***	-0.00506***
				(0.001)	(0.002)	(0.002)
Days of HW (T_{MAX} > 30°C) at t-2				-0.00696***	-0.00785***	-0.00647***
				(0.001)	(0.002)	(0.002)
Marginal Effects						
Days of CW (T_{MIN} < 5th perc)	-0.0125***	-0.0155***	-0.0138***			
	(0.003)	(0.003)	(0.004)			
Days of HW (T_{MAX} > 95th perc)	-0.0103***	-0.0135***	-0.0111***			
	(0.003)	(0.003)	(0.003)			
Days of CW (T_{MIN} < -10°C)				0.000995	-0.00101	0.00296
				(0.003)	(0.004)	(0.003)
Days of HW (T_{MAX} > 30°C)				-0.0220***	-0.0247***	-0.0207***
				(0.003)	(0.003)	(0.003)
Precipitation control	Yes	Yes	Yes	Yes	Yes	Yes
Location, Generation,Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Individual, labour market controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	No	Yes	Yes	No	Yes	Yes
Individual by Occupation (isco1) FE	No	No	Yes	No	No	Yes
Individuals	36443	20727	17338	36443	20727	17338
Observations	82389	67586	49737	82389	67586	49737
Adjusted R^2	0.197	0.489	0.564	0.199	0.491	0.565

Notes. The dependent variable is the inverse hyperbolic transformation of income expressed in dollars (base year 2010). Covariates: squared Age, level of education, cumulative days lost due to disability, books at age 10, rooms at age 10. Clustered standard errors at location (sub-minimum NUTS) level in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table A14: Temperature Impact on Income (All Job Episodes) - Log Transformation, Hybrid Thresholds

	Outcome: Log-Income					
	(1)	(2)	(3)	(4)	(5)	(6)
Days of CW (T_{MAX} < -10°C or 5th perc., min)	-0.00717***	-0.00863***	-0.00571	-0.00569**	-0.00674**	-0.00402
	(0.003)	(0.003)	(0.004)	(0.002)	(0.003)	(0.003)
Days of HW (T_{MAX} > 30°C or 95th perc., min)	-0.0202***	-0.0197***	-0.0144***	-0.0166***	-0.0147***	-0.0104***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Days of CW (T_{MAX} < -10°C or 5th perc., min) at t-1				-0.00436	-0.00512*	-0.00709*
				(0.003)	(0.003)	(0.004)
Days of CW (T_{MAX} < -10°C or 5th perc., min) at t-2				-0.00657***	-0.00756***	-0.00384
				(0.003)	(0.003)	(0.003)
Days of HW (T_{MAX} > 30°C or 95th perc., min) at t-1				-0.00484**	-0.00743***	-0.00646***
				(0.002)	(0.002)	(0.002)
Days of HW (T_{MAX} > 30°C or 95th perc., min) at t-2				-0.00862***	-0.0115***	-0.00848***
				(0.002)	(0.003)	(0.003)
Marginal Effects						
Days of CW (T_{MAX} < -10°C or 5th perc., min)				-0.0166***	-0.0194***	-0.0150**
				(0.006)	(0.006)	(0.007)
Days of HW (T_{MAX} > 30°C or 95th perc., min)				-0.0301***	-0.0335***	-0.0254***
				(0.004)	(0.006)	(0.005)
Precipitation control	Yes	Yes	Yes	Yes	Yes	Yes
Location, Generation,Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Individual, labour market controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	No	Yes	Yes	No	Yes	Yes
Individual by Occupation (isco1) FE	No	No	Yes	No	No	Yes
Individuals	36684	21149	17716	36443	21026	17716
Observations	84028	68490	50430	82389	67586	49737
Adjusted R^2	0.277	0.499	0.544	0.280	0.501	0.546

Notes. The dependent variable is the inverse hyperbolic transformation of income expressed in dollars (base year 2010). Covariates: squared Age, level of education, cumulative days lost due to disability, books at age 10, rooms at age 10. Clustered standard errors at location (sub-minimum NUTS) level in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table A15: Temperature Impact on Income - Robustness Excluding One Country

	Days of Heat Wave			Summary Statistics		
Excluded Country	**Rel. Thresholds (T_{MAX} > 95th perc.)**	**Abs. Thresholds (T_{MAX} > 30°C)**	**Hybrid Threshold (> 30°C or 95th perc., min)**	**Ind.**	**Obs.**	**Adj. R^2**
Austria	-0.00729***	-0.0149***	-0.0198***	19211	61913	0.492
	(0.00165)	(0.00199)	(0.00328)			
Belgium	-0.00644***	-0.0163***	-0.0189***	20322	66347	0.502
	(0.00168)	(0.00198)	(0.00340)			
Czech Republic	-0.00640***	-0.0163***	-0.0191***	20525	66919	0.497
	(0.00168)	(0.00200)	(0.00344)			
Denmark	-0.00757***	-0.0163***	-0.0189***	18749	59002	0.489
	(0.00194)	(0.00212)	(0.00349)			
France	-0.00679***	-0.0161***	-0.0204***	18990	65345	0.502
	(0.00176)	(0.00211)	(0.00370)			
Germany	-0.00628***	-0.0163***	-0.0190***	19985	65808	0.489
	(0.00168)	(0.00199)	(0.00342)			
Greece	-0.00505***	-0.0154***	-0.0171***	20077	60467	0.518
	(0.00165)	(0.00212)	(0.00356)			
Italy	-0.00610***	-0.0182***	-0.0248***	18514	66326	0.494
	(0.00198)	(0.00270)	(0.00513)			
Poland	-0.00587***	-0.0154***	-0.0179***	20285	66966	0.505
	(0.00164)	(0.00197)	(0.00333)			
Portugal	-0.00662***	-0.0170***	-0.0196***	20677	67974	0.501
	(0.00169)	(0.00202)	(0.00352)			
Slovenia	-0.00641***	-0.0162***	-0.0188***	20930	63845	0.504
	(0.00168)	(0.00199)	(0.00343)			
Spain	-0.00619***	-0.0196***	-0.0202***	19572	59782	0.491
	(0.00177)	(0.00225)	(0.00384)			
Sweden	-0.00835***	-0.0179***	-0.0210***	18781	61636	0.500
	(0.00188)	(0.00206)	(0.00344)			
Switzerland	-0.00679***	-0.0140***	-0.0163***	19429	61636	0.500
	(0.00165)	(0.00193)	(0.00330)			

Notes. The dependent variable is the inverse hyperbolic transformation of income expressed in dollars (base year 2010). Each coefficient corresponds to estimates from models with individual fixed effects for the subsample of individuals residing in a given country. The models also include location, generation, and year fixed effects, as well as a second-degree polynomial of annual average precipitation. Covariates: age and age squared by gender, level of education, cumulative days lost due to disability, books at age 10, rooms at age 10. Clustered standard errors at sub-minimum NUTS level in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

C Heterogeneity Analysis - Complementary Results

Table A16: Temperature Impact on Income - Heterogeneity on Individual Dimensions

	Outcome: IHS Income					
	Gender omitted: male		Age omitted: age $<$ 25		Health omitted: loss$<$ 99p	
	(1)	(2)	(3)	(4)	(5)	(6)
Days of HW (T_{MAX} > 95th perc)	-0.00488***		0.00217		-0.00598***	
	(0.002)		(0.002)		(0.002)	
Days of HW (T_{MAX} > 30°C)		-0.0154***		0.00157		-0.0157***
		(0.002)		(0.003)		(0.002)
Gender (female) x HW (T_{MAX} > 95th perc)	-0.00292*					
	(0.002)					
Gender (female) x HW (T_{MAX} > 30°C)		-0.00184				
		(0.002)				
Age (25 – 44) x HW (T_{MAX} > 95th perc)			-0.00856***			
			(0.003)			
Age (25 – 44) x HW (T_{MAX} > 30°C)				-0.0106***		
				(0.003)		
Age (> 44) x HW (T_{MAX} > 95th perc)			-0.0142***			
			(0.003)			
Age (> 44) x HW (T_{MAX} > 30°C)				-0.0197***		
				(0.004)		
Health (loss > 99p) x HW (T_{MAX} > 95th perc)					-0.0168**	
					(0.008)	
Health (loss > 99p) x HW (T_{MAX} > 30°C)						-0.0186***
						(0.005)
Precipitation control	Yes	Yes	Yes	Yes	Yes	Yes
Location, Generation,Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Individuals	21458	21458	21458	21458	21458	21458
Observations	69444	69444	69444	69444	71357	71357
Adjusted R^2	0.495	0.498	0.496	0.502	0.496	0.499

Notes. The dependent variable is the inverse hyperbolic transformation of income expressed in dollars (base year 2010). Clustered standard errors at location (sub-minimum NUTS) level in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table A17: Temperature Impact on Income - Heterogeneity on Individual Dimensions

	Outcome: IHS Income			
	Education omitted: no edu		**Geographic Area** omitted: Alpine Regions	
	(1)	(2)	(3)	(4)
Days of HW (T_{MAX} > 95th perc)	-0.0151**		0.0257***	
	(0.007)		(0.003)	
Days of HW (T_{MAX} > 30°C)		-0.0142***		0.0326***
		(0.005)		(0.005)
Education (primary) x HW (T_{MAX} > 95th perc)	0.00358			
	(0.008)			
Education (secondary) x HW (T_{MAX} > 95th perc)	0.00884			
	(0.007)			
Education (tertiary) x HW (T_{MAX} > 95th perc)	0.0142*			
	(0.008)			
Education (primary) x HW (T_{MAX} > 30°C)		-0.00302		
		(0.005)		
Education (secondary) x HW (T_{MAX} > 30°C)		-0.00348		
		(0.005)		
Education (tertiary) x HW (T_{MAX} > 30°C)		0.00333		
		(0.006)		
Region (Continental) x HW (T_{MAX} > 95th perc)			-0.0675***	
			(0.008)	
Region (Mediterranean) x HW (T_{MAX} > 95th perc)			-0.0430***	
			(0.004)	
Region (Scandinavia) x HW (T_{MAX} > 95th perc)			-0.0251***	
			(0.003)	
Region (Continental) x HW (T_{MAX} > 30°C)				-0.104***
				(0.019)
Region (Mediterranean) x HW (T_{MAX} > 30°C)				-0.0483***
				(0.006)
Region (Scandinavia) x HW (T_{MAX} > 30°C)				-0.0130
				(0.025)
Precipitation control	Yes	Yes	Yes	Yes
Location, Generation,Year FE	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Individuals	21200	21200	20340	20340
Observations	68601	68601	66115	66115
Adjusted R^2	0.496	0.498	0.512	0.512

Notes. The dependent variable is the inverse hyperbolic transformation of income expressed in dollars (base year 2010). Clustered standard errors at location (sub-minimum NUTS) level in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table A18: Temperature Impact on Income - Heterogeneity on Labour Market Dimensions

	Outcome: IHS Income			
	Outdoor Occupations omitted: not exposed		**Wage Bargaining** omitted: high centralization	
	(1)	(2)	(3)	(4)
Days of HW (T_{MAX} > 95th perc)	-0.00340*		0.00485	
	(0.002)		(0.003)	
Days of HW (T_{MAX} > 30°C)		-0.0159***		-0.00752***
		(0.003)		(0.002)
Outdoor Heat Exposed Occupations x HW (T_{MAX} > 95th perc)	-0.00669*			
	(0.004)			
Outdoor Heat Exposed Occupations x HW (T_{MAX} > 30°C)		-0.00218		
		(0.003)		
Bargaining (Large deregulation) x HW (T_{MAX} > 95th perc)			-0.0511***	
			(0.008)	
Bargaining (Large deregulation) x HW (T_{MAX} > 30°C)				-0.0704***
				(0.018)
Bargaining (Sectoral regulation) x HW (T_{MAX} > 95th perc)			-0.00916**	
			(0.004)	
Bargaining (Sectoral regulation) x HW (T_{MAX} > 30°C)				-0.00822***
				(0.003)
Precipitation control	Yes	Yes	Yes	Yes
Location, Generation, Year FE	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Individuals	10318	10318	20340	20340
Observations	32179	32179	66115	66115
Adjusted R^2	0.498	0.500	0.508	0.510

Notes. The dependent variable is the inverse hyperbolic transformation of income expressed in dollars (base year 2010). Clustered standard errors at location (sub-minimum NUTS) level in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table A19: Temperature Impact on Income - Robustness on Heterogeneity

	Outcome: IHS Income						
	Gender	**Age**	**Health**	**Edu**	**Geog. Area**	**Out. Occupations**	**Wage Bargaining**
	omitted group:						
	male	age < 25	loss$< 99p$	no edu	Alpine Regions	not exposed	high centr.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Days of HW (T_{MAX} > 30°C or 95th perc., min)	-0.0173***	0.0192***	-0.0186***	-0.0254***	0.0358***	-0.0163***	-0.0112***
	(0.004)	(0.004)	(0.003)	(0.009)	(0.006)	(0.004)	(0.004)
Gender (female) x HW (T_{MAX} > 30°C or 95th perc., min)	-0.00341						
	(0.003)						
Age ($25 - 44$) x HW (T_{MAX} > 30°C or 95th perc., min)		-0.0310***					
		(0.005)					
Age (> 44) x HW (T_{MAX} > 30°C or 95th perc., min)		-0.0487***					
		(0.005)					
Health (loss > 99p) x HW (T_{MAX} > 30°C or 95th perc., min)			-0.0415***				
			(0.012)				
Education (primary) x HW (T_{MAX} > 30°C or 95th perc., min)				0.00501			
				(0.009)			
Education (secondary) x HW (T_{MAX} > 30°C or 95th perc., min)				0.00559			
				(0.009)			
Education (tertiary) x HW (T_{MAX} > 30°C or 95th perc., min)				0.0147			
				(0.010)			
Region (Continental) x HW (T_{MAX} > 30°C or 95th perc., min)					-0.107***		
					(0.019)		
Region (Mediterranean) x HW (T_{MAX} > 30°C or 95th perc., min)					-0.0563***		
					(0.006)		
Region (Scandinavia) x HW (T_{MAX} > 30°C or 95th perc., min)					-0.0255		
					(0.024)		
Outdoor Heat Exposed Occupations x HW (T_{MAX} > 30°C or 95th perc., min)						-0.00659	
						(0.005)	
Bargaining (Large deregulation) x HW (T_{MAX} > 30°C or 95th perc., min)							-0.0663***
							(0.018)
Bargaining (Sectoral regulation) x HW (T_{MAX} > 30°C or 95th perc., min)							-0.00187
							(0.005)
Precipitation control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location, Generation, Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individuals	21458	21458	21901	21200	20340	10318	20340
Observations	69444	69444	71357	68601	66115	32179	66115
Adjusted R^2	0.496	0.502	0.498	0.497	0.511	0.499	0.508

Notes. The dependent variable is the inverse hyperbolic transformation of income expressed in dollars (base year 2010). Clustered standard errors at location (sub-minimum NUTS) level in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table A20: Temperature Impact on Income - Heterogeneity on Individuals' Health

	Outcome: IHS Income Health					
	omitted: loss$< 95p$			omitted: loss$< 97p$		
	(1)	(2)	(3)	(4)	(5)	(6)
Days of HW (T_{MAX} > 95th perc)	-0.00481***			-0.00478***		
	(0.002)			(0.002)		
Days of HW (T_{MAX} > 30°C)		-0.0135***			-0.0136***	
		(0.002)			(0.002)	
Days of HW (T_{MAX} > 30°C or 95th perc., min)			-0.0142***			-0.0144***
			(0.003)			(0.003)
Health (loss > 95p) x HW (T_{MAX} > 95th perc)	-0.00209					
	(0.004)					
Health (loss > 95p) x HW (T_{MAX} > 30°C)		-0.00876***				
		(0.003)				
Health (loss > 95p) x HW (T_{MAX} > 30°C or 95th perc., min)			-0.0162***			
			(0.006)			
Health (loss > 97p) x HW (T_{MAX} > 95th perc)				-0.00670		
				(0.008)		
Health (loss > 97p) x HW (T_{MAX} > 30°C)					-0.0146***	
					(0.005)	
Health (loss > 97p) x HW (T_{MAX} > 30°C or 95th perc., min)						-0.0251**
						(0.011)
Precipitation control	Yes	Yes	Yes	Yes	Yes	Yes
Location, Generation,Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Individuals	21458	21458	21458	21458	21458	21458
Observations	71357	71357	71357	71357	71357	71357
Adjusted R^2	0.496	0.499	0.498	0.496	0.499	0.498

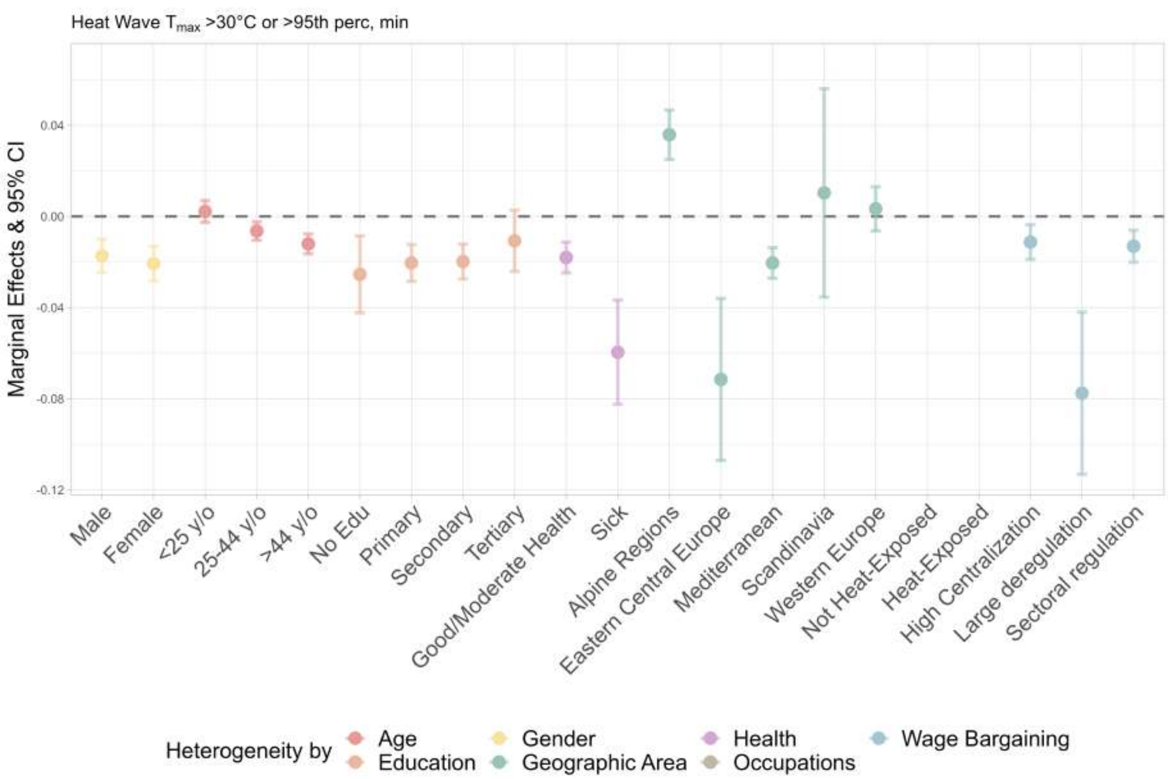
Notes. The dependent variable is the inverse hyperbolic transformation of income expressed in dollars (base year 2010). Clustered standard errors at location (sub-minimum NUTS) level in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table A21: Temperature Impact on Income, Heterogeneity by Occupation - Robustness excluding One Country

	AUS	BEL	CZE	DNK	FRA	DEU	GRC	ITA	POL	PRT	SVN	ESP	SWE	CHE
Days of HW (T_{MAX} > 95th perc)	-0.00531**	-0.00328	-0.00346*	-0.00414*	-0.00297	-0.00318	-0.00263	-0.00152	-0.00322	-0.00431**	-0.00347*	-0.00287	-0.00535**	-0.00389*
	(0.00209)	(0.00203)	(0.00203)	(0.00224)	(0.00212)	(0.00202)	(0.00201)	(0.00221)	(0.00196)	(0.00201)	(0.00202)	(0.00217)	(0.00231)	(0.00204)
OHEO x HW (T_{MAX} > 95th perc)	-0.00797**	-0.00779**	-0.00711**	-0.00738*	-0.00908**	-0.00803**	-0.00724**	-0.00694*	-0.00534*	-0.00781**	-0.00710**	-0.00674*	-0.00676*	-0.00819**
	(0.00373)	(0.00358)	(0.00361)	(0.00387)	(0.00378)	(0.00366)	(0.00357)	(0.00392)	(0.00322)	(0.00360)	(0.00354)	(0.00380)	(0.00384)	(0.00370)
Days of HW (T_{MAX} > 30°C)	-0.0147***	-0.0163***	-0.0161***	-0.0165***	-0.0162***	-0.0162***	-0.0159***	-0.0150***	-0.0149***	-0.0177***	-0.0159***	-0.0181***	-0.0179***	-0.0136***
	(0.00254)	(0.00251)	(0.00254)	(0.00255)	(0.00262)	(0.00252)	(0.00256)	(0.00366)	(0.00250)	(0.00255)	(0.00252)	(0.00277)	(0.00253)	(0.00248)
OHEO x HW (T_{MAX} > 30°C)	-0.00189	-0.00263	-0.00252	-0.00281	-0.00297	-0.00254	-0.00105	-0.000925	-0.00207	-0.00311	-0.00259	-0.00822**	-0.00298	-0.00231
	(0.00304)	(0.00304)	(0.00304)	(0.00308)	(0.00310)	(0.00304)	(0.00305)	(0.00383)	(0.00298)	(0.00316)	(0.00305)	(0.00355)	(0.00310)	(0.00304)
Days of HW (T_{MAX} > 30°C or 95th perc., min)	-0.0191***	-0.0166***	-0.0168***	-0.0169***	-0.0170***	-0.0167***	-0.0158***	-0.0178***	-0.0157***	-0.0177***	-0.0161***	-0.0165***	-0.0188***	-0.0140***
	(0.00363)	(0.00406)	(0.00413)	(0.00405)	(0.00428)	(0.00408)	(0.00412)	(0.00577)	(0.00398)	(0.00423)	(0.00409)	(0.00473)	(0.00401)	(0.00401)
OHEO x HW (T_{MAX} > 30°C or 95th perc., min)	-0.00697	-0.00761	-0.00719	-0.00786*	-0.00833*	-0.00739	-0.00660	-0.00622	-0.00554	-0.00888*	-0.00753	-0.00879	-0.00834*	-0.00705
	(0.00485)	(0.00465)	(0.00470)	(0.00469)	(0.00473)	(0.00469)	(0.00474)	(0.00616)	(0.00450)	(0.00473)	(0.00469)	(0.00563)	(0.00475)	(0.00467)
Precipitation control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geo id, Generation,Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual by Occupation (isco1) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individuals	8884	9710	9846	9465	9436	9538	10080	9146	9705	9863	10059	9547	9103	9289
Observations	27419	30579	30943	29279	29274	30060	31512	28686	30631	30788	31522	29958	27974	28321
Adjusted R^2	0.478	0.495	0.486	0.486	0.497	0.492	0.495	0.509	0.487	0.497	0.494	0.498	0.474	0.484

Notes. The dependent variable is the inverse hyperbolic transformation of income expressed in dollars (base year 2010). Covariates: age and age squared by gender, level of education, cumulative days lost due to disability, books at age 10, rooms at age 10. Clustered standard errors at sub-minimum NUTS level in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Figure A2: Heterogenous Impact of Temperature on Income - Hybrid Thresholds



D Unconditional Quantile Regression - Complementary Results

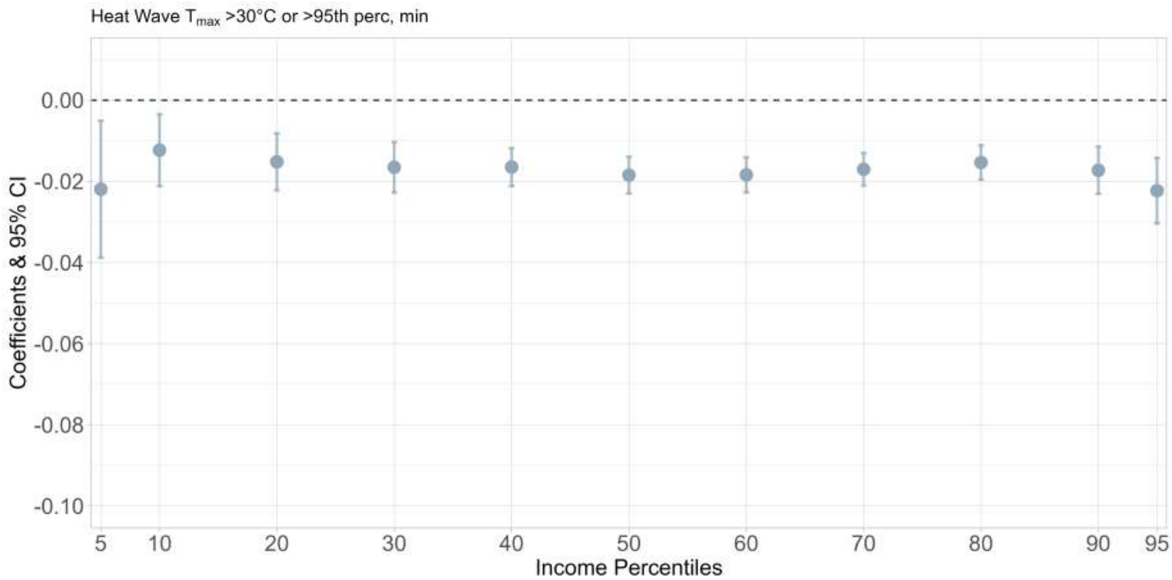


Figure A3: Impact of Temperature on Income - Hybrid Thresholds

Table A22: Unconditional Quantile Regression

	q5	q10	q20	q30	q40	q50	q60	q70	q80	q90	q95
Days of CW (T_{MIN} < -10°C)	0.00201	0.00256	0.00196	0.000793	0.000165	-0.00149	-0.000642	0.00169	0.00384***	0.0129***	0.0151***
	(0.008)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)
Days of HW (T_{MAX} > 30°C)	-0.0150**	-0.00954***	-0.0111***	-0.0121***	-0.0133***	-0.0169***	-0.0178***	-0.0170***	-0.0155***	-0.0169***	-0.0215***
	(0.007)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
Days of CW (T_{MIN} < 5th perc)	-0.00441	-0.0121***	-0.00938***	-0.00911***	-0.00650***	-0.00724***	-0.00700***	-0.00468***	-0.00364***	0.00211	0.00147
	(0.009)	(0.004)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Days of HW (T_{MAX} > 95th perc)	-0.0170***	-0.00931***	-0.00689***	-0.00578***	-0.00422***	-0.00532***	-0.00473***	-0.00388***	-0.00178	-0.00243	-0.00278
	(0.005)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Days of CW (T_{MAX} < -10°C or 5th perc., min)	-0.0248	-0.0192***	-0.0137***	-0.0127***	-0.00858***	-0.00798***	-0.00490***	-0.00393**	-0.00341*	0.00219	-0.000598
	(0.015)	(0.007)	(0.004)	(0.003)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
Days of HW (T_{MAX} > 30°C or 95th perc., min)	-0.0219**	-0.0123***	-0.0152***	-0.0165***	-0.0165***	-0.0185***	-0.0184***	-0.0170***	-0.0154***	-0.0173***	-0.0223***
	(0.009)	(0.005)	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
Precipitation control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location, Generation,Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individuals	36684	36684	36684	36684	36684	36684	36684	36684	36684	36684	36684
Adjusted R^2	0.116	0.179	0.293	0.360	0.377	0.359	0.321	0.266	0.195	0.117	0.082
Observations	84028	84028	84028	84028	84028	84028	84028	84028	84028	84028	84028

Notes: Clustered standard errors at geo unit in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

E Impact of Temperature on Job Transitions - Complementary Results

Table A23: Temperature Impact on Changing Occupation - Hybrid Thresholds

	Outcome: Probability of Changing Occupation			
	(1)	(2)	(3)	(4)
Days of HW (T_{MAX} > 30°C or 95th perc., min)	0.000166***	0.000128	0.000146***	0.000119
	(0.000)	(0.000)	(0.000)	(0.000)
Days of HW (T_{MAX} > 30°C or 95th perc., min), t-1			0.0000818*	0.0000613
			(0.000)	(0.000)
Days of HW (T_{MAX} > 30°C or 95th perc., min), t-2			0.000102**	0.000108
			(0.000)	(0.000)
Outdoor Heat Exposed Occupations x HW (T_{MAX} > 30°C or 95th perc., min)		-0.000466***		-0.000382***
		(0.000)		(0.000)
Outdoor Heat Exposed Occupations x HW (T_{MAX} > 30°C or 95th perc., min), t-1				-0.000234*
				(0.000)
Outdoor Heat Exposed Occupations x HW (T_{MAX} > 30°C or 95th perc., min), t-2				-0.000266*
				(0.000)
Marginal Effects				
Days of HW (T_{MAX} > 30°C or 95th perc., min)			0.000330***	
			(0.000)	
At Outdoor Heat Exposed Occupations=0		0.000128		0.000288**
		(0.000)		(0.000)
At Outdoor Heat Exposed Occupations=1		-0.000338***		-0.000594***
		(0.000)		(0.001)
Precipitation control	Yes	Yes	Yes	Yes
Location, year FE	Yes	Yes	Yes	Yes
Generation FE	Yes	Yes	Yes	Yes
Individual, labour market controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Individuals	21147	11042	21139	11033
Observations	736459	351640	733263	350382
Adjusted R^2	0.058	0.043	0.057	0.042

Notes. The dependent variable is a dummy indicator equal to 1 if an individual changes occupation. Clustered standard errors at location (sub-minimum NUTS) level in parentheses. * $(p < 0.10)$, ** $(p < 0.05)$, *** $(p < 0.01)$.

Table A24: Temperature Impact on Changing Occupation

	Outcome: Probability of Changing Occupation							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Days of HW (T_{MAX} > 95th perc)	0.0000898**	0.00000119	0.0000895**	0.0000146				
	(0.000)	(0.000)	(0.000)	(0.000)				
Days of HW (T_{MAX} > 95th perc), t-1			0.000118***	0.0000744				
			(0.000)	(0.000)				
Days of HW (T_{MAX} > 95th perc), t-2			0.0000118	-0.0000120				
			(0.000)	(0.000)				
Outdoor Heat Exposed Occupations x HW (T_{MAX} > 95th perc)		-0.000207*		-0.000192*				
		(0.000)		(0.000)				
Outdoor Heat Exposed Occupations x HW (T_{MAX} > 95th perc), t-1				-0.000191*				
				(0.000)				
Outdoor Heat Exposed Occupations x HW (T_{MAX} > 95th perc), t-2				-0.000154				
				(0.000)				
Days of HW (T_{MAX} > 30°C)					0.0000506	0.0000683	0.0000280	0.0000536
					(0.000)	(0.000)	(0.000)	(0.000)
Days of HW (T_{MAX} > 30°C), t-1							0.0000279	0.0000220
							(0.000)	(0.000)
Days of HW (T_{MAX} > 30°C), t-2							0.0000665*	0.0000391
							(0.000)	(0.000)
Outdoor Heat Exposed Occupations x HW (T_{MAX} > 30°C)						-0.000402***		-0.000312***
						(0.000)		(0.000)
Outdoor Heat Exposed Occupations x HW (T_{MAX} > 30°C), t-1								-0.000108
								(0.000)
Outdoor Heat Exposed Occupations x HW (T_{MAX} > 30°C), t-2								-0.0000385
								(0.000)
Marginal Effects								
Days of HW			0.000219***				0.000122*	
			(0.000)				(0.000)	
At Outdoor Heat Exposed Occupations=0		0.00000119		0.0000770		0.0000683		0.000115
		(0.000)		(0.000)		(0.000)		(0.000)
At Outdoor Heat Exposed Occupations=1		-0.000206**		-0.000460**		-0.000334***		-0.000344**
		(0.000)		(0.000)		(0.000)		(0.000)
Precipitation control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location, Generation, Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individuals	21147	11042	21139	11033	21147	11042	21139	11033
Observations	736459	351640	733263	350382	736459	351640	736459	351640
Adjusted R^2	0.058	0.042	0.056	0.042	0.058	0.043	0.058	0.043

Notes. The dependent variable is a dummy indicator equal to 1 if an individual changes occupation. Clustered standard errors at location (sub-minimum NUTS) level in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table A25: Impact of Temperature on Transitions from Outdoor Heat-Stress-Risk Occupations to Non-Risk Occupations

	Outcome: Probability of Transitioning from Outdoor Occupations at Risk of Heat Stress to Non-Risk Occupations					
	(1)	(2)	(3)	(4)	(5)	(6)
Days of HW (T_{MAX} > 95th perc)	0.00000613	0.00000428				
	(0.000)	(0.000)				
Days of HW (T_{MAX} > 95th perc), t-1		0.00000725				
		(0.000)				
Days of HW (T_{MAX} > 95th perc), t-2		0.0000242**				
		(0.000)				
Days of HW (T_{MAX} > 30°C)			0.0000113	0.00000392		
			(0.000)	(0.000)		
Days of HW (T_{MAX} > 30°C), t-1				0.0000103		
				(0.000)		
Days of HW (T_{MAX} > 30°C), t-2				0.0000315***		
				(0.000)		
Days of HW (T_{MAX} > 30°C or 95th perc., min)					0.0000117	0.00000817
					(0.000)	(0.000)
Days of HW (T_{MAX} > 30°C or 95th perc., min), t-1						-0.00000310
						(0.000)
Days of HW (T_{MAX} > 30°C or 95th perc., min), t-2						0.0000414***
						(0.000)
Marginal Effects						
Days of HW		0.0000357*		0.0000457**		0.0000465**
		(0.000)		(0.000)		(0.000)
Precipitation control	Yes	Yes	Yes	Yes	Yes	Yes
Location, Generation, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Individuals	21142	21133	21142	21133	21142	21133
Observations	724827	721807	724827	721807	724827	721807
Adjusted R^2	0.007	0.007	0.007	0.007	0.007	0.007

Notes. The dependent variable is a binary indicator equal to 1 if an individual transitions from an outdoor occupation at risk of heat stress to a non-risk occupation. Clustered standard errors at location (sub-minimum NUTS) level in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

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