

Heat Waves and Earnings: Distributional Impacts and the Role of Labor Market Institutions ^{*†}

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Abstract

Despite evidence that heat reduces labor supply and productivity, its direct impact on worker welfare through earnings remains unclear. Using SHARE longitudinal data matched with high-resolution E-OBS weather records for over 32,000 workers across 14 European countries (1955–2018), we exploit plausibly exogenous variation in heat wave exposure across cohorts within the same generation and location, controlling for individual fixed effects and occupational sorting. Each additional heat wave day reduces total earnings by 0.31%, with the burden falling disproportionately on exposed occupations and on low-income and disadvantaged workers. Labor market institutions substantially attenuate these losses, revealing their mediating role.

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1 Introduction

Extreme temperatures substantially affect how people work, impacting both labor supply and productivity (Graff Zivin and Neidell, 2014; Somanathan et al., 2021; Zhang et al., 2018; Rode et al., 2022, among others). Much less is known about whether, and to what extent, workers directly bear the costs of heat exposure. Disruptions to productivity and labor supply can translate into reductions in workers’ earnings, thereby directly compromising their welfare. Yet, this pass-through is not mechanical and even when productivity falls, whether earnings adjust depends on the structure of compensation contracts and the institutional environment governing wage setting. Despite the importance of understanding how heat exposure translates into earnings losses, individual-level evidence remains extremely limited.

This paper addresses this gap by quantifying the effect of extreme temperatures on individual earnings using longitudinal, individual-level data from 14 European countries spanning more than six decades (1955–2018). The European context offers a particularly valuable setting for this analysis. Beyond providing evidence from developed economies across a broad range of occupations and sectors, the richness of European labor market institutions — including centralized collective bargaining, statutory minimum wages, and high union coverage — allows us to examine whether institutional arrangements mediate the pass-through of temperature shocks to individual earnings, a question largely unexplored in the existing literature. Motivated by recent evidence highlighting the importance of both the intensity and the duration of extreme temperature exposure for human well-being (IPCC, 2023a; Miller et al., 2021), we focus on heat waves (HWs), defined as periods of more than five consecutive days during which the daily maximum temperature exceeds the 95th percentile of the local historical temperature distribution. We rely on retrospective data from the Survey of Health, Ageing and Retirement in Europe (SHARE), which allow us to reconstruct the complete employment histories of a representative sample of individuals aged 50 and above. These data provide rich information on job episodes, earnings, socio-demographic characteristics, health status, parental background, and occupational and sectoral employment. We combine the SHARE data with

high-frequency weather information from the E-OBS dataset provided by Copernicus. This enables us to compute annual measures of HW exposure at a spatial resolution that varies across countries, determined by the minimum NUTS level available in SHARE for each country, further partitioned into five sub-groups based on degree of urbanization (see Appendix A). This unit – which we refer to as *sub-minimum NUTS* – corresponds, on average, to a spatial scale between a region (NUTS2) and a province (NUTS3).

Our empirical strategy exploits plausibly exogenous variation in HWs across individuals from different cohorts within the same generation (defined over a 10-year window) and residing in the same location (sub-minimum NUTS), conditional on a rich set of socio-demographic and labor market controls. In practice, we compare otherwise similar individuals who live in the same location and belonging to the same generation, who differ, arguably at random, in the timing (age and career stage) of their exposure to extreme heat events. To support the plausibility of a causal interpretation of our results, we expand our identification strategy in two directions. First, we exploit the longitudinal structure of the data by including individual fixed effects, thereby controlling for time-invariant unobserved individual characteristics. This allows to rule out the possibility that workers with higher or lower unobserved productivity, which affects their potential earnings, are systematically more likely to experience a heat wave. As suggested by Altonji et al. (2005), we pair this analysis by inspecting the balancing of HW exposure also with respect to observable socio-demographic characteristics. Second, we address potential bias from non-random sorting of individuals into heat-exposed (and thus arguably more affected) occupations by including individual-by-occupation fixed effects in the earning regression, following the literature on returns to skills (Autor and Handel, 2013). The latter specification helps account for the possibility that workers self-select into heat-exposed jobs based on unobserved characteristics that may also correlate with the probability of experiencing heat exposure. For instance, more vulnerable individuals may systematically avoid heat-exposed occupations. In the absence of this correction, heat waves could not be randomly assigned across workers, and estimated effects would reflect lower-bound estimates of the true impact of temperature on wages.

Our results reveal that an additional day in a HW reduces individual annual earnings

by approximately 0.31%, implying an average annual earnings loss of roughly \$159.63 per person. These results are robust to a variety of specification checks, including models with individual and occupation-by-individual fixed effects. Importantly, since our sample is restricted to employed workers, the estimated effect abstracts from heat-induced job displacement and should therefore be interpreted as a lower bound of the total earnings impact.

Beyond the average effect, we document substantial heterogeneity across several dimensions, uncovering the distributional consequences of heat exposure and offering insights into the mechanisms underlying the earnings response. We first examine heterogeneity across occupations and sectors. Crucially, gaps in losses are substantially more pronounced when exposure is defined at the occupational rather than the sectoral level, pointing to match-specific productivity—determined by the precise combination of tasks and individual characteristics—as the primary driver of heat-induced earnings losses. Indeed, these are substantially larger for workers in heat-exposed occupations (−0.57%) compared to non-exposed workers (−0.22%), while differences between exposed and non-exposed sectors are not statistically significant. However, when disaggregating more granularly by sector, Agriculture & Fishing stands out as the most affected (−0.97%), reflecting both the high prevalence of outdoor work and the widespread use of piece-rate contracts, which directly tie pay to individual productivity. Exploring the characteristics of individuals sorting into exposed occupations, we find that these workers tend to have lower educational attainment and come from more disadvantaged socio-economic backgrounds. Distributional consequences are also evident within the earnings distribution, where low-income workers bear the largest relative burden. Together, these findings suggest that extreme heat not only reinforces existing socio-economic inequalities but also contributes to their intergenerational transmission.

Finally, we examine the mediating role of labor market institutions. Exploiting variation across and within countries over time, we provide novel evidence that higher levels of wage-setting coordination, binding bargaining norms, minimum wage protections, and union density are each effective in limiting the pass-through of heat-induced earnings losses to workers. Where such institutional protections are in place, the adverse

effect of heat waves on earnings is substantially attenuated, and in some cases nearly fully offset. Because unions and most labor market institutions in the EU bargain mainly on wages rather than on hours worked, this attenuation is consistent with a decline in hourly wages driven by lost productivity—rather than a reduction in hours worked—as the predominant channel behind the earnings loss. This evidence remains suggestive, however, as we cannot directly observe changes in hours worked.

Related Literature and Contributions. A growing body of economic research documents the widespread effects of weather shocks and climate change on human well-being and economic activity (Carleton and Hsiang, 2016). While early contributions focused primarily on assessing aggregate economic damages (Burke et al., 2015; Newell et al., 2021; Bilal and Känzig, 2024), subsequent work has increasingly focused on the specific factors behind these macroeconomic effects. Labor is the production input most adversely affected by rising temperatures (Cachon et al., 2012; Somanathan et al., 2021). Although heat exposure impairs performance even in less physically demanding or indoor jobs (Niemelä et al., 2002; LoPalo, 2023) and in capital-intensive industries (Cachon et al., 2012; Zhang et al., 2018), the most substantial and economically relevant impacts are driven by reductions in labor input, with productivity losses concentrated in manual tasks (Cai et al., 2018).

Beyond its effects on productivity (Zhang et al., 2018; Chen and Yang, 2019; Somanathan et al., 2021), heat also reduces labor supply, as reflected in shorter working hours (Graff Zivin and Neidell, 2014; Neidell et al., 2021; Rode et al., 2022) and higher absenteeism (Somanathan et al., 2021), and reduce workplace safety (Park et al., 2021). Over longer horizons, temperature shocks can induce broader labor market adjustments, including sectoral reallocation (Colmer, 2021), particularly out of agriculture (Liu et al., 2023), and declines in wage and non-farm employment (Jessoe et al., 2018). Extreme temperatures also directly adversely affect health (Gould et al., 2025)—including through mortality impacts (Carleton et al., 2022)—hampering human capital accumulation (Graff Zivin et al., 2018; Park, 2022). While recent study focus on the quantification of the welfare costs of labor supply disruptions due to extreme temperature shocks (Rode et al., 2022), there remains limited evidence on the extent to which such shocks translate into measurable

losses in worker well-being also through reductions in earnings.

This paper builds on prior work on the consequences of extreme heat on the labor market, by providing new evidence on an overlooked but relevant dimension of its impact: the direct reduction in workers' welfare through earnings losses. Earlier studies have primarily investigated the effects of temperature exposure on income at more aggregated levels, including counties (Deryugina and Hsiang, 2014; Behrer et al., 2021; Colmer, 2021). To our knowledge, evidence on earnings impacts at the individual level is very scarce. Related work has shown that early-life shocks can affect long-term earnings through their impact on health and human capital (Isen et al., 2017). However, evidence on the effects of contemporaneous heat exposure on earnings remains limited, with existing studies (Oliveira et al., 2021; Li and Pan, 2021) focusing primarily on developing countries and on specific segments of the labor force.¹ Our paper substantially advances this literature in several ways. First, we provide evidence from developed economies with heterogeneous wage-setting institutions, which is fundamentally different from the high-informality context of developing countries analyzed in prior work. Second, we cover a broad range of occupations across both agricultural and non-agricultural sectors, including employees and the self-employed. Finally, we strengthen the credibility of a causal interpretation of our estimates by controlling for individual fixed effects, accounting for occupational sorting, and testing for covariates' balance.

Our work also contributes to the understanding of the distributional effects of climate exposure. We examine various channels through which heat waves compound with existing inequalities, related to occupational tasks, socio-demographic characteristics, parental background and quantiles of the income distribution. Prior research has documented that the economic impacts of climate change are regressive, both across countries (Burke et al., 2015; Carleton and Hsiang, 2016; Diffenbaugh and Burke, 2019), within countries (Hsiang et al., 2017; Park et al., 2018; Behrer et al., 2021; Zhang et al., 2024; Gilli et al., 2024) and can have substantial heterogeneous effect across firms (Yuan et al., 2024; Tarsia, 2024). Poorer

¹Oliveira et al. (2021) analyze impacts on non-agricultural wages in Brazil, using monthly information but only for two years (2015–2016). Li and Pan (2021) study the effect of extreme temperatures on employees' annual rural wages in China from 1989 to 2011, but their analysis remains confined to the rural labor force.

households are more likely to live in climate-vulnerable areas, and lower-income workers are overrepresented in heat-exposed occupations (Park et al., 2018). However, evidence on within-region heterogeneity remains limited. We extend this literature by documenting heterogeneity in earnings responses to temperature shocks across occupations, along the earnings distribution, and by socio-demographic characteristics. We find stronger negative effects among workers in occupations with predominantly outdoor tasks, individuals from disadvantaged family backgrounds, and those at the bottom of the earnings distribution. Our results also speak to the literature connecting environmental hazards and intergenerational inequality (Colmer and Voorheis, 2020), and inform the debate on a just green transition by highlighting the role of preexisting inequalities and multidimensional distributional effects (Vona, 2023; Hernandez et al., 2026).

Finally, we provide novel evidence on labor market institutions as a mediating factor in the transmission of temperature shocks to earnings (Jesoe et al., 2018; Colmer, 2021; Somanathan et al., 2021; Neidell et al., 2021; Acevedo et al., 2020; Yuan et al., 2024). In particular, we examine how different level and coordination of wage-bargaining, minimum wage, union density shape the earnings response to heat waves, highlighting the importance of institutional context in determining the distribution and magnitude of climate-related impacts. While this analysis exploiting within-country, over-time variation is suggestive of the role of labor market institutions, our findings call for further research that incorporates these institutional features into bottom-up approaches to climate impact assessment and policy evaluation (see, e.g., Carleton et al. (2022) and Rode et al. (2022)).

2 Conceptual Framework

Several empirical works have documented that temperature above the optimal level reduces output (Burke et al., 2015; Hsiang et al., 2017; Somanathan et al., 2021; Adhvaryu et al., 2020) through channels that include reduced total factor productivity (Zhang et al., 2018), lower marginal productivity of labor (Cai et al., 2018; Somanathan et al., 2021), and input misallocation (Liu and Xu, 2024). These effects generate a leftward shift in the labor demand curve ($D_L \rightarrow D'_L$, Figure 1): as employing labor becomes less profitable, firms demand less of it at each wage level. At the same time, extreme heat increases the dis-

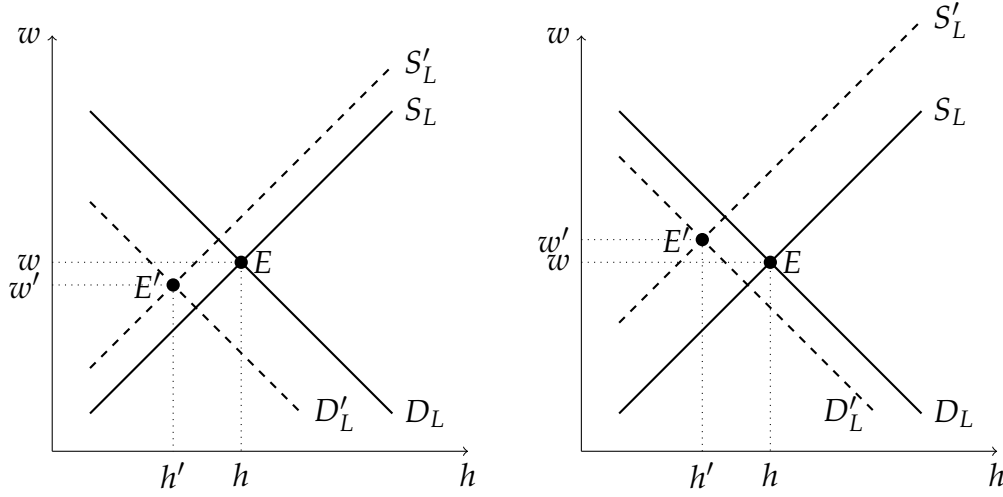


Figure 1: Heat Wave Effect on Labor Supply and Demand. The figure shows that heat waves cause a leftward shift in both labor demand ($D_L \rightarrow D'_L$) and labor supply ($S_L \rightarrow S'_L$), reducing hours worked ($h \rightarrow h'$). But the effect on wages is ambiguous. In the left-side panel, the demand shift dominates and wages fall ($w' < w$); in the right-side panel, the supply shift dominates and wages rise ($w' > w$).

tility of labor (Rode et al., 2022), inducing workers to reduce hours worked² or withdraw from the labor market (Graff Zivin and Neidell, 2014; Neidell et al., 2021; Rode et al., 2022), effectively shifting the labor supply curve leftward as well ($S_L \rightarrow S'_L$): as disutility increases, workers supply less labor at each wage level. Crucially, as shown by Figure 1, HW exposure reduces hours worked (h) at the new equilibrium (E'), but the direction of the effect on hourly wage (w) is ambiguous.³ Likewise, it is unclear the HW effect on workers' well-being, which can be proxied by total earnings ($W = w \cdot h$). Following the insights from Figure 1, we can approximate the effect of HW on total earnings as:

$$\frac{dW}{dT} = \underbrace{\frac{dh}{dT} \cdot w}_{\text{hours channel } (<0)} + \underbrace{\frac{\partial w}{\partial \text{MLP}} \cdot \frac{d \text{MLP}}{dT} \cdot h}_{\text{productivity channel } (<0)} + \underbrace{\frac{\partial w}{\partial D} \cdot \frac{dD}{dT} \cdot h}_{\text{disutility channel } (>0)} \quad (1)$$

²This aggregate shift may mask sectoral heterogeneity: Papp (2024) shows that gig food-delivery workers increase hours worked on hot days at unchanged wages, as demand for such services rises with heat and workers fear that turning down requests during peak demand will lead platforms to deprioritize them for future work

³Theoretically, in equilibrium, the marginal disutility of labor and marginal product of labor within each sector both equal the wage (Rode et al., 2022). Therefore, the sign of $\frac{dw}{dHW}$ depends on which of the two curve shifts is larger. The disutility effect prevails when the increase in the marginal disutility of work, shifting the supply curve leftward, outweighs the leftward shift in the demand due to the fall in the marginal product of labor.

where MPL is the marginal labor productivity and D is the disutility of work. Equation 1 reveals the two diverging forces driving the effect of HW on hourly wages. On the one hand, the higher disutility from working in extreme heat needs to be compensated by higher wages to mitigate labor supply disruption (Roback, 1982; Rosen, 1986; Viscusi and Aldy, 2003). On the other hand, losses in the marginal productivity of labor⁴ are expected to translate into lower wages, with a larger effect on exposed workers.

Which mechanism dominates is therefore an empirical question. Although we cannot fully disentangle the two, the sign of our estimates is informative about which of the two opposing forces operating through wages prevails. At the same time, since we do not observe hours worked at the individual level, we cannot separately identify the labor supply effect from the hourly wage effect. To address this and shed light on their relative role, we complement this evidence with an empirical analysis of labor market institutions. While in perfectly competitive labor markets adjustment to shocks tends to occur through wages (Krugman et al., 1994), in settings with a rich institutional context, as in Europe, the pass-through of firm- and sector-specific shocks into wages may be limited by rigid institutions and centralized or sectoral bargaining, with potential repercussions for employment (Blanchard and Wolfers, 2000). In particular, because wage-setting institutions act specifically on the link between productivity and pay, without directly affecting other adjustment margins such as hours worked, the attenuation of the wage response precisely where these institutions are strongest indicates that temperature affects earnings primarily through wages rather than hours. Overall, our results offer suggestive evidence on the relevance of the productivity/disutility channel relative to labor supply adjustments, and on the moderating role of labor market institutions.

Our empirical analysis leverage this rich institutional setting available in Europe, where collective bargaining is pervasive across countries, even though the last 40 years have seen a general trend toward decentralization, with a lower degree of coordination and a decline in union density. The types of institutions and the main features of these sys-

⁴A large body of literature documents the negative effects of extreme heat on total factor productivity through multiple channels, including impaired labor performance (Zivin and Shrader, 2016; Zivin et al., 2020; Krebs, 2024), reduced efficiency of physical capital (Zhang et al., 2018), and input misallocation (Graff Zivin and Neidell, 2014; Neidell et al., 2021).

tems differ substantially across countries, resulting in a heterogeneous setting. Indeed, even countries with similar levels of GDP, or comparable shares of unionized workers, can exhibit different wage bargaining structures (Bhuller et al., 2022).

Given the relevant institutional differences across countries, we examine several dimensions of labor market institutions, each expected to affect the wedge between the marginal productivity/disutility of labor and workers' pay (Tito, 2011), though through distinct mechanisms. First, the degree of coordination of wage bargaining — measuring the extent to which wage outcomes across different workers are aligned, whether through binding central norms, government-issued guidelines, or pattern-setting by leading sectors or unions — contributes to determining the degree of wage compression, tying pay to average, economy-wide productivity rather than to local conditions (Moene and Wallerstein, 1997). Local productivity shocks therefore have little effect on pay when wage bargaining is highly coordinated, since the relevant benchmark is aggregate rather than local productivity. Second, the predominant level at which bargaining formally takes place — firm, sector, or economy-wide — defines the scope of a single wage agreement, that is, how many firms and workers are directly bound by the same contractual terms (Visser, 2016). Third, the presence of a statutory minimum wage sets a floor below which pay cannot fall regardless of the size of the productivity shock, insulating the workers most exposed to heat — typically those at the bottom of the earnings distribution — from the full extent of the wage response. However, minimum wage effects are not confined to the bottom of the distribution. Compression effects may also affect the top and bottom of the wage distribution, suggesting spillovers beyond the workers directly bound by the statutory floor (Koeniger et al., 2007). Finally, union density captures unions' ability to sustain wage growth independent of firm-specific productivity conditions; in the European context, unions bargain primarily over wages, and wage variation reflects mainly local and sectoral conditions rather than individual worker or firm characteristics (Bhuller et al., 2022). Note that union density may understate the effective reach of collective bargaining in several continental European countries, where agreements are often extended beyond union members and, in some countries, beyond signatory employers, via *erga omnes* clauses or administrative extension (Koeniger et al., 2007). Taken together, these

institutions anchor wages to collective agreements or aggregate benchmarks rather than to individual or firm-level marginal productivity, so an adverse, spatially concentrated productivity shock is less likely to translate into a wage decline. We therefore expect the wage response to temperature to be largest where these institutions are weak or absent, and attenuated where they are strong.

3 Data and Measures

To examine the impact of temperature on earnings, this paper uses retrospective data from the Survey on Health, Ageing and Retirement in Europe (SHARE),⁵ which collects detailed information on the life histories of individuals aged 50 and above, including job and residential records, family background, childhood conditions, lifetime health, educational attainment, and other socio-demographic characteristics, across several European countries and spanning more than six decades.

Importantly, the modules on residential histories allow us to link individual records to high-frequency weather variables from the E-OBS dataset provided by Copernicus, at a granular spatial scale, generally falling between the NUTS2 (regional) and NUTS3 (provincial) levels (Midões et al., 2024; Valenti et al., 2026). This is achieved by partitioning the minimum NUTS level available for each country⁶ into five sub-regions based on individuals' self-reported degree of urbanization, matched to grid cells classified under DEGURBA (European Commission, 2021) (see Appendix A for further details). This increases the variability in individuals' exposure to climatic variables relative to SHARE's available NUTS-level resolution.

Earnings, Occupations and Sectors. Information on respondents' residences and working histories - such as earnings, working hours (full-time vs. part-time), occupation (ISCO codes), and employment status (employee vs. self-employed) - is retrieved from the ret-

⁵The survey is conducted in repeated waves, each of which not only follows respondents from earlier rounds while also introducing refreshment samples to incorporate new cohorts and to compensate for panel attrition.

⁶NUTS1 for Belgium, France, and Germany; NUTS2 for Austria, Denmark, Greece, Poland, Portugal, Spain, Sweden, and Switzerland; NUTS3 for the Czech Republic and Slovenia.

rospective modules of SHARE waves 3 and 7.⁷ The retrospective nature of these data - collected at one point in time but referring to different periods in respondents' lives - required harmonizing the raw data to ensure consistency and comparability of reported values across different time periods and currencies (see Section A in Appendix for further details). In SHARE earnings are labeled differently as "income" (self-employment earnings) and "wage" (earnings from employment), while we use the terms interchangeably to refer to gross monthly labor earnings from employment or self-employment, before taxes and social contributions.

For each job episode, it is available information on the International Standard Classification of Occupations (ISCO) at 4-digit level,⁸ that we use to classify if workers are involved primarily in outdoor or indoor tasks (see classification in Table B2). Across sectors, we classify Agriculture & Fishing, Construction, Mining & Quarrying, Manufacturing, Utilities and Transport, Storage & Communication - which even if performed mainly indoors are likely to be in non-climate controlled environment - as heat-exposed (Following Graff Zivin and Neidell (2014)). Compared to previous research that focuses on sector-level exposure (Graff Zivin and Neidell, 2014; Neidell et al., 2021), our occupational-level refinement allows us to more precisely capture the task-specific component of productivity shocks. By considering the main tasks performed within each occupation, we better account for workers' susceptibility to heat exposure based on the nature of their role (e.g., physically demanding or outdoor tasks). That is, the effect of heat exposure can vary depending on specific job characteristics (Klauber et al., 2025), effects that sector-level analyses may overlook.

⁷Previous research (Garrouste, Paccagnella, et al., 2011; Havari and Mazzonna, 2015) shows that recall bias in SHARELIFE data is limited, likely due to the type of survey design. Respondents are first guided through easily memorable life episodes, beginning with domains that are easier to remember and gradually moving to more specific details.

⁸For our primary estimation sample, 91,7% of observations have occupational information coded at the 1-digit ISCO level and 49,4% at the 4-digit ISCO level, allowing for precise identification of job roles and tasks. When 4-digit ISCO codes are missing, we classify workers using their 1-digit ISCO group combined with their sector of employment. Specifically, workers in groups 3 (Technicians and Associate Professionals), 5 (Clerical Support Workers), 6 (Skilled Agricultural, Forestry and Fishery Workers), 7 (Craft and Related Trades Workers), 8 (Plant and Machine Operators and Assemblers), and 9 (Elementary Occupations) are classified as heat-exposed if employed in Agriculture, Construction, or Mining & Quarrying — sectors known to have higher heat risk because typically characterized by outdoor work.

Weather Data and Heat Waves Measures. Weather data are sourced from the E-OBS dataset (Copernicus Climate Change Service, C3S), which provides daily gridded weather observations across Europe at $0.1^\circ \times 0.1^\circ$ resolution. A key advantage of E-OBS is its long temporal coverage, which enables effective linkage with SHARE’s retrospective socio-economic data, extending back to the early 1950s. Although E-OBS data are available daily, they are aggregated annually to match the temporal resolution of the SHARE data. In our analysis, temperature is the primary weather variable of interest, while average annual precipitation is included as a control in the absence of humidity data. To capture exposure to extreme heat, we construct a measure of heat waves (HWs) (Miller et al., 2021), reflecting both the intensity and persistence of thermal stress and challenging adaptation due to prolonged exposure over several consecutive days. HWs, historically extreme episodes, have recently become more frequent and are expected to intensify further with climate change across most land areas (IPCC, 2023b)⁹. HWs have already been used in the literature to assess socio-economic impacts, such as on local income and investments (Bilal and Rossi-Hansberg, 2023), agricultural output (Miller et al., 2021), firm productivity (Costa et al., 2024), sick leave incidence (Klauber et al., 2025), and environmental attitudes and voting behavior (Hoffmann et al., 2022).

We define HWs as a periods of at least 5 consecutive days when daily maximum temperature exceeds the 95th percentile of a 30-year moving distribution of daily values. Our main metric counts the annual number of days that fall within such events. This definition relies on relative temperature thresholds,¹⁰ which adjust to evolving local climate conditions and local adaptation, allowing us to capture unexpected temperature shocks. Relative thresholds have the advantage of (i) preserving important variability in the data, limited under absolute thresholds, especially in colder regions, and (ii) capturing shocks that are extreme relative to local climate and adaptation.¹¹

⁹It has been estimated that, relative to the pre-industrial period (1850–1900), global warming has made the median HWs event about 200 times more likely, and that a quarter of such events would have been virtually impossible without climate change (Quilcaille et al., 2025).

¹⁰In contrast, absolute thresholds (e.g., five consecutive days above 30°C) vary dramatically across countries: they occur frequently in southern Europe (Greece, Spain) but are extremely rare in northern countries (Table B7), limiting the identification of meaningful heat shocks. For completeness, Appendix D presents and discusses results using temperature bins, a common approach in the climate economics literature (Hsiang, 2016), and heat waves defined with absolute thresholds.

¹¹In addition, these relative, location-specific thresholds also partially prevent bias arising from poten-

Labor Market Institutions. We complement our data with information on labor market institutions, drawing on the OECD/AIAS database on Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts (ICTWSS) (OECD and AIAS, 2025). The database collects since 1960 the rich variation, across countries and over time, on the organisation and coordination of collective bargaining and wage setting across EU countries (see Figure B2). We focus on five institutional dimensions. First, the degree of coordination of wage bargaining, ranging from none or some coordination to binding norms.¹² Second, the predominant level at which bargaining takes place, ranging from firm- to central-level bargaining. Third, whether a statutory minimum wage is in place. Fourth, union density is measured as the share of employees who are trade union members. Fifth, opening clauses in sectoral agreements (OCG), which capture whether sectoral agreements allow renegotiation of contractual matters at the firm level, distinguishing between clauses covering non-wage issues only (working hours, working time schedules, unsocial hours, etc.) and those explicitly allowing wage renegotiation.

While some of these measures show a certain degree of correlation (Figure B13)—for instance, coordination with bargaining level and union density, consistent with the well-documented complementarity between centralised bargaining structures and high unionization rates (Calmfors and Driffill, 1988)—overall, these indicators capture meaningfully distinct dimensions of the institutional framework.¹³

Final Dataset and Descriptive Statistics. The final dataset¹⁴ comprises 32,782 individuals from 14 European countries—Austria, Belgium, the Czech Republic, Denmark, France, Germany, Greece, Italy, Poland, Portugal, Slovenia, Spain, Sweden, and Switzerland—across 643 sub-NUTS regions, over the period 1955–2019. Summary statistics for all variables used in the main analysis are reported in Appendix B.

tial correlations between long-term temperature trends and outcomes, the so-called binning bias concerns highlighted by Jones et al. (2025) and discussed in Appendix D.

¹²Binding norms refer to legally or collectively enforceable rules on wages—such as caps, floors, or freeze schedules—established either through centralized bargaining between central union and employer associations (with or without government involvement) or through direct government intervention.

¹³This evidence, combined with the within-country variation documented in Figure B2, limits concerns about potentially confounding the role of institutions with structural features common to broader groups of countries.

¹⁴Out of 79,029 available earnings records, we retain 75,258 observations (3,2782 individuals) with complete information on the main regressors and control variables (Table 1).

Table B4 reports the distribution of individuals by the number of available earnings records, of which approximately 58% of the sample have multiple observations, and this is the sub-sample that we use for individual fixed effects specifications. Tables B5 and B6 present summary statistics for earnings by country and by occupation–sector groups, respectively. Figure B1 shows the weighted average number of HWs, defined according to absolute and relative temperature thresholds, over time. While absolute-threshold HWs display a clear upward trend, relative ones present peaks in several years. Tables B7, B8, and B9 document average HWs exposure by country, income percentile, and occupation–sector groups. The distribution of absolute-threshold HWs is heavily concentrated among southern countries, whereas relative-threshold HWs preserve meaningful variability across countries. Finally, Tables B10, B11, and B12 report the distribution of exposed versus non-exposed occupations—as defined in Table B2—by country, income percentiles, and occupation–sector groups. Overall, exposure levels vary across countries, with higher shares of workers in classified exposed occupations in Southern and Central European economies such as Italy, Spain, and the Czech Republic, and lower ones in Northern countries like Sweden and Denmark. Looking across the earnings distribution, workers in exposed sectors are present throughout, whereas the share of workers in exposed occupations declines progressively from the lower to the upper tail. Finally, the breakdown by sector and occupation group shows that outdoor exposed occupations are particularly pronounced in Construction, Agriculture, and Industry.

4 Empirical Strategy

In this section, we estimate the earning effects of HWs exploiting variation in heat wave exposure across cohorts within the same generation (defined over a 10-year window) and location. To illustrate, consider two workers from different cohorts within the same generation and location who experience an additional HW day in the same year, but at different ages and stages of their careers. By controlling for a rich set of individual and labor market characteristics, these workers are similar enough to be comparable and thus differ only in their exposure to randomly assigned HWs, allowing us to isolate the impact of the temperature shock.

Specifically, we estimate the following model:

$$E_{ily} = \beta f(T)_{l(i)y} + \gamma g(P)_{l(i)y} + \theta X_{ily} + \psi_{g(i)} + \mu_l + \lambda_y + \theta_{c(l)} \times y + \epsilon_{ily} \quad (2)$$

where i , l , and y index individuals, locations (sub-minimum NUTS level described in Section A), and years, respectively. The outcome variable E_{ily} denotes the logarithm of individual average monthly earnings in year y . The variable $f(T)_{l(i)y}$ captures temperature exposure, modeled as the number of days spent in a HW¹⁵. We also add a second-degree polynomial in average annual precipitation ($f(P)_{l(i)y}$) as control. We include year, location, and generation (10-year) fixed effects, denoted by λ_y , μ_l , and $\psi_{g(i)}$, respectively. The latter two sets of fixed effects allow to isolate the source of identifying variation used in this paper: we compare two individuals living in the same location and of the same generation, differing only for their exposure to HWs. Among the additional covariates that make this comparison more credible, we include a vector X_{ily} of individual socio-demographic characteristics and standard labor market controls in Mincerian wage regression¹⁶ and country-year specific linear trends ($\theta_{c(i)} \times y$), which account for time-varying country-level dynamics - such as macroeconomic and labor dynamics - that could confound the relationship between temperature shocks and wages. Standard errors are clustered at the sub-minimum NUTS level l because this is the level of spatial disaggregation that determines the assignment of temperature exposure to individuals.

Testing the identifying assumption. In climate econometric research (Hsiang, 2016; Hogan and Schlenker, 2024), unexpected weather shocks are treated as plausibly random at the location level (sub-minimum NUTS) by controlling—as we do—for location fixed effects λ_y . Using individual-level data, identification of the effects of HWs becomes more challenging. The assumption that HWs are as good-as-randomly assigned conditional on the covariates described above can be violated if workers' exposure to HWs is correlated

¹⁵Recall that we define a HW as a period of more than five consecutive days with maximum daily temperature above the 95th percentile of the local temperature distribution. The percentile is computed over a 30-year moving window using all daily temperatures from the preceding 30 years.

¹⁶These are: age and age squared interacted by a gender dummy, education attainments (no education or primary, lower secondary, upper secondary, tertiary), cumulative days lost due to disability (as a proxy for health, see Valenti et al. (2026)), the number of books at age 10, as a proxy for parental background (Brunello et al., 2017), two second-order polynomials in experience and job seniority, dummies for part-time and self-employment status.

with observable and unobservable characteristics that also influence earnings (Altonji et al., 2005). To support this identifying assumption, we conduct three validation tests.

First, we assess whether the probability of experiencing a heat wave is balanced across observable covariates included in Equation 2. To do so, we regress these covariates on a dummy variable that takes the value of 1 if a heat wave occurs and 0 otherwise.¹⁷ The results are presented in Table C14 in Appendix C. Our findings indicate that, when using HWs longer than 5 consecutive days, the coefficients of most covariates are not statistically significant, suggesting that exposure to HW is not systematically correlated with drivers of earnings dynamics. The only relevant exception is the 'always part-time' variable in column (1), which appears to be consistently associated with the likelihood of experiencing a heat wave and may be of concern for our results. To address this, we perform robustness checks in Section 5, where we show that restricting the sample to full-time workers does not affect the results.

Second, while the degree of selection on observables provides a useful indication of potential selection on unobservables (Altonji et al., 2005), we can explicitly assess the role of unobservable characteristics by exploiting the longitudinal dimension of our earnings and climatic data in a fixed effect model. Individual fixed effects account for unobserved, time-invariant characteristics, such as innate ability, that are difficult to observe or measure and may be correlated with both earnings and HWs exposure. While results are discussed in detail in the next section, they are consistent with those from the main specification without individual fixed effects.

Finally, we know from previous literature that the effects of HWs are heterogeneous depending on the heat-exposure of the occupation or sector of employment (Graff Zivin and Neidell, 2014; Neidell et al., 2021; Gagliardi et al., 2024). The effect of HWs on earnings estimated in our main specification can be biased if individuals sort into particular occupations based on preexisting characteristics that are correlated both with the exposure to temperature and with earnings outcomes. For instance, one potential form of sorting arises if individuals in poorer health systematically avoid occupations with higher exposure to extreme temperatures. Since health is also a key determinant of human capital

¹⁷We estimate these regressions at the individual level.

and earnings, failing to account for this may underestimate the temperature effect. Conversely, individuals with lower skills or education may be more likely to accept jobs with greater exposure, while these same characteristics are strongly correlated with earnings.

We carefully examine this issue by estimating the main model including individual-by-occupation (ISCO-1) fixed effects, which directly control for the main unobservable factors affecting the sorting of individuals to occupations (Autor and Handel, 2013).¹⁸ We argue that our main identification strategy, which relies on the random assignments of HWs conditional on observables, is credible if the addition of individual-by-occupation fixed effect does not change the effect of HW on earnings.

Interpretation of the coefficients. Even if HWs are good as randomly assigned, the interpretation of the effect of HWs on earnings is not straightforward. Note that, by adding location fixed effects, we account for the permanent component of climate. Thus, our identification strategy estimates only the impact of weather shocks on earnings, but 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). While we cannot fully corroborate this assumption, we argue that it is more plausible in contexts, such as HW shocks, with limited effective adaptation or greater adaptation challenges than isolated extreme temperature days.

The second issue concerns the recurrence of heat waves. Some locations may experience serially correlated heat wave events that, depending on the effectiveness of adaptation, could either amplify or mitigate their effects on earnings. To assess this, we test for serial correlation in HWs occurrence by estimating whether the probability of experiencing a HW at time t depends on having experienced one at time $t - 1$. Table C15 in Appendix C presents estimates using two alternative heat wave definitions. Columns (1–2) correspond to our baseline measure of prolonged heat waves (exceeding five consecutive days), while columns (3–4) adopt a shorter-duration definition (fewer than two

¹⁸When we include individual-by-occupation fixed effects, we are effectively comparing individuals with the same unobserved characteristics (e.g. skills), within the same occupational position, who differ only in their exposure to HWs.

consecutive days). For prolonged heat waves, we find a weak negative relationship, indicating that these events are not positively serially correlated. This suggests that our contemporaneous estimates are unlikely to be confounded by adaptation or cumulative effects, supporting the interpretation of heat waves as quasi-random shocks. In contrast, the shorter HWs reveals significant serial dependence, particularly in absence of individual fixed effects. Overall, these findings support our preferred definition of heat waves as capturing unexpected and quasi-random temperature shocks.

A final issue is that some covariates in Equation 2, particularly experience, seniority and days lost due to disability, may also be affected by HWs. Including them ensures comparability across cohorts within a generation, but also affects the size of the HW effects conjuring a "bad controls" problem (Angrist and Pischke, 2009). In column (1) of Table 1, we test our main model excluding these potentially problematic controls to assess whether this changes the size of the estimated coefficients.

Heterogeneous effects. A key contribution of this paper is to investigate the heterogeneous effects of heat waves (HWs) on earnings, documenting previously unexplored dimensions of the distributional impacts of weather shocks. Specifically, we examine how HWs impact earnings along the earnings distribution. To this end, we employ the well-known framework proposed by Firpo et al. (2009), which allows estimating the impact of changes in regressors on a specific quantile, q^{th} , of the unconditional distribution of the dependent variable.¹⁹ In our analysis, this approach enables us to detect the impact of HWs on workers at different percentiles of the earnings distribution, independent of the underlying mechanisms driving such effects.

The next step is to unpack the profile of those workers that are more affected by HWs. This complements the unconditional quantile regression analysis by looking at whether more vulnerable groups are also more impacted by HWs. In doing so, we extend our baseline model by interacting temperature shocks with a dummy or categorical vari-

¹⁹The method relies on the Recentered Influence Function (RIF), a transformation of the outcome variable that captures deviations around the quantile of interest. By regressing the RIF on explanatory variables, we can estimate the effect of covariates on the unconditional distributional statistic of interest, in this case, the unconditional earnings percentiles. Unlike standard quantile regression (Koenker and Bassett, 1978), a key advantage of this method is that the estimated effects pertain to the distribution of earnings itself, rather than to the distribution of residuals from a reweighted earnings regression. Consequently, the effect at the n^{th} percentile can be interpreted as the effect for workers at that specific earnings level.

able that captures an workplace characteristic (heat-exposed occupations and sectors), a socio-demographic attribute (parental background, gender, age, health status), or a labor market characteristics (level and type of collective bargaining, minimum wage, union density). Besides shedding light on the distributional impacts of HWs, these analyses also sheds light on potential mechanisms through which temperature affects individual earnings, particularly those pertaining the heterogeneous effects across occupations and sectors.

5 The Effect of Heat Waves on Earnings

This section presents the results on the impact of heat waves on earnings. Column (2) of Table 1, our favorite estimate,²⁰ indicates that each additional day spent in a heat wave lasting more than five consecutive days reduces the average monthly earnings by approximately 0.31%.

These results are robust to alternative model specifications. In column (1), we use a more parsimonious set of individual-level controls to mitigate concerns about bad controls.²¹ Although the point estimates are not directly comparable across columns due to differences in sample size, the coefficient on earnings losses remains virtually unchanged relative to column (2). In column (3), we estimate the specification of column 2 for the reduced sample for which we can estimate also the fixed effect model. Here we observe a negligible increase of the HW effect (from -0.31% to -0.32%). When individual fixed effects are added in column (4), the results remain robust, although the magnitude of the coefficient declines slightly. This finding is consistent with the balancing tests on the probability of experiencing a heat wave reported in Table C14 in Appendix C, where balance on observables provided reassurance regarding selection on unobservables as well (Altonji et al., 2005). Finally, the effect of heat waves on earnings remains robust to the inclusion of individual-by-occupation fixed effects in column (5), which account for unobserved sorting of individuals into specific occupations.

²⁰We label this specification as preferred because it includes the full set of individual and labor market controls while excluding the more demanding individual and individual-by-sorting fixed effects, which substantially reduce the sample size.

²¹Health, experience and seniority may be influenced by HW as well.

The stability of the coefficients across specifications suggests that HW exposure is plausibly as-good-as-random conditional on controls, and that omitting these additional fixed effects does not introduce substantial bias. While accounting for individual fixed effects and occupational sorting are in principle important to lend support to our identifying assumption, our comprehensive set of controls already rule out severe selection-biases. In light of these results, we confidently use the specification in column (2), and its correspondingly larger sample, to analyze heterogeneity across groups and along the earnings distribution.

Table 1: Effect of Heat Waves on Earnings

	(1)	(2)	(3)	(4)	(5)
HW days ($T_{MAX} > 95\text{th perc}$)	-0.00291*** (0.0009)	-0.00310*** (0.0008)	-0.00320*** (0.0010)	-0.00236* (0.0013)	-0.00248* (0.0014)
Precipitation control	✓	✓	✓	✓	✓
Location, Generation, Year FE	✓	✓	✓	✓	✓
Main Covariates	✓	✓	✓	✓	✓
Extended Covariates		✓	✓	✓	✓
Country-Year Linear Trends	✓	✓	✓	✓	✓
Individual FE				✓	✓
Individual $\times$ Occupation (ISCO1) FE					✓
Individuals	32,782	32,337	15,580	15,580	15,580
Observations	75,258	73,577	44,271	44,271	44,271
Adjusted R^2	0.51744	0.51754	0.52100	0.66158	0.67177

Notes. The dependent variable is the log transformation of earnings expressed in dollars (base year 2010). HW days count the number of days spent in a heat wave ($T_{MAX} > 95\text{th perc}$) longer than 5 consecutive days. Main covariates: age and age squared by gender, the level of education, the number of books at age 10, part-time and self-employment status. Extended covariates also include the cumulative days lost due to disability (health loss), experience and experience squared, seniority within the job and seniority squared. Clustered standard errors at the location level (sub-minimum NUTS level, the source of temperature variation) are reported in parentheses * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

In Section 4, we show that HWs are not serially correlated. Yet, the effect of repeated HWs can be reduced, i.e. through adaptation responses, or amplified, i.e. through health consequences or skill losses due to inactivity. We further explore this empirical issue by augmenting our favourite specification with the lagged HW indicators at time $t - 1$ and $t - 2$. Table D20 shows that, as indicated by the cumulative marginal effects (row 4), the impact of heat exposure over a three-year windows remains negative and statistically significant and is larger in magnitude (-0.521%) than the contemporaneous effect alone (-0.310%). While the contemporaneous effect (at time t) likely captures the direct impact of temperature shocks on labor productivity and labor supply, the lagged effect may operate

through multiple channels. At the micro level, it may reflect human capital losses—in health, education, skills, or experience—accumulated in response to the shock. At a more aggregate level, it may instead capture indirect effects and spillovers, such as persistent firm-, sector-, or region-level output disruptions, as well as the gradual reallocation of labor across sectors (Colmer, 2021).²²

Quantifying the Impact. Based on our estimated marginal effect, each additional heat wave day reduces monthly earnings by 0.310%. Multiplying the estimated effect by the average monthly earnings, the number of months (12), and the expected number of HW days occurring on workdays,²³ we obtain an average annual earning loss of approximately \$159.63 per person (Table 2), reflecting workers’ actual average exposure to HWs during a year.²⁴ By contrast, quantifying the marginal effect of a single additional heat wave day corresponds to an earning loss of $-0.00310 \times \$2,070.14 \times 12 \approx -\77.01 .²⁵

We benchmark the marginal earning loss from an additional heat wave day (\$77.01) against the potential loss associated with a full labor supply disruption—i.e., complete absenteeism from work (Somanathan et al., 2021)—which corresponds to the full daily wage of \$94.10.²⁶ This full-absenteeism benchmark reflects a scenario in which the earning loss arises entirely from a reduction in labor supply. While our estimated marginal loss is smaller than this hypothetical full-day loss, the effect remains economically meaningful,

²²Our results align with previous research that has documented that weather shocks can have delayed impacts on firm output in China (Chen and Yang, 2019) and global economic production (Burke et al., 2015). Similar lagged effects have not been observed for annual income per capita across U.S. counties, where part of the impact appears to be recovered in the following year (Deryugina and Hsiang, 2014).

²³The average individual in our sample experiences approximately 2.91 HW days per year (Table B7). Assuming a standard 260-day work year (71% of the calendar year, uniformly distributed) yields an upper-bound estimate of 2.07 working-day HW days.

²⁴Average Annual Earning Loss = $-0.00310 \times 2,070.14 \times 12 \times 2.07 \approx -\159.63

²⁵Direct comparison with prior estimates is not straightforward, given differences in data granularity, exposure definitions, and institutional context. Deryugina and Hsiang (2014) estimate an income loss of approximately \$20 per person for each additional weekday above 30°C (86°F) across U.S. counties; unlike their focus on isolated hot days, we examine prolonged exposure. In addition, Deryugina and Hsiang’s estimate applies to the full population, whereas ours is restricted to workers. Scaling our worker-level estimate by the employment-to-population ratio to make it comparable at the population level—the EU average ratio over 1983–2023 was approximately 50.8% (World Bank, World Development Indicators), although it was likely lower during our study period due to historically low female labor force participation—yields a population-level loss of roughly \$39.12 per person. The remaining gap is likely explained by other contextual and institutional differences, as shown in Section 7.

²⁶Given an average monthly wage of \$2,070.14 and assuming 22 working days per month, the implied daily wage is approximately \$94.10.

corresponding to approximately 82% of a full day’s earnings. Finally, HWs are expected to become longer, more frequent, and more intense as a consequence of climate change (IPCC, 2023b; Quilcaille et al., 2025). Under the moderate-emissions scenario (RCP 4.5), projections for the European Union suggest that the average annual number of heat wave days²⁷ will rise to approximately 5.8 over the period 2071–2085 (Hooyberghs et al., 2019). Applying our estimates²⁸ and assuming the same 71% workday adjustment described above, no further adaptation, and our sample average income, this increase would translate into an average annual earning loss of approximately \$263.9 per worker (Table 2).

Table 2: Magnitude of Earnings Losses from Heat Waves

Avg. annual income loss	Benchmark: full-day absence	Additional HW day	HW day loss (population-scaled)	Avg. annual projected loss RCP4.5 (2071–2085) ^b
\$-111.6 ^a to -159.6	\$-94.1	\$-77.0	\$-39.1 per person	\$184.7 to -263.9

Notes. All figures are expressed in dollars (base year 2010).

^a As a lower bound, we assume HW days and annual leave (20 days) both concentrate in June–August (92 days), leaving only 45.75 working days (49.7%) in that window; applying this share to all 2.91 HW days gives $2.91 \times 45.75/92 \approx 1.45$.

^b Applies the same 1.45–2.07 working-day-adjusted range to the projected 5.8 average annual HW days under RCP4.5 for 2071–2085 (Hooyberghs et al., 2019), using the coefficient from the short (three-day, 95th percentile) HW definition reported in Table D23.

Robustness Checks. The results remain robust to a wide range of alternative specifications (Appendix D). First, Table D21 reports results estimated without country-year specific linear trends, allowing us to assess robustness in the absence of controls for macroeconomic dynamics that may be correlated with climatic events (Bilal and Känzig, 2024). In contrast, Table D22 includes more flexible, spatially disaggregated NUTS1-year trends to account for local evolution in climate, labor market conditions, and other unobserved factors that may confound their relationship.

Subsample analyses by historical period (Table D24) show that the effect of heat waves on earnings is statistically significant across all periods. The estimated impact is slightly larger in the earliest period, indicating that partial adaptation may have had a modest mitigating effect. Leave-one-country-out estimates (Table D25) confirm that our main

²⁷Heat waves are here defined as periods of at least three consecutive days exceeding the 99th percentile of the climatological distribution of daily maxima (Hooyberghs et al., 2019).

²⁸For comparability, we use the estimates corresponding to the shorter (three-day) HW definition based on the 95th percentile, presented in the robustness check in Table D23 of Appendix D, where each additional HW day is associated with a 0.258% reduction in earnings.

findings are not driven by any single country.

As discussed in Section 4, observable characteristics are balanced between exposed and unexposed individuals (Table C14), supporting the identifying assumption that HW exposure is as good as random. This balance also suggests limited selection on unobservables (Altonji et al., 2005). The only significant difference concerns part-time status. Re-estimating the main models on full-time workers only (Table D26) leaves results unchanged. In addition, our results are robust when restricting the sample to location (Table D16), sector (Table D17), or occupation (Table D18) stayers only.

To account for the possibility that individuals may sort into occupations that are both more prevalent in hotter regions and more vulnerable to heat exposure (e.g., outdoor or physically intensive jobs), we test our initial baseline specification (Table 1, columns 1–4) by including location-by-occupation fixed effects. These absorb any time-invariant heterogeneity within broad occupation groups specific to the local labor market, controlling for the potential prevalence of certain occupations and for earnings differences in areas systematically more exposed to heat. Results, presented in Table D27, remain very similar to the baseline specification, indicating that our estimates are not driven by pre-existing spatial and occupational characteristics that jointly determine heat exposure and earnings potential.

We also examine alternative HW definitions, by shortening the minimum duration requirement to three consecutive days above the threshold (Table D23), and using binned HW exposure (0, 1–2, 3–5, and >5 consecutive days) (Table D19). Estimates are robust to both alternatives. As Figure D3 shows that the point estimates for the 1–2, 3–5, and >5 bins are not statistically distinguishable from one another.

Finally, we also define heat exposure using absolute temperature thresholds HWs (Tables D28 and D29), and temperature bins (Table D30, D31, and Figure D4). The motivation for adopting relative thresholds, as well as the challenges and limitations associated with absolute measures, were introduced in Section 3 and are further discussed, together with the corresponding results, in Appendix D.

6 Distributional and Heterogeneous Effects of Heat Waves

Moving beyond average effects, this section unpacks heterogeneity along several dimensions - sector and occupation, position in the earnings distribution, and socio-demographic characteristics - to uncover where heat-wave-induced welfare losses are most concentrated and whom they leave most affected. Understanding these distributional implications is also relevant for adaptation policy. To the extent that climate change exacerbates inequality, it provides a welfare-based justification for public adaptation interventions, even in the absence of market failures (Carleton et al., 2024).

6.1 Heterogeneity across Occupations and Sectors

Figure 2 summarizes the results (Table E32) on the heterogeneous effects of heat waves across individuals employed in different sectors and occupations. Each panel reports marginal effects from estimating Equation 2, where HW are interacted with (i) an exposed-sector dummy (*Panel A*); (ii) sector categorical variables (*Panel B*); (iii) an exposed-occupation dummy (*Panel C*); and (iv) occupation categorical variables (*Panel D*).

Panel A shows that both exposed and not exposed sectors experience earnings losses but that the difference among the two groups is not statistically significant. To assess whether meaningful differences arise at a more disaggregated level, *Panel B* further breaks down the analysis. Losses are particularly pronounced in Agriculture & Fishing (0.98% reduction, three times larger of the average effect), with significant, but smaller impacts also in Wholesale & Retail Trade, Industry (covering Manufacturing, Mining & Quarrying, and Utility) and in Public & Other Services. Notably, even some of these sectors, characterized by high share of work performed indoor, are not immune to heat-related declines in earnings, consistent with the fact that most workplaces in Europe lacked climate control during our sample period.²⁹ The strong effect observed in Agriculture & Fishing may be attributed not only to the higher prevalence of outdoor work, but also to the weaker institutional protection in this sector, including a higher share of informal or piece-rate employment arrangements and lower collective bargaining coverage (see

²⁹The share of households equipped with air conditioning (AC) in Europe was 15% in 2015, compared to 91% in Japan, 89% in the US, and 53% in China (International Energy Agency, 2026).

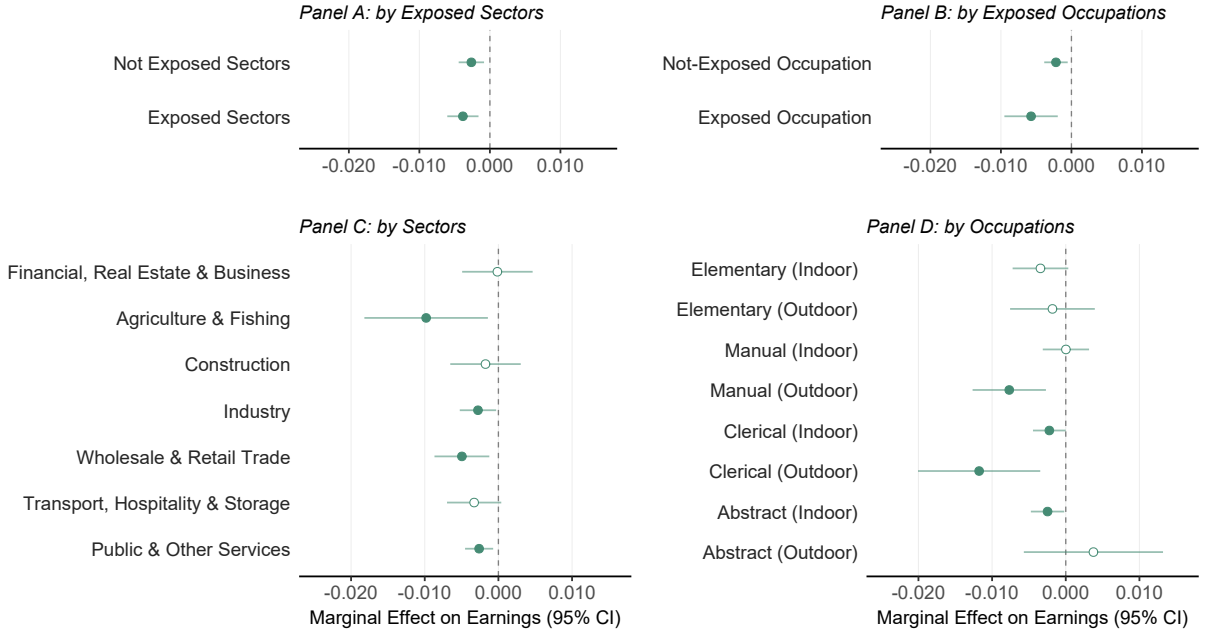


Figure 2: Marginal Effect of Heat Waves by Occupation and Sector

The figure displays the marginal effects and corresponding 95% CIs from the regressions estimated in Equation 2, where heat waves are interacted with (i) a dummy for heat-exposed sectors (Column 1 of Table E32), (ii) a categorical variable for sectors (Column 2), (iii) a dummy for heat-exposed occupations (Column 3), (iv) a categorical variable classifying occupation groups (Column 4).

Section 7 on the protective role of labor market institutions). By contrast, Financial, Real Estate & Business Services appear largely unaffected. For construction, surprisingly, we do not identify a clear impact, as confidence intervals (CIs) remain wide. While previous literature (Graff Zivin and Neidell, 2014; Somanathan et al., 2021) shows that heat exposure reduces labor supply in this sector, these effects are typically measured as very short-run (daily) responses. Our evidence suggests that such short-run productivity or labor supply losses, although likely present in this exposed sector, may not translate into losses in overall annual earnings, possibly because of the high seasonality that characterizes this sector, and the flexibility firms have in adjusting working hours in response to weather conditions.

In addition to sectoral differences, we uncover further heterogeneity across occupations. As motivated in Section 2, match-specific productivity can drive gaps in losses across workers in different occupations, as the degree of vulnerability depends on the match between the nature of the tasks performed and individual worker characteristics.

The corresponding results, presented in *Panel C* of Figure 2, show a significant more pronounced impact for workers in exposed occupations, equal to an additional decline of -0.353% with respect to the others. This evidence hints to predominance of task characteristics in shaping the effect of heat on earnings. To further disentangle losses by the type of tasks performed—while still distinguishing between outdoor and indoor activities—we also explore heterogeneity across four broad occupational categories: Elementary, Manual, Clerical, and Abstract (*Panel D*). Outdoor Manual (-0.767%) and Clerical (-1.176%) workers experience the most pronounced earning reductions. While the former are exposed to sustained physical tasks in environments without temperature control, they may partly benefit from the scheduling adaptability discussed for Construction. Clerical workers—including mail carriers, transport clerks, and salespersons in our classification—are more likely to be paid through piece-rate or commission-based arrangements, more directly tying earnings to heat-related declines in productivity. Losses for Abstract indoor workers³⁰ are consistent with the average effect and aligns with previous evidence showing that heat also affects cognitive performance (Zivin and Shrader, 2016; Zivin et al., 2020; Krebs, 2024). Elementary Occupations do not show statistically significant losses. Wage stickiness at the lower end of the income distribution may explain why earnings fail to adjust even when productivity falls. At the same time, these jobs are more likely to benefit from compensating differentials (see Section 2 for the mechanisms), given their often uncomfortable working conditions, plausibly rendering earnings structurally less responsive to heat shocks. Notably, the most-exposed categories, such as Manual and Clerical workers, were already vulnerable as more negatively exposed to routine-replacing technological change (Autor and Handel, 2013) and automation (Acemoglu and Restrepo, 2019). In addition, Manual workers are also more negatively impacted by import competition (Autor et al., 2013) and climate policy (Marin and Vona, 2019).

We follow the same logic outlined in Section 5 to compute the average annual earnings loss for each category.³¹ Given the in-sample average exposure to HW by group, work-

³⁰The absence of a statistically significant effect for Abstract outdoor workers is likely driven by the limited number of observations in this group, which results in wide confidence intervals.

³¹All descriptive statistics used in these calculations are obtained from the relevant subsample. See Table H42 in Appendix H for key statistics by subgroup and for the results of the quantification.

ers in outdoor-exposed occupations experience an average annual income reduction of approximately \$272.57, corresponding to a 1.23% decline in yearly earnings. Workers employed in Exposed Sectors face an average loss of about \$181.30 (-0.82%). The burden is even larger for certain subgroups: Manual and Clerical outdoor workers incur an average annual loss of respectively \$375.58 and \$492.19 while, among sectors, those employed in Agriculture & Fishing suffer the highest estimated loss, at around \$414.89 per year.

Sorting into Exposed Occupations and Sectors. To complement the analysis of distributional effects across workers, it is useful to better understand who sorts into the most exposed occupations, those suffering the largest losses. Results on sorting, shown in Table E33, indicate that individuals who are male, younger, less educated, and from lower socio-economic backgrounds are significantly more likely to sort into heat-exposed jobs. Since occupational and sectoral heat exposure is correlated with key drivers of earnings dynamics, and the largest income losses are concentrated in these occupations, exposure to heatwaves reinforce existing inequalities, acting as a channel through which socio-economic disparities are further exacerbated.

6.2 Effects Along the Earning Distribution

Building on this evidence of unequal losses across workers in different occupations and sectors, we next investigate whether HWs also generate distributional impacts, differentially affecting workers at different points of the earnings distribution. Figure 3 (and Table F35) reports the results from the unconditional quantile regression (Firpo et al., 2009), revealing the most pronounced losses at the bottom of the distribution, notably for the 5th percentile (-1.31%). Yet the impact is also statistically significant at the upper tail, revealing distributional consequences that extend beyond low-income workers. These findings contribute to the growing evidence that climate change disproportionately harms low-income households (Hallegatte and Rozenberg, 2017), and document, at the individual level, that heat exposure widens within-country income inequality (Behrer et al., 2021; Gilli et al., 2024). The significant effect at the upper tail further suggests that extreme heat also threatens high-income earners, who are disproportionately engaged in cognitively intensive tasks, consistent with a well-established literature documenting

that thermal stress impairs cognitive performance (Park et al., 2020; Graff Zivin et al., 2018). Moreover, the upper-tail effect may partly reflect the greater share of variable and performance-linked compensation among high-income workers (Lemieux et al., 2009) — including bonuses, profit sharing, and self-employment income — all of which are potentially affected by heat-induced losses in firm productivity and output.³²

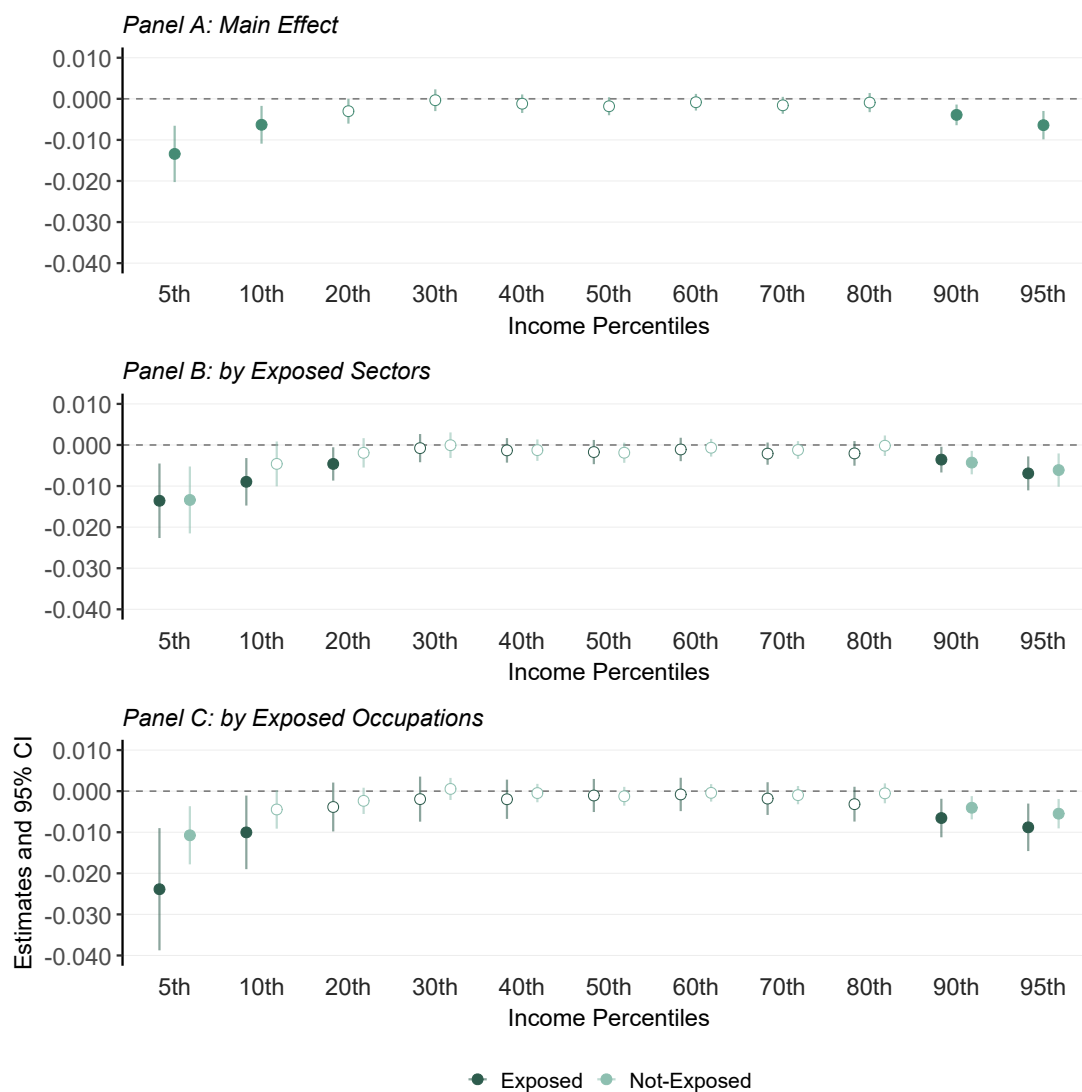


Figure 3: Temperature Impact on Earnings - Unconditional Quantile Regression

Estimates and 95% confidence intervals from 11 separate regressions, each using as the dependent variable the RIF transformation corresponding to a specific decile of the dependent variable (the log of earnings in 2010 U.S. dollars).

³²In the European context, however, this effect may be mediated by the presence of collective bargaining (Barth et al., 2012), as discussed in Section 7.

We also re-estimate the quantile regressions interacting HWs with dummies for outdoor-exposed sectors and occupations (Figure 3, Panels B–C; Tables F36 and F37), building on the heterogeneity documented across workers. Findings show losses amplified among poor workers employed in heat-exposed occupations, while the pattern along the distribution reveals no significant differences across exposed sectors, consistent with match-specific productivity driving heat-related earnings losses.

Quantifying the impact (Table H42), across workers in exposed occupations, the average annual income loss amounts to \$68.71 at the 5th percentile, compared to \$1400.91 at the 95th percentile. While the absolute loss is larger for the latter, the relative burden is significantly greater for low-income workers—4.47% versus 1.55% of annual income—further supporting the contribution of HWs exposure in exacerbating existing labor market inequalities.

6.3 Socio-Demographics Vulnerabilities

Beyond the heterogeneity documented across sectors, occupations, and the earnings distribution, losses also vary markedly across socio-demographic groups (Figure 4; Table E34). Our results document that very young workers below 25 years old are the least affected, showing no statistically significant effects. No meaningful differences emerge by gender or health status, though confidence intervals are wide for individuals reporting poor health. Educational attainment reveals limited heterogeneity, but importantly the adverse effect is absent among workers with tertiary qualifications, consistent with their concentration in less physically demanding and better-protected jobs.

Finally, workers from more advantaged social backgrounds — proxied by the number of books at home — show no significant earnings response to heat wave exposure, whereas those from less advantaged backgrounds bear significant losses. Quantification (Table H42) highlights that the latter on average experience an annual loss of \$235.64, whereas those from the highest parental background (two bookcases) exhibit a much smaller, statistically insignificant gain of \$1.12. This corroborates that HWs reinforce pre-existing socio-economic inequalities across generations, disproportionately harming workers from less advantaged backgrounds.

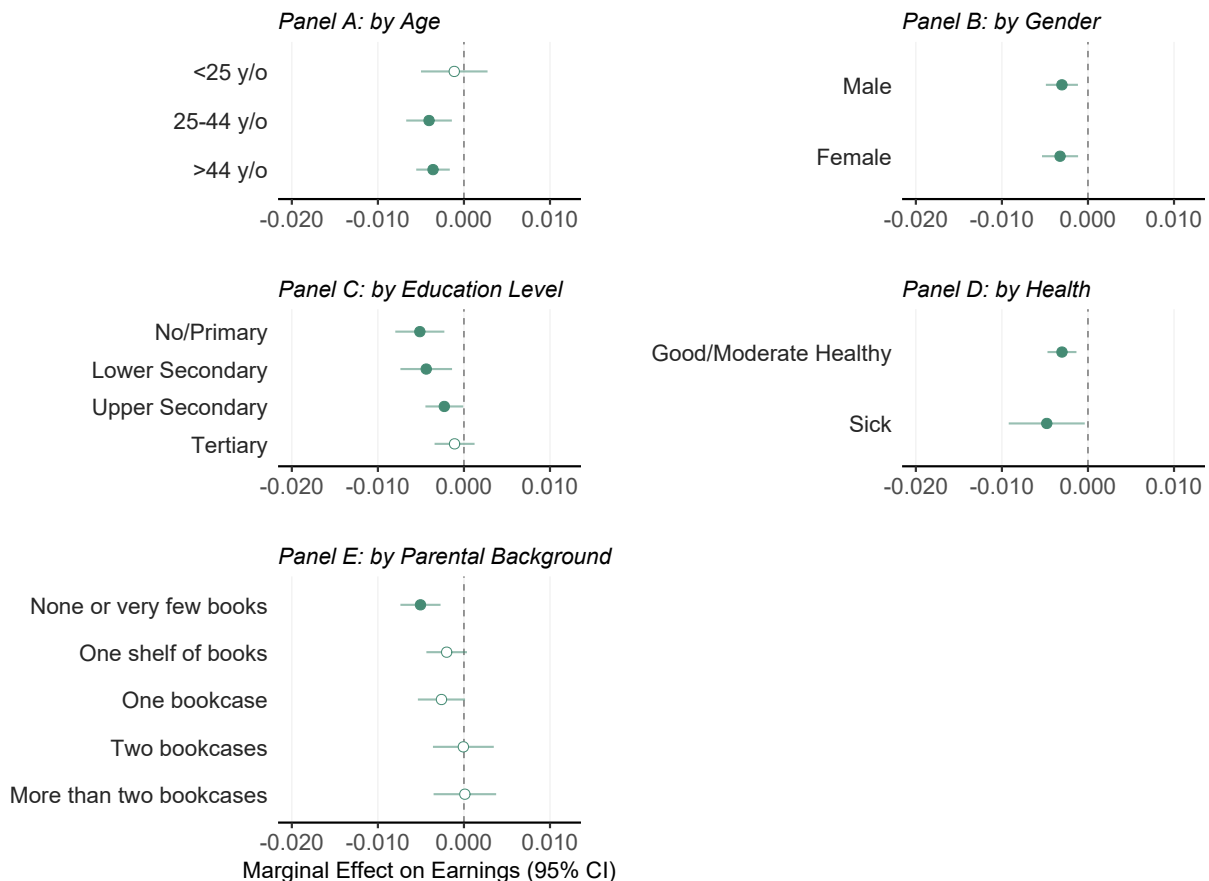


Figure 4: Marginal Effect of Heat Waves by Socio-demographic Dimensions

The figure reports marginal effects and 95% confidence intervals from regressions based on Equation 2, where heat waves are interacted with: (i) a gender indicator (column 1); (ii) a categorical variable for age groups (column 2); (iii) an indicator for deteriorated health, defined as days lost due to disability above the 95th percentile (column 3); (iv) a categorical variable for education level (column 4); and (v) a categorical variable capturing the number of books at age 10, used as a proxy for parental background (column 5).

7 Mediating Role of Labor Market Institutions

Our main results document a negative sign of the HW effect on earnings, reflecting substantial earnings losses across workers, while the heterogeneity evidence indirectly reveals the role of match-specific productivity in explaining differential impacts. Together, these results suggest that the productivity channel, rather than the disutility channel, primarily drives the hourly wage response to HW exposure (Equation 1). Following our Conceptual Framework (Section 2), we now complement these findings, turning to the results on labor market institutions, which provide suggestive evidence on the relative

contribution of hours worked (h) and hourly wage (w) adjustments to the reduction in total earnings.

Table 3: Effect of HWs on Earning: The Role of Collective Bargaining Institutions

	(1)	(2)	(3)	(4)	(5)	(6)
HW days ($T_{MAX} > 95$ th perc)	-0.0079887*** (0.00195)	-0.0095825** (0.00407)	-0.0021622** (0.00094)	-0.0040002** (0.00156)	-0.0042419*** (0.00102)	-0.0040206*** (0.00091)
Some coord. $\times$ HW	0.0019237 (0.00290)					
Procedural guidelines $\times$ HW	0.0044544* (0.00229)					
Non-binding norms $\times$ HW	0.0057509*** (0.00211)					
Binding norms $\times$ HW	0.011245*** (0.00247)					
Sector-company $\times$ HW		0.0054345 (0.00570)				
Sector $\times$ HW		0.0048746 (0.00406)				
Central-sector $\times$ HW		0.0081550* (0.00429)				
Central $\times$ HW		0.012355*** (0.00439)				
Minimum Wage $\times$ HW			0.0025411* (0.00140)			
UD $\times$ HW				0.000015990 (0.00003)		
UD $> p66 \times$ HW					0.0027842* (0.00149)	
Non-wage opening clauses $\times$ HW						0.0072609*** (0.00178)
Wage opening clauses $\times$ HW						0.0062570*** (0.00213)
Precipitation control	Yes	Yes	Yes	Yes	Yes	Yes
Geo id, Generation, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Main Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Extended Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Bargaining variable	Coordination	Level	Min. Wage	UD	UD $> p66$	OCG
Individuals	31651	31651	27818	28874	28874	30279
Observations	70991	70991	48000	67098	67098	68931
Adjusted R ²	0.53601	0.53548	0.57627	0.53351	0.53354	0.52442

Notes. The dependent variable is the log transformation of earnings expressed in dollars (base year 2010). HW days count the number of days spent in a heat wave ($T_{MAX} > 95$ th perc) longer than 5 consecutive days. Each column interacts *HW days* with a distinct measure of labor market institutions. Columns (1)–(2) use ordered categorical measures of wage-setting coordination (5 categories, from no or fragmented to fully centralized coordination) and the predominant level of bargaining (5 categories, from company to central), respectively, with the lowest category as baseline. Column (3) interacts with a dummy for minimum wage. Columns (4)–(5) interact with union density — the share of employees holding trade union membership — entered respectively as a continuous variable and as an indicator for above-66th-percentile density. Column (6) captures opening clauses (OCG) in sectoral agreements (0=none; 1=non-wage renegotiation allowed; 2=wage renegotiation allowed; baseline: OCG=0). Main covariates: age and age squared by gender, the level of education, the number of books at age 10, part-time and self-employment status. Extended covariates also include the cumulative days lost due to disability (health loss), experience and experience squared, seniority within the job and seniority squared. Clustered standard errors at the location level (sub-minimum NUTS level, the source of temperature variation) are reported in parentheses * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table 3 shows results when we interact HWs with several measures of labor market institutions (discussed in Sections 2 and 3). The negative effect of HWs on earnings is progressively attenuated in systems with higher levels of coordination in wage setting.

Some protection starts with the presence of procedural negotiation guidelines and losses are fully offset when binding norms are in place (Column 1) thanks to centralized bargaining or unilateral government imposition. We also find that the predominant level at which bargaining takes place matters (Column 2): when most of the negotiations within a country occur at a more aggregated level - such as central level - the adverse effect vanishes. Another key mediating mechanism is the presence of minimum wage protections (Column 3), which, by providing a wage floor, are effective in limiting downward adjustments in response to heat-wave-driven productivity losses. Union density does not mediate the earnings response to HW exposure (Column 4). However, when we consider a dummy for union density above the 66th percentile, we find a significant protective effect (Column 5), suggesting that it is only at sufficiently high levels of unionization that collective bargaining power effectively pushes up wages and prevents employers from fully passing productivity shocks onto workers, translating into meaningful insulation from heat-related earnings losses. Finally, findings on OCG clauses (Column 6) show that they are effective in attenuating the adverse effect of HWs on individual earnings. Notably, this mainly holds for clauses operating on non-wage issues (working hours, working time schedules, etc.), but also when renegotiation of contractual wages is allowed, hinting that contractual flexibility, when embedded within a collective bargaining framework, can help firms absorb heat-related shocks in ways that also benefit workers.

These findings offer four sets of insights. First, they highlight the importance of examining effects on earnings, as these do not mirror the direct impact on productivity in non-competitive market settings. Second, they show that labor market institutions act as an effective buffer against climate-related earnings losses, protecting workers by mitigating the pass-through of productivity shocks onto earnings. Third, the near-complete offsetting of the HW effect on earnings under collective wage bargaining institutions suggests that the effect on total annual earnings is primarily driven by a reduction in hourly wages rather than a substantial reduction in hours worked. This evidence remains suggestive, however, as we cannot directly observe changes in hours worked. Finally, the results on OCG clauses suggest that contractual flexibility, when embedded within a collective bargaining framework, can help firms absorb heat-related shocks in ways that also

benefit workers.

Results are largely robust to two alternative sample reductions. First, we restrict the sample to full-time workers (Table G38), who represent the only covariate found to be unbalanced between exposed and unexposed individuals in our covariate balance test (Table C14). Second, we exclude self-employed workers, for whom labour market institutions are less likely to directly determine earnings (Table G39).

To complement the analysis, we examine whether the protective effect of institutions differs across workers in different occupations and sectors by testing a triple interaction between HWs, the institutional setting, and each category. Our findings (see Tables G40 and G41) suggest that the only labor market dimension discriminating the losses across sectors is the minimum wage, which fails to protect workers in exposed sectors, likely due to the high incidence of informal employment in these sectors. Across occupations, by contrast, we find that OCG clauses are significantly more beneficial for workers in heat-exposed occupations. This result is consistent with the nature of the tasks performed by these workers, which are predominantly outdoor, and with the hypothesis that the greater flexibility granted by opening clauses — for instance, through adjustments to working time schedules — can meaningfully mitigate the productivity losses induced by HWs. Finally, we test a triple interaction between income quantiles and minimum wage protection. Building on our findings on larger losses at the bottom of the income distribution, and considering that minimum wage is specifically designed to protect low-income workers, we examine whether its presence is differentially effective in mitigating heat-related earnings losses across the distribution. The results in Figure G5 confirm this hypothesis. Minimum wage protections are effective precisely where workers suffer the largest losses, largely offsetting the negative impact on earnings at the bottom of the distribution.

8 Discussion and Conclusions

While prior literature links heat to lower labor productivity and reduced labor supply, its pass-through to earnings is not mechanical in imperfectly competitive labor markets, such as Europe's, where collective wage bargaining is widespread. This paper provides the first broad evidence on how extreme heat affects earnings, using individual-level panel

data covering 14 European countries over six decades. Our findings reveal that each additional HW day lowers average monthly earnings by approximately 0.31% (an average annual loss of roughly \$160 per worker). These estimates capture only the effect on workers who remain employed, and thus represent a lower bound, abstracting from earnings losses due to heat-induced job displacement.

Four main findings emerge. First, although we cannot fully disentangle whether the impact on total earnings is driven by changes in hourly wage or hours worked, our results on the role of labor market institutions provide suggestive evidence that the hourly wage channel is predominant. Second, the negative sign of the effect, together with its heterogeneity across occupations, suggests that the wage response is driven primarily by losses in match-specific productivity rather than by a compensating differential for the increased disutility of work. Third, earnings losses are deeply unequal. Workers at the bottom of the earnings distribution, those with lower educational attainment, and individuals from less advantaged family backgrounds bear a disproportionate share of the burden, exacerbating existing inequalities. Finally, losses are substantially attenuated where collective bargaining is more centralized, where binding norms and minimum wage are in place, and where union density is higher, uncovering the potential of labor market institutions to limit the pass-through of productivity losses from firms to workers.

These findings carry direct implications for the debate on climate damages and policy. While the unequal incidence of heat-induced earnings losses may justify targeted public intervention (Carleton et al., [2024](#)), our results show that labor market institutions can themselves buffer the welfare costs of climate shocks.

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Appendices

A Complementary Data Information

Earnings. In SHARE, earnings are classified based on the timing within the job episode (e.g., first, last and current wage or income and the source of income (self-employment vs. employment). The survey provides 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. In our analysis, we leverage all available earnings information, accounting for the source of earnings by including a dummy variable for self-employment and controlling for both labor market experience and within-job seniority (see Section 4).

All earnings information in SHARE is reported as the average monthly earnings in a specific year. Values are expressed in nominal currencies, typically 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”). The data cleaning proceeds in several steps (Table A1) and builds on the approach proposed by Trevisan et al. (2011). We follow the same core steps, adjusting for inflation using CPI series and excluding implausible outliers, but we do not apply PPP adjustments, as country fixed effects in our empirical models absorb cross-country differences in purchasing power. All monetary amounts are expressed in 2010 U.S. dollars using the CPI (2010 = 100) from the World Bank. Periods affected by major political or monetary instability—such as East Germany, Poland, and Greece before 1991—display numerous implausible wage outliers, likely reflecting distortions associated with economic transitions, chronic inflation, or inconsistent reporting; these early observations are excluded. Finally, we trim the lower 0.5th and upper 99th percentiles of the wage distribution within each country to remove residual extreme values. The trimming threshold is asymmetric, reflecting the presence of disproportionately many implausibly high wage observations that would otherwise bias upward the mean and variance of earnings, so as to eliminate values that are implausible or historically inconsistent. Table A1 reports the

evolution of the sample size and distribution across successive cleaning steps.

Table A1: Earnings Data Cleaning: Sample Size and Distribution

Variable	N	Mean	SD	p5	p25	p50	p75	p95
Step 0	196,463	1,679,483	3.95e+07	69.0	500.0	1,500	6,000	80,000
Step 1	110,827	1,913,281	4.19e+07	200.0	1,000	2,900	14,000	150,000
Step 2	109,349	1,927,449	4.21e+07	200.0	1,000	3,000	14,000	150,000
Step 3	97,826	1,195,408	3.31e+07	200.0	1,050	3,000	15,000	150,000
Step 4	87,944	252,387	1.28e+07	20.03	193.46	715.71	1,803.83	4,172.46
Step 5	83,537	1.24e+07	1.42e+09	199.55	791.96	1,628.60	2,854.42	7,310.72
Step 6	81,526	431,858	1.93e+07	201.10	788.08	1,603.10	2,791.31	6,677.50
Step 7	77,029	2,066.72	1,781.41	236.51	811.86	1,604.94	2,737.29	5,651.64

Notes. Each step of the cleaning procedure reports the sample size and the distribution of earnings as the data are progressively refined. Initially, we have earnings information for 196,463 observations (**step 0**). The sample is reduced to 110,827 observations in **step 1**, after retaining only income records that can be linked to a specific SHARE country, allowing the reconstruction of location and exposure to temperature. In **step 2**, we restrict the sample to 109,349 observations for which the currency is known. **Step 3** further limits the sample to observations with codable currencies: either standard ISO 4217 codes or generic labels that can be confidently assigned to a specific currency. This assignment is based on whether the income value falls within the range of observed values for that currency within a three-year moving window, reducing the sample to 97,826 observations. **Step 4** converts all monetary values into U.S. dollars using exchange rates provided by the Bank of Italy. **Step 5** adjusts for inflation over time by normalizing wages to 2010 U.S. dollars using the Consumer Price Index (CPI, 2010 = 100) provided by the World Bank. **Step 6** removes observations affected by extreme historical or political conditions: for example, wages in East Germany, Poland and Greece are retained only from 1991 onward due to the presence of extreme outliers likely associated with the economic transition, political instability and episodes of high chronic inflation. Finally, **step 7** removes implausibly high or low wage observations within each country by trimming outliers below the 0.5th percentile and above the 99th percentile, first at the country level and then in the overall sample. We adopt a less conservative approach on the upper tail of the distribution, given that several implausible high values were reported.

Socio-demographic characteristics. In addition to comprehensive income data, SHARE provides extensive information on various aspects of individuals' lives, allowing us to control for both time-varying and time-invariant factors at the individual level that may be correlated with earnings. Beyond main demographic characteristics such as gender, age, and education, a key feature for our analysis is information on preexisting vulnerability. For example, parental background—proxied by the number of books at home (Brunello et al., 2017)—is used to assess whether the impact of heat waves is stronger for individuals from disadvantaged families. Moreover, data on illnesses experienced at different points in life—measured by the days lost due to disability (Valenti et al., 2026)—allow us to account for health-related vulnerabilities that may amplify susceptibility to external shocks.

Spatial Resolution and Urbanization Data. The SHARE dataset provides spatial information on place of residence varying in granularity across countries. Specifically, residence data are available at the NUTS1, NUTS2, or NUTS3 level, depending on the country: NUTS1 for Belgium, France, and Germany; NUTS2 for Austria, Denmark, Greece, Poland, Portugal, Spain, Sweden, and Switzerland; NUTS3 for the Czech Republic and Slovenia.

To improve spatial resolution, we exploit additional information available in SHARE on the degree of urbanization (Midões et al., 2024). For each residential episode over the life course, respondents report both the corresponding minimum NUTS region — at the country-specific level described above — and the degree of urbanization of that residence, classified into five categories: "big city," "suburbs or outskirts of a big city," "large town," "small town," and "rural area or village." These self-declared categories are matched to the DEGURBA grid-cell classification issued by the European Union (European Commission, 2021), and this match is used to partition each country-specific minimum NUTS region (e.g., NUTS2 for Austria, NUTS3 for the Czech Republic) into five artificial sub-NUTS regions defined by degree of urbanization (Midões et al., 2024; Valenti et al., 2026). All climatic variables (e.g., daily temperature) are then aggregated from the grid level to this artificial sub-NUTS level using a population-weighted average across grid cells falling within each sub-NUTS region. This approach improves the variability in individuals' exposure to climatic variables, capturing within-NUTS differences between more rural and more urban areas — including substantial differences driven by the heat-island effect.

B Additional Descriptive Statistics

Table B2: Classification of Occupations at Risk of Heat Stress

ISCO-08	Definition ISCO-08	Heat-Exposed	Main task
1311	Agricultural and Forestry Production Managers	1	<i>Abstract</i>
1312	Aquaculture and Fisheries Production Managers	1	<i>Abstract</i>
1322	Mining Managers	1	<i>Abstract</i>
1323	Construction Managers	1	<i>Abstract</i>
2132	Farming, Forestry and Fisheries Advisers	1	<i>Abstract</i>
3117	Mining and metallurgical technicians	1	<i>Abstract</i>
3121	Mining Supervisors	1	<i>Abstract</i>
3123	Construction Supervisors	1	<i>Abstract</i>
3134	Petroleum and Natural Gas Refining Plant Operators	1	<i>Abstract</i>
3142	Agricultural Technicians	1	<i>Abstract</i>
3143	Forestry Technicians	1	<i>Abstract</i>
3152	Ships' Deck Officers and Pilots	1	<i>Abstract</i>
4323	Transport Clerks	1	<i>Clerical</i>
4412	Mail Carriers and Sorting Clerks	1	<i>Clerical</i>
5112	Transport Conductors	1	<i>Clerical</i>
5113	Travel Guides	1	<i>Clerical</i>
5165	Driving Instructors	1	<i>Clerical</i>
5211	Stall and Market Salespersons	1	<i>Clerical</i>
5212	Street Food Salespersons	1	<i>Clerical</i>
5243	Door-to-door Salespersons	1	<i>Clerical</i>
5411	Fire Fighters	1	<i>Clerical</i>
5412	Police Officers	1	<i>Clerical</i>
5414	Security Guards	1	<i>Clerical</i>
5419	Protective Services Workers Not Elsewhere Classified	1	<i>Clerical</i>
6111	Field Crop and Vegetable Growers	1	<i>Manual</i>
6112	Tree and Shrub Crop Growers	1	<i>Manual</i>
6113	Gardeners, Horticultural and Nursery Growers	1	<i>Manual</i>
6114	Mixed Crop Growers	1	<i>Manual</i>
6121	Livestock and Dairy Producers	1	<i>Manual</i>
6123	Apiarists and Sericulturists	1	<i>Manual</i>
6129	Animal Producers Not Elsewhere Classified	1	<i>Manual</i>
6130	Mixed Crop and Animal Producers	1	<i>Manual</i>
6210	Forestry and Related Workers	1	<i>Manual</i>
6221	Aquaculture Workers	1	<i>Manual</i>
6222	Inland and Coastal Waters Fishery Workers	1	<i>Manual</i>
6223	Deep-sea Fishery Workers	1	<i>Manual</i>
6224	Hunters and Trappers	1	<i>Manual</i>
6310	Subsistence Crop Farmers	1	<i>Manual</i>
6320	Subsistence Livestock Farmers	1	<i>Manual</i>
6330	Subsistence Mixed Crop and Livestock Farmers	1	<i>Manual</i>
6340	Subsistence Fishers, Hunters, Trappers and Gatherers	1	<i>Manual</i>
7111	House Builders	1	<i>Manual</i>
7112	Bricklayers and Related Workers	1	<i>Manual</i>
7113	Stonemasons, Stone Cutters, Splitters and Carvers	1	<i>Manual</i>

ISCO-08	Definition ISCO-08	Heat-Exposed	Occupation
7114	Concrete Placers, Concrete Finishers and Related Workers	1	Manual
7115	Carpenters and Joiners	1	Manual
7119	Building Frame and Related Trades Workers Not Elsewhere Classified	1	Manual
7121	Roofers	1	Manual
7124	Insulation Workers	1	Manual
7126	Plumbers and Pipe Fitters	1	Manual
7127	Air Conditioning and Refrigeration Mechanics	1	Manual
7133	Building Structure Cleaners	1	Manual
7413	Electrical Line Installers and Repairers	1	Manual
7542	Shotfirers and Blasters	1	Manual
7544	Fumigators and Other Pest and Weed Controllers	1	Manual
8111	Miners and Quarriers	1	Manual
8112	Mineral and Stone Processing Plant Operators	1	Manual
8113	Well Drillers and Borers and Related Workers	1	Manual
8114	Cement, Stone and Other Mineral Products Machine Operators	1	Manual
8311	Locomotive Engine Drivers	1	Manual
8312	Railway Brake, Signal and Switch Operators	1	Manual
8322	Car, Taxi and Van Drivers	1	Manual
8331	Bus and Tram Drivers	1	Manual
8332	Heavy Truck and Lorry Drivers	1	Manual
8341	Mobile Farm and Forestry Plant Operators	1	Manual
8342	Earthmoving and Related Plant Operators	1	Manual
8343	Crane, hoist and related plant operators	1	Manual
8344	Lifting Truck Operators	1	Manual
8350	Ships' Deck Crews and Related Workers	1	Manual
9121	Hand Launderers and Pressers	1	Elementary
9122	Vehicle Cleaners	1	Elementary
9123	Window Cleaners	1	Elementary
9129	Other Cleaning Workers	1	Elementary
9211	Crop Farm Labourers	1	Elementary
9212	Livestock Farm Labourers	1	Elementary
9213	Mixed Crop and Livestock Farm Labourers	1	Elementary
9214	Garden and Horticultural Labourers	1	Elementary
9215	Forestry Labourers	1	Elementary
9216	Fishery and Aquaculture Labourers	1	Elementary
9311	Mining and Quarrying Labourers	1	Elementary
9312	Civil Engineering Labourers	1	Elementary
9313	Building Construction Labourers	1	Elementary
9331	Hand and Pedal Vehicle Drivers	1	Elementary
9332	Drivers of Animal-drawn Vehicles and Machinery	1	Elementary
9333	Freight Handlers	1	Elementary
9510	Street and Related Service Workers	1	Elementary
9520	Street Vendors (excluding Food)	1	Elementary
9611	Garbage and Recycling Collectors	1	Elementary
9612	Refuse Sorters	1	Elementary
9613	Sweepers and Related Labourers	1	Elementary
9621	Messengers, Package Deliverers and Luggage Porters	1	Elementary
9622	Odd Job Persons	1	Elementary
9623	Meter Readers and Vending-machine Collectors	1	Elementary

Notes. The table lists the 4-digit ISCO-08 occupations classified as heat-exposed: occupations that predominantly involve outdoor work or physically demanding tasks performed in non-climate-controlled environments, as explained in Section 3. Occupations not listed in the table are classified as not heat-exposed. The last column reports the broad occupational-task group (Abstract, Clerical, Manual, or Elementary) to which each occupation pertains, based on its predominant task content.

Table B3: Summary Statistics

	Variable	Obs	Mean	Median	SD	Min	Max
<i>Dependent Variable</i>							
Earnings	continuous	75,258	2,070.14	1,608.82	1,782.01	16.71	11,595.59
<i>Main Regressors</i>							
T $\geq$ 95th perc, 3 days	discrete	75,258	8.53	7.00	7.49	0	69
T $\geq$ 95th perc, 5 days	discrete	75,258	2.91	1.00	4.62	0	60
T $\geq$ 30 °C, 3 days	discrete	75,258	5.65	0.00	13.29	0	108
T $\geq$ 30 °C, 5 days	discrete	75,258	2.98	0.00	9.26	0	86
<i>Main Covariates</i>							
Avg. prec.	continuous	75,258	2.10	2.00	0.71	0.27	7.70
Age	discrete	75,258	39.96	40.00	16.55	9	92
Gender	dummy	75,258	1.49	1	0.50	1	2
Education	categorical	75,258	1.79	2	1.01	0	3
Books at age 10	categorical	75,258	2.44	2	1.29	1	5
Part-time (working hours)	categorical	75,258	1.21	1	0.62	1	5
Self-Employment	dummy	75,258	0.07	0	0.26	0	1
<i>Extended Covariates</i>							
Cumulative Days Lost (Disability)	discrete	73,577	598.86	49.00	1,309.82	0	21,475
Experience	discrete	75,258	19.39	17.00	15.76	1	64
Seniority (within job)	discrete	75,258	7.87	0.00	13.17	0	62
<i>Additional Variables</i>							
Exposed Sector	dummy	75,092	0.37	0	0.48	0	1
Sector Groups	categorical	75,092	5.24	6	1.83	1	7
Exposed Occupation	dummy	69,018	0.15	0	0.35	0	1
Occupation Groups	categorical	68,717	4.84	5	1.97	1	8
<i>Institutional Variables</i>							
Coordination	categorical	72,667	3.35	4	1.30	1	5
Bargaining level	categorical	72,667	3.39	3	0.88	1	5
Minimum wage	dummy	49,045	0.50	1	0.50	0	1
Union density	continuous	68,777	40.89	37.70	21.40	7.80	87.60
Opening clauses (OCG)	categorical	70,626	0.38	0	0.65	0	2

Notes. The table reports summary statistics for the main estimation sample used throughout the paper.

B.1 Earnings

Table B4: Number of Earnings Information Available at Individual Level

Earnings Info	Individuals (Frequency)	Percentage	Cumulative
1 Obs	13,869	42.31%	42.31%
2 Obs	7,902	24.10%	66.41%
3 Obs	5,177	15.79%	82.20%
4 Obs	2,735	8.34%	90.55%
5 Obs	1,393	4.25%	94.80%
6 Obs	787	2.40%	97.20%
7 Obs	418	1.28%	98.47%
8 Obs	252	0.77%	99.24%
9 Obs	125	0.38%	99.62%
10 Obs	63	0.19%	99.81%
> 10 Obs	61	0.19%	100.00%
Total	32782	100.00%	

Notes. The table reports the distribution of individuals by the number of available earnings observations. Individuals with two or more observations (57.69% of the sample) constitute the sub-sample used in the specifications that include individual fixed effects (Column 3-6 of Table 1).

Table B5: Earnings by Country of Residence

Country	Individuals	Obs.	Mean	SD	p25	p50	p75	p95
Austria	2,337	5,959	1,179.46	1,125.16	301.65	842.64	1,744.11	3,399.89
Belgium	4,084	9,892	1,735.74	1,222.02	880.86	1,508.72	2,262.24	3,986.23
Czech Republic	2,098	3,021	601.51	348.57	354.83	540.04	771.86	1,275.53
Denmark	3,114	9,556	2,907.31	1,722.42	1,762.19	2,675.44	3,662.53	6,132.04
France	2,834	6,938	1,940.68	1,663.87	890.48	1,489.17	2,447.41	5,216.67
Germany	2,880	4,691	1,902.01	1,410.38	895.89	1,546.46	2,474.34	4,785.25
Greece	1,284	1,484	1,775.56	1,330.64	948.24	1,456.37	2,184.55	4,274.09
Italy	3,471	7,982	2,110.23	1,770.64	1,026.75	1,643.84	2,544.70	5,812.89
Poland	1,428	2,116	687.78	673.04	386.37	530.71	749.89	1,569.62
Portugal	642	1,405	1,848.02	2,082.58	598.98	1,032.73	2,332.69	6,433.27
Slovenia	895	1,112	1,368.66	1,117.71	789.21	1,072.02	1,574.54	3,073.39
Spain	2,236	4,624	1,610.55	1,596.78	582.86	1,248.32	2,043.17	4,614.83
Sweden	3,060	8,260	2,957.23	1,961.17	1,688.57	2,492.46	3,619.59	7,239.19
Switzerland	2,419	8,218	2,760.27	2,321.84	939.96	2,066.86	3,928.52	7,604.91
Total	32,782	75,258	2,070.14	1,782.01	812.20	1,608.82	2,742.94	5,661.05

Notes. The table reports summary statistics for monthly earnings (expressed in 2010 U.S. dollars), by country of residence, for the main estimation sample.

Table B6: Earnings by Occupation

	Observations	Mean	SD	p25	p50	p75	p95
<i>By Sector Exposure</i>							
Not-Exposed	46,934	2,062.87	1,758.36	822.84	1,610.84	2,736.73	5,557.14
Exposed	28,158	2,082.81	1,821.45	791.48	1,605.35	2,752.29	5,769.90
Total	75,092	2,070.35	1,782.29	812.20	1,608.90	2,743.40	5,659.06
<i>By Sector Group</i>							
Financial, Real Estate and Business	3,735	2,592.06	2,007.12	1,098.39	2,085.72	3,491.84	6,730.95
Agriculture & Fishing	3,119	1,632.89	1,623.75	553.21	1,133.30	2,146.43	4,769.84
Construction	5,472	2,310.44	1,941.72	957.25	1,793.34	3,005.41	6,347.22
Industry	15,575	2,016.21	1,788.96	747.89	1,543.49	2,671.71	5,550.19
Wholesale and Retail Trade	9,353	1,804.34	1,671.62	678.62	1,361.19	2,352.07	5,109.29
Transport, Hospitality & Storage	6,534	2,091.06	1,765.20	849.04	1,664.44	2,730.16	5,733.10
Public & Other Services	31,304	2,111.81	1,747.73	873.82	1,694.15	2,790.20	5,553.93
Total	75,092	2,070.35	1,782.29	812.20	1,608.90	2,743.40	5,659.06
<i>By Occupation Exposure</i>							
Not-Exposed	58,827	2,101.29	1,791.98	835.98	1,645.22	2,777.61	5,711.92
Exposed	10,191	1,852.06	1,695.42	697.83	1,412.12	2,418.19	5,181.57
Total	69,018	2,064.49	1,780.24	811.86	1,602.78	2,728.37	5,648.46
<i>By Occupation Group</i>							
Elementary (Indoor)	6,859	1,360.52	1,279.80	514.45	1,044.32	1,782.59	3,635.29
Elementary (Outdoor)	2,441	1,470.11	1,425.64	564.17	1,133.45	1,846.36	3,915.04
Manual (Indoor)	8,853	1,774.35	1,641.80	639.72	1,377.91	2,354.40	4,946.54
Manual (Outdoor)	5,617	1,896.87	1,694.84	731.68	1,475.58	2,448.03	5,325.51
Clerical (Indoor)	21,375	1,825.07	1,545.94	773.23	1,455.80	2,379.55	4,753.07
Clerical (Outdoor)	1,181	1,786.97	1,613.07	618.58	1,431.68	2,478.74	4,682.46
Abstract (Indoor)	21,443	2,744.70	2,008.03	1,296.39	2,309.33	3,612.01	6,917.86
Abstract (Outdoor)	948	2,645.02	2,090.60	1,045.29	2,134.44	3,634.22	7,149.44
Total	68,717	2,063.05	1,779.74	811.64	1,602.01	2,724.23	5,648.46

Notes. The table reports summary statistics for monthly earnings (expressed in 2010 U.S. dollars) by sector exposure, sector group, occupation exposure, and occupation group, for the main estimation sample. Heat-exposure classifications for sectors and occupations follow the criteria described in Section 3 and reported in Table B2.

B.2 Heat Waves

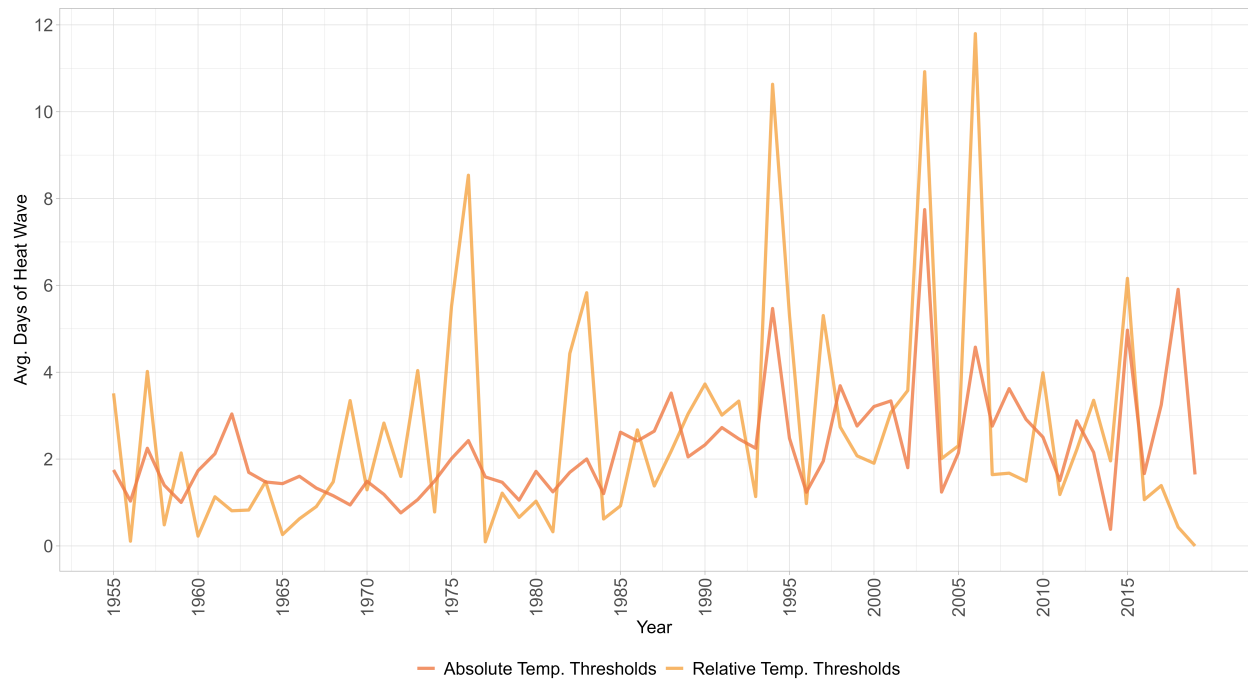


Figure B1: Average Days of Heat Wave over Time

The figure displays the sample-weighted average number of heat wave days over time, based on two threshold definitions. The relative threshold measure defines a heat wave as at least five consecutive days with maximum temperatures above the 95th percentile of the location-specific historical distribution. The absolute threshold measure defines a heat wave as at least five consecutive days with maximum temperatures exceeding 30°C. The number of heat wave days under the absolute threshold shows a clear upward trend over time, reflecting rising temperatures. In contrast, heat wave frequency under the relative threshold exhibits recurring peaks but no consistent upward trend, as this measure is based on the 95th percentile of daily maximum temperatures calculated over a rolling 30-year window.

Table B7: Heat Waves Exposure by Country of Residence

	T ≥ 95th perc, 2 days		T ≥ 95th perc, 5 days		T ≥ 30 °C, 2 days		T ≥ 30 °C, 5 days	
	Obs	Mean	Obs	Mean	Obs	Mean	Obs	Mean
Austria	5,959	8.40	5,959	2.33	5,959	2.35	5,959	0.57
Belgium	9,892	6.03	9,892	1.52	9,892	0.68	9,892	0.12
Czech Republic	3,021	8.86	3,021	2.65	3,021	2.33	3,021	0.75
Denmark	9,556	8.63	9,556	3.50	9,556	0.03	9,556	0.00
France	6,938	8.18	6,938	2.75	6,938	3.48	6,938	1.21
Germany	4,691	7.73	4,691	1.85	4,691	1.22	4,691	0.24
Greece	1,484	10.05	1,484	3.57	1,484	44.06	1,484	29.10
Italy	7,982	12.15	7,982	5.35	7,982	16.01	7,982	8.36
Poland	2,116	7.86	2,116	2.17	2,116	1.81	2,116	0.31
Portugal	1,405	8.16	1,405	1.87	1,405	14.94	1,405	5.23
Slovenia	1,112	16.38	1,112	6.19	1,112	9.43	1,112	2.78
Spain	4,624	9.41	4,624	3.16	4,624	28.50	4,624	18.45
Sweden	8,260	8.79	8,260	3.49	8,260	0.13	8,260	0.03
Switzerland	8,218	6.75	8,218	1.84	8,218	0.72	8,218	0.14
Total	75,258	8.53	75,258	2.91	75,258	5.65	75,258	2.98

Notes. The table reports, by country of residence, the number of observations and the average number of HW days per year under two alternative threshold definitions: (i) relative thresholds, defined as daily maximum temperature above the location-specific 95th percentile of the 30-year moving distribution; and (ii) absolute thresholds, defined as daily maximum temperature at or above 30°C. Summary statistics are reported separately for short and long HWs, defined as spells of more than 2 and 5 consecutive days, respectively.

Table B8: Heat Waves Exposure by Earnings Decile

	T ≥ 95th perc, 2 days		T ≥ 95th perc, 5 days		T ≥ 30 °C, 2 days		T ≥ 30 °C, 5 days	
	Obs	Mean	Obs	Mean	Obs	Mean	Obs	Mean
0-5th percentile	3,761	7.65	3,761	2.31	3,761	5.90	3,761	3.20
5th-10th percentile	3,766	7.73	3,766	2.34	3,766	4.48	3,766	2.20
10th-20th percentile	7,531	8.09	7,531	2.54	7,531	5.45	7,531	2.71
20th-30th percentile	7,512	8.22	7,512	2.64	7,512	6.43	7,512	3.36
30th-40th percentile	7,520	9.07	7,520	3.13	7,520	7.95	7,520	4.37
40th-50th percentile	7,527	9.15	7,527	3.18	7,527	7.93	7,527	4.28
50th-60th percentile	7,529	9.01	7,529	3.18	7,529	7.27	7,529	4.01
60th-70th percentile	7,528	8.79	7,528	3.20	7,528	5.63	7,528	3.04
70th-80th percentile	7,525	8.26	7,525	2.91	7,525	4.00	7,525	2.04
80th-90th percentile	7,533	8.58	7,533	3.11	7,533	3.38	7,533	1.73
90th-95th percentile	3,760	8.46	3,760	2.95	3,760	3.22	3,760	1.56
95th-100th percentile	3,766	8.39	3,766	2.73	3,766	3.33	3,766	1.48
Total	75,258	8.53	75,258	2.91	75,258	5.65	75,258	2.98

Notes. The table reports, by earnings percentile group, the number of observations and the average number of HW days per year under two alternative threshold definitions: (i) relative thresholds, defined as daily maximum temperature above the location-specific 95th percentile of the 30-year moving distribution; and (ii) absolute thresholds, defined as daily maximum temperature at or above 30°C. Summary statistics are reported separately for short and long HWs, defined as spells of more than 2 and 5 consecutive days, respectively.

Table B9: Heat Waves Exposure by Exposed Occupations and Sectors

	T ≥ 95th perc, 2 days		T ≥ 95th perc, 5 days		T ≥ 30 °C, 2 days		T ≥ 30 °C, 5 days	
	Obs	Mean	Obs	Mean	Obs	Mean	Obs	Mean
<i>By Sector Exposure</i>								
Not-Exposed	46,934	8.53	46,934	2.89	46,934	5.47	46,934	2.87
Exposed	28,158	8.52	28,158	2.93	28,158	5.93	28,158	3.13
Total	75,092	8.53	75,092	2.91	75,092	5.64	75,092	2.97
<i>By Sector Group</i>								
Financial, Real Estate and Business	3,735	8.54	3,735	2.96	3,735	4.12	3,735	2.02
Agriculture & Fishing	3,119	8.77	3,119	3.03	3,119	9.67	3,119	5.59
Construction	5,472	8.51	5,472	2.97	5,472	6.81	5,472	3.83
Industry	15,575	8.46	15,575	2.88	15,575	5.03	15,575	2.48
Wholesale and Retail Trade	9,353	8.31	9,353	2.79	9,353	5.55	9,353	2.90
Transport, Hospitality & Storage	6,534	8.59	6,534	2.95	6,534	6.18	6,534	3.37
Public & Other Services	31,304	8.59	31,304	2.92	31,304	5.43	31,304	2.85
Total	75,092	8.53	75,092	2.91	75,092	5.64	75,092	2.97
<i>By Occupation Exposure</i>								
Not-Exposed	58,827	8.50	58,827	2.91	58,827	5.45	58,827	2.88
Exposed	10,191	8.77	10,191	2.99	10,191	7.88	10,191	4.33
Total	69,018	8.54	69,018	2.92	69,018	5.81	69,018	3.10
<i>By Occupation Group</i>								
Elementary (Indoor)	6,859	8.82	6,859	3.20	6,859	7.89	6,859	4.44
Elementary (Outdoor)	2,441	9.11	2,441	3.17	2,441	10.57	2,441	6.02
Manual (Indoor)	8,853	8.35	8,853	2.80	8,853	6.22	8,853	3.26
Manual (Outdoor)	5,617	8.77	5,617	3.02	5,617	7.90	5,617	4.36
Clerical (Indoor)	21,375	8.40	21,375	2.87	21,375	5.58	21,375	3.03
Clerical (Outdoor)	1,181	8.48	1,181	2.74	1,181	5.05	1,181	2.42
Abstract (Indoor)	21,443	8.54	21,443	2.90	21,443	4.18	21,443	2.05
Abstract (Outdoor)	948	8.24	948	2.66	948	4.35	948	2.13
Total	68,717	8.53	68,717	2.92	68,717	5.80	68,717	3.09

Notes. The table reports, by sector exposure, sector group, occupation exposure, and occupation group, the number of of observations and the average number of HW days per year under. Heat-exposure classifications for sectors and occupations follow the criteria described in Section 3 and reported in Table B2. HW days are defined under two alternative threshold definitions: (i) relative thresholds, defined as daily maximum temperature above the location-specific 95th percentile of the 30-year moving distribution; and (ii) absolute thresholds, defined as daily maximum temperature at or above 30°C. Summary statistics are reported separately for short and long HWs, defined as spells of more than 2 and 5 consecutive days, respectively.

B.3 Occupational and Sectoral Exposure

Table B10: Exposed Occupations and Sectors by Country of Residence

	<i>Sectors</i>			<i>Occupations</i>		
	Not-Exposed	Exposed	Total	Not-Exposed	Exposed	Total
Austria	3,713	2,240	5,953	4,318	941	5,259
Belgium	6,537	3,307	9,844	8,055	930	8,985
Czech Republic	1,522	1,499	3,021	2,455	478	2,933
Denmark	5,922	3,632	9,554	7,191	918	8,109
France	4,455	2,476	6,931	5,364	926	6,290
Germany	3,117	1,562	4,679	3,651	636	4,287
Greece	908	549	1,457	1,119	284	1,403
Italy	4,657	3,323	7,980	6,333	1,404	7,737
Poland	1,131	984	2,115	1,300	532	1,832
Portugal	823	577	1,400	861	242	1,103
Slovenia	596	516	1,112	696	198	894
Spain	2,393	2,227	4,620	3,420	1,092	4,512
Sweden	5,374	2,849	8,223	7,355	761	8,116
Switzerland	5,786	2,417	8,203	6,709	849	7,558
Total	46,934	28,158	75,092	58,827	10,191	69,018

Notes. The table reports, for each country of residence, the number of observations employed in heat-exposed versus not-exposed sectors and occupations. Heat-exposure classifications for sectors and occupations follow the criteria described in Section 3 and reported in Table B2.

Table B11: Exposed Occupations and Sectors by Earnings Percentile

	<i>Sectors</i>			<i>Occupations</i>		
	Not-Exposed	Exposed	Total	Not-Exposed	Exposed	Total
0–5th percentile	2,284	1,468	3,752	2,790	650	3,440
5th–10th percentile	2,306	1,454	3,760	2,796	634	3,430
10th–20th percentile	4,600	2,913	7,513	5,784	1,171	6,955
20th–30th percentile	4,708	2,792	7,500	5,762	1,143	6,905
30th–40th percentile	4,727	2,776	7,503	5,837	1,086	6,923
40th–50th percentile	4,810	2,692	7,502	5,899	1,051	6,950
50th–60th percentile	4,757	2,757	7,514	5,915	1,055	6,970
60th–70th percentile	4,697	2,814	7,511	5,999	919	6,918
70th–80th percentile	4,771	2,734	7,505	5,990	828	6,818
80th–90th percentile	4,706	2,814	7,520	5,992	845	6,837
90th–95th percentile	2,311	1,445	3,756	3,056	374	3,430
95th–100th percentile	2,257	1,499	3,756	3,007	435	3,442
Total	46,934	28,158	75,092	58,827	10,191	69,018

Notes. The table reports, by earnings percentile group, the number of observations employed in heat-exposed versus not-exposed sectors and occupations. Heat-exposure classifications for sectors and occupations follow the criteria described in Section 3 and reported in Table B2.

Table B12: Exposed Occupations by Sector and Occupation Group

	Indoor	Outdoor	Total
<i>By Sector Group</i>			
Financial, Real Estate and Business	3,376	62	3,438
Agriculture & Fishing	528	2,329	2,857
Construction	1,884	3,256	5,140
Industry	12,829	1,418	14,247
Wholesale and Retail Trade	7,901	656	8,557
Transport, Hospitality & Storage	5,033	967	6,000
Public & Other Services	27,157	1,496	28,653
Total	58,708	10,184	68,892
<i>By Occupation Group</i>			
Elementary	6,859	2,441	9,300
Manual	8,853	5,617	14,470
Clerical	21,375	1,181	22,556
Abstract	21,443	948	22,391
Total	58,530	10,187	68,717

Notes. The table reports the number of observations, broken down by indoor versus outdoor main task, for each sector group and for each occupation group (Elementary, Manual, Clerical, Abstract). The classification in indoor or outdoor occupation determine the related heat exposed classifications for occupations as described in Section 3 and reported in Table B2.

B.4 Labor Market Institutions

Predominant Level of Wage Bargaining	Central	SI (1994) SE (1985–1987) SE (1980–1982) DK (1985) DK (1983) DK (1980–1981)	SI (1999–2002) SI (1995–1996) ES (1983–1985) ES (1980–1981) BE (1981)		SI (2003–2005) BE (2011–2016) BE (2005–2006) BE (1997–1998) BE (1982–1986)		
	Central–sect. mix	SE (1991–1992) IT (1983–1984) DK (1998) DK (1987) AT (1980–1982)	PT (1996–1998) PT (1990–1992) PT (1986–1988) PL (1993) GR (1991–2010) CZ (1994)	IT (2011–2012) IT (2009)	SI (2015) SI (2007–2009) ES (2002–2008) BE (2017) BE (2007–2010) BE (1999–2004) BE (1987–1996)		
	Sectoral	SI (1991–1993) SE (1993–2017) SE (1988–1990) SE (1983–1984) IT (1985–2008) IT (1980–1982) DK (1999–2017) DK (1988–1997) DK (1986) DK (1984) DK (1982) CH (1980–1995) AT (1983)	SI (1997–1998) PT (1999–2011) PT (1993–1995) PT (1989) PT (1980–1985) GR (1980) FR (1980–2007) ES (1986–1996) ES (1982) BE (1980)	IT (2013–2017) IT (2010) DE (1990–1992) CH (1996–2016) AT (1984–1992)	SI (2016–2017) SI (2010–2014) SI (2006) PT (2012–2018) FR (2008–2017) ES (2009–2011) ES (1997–2001) CH (2017)	DE (1993–1996) AT (1993–2017)	ES (2012–2017) DE (1997–2017)
	Sect.–firm mix		PL (1994–1996) PL (1991–1992) CZ (1995–2017)				GR (2011–2017)
			No opening clauses		Non-wage flexibility		Wage renegotiation
		Sectoral Opening Clauses (OCG)					
		a No minimum wage a Minimum wage					

Figure B2: Distribution of Countries by Bargaining Level and Sectoral Opening Clauses.

The figure plots each country in its wage-bargaining configuration, defined by the level at which bargaining predominantly takes place (vertical axis: 1 = company-level, 5 = central) and the type of opening clauses in sectoral collective agreements (horizontal axis: OCG = 0, no clauses; OCG = 1, non-wage renegotiation; OCG = 2, wage renegotiation). Each entry reports the country and the years spent in that configuration; countries that changed institutional setting appear in multiple cells. Grey labels denote countries without a statutory minimum wage; teal labels denote countries with a statutory minimum wage. Data from ICTWSS.

Correlation Across Institutional Indicators. We test the degree of correlation across our institutional indicators (Table B13). Coordination is moderately correlated with bargaining level and union density, consistent with the well-documented complementarity between centralised bargaining structures and high unionization rates (Calmfors and Drifill, 1988). Minimum wage is low correlated with the bargaining level and the presence of opening clauses, while it is moderately negative correlated with the level of coordination and the union density. The negative correlation between wage coordination and the presence of a statutory minimum wage may be explained, on one side, by Scandina-

vian countries, which combine highly centralised bargaining systems and strong union representation with no statutory wage floor; on the other, several Central and Eastern European countries, where weaker centralization of collective bargaining has been paired with the introduction of a universal minimum wage. This pattern reflects a broader logic of functional substitutability between coordinated bargaining and statutory regulation as alternative mechanisms for setting wage floors. Opening clauses display only modest correlations with the remaining indicators. Overall, the correlation structure confirms that these indicators capture meaningfully distinct dimensions of the institutional framework.

Table B13: Correlation Matrix of Labor Market Institution Variables

	(1) <i>Coordination</i>	(2) <i>Bargaining level</i>	(3) <i>Minimum wage</i>	(4) <i>Union density</i>
(2) Bargaining level	0.562***			
(3) Minimum wage	-0.359***	0.080		
(4) Union density	0.551***	0.287***	-0.516***	
(5) Opening clauses	0.301***	0.043	0.092*	-0.272***

Notes. The table reports pairwise correlation coefficients across the five labor market institution variables described in Section 3 and drawn from the OECD/AIAS ICTWSS database (OECD and AIAS, 2025): the degree of coordination of wage bargaining, the predominant bargaining level, the presence of a statutory minimum wage, union density, and the presence of opening clauses in sectoral agreements (OCG). * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$). B2.

C Validation of the Identifying Assumption

Table C14: Testing for Covariates' Imbalance in Heat Wave Exposure

	T _{MAX} > 95th perc >5 consecutive days		T _{MAX} > 95th perc >2 consecutive days	
	(1)	(2)	(3)	(4)
Age	0.000302 (0.0016)		0.000823 (0.0009)	
Gender × Age	-0.00195 (0.0013)	-0.00370 (0.0028)	-0.00244*** (0.0007)	-0.00204 (0.0019)
Age Squared	-0.00000925 (0.0000)	-0.0000327 (0.0000)	-0.00000430 (0.0000)	-0.0000250 (0.0000)
Gender × Age Squared	0.0000290* (0.0000)	0.0000508 (0.0000)	0.0000352*** (0.0000)	0.0000314 (0.0000)
Lower Secondary Edu	-0.00737 (0.0063)		0.00186 (0.0037)	
Upper Secondary Edu	0.000936 (0.0052)		0.00620* (0.0032)	
Tertiary Edu	-0.00540 (0.0059)		0.00421 (0.0038)	
One shelf of books (at age 10)	0.00195 (0.0049)		-0.00127 (0.0026)	
One bookcase (at age 10)	0.00759 (0.0047)		0.00133 (0.0028)	
Two bookcases (at age 10)	0.0101* (0.0060)		0.000212 (0.0034)	
More than two bookcases (at age 10)	0.00784 (0.0061)		0.00325 (0.0036)	
Health loss	0.00000148 (0.0000)	0.00000550 (0.0000)	0.000000779 (0.0000)	0.00000531* (0.0000)
Always Part-time	0.0159*** (0.0059)	0.0119 (0.0156)	0.00139 (0.0030)	-0.0122 (0.0082)
From part- to full-time	-0.00382 (0.0110)	0.0180 (0.0259)	0.00477 (0.0076)	-0.0149 (0.0196)
From full- to part-time	-0.0146 (0.0152)	-0.109** (0.0447)	0.00732 (0.0102)	-0.0236 (0.0297)
Changed multiple time part-/full-time	0.0156 (0.0156)	-0.00185 (0.0494)	-0.0133 (0.0099)	-0.0527 (0.0378)
Self Employed	0.00337 (0.0064)	0.0193 (0.0168)	0.00351 (0.0039)	0.00506 (0.0098)
Experience	-0.000317 (0.0007)	-0.00389* (0.0023)	0.0000887 (0.0004)	-0.00126 (0.0013)
Experience Squared	0.0000104 (0.0000)	0.0000513** (0.0000)	-0.00000356 (0.0000)	0.0000180 (0.0000)
Seniority	-0.000616 (0.0006)	-0.00244* (0.0014)	-0.000888** (0.0004)	-0.00111 (0.0009)
Seniority Squared	0.0000274* (0.0000)	0.0000782** (0.0000)	0.0000181** (0.0000)	0.0000134 (0.0000)
Location, Generation, Year FE	✓	✓	✓	✓
Country-Year Linear Trends	✓	✓	✓	✓
Individual FE		✓		✓
Individuals	32,337	15,580	32,337	15,580
Observations	73,577	44,271	73,577	44,271
Adjusted R ²	0.29645	0.28196	0.21827	0.17257

Notes. The table reports OLS estimates of a linear probability model (LPM). The dependent variable is a binary indicator that takes the value 1 if a heat wave occurs, and 0 otherwise. Clustered standard errors at the location level (sub-minimum NUTS level, the source of temperature variation) are reported in parentheses * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table C15: Testing for Serial Correlation in Heat Wave Occurrence

	(1)	(2)	(3)	(4)
Shock ($T_{MAX} > 95\text{th perc, } >5 \text{ consecutive days}$) $t-1$	-0.0188* (0.0113)	-0.0133 (0.0162)		
Shock ($T_{MAX} > 95\text{th perc, } >2 \text{ consecutive days}$) $t-1$			0.0310** (0.0156)	0.0208 (0.0196)
Precipitation control	✓	✓	✓	✓
Location, Generation, Year FE	✓	✓	✓	✓
Covariates	✓	✓	✓	✓
Country-Year Linear Trends	✓	✓	✓	✓
Individual FE		✓		✓
Individuals	32,188	15,399	32,188	15,399
Observations	72,674	43,590	72,674	43,590
Adjusted R^2	0.31517	0.29838	0.23418	0.18762

Notes. The dependent variable is a binary indicator that takes the value 1 if a heat wave occurs, and 0 otherwise. The main regressor is a dummy for the occurrence of the heat wave at time $t-1$. Covariates: age and age squared by gender, experience and experience squared, seniority within the job and seniority squared, part-time and self-employment status. Clustered standard errors at the location level (sub-minimum NUTS level, the source of temperature variation) are reported in parentheses * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

D Additional Results: Temperature Impact on Earnings

Table D16: Temperature Impact on Income - Location Stayers

	(1)	(2)	(3)	(4)	(5)
Days of HW ($T_{MAX} > 95\text{th perc}$)	-0.00303*** (0.0011)	-0.00302*** (0.0011)	-0.00389*** (0.0015)	-0.00339** (0.0014)	-0.00360*** (0.0014)
Precipitation control	Yes	Yes	Yes	Yes	Yes
Geo id, Generation, Year FE	Yes	Yes	Yes	Yes	Yes
Main Covariates	Yes	Yes	Yes	Yes	Yes
Extended Covariates	No	Yes	Yes	Yes	Yes
Country-Time Trends	Yes	Yes	Yes	Yes	Yes
Individual FE	No	No	No	Yes	Yes
Individual by Occupation (isco1) FE	No	No	No	No	Yes
Individuals	25,140	24,855	9,246	9,246	9,246
Observations	46,444	45,682	23,772	23,772	23,772
Adjusted R ²	0.51447	0.51590	0.52137	0.65512	0.66212

Notes. Sample is restricted to stayers individuals. The dependent variable is the log transformation of earnings expressed in dollars (base year 2010). Days of HW count the number of days spent in a heatwave ($T_{MAX} > 95\text{th perc}$) longer than 5 consecutive days. Main covariates: age and age squared by gender, the level of education, the number of books at age 10, part-time and self-employment status. Extended covariates also include the cumulative days lost due to disability (health loss), experience and experience squared, seniority within the job and seniority squared. Clustered standard errors at sub-minimum NUTS level (the source of temperature variation) in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table D17: Temperature Impact on Income - Sectoral Stayers

	(1)	(2)	(3)	(4)	(5)
Days of HW ($T_{MAX} > 95\text{th perc}$)	-0.00288*** (0.0010)	-0.00305*** (0.0010)	-0.00265* (0.0014)	-0.00147 (0.0018)	-0.00142 (0.0019)
Precipitation control	Yes	Yes	Yes	Yes	Yes
Geo id, Generation, Year FE	Yes	Yes	Yes	Yes	Yes
Main Covariates	Yes	Yes	Yes	Yes	Yes
Extended Covariates	No	Yes	Yes	Yes	Yes
Country-Time Trends	Yes	Yes	Yes	Yes	Yes
Individual FE	No	No	No	Yes	Yes
Individual by Occupation (isco1) FE	No	No	No	No	Yes
Individuals	24,898	24,596	9,418	9,418	9,418
Observations	43,601	42,754	23,488	23,488	23,488
Adjusted R ²	0.52358	0.52434	0.52452	0.67385	0.67695

Notes. Sample is restricted to stayers individuals. The dependent variable is the log transformation of earnings expressed in dollars (base year 2010). Days of HW count the number of days spent in a heatwave ($T_{MAX} > 95\text{th perc}$) longer than 5 consecutive days. Main covariates: age and age squared by gender, the level of education, the number of books at age 10, part-time and self-employment status. Extended covariates also include the cumulative days lost due to disability (health loss), experience and experience squared, seniority within the job and seniority squared. Clustered standard errors at sub-minimum NUTS level (the source of temperature variation) in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table D18: Temperature Impact on Income - Occupational Stayers

	(1)	(2)	(3)	(4)	(5)
Days of HW ($T_{MAX} > 95\text{th perc}$)	-0.00267*** (0.0010)	-0.00293*** (0.0010)	-0.00329*** (0.0012)	-0.00294** (0.0015)	-0.00353** (0.0015)
Precipitation control	Yes	Yes	Yes	Yes	Yes
Geo id, Generation, Year FE	Yes	Yes	Yes	Yes	Yes
Main Covariates	Yes	Yes	Yes	Yes	Yes
Extended Covariates	No	Yes	Yes	Yes	Yes
Country-Time Trends	Yes	Yes	Yes	Yes	Yes
Individual FE	No	No	No	Yes	Yes
Individual by Occupation (isco1) FE	No	No	No	No	Yes
Individuals	27,759	27,315	11,955	11,955	11,955
Observations	55,675	54,061	33,303	33,303	33,303
Adjusted R ²	0.51545	0.51474	0.51641	0.65709	0.66567

Notes. Sample is restricted to stayers individuals. The dependent variable is the log transformation of earnings expressed in dollars (base year 2010). Days of HW count the number of days spent in a heatwave ($T_{MAX} > 95\text{th perc}$) longer than 5 consecutive days. Main covariates: age and age squared by gender, the level of education, the number of books at age 10, part-time and self-employment status. Extended covariates also include the cumulative days lost due to disability (health loss), experience and experience squared, seniority within the job and seniority squared. Clustered standard errors at sub-minimum NUTS level (the source of temperature variation) in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table D19: Temperature Impact on Income - Binned HW days

	(1)	(2)	(3)	(4)	(5)
Days of HW ($T_{MAX} > 95$ th perc, bin 1-2)	-0.000512 (0.0009)	-0.000578 (0.0009)	0.000304 (0.0011)	-0.000723 (0.0013)	-0.00166 (0.0014)
Days of HW ($T_{MAX} > 95$ th perc, bin 3-5)	-0.00264** (0.0012)	-0.00295** (0.0012)	-0.00251* (0.0015)	-0.00107 (0.0018)	-0.000340 (0.0018)
Days of HW ($T_{MAX} > 95$ th perc, bin >5)	-0.00196** (0.0010)	-0.00203** (0.0010)	-0.00239** (0.0012)	-0.00193 (0.0015)	-0.00221 (0.0015)
Precipitation control	Yes	Yes	Yes	Yes	Yes
Geo id, Generation, Year FE	Yes	Yes	Yes	Yes	Yes
Main Covariates	Yes	Yes	Yes	Yes	Yes
Extended Covariates	No	Yes	Yes	Yes	Yes
Country-Time Trends	Yes	Yes	Yes	Yes	Yes
Individual FE	No	No	No	Yes	Yes
Individual by Occupation (isco1) FE	No	No	No	No	Yes
Individuals	32,782	32,337	15,580	15,580	15,580
Observations	75,258	73,577	44,271	44,271	44,271
Adjusted R ²	0.51750	0.51762	0.52103	0.66159	0.67180
p-value: bin(1-2)=bin(3-5)	0.233	0.194	0.210	0.892	0.621
p-value: bin(3-5)=bin(>5)	0.712	0.624	0.958	0.757	0.504
p-value: joint equality	0.314	0.274	0.143	0.805	0.800

Notes. The dependent variable is the log transformation of earnings expressed in dollars (base year 2010). Days of HW count the number of days spent in a heatwave ($T_{MAX} > 95$ th perc) longer than 5 consecutive days. Main covariates: age and age squared by gender, the level of education, the number of books at age 10, part-time and self-employment status. Extended covariates also include the cumulative days lost due to disability (health loss), experience and experience squared, seniority within the job and seniority squared. Clustered standard errors at sub-minimum NUTS level (the source of temperature variation) in parentheses. Wald tests report the p-value for equality of the position-bin coefficients. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

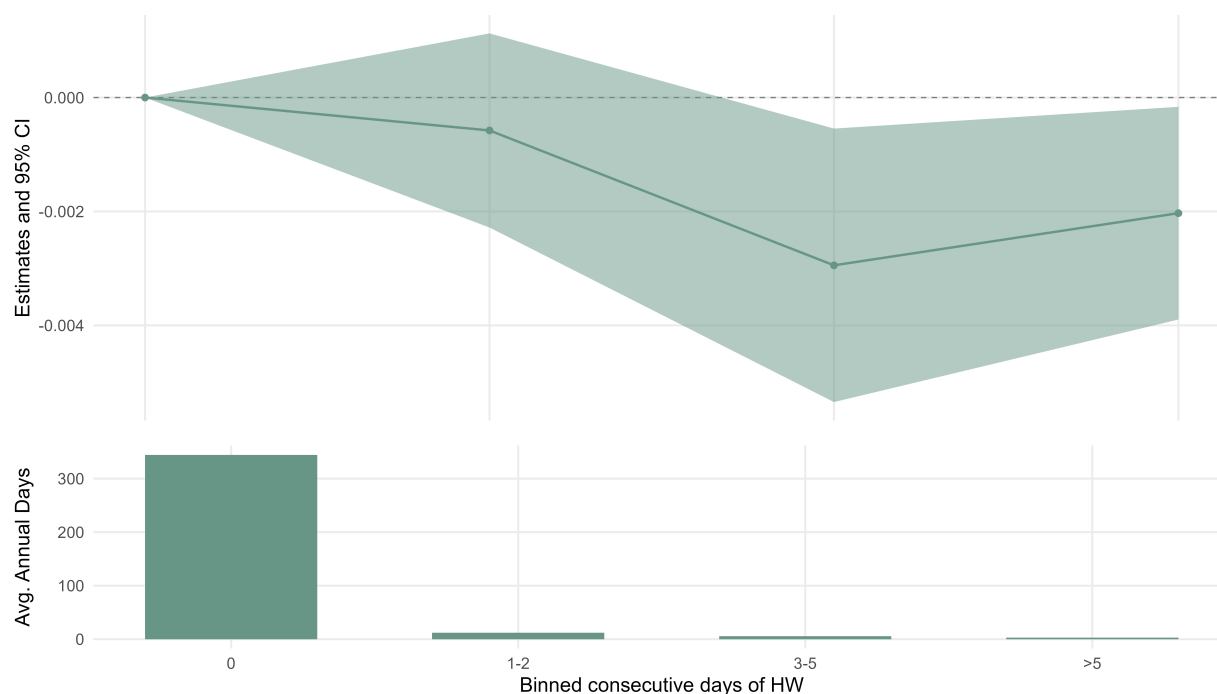


Figure D3: Effect of HW Bins on Earnings

Notes. The upper panel plots the marginal effect on earnings for each HW bin; estimates correspond to Table D19, column (2). The dependent variable is the log transformation of earnings expressed in dollars (base year 2010). Our main regressors are the number of days in each HW bin ($T_{MAX} > 95\text{th perc}$): 1-2, 3-5, and >5 consecutive days. The omitted category is zero days spent in a heat wave (i.e., no days with T_{MAX} above the 95th percentile). Main covariates: age and age squared by gender, the level of education, the number of books at age 10, part-time and self-employment status. Extended covariates also include the cumulative days lost due to disability (health loss), experience and experience squared, seniority within the job and seniority squared. Clustered standard errors at the location level (sub-minimum NUTS level, the source of temperature variation) are reported in parentheses * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$). The bottom panel plots, for each bin, the average number of days per year falling into that bin.

Table D20: Effect of Heat Waves on Earnings, Lags at t-1, t-2

	(1)	(2)	(3)	(4)	(5)
HW days ($T_{MAX} > 95\text{th perc}$)	-0.00280*** (0.0008)	-0.00299*** (0.0008)	-0.00304*** (0.0010)	-0.00207 (0.0014)	-0.00220 (0.0014)
HW days ($T_{MAX} > 95\text{th perc}$) at t-1	-0.00134 (0.0009)	-0.00145* (0.0008)	-0.00248*** (0.0009)	-0.00204* (0.0012)	-0.00228* (0.0012)
HW days ($T_{MAX} > 95\text{th perc}$) at t-2	-0.000999 (0.0009)	-0.000774 (0.0009)	-0.000932 (0.0010)	-0.00164 (0.0011)	-0.00186 (0.0012)
<i>Cumulative Marginal Effects</i>					
HW days ($T_{MAX} > 95\text{th perc}$)	-0.00513*** (0.0017)	-0.00521*** (0.0017)	-0.00645*** (0.0018)	-0.00576*** (0.0022)	-0.00622*** (0.0022)
Precipitation control	✓	✓	✓	✓	✓
Location, Generation, Year FE	✓	✓	✓	✓	✓
Main Covariates	✓	✓	✓	✓	✓
Extended Covariates		✓	✓	✓	✓
Country-Year Linear Trends	✓	✓	✓	✓	✓
Individual FE				✓	✓
Individual $\times$ Occupation (ISCO1) FE					✓
Individuals	32,582	32,134	15,281	15,281	15,281
Observations	73,853	72,229	43,134	43,134	43,134
Adjusted R ²	0.51917	0.51944	0.52246	0.66233	0.67260

Notes. The dependent variable is the log transformation of earnings expressed in dollars (base year 2010). HW days count the number of days spent in a heat wave ($T_{MAX} > 95\text{th perc}$) longer than 5 consecutive days. Main covariates: age and age squared by gender, the level of education, the number of books at age 10, part-time and self-employment status. Extended covariates also include the cumulative days lost due to disability (health loss), experience and experience squared, seniority within the job and seniority squared. Clustered standard errors at the location level (sub-minimum NUTS level, the source of temperature variation) are reported in parentheses * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table D21: Effect of Heat Waves on Earnings, Without Country-Year Linear Trends

	(1)	(2)	(3)	(4)	(5)
HW days ($T_{MAX} > 95\text{th perc}$)	-0.00612*** (0.0013)	-0.00601*** (0.0013)	-0.00615*** (0.0015)	-0.00511*** (0.0019)	-0.00485*** (0.0019)
Precipitation control	✓	✓	✓	✓	✓
Location, Generation, Year FE	✓	✓	✓	✓	✓
Main Covariates	✓	✓	✓	✓	✓
Extended Covariates		✓	✓	✓	✓
Country-Year Linear Trends					
Individual FE				✓	✓
Individual $\times$ Occupation (ISCO1) FE					✓
Individuals	32,782	32,337	15,580	15,580	15,580
Observations	75,258	73,577	44,271	44,271	44,271
Adjusted R ²	0.45921	0.45954	0.45797	0.59877	0.61307

Notes. The dependent variable is the log transformation of earnings expressed in dollars (base year 2010). HW days count the number of days spent in a heat wave ($T_{MAX} > 95\text{th perc}$) longer than 5 consecutive days. Main covariates: age and age squared by gender, the level of education, the number of books at age 10, part-time and self-employment status. Extended covariates also include the cumulative days lost due to disability (health loss), experience and experience squared, seniority within the job and seniority squared. Clustered standard errors at the location level (sub-minimum NUTS level, the source of temperature variation) are reported in parentheses * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table D22: Effect of Heat Waves on Earnings, with NUTS1-Year Linear Trends

	(1)	(2)	(3)	(4)	(5)
HW days ($T_{MAX} > 95\text{th perc}$)	-0.00311*** (0.0009)	-0.00327*** (0.0009)	-0.00314*** (0.0011)	-0.00242* (0.0013)	-0.00254* (0.0014)
Precipitation control	✓	✓	✓	✓	✓
Location, Generation, Year FE	✓	✓	✓	✓	✓
Main Covariates	✓	✓	✓	✓	✓
Extended Covariates		✓	✓	✓	✓
NUTS1-Year Linear Trends	✓	✓	✓	✓	✓
Individual FE				✓	✓
Individual $\times$ Occupation (ISCO1) FE					✓
Individuals	31,671	31,232	15,455	15,455	15,455
Observations	73,977	72,305	43,997	43,997	43,997
Adjusted R ²	0.52023	0.52041	0.52159	0.66237	0.67252

Notes. The dependent variable is the log transformation of earnings expressed in dollars (base year 2010). HW days count the number of days spent in a heat wave ($T_{MAX} > 95\text{th perc}$) longer than 5 consecutive days. Main covariates: age and age squared by gender, the level of education, the number of books at age 10, part-time and self-employment status. Extended covariates also include the cumulative days lost due to disability (health loss), experience and experience squared, seniority within the job and seniority squared. Clustered standard errors at the location level (sub-minimum NUTS level, the source of temperature variation) are reported in parentheses * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table D23: Effect of Heat Waves on Monthly Earnings, Short Heat Waves

	(1)	(2)	(3)	(4)	(5)
HW days ($T_{MAX} > 95\text{th perc}$)	-0.00239*** (0.0005)	-0.00258*** (0.0005)	-0.00237*** (0.0006)	-0.00173** (0.0008)	-0.00180** (0.0009)
Precipitation control	✓	✓	✓	✓	✓
Location, Generation, Year FE	✓	✓	✓	✓	✓
Main Covariates	✓	✓	✓	✓	✓
Extended Covariates		✓	✓	✓	✓
Country-Year Linear Trends	✓	✓	✓	✓	✓
Individual FE				✓	✓
Individual $\times$ Occupation (ISCO1) FE					✓
Individuals	32,782	32,337	15,580	15,580	15,580
Observations	75,258	73,577	44,271	44,271	44,271
Adjusted R ²	0.51750	0.51762	0.52105	0.66160	0.67179

Notes. The dependent variable is the log transformation of earnings expressed in dollars (base year 2010). HW days count the number of days spent in a heat wave ($T_{MAX} > 95\text{th perc}$) longer than 2 consecutive days. Main covariates: age and age squared by gender, the level of education, the number of books at age 10, part-time and self-employment status. Extended covariates also include the cumulative days lost due to disability (health loss), experience and experience squared, seniority within the job and seniority squared. Clustered standard errors at the location level (sub-minimum NUTS level, the source of temperature variation) are reported in parentheses * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table D24: Effect of Heat Waves on Monthly Earnings, by Period

	1960-1990	1975-2005	1990-2020
	(1)	(2)	(3)
HW days ($T_{MAX} > 95\text{th perc}$)	-0.00320* (0.0018)	-0.00188** (0.0009)	-0.00208** (0.0008)
Precipitation control	✓	✓	✓
Location, Generation, Year FE	✓	✓	✓
Main Covariates	✓	✓	✓
Extended Covariates	✓	✓	✓
Country-Year Linear Trends	✓	✓	✓
Individual FE			
Individual by Occupation (iscol) FE			
Individuals	18,654	19,754	25,897
Observations	35,252	33,000	38,313
Adjusted R^2	0.45833	0.48493	0.63109

Notes. The dependent variable is the log transformation of earnings expressed in dollars (base year 2010). HW days count the number of days spent in a heat wave ($T_{MAX} > 95\text{th perc}$) longer than 5 consecutive days. Main covariates: age and age squared by gender, the level of education, the number of books at age 10, part-time and self-employment status. Extended covariates also include the cumulative days lost due to disability (health loss), experience and experience squared, seniority within the job and seniority squared. Clustered standard errors at the location level (sub-minimum NUTS level, the source of temperature variation) are reported in parentheses * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table D25: Effect of Heat Waves on Monthly Earnings, Leave-One-Country-Out Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Austria	Belgium	Czech Republic	Denmark	France	Germany	Greece
HW days ($T_{MAX} > 95th\ perc$)	-0.00259*** (0.0009)	-0.00321*** (0.0009)	-0.00335*** (0.0009)	-0.00411*** (0.0009)	-0.00281*** (0.0009)	-0.00320*** (0.0009)	-0.00306*** (0.0009)
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Italy	Poland	Portugal	Slovenia	Spain	Sweden	Switzerland
	-0.00156* (0.0009)	-0.00328*** (0.0009)	-0.00282*** (0.0009)	-0.00334*** (0.0009)	-0.00347*** (0.0009)	-0.00301*** (0.0009)	-0.00299*** (0.0009)
Precipitation control	✓	✓	✓	✓	✓	✓	✓
Geo id, Generation, Year FE	✓	✓	✓	✓	✓	✓	✓
Covariates	✓	✓	✓	✓	✓	✓	✓
Country-Time Trends	✓	✓	✓	✓	✓	✓	✓
Individual FE							
Individual by Occupation (isco1) FE							
Individuals	30,001 28,871	28,260 30,909	30,250 31,702	29,225 31,444	29,511 30,112	29,466 29,280	31,059 30,291
Observations	67,619 65,604	63,701 71,461	70,568 72,179	64,024 72,467	66,661 68,967	68,900 65,322	72,102 66,926
Adjusted R ²	0.48832 0.54430	0.52717 0.50744	0.49552 0.52540	0.50444 0.51887	0.53049 0.53998	0.51819 0.50806	0.52025 0.50788

Notes. Each column reports the regression results for the sample of countries, excluding the one indicated at the top of the column. The dependent variable is the log transformation of earnings expressed in dollars (base year 2010). HW days count the number of days spent in a heat wave ($T_{MAX} > 95th\ perc$) longer than 5 consecutive days. Covariates include: age and age squared by gender, the level of education, the number of books at age 10, the cumulative days lost due to disability (health loss), part-time and self-employment status, experience and experience squared, seniority within the job and seniority squared. Clustered standard errors at the location level (sub-minimum NUTS level, the source of temperature variation) are reported in parentheses * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table D26: Effect of Heat Waves on Monthly Earnings, Full-Time Workers

	(1)	(2)	(3)	(4)	(5)
HW days ($T_{MAX} > 95\text{th perc}$)	-0.00280*** (0.0009)	-0.00292*** (0.0009)	-0.00311*** (0.0011)	-0.00211 (0.0014)	-0.00218 (0.0014)
Precipitation control	✓	✓	✓	✓	✓
Location, Generation, Year FE	✓	✓	✓	✓	✓
Main Covariates	✓	✓	✓	✓	✓
Extended Covariates		✓	✓	✓	✓
Country-Year Linear Trends	✓	✓	✓	✓	✓
Individual FE				✓	✓
Individual $\times$ Occupation (ISCO1) FE					✓
Individuals	29,934	29,540	13,262	13,262	13,262
Observations	64,788	63,567	36,628	36,628	36,628
Adjusted R ²	0.52431	0.52229	0.51666	0.65847	0.66721

Notes. The sample is restricted to full-time workers. The dependent variable is the log transformation of income expressed in dollars (base year 2010). HW days count the number of days spent in a heat wave ($T_{MAX} > 95\text{th perc}$) longer than 5 consecutive days. Main covariates: age and age squared by gender, the level of education, the number of books at age 10, part-time and self-employment status. Extended covariates also include the cumulative days lost due to disability (health loss), experience and experience squared, seniority within the job and seniority squared. Clustered standard errors at the location level (sub-minimum NUTS level, the source of temperature variation) are reported in parentheses * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table D27: Effect of Heat Waves on Monthly Earnings, with Location by Occupation FE

	(1)	(2)	(3)	(4)
HW days ($T_{MAX} > 95\text{th perc}$)	-0.00583*** (0.0014)	-0.00559*** (0.0014)	-0.00576*** (0.0015)	-0.00525*** (0.0019)
Precipitation control	✓	✓	✓	✓
Location, Generation, Year FE	✓	✓	✓	✓
Main Covariates	✓	✓	✓	✓
Extended Covariates		✓	✓	✓
Country-Year Linear Trends	✓	✓	✓	✓
Location $\times$ Occupation (ISCO1) FE	✓	✓	✓	✓
Individual FE				✓
Individuals	30,360	29,916	16,929	16,929
Observations	68,309	66,653	53,450	53,450
Adjusted R ²	0.48449	0.48427	0.48506	0.59463

Notes. The dependent variable is the log transformation of income expressed in dollars (base year 2010). HW days count the number of days spent in a heat wave ($T_{MAX} > 95\text{th perc}$) longer than 5 consecutive days. Main covariates: age and age squared by gender, the level of education, the number of books at age 10, part-time and self-employment status. Extended covariates also include the cumulative days lost due to disability (health loss), experience and experience squared, seniority within the job and seniority squared. Clustered standard errors at the location level (sub-minimum NUTS level, the source of temperature variation) are reported in parentheses * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Absolute Temperature Measures. In this section of the appendix, we re-estimate our main results using absolute temperature thresholds, defining heat wave days as those with $T_{\text{MAX}} \geq 30^{\circ}\text{C}$ for at least five consecutive days (Tables D28 and D29). We also explore the effects of temperature across the full distribution by modeling exposure through temperature bins (Tables D30, D31, and Figure D4), with the 10–15°C range as the omitted category, following prior literature that identifies it as optimal for productivity (Burke et al., 2015).

Although adopting absolute thresholds reduces the number of identified heat wave events—particularly in Northern European countries—we continue to find economically and statistically significant effects when country-year linear trends are excluded. In our preferred specification (Table D28, column 2), an additional day in a heat wave of at least five consecutive days lowers income by approximately 1%, while Table D30 shows that each additional day above 30°C reduces earnings by about 1.3%. These magnitudes are consistent with, though somewhat larger than, those obtained using relative thresholds.

When we include country-year linear trends (Tables D29 and D31), the estimated effects largely disappear. This pattern is consistent with the binning bias documented by Jones et al. (2025). Under global warming, the number of days exceeding an absolute threshold increases mechanically over time, and this increase is larger in countries that are already warm. If long-run income dynamics also differ systematically with baseline climate—as is plausible across European countries—the panel regression conflates these parallel differential trends with causal short-run temperature effects. Controlling for country-specific linear trends absorbs this spurious variation, but at the cost of also removing most of the identifying variation in absolute temperature exposure, which is itself largely trend-driven. The attenuation of effects therefore likely reflects the removal of a trends-on-trends correlation rather than the absence of genuine short-run temperature impacts.

Table D28: Effect of Heat Waves (Absolute Measures, $T_{MAX} > 30^{\circ}C$) on Earnings, Without Country-Year Linear Trends

	(1)	(2)	(3)	(4)	(5)
HW days ($T_{MAX} > 30^{\circ}C$)	-0.0111*** (0.0016)	-0.0108*** (0.0016)	-0.0107*** (0.0018)	-0.00993*** (0.0021)	-0.00976*** (0.0021)
Precipitation control	✓	✓	✓	✓	✓
Location, Generation, Year FE	✓	✓	✓	✓	✓
Main Covariates	✓	✓	✓	✓	✓
Extended Covariates		✓	✓	✓	✓
Country-Year Linear Trends					
Individual FE				✓	✓
Individual $\times$ Occupation (ISCO1) FE					✓
Individuals	32,782	32,337	15,580	15,580	15,580
Observations	75,258	73,577	44,271	44,271	44,271
Adjusted R ²	0.46122	0.46148	0.45989	0.60049	0.61476

Notes. The dependent variable is the log transformation of earnings expressed in dollars (base year 2010). HW days count the number of days spent in a heat wave ($T_{MAX} > 30^{\circ}C$) longer than 5 consecutive days. Main covariates: age and age squared by gender, the level of education, the number of books at age 10, part-time and self-employment status. Extended covariates also include the cumulative days lost due to disability (health loss), experience and experience squared, seniority within the job and seniority squared. Clustered standard errors at the location level (sub-minimum NUTS level, the source of temperature variation) are reported in parentheses * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table D29: Effect of Heat Waves (Absolute Measures, $T_{MAX} > 30^{\circ}C$) on Earnings, With Country-Year Linear Trends

	(1)	(2)	(3)	(4)	(5)
HW days ($T_{MAX} > 30^{\circ}C$)	0.000220 (0.0009)	0.000186 (0.0008)	0.00132 (0.0011)	0.00202 (0.0015)	0.00217 (0.0015)
Precipitation control	✓	✓	✓	✓	✓
Location, Generation, Year FE	✓	✓	✓	✓	✓
Main Covariates	✓	✓	✓	✓	✓
Extended Covariates		✓	✓	✓	✓
Country-Year Linear Trends	✓	✓	✓	✓	✓
Individual FE				✓	✓
Individual $\times$ Occupation (ISCO1) FE					✓
Individuals	32,782	32,337	15,580	15,580	15,580
Observations	75,258	73,577	44,271	44,271	44,271
Adjusted R ²	0.51733	0.51741	0.52089	0.66157	0.67177

Notes. The dependent variable is the log transformation of earnings expressed in dollars (base year 2010). HW days count the number of days spent in a heat wave ($T_{MAX} > 30^{\circ}C$) longer than 5 consecutive days. Main covariates: age and age squared by gender, the level of education, the number of books at age 10, part-time and self-employment status. Extended covariates also include the cumulative days lost due to disability (health loss), experience and experience squared, seniority within the job and seniority squared. Clustered standard errors at the location level (sub-minimum NUTS level, the source of temperature variation) are reported in parentheses * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table D30: Effect of Temperature Bins on Earnings, Without Country-Year Linear Trends

	(1)	(2)	(3)	(4)	(5)
$T_{AVG} < -5^{\circ}C$	0.00380*** (0.0013)	0.00342*** (0.0013)	0.00475*** (0.0014)	0.00409*** (0.0015)	0.00309* (0.0016)
$-5^{\circ}C \geq T_{AVG} < 0^{\circ}C$	0.000328 (0.0011)	-0.000114 (0.0011)	0.000893 (0.0011)	0.00132 (0.0013)	0.00104 (0.0013)
$0^{\circ}C \geq T_{AVG} < 5^{\circ}C$	-0.000261 (0.0010)	-0.000419 (0.0010)	0.0000820 (0.0011)	-0.000323 (0.0012)	-0.000724 (0.0012)
$5^{\circ}C \geq T_{AVG} < 10^{\circ}C$	0.000139 (0.0007)	-0.0000106 (0.0007)	0.000355 (0.0008)	0.000148 (0.0009)	0.000140 (0.0009)
$15^{\circ}C \geq T_{AVG} < 20^{\circ}C$	-0.000936* (0.0005)	-0.000852 (0.0005)	-0.000813 (0.0006)	-0.00107 (0.0007)	-0.00112 (0.0007)
$20^{\circ}C \geq T_{AVG} < 25^{\circ}C$	0.00312*** (0.0008)	0.00312*** (0.0007)	0.00348*** (0.0008)	0.00387*** (0.0010)	0.00355*** (0.0010)
$25^{\circ}C \geq T_{AVG} < 30^{\circ}C$	-0.0115*** (0.0017)	-0.0112*** (0.0017)	-0.00942*** (0.0018)	-0.00894*** (0.0022)	-0.00884*** (0.0023)
$T_{AVG} > 30^{\circ}C$	-0.0137*** (0.0044)	-0.0136*** (0.0044)	-0.0211*** (0.0051)	-0.0150** (0.0065)	-0.0154** (0.0068)
Precipitation control	✓	✓	✓	✓	✓
Location, Generation, Year FE	✓	✓	✓	✓	✓
Main Covariates	✓	✓	✓	✓	✓
Extended Covariates		✓	✓	✓	✓
Country-Year Linear Trends					
Individual FE				✓	✓
Individual $\times$ Occupation (ISCO1) FE					✓
Individuals	32,779	32,334	15,580	15,580	15,580
Observations	75,255	73,574	44,271	44,271	44,271
Adjusted R ²	0.46443	0.46458	0.46335	0.60384	0.61780

Notes. The dependent variable is the log transformation of earnings expressed in dollars (base year 2010). The omitted temperature bin is $5^{\circ}C \geq T_{AVG} < 10^{\circ}C$. Main covariates: age and age squared by gender, the level of education, the number of books at age 10, part-time and self-employment status. Extended covariates also include the cumulative days lost due to disability (health loss), experience and experience squared, seniority within the job and seniority squared. Clustered standard errors at the location level (sub-minimum NUTS level, the source of temperature variation) are reported in parentheses * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table D31: Effect of Temperature Bins on Earnings, With Country-Year Linear Trends

	(1)	(2)	(3)	(4)	(5)
$T_{AVG} < -5^{\circ}\text{C}$	0.000270 (0.0008)	0.000486 (0.0008)	0.00116 (0.0010)	0.000860 (0.0012)	0.000280 (0.0013)
$-5^{\circ}\text{C} \geq T_{AVG} < 0^{\circ}\text{C}$	-0.000519 (0.0006)	-0.000214 (0.0006)	0.000645 (0.0008)	0.00143 (0.0009)	0.00111 (0.0009)
$0^{\circ}\text{C} \geq T_{AVG} < 5^{\circ}\text{C}$	-0.000560 (0.0005)	-0.000294 (0.0006)	0.000250 (0.0007)	0.000756 (0.0008)	0.000299 (0.0008)
$5^{\circ}\text{C} \geq T_{AVG} < 10^{\circ}\text{C}$	-0.000467 (0.0005)	-0.000450 (0.0005)	-0.000137 (0.0006)	0.000626 (0.0007)	0.000508 (0.0007)
$15^{\circ}\text{C} \geq T_{AVG} < 20^{\circ}\text{C}$	-0.000975** (0.0005)	-0.00101** (0.0005)	-0.000619 (0.0005)	-0.000636 (0.0006)	-0.000774 (0.0006)
$20^{\circ}\text{C} \geq T_{AVG} < 25^{\circ}\text{C}$	-0.00235*** (0.0005)	-0.00240*** (0.0005)	-0.00194*** (0.0006)	-0.00206*** (0.0007)	-0.00217*** (0.0007)
$25^{\circ}\text{C} \geq T_{AVG} < 30^{\circ}\text{C}$	-0.00177** (0.0008)	-0.00172** (0.0008)	0.000260 (0.0010)	0.000928 (0.0014)	0.000998 (0.0014)
$T_{AVG} > 30^{\circ}\text{C}$	-0.00303 (0.0029)	-0.00289 (0.0029)	-0.000174 (0.0057)	0.00344 (0.0051)	0.00217 (0.0051)
Precipitation control	✓	✓	✓	✓	✓
Location, Generation, Year FE	✓	✓	✓	✓	✓
Main Covariates	✓	✓	✓	✓	✓
Extended Covariates		✓	✓	✓	✓
Country-Year Linear Trends	✓	✓	✓	✓	✓
Individual FE				✓	✓
Individual $\times$ Occupation (ISCO1) FE					✓
Individuals	32,779	32,334	15,580	15,580	15,580
Observations	75,255	73,574	44,271	44,271	44,271
Adjusted R ²	0.51753	0.51762	0.52102	0.66178	0.67197

Notes. The dependent variable is the log transformation of earnings expressed in dollars (base year 2010). The omitted temperature bin is $5^{\circ}\text{C} \geq T_{AVG} < 10^{\circ}\text{C}$. Main covariates: age and age squared by gender, the level of education, the number of books at age 10, part-time and self-employment status. Extended covariates also include the cumulative days lost due to disability (health loss), experience and experience squared, seniority within the job and seniority squared. Clustered standard errors at the location level (sub-minimum NUTS level, the source of temperature variation) are reported in parentheses * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

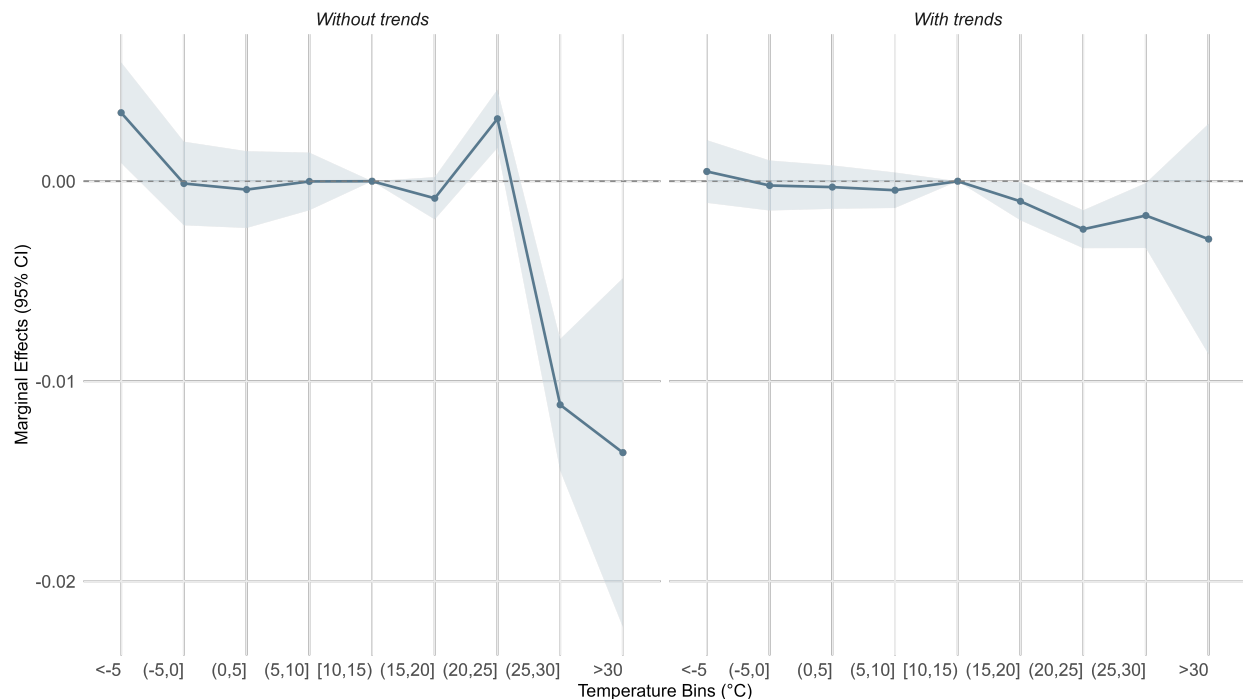


Figure D4: Effect of Temperature Bins on Earnings, With Country-Year Linear Trends

Notes. The figure displays the estimates from column (2) of Tables D30 and D31, without and with country-year linear trends, respectively. The dependent variable is the log transformation of earnings expressed in dollars (base year 2010). The omitted temperature bin is $5^{\circ}\text{C} \geq T_{\text{AVG}} < 10^{\circ}\text{C}$. Main covariates: age and age squared by gender, the level of education, the number of books at age 10, part-time and self-employment status. Extended covariates also include the cumulative days lost due to disability (health loss), experience and experience squared, seniority within the job and seniority squared. Clustered standard errors at the location level (sub-minimum NUTS level, the source of temperature variation) are reported in parentheses * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

E Additional Results: Distributional and Heterogeneous Effects of Heat Waves

Table E32: Effect of Heat Waves on Monthly Earnings, Heterogeneity by Occupation and Sector

	(1)	(2)	(3)	(4)
HW days ($T_{MAX} > 95\text{th perc}$)	-0.00263*** (0.0009)	-0.000138 (0.0024)	-0.00219*** (0.0008)	-0.00343* (0.0019)
<i>Panel A: By Exposed Sectors</i>				
Exposed Sectors x HW ($T_{MAX} > 95\text{th perc}$)	-0.00120 (0.0011)			
<i>Panel B: By Sector</i>				
Agriculture & Fishing x HW ($T_{MAX} > 95\text{th perc}$)		-0.00967** (0.0048)		
Construction x HW ($T_{MAX} > 95\text{th perc}$)		-0.00161 (0.0034)		
Industry x HW ($T_{MAX} > 95\text{th perc}$)		-0.00264 (0.0027)		
Wholesale & Retail Trade x HW ($T_{MAX} > 95\text{th perc}$)		-0.00482 (0.0031)		
Transport, Hospitality & Storage x HW ($T_{MAX} > 95\text{th perc}$)		-0.00316 (0.0029)		
Public & Other Services x HW ($T_{MAX} > 95\text{th perc}$)		-0.00248 (0.0026)		
<i>Panel C: By Exposed Occupations</i>				
Outdoor Exposed Occupations x HW ($T_{MAX} > 95\text{th perc}$)			-0.00353* (0.0018)	
<i>Panel D: By Occupations</i>				
Elementary (Outdoor) x HW ($T_{MAX} > 95\text{th perc}$)				0.00163 (0.0031)
Manual (Indoor) x HW ($T_{MAX} > 95\text{th perc}$)				0.00346 (0.0024)
Manual (Outdoor) x HW ($T_{MAX} > 95\text{th perc}$)				-0.00424 (0.0029)
Clerical (Indoor) x HW ($T_{MAX} > 95\text{th perc}$)				0.00121 (0.0021)
Clerical (Outdoor) x HW ($T_{MAX} > 95\text{th perc}$)				-0.00833* (0.0047)
Abstract (Indoor) x HW ($T_{MAX} > 95\text{th perc}$)				0.000962 (0.0022)
Abstract (Outdoor) x HW ($T_{MAX} > 95\text{th perc}$)				0.00719 (0.0052)
Precipitation control	✓	✓	✓	✓
Location, Generation, Year FE	✓	✓	✓	✓
Covariates	✓	✓	✓	✓
Country-Year Linear Trends	✓	✓	✓	✓
Individuals	32,269	32,269	30,318	30,218
Observations	73,413	73,413	67,355	67,057
Adjusted R ²	0.51793	0.52036	0.51738	0.52807

Notes. The dependent variable is the log transformation of earnings expressed in dollars (base year 2010). HW days count the number of days spent in a heat wave ($T_{MAX} > 95\text{th perc}$) > 5 consecutive days. The reference category is Not Exposed Sectors in column (1); Financial, Real Estate and Business in column (2); Not Outdoor Exposed Occupations in column (3); and Armed Forces, Managers, Professionals in column (4). Covariates: age and age squared by gender, experience and experience squared, seniority within the job and seniority squared, part-time and self-employment status, level of education, cumulative days lost due to disability (health loss), and the number of books at age 10. Clustered standard errors at the location level (sub-minimum NUTS level, the source of temperature variation) are reported in parentheses * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table E33: Sorting into Exposed Occupations and Sectors

	(1) Exposed Occupations	(2) Exposed Sectors
Female	-0.219*** (0.010)	-0.282*** (0.012)
25 ≤ Age < 45	-0.0286*** (0.008)	0.00105 (0.011)
Age ≥ 45	-0.0408*** (0.011)	0.0172 (0.015)
Female x 25 ≤ Age < 45	0.0613*** (0.009)	-0.0145 (0.012)
Female x Age ≥ 45	0.0664*** (0.010)	-0.0209* (0.012)
Lower Secondary Edu	-0.0552*** (0.008)	-0.0514*** (0.009)
Upper Secondary Edu	-0.0992*** (0.007)	-0.103*** (0.009)
Tertiary Edu	-0.162*** (0.008)	-0.208*** (0.011)
One shelf of books (at age 10)	-0.0275*** (0.006)	-0.0270*** (0.007)
One bookcase (at age 10)	-0.0355*** (0.006)	-0.0391*** (0.007)
Two bookcases (at age 10)	-0.0347*** (0.008)	-0.0450*** (0.009)
More than two bookcases (at age 10)	-0.0454*** (0.006)	-0.0706*** (0.009)
Health Loss	0.00495 (0.007)	0.00144 (0.010)
Experience	-0.00247*** (0.000)	0.00125* (0.001)
Experience Squared	0.0000668*** (0.000)	-0.0000252* (0.000)
Location, Generation, Year FE	✓	✓
Country-Year Time Trends	✓	✓
Individuals	30,310	32,261
Observations	54,741	59,768
Adjusted R ²	0.14515	0.17010

Notes. The table reports OLS estimates of a linear probability model (LPM). The dependent variable is the dummy for exposed outdoor-occupations in column (1) and a dummy for exposed sectors in column (2). The reference category is Male for gender; Age < 25 for age group; Good Health (Health Loss < 95th percentile) for health loss; No or primary education for education level; None or very few books (at age 10) for parental background. Clustered standard errors at the location level (sub-minimum NUTS level, the source of temperature variation) are reported in parentheses * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table E34: Effect of Heat Waves on Monthly Earnings, Heterogeneity by Socio-demographic Factors

	(1)	(2)	(3)	(4)	(5)
HW days ($T_{MAX} > 95\text{th perc}$)	-0.00303*** (0.0010)	-0.00112 (0.0020)	-0.00302*** (0.0009)	-0.00513*** (0.0015)	-0.00505*** (0.0012)
<i>By Gender</i>					
Female x HW ($T_{MAX} > 95\text{th perc}$)	-0.000216 (0.0011)				
<i>By Age</i>					
$25 \leq \text{Age} < 45$ x HW ($T_{MAX} > 95\text{th perc}$)		-0.00293 (0.0024)			
$\text{Age} \geq x$ HW ($T_{MAX} > 95\text{th perc}$)		-0.00247			
<i>By Health Condition</i>					
Health Loss x HW ($T_{MAX} > 95\text{th perc}$)			-0.00177 (0.0022)		
<i>By Education</i>					
Lower Secondary Edu x HW ($T_{MAX} > 95\text{th perc}$)				0.000746 (0.0020)	
Upper Secondary Edu x HW ($T_{MAX} > 95\text{th perc}$)				0.00285* (0.0017)	
Tertiary Edu x HW ($T_{MAX} > 95\text{th perc}$)				0.00404** (0.0018)	
<i>By Parental Background</i>					
One shelf of books (at age 10) x HW ($T_{MAX} > 95\text{th perc}$)					0.00304** (0.0014)
One bookcase (at age 10) x HW ($T_{MAX} > 95\text{th perc}$)					0.00244 (0.0018)
Two bookcases (at age 10) x HW ($T_{MAX} > 95\text{th perc}$)					0.00498*** (0.0019)
More than two bookcases (at age 10) x HW ($T_{MAX} > 95\text{th perc}$)					0.00516** (0.0021)
Precipitation, Geo id, Generation, Year FE	✓	✓	✓	✓	✓
Covariates	✓	✓	✓	✓	✓
Country-Year Linear Trends	✓	✓	✓	✓	✓
Individuals	32,337	32,337	32,390	32,337	32,337
Observations	73,577	73,577	73,661	73,577	73,577
Adjusted R ²	0.51639	0.50783	0.51769	0.51757	0.51758

Notes. The dependent variable is the log transformation of earnings expressed in dollars (base year 2010). HW days count the number of days spent in a heat wave ($T_{MAX} > 95\text{th perc}$) > 5 consecutive days. The reference category is Male in column (1); Age < 25 in column (2); Good Health (Health Loss $< 95\text{th}$ percentile) in column (3); No education in column (4); None or very few books (at age 10) in column (5). Covariates: age and age squared by gender, experience and experience squared, seniority within the job and seniority squared, part-time and self-employment status, level of education, cumulative days lost due to disability (health loss), and the number of books at age 10. In each column, the covariate corresponding to the heterogeneity dimension is excluded from the set of controls. Clustered standard errors at the location level (sub-minimum NUTS level, the source of temperature variation) are reported in parentheses * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

F Additional Results: Unconditional Quantile Regression

Table F35: Unconditional Quantile Regression

HW days ($T_{MAX} > 95th\ perc$)	q5	q10	q20	q30	q40	q50
	-0.0131*** (0.004)	-0.00235 (0.003)	-0.00165 (0.002)	-0.000147 (0.001)	-0.00169 (0.001)	-0.00261** (0.001)
	q60	q70	q80	q90	q95	
	-0.00164 (0.001)	-0.00167 (0.001)	-0.000253 (0.001)	-0.00268** (0.001)	-0.00409*** (0.001)	
Precipitation, Geo id, Generation, Year FE	✓	✓	✓	✓	✓	✓
Main Covariates	✓	✓	✓	✓	✓	✓
Extended Covariates	✓	✓	✓	✓	✓	✓
Country-Year Linear Trends	✓	✓	✓	✓	✓	✓
Individual FE						
Individuals	32,364	32,364	32,364	32,364	32,364	32,364
Observations	32,364	32,364	32,364	32,364	32,364	32,364
	73,514	73,514	73,514	73,514	73,514	73,514
	73,514	73,514	73,514	73,514	73,514	73,514
Adjusted R ²	0.16306	0.24717	0.35730	0.41993	0.44087	0.43430
	0.40975	0.36052	0.28718	0.19674	0.14299	

Notes. The table reports estimates from 11 separate regressions, each using as the dependent variable the RIF (Recentered Influence Function) transformation corresponding to a specific decile of the dependent variable (the log of income in 2010 U.S. dollars). HW days count the number of days spent in a heat wave ($T_{MAX} > 95th\ perc$) longer than 5 consecutive days. Main covariates: age and age squared by gender, experience and experience squared, seniority within the job and seniority squared, part-time and self-employment status. Extended covariates also include the level of education, the cumulative days lost due to disability (health loss), and the number of books at age 10. Clustered standard errors at the location level (sub-minimum NUTS level, the source of temperature variation) are reported in parentheses * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table F36: Unconditional Quantile Regression, Heterogeneity by Sector

HW days ($T_{MAX} > 95th\text{ perc}$)						
	q5	q10	q20	q30	q40	q50
Outdoor Exposed Sectors $\times$ HW ($T_{MAX} > 95th\text{ perc}$)	-0.00917** (0.004)	0.000810 (0.003)	-0.000199 (0.002)	-0.000315 (0.002)	-0.00180 (0.001)	-0.00261** (0.001)
	-0.00965 (0.006)	-0.00795** (0.004)	-0.00362 (0.003)	0.000216 (0.002)	0.000203 (0.002)	-0.0000840 (0.002)
	q60	q70	q80	q90	q95	
	-0.00153 (0.001)	-0.00154 (0.001)	0.000292 (0.001)	-0.00319** (0.001)	-0.00364** (0.002)	
	-0.000319 (0.001)	-0.000313 (0.001)	-0.00143 (0.001)	0.00114 (0.002)	-0.00138 (0.002)	
Precipitation control	✓	✓	✓	✓	✓	✓
Geo id, Generation, Year FE	✓	✓	✓	✓	✓	✓
Main Covariates	✓	✓	✓	✓	✓	✓
Extended Covariates	✓	✓	✓	✓	✓	✓
Country-Year Linear Trends	✓	✓	✓	✓	✓	✓
Individuals	32,296	32,296	32,296	32,296	32,296	32,296
Observations	32,296	32,296	32,296	32,296	32,296	73,347
	73,347	73,347	73,347	73,347	73,347	73,347
	73,347	73,347	73,347	73,347	73,347	
Adjusted R ²	0.16292	0.24744	0.35772	0.42001	0.44109	0.43452
	0.40994	0.36065	0.28764	0.19721	0.14355	

Notes. The table reports the marginal effect by occupation from 11 separate regressions, each using as the dependent variable the RIF (Recentered Influence Function) transformation corresponding to a specific decile of the dependent variable (the log of earnings in 2010 U.S. dollars). HW days count the number of days spent in a heat wave ($T_{MAX} > 95th\text{ perc}$) longer than 5 consecutive days. Main covariates: age and age squared by gender, experience and experience squared, seniority within the job and seniority squared, part-time and self-employment status. Extended covariates also include the level of education, the cumulative days lost due to disability (health loss), and the number of books at age 10. Clustered standard errors at the location level (sub-minimum NUTS level, the source of temperature variation) are reported in parentheses * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table F37: Unconditional Quantile Regression, Heterogeneity by Occupation

	q5	q10	q20	q30	q40	q50
HW days ($T_{MAX} > 95th$ perc)	-0.00691* (0.004)	0.000494 (0.003)	-0.000357 (0.002)	0.000490 (0.001)	-0.000687 (0.001)	-0.00155 (0.001)
Outdoor Exposed Occupations x HW ($T_{MAX} > 95th$ perc)	-0.0251*** (0.009)	-0.0118*** (0.004)	-0.00537* (0.003)	-0.00173 (0.003)	-0.00197 (0.002)	-0.000886 (0.002)
	q60	q70	q80	q90	q95	
	-0.00157 (0.001)	-0.00163 (0.001)	0.0000776 (0.001)	-0.00207 (0.001)	-0.00367** (0.001)	
	0.00163 (0.002)	-0.000144 (0.002)	-0.00217 (0.002)	-0.00408* (0.002)	-0.00296 (0.002)	
Precipitation control	✓	✓	✓	✓	✓	✓
Geo id, Generation, Year FE	✓	✓	✓	✓	✓	✓
Main Covariates	✓	✓	✓	✓	✓	✓
Extended Covariates	✓	✓	✓	✓	✓	✓
Country-Year Linear Trends	✓	✓	✓	✓	✓	✓
Individuals	30,347 30,347	30,347 30,347	30,347 30,347	30,347 30,347	30,347 30,347	30,347
Observations	67,288 67,288	67,288 67,288	67,288 67,288	67,288 67,288	67,288 67,288	67,288
Adjusted R ²	0.16377 0.40569	0.24784 0.36079	0.35750 0.28514	0.42146 0.19773	0.44062 0.14238	0.43152

Notes. The table reports the marginal effect by occupation from 11 separate regressions, each using as the dependent variable the RIF (Recentered Influence Function) transformation corresponding to a specific decile of the dependent variable (the log of earnings in 2010 U.S. dollars). HW days count the number of days spent in a heat wave ($T_{MAX} > 95th$ perc) longer than 5 consecutive days. Main covariates: age and age squared by gender, experience and experience squared, seniority within the job and seniority squared, part-time and self-employment status. Extended covariates also include the level of education, the cumulative days lost due to disability (health loss), and the number of books at age 10. Clustered standard errors at the location level (sub-minimum NUTS level, the source of temperature variation) are reported in parentheses * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

G Additional Results: Mediating Role of Labor Market Institutions

Table G38: Effect of Heat Waves on Monthly Earnings: Heterogeneity by Collective Bargaining Institutions (Full-Time Workers)

	(1)	(2)	(3)	(4)	(5)	(6)
HW days ($T_{MAX} > 95$ th perc)	-0.00876*** (0.0020)	-0.0113*** (0.0042)	-0.00173* (0.0010)	-0.00310* (0.0017)	-0.00370*** (0.0011)	-0.00387*** (0.0010)
Some coord. $\times$ HW	0.00354 (0.0030)					
Procedural guidelines $\times$ HW	0.00569** (0.0024)					
Non-binding norms $\times$ HW	0.00720*** (0.0022)					
Binding norms $\times$ HW	0.0123*** (0.0025)					
Sector/firm mix $\times$ HW		0.00866 (0.0059)				
Sectoral $\times$ HW		0.00678 (0.0041)				
Central/sector mix $\times$ HW		0.0102** (0.0044)				
Central $\times$ HW		0.0143*** (0.0045)				
Minimum Wage $\times$ HW			0.00225 (0.0015)			
UD $\times$ HW				0.00000285 (0.0000)		
UD $> p66 \times$ HW					0.00215 (0.0016)	
Non-wage opening clauses $\times$ HW						0.00917*** (0.0020)
Wage opening clauses $\times$ HW						0.00694*** (0.0025)
Precipitation control	Yes	Yes	Yes	Yes	Yes	Yes
Geo id, Generation, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Bargaining variable	Coordination	Level	Min. Wage	UD	UD $> p66$	OCG
Individuals	28,845	28,845	24,250	26,179	26,179	27,543
Observations	61,078	61,078	39,848	57,393	57,393	59,162
Adjusted R ²	0.54328	0.54280	0.58119	0.54147	0.54148	0.53091

Notes. The sample includes only full-time workers. The dependent variable is the log transformation of earnings expressed in dollars (base year 2010). HW days count the number of days spent in a heat wave ($T_{MAX} > 95$ th perc) longer than 5 consecutive days. Each column interacts HW days with a distinct measure of labor market institutions. Columns (1)–(2) use ordered categorical measures of wage-setting coordination (5 categories, from fragmented to fully centralized) and the predominant level of bargaining (5 categories, from firm-level to economy-wide), respectively, with the lowest category as baseline. Column (3) interacts with a dummy for minimum wage. Columns (4)–(5) interact with union density — the share of employees holding trade union membership — entered respectively as a continuous variable and as an indicator for above-66th-percentile density. Column (6) captures opening clauses (OCG) in sectoral agreements (0=none; 1=non-wage renegotiation allowed; 2=wage renegotiation allowed; baseline: OCG=0). Standard errors clustered at the sub-national (sub-minimum NUTS) level in parentheses. Covariates: age and age squared by gender, experience and experience squared, seniority within the job and seniority squared, part-time and self-employment status, level of education, cumulative days lost due to disability (health loss), and the number of books at age 10. Clustered standard errors at the location level (sub-minimum NUTS level, the source of temperature variation) are reported in parentheses * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table G39: Effect of Heat Waves on Monthly Earnings: Heterogeneity by Collective Bargaining Institutions (Employed Workers)

	(1)	(2)	(3)	(4)	(5)	(6)
HW days ($T_{MAX} > 95\text{th perc}$)	-0.00654*** (0.0019)	-0.00878** (0.0041)	-0.00231** (0.0010)	-0.00325** (0.0015)	-0.00362*** (0.0010)	-0.00351*** (0.0009)
Some coord. $\times$ HW	0.00105 (0.0029)					
Procedural guidelines $\times$ HW	0.00308 (0.0024)					
Non-binding norms $\times$ HW	0.00434** (0.0020)					
Binding norms $\times$ HW	0.00937*** (0.0024)					
Sector/firm mix $\times$ HW		0.00482 (0.0053)				
Sectoral $\times$ HW		0.00456 (0.0041)				
Central/sector mix $\times$ HW		0.00816* (0.0044)				
Central $\times$ HW		0.0112** (0.0045)				
Minimum Wage $\times$ HW			0.00300** (0.0014)			
UD $\times$ HW				0.00000806 (0.0000)		
UD > p66 $\times$ HW					0.00211 (0.0014)	
Non-wage opening clauses $\times$ HW						0.00667*** (0.0017)
Wage opening clauses $\times$ HW						0.00460* (0.0024)
Precipitation control	Yes	Yes	Yes	Yes	Yes	Yes
Geo id, Generation, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Bargaining variable	Coordination	Level	Min. Wage	UD	UD > p66	UD > p75
Individuals	29,750	29,750	25,460	27,425	27,425	
Observations	65,782	65,782	43,638	62,458	62,458	63,862
Adjusted R ²	0.55439	0.55380	0.60262	0.55181	0.55185	0.54299

Notes. The sample includes only employed workers. The dependent variable is the log transformation of earnings expressed in dollars (base year 2010). HW days count the number of days spent in a heat wave ($T_{MAX} > 95\text{th perc}$) longer than 5 consecutive days. Each column interacts HW days with a distinct measure of labor market institutions. Columns (1)–(2) use ordered categorical measures of wage-setting coordination (5 categories, from fragmented to fully centralized) and the predominant level of bargaining (5 categories, from firm-level to economy-wide), respectively, with the lowest category as baseline. Column (3) interacts with a dummy for minimum wage. Columns (4)–(5) interact with union density — the share of employees holding trade union membership — entered respectively as a continuous variable and as an indicator for above-66th-percentile density. Column (6) captures opening clauses (OCG) in sectoral agreements (0=none; 1=non-wage renegotiation allowed; 2=wage renegotiation allowed; baseline: OCG=0). Standard errors clustered at the sub-national (sub-minimum NUTS) level in parentheses. Covariates: age and age squared by gender, experience and experience squared, seniority within the job and seniority squared, part-time and self-employment status, level of education, cumulative days lost due to disability (health loss), and the number of books at age 10. Clustered standard errors at the location level (sub-minimum NUTS level, the source of temperature variation) are reported in parentheses * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table G40: Heterogeneity by Collective Bargaining Institutions - Interaction with Exposed Industry

	(1)	(2)	(3)	(4)	(5)	(6)
HW days ($T_{MAX} > 95$ th perc)	-0.00824*** (0.0023)	-0.00727 (0.0054)	-0.00328*** (0.0011)	-0.00398** (0.0017)	-0.00429*** (0.0011)	-0.00368*** (0.0010)
Exposed Industry $\times$ HW	0.000158 (0.0032)	-0.00513 (0.0079)	0.00308** (0.0015)	-0.0000450 (0.0024)	0.00000473 (0.0015)	-0.000867 (0.0014)
Some coord. $\times$ HW	0.00389 (0.0032)					
Procedural guidelines $\times$ HW	0.00502** (0.0025)					
Non-binding norms $\times$ HW	0.00571** (0.0025)					
Binding norms $\times$ HW	0.0111*** (0.0030)					
Exposed Industry $\times$ Some coord. $\times$ HW	-0.00444 (0.0044)					
Exposed Industry $\times$ Procedural guidelines $\times$ HW	-0.00124 (0.0037)					
Exposed Industry $\times$ Non-binding norms $\times$ HW	0.000716 (0.0037)					
Exposed Industry $\times$ Binding norms $\times$ HW	0.000831 (0.0042)					
Sector/firm mix $\times$ HW		0.00320 (0.0076)				
Sectoral $\times$ HW		0.00268 (0.0054)				
Central/sector mix $\times$ HW		0.00739 (0.0056)				
Central $\times$ HW		0.00986* (0.0058)				
Exposed Industry $\times$ Sector/firm mix $\times$ HW		0.00494 (0.0104)				
Exposed Industry $\times$ Sectoral $\times$ HW		0.00477 (0.0080)				
Exposed Industry $\times$ Central/sector mix $\times$ HW		0.00108 (0.0084)				
Exposed Industry $\times$ Central $\times$ HW		0.00572 (0.0084)				
Minimum Wage $\times$ HW			0.00435*** (0.0016)			
Exposed Industry $\times$ Min. Wage $\times$ HW			-0.00497** (0.0024)			
UD $\times$ HW				0.0000195 (0.0000)		
Exposed Industry $\times$ UD $\times$ HW				-0.0000113 (0.0000)		
UD $>$ p66 $\times$ HW					0.00345** (0.0017)	
Exposed Industry $\times$ UD $>$ p66 $\times$ HW					-0.00179 (0.0025)	
Non-wage opening clauses $\times$ HW						0.00690*** (0.0021)
Wage opening clauses $\times$ HW						0.00399 (0.0027)
Exposed Industry $\times$ Non-wage clauses $\times$ HW						0.000576 (0.0029)
Exposed Industry $\times$ Wage clauses $\times$ HW						0.00491 (0.0040)
Precipitation control	Yes	Yes	Yes	Yes	Yes	Yes
Geo id, Generation, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Bargaining variable	Coordination	Level	Min. Wage	UD	UD $>$ p66	UD $>$ p75
Individuals	31,583	31,583	27,758	28,824	28,824	
Observations	70,832	70,832	47,895	66,961	66,961	68,773
Adjusted R ²	0.53658	0.53600	0.57675	0.53414	0.53416	0.52500

Notes. The dependent variable is the log transformation of earnings expressed in dollars (base year 2010). HW days count the number of days spent in a heat wave ($T_{MAX} > 95$ th perc) longer than 5 consecutive days. Each column adds a triple interaction between *HW days*, a labour-market institution measure, and *Exposed Industry* (= 1 for the exposed group, baseline = 0). Columns (1)–(2) use ordered categorical measures of wage-setting coordination (5 categories, from fragmented to fully centralized) and the predominant level of bargaining (5 categories, from firm-level to economy-wide), respectively, with the lowest category as baseline. Column (3) interacts with a dummy for minimum wage. Columns (4)–(5) interact with union density — the share of employees holding trade union membership — entered respectively as a continuous variable and as an indicator for above-66th-percentile density. Column (6) captures opening clauses (OCC) in sectoral agreements (0=none; 1=non-wage renegotiation allowed; 2=wage renegotiation allowed; baseline: OCC=0). Standard errors clustered at the sub-national (sub-minimum NUTS) level in parentheses. Covariates: age and age squared by gender, experience and experience squared, seniority within the job and seniority squared, part-time and self-employment status, level of education, cumulative days lost due to disability (health loss), and the number of books at age 10. Clustered standard errors at the location level (sub-minimum NUTS level, the source of temperature variation) are reported in parentheses * ($p < 0.10$), ** ($p < 0.05$), *** $p < 0.01$.

Table G41: Effect of Heat Waves on Monthly Earnings: Heterogeneity by Collective Bargaining Institutions - Interaction with Outdoor Occupation

	(1)	(2)	(3)	(4)	(5)	(6)
HW days ($T_{MAX} > 95$ th perc)	-0.00715*** (0.0020)	-0.00669 (0.0051)	-0.00173* (0.0010)	-0.00302* (0.0016)	-0.00329*** (0.0010)	-0.00278*** (0.0009)
Outdoor Occupation $\times$ HW	-0.00210 (0.0044)	-0.000728 (0.0089)	-0.000745 (0.0026)	0.000239 (0.0039)	-0.00304 (0.0023)	-0.00609*** (0.0024)
Some coord. $\times$ HW	0.00318 (0.0028)					
Procedural guidelines $\times$ HW	0.00392 (0.0025)					
Non-binding norms $\times$ HW	0.00568** (0.0023)					
Binding norms $\times$ HW	0.0102*** (0.0026)					
Outdoor Occupation $\times$ Some coord. $\times$ HW	-0.00767 (0.0070)					
Outdoor Occupation $\times$ Procedural guidelines $\times$ HW	0.00248 (0.0055)					
Outdoor Occupation $\times$ Non-binding norms $\times$ HW	-0.00225 (0.0051)					
Outdoor Occupation $\times$ Binding norms $\times$ HW	0.00204 (0.0062)					
Sector/firm mix $\times$ HW		0.00480 (0.0064)				
Sectoral $\times$ HW		0.00294 (0.0051)				
Central/sector mix $\times$ HW		0.00631 (0.0052)				
Central $\times$ HW		0.00960* (0.0054)				
Outdoor Occupation $\times$ Sector/firm mix $\times$ HW		-0.00689 (0.0118)				
Outdoor Occupation $\times$ Sectoral $\times$ HW		-0.00319 (0.0093)				
Outdoor Occupation $\times$ Central/sector mix $\times$ HW		-0.00333 (0.0099)				
Outdoor Occupation $\times$ Central $\times$ HW		0.00168 (0.0101)				
Minimum Wage $\times$ HW			0.00303** (0.0015)			
Outdoor Occupation $\times$ Min. Wage $\times$ HW			-0.000394 (0.0038)			
UD $\times$ HW				0.0000134 (0.0000)		
Outdoor Occupation $\times$ UD $\times$ HW				-0.000105 (0.0001)		
UD $> p66 \times$ HW					0.00247 (0.0016)	
Outdoor Occupation $\times$ UD $> p66 \times$ HW					-0.00142 (0.0038)	
Non-wage opening clauses $\times$ HW						0.00533*** (0.0018)
Wage opening clauses $\times$ HW						0.00622** (0.0024)
Outdoor Occupation $\times$ Non-wage clauses $\times$ HW						0.0116*** (0.0040)
Outdoor Occupation $\times$ Wage clauses $\times$ HW						0.00624 (0.0051)
Precipitation control	Yes	Yes	Yes	Yes	Yes	Yes
Geo id, Generation, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Main Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Extended Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Bargaining variable	Coordination	Level	Min. Wage	UD	UD $> p66$	UD $> p75$
Individuals	29,651	29,651	25,874	27,202	27,202	
Observations	64,955	64,955	43,528	61,569	61,569	63,174
Adjusted R ²	0.53670	0.53604	0.57916	0.53411	0.53409	0.52578

Notes. The dependent variable is the log transformation of earnings expressed in dollars (base year 2010). HW days count the number of days spent in a heat wave ($T_{MAX} > 95$ th perc) longer than 5 consecutive days. Each column adds a triple interaction between *HW days*, a labour-market institution measure, and *Outdoor Occupation* (= 1 for the exposed group, baseline = 0). Columns (1)–(2) use ordered categorical measures of wage-setting coordination (5 categories, from fragmented to fully centralized) and the predominant level of bargaining (5 categories, from firm-level to economy-wide), respectively, with the lowest category as baseline. Column (3) interacts with a dummy for minimum wage. Columns (4)–(5) interact with union density — the share of employees holding trade union membership — entered respectively as a continuous variable and as an indicator for above-66th-percentile density. Column (6) captures opening clauses (OCG) in sectoral agreements (0=none; 1=non-wage renegotiation allowed; 2=wage renegotiation allowed; baseline: OCG=0). Standard errors clustered at the sub-national (sub-minimum NUTS) level in parentheses. Covariates: age and age squared by gender, experience and experience squared, seniority within the job and seniority squared, part-time and self-employment status, level of education, cumulative days lost due to disability (health loss), and the number of books at age 10. Clustered standard errors at the location level (sub-minimum NUTS level, the source of temperature variation) are reported in parentheses * ($p < 0.10$), ** ($p < 0.05$), ***.

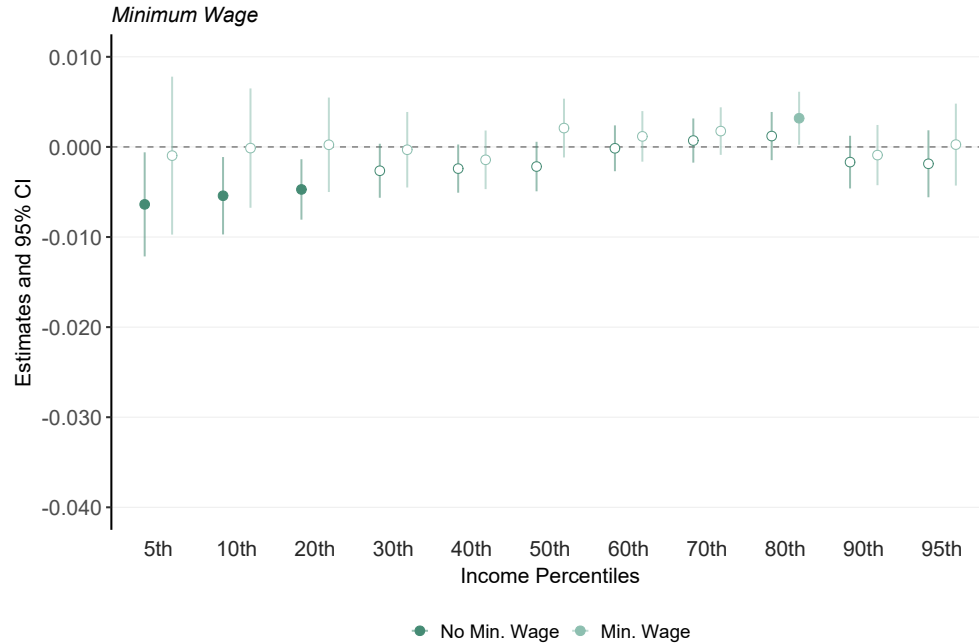


Figure G5: Temperature Impact on Earnings across the Distribution: Heterogeneity by Minimum Wage

The figure displays estimates and 95% confidence intervals from 11 separate RIF-regressions (Recentered Influence Function) for each quantile of the log earnings distribution (in 2010 U.S. dollars), interacted with a dummy for minimum wage. HW days count the number of days spent in a heat wave ($T_{MAX} > 95\text{th percentile}$) longer than 5 consecutive days. All regressions include fixed effects for location, generation, and year, as well as a second-degree polynomial in annual average precipitation and country-year linear time trends. Covariates include age and age squared by gender, the level of education, the cumulative days lost due to disability (health loss), number of books at age 10, experience and experience squared, job seniority and its square, and indicators for part-time and self-employment status. Filled markers denote estimates statistically different from zero at the 10% level; hollow markers denote insignificant estimates. Clustered standard errors at sub-minimum NUTS level. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

H Quantification of the Impacts

Table H42: Quantification of the Average Annual Loss in Earnings by Category

	Marginal Effect	Avg. Monthly Earnings (\$)	Avg. Annual Heat Waves (days)	Avg. Annual Loss (\$)	% Loss on Annual Earnings
Full Sample	-0.00310***	2,070.14	2.91	-159.63	-0.64
Not-Exposed Sectors	-0.00263**	2,101.29	2.91	-137.47	-0.55
Exposed Sectors	-0.00383***	1,852.06	2.99	-181.30	-0.82
Financial, Real Estate & Business	-0.00014	2,592.06	2.96	-9.18	-0.03
Agriculture & Fishing	-0.00981**	1,632.89	3.03	-414.89	-2.12
Construction	-0.00175	2,310.44	2.97	-102.65	-0.37
Industry	-0.00278**	2,016.21	2.88	-137.99	-0.57
Wholesale & Retail Trade	-0.00496**	1,804.34	2.79	-213.44	-0.99
Transport, Hospitality & Storage	-0.00329*	2,091.06	2.95	-173.48	-0.69
Public & Other Services	-0.00262**	2,111.81	2.92	-138.10	-0.54
Not-Exposed Occupations	-0.00219**	2,101.29	2.91	-114.47	-0.45
Exposed Occupations	-0.00572**	1,852.06	3.01	-272.57	-1.23
Elementary (Indoor)	-0.00343*	1,360.52	3.20	-127.65	-0.78
Elementary (Outdoor)	-0.00247*	1,470.11	3.17	-98.39	-0.56
Manual (Indoor)	0.00376	1,774.35	2.80	159.68	0.75
Manual (Outdoor)	-0.00767**	1,896.88	3.02	-375.58	-1.65
Clerical (Indoor)	-0.00223*	1,825.07	2.87	-99.85	-0.46
Clerical (Outdoor)	-0.01176**	1,786.97	2.74	-492.19	-2.30
Abstract (Indoor)	-0.00247*	2,744.70	2.90	-168.06	-0.51
Abstract (Outdoor)	0.00376	2,645.02	2.66	226.13	0.71
Full Sample (5th perc)	-0.01341***	136.06	2.31	-36.03	-2.21
Full Sample (95th perc)	-0.00641***	7,540.31	2.73	-1,127.90	-1.25
Exposed Sectors (5th perc)	-0.01358***	128.05	2.63	-39.09	-2.54
Exposed Sectors (95th perc)	-0.00691***	7,509.56	2.48	-1,100.03	-1.22
Exposed Occupations (5th perc)	-0.02387***	128.05	2.63	-68.71	-4.47
Exposed Occupations (95th perc)	-0.00880***	7,509.56	2.48	-1,400.91	-1.55
Age <25 y/o	-0.00112	1,553.75	2.25	-33.47	-0.18
Age 25-44 y/o	-0.00406**	2,297.53	3.04	-242.39	-0.88
Age >44 y/o	-0.00359***	2,241.37	3.22	-221.48	-0.82
Male	-0.00303***	2,464.74	2.93	-187.04	-0.63
Female	-0.00324***	1,652.43	2.88	-131.80	-0.66
No/Primary Edu	-0.00513***	1,695.29	3.40	-252.76	-1.24
Lower Secondary Edu	-0.00438**	1,675.33	3.05	-191.31	-0.95
Upper Secondary Edu	-0.00228*	1,962.75	2.74	-104.81	-0.45
Tertiary Edu	-0.00109	2,688.15	2.78	-69.63	-0.22
Health Good/Moderate Healthy	-0.00302***	2,053.81	2.92	-154.81	-0.63
Health Sick	-0.00479*	1,964.24	3.20	-257.36	-1.09
None/few books (at age 10)	-0.00505***	1,749.62	3.12	-235.64	-1.12
One shelf (at age 10)	-0.00201	1,959.81	2.86	-96.30	-0.41
One bookcase (at age 10)	-0.00261	2,205.99	2.77	-136.33	-0.51
Two bookcases (at age 10)	-0.00007	2,422.66	2.81	-4.07	-0.01
More than two bookcases (at age 10)	0.00011	2,625.52	2.78	6.86	0.02

Notes. Average annual earnings losses are computed by multiplying the average monthly earnings of each subgroup by 12 (months), the subgroup-specific marginal effect, and the share of working days in a year (260/365) of the average number of heat wave days for that subgroup. The final column expresses the implied loss as a percentage of annual earnings.