December 2024

Fondazione Eni Enrico Mattei

Working Paper

31.2024

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

Giulia Valenti, Francesco Vona

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

Giulia Valenti (Ca' Foscari University of Venice and Fondazione Eni Enrico Mattei); **Francesco Vona** (University of Milan and Fondazione Eni Enrico Mattei)

Summary

We investigate the impact of heat waves on individual earnings using retrospective panel data (SHARE) matched with high-resolution weather data (E-OBS), covering over 32000 work-ers across 14 European countries (1955–2019) from diverse sectors and occupations. Exploiting plausibly exogenous variation in heat wave exposure across cohorts within the same genera-tion and region, and controlling for individual fixed effects, occupational sorting, and covariate balance, we find each additional heat wave day reduces earnings by 0.31%. Losses are larger in outdoor, manual, and clerical occupations, disproportionately affecting lower-income work-ers and those from disadvantaged family backgrounds, but are mitigated in countries with centralized collective bargaining.

Keywords: Temperature, Heat Waves, Earnings, Labor Market, Inequalities, Climate Change

JEL classification: J30, Q54

Corresponding Author
Giulia Valenti
Fondazione Eni Enrico Mattei
Corso Magenta, 63 - 20123 Milano
e-mail: giulia.valenti@feem.it

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

Giulia Valenti[‡] Francesco Vona[§]

November 4, 2025

Abstract

We investigate the impact of heat waves on individual earnings using retrospective panel data (SHARE) matched with high-resolution weather data (E-OBS), covering over 32000 workers across 14 European countries (1955–2019) from diverse sectors and occupations. Exploiting plausibly exogenous variation in heat wave exposure across cohorts within the same generation and region, and controlling for individual fixed effects, occupational sorting, and covariate balance, we find each additional heat wave day reduces earnings by 0.31%. Losses are larger in outdoor, manual, and clerical occupations, disproportionately affecting lower-income workers and those from disadvantaged family backgrounds, but are mitigated in countries with centralized collective bargaining.

JEL Classification: J30, Q54

Keywords: Temperature, Heat Waves, Earnings, Labor Market, Inequalities, Climate Change

[*]We are grateful to Francois Cohen, Enrica De Cian, Federico Fabio Frattini, Irene Mammi, Giovanni Marin, Alessandro Olper, Nico Pestel, Filippo Pavanello, and Guglielmo Zappalà, as well as to participants at various conferences for their helpful comments. We also thank Catarina Midões for building the environmental variables used, as part of ongoing joint work.

[†]This study was carried out within the PRICE (PRoductivity and equity Implications of Climate change in Europe) projected funded by the European Union Next-GenerationEU - National Recovery and Resilience Plan (NRRP) – MISSION 4 COMPONENT 2, INVESTIMENT 1.1 Fondo per il Programma Nazionale di Ricerca e Progetti di Rilevante Interesse Nazionale (PRIN) – CUP N. H53D23005070006. This manuscript reflects only the authors' views and opinions, neither the European Union nor the European Commission can be considered responsible for them

[‡]**Corresponding Author**. Fondazione Eni Enrico Mattei (FEEM), Ca' Foscari University of Venice; e-mail: giulia.valenti@feem.it

[§]University of Milan and Fondazione Eni Enrico Mattei (FEEM); e-mail: francesco.vona@unimi.it

1 Introduction

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 studies assessed the aggregate economic costs (Dell et al., 2009; Hsiang, 2010; Dell et al., 2012; Park and Heal, 2013; Burke et al., 2015; Newell et al., 2021), subsequent work has increasingly focused on the specific mechanisms behind these effects, highlighting that labor is the production factor most affected by climate change (Cachon et al., 2012; Somanathan et al., 2021; Park, 2016). In particular, extreme heat has been shown to impair firm productivity (Zhang et al., 2018; Chen and Yang, 2019; Somanathan et al., 2021), alter labor supply decisions (Graff Zivin and Neidell, 2014; Neidell et al., 2021; Rode et al., 2022), increase absenteeism (Somanathan et al., 2021), reduce workplace safety (Park et al., 2021; Behrer et al., 2024), and induce labor reallocation across sectors (Colmer, 2021; Liu et al., 2023). Extreme temperatures also adversely affect health (White, 2017; Gould et al., 2025; Aguilar-Gomez et al., 2025), including through mortality impacts (Deschênes and Greenstone, 2011; Barreca et al., 2016; Agarwal et al., 2021; Carleton et al., 2022), and hamper human capital accumulation (Graff Zivin et al., 2018; Park et al., 2020; 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 contributes to the literature on the labor market impacts of temperature extremes by leveraging individual-level longitudinal data for 14 European countries spanning more than six decades (1955–2018). In line with recent studies emphasizing the relevance of the duration of extreme temperature exposure on human well-being (IPCC, 2023; Miller et al., 2021; Hoffmann et al., 2022), we focus on heat waves— defined as a period of more than five consecutive days during which the daily maximum temperature exceeds the 95th percentile of the local historical temperature distribution. Our primary objective is to estimate the impact of heat waves on earnings, the key measure of both labor productivity and workers' material well-being, and to examine the distributional consequences of heat waves across workers with different socio-demographic characteristics and preexisting vulnerabilities. We rely on retrospective data from the Survey of Health, Ageing and Retirement in Europe (SHARE), which allows 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 use the SHARE data merged with high-frequency weather information from the E-OBS dataset provided by Copernicus, as constructed by Midões et al. (2024). This allows us to compute annual measures of heat wave exposure at a spatial resolution that varies across countries but corresponds, on average, to a level between a region (NUTS2) and a province (NUTS3, see Section 3 for details).

Our empirical strategy exploits plausibly exogenous variation in heat waves across individuals from different cohorts within the same generation (defined over a 10-year window) and residing in the same location (sub-minimum NUTS area), 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 belong to the same generation but differ, arguably at random, in their exposure to extreme temperature events.

To support the plausibility of a causal interpretation of our results, we expand our identification strategy in two directions. First and foremost, we exploit the longitudinal structure of the data by including individual fixed effects, thereby controlling for time-invariant unobserved heterogeneity across individuals. 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 heat wave exposure also with respect to observable sociodemographic 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.

To further inspect the distributional effects of heat waves, we explore several dimensions of heterogeneity. First, we allow the effects to vary across occupations, sectors and institutional settings. Specifically, we focus on workers employed in outdoor occupations or in sectors with greater exposure to extreme temperatures, and we exploit cross-country variation in collective bargaining coverage. We expect larger losses in earnings among those in heat-exposed jobs and in countries with more flexible wage-setting institutions, where wages are more responsive to labor market shocks due to weaker bargaining protections. Second, we uncover the extent to which the effect of heat waves compounds with preexisting vulnerabilities by looking at the heterogeneous effects along the earning distribution or for specific socio-demographic characteristics, e.g. age, education or parental background.

Our results suggest that an additional day in a heat wave 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 specifications, including models with individual and occupation-by-individual fixed effects, suggesting that the estimated effects are not driven by unobserved heterogeneity or occupational sorting.

Beyond the average effect, we document substantial heterogeneity in the impact of heat waves on earnings across occupations, sectors, institutional settings, and sociodemographic groups. As would be expected, earnings losses are substantially larger for workers in heat-exposed occupations (-1.23% on annual earnings) compared to those in non-exposed (-0.45%) roles, underscoring that the nature of the tasks performed is a key driver of vulnerability to heat stress. The effect is particularly severe among those working outdoor and performing not only manual tasks, but also - although to a less extent- clerical ones. Among sectors, Agriculture and Fishing stands out, followed by Industry (which includes Manufacturing, Mining & Quarrying, and Utility). The pronounced impact in agriculture is likely driven not only by the high prevalence of outdoor work in this sector but also by the widespread use of piece-rate contracts, which directly tie productivity losses to reductions in income. By investigating the role of worker sorting into heat-exposed occupations, we also highlight that these effects may exacerbate existing inequalities. Indeed, our analysis shows that individuals in these roles tend to have lower levels of education and come from more disadvantaged socioeconomic backgrounds.

We also document that, along the earnings distribution, the adverse effects are more severe among low-income workers, particularly within outdoor occupations. Earnings losses are also larger among socio-demographically vulnerable groups, such as the elderly, less educated or from more disadvantaged family backgrounds. These patterns suggest that extreme heat may reinforce preexisting socioeconomic inequalities.

In addition to worker characteristics, we find that labor market institutions play a critical mediating role: countries with decentralised or deregulated wage-setting systems exhibit significantly larger income losses from heat exposure compared to those with centralised or sectoral bargaining, where heat waves have no effect on wages. This suggests that stronger and well-enforced collective bargaining mechanisms may provide important protection against climate-induced earnings shocks.

Related Literature and Contributions. This paper contributes to the growing literature on the labor market impacts of extreme temperature exposure. Although heat exposure has been shown to reduce performance even in less physically demanding or indoor occupations (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 effects operate through reductions in labor input, with productivity losses concentrated in manual labor–intensive sectors (Cai et al., 2018). Heat impairs labor productivity primarily through physiological stress, fatigue, and reduced cognitive performance (Heal and Park, 2016). Beyond its effects on productivity, 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). 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).

This paper builds on prior work on the consequences of extreme heat on labor, by providing new evidence on the impact on workers' earnings. Earlier studies have primarily investigated the effects of extreme weather events—such as hurricanes (Belasen and Polachek, 2008; Deryugina et al., 2018)—and temperature exposure on income at more aggregated levels, including counties (Deryugina and Hsiang, 2014; Deryugina, 2017; Park, 2016; Behrer et al., 2021; Colmer, 2021). To our knowledge, only two studies (Oliveira et al., 2021; Li and Pan, 2021) have examined earnings effects at the individual level. However, both remain limited in scope, focusing primarily on developing countries and specific segments of the labor force.[1] Our paper advances this literature by providing evidence on high and middle income countries, analyzing losses on individual-level earnings, by using longitudinal data from several European countries over an extended time horizon. In contrast with previous studies, our analysis includes both employees and the self-employed, spanning a wide range of occupations across agricultural and non-agricultural sectors.

Furthermore, we contribute to the understanding of the distributional effects of exposure to the negative effects of environmental damage. We are the first to examine various channels through which heat waves compound with existing inequalities, related to workers' tasks, sociodemographic 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; Heal and Park, 2016; Diffenbaugh and Burke, 2019), within countries (Hsiang et al., 2017; Park et al., 2018; Burke and Tanutama, 2019; Behrer et al., 2021; Dasgupta et al., 2024; Zhang et al., 2024; Gilli et al., 2024) and can have substantial heterogenous effect across firms (Yuan et al., 2024; Tarsia, 2024). The key mechanism is the spatial sorting of individuals: poorer households are more likely to reside in climate-vulnerable areas, and lower-income workers are disproportionately represented in occupations with high exposure to heat stress (Park et al., 2018). However, evidence on how these shocks affect different groups of workers within the same region remains limited. We extend this literature by documenting heterogeneity in the earnings response to temperature shocks across occupations performing different tasks. As an additional contribution, we explore the distributional effects along the earnings distribution and across workers with different sociodemographic characteristics—finding stronger negative effects among individuals with worse family background and very low earnings. Here we contribute to the broader literature on the effects of environmental hazards on intergenerational, gender and ethnic inequalities (Banzhaf et al., 2019; Colmer and Voorheis, 2020; Currie et al., 2023). As in this literature, we find that heat waves exacerbate existing inequalities along non-income dimensions. From a policy perspective, our findings inform the debate on the so-called just energy transition emphasizing the importance of considering the issue of recognition justice - which is related to preexisting non—income related inequalities—and the multidimensionality of distributional effects (Vona, 2023; Hernandez et al., 2026).

Finally, we provide novel evidence on the role of unexplored mediating factors in shaping the relationship between temperature and labor outcomes (Jessoe 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 wage-bargaining structures shape the earnings response to temperature shocks, highlighting the importance of institutional context in determining the distribution and magnitude of climate-related impacts. While this analysis remains suggestive given the limitations in capturing differences in labor market institutions, our findings call for further research that incorporates these institutional features into bottom-up approaches to climate impact assess-

[1] Oliveira et al. (2021) analyze impacts on non-agriculture wages in Brazil, leveraging monthly information but only for two years (2015-2016). Li and Pan (2021) explore extreme temperature effect on employees' annual rural wages in China from 1989 to 2011, but their focus remains confined to the rural labor force.

ment and policy evaluation (see, e.g., Carleton et al. (2022) and Rode et al. (2022)).

The remainder of the paper is structured as follows. Section 2 outlines the conceptual framework, detailing the key mechanisms through which high temperatures may influence earnings. Section 3 introduces the data used in the analysis. Section 4 presents the empirical strategy. Section 5 reports the main results on the impact of temperature on earnings, while Section 6 investigates heterogeneity across occupations, sectors, labor market institutions, and sociodemographic characteristics. Section 7 concludes with a summary of findings and a discussion of their broader implications.

2 Conceptual Framework

Previous research on the direct impact of extreme temperatures on individual earnings remains limited (Oliveira et al., 2021; Li and Pan, 2021). To guide our empirical analysis and conceptualize the mechanisms through which temperature affects monthly earnings, we draw insights both from the climate impact literature and from the broader labor economics literature on the effect of productivity shocks on wages.

In competitive labor markets, earnings reflect both the marginal productivity of labor and workers' labor supply decisions. In our setting, however, labor supply responses are likely limited, as we observe average monthly earnings within a given year. In turn, labor productivity can be disentangled in two components: (i) aggregate productivity, usually measured with Total Factor Productivity (TFP), and (ii) match-specific productivity, which depends on the quality of the alignment between workers' skills and the tasks they perform (Acemoglu and Autor, 2011; Guvenen et al., 2020). Both components of labor productivity may be affected by extreme temperatures, but the match-specific one drives wage differentials across workers in different occupations.

Wage responses to productivity shocks also depend to the institutional context. The assumption of a perfectly competitive labor market often fails in practice, particularly where institutions such as unions and governments play a direct role in wage setting through collective bargaining agreements, minimum wage regulations, and employment protection laws. As well-known since the 1990s (Krugman et al., 1994), in flexible labor markets, wages are more responsive to productivity shocks, while, in rigid markets, institutions may buffer short-term wage fluctuations leading to larger effects on employment.

Building on these insights, we conceptualise five main channels through which temperature shocks may affect earnings E_{ily} of individual i, in location l and year y as:

$$E_{ily} = f\left(\text{TFP}_{ily}(T_{ly}), \text{Match}_{ily}(T_{ly}), \text{LS}_{ily}(T_{ly}), \text{LR}_{ily}(T_{ly}), \text{Inst}_{ily}\right) \tag{1}$$

where TFP_{ily}, match-specific productivity (Match_{ily}), labor supply (LS_{ily}), and labor reallocation across sectors (LR_{ily}) are functions of temperature extremes T_{ly}, while labor market institutions (Inst_{ily}) are a mediating factor. Borrowing insights from previous literature, we will briefly discuss the potential effects of heat extremes through each of these channels. The empirical analysis will provide new evidence on the relevance of match-specific effects and labor market institutions, two less-explored mechanisms.

Total Factor Productivity. It is well-documented in the literature that extreme heat can reduce overall economic efficiency and TFP through multiple channels: i. by impairing labor performance, e.g. fatigue and cognitive impairment (Zivin and Shrader, 2016; Zivin et al., 2020; Krebs, 2024); ii. by reducing the efficiency of physical capital, e.g., machinery overheating, energy inefficiency (Zhang et al., 2018); iii. by increasing input misallocation due to uncoordinated work interruptions and disruptions (Graff Zivin and Neidell, 2014; Neidell et al., 2021). Recent evidence also suggests that - as for natural disasters (Miao and Popp, 2014) - extreme temperatures can trigger effective adaptation through regulation-induced investments, such as in capital equipment (Adhvaryu et al., 2020; Zhang et al., 2023; Ortiz-Molina et al., 2024)—or by driving innovation in adaptation strategies (Auci et al., 2021), which may partially offset productivity losses or even enhance firms' economic performance. Successful adaptation responses are more likely to curb the negative productivity effect of HWs in our sample of high- and middle-income countries, which benefit from greater access to adaptive technologies and resources. Importantly, aggregate productivity shocks are unlikely to amplify wage inequality, conditional on sectoral or occupational characteristics.

Match-specific productivity. As well-known in labor economics, labor productivity is not determined by worker characteristics or task attributes in isolation, but rather by the quality of the match between the two (Jovanovic, 1979; Mortensen and Pissarides, 1994; Acemoglu and Autor, 2011; Guvenen et al., 2020). This notion of match-specific productivity implies that the effects of external shocks—such as extreme temperatures—are inherently heterogeneous depending on three factors. First, jobs are not equally exposed to weather shocks. As documented in the literature, workers in sectors where most tasks are performed outdoors (e.g. agriculture, mining, construction) (Acevedo et al., 2020; Graff Zivin and Neidell, 2014; Neidell et al., 2021; Gagliardi et al., 2024), in non-climate-controlled environments (e.g., manufacturing, transportation) with limited adaptation options (Kjellstrom et al., 2009; Zhang et al., 2023), or in physically demanding occupations are more vulnerable to these shocks. Second, the workers' skills and capabilities to perform a given task under new conditions (under heat stress or not) may vary depending on factors such as educational level, age, health and gender. Third, match-specific productivity is also affected by the sorting of workers with different characteristics to tasks. For instance, workers with poor health or older can systematically avoid jobs more exposed to heat stress. A successful task-skill match can also enhance labor productivity through learning effects (Gathmann and Schönberg, 2010; Guvenen et al., 2020). Our data are well-suited to explore this channels as we have detailed information on the main task performed by the worker (through detailed ISCO 4-digit occupational codes) and of the main sector of work. Moreover, the longitudinal dimension of our data allows to uncover the potential role of sorting into heat-exposed workplaces of individuals with different capabilities (health, education, age).

Labor supply responses. Alongside changes in productivity, labor supply responses have been identified as a key channel through which extreme temperature affects labor dynamics (Graff Zivin and Neidell, 2014; Neidell et al., 2021; Garg et al., 2020; Rode et al., 2022; Lai et al., 2023). In occupations that are intensive of physical tasks and offer limited possibilities for adaptation—such as outdoor manual work—extreme heat may lead to increased absenteeism and shorter working hours, in addition to reductions in work intensity (Graff Zivin and Neidell, 2014; Neidell et al., 2021; Somanathan et al., 2021). These responses are often driven by heat-induced fatigue (Graff Zivin and Neidell, 2014), discomfort (Picchio and Van Ours, 2025), and avoidance of health risks (Kjellstrom et al., 2009; Dillender, 2021; Park et al., 2021; Ireland et al., 2023; Behrer et al., 2024; Bressler et al., 2025). Especially in sectors where piece-rate contracts are more diffused or in countries where wage setting is more flexible, earnings may decline through reduced labor supply even if employment status remains unchanged. In absence of detailed information on hours or days worked, beyond a binary indicator for full versus part-time employment, our data do not allow to disentangle the effects of productivity changes from those driven by labor supply adjustments. However, because we observe average monthly wages, short-term labor supply adjustments—such as workers reducing hours on extremely hot days and compensating later in the month—are likely to be smoothed out. As a result, the estimated effects primarily capture productivity-related channels rather than transitory fluctuations in hours worked.

Labor Reallocation. Recent research highlights labor reallocation as an additional potential mechanism linking temperature shocks to wage dynamics. Heat-induced productivity declines in agriculture (Schlenker and Roberts, 2009; Hultgren et al., 2025) reduce labor demand in rural activities, prompting workers to move into non-agricultural sectors (Emerick, 2018; Colmer, 2021). The resulting increase in labor supply exerts downward pressure on wages in these receiving sectors. Although most evidence on such cross-sectoral adjustments originates from developing economies (Emerick, 2018; Colmer, 2021; Liu et al., 2023), recent findings for European regions (Zilia et al., 2025) suggest that similar dynamics may also operate within advanced labor markets. While our data do not allow us to directly observe and empirically test labor reallocation, the pattern of wage responses we document is consistent with this mechanism: wage reductions following episodes of extreme heat are not confined to agriculture but extend to industry (including manufacturing), public and other services, and wholesale and retail trade. This evidence points to labor reallocation as a plausible channel through which climate shocks propagate across sectors and affect aggregate wage outcomes.

Labor Market Institutions. The extent to which productivity shocks translate into wage adjustments crucially depends on the institutional configuration of the labor market. Prior work has shown that rigid employment protection and centralized bargaining systems can dampen the wage response to firm- or sector-specific shocks (Calmfors and Driffill, 1988; Blanchard and Wolfers, 2000; Blanchard and Philippon, 2004; Boeri and Garibaldi, 2007). These institutions create a buffer between productivity and pay, thereby reducing the transmission of transitory shocks into earnings dynamics. In the context of climate-induced productivity shocks, Yuan et al. (2024) show that disparities in bargaining power within firms—specifically between managers and employees—can modulate the extent to which such shocks exacerbate within-firm wage inequality. Analogously, at a more aggregate level, we expect that in labor markets where wage bargaining is coordinated across unions at the national or sectoral level, wages exhibit limited responsiveness to productivity shocks. Typically, collective wage bargaining entails institutionalized rigidities (e.g., minimum wages, sectoral agreements, automatic seniority-based pay increases in the public sector) (Babecký et al., 2010), which constrain the transmission of temperature-induced productivity losses into individual earnings. Similarly, binding minimum wage regulations impose a lower bound on compensation, preventing wage adjustments for low-productivity workers and thereby further decoupling wages from output. In these contexts, the direct link between productivity and wages is attenuated. Our empirical analysis tests this hypothesis by examining whether the transmission of temperature-induced productivity shocks is mediated by wage-setting institutions.

3 Data and Measures

To examine the impact of temperature on earnings, this paper uses retrospective data from waves 3 and 7 of the Survey on Health, Ageing and Retirement in Europe (SHARE), which provides rich information on individuals' life histories, including detailed job and residential records. These data are linked to high-frequency weather variables from the E-OBS dataset provided by Copernicus (Midões et al., 2024). The linkage matches individuals' locations of residence during each job episode with corresponding temperature and precipitation records. The resulting dataset enables individual-level analysis of heat-wave exposure at a fine spatial resolution—typically between the NUTS2 (region) and NUTS3 (province) levels—across several European countries and spanning more than six decades. This section described the data and measures adopted in greater details.

SHARE Data. The SHARE survey collects rich information on individuals aged 50 and above, covering multiple dimensions of their lives. The survey includes a wide range of variables related to family background, childhood conditions, lifetime health, educational attainment, and other sociodemographic characteristics. Importantly, the SHARE dataset includes modules on residential histories: these information allow to link the share data to weather variables and are discussed below. The 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.

We use only waves 3 and 7 which include retrospective modules collecting information on past life events.[2] Of particular importance for this work, these modules provide comprehensive

[2]Previous 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.

data on respondents' working histories, including unemployment spells, earnings, working hours (full-time vs. part-time), occupation (ISCO codes), and employment status (employee vs. self-employed).

Earnings. The retrospective nature of SHARE data implies that information is collected at one point in time (the year of the survey), but refers to different periods in respondents' lives, which may raise concerns regarding the comparability and accuracy of wage reports across time. To account for heterogeneity in time and currencies, we harmonize the raw data using a procedure detailed in Table A4 in Appendix A.

The survey differentiates between "income," referring to self-employment earnings, and "wage," referring to earnings from employment.[3] The survey also classifies earnings based on the timing within the job episode (e.g., first, last and current wage or income[4]) and the source of income (self-employment vs. employment). In our analysis, we aggregate all available earnings information, accounting for the source of income by including a dummy variable for self-employment and controlling for both labor market experience and within-job seniority (see Section 4).

Sociodemographic 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—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 — allow us to account for health-related vulnerabilities that may amplify susceptibility to external shocks.

Occupations and Sectors. A key advantage of the SHARE dataset is that it allows for a precise identification of heat-exposure in the workplace by providing detailed occupational information for each job episode using the International Standard Classification of Occupations (ISCO). For 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. Leveraging this information, we manually classify occupations predominantly involving outdoor tasks as heat-exposed. Table A1 in Appendix A lists the 4-digit ISCO codes identified as heat-exposed (coded as 1) as well as the main general task they perform (abstract, routine, manual). 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

[3]In what follows, we use "income" and "wage" interchangeably to denote the worker's gross labor earnings, i.e., monthly compensation from employment or self-employment before taxes and social contributions.

[4]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

precisely capture the match-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—effects that sector-level analyses may overlook.

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 and quarrying — sectors known to have higher heat risk because typically characterized by outdoor work. These sectors along with manufacturing, utilities, and transport, storage and communication which even if performed mainly indoor are likely to be in non-climate controlled environment, are classified as exposed sectors when we explore sectoral heterogeneity in the effect of HWs (Graff Zivin and Neidell, 2014).

Weather Data and Heat Waves Measures. Weather data are sourced from the E-OBS dataset, distributed through the Copernicus Climate Change Service (C3S), which offers daily gridded weather observations across Europe at a spatial resolution of $0.1° \times 0.1°$. This dataset has been integrated with the SHARE survey through the so-called SHARE-ENV dataset (Midões et al., 2024), a novel and publicly accessible resource. A key advantage of E-OBS is its long temporal coverage, which enables effective linkage with SHARE's retrospective socioeconomic 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 follow Miller et al. (2021) and construct measures of heat waves. Unlike average temperature, heat wave metrics capture both the intensity and persistence of thermal stress, which will increase with climate change across most land areas (Climate Change (IPCC), 2023).[5] Epidemiological evidence shows that prolonged periods of extreme heat are associated with excess mortality beyond the general temperature–mortality relationship, underscoring the importance of duration of exposure.[6] Moreover, adaptation to consecutive hot days is more challenging than adaptation to isolated events, making heat waves a particularly relevant measure for assessing socioeconomic 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.,

[5]It has been estimated that, relative to the pre-industrial period (1850–1900), global warming has made the median heatwave 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).

[6]Heat wave indicators are widely used in the medical and epidemiological literature to assess health impacts (Hajat et al., 2006; Peng et al., 2011; Barnett et al., 2012).

2022). Heat waves are identified 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, updated annually to reflect evolving local conditions. Our main metric is the annual number of days that fall within such events.

We define heat waves using relative temperature thresholds, which adjust to evolving local climate conditions and local adaptation, allowing us to capture unexpected temperature shocks. Location fixed effects, as described in Section 4, account for average differences across locations but do not capture long-term climate trends. Relative thresholds are therefore particularly suitable because they (i) avoid bias arising from potential correlations between long-term temperature trends and outcome trends (Jones et al., 2025), (ii) preserve important observations that would be missed using absolute thresholds—especially in colder regions—and (iii) capture shocks that are extreme relative to local climate and adaptation. In 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 A7), 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 (Deryugina and Hsiang, 2014; Deschênes and Greenstone, 2011; Hsiang, 2016), and heat waves defined with absolute thresholds.

Spatial Resolution and Urbanization Data. A potential concern with E-OBS is that its gridded values are based on spatial interpolation from station data, which may introduce measurement error. Moreover, in the SHARE dataset, the spatial information on place of residence vary in granularity across countries. Specifically, residence data are available at the NUTS1, NUTS2, or NUTS3 level, depending on the country.[7]

To improve spatial resolution, additional information on the degree of urbanisation for each residential location is incorporated (Midões et al., 2024). Specifically, each minimum available NUTS region is subdivided into five urbanisation categories: "big city," "suburbs or outskirts of a big city," "large town," "small town," and "rural area or village."[8] Average weather data (e.g., daily temperature) are then calculated using a population-weighted average of grid-level data across cells within each artificial sub-minimum NUTS region, constructed based on the finest available NUTS level and the degree of urbanisation within each region. Overall, this procedure mitigates concerns that interpolation-related measurement error could meaningfully bias the estimates. This disaggregation strategy also enhances the accuracy of our temperature exposure measure and strengthens the detection of spatial variation in weather shocks.

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

[8]This classification follows the criteria established in the DEGURBA Manual by the European Union (**union2021applying**).

Final Dataset and Descriptive Statistics. After data cleaning (see Table A4 in Appendix A), the final dataset[9] comprises 32782 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, spanning the period 1955–2019. Summary statistics for all variables used in the main analysis are reported in Table A2 of Appendix A.

Table A3 reports the distribution of individuals by the number of available earnings records. Of the 32,782 individuals in the sample, approximately 42% have only a single observation, indicating limited longitudinal information for a substantial share of the sample. Conversely, about one-third (34%) have more than three observations, providing sufficient variation for panel specifications, while fewer than 1% have more than ten records. Tables A5 and A6 present summary statistics for earnings by country and by occupation–sector groups, respectively. The latter exhibits a slightly lower number of observations due to missing ISCO codes or sectoral classifications. The combination of limited repeated observations and missing occupation-sector information accounts for the reduction in sample size in more demanding specifications that include individual and individual-by-occupation fixed effects (Table 1).

Figure A1 shows the weighted average number of heatwaves, defined according to absolute and relative temperature thresholds, over time. While absolute-threshold heatwaves display a clear upward trend, relative ones show irregular shocks, with pronounced peaks in several years. Tables A7, A8, and A9 document average heatwave exposure by country, income percentile, and occupation–sector groups. While the distribution of absolute temperature shocks varies substantially across countries, reflecting underlying climate differences, cross-country variation is much smaller for relative-threshold heatwaves. Similarly, absolute temperatures generate sizable differences across earnings deciles, with exposure tending to decline as income rises, whereas relative measures exhibit much less variation along the earnings distribution. Among occupations and sectors, gaps in exposure are also larger under absolute measures: although the most susceptible occupations and sectors experience slightly higher average exposure, these differences are negligible when relative thresholds are considered.

Finally, Tables A10, A11, and A12 report the distribution of exposed versus non-exposed occupations—as defined in Table A1—by country, income percentiles, and occupation–sector groups. Overall, exposure levels vary across countries, with higher shares of exposed workers in Southern and Central European economies such as Italy, Spain, and the Czech Republic, and lower ones in Northern countries like Sweden and Denmark. When looking across the earnings distribution, exposure appears relatively evenly spread across percentiles, though it tends to be slightly higher in the lower and middle parts of the income scale, reflecting the greater concentration of manual and service occupations in these groups. Finally, the breakdown by sector and occupation group shows that outdoor exposed occupations are particularly pronounced in construction, agriculture, and industry, as well as among manual and elementary occupations.

[9] Out of 79029 available earnings records, we retain 75258 observations (32782 individuals) with complete information on the main regressors and control variables (Table 1).

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:

$$E_{ily} = \beta f(T)_{ily} + \gamma g(P)_{ily} + \theta X_{ily} + \psi_g + \phi_l + \lambda_y + \theta_c t_y + \epsilon_{ily} \quad (2)$$

where i, l, and y index individuals, locations (sub-minimum NUTS level described in Section 3), and years, respectively. The outcome variable E_{ily} denotes the logarithm of individual average monthly earnings in year y. The variable $f(T)_{ily}$ captures temperature exposure, modeled as the number of days spent in a HW.[10] We include year, location, and generation (10-year) fixed effects are denoted by λ_y, μ_l, and ψ_g, 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 second-degree polynomial in average annual precipitation ($f(P)_{ily}$), a vector X_{ily} of individual socio-demographic characteristics and standard labor market controls in Mincerian wage regression[11] and country-year specific linear trends ($\theta_c t_y$), 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 with observable and unobservable characteristics

[10] Recall 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.

[11] These 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), 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.

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 heatwave 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 heatwave occurs and 0 otherwise.[12] The results are presented in Table B.13 in Appendix B. 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 heatwave 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 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).[13] 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.

[12] We estimate these regressions at the individual level.

[13] When 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.

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 persistence of heatwaves. Some locations may experience serially correlated heatwave 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 B.14 in Appendix B presents estimates using two alternative heatwave definitions. Columns (1–2) correspond to our baseline measure of prolonged heatwaves (exceeding five consecutive days), while columns (3–4) adopt a shorter-duration definition (fewer than two consecutive days). For prolonged heatwaves, 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 heatwaves 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 heatwaves 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 heatwaves (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. The 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; Koenker, 2005), 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. 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 variable that captures an workplace characteristic (heat-exposed occupations and sectors), a sociodemographic attribute (parental background, gender, age, health status), or a labor market (collective bargaining) or regional characteristics (broad climatic conditions). 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.

Formally, we augment the specification of Equation 2 by interacting the main regressor, $f(T)_{ily}$, with a group-defining variable $D_{d(il)}$, which denotes membership in a particular category based on personal, regional or occupational characteristics. The resulting equation reads as follows:

$$E_{ily} = \beta f(T)_{ily} + \delta f(T)_{ily} \times D_{d(il)} + \eta D_{d(il)} + \gamma f(P)_{ily} + \theta X_{ily} + \psi_g + \phi_l + \lambda_y + \theta_c t_y + \epsilon_{ily} \quad (3)$$

The coefficients δ capture whether the effect of temperature on earnings differs significantly across groups within a given dimension, relative to the omitted (reference) group.

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,[14] 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 across alternative model specifications. In column (1), we use a more parsimonious set of individual-level controls to mitigate concerns about bad controls. The estimated earnings loss remains virtually unchanged relative to column (2), differing by only 0.019 percentage points. 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

[14] We 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.

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 B.13 in Appendix B. Finally, the estimated 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.

The stability of the coefficients across specifications suggests that heat wave 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 can confidently use the model of column 2 and the related largest sample as the reference specification for analyzing heterogeneity across groups and along the earnings distribution.

Table 1: Effect of Heat Waves on Earnings

	(1)	(2)	(3)	(4)	(5)
Days of HW (T_{MAX} > 95th perc)	-0.00291***	-0.00310***	-0.00320***	-0.00236*	-0.00248*
	(0.0009)	(0.0008)	(0.0010)	(0.0013)	(0.0014)
Precipitation control	✓	✓	✓	✓	✓
Location, Generation, Year FE	✓	✓	✓	✓	✓
Main Covariates	✓	✓	✓	✓	✓
Extended Covariates		✓	✓	✓	✓
Country-Year Linear Trends	✓	✓	✓	✓	✓
Individual FE				✓	✓
Individual $\times$ Occupation (ISCO1) FE					✓
Individuals	32782	32337	15580	15580	15580
Observations	75258	73577	44271	44271	44271
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). Days of HW count the number of days spent in a heatwave (T_{MAX} > 95th 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 reduced on-the-job skill formation. We further explore this empirical issue by augmenting our favourite specification with the lagged HW indicators at time $t-1$ and $t-2$. Table 2 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 is more plausibly driven by broader, indirect effects and spillovers operating at various level of aggregation. These include firm-, sector-, or region-level output disruptions that persist over time, and labor reallocation across sectors, which tends to unfold gradually as workers adjust to shifting relative productivities and labor demands. At the micro level, persistent impacts may also stem from individual productivity losses due to skill deterioration or slower on-the-job learning. Our results resonates 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).

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

	(1)	(2)	(3)	(4)	(5)
Days of HW (T_{MAX} > 95th perc)	-0.00280***	-0.00299***	-0.00304***	-0.00207	-0.00220
	(0.0008)	(0.0008)	(0.0010)	(0.0014)	(0.0014)
Days of HW (T_{MAX} > 95th perc) at t-1	-0.00134	-0.00145*	-0.00248***	-0.00204*	-0.00228*
	(0.0009)	(0.0008)	(0.0009)	(0.0012)	(0.0012)
Days of HW (T_{MAX} > 95th perc) at t-2	-0.000999	-0.000774	-0.000932	-0.00164	-0.00186
	(0.0009)	(0.0009)	(0.0010)	(0.0011)	(0.0012)
			Cumulative Marginal Effects		
Days of HW (T_{MAX} > 95th perc)	-0.00513***	-0.00521***	-0.00645***	-0.00576***	-0.00622***
	(0.0017)	(0.0017)	(0.0018)	(0.0022)	(0.0022)
Precipitation control	✓	✓	✓	✓	✓
Location, Generation, Year FE	✓	✓	✓	✓	✓
Main Covariates	✓	✓	✓	✓	✓
Extended Covariates		✓	✓	✓	✓
Country-Year Linear Trends	✓	✓	✓	✓	✓
Individual FE				✓	✓
Individual × Occupation (ISCO1) FE					✓
Individuals	32582	32134	15281	15281	15281
Observations	73853	72229	43134	43134	43134
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). Days of HW count the number of days spent in a heatwave (T_{MAX} > 95th 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 * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Quantifying the Impact. The average individual in our sample experiences approximately 2.91 HW days per year (Table A7). Assuming a standard 260-day work year—roughly 71% of the calendar year—this implies an expected 2.07 heatwave days falling on working days. The average monthly income in our sample is $2070.14 per person (Table A5). Based on our estimated marginal effect, each additional heatwave day reduces income by 0.310%. Overall, multiplying the estimated effect by the average monthly income, the number of months in a year (12), and the expected number of HW days occurring on workdays, we obtain an estimated annual income loss of approximately \$159.63 per person:

$$\text{Average Annual Earning Loss} = -0.00310 \times 2070.14 \times 12 \times 2.07 \approx -\$159.63.$$

We compare our quantified annual income loss due to heatwaves with the potential earnings loss associated with a full labor supply disruption—i.e., absenteeism at work—which previous studies (Somanathan et al., 2021) have shown can be one of the consequences of extreme heat, alongside decreases in productivity and reduced working hours. Given an average monthly income of \$2,070.14, the implied daily income—assuming 22 working days per month—is approximately \$94.10. If a worker is fully absent, the average annual earnings loss amounts to:

$$\text{Average Annual Earnings Loss} = \$94.098 \times 2.073 \approx \$195.12.$$

This quantified loss reflects a scenario in which workers lack any form of adaptation and are compelled to miss work entirely due to extreme heat. In this case, the income loss arises not from reduced productivity, but from a pure labor supply reduction.

As noted, the estimated total earnings loss is smaller than the hypothetical loss that would occur if workers were fully absent on heat wave days. While we cannot disentangle whether this effect reflects reduced labor productivity or lower labor supply, its magnitude suggests that heat waves have a meaningful impact on earnings. Even if workers do not miss work entirely, their productivity may be severely impaired on those days. Alternatively, the observed effect may capture a more persistent reduction in earnings extending beyond the heat wave itself, potentially driven by heat-related health issues or cumulative fatigue.

While previous studies have identified potential channels through which temperature shocks affect income—such as reductions in agricultural yields (Schlenker and Roberts, 2009) and labor supply (Graff Zivin and Neidell, 2014)—less is known about how these effects translate into actual monetary losses across different sectors. Direct comparisons with prior research are not straightforward, due to differences in data granularity, exposure definitions, and institutional contexts. For instance, 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. In comparison, we estimate that each additional heatwave day reduces, on average, annual income by approximately $-0.00310 \times \$2070.14 \times 12 \approx -\$77.01$.[15] Scaling our estimate[16] by the employment-to-population ratio[17], we obtain a lower average income loss, roughly \$39.12 per person. Moreover, individual-level effects on employed workers are plausibly expected to be larger, as prior literature has shown

[15] A factor contributing to this difference is the severity and duration of the temperature episodes considered. While their measure captures isolated hot days, ours reflects a sustained exposure, periods of at least five consecutive days above a temperature threshold. Accordingly, our estimated income loss should be interpreted as the incremental effect of prolonged extreme heat, rather than the effect of a single hot day.

[16] Our sample focuses on employed individuals, whereas Deryugina and Hsiang (2014) estimates income losses at the population level.

[17] In the European Union, the average between 1983 and 2023 is approximately 50.8% (World Bank - World Development Indicators: Employment to population ratio, 15+, total, %). This value was likely lower during our study period due to historically low female labor force participation.

that temperature shocks affect labor income more than capital returns. Finally, contextual differences between Europe and the United States—particularly in institutions, labor market regulation, and wage-setting mechanisms—likely shape the degree of vulnerability to extreme heat. As shown in Section 6.2, in settings characterized by higher levels of labor market deregulation, the adverse effects of heat exposure appear to be substantially larger, suggesting that institutions can play a protective role by limiting the transmission of climate shocks to workers.

Heat waves are expected to become longer, more frequent, and more intense as a consequence of climate change (Climate Change (IPCC), 2023; Quilcaille et al., 2025). Under the high-emissions scenario (RCP 8.5), projections for the European Union suggest that the average annual number of heatwave days[18] during the period 2071–2100 will rise approximately to 14 (Russo et al., 2014; Hooyberghs et al., 2019). Based on our estimates, and assuming no further adaptation, this increase would translate into an average annual income loss of approximately \$897.5 per person.[19] These estimates can serve as inputs for Integrated Assessment Models (IAMs), providing more comprehensive, empirically grounded projections of heat wave–induced economic impacts at the individual level, disaggregated by sector and occupation.

Robustness Checks. The core findings remain robust across a range of alternative specifications, as detailed in Appendix C. First, Table C.15 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 C.16 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. Then, we assess the sensitivity of our findings to alternative definitions of heat waves (HWs) by relaxing the duration criterion to at least three consecutive days above the temperature threshold (Table C.17). The results remain robust across all specifications. As expected, the estimated effects are smaller in magnitude, consistent with the shorter exposure period. This evidence suggests that it is important to account not only for exposure to extreme temperatures but also for the duration of such exposure, as this dimension can influence the marginal effect of temperature on the outcome variable, in this case, earnings.

Subsample analyses by historical period (Table C.18) 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 while heat waves consistently affect wages, partial adaptation may have had a modest mitigating effect; however, these estimates are not directly comparable, as they

[18]Heat waves are here defined as periods of at least three consecutive days with maximum daily temperatures above the 90th percentile, calculated with a centered 31-day window (Russo et al., 2014), or alternatively as periods exceeding the 99th percentile of the climatological distribution of daily maxima (Hooyberghs et al., 2019). Our measure is based on the 95th percentile, which lies between these two definitions. Since both studies project approximately 14 heatwave days under RCP 8.5, we can reasonably assume a comparable number of days for our definition.

[19]This calculation relies on the estimates from our robustness check with shorter heatwave definitions (see Table C.17 in Appendix C). Each additional HW day is associated with a 0.258% reduction in earnings. The computation follows the same formula introduced earlier, adjusting for the probability that a heatwave day falls on a working day, and using the average income observed in our sample.

pertain to different samples. Analyses by leave-one-country-out estimations (Table C.19) confirm that our main findings are not driven by any single country.

As discussed in the Empirical Strategy (Section 4), we provide evidence that observable covariates are balanced between individuals exposed and unexposed to heatwaves, supporting the identifying assumption that HWs are as good as randomly assigned. This balance also suggests that unobserved characteristics are expected to be balanced among the two groups (Altonji et al., 2005). The only notable exception is part-time employment status, which differs significantly between the treated and control groups. To address potential related concerns, we re-estimate our main specifications on the subsample of individuals consistently employed in full-time positions (Table C.20). The results remain robust, indicating that our findings are not driven by the higher exposure among part-time workers. 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 controls absorb any time-invariant heterogeneity across occupations within geographic areas. Results, presented in Table C.21, remain robust, indicating that our estimates are not driven by pre-existing spatial and occupational characteristics that jointly determine heat exposure and earnings potential.

Finally, we also report estimates of the impact of extreme temperatures on earnings using heat waves defined according to absolute temperature thresholds (Tables D.22 and D.23), and temperature bins (Table D.24, D.25, and Figure A2). 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

In this section, we explore the heterogeneity of the effects to shed light on the distributional implications of heat waves beyond their average impact. The analysis relies on our preferred specification from Column (2) of Table 1, which includes the complete set of controls while excluding individual and individual-by-occupation fixed effects. This choice enables us to retain the largest possible sample and is supported by the remarkable stability of our baseline results (Section 5).

6.1 Heterogeneity across Occupations and Sectors

Figure 1 summarizes the results (see also Table E.26 in the Appendix E) on the heterogeneous effects of heat waves across individuals employed in different sectors and occupations. Each panel reports marginal effects from estimating equation 3, where temperature shocks 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*).

First, we explore heterogeneity across exposed sectors[20]. *Panel A* shows that workers em-

[20]Following Graff Zivin and Neidell (2014), we classify Agriculture & Fishing, Construction, Mining & Quarrying,

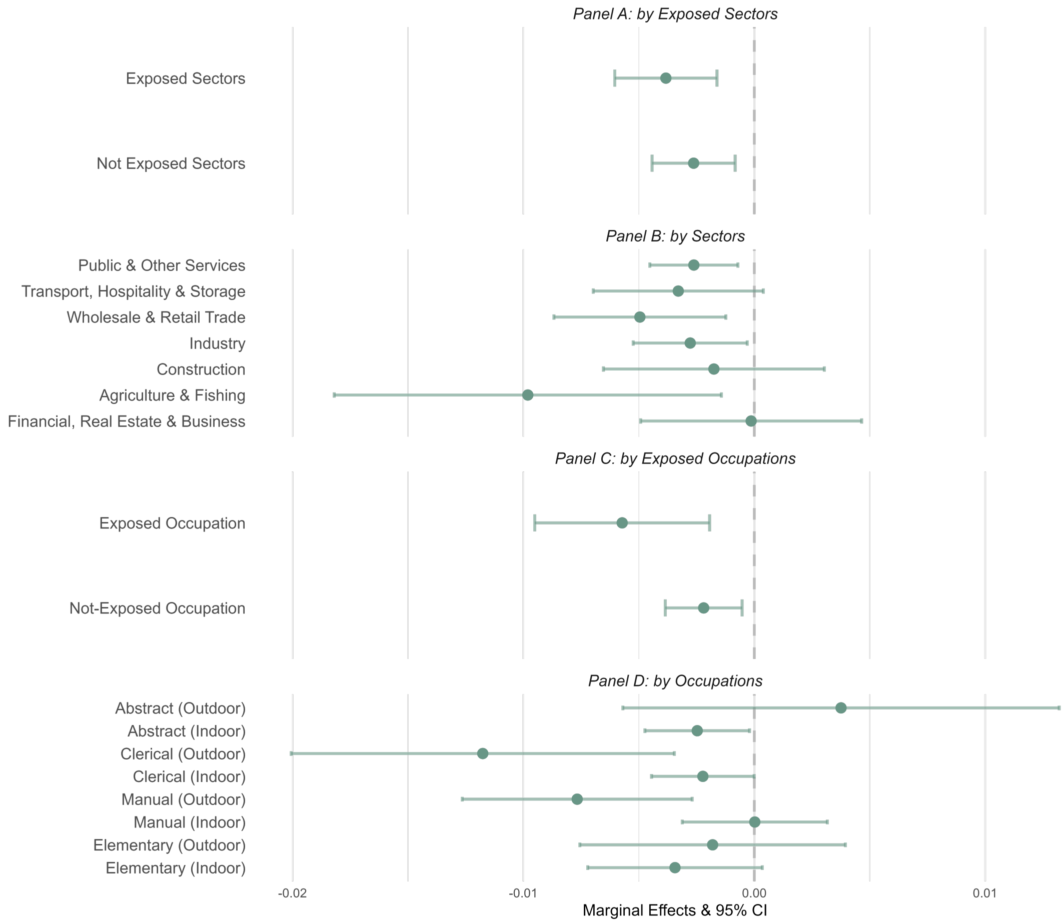

Figure 1: Marginal Effect of Heat Waves by Occupation and Sector

The figure displays the marginal effects and corresponding 95% confidence intervals from the regressions estimated in Equation 3, where heat waves are interacted with (i) a dummy for heat-exposed sectors (column 1 of Table E.26), (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).

ployed in these sectors experience larger earnings losses relative to those in non-exposed sectors, although the difference among the two groups is not statistically significant. To assess whether meaningful differences arise at a more disaggregated level—such as between predominantly outdoor sectors (e.g., Agriculture & Fishing) and predominantly indoor sectors (e.g., Manufacturing) — *Panel B* further breaks down the analysis by sector. Losses are particularly pronounced in Agriculture & Fishing, with significant impacts also observed in Wholesale & Retail Trade, Industry (covering Manufacturing, Mining & Quarrying, and Utility) and in Public & Other Services. For Construction, we do not identify a clear impact, as confidence intervals (CIs) remain wide. By contrast, Financial, Real Estate & Business Services appear largely unaffected. Notably, even

Manufacturing, Utilities and Transport, Storage & Communication as heat-exposed sectors.

industries in which most tasks are performed indoors are not immune to heat-related declines in earnings, likely because many workplaces lack climate control. The strong effect observed in Agriculture & Fishing may be attributed not only to the higher prevalence of outdoor work but also to the greater incidence of piece-rate contracts. These contracts tie earnings directly to productivity, making income more immediately sensitive to productivity losses during extreme heat events.

Given that exposure to heat is not uniform within the same sector, and that even among outdoor workers the degree of vulnerability differs depending on the nature of the task performed, we also examine heterogeneity across occupations. We first manually classify all 4-digit ISCO occupations as "exposed" if the typical tasks are carried out primarily outdoors (see Table A1 in Appendix A).[21] The corresponding results, presented in *Panel C* of Figure 1, show that the gap in the marginal effect of HWs is more pronounced when workers are grouped by occupation. Exposed occupations experience a statistically significant larger impact than non-exposed occupations, corresponding to an additional earnings loss of –0.353%. This highlights the critical role of task characteristics in shaping the impact of heat on income. To further capture heterogeneity in the type of tasks performed—while still distinguishing between outdoor and indoor activities — we also classify occupations into four broad categories: elementary, manual, clerical, and abstract (*Panel D*). Among occupations, Manual workers and Clerical in outdoor settings experience the most pronounced income reductions. For Manual workers, many tasks involve sustained physical effort in environments without temperature control, so extreme heat reduces productivity primarily through increased fatigue and lower work intensity. For outdoor Clerical occupations—such as mail carriers, transport clerks, and salespersons — extreme heat compromises timely task execution. The result for Abstract indoor workers is consistent with the average impact. Even though they're not physically exposed, heat can still affect cognitive performance (Zivin and Shrader, 2016; Zivin et al., 2020; Krebs, 2024), and in many of these jobs, wages are directly linked to productivity, so any drop in performance could affect earnings. The 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. For Elementary Occupations, the estimated effect is also not statistically significant. A plausible explanation is wage stickiness at the lower end of the distribution. These jobs often have fixed or minimum wages, or are paid per day rather than per unit of output, so even if productivity drops, earnings may not change significantly.

We follow the same logic outlined in Section 5 to compute the average annual earnings loss for each category.[22] Workers in outdoor-exposed occupations experience an average annual income reduction of approximately $272.57, corresponding to a 1.23% decline in yearly earnings. Workers

[21] When 4-digit information is missing but available at the 1-digit level, we classify an occupation as exposed if it belongs to major group 6 (Skilled Agricultural, Forestry and Fishery Workers). In addition, groups 3 (Technicians and Associate Professionals), 7 (Craft and Related Trades Workers), 8 (Plant and Machine Operators, and Assemblers), and 9 (Elementary Occupations) are classified as exposed when they occur in sectors that are typically outdoor, such as Agriculture & Fishing, Construction, and Mining & Quarrying.

[22] All descriptive statistics used in these calculations are obtained from the relevant subsample. See Table G.32 in Appendix G for key statistics by subgroup and for the results of the quantification.

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.

Overall, outdoor workers face significant constraints in accessing adaptive measures to mitigate heat exposure, such as air conditioning or other cooling technologies, and often have limited flexibility to adjust their work schedules. Our findings are consistent with previous research identifying environmentally exposed sectors as particularly susceptible to temperature shocks (Graff Zivin and Neidell, 2014; Kahn, 2016; Park, 2016; Neidell et al., 2021; Rode et al., 2022) but also highlight the heterogeneous effect across occupational groups. Particularly, we show that Manual and Clerical workers performing tasks mainly outdoor are particularly damaged by HWs. Note that both groups were already vulnerable as more negatively exposed to routine-replacing technological change (Autor and Handel, 2013) and automation (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2019). In addition, manual workers are also more negatively impacted by import competition (Autor et al., 2013; Acemoglu et al., 2016) and climate policy (Marin and Vona, 2019).

Sorting into Exposed Occupations and Sectors. Our results indicate that workers in heat-exposed occupations experience significantly larger earnings losses. To better understand the mechanisms through which heat exposure may exacerbate income inequality, we examine the individual characteristics that predict sorting into these occupations. As shown in Table 3, individuals who are male, younger, have lower levels of education, and come 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 HWs may reinforce existing inequalities, acting as a channel through which socio-economic disparities are further amplified

6.2 Mediating Role of Labor Market Institutions

Our conceptual framework suggests that the impacts of productivity shocks on wages are not obvious in countries that, such European ones, have different system of wage settings. We expect that, in systems with more centralized and coordinated collective bargaining, wages are downward rigid and thus the negative effect of HWs on wages will be smaller, while the effect on employment bigger (Krugman et al., 1994). We can test this conjecture exploiting substantial cross-country variation in wage setting institutions across Europe. More specifically, we investigate the potential heterogeneity in the impact of temperature across countries with differing systems of wage determination. Figure 2 presents the results that are detailed in Table E.27.

While the majority of European nations rely on labor union negotiations for wage-setting, the extent of wage coordination exhibits considerable variation (Bhuller et al., 2022; Momferatou et al., 2008). Over the past four decades, there has been a general trend toward greater decentralisation in wage-setting systems; however, significant differences persist in bargaining structures and prac-

Table 3: Sorting into Exposed Occupations and Sectors

	(1) Exposed Occupations	(2) Exposed Sectors
Female	-0.219***	-0.282***
	(0.010)	(0.012)
$25 \leq$ Age<45	-0.0286***	0.00105
	(0.008)	(0.011)
Age ≥ 45	-0.0408***	0.0172
	(0.011)	(0.015)
Female x $25 \leq$ Age<45	0.0613***	-0.0145
	(0.009)	(0.012)
Female x Age ≥ 45	0.0664***	-0.0209*
	(0.010)	(0.012)
Lower Secondary Edu	-0.0552***	-0.0514***
	(0.008)	(0.009)
Upper Secondary Edu	-0.0992***	-0.103***
	(0.007)	(0.009)
Tertiary Edu	-0.162***	-0.208***
	(0.008)	(0.011)
One shelf of books (at age 10)	-0.0275***	-0.0270***
	(0.006)	(0.007)
One bookcase (at age 10)	-0.0355***	-0.0391***
	(0.006)	(0.007)
Two bookcases (at age 10)	-0.0347***	-0.0450***
	(0.008)	(0.009)
More than two bookcases (at age 10)	-0.0454***	-0.0706***
	(0.006)	(0.009)
Health Loss	0.00495	0.00144
	(0.007)	(0.010)
Experience	-0.00247***	0.00125*
	(0.000)	(0.001)
Experience Squared	0.0000668***	-0.0000252*
	(0.000)	(0.000)
Location, Generation,Year FE	✓	✓
Country-Year Time Trends	✓	✓
Individuals	30310	32261
Observations	54741	59768
Adjusted R^2	0.14515	0.17010

Notes. 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 * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

tices across countries. Following (Momferatou et al., 2008), We classify these systems into three categories: highly centralised, sectorally regulated, and largely deregulated. The first category includes countries[23] with centralised systems with a substantial role in government intervention

[23]Belgium, Slovenia, and Spain.

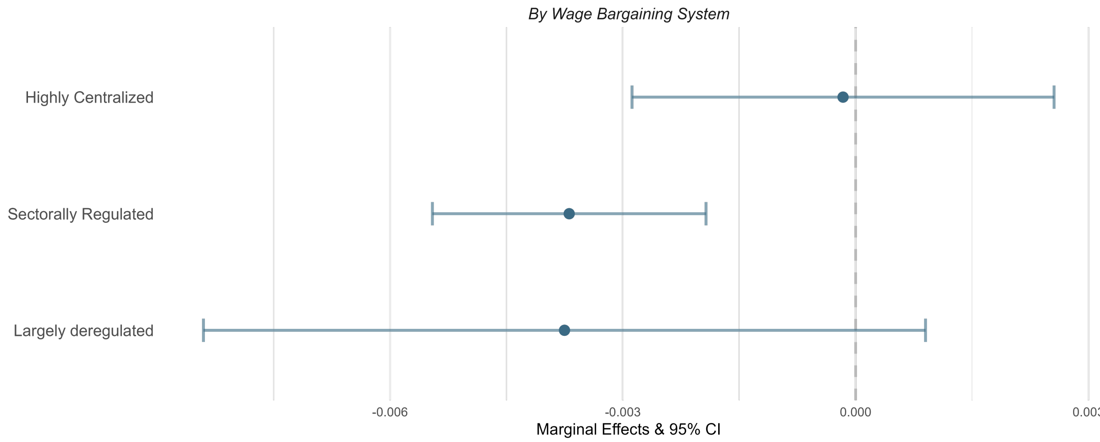

Figure 2: Marginal Effect of Heat Waves by Institutional Setting and Geographical Area

The figure displays the marginal effects and corresponding 95% confidence intervals from the regressions estimated in Equation 3, where heat waves are interacted with (i) a categorical variable classifying the type of bargaining systems.

in addition to sectoral and intersectoral agreements. The second category encompasses nations[24] where wage-setting is predominantly regulated at the sectoral level with some firm-level coordination. Finally, the third group consists of countries[25] with largely deregulated systems, where wage bargaining is primarily decentralised.

As shown in Figure 2, highly centralized bargaining systems appear to act as a buffer, mitigating the adverse effects of heat-wave exposure on earnings. In contrast, workers in sectorally and largely deregulated bargaining systems experience substantially greater income losses—on average \$236.08 (-0.88%) and \$50.03 (-0.65%) per year, respectively (Table G.32 in Appendix G). The effect is statistically significant only for countries with sectorally regulated bargaining systems; however, despite the wider confidence intervals for largely deregulated systems, their point estimates are of comparable magnitude. These patterns indicate that only highly coordinated wage-setting systems are effective in insulating workers' earnings from temperature-induced productivity shocks, whereas in less centralized systems—where institutional protections are weaker—workers remain more vulnerable. Given the limited cross-country variation in bargaining institutions, these results should be interpreted as suggestive rather than conclusive. Nonetheless, they underscore the mediating role of collective bargaining and wage-setting arrangements in protecting labor income from climate-related shocks.

[24] Austria, Denmark, France, Germany, Greece, Italy, Portugal, and Sweden.
[25] The Czech Republic and Poland.

6.3 Effects Along the Earning Distribution

Our results from the unconditional quantile regression are reported in Figure 3. The negative effects of HWs are widespread across the earnings distribution. However, a visual inspection of the confidence intervals and the point estimate reveals that the impact at the lower tail—particularly at the 5th percentile—is significantly larger than at most other deciles. Our findings provide new evidence to the fact that climate change harms disproportionally low-income households (Hallegatte and Rozenberg, 2017) harming within-country income inequality (Behrer et al., 2021; Gilli et al., 2024).

Because sectoral and occupational exposure to heat shocks drive the average results, we replicate the quantile regression analysis for the specification allowing for a differential effects for highly exposed categories. *Panel B* of Figure 3 presents quantile regression estimates interacting heat wave exposure with a dummy for outdoor-exposed sectors, while *Panel C* shows analogous estimates using a dummy for outdoor-exposed occupations. As would be expected, both sets of results follow a similar pattern to the baseline estimates— low-income workers are particularly damaged by HWs when they are in exposed workplaces. Notably, the pattern is particularly evident when using occupational rather than sectoral exposure to HWs. This finding supports the insight of our conceptual framework where the nature of the tasks performed is the primary driver of the adverse impact of heat waves on wages.

Quantifying the impact (Table G.32), we observe that workers at the 5th percentile within exposed occupations experience an average annual income loss of $68.71, compared to $1400.91 for those at the 95th percentile. While the absolute loss is larger for higher earners, the relative burden is significantly greater for low-income workers: the loss represents approximately 4.47% of their annual income versus the 1.55% for those in the top income bracket. This further reinforces one of the key findings of this paper: the increasing incidence of heat waves is likely to exacerbate existing labor market inequalities.

6.4 The Role of Socio-Demographics Vulnerabilities

Table E.28 and Figure 4 present heterogeneity in the estimated effects across socio-demographic groups. The results indicate variation by age, with statistically significant effects only among individuals older than 25. This pattern is consistent with the lower capacity of older workers to perform physically demanding tasks on hot days, implying that their productivity—closely tied to individual capabilities—declines more sharply. No meaningful differences are observed by gender or health status. Our results on sorting (Table 3) show that women are less frequently employed in these occupations. While we do not find statistically significant differences for individuals in poor health, it is plausible that they try to avoid such jobs, if possible. Educational attainment does not reveal strong heterogeneity overall, although, the adverse effect of heat waves is absent among individuals with the highest level of education—those with tertiary qualifications. Finally, results highlight that HWs trigger also a mechanism of intergenerational inequality: workers from more advantaged social backgrounds (proxied by the number of books at home) show no significant

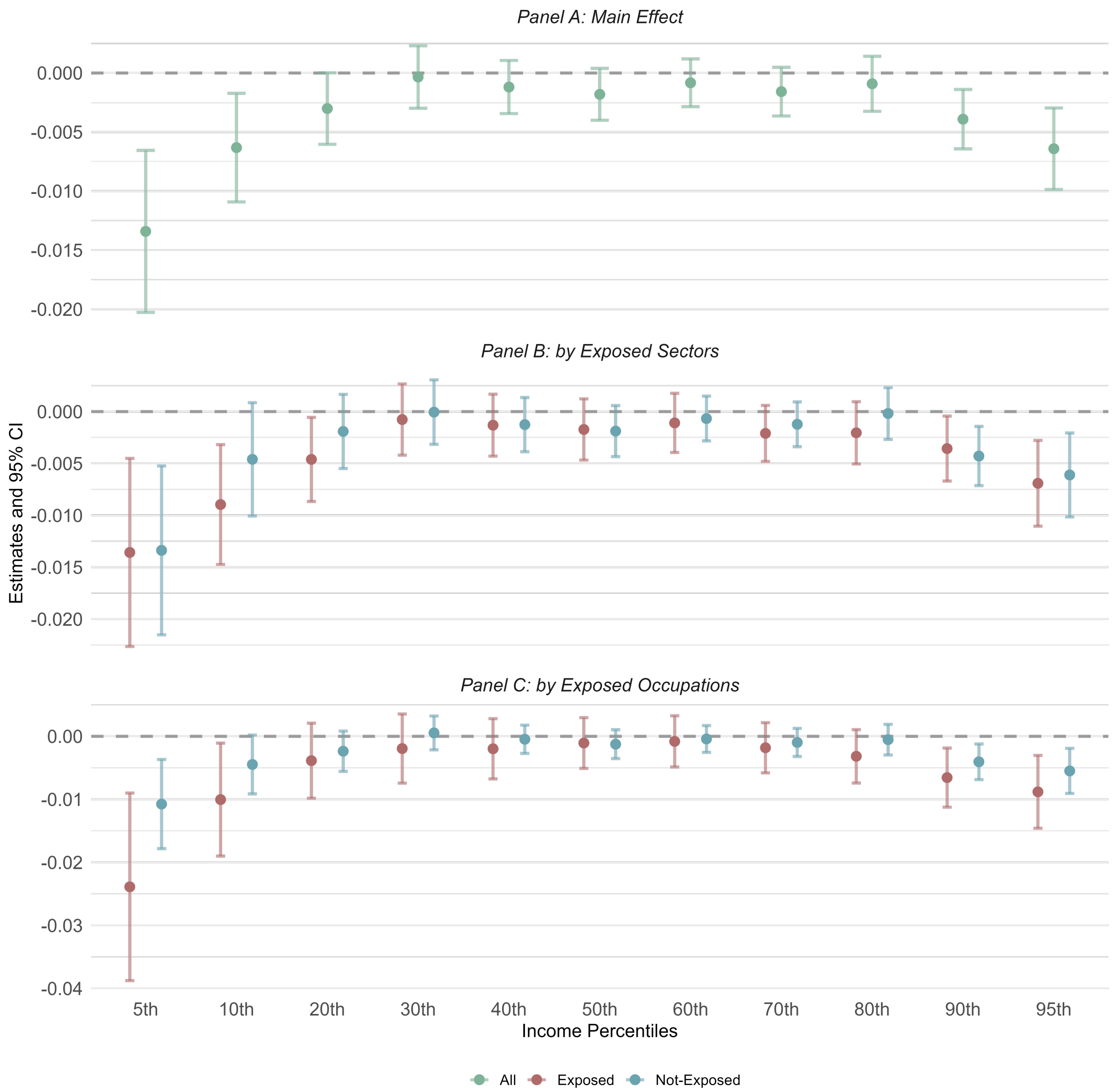

Figure 3: Temperature Impact on Earnings - Unconditional Quantile Regression

The figure displays estimates and 95% confidence intervals 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). 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. Clustered standard errors at sub-minimum NUTS level (the source of temperature variation) in parentheses. * $(p < 0.10)$, ** $(p < 0.05)$, *** $(p < 0.01)$.

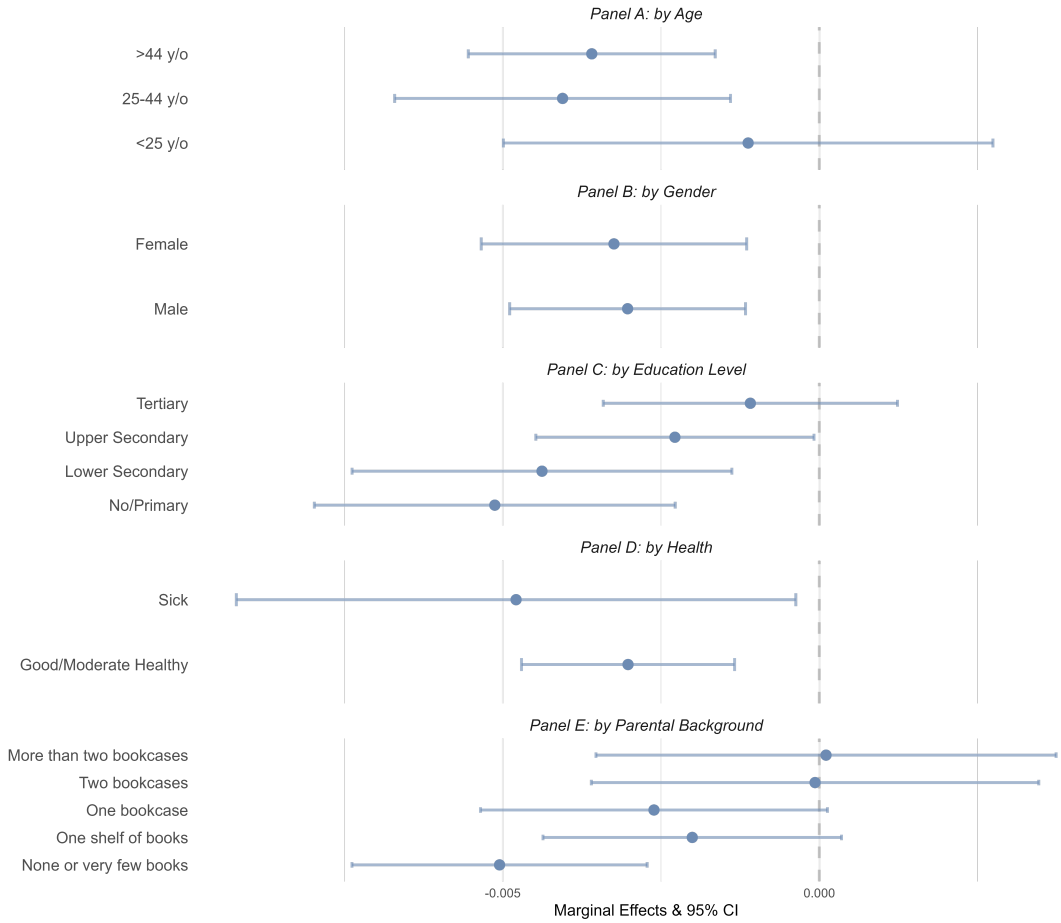

Figure 4: Marginal Effect of Heat Waves by Socio-Demographic Dimensions

The figure reports marginal effects and 95% confidence intervals from regressions based on Equation 3, 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).

earnings response to heat wave exposure, suggesting that climate shocks can exacerbate existing social inequalities. Our findings support previous evidence of regressive impacts observed at the county level (Behrer et al., 2021), but enrich them by uncovering the most vulnerable workers along several dimensions.

Overall, although the difference in the marginal effects of HWs is not always statistically significant across groups within a given dimension, our results indicate that the average annual loss in earnings (Table G.32 of Appendix G) is often larger among more disadvantaged groups. For instance, workers from low parental backgrounds (proxied by having none or few books at home at age 10) experience an average 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 highlights how exposure to extreme heat may act as a mechanism that reinforces pre-existing socio-economic inequalities, both within and across generations.

7 Conclusions

This paper provides new evidence on the earnings impact of extreme heat using rich, individual-level longitudinal data for 14 European countries spanning more than six decades. We find that heatcwaves exposure has a significant negative effect, with each additional day lowering average monthly earnings by approximately 0.31%, corresponding to an average annual income loss of around $159.63.

Earnings losses are highly uneven across workers. Individuals employed in more exposed occupations and sectors—particularly outdoor manual and clerical jobs, as well as in agriculture—experience the largest reductions in income. We show that these roles are more likely to be held by individuals with lower educational attainment and more disadvantaged socio-economic backgrounds, suggesting that extreme heat serves as a reinforcing mechanism for existing inequalities.

Institutional context plays a critical mediating role. In countries with more decentralised or deregulated wage-setting systems, we observe significantly larger earnings losses from heat exposure. By contrast, collective bargaining appears to offer a buffer, protecting workers' incomes from climate-related shocks. This finding highlights the importance of wage institutions in shaping the incidence and severity of climate impacts on the labor market.

We also document that earnings losses are disproportionately concentrated among vulnerable sociodemographic groups, particularly low-income individuals (5th poorest percentile), adults and the elderly, individuals with low educational attainment, and those from less advantaged family backgrounds. These results further underscore that the labor market consequences of climate change are not evenly distributed. The unequal nature of climate-induced earnings losses calls for targeted public policy responses; indeed, unequal damages from climate shocks can justify public intervention even in the absence of conventional market failures (Carleton et al., 2024). Policies that strengthen labor protections, support adaptation in vulnerable sectors, and address distributional disparities are essential to prevent climate change from exacerbating pre-existing inequalities.

References

Acemoglu, Daron and David Autor (2011). "Skills, tasks and technologies: Implications for employment and earnings". In: *Handbook of Labor Economics*. Vol. 4. Elsevier, pp. 1043–1171.

Acemoglu, Daron, David Autor, David Dorn, Gordon H Hanson, and Brendan Price (2016). "Import competition and the great US employment sag of the 2000s". In: *Journal of Labor Economics* 34.S1, S141–S198.

Acemoglu, Daron and Pascual Restrepo (2019). "Automation and new tasks: How technology displaces and reinstates labor". In: *Journal of Economic Perspectives* 33.2, pp. 3–30.

Acevedo, Sebastian, Mico Mrkaic, Natalija Novta, Evgenia Pugacheva, and Petia Topalova (2020). "The effects of weather shocks on economic activity: what are the channels of impact?" In: *Journal of Macroeconomics* 65, p. 103207.

Adhvaryu, Achyuta, Namrata Kala, and Anant Nyshadham (2020). "The light and the heat: Productivity co-benefits of energy-saving technology". In: *Review of Economics and Statistics* 102.4, pp. 779–792.

Agarwal, Sumit, Yu Qin, Luwen Shi, Guoxu Wei, and Hongjia Zhu (2021). "Impact of temperature on morbidity: New evidence from China". In: *Journal of Environmental Economics and Management* 109, p. 102495.

Aguilar-Gomez, Sandra, Joshua S. Graff Zivin, and Matthew J. Neidell (2025). "Killer Congestion: Temperature, Healthcare Utilization and Patient Outcomes". In: 33491. DOI: `10.3386/w33491`. URL: `https://doi.org/10.3386/w33491`.

Altonji, Joseph G, Todd E Elder, and Christopher R Taber (2005). "Selection on observed and unobserved variables: Assessing the effectiveness of Catholic schools". In: *Journal of Political Economy* 113.1, pp. 151–184.

Angrist, Joshua D and Jörn-Steffen Pischke (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton university press.

Auci, Sabrina, Nicolò Barbieri, Manuela Coromaldi, and Melania Michetti (2021). "Climate variability, innovation and firm performance: evidence from the European agricultural sector". In: *European Review of Agricultural Economics* 48.5, pp. 1074–1108.

Autor, David H, David Dorn, and Gordon H Hanson (2013). "The China syndrome: Local labor market effects of import competition in the United States". In: *American economic review* 103.6, pp. 2121–2168.

Autor, David H and Michael J Handel (2013). "Putting tasks to the test: Human capital, job tasks, and wages". In: *Journal of labor Economics* 31.S1, S59–S96.

Babeckỳ, Jan, Philip Du Caju, Theodora Kosma, Martina Lawless, Julián Messina, and Tairi Rõõm (2010). "Downward nominal and real wage rigidity: Survey evidence from European firms". In: *Scandinavian Journal of Economics* 112.4, pp. 884–910.

Banzhaf, H Spencer, Lala Ma, and Christopher Timmins (2019). "Environmental justice: Establishing causal relationships". In: *Annual Review of Resource Economics* 11.1, pp. 377–398.

Barnett, AG, Shakoor Hajat, Antonio Gasparrini, and Joacim Rocklöv (2012). "Cold and heat waves in the United States". In: *Environmental research* 112, pp. 218–224.

Barreca, Alan, Karen Clay, Olivier Deschenes, Michael Greenstone, and Joseph S Shapiro (2016). "Adapting to climate change: The remarkable decline in the US temperature-mortality relationship over the twentieth century". In: *Journal of Political Economy* 124.1, pp. 105–159.

Behrer, A Patrick, R Jisung Park, Gernot Wagner, Colleen M Golja, and David W Keith (2021). "Heat has larger impacts on labor in poorer areas". In: *Environmental Research Communications* 3.9, p. 095001.

Behrer, A. Patrick, Nora M. C. Pankratz, and R. Jisung Park (2024). "Mandated versus Voluntary Firm Investment in Climate Adaptation". Mimeo. URL: https://www.clemson.edu/centers-institutes/hayek/documents/bpp-mandated-disclosure-climate-adaptation.pdf.

Belasen, Ariel R and Solomon W Polachek (2008). "How hurricanes affect wages and employment in local labor markets". In: *American Economic Review* 98.2, pp. 49–53.

Bhuller, Manudeep, Karl Ove Moene, Magne Mogstad, and Ola L Vestad (2022). "Facts and fantasies about wage setting and collective bargaining". In: *Journal of Economic Perspectives* 36.4, pp. 29–52.

Bilal, Adrien and Diego R Känzig (2024). *The macroeconomic impact of climate change: Global vs. local temperature*. Tech. rep. National Bureau of Economic Research.

Bilal, Adrien and Esteban Rossi-Hansberg (2023). *Anticipating Climate Change Across the United States*. NBER Working Paper 31323. National Bureau of Economic Research. DOI: 10.3386/w31323. URL: https://doi.org/10.3386/w31323.

Blanchard, Olivier and Justin Wolfers (2000). "The Role of Shocks and Institutions in the Rise of European Unemployment: the". In: *Monetary Policy and Unemployment*, pp. 25–56.

Blanchard, Olivier J. and Thomas Philippon (2004). *The Quality of Labor Relations and Unemployment*. NBER Working Paper 10590. National Bureau of Economic Research. DOI: 10.3386/w10590. URL: https://doi.org/10.3386/w10590.

Boeri, Tito and Pietro Garibaldi (2007). "Two tier reforms of employment protection: A honeymoon effect?" In: *The Economic Journal* 117.521, F357–F385.

Bressler, R Daniel, Anna Papp, Luis Sarmiento, Jeffrey Shrader, and Andrew Wilson (2025). "Working Under the Sun: The Role of Occupation in Temperature-Related Mortality in Mexico". In.

Brunello, Giorgio, Guglielmo Weber, and Christoph T Weiss (2017). "Books are forever: Early life conditions, education and lifetime earnings in Europe". In: *The Economic Journal* 127.600, pp. 271–296.

Burke, Marshall, Solomon M Hsiang, and Edward Miguel (2015). "Global non-linear effect of temperature on economic production". In: *Nature* 527.7577, pp. 235–239.

Burke, Marshall and Vincent Tanutama (2019). *Climatic Constraints on Aggregate Economic Output*. NBER Working Paper 25779. National Bureau of Economic Research. DOI: 10.3386/w25779. URL: https://doi.org/10.3386/w25779.

Cachon, Gerard P, Santiago Gallino, and Marcelo Olivares (2012). "Severe weather and automobile assembly productivity". In: *Columbia Business School Research Paper* 12/37.

Cai, Xiqian, Yi Lu, and Jin Wang (2018). "The impact of temperature on manufacturing worker productivity: evidence from personnel data". In: *Journal of Comparative Economics* 46.4, pp. 889–905.

Calmfors, Lars and John Driffill (1988). "Bargaining structure, corporatism and macroeconomic performance". In: *Economic Policy* 3.6, pp. 13–61.

Carleton, Tamma, Esther Duflo, B Kelsey Jack, and Guglielmo Zappalà (2024). "Adaptation to climate change". In: *Handbook of the Economics of Climate Change*. Vol. 1. 1. Elsevier, pp. 143–248.

Carleton, Tamma, Amir Jina, Michael Delgado, Michael Greenstone, Trevor Houser, Solomon Hsiang, Andrew Hultgren, Robert E Kopp, Kelly E McCusker, Ishan Nath, et al. (2022). "Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits". In: *The Quarterly Journal of Economics* 137.4, pp. 2037–2105.

Carleton, Tamma A and Solomon M Hsiang (2016). "Social and economic impacts of climate". In: *Science* 353.6304, aad9837.

Chen, Xiaoguang and Lu Yang (2019). "Temperature and industrial output: Firm-level evidence from China". In: *Journal of Environmental Economics and Management* 95, pp. 257–274.

Climate Change (IPCC), Intergovernmental Panel on (2023). "Weather and Climate Extreme Events in a Changing Climate". In: *Climate Change 2021 – The Physical Science Basis: Working Group I Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, pp. 1513–1766.

Colmer, Jonathan (2021). "Temperature, labor reallocation, and industrial production: Evidence from India". In: *American Economic Journal: Applied Economics* 13.4, pp. 101–124.

Colmer, Jonathan and John Voorheis (2020). *The Grandkids Aren't Alright: The Intergenerational Effects of Prenatal Pollution Exposure*. CES Working Paper 20-36. Center for Economic Studies, U.S. Census Bureau. URL: https://ideas.repec.org/p/cen/wpaper/20-36.html.

Costa, Hélia, Guido Franco, Filiz Ünsal, Sarath Mudigonda, and Maria Paula Caldas (2024). *The Heat Is On: Heat Stress, Productivity and Adaptation Among Firms*. OECD Economics Department Working Paper 1828. Paris: Organisation for Economic Co-operation and Development. DOI: 10.1787/19d94638-en. URL: https://doi.org/10.1787/19d94638-en.

Currie, Janet, John Voorheis, and Reed Walker (2023). "What caused racial disparities in particulate exposure to fall? New evidence from the Clean Air Act and satellite-based measures of air quality". In: *American Economic Review* 113.1, pp. 71–97.

Dasgupta, Shouro, Elizabeth JZ Robinson, Soheil Shayegh, Francesco Bosello, R Jisung Park, and Simon N Gosling (2024). "Heat stress and the labour force". In: *Nature Reviews Earth & Environment* 5.12, pp. 859–872.

Dell, Melissa, Benjamin F Jones, and Benjamin A Olken (2009). "Temperature and income: reconciling new cross-sectional and panel estimates". In: *American Economic Review* 99.2, pp. 198–204.

— (2012). "Temperature shocks and economic growth: Evidence from the last half century". In: *American Economic Journal: Macroeconomics* 4.3, pp. 66–95.

Deryugina, Tatyana (2017). "The fiscal cost of hurricanes: Disaster aid versus social insurance". In: *American Economic Journal: Economic Policy* 9.3, pp. 168–198.

Deryugina, Tatyana and Solomon M. Hsiang (2014). *Does the Environment Still Matter? Daily Temperature and Income in the United States*. NBER Working Paper 20750. National Bureau of Economic Research. DOI: 10.3386/w20750. URL: https://doi.org/10.3386/w20750.

Deryugina, Tatyana, Laura Kawano, and Steven Levitt (2018). "The economic impact of Hurricane Katrina on its victims: Evidence from individual tax returns". In: *American Economic Journal: Applied Economics* 10.2, pp. 202–233.

Deschênes, Olivier and Michael Greenstone (2011). "Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US". In: *American Economic Journal: Applied Economics* 3.4, pp. 152–185.

Diffenbaugh, Noah S and Marshall Burke (2019). "Global warming has increased global economic inequality". In: *Proceedings of the National Academy of Sciences* 116.20, pp. 9808–9813.

Dillender, Marcus (2021). "Climate change and occupational health: Are there limits to our ability to adapt?" In: *Journal of Human Resources* 56.1, pp. 184–224.

Emerick, Kyle (2018). "Agricultural productivity and the sectoral reallocation of labor in rural India". In: *Journal of Development Economics* 135, pp. 488–503.

Firpo, Sergio, Nicole M Fortin, and Thomas Lemieux (2009). "Unconditional quantile regressions". In: *Econometrica* 77.3, pp. 953–973.

Gagliardi, Nicola, Elena Grinza, and François Rycx (2024). "The Productivity Impact of Global Warming: Firm-Level Evidence for Europe". In: *IZA Discussion Papers No. 17241, IZA Institute for Labor Economics*.

Garg, Teevrat, Matthew Gibson, and Fanglin Sun (2020). "Extreme temperatures and time use in China". In: *Journal of Economic Behavior & Organization* 180, pp. 309–324.

Garrouste, Christelle, Omar Paccagnella, et al. (2011). "Data quality: Three examples of consistency across SHARE and SHARELIFE data". In: *Retrospective Data Collection in the Survey of Health, Ageing and Retirement in Europe. SHARELIFE Methodology. Mannheim Research Institute for the Economics of Ageing (MEA): Mannheim*, pp. 62–72.

Gathmann, Christina and Uta Schönberg (2010). "How general is human capital? A task-based approach". In: *Journal of Labor Economics* 28.1, pp. 1–49.

Gilli, Martino, Matteo Calcaterra, Johannes Emmerling, and Francesco Granella (2024). "Climate change impacts on the within-country income distributions". In: *Journal of Environmental Economics and Management* 127, p. 103012.

Gould, Carlos F, Sam Heft-Neal, Alexandra K Heaney, Eran Bendavid, Christopher W Callahan, Mathew V Kiang, Josh Graff Zivin, and Marshall Burke (2025). "Temperature extremes impact mortality and morbidity differently". In: *Science Advances* 11.31, eadr3070.

Graetz, Georg and Guy Michaels (2018). "Robots at work". In: *Review of economics and statistics* 100.5, pp. 753–768.

Graff Zivin, Joshua, Solomon M Hsiang, and Matthew Neidell (2018). "Temperature and human capital in the short and long run". In: *Journal of the Association of Environmental and Resource Economists* 5.1, pp. 77–105.

Graff Zivin, Joshua and Matthew Neidell (2014). "Temperature and the allocation of time: Implications for climate change". In: *Journal of Labor Economics* 32.1, pp. 1–26.

Guvenen, Fatih, Burhan Kuruscu, Satoshi Tanaka, and David Wiczer (2020). "Multidimensional skill mismatch". In: *American Economic Journal: Macroeconomics* 12.1, pp. 210–244.

Hajat, Shakoor, Ben Armstrong, Michela Baccini, Annibale Biggeri, Luigi Bisanti, Antonio Russo, Anna Paldy, Bettina Menne, and Tom Kosatsky (2006). "Impact of high temperatures on mortality: is there an added heat wave effect?" In: *Epidemiology* 17.6, pp. 632–638.

Hallegatte, Stephane and Julie Rozenberg (2017). "Climate change through a poverty lens". In: *Nature Climate Change* 7.4, pp. 250–256.

Havari, Enkelejda and Fabrizio Mazzonna (2015). "Can we trust older people's statements on their childhood circumstances? Evidence from SHARELIFE". In: *European Journal of Population* 31.3, pp. 233–257.

Heal, Geoffrey and Jisung Park (2016). "Reflections—Temperature Stress and the Direct Impact of Climate Change: A Review of an Emerging Literature". In: *Review of Environmental Economics and Policy* 10.2, pp. 347–362. DOI: 10.1093/reep/rew007. URL: https://doi.org/10.1093/reep/rew007.

Hernandez, I., J. Steckel, M. Tavoni, E Verdolini, and F. Vona (2026). "The Economics of the Just Energy Transition". In: *Review of Environmental Economics and Policy, forthcoming*.

Hoffmann, Roman, Raya Muttarak, Jonas Peisker, and Piero Stanig (2022). "Climate change experiences raise environmental concerns and promote Green voting". In: *Nature Climate Change* 12.2, pp. 148–155.

Hogan, Dylan and Wolfram Schlenker (2024). "Empirical approaches to climate change impact quantification". In: *Handbook of the Economics of Climate Change*. Vol. 1. 1. Elsevier, pp. 53–111.

Hooyberghs, H, J Berckmans, F Lefebre, and K De Ridder (2019). "Heat waves and cold spells in Europe derived from climate projections". In: *Copernicus Climate Change Service (C3S) Climate Data Store (CDS)* 10.

Hsiang, Solomon (2016). "Climate econometrics". In: *Annual Review of Resource Economics* 8.1, pp. 43–75.

Hsiang, Solomon, Robert Kopp, Amir Jina, James Rising, Michael Delgado, Shashank Mohan, Robert Muir-Wood, Paul Wilson, Michael Oppenheimer, et al. (2017). "Estimating economic damage from climate change in the United States". In: *Science* 356.6345, pp. 1362–1369.

Hsiang, Solomon M (2010). "Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America". In: *Proceedings of the National Academy of sciences* 107.35, pp. 15367–15372.

Hultgren, Andrew, Tamma Carleton, Michael Delgado, Diana R. Gergel, Michael Greenstone, Trevor Houser, Solomon Hsiang, Amir Jina, Robert E. Kopp, Steven B. Malevich, Kelly E. McCusker, and ... (2025). "Impacts of Climate Change on Global Agriculture Accounting for

Adaptation". In: *Nature* 642.8068, pp. 644–652. DOI: 10.1038/s41586-025-09085-w. URL: https://doi.org/10.1038/s41586-025-09085-w.

IPCC (2023). "Technical Summary". In: *Climate Change 2021 – The Physical Science Basis: Working Group I Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, pp. 35–144.

Ireland, Andrew, David Johnston, and Rachel Knott (2023). "Heat and worker health". In: *Journal of health economics* 91, p. 102800.

Jessoe, Katrina, Dale T Manning, and J Edward Taylor (2018). "Climate change and labour allocation in rural Mexico: Evidence from annual fluctuations in weather". In: *The Economic Journal* 128.608, pp. 230–261.

Jones, B. F., J. Moscona, B. A. Olken, and C. von Dessauer (2025). "With or Without U? Binning Bias and the Causal Effects of Temperature Shocks". In: *Mimeo*.

Jovanovic, Boyan (1979). "Job matching and the theory of turnover". In: *Journal of political economy* 87.5, Part 1, pp. 972–990.

Kahn, Matthew E. (2016). "The Climate Change Adaptation Literature". In: *Review of Environmental Economics and Policy* 10.1, pp. 166–178. DOI: 10.1093/reep/rew006. URL: https://doi.org/10.1093/reep/rew006.

Kjellstrom, Tord, Ingvar Holmer, and Bruno Lemke (2009). "Workplace heat stress, health and productivity–an increasing challenge for low and middle-income countries during climate change". In: *Global health action* 2.1, p. 2047.

Klauber, Hannah, Nicolas Koch, and Nico Pestel (2025). *The Immediate and Lasting Effects of Heat Waves on Workers*. IZA Discussion Paper 18176. Institute of Labor Economics (IZA). URL: https://www.iza.org/publications/dp/18176/the-immediate-and-lasting-effects-of-heat-waves-on-workers.

Koenker, Roger (2005). *Quantile Regression*. Cambridge, UK: Cambridge University Press. ISBN: 978-0-521-82743-0. URL: https://www.cambridge.org/core/books/quantile-regression/C18AE7BCF3EC43C16937390D44A328B1.

Koenker, Roger and Gilbert Bassett (1978). "Regression Quantiles". In: *Econometrica* 46.1, pp. 33–50. URL: https://www.jstor.org/stable/1913643.

Krebs, Benjamin (2024). "Temperature and cognitive performance: Evidence from mental arithmetic training". In: *Environmental and Resource Economics* 87.7, pp. 2035–2065.

Krugman, Paul et al. (1994). "Past and prospective causes of high unemployment". In: *Reducing unemployment: Current issues and policy options*, pp. 49–80.

Lai, Wangyang, Yun Qiu, Qu Tang, Chen Xi, and Peng Zhang (2023). "The effects of temperature on labor productivity". In: *Annual Review of Resource Economics* 15.1, pp. 213–232.

Li, Chengzheng and Zheng Pan (2021). "How do extremely high temperatures affect labor market performance? Evidence from rural China". In: *Empirical Economics* 61.4, pp. 2265–2291.

Liu, Maggie, Yogita Shamdasani, and Vis Taraz (2023). "Climate change and labor reallocation: Evidence from six decades of the Indian Census". In: *American Economic Journal: Economic Policy* 15.2, pp. 395–423.

LoPalo, Melissa (2023). “Temperature, worker productivity, and adaptation: evidence from survey data production”. In: *American Economic Journal: Applied Economics* 15.1, pp. 192–229.

Marin, Giovanni and Francesco Vona (2019). “Climate policies and skill-biased employment dynamics: Evidence from EU countries”. In: *Journal of Environmental Economics and Management* 98, p. 102253.

Miao, Qing and David Popp (2014). “Necessity as the mother of invention: Innovative responses to natural disasters”. In: *Journal of Environmental Economics and Management* 68.2, pp. 280–295.

Midões, Catarina, Enrica De Cian, Giacomo Pasini, Sara Pesenti, and Malcolm N Mistry (2024). “SHARE-ENV: A Data Set to Advance Our Knowledge of the Environment–Wellbeing Relationship”. In: *Environment & Health* 2.2, pp. 95–104.

Miller, Steve, Kenn Chua, Jay Coggins, and Hamid Mohtadi (2021). “Heat waves, climate change, and economic output”. In: *Journal of the European Economic Association* 19.5, pp. 2658–2694.

Momferatou, Daphne, Melanie E. Ward-Warmedinger, Erwan Gautier, and Philip Du Caju (2008). *Institutional Features of Wage Bargaining in 23 European Countries, the US and Japan*. Working Paper Series 974. European Central Bank. URL: https://www.ecb.europa.eu/pub/pdf/scpwps/ecbwp974.pdf.

Mortensen, Dale T and Christopher A Pissarides (1994). “Job creation and job destruction in the theory of unemployment”. In: *The review of economic studies* 61.3, pp. 397–415.

Neidell, Matthew, Joshua Graff Zivin, Megan Sheahan, Jacqueline Willwerth, Charles Fant, Marcus Sarofim, and Jeremy Martinich (2021). “Temperature and work: Time allocated to work under varying climate and labor market conditions”. In: *PloS one* 16.8, e0254224.

Newell, Richard G, Brian C Prest, and Steven E Sexton (2021). “The GDP-temperature relationship: implications for climate change damages”. In: *Journal of Environmental Economics and Management* 108, p. 102445.

Niemelä, Raimo, Mika Hannula, Sari Rautio, Kari Reijula, and Jorma Railio (2002). “The effect of air temperature on labour productivity in call centres—a case study”. In: *Energy and buildings* 34.8, pp. 759–764.

Oliveira, Jaqueline, Bruno Palialol, and Paula Pereda (2021). “Do temperature shocks affect non-agriculture wages in Brazil? Evidence from individual-level panel data”. In: *Environment and Development Economics* 26.5-6, pp. 450–465.

Ortiz-Molina, Hernán, Zhanbing Xiao, and Xin Zheng (2024). “Adaptation to Climate-induced Regulatory Risk: A Labor Perspective”. Mimeo.

Park, Jisung (2016). “Will We Adapt? Temperature Shocks, Labor Productivity, and Adaptation to Climate Change in the United States”. Mimeo. URL: https://scholar.harvard.edu/files/jisungpark/files/park_2016_-_will_we_adapt_-_april_2016_draft.pdf.

Park, Jisung, Mook Bangalore, Stephane Hallegatte, and Evan Sandhoefner (2018). “Households and heat stress: estimating the distributional consequences of climate change”. In: *Environment and Development Economics* 23.3, pp. 349–368.

Park, Jisung and Geoffrey Heal (2013). “Feeling the heat: Temperature, physiology & the wealth of nations”. In: *No. w19725). National Bureau of Economic Research*.

Park, Jisung, Nora Pankratz, and Arnold Behrer (2021). *Temperature, Workplace Safety, and Labor Market Inequality*. IZA Discussion Paper 14560. IZA – Institute of Labor Economics. URL: https://www.iza.org/publications/dp/14560/temperature-workplace-safety-and-labor-market-inequality.

Park, R Jisung (2022). "Hot temperature and high-stakes performance". In: *Journal of Human Resources* 57.2, pp. 400–434.

Park, R Jisung, Joshua Goodman, Michael Hurwitz, and Jonathan Smith (2020). "Heat and learning". In: *American Economic Journal: Economic Policy* 12.2, pp. 306–339.

Peng, Roger D, Jennifer F Bobb, Claudia Tebaldi, Larry McDaniel, Michelle L Bell, and Francesca Dominici (2011). "Toward a quantitative estimate of future heat wave mortality under global climate change". In: *Environmental health perspectives* 119.5, pp. 701–706.

Picchio, Matteo and Jan C Van Ours (2025). "High temperatures and workplace injuries". In: *Empirical Economics*, pp. 1–31.

Quilcaille, Yann, Lukas Gudmundsson, Dominik L Schumacher, Thomas Gasser, Richard Heede, Corina Heri, Quentin Lejeune, Shruti Nath, Philippe Naveau, Wim Thiery, et al. (2025). "Systematic attribution of heatwaves to the emissions of carbon majors". In: *Nature* 645.8080, pp. 392–398.

Rode, Ashwin, Rachel E. Baker, Tamma Carleton, Anthony D'Agostino, Michael Delgado, Timothy Foreman, Diana R. Gergel, Michael Greenstone, Trevor Houser, Solomon Hsiang, Andrew Hultgren, Amir Jina, Robert E. Kopp, Steven B. Malevich, Kelly McCusker, Ishan Nath, Matthew Pecenco, James Rising, and Jiacan Yuan (2022). "Labor Disutility in a Warmer World: The Impact of Climate Change on the Global Workforce". Available at SSRN: https://ssrn.com/abstract=4221478 or DOI: 10.2139/ssrn.4221478.

Russo, Simone, Alessandro Dosio, Rune G Graversen, Jana Sillmann, Hugo Carrao, Martha B Dunbar, Andrew Singleton, Paolo Montagna, Paulo Barbola, and Jürgen V Vogt (2014). "Magnitude of extreme heat waves in present climate and their projection in a warming world". In: *Journal of Geophysical Research: Atmospheres* 119.22, pp. 12–500.

Schlenker, Wolfram and Michael J Roberts (2009). "Nonlinear temperature effects indicate severe damages to US crop yields under climate change". In: *Proceedings of the National Academy of sciences* 106.37, pp. 15594–15598.

Somanathan, Eswaran, Rohini Somanathan, Anant Sudarshan, and Meenu Tewari (2021). "The impact of temperature on productivity and labor supply: Evidence from Indian manufacturing". In: *Journal of Political Economy* 129.6, pp. 1797–1827.

Tarsia, Romano (2024). "Heterogeneous Effects of Weather Shocks on Firm Economic Performance". Available at SSRN: https://ssrn.com/abstract=4672552 or DOI: 10.2139/ssrn.4672552.

Trevisan, Elisabetta, Giacomo Pasini, Roberta Rainato, et al. (2011). "Cross-country comparison of monetary values from SHARELIFE". In: *SHARE Working Paper Series 02-2011*.

Vona, Francesco (2023). "Managing the distributional effects of climate policies: A narrow path to a just transition". In: *Ecological Economics* 205, p. 107689.

White, Corey (2017). “The dynamic relationship between temperature and morbidity”. In: *Journal of the Association of Environmental and Resource Economists* 4.4, pp. 1155–1198.

Yuan, Zhengrong, Hai Ding, and Qiuzuo Yu (2024). “High temperature, bargaining power and within-firm wage inequality: Evidence from China”. In: *Economic Modelling* 135, p. 106729.

Zhang, Jingfang, Emir Malikov, and Ruiqing Miao (2024). “Distributional effects of the increasing heat incidence on labor productivity”. In: *Journal of Environmental Economics and Management* 125, p. 102998.

Zhang, Peng, Olivier Deschenes, Kyle Meng, and Junjie Zhang (2018). “Temperature effects on productivity and factor reallocation: Evidence from a half million Chinese manufacturing plants”. In: *Journal of Environmental Economics and Management* 88, pp. 1–17.

Zhang, Wei, Ning Ding, Yilong Han, Jie He, and Na Zhang (2023). “The impact of temperature on labor productivity——evidence from temperature-sensitive enterprises”. In: *Frontiers in Environmental Science* 10, p. 1039668.

Zilia, Federico, Paolo Nota, and Alessandro Olper (2025). “Weather Shocks and Sectoral Labour Reallocation in the European Sub-national Units”. Mimeo. URL: https://ageconsearch.umn.edu/record/356767/?v=pdf.

Zivin, Joshua Graff and Jeffrey Shrader (2016). “Temperature extremes, health, and human capital”. In: *The Future of Children*, pp. 31–50.

Zivin, Joshua Graff, Yingquan Song, Qu Tang, and Peng Zhang (2020). “Temperature and high-stakes cognitive performance: Evidence from the national college entrance examination in China”. In: *Journal of Environmental Economics and Management* 104, p. 102365.

Appendices

A Descriptive Statistics

Table A1: Classification of Occupations at Risk of Heat Stress

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

ISCO-08	Definition ISCO-08	Heat-Exposed	Occupation
7111	House Builders	1	*Manual*
7112	Bricklayers and Related Workers	1	*Manual*
7113	Stonemasons, Stone Cutters, Splitters and Carvers	1	*Manual*
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*

Table A2: Summary Statistics

	Variable	Obs	Mean	Median	SD	Min	Max
			Dependent Variable				
Earnings	continuous	75258	2070.14	1608.82	1782.01	16.71	11595.59
			Main Regressors				
T $\geq$ 95th perc, 3 days	discrete	75258	8.53	7.00	7.49	0	69
T $\geq$ 95th perc, 5 days	discrete	75258	2.91	1.00	4.62	0	60
T $\geq$ 30 °C, 3 days	discrete	75258	5.65	0.00	13.29	0	108
T $\geq$ 30 °C, 5 days	discrete	75258	2.98	0.00	9.26	0	86
			Main Covariates				
Avg. prec.	continuous	75258	2.10	2.00	0.71	0.27	7.70
Age	discrete	75258	39.96	40.00	16.55	9	92
Gender	dummy	75258	1.49	1	0.50	1	2
Education	categorical	75258	1.79	2	1.01	0	3
Books at age 10	categorical	75258	2.44	2	1.29	1	5
Part-time (working hours)	categorical	75258	1.21	1	0.62	1	5
Self-Employment	dummy	75258	0.07	0	0.26	0	1
			Extended Covariates				
Cumulative Days Lost (Disability)	discrete	73577	598.86	49.00	1309.82	0	21475
Experience	discrete	75258	19.39	17.00	15.76	1	64
Seniority (within job)	discrete	75258	7.87	0.00	13.17	0	62
			Additional Variables				
Exposed Sector	dummy	75092	0.37	0	0.48	0	1
Sector Groups	categorical	75092	5.24	6	1.83	1	7
Exposed Occupation	dummy	69018	0.15	0	0.35	0	1
Occupation Groups	categorical	68717	4.84	5	1.97	1	8

Table A3: Number of Earnings Information Available at Individual Level

Earnings Info	Individuals (Frequency)	Percentage	Cumulative
1 Obs	13869	42.31%	42.31%
2 Obs	7902	24.10%	66.41%
3 Obs	5177	15.79%	82.20%
4 Obs	2735	8.34%	90.55%
5 Obs	1393	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%	

A.1 Earnings

Table A4: Wage Data Cleaning: Sample Size and Distribution

Variable	N	Mean	SD	p5	p25	p50	p75	p95
Step 0	196463	1679483	3.95e+07	69.0	500.0	1500	6000	80000
Step 1	110827	1913281	4.19e+07	200.0	1000	2900	14000	150000
Step 2	109349	1927449	4.21e+07	200.0	1000	3000	14000	150000
Step 3	97826	1195408	3.31e+07	200.0	1050	3000	15000	150000
Step 4	87944	252387	1.28e+07	20.03	193.46	715.71	1803.83	4172.46
Step 5	83537	1.24e+07	1.42e+09	199.55	791.96	1628.60	2854.42	7310.72
Step 6	81526	431858	1.93e+07	201.10	788.08	1603.10	2791.31	6677.50
Step 7	77029	2066.72	1781.41	236.51	811.86	1604.94	2737.29	5651.64

Notes. Each step of the cleaning procedure reports the sample size and the distribution of wages 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 observations for which the currency is known, reducing the sample to 109349. **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.

All earnings information in SHARE is reported as the average monthly income 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 A4) 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 re-move 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. This procedure preserves the integrity of the underlying wage distribution while eliminating values that are implausible or historically inconsistent. Table A4 reports the evolution of the sample size and distribution across successive cleaning steps.

Table A5: Earnings by Country of Residence

Country	Individuals	Obs.	Mean	SD	p25	p50	p75	p95
Austria	2337	5959	1179.46	1125.16	301.65	842.64	1744.11	3399.89
Belgium	4084	9892	1735.74	1222.02	880.86	1508.72	2262.24	3986.23
Czech Republic	2098	3021	601.51	348.57	354.83	540.04	771.86	1275.53
Denmark	3114	9556	2907.31	1722.42	1762.19	2675.44	3662.53	6132.04
France	2834	6938	1940.68	1663.87	890.48	1489.17	2447.41	5216.67
Germany	2880	4691	1902.01	1410.38	895.89	1546.46	2474.34	4785.25
Greece	1284	1484	1775.56	1330.64	948.24	1456.37	2184.55	4274.09
Italy	3471	7982	2110.23	1770.64	1026.75	1643.84	2544.70	5812.89
Poland	1428	2116	687.78	673.04	386.37	530.71	749.89	1569.62
Portugal	642	1405	1848.02	2082.58	598.98	1032.73	2332.69	6433.27
Slovenia	895	1112	1368.66	1117.71	789.21	1072.02	1574.54	3073.39
Spain	2236	4624	1610.55	1596.78	582.86	1248.32	2043.17	4614.83
Sweden	3060	8260	2957.23	1961.17	1688.57	2492.46	3619.59	7239.19
Switzerland	2419	8218	2760.27	2321.84	939.96	2066.86	3928.52	7604.91
Total	32782	75258	2070.14	1782.01	812.20	1608.82	2742.94	5661.05

Table A6: Earnings by Occupation

	Observations	Mean	SD	p25	p50	p75	p95
			By Sector Exposure				
Not-Exposed	46934	2062.87	1758.36	822.84	1610.84	2736.73	5557.14
Exposed	28158	2082.81	1821.45	791.48	1605.35	2752.29	5769.90
Total	75092	2070.35	1782.29	812.20	1608.90	2743.40	5659.06
			By Sector Group				
Financial, Real Estate and Business	3735	2592.06	2007.12	1098.39	2085.72	3491.84	6730.95
Agriculture & Fishing	3119	1632.89	1623.75	553.21	1133.30	2146.43	4769.84
Construction	5472	2310.44	1941.72	957.25	1793.34	3005.41	6347.22
Industry	15575	2016.21	1788.96	747.89	1543.49	2671.71	5550.19
Wholesale and Retail Trade	9353	1804.34	1671.62	678.62	1361.19	2352.07	5109.29
Transport, Hospitality & Storage	6534	2091.06	1765.20	849.04	1664.44	2730.16	5733.10
Public & Other Services	31304	2111.81	1747.73	873.82	1694.15	2790.20	5553.93
Total	75092	2070.35	1782.29	812.20	1608.90	2743.40	5659.06
			By Occupation Exposure				
Not-Exposed	58827	2101.29	1791.98	835.98	1645.22	2777.61	5711.92
Exposed	10191	1852.06	1695.42	697.83	1412.12	2418.19	5181.57
Total	69018	2064.49	1780.24	811.86	1602.78	2728.37	5648.46
			By Occupation Group				
Elementary (Indoor)	6859	1360.52	1279.80	514.45	1044.32	1782.59	3635.29
Elementary (Outdoor)	2441	1470.11	1425.64	564.17	1133.45	1846.36	3915.04
Manual (Indoor)	8853	1774.35	1641.80	639.72	1377.91	2354.40	4946.54
Manual (Outdoor)	5617	1896.87	1694.84	731.68	1475.58	2448.03	5325.51
Clerical (Indoor)	21375	1825.07	1545.94	773.23	1455.80	2379.55	4753.07
Clerical (Outdoor)	1181	1786.97	1613.07	618.58	1431.68	2478.74	4682.46
Abstract (Indoor)	21443	2744.70	2008.03	1296.39	2309.33	3612.01	6917.86
Abstract (Outdoor)	948	2645.02	2090.60	1045.29	2134.44	3634.22	7149.44
Total	68717	2063.05	1779.74	811.64	1602.01	2724.23	5648.46

A.2 Heat Waves

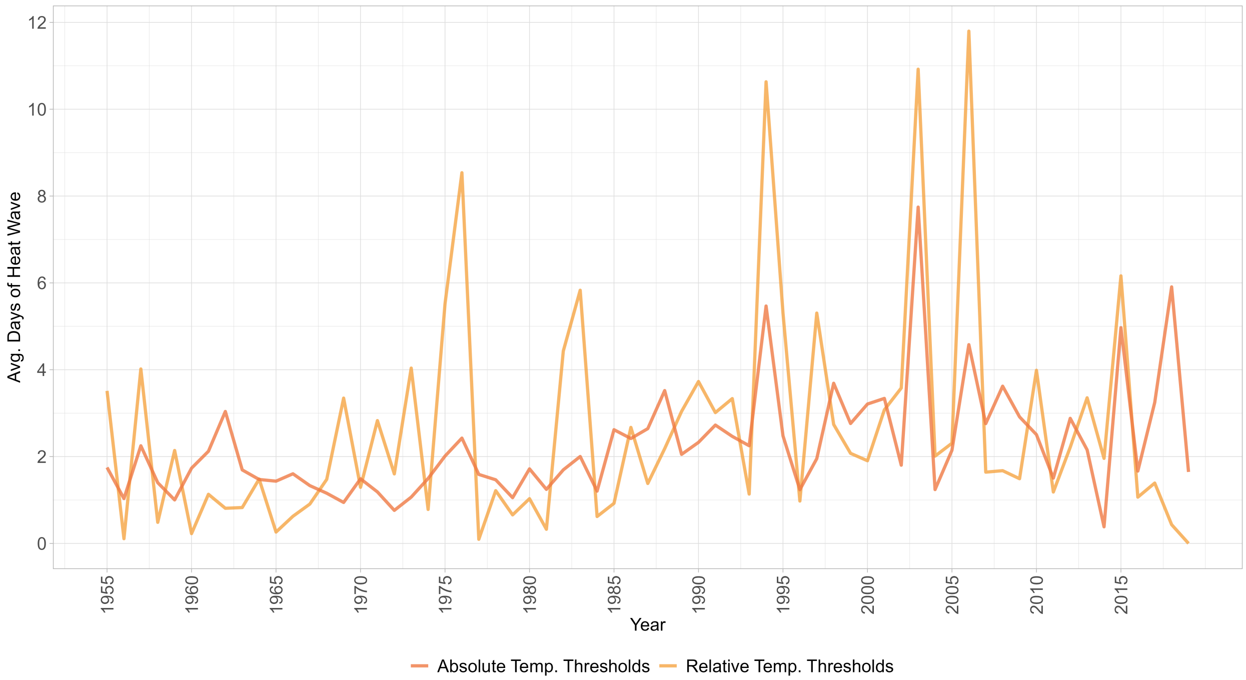

Figure A1: Average Days of Heat Wave over Time

The figure displays the sample-weighted average number of heatwave days over time, based on two threshold definitions. The relative threshold measure defines a heatwave 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 heatwave as at least five consecutive days with maximum temperatures exceeding 30°C. The number of heatwave days under the absolute threshold shows a clear upward trend over time, reflecting rising temperatures. In contrast, heatwave 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 A7: Heat Waves Exposure by Country of Residence

	$T \geq$ 95th perc, 2 days		$T \geq$ 95th perc, 5 days		$T \geq 30$ °C, 2 days		$T \geq 30$ °C, 5 days	
	Obs	Mean	Obs	Mean	Obs	Mean	Obs	Mean
Austria	5959	8.40	5959	2.33	5959	2.35	5959	0.57
Belgium	9892	6.03	9892	1.52	9892	0.68	9892	0.12
Czech Republic	3021	8.86	3021	2.65	3021	2.33	3021	0.75
Denmark	9556	8.63	9556	3.50	9556	0.03	9556	0.00
France	6938	8.18	6938	2.75	6938	3.48	6938	1.21
Germany	4691	7.73	4691	1.85	4691	1.22	4691	0.24
Greece	1484	10.05	1484	3.57	1484	44.06	1484	29.10
Italy	7982	12.15	7982	5.35	7982	16.01	7982	8.36
Poland	2116	7.86	2116	2.17	2116	1.81	2116	0.31
Portugal	1405	8.16	1405	1.87	1405	14.94	1405	5.23
Slovenia	1112	16.38	1112	6.19	1112	9.43	1112	2.78
Spain	4624	9.41	4624	3.16	4624	28.50	4624	18.45
Sweden	8260	8.79	8260	3.49	8260	0.13	8260	0.03
Switzerland	8218	6.75	8218	1.84	8218	0.72	8218	0.14
Total	75258	8.53	75258	2.91	75258	5.65	75258	2.98

Table A8: Heat Waves Exposure by Earnings Decile

	$T \geq$ 95th perc, 2 days		$T \geq$ 95th perc, 5 days		$T \geq 30$ °C, 2 days		$T \geq 30$ °C, 5 days	
	Obs	Mean	Obs	Mean	Obs	Mean	Obs	Mean
0-5th percentile	3761	7.65	3761	2.31	3761	5.90	3761	3.20
10th-20th percentile	7531	8.09	7531	2.54	7531	5.45	7531	2.71
20th-30th percentile	7512	8.22	7512	2.64	7512	6.43	7512	3.36
30th-40th percentile	7520	9.07	7520	3.13	7520	7.95	7520	4.37
40th-50th percentile	7527	9.15	7527	3.18	7527	7.93	7527	4.28
50th-60th percentile	7529	9.01	7529	3.18	7529	7.27	7529	4.01
5th-10th percentile	3766	7.73	3766	2.34	3766	4.48	3766	2.20
60th-70th percentile	7528	8.79	7528	3.20	7528	5.63	7528	3.04
70th-80th percentile	7525	8.26	7525	2.91	7525	4.00	7525	2.04
80th-90th percentile	7533	8.58	7533	3.11	7533	3.38	7533	1.73
90th-95th percentile	3760	8.46	3760	2.95	3760	3.22	3760	1.56
95th-100th percentile	3766	8.39	3766	2.73	3766	3.33	3766	1.48
Total	75258	8.53	75258	2.91	75258	5.65	75258	2.98

Table A9: 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
				By Sector Exposure				
Not-Exposed	46934	8.53	46934	2.89	46934	5.47	46934	2.87
Exposed	28158	8.52	28158	2.93	28158	5.93	28158	3.13
Total	75092	8.53	75092	2.91	75092	5.64	75092	2.97
				By Sector Group				
Financial, Real Estate and Business	3735	8.54	3735	2.96	3735	4.12	3735	2.02
Agriculture & Fishing	3119	8.77	3119	3.03	3119	9.67	3119	5.59
Construction	5472	8.51	5472	2.97	5472	6.81	5472	3.83
Industry	15575	8.46	15575	2.88	15575	5.03	15575	2.48
Wholesale and Retail Trade	9353	8.31	9353	2.79	9353	5.55	9353	2.90
Transport, Hospitality & Storage	6534	8.59	6534	2.95	6534	6.18	6534	3.37
Public & Other Services	31304	8.59	31304	2.92	31304	5.43	31304	2.85
Total	75092	8.53	75092	2.91	75092	5.64	75092	2.97
				By Occupation Exposure				
Not-Exposed	58827	8.50	58827	2.91	58827	5.45	58827	2.88
Exposed	10191	8.77	10191	2.99	10191	7.88	10191	4.33
Total	69018	8.54	69018	2.92	69018	5.81	69018	3.10
				By Occupation Group				
Elementary (Indoor)	6859	8.82	6859	3.20	6859	7.89	6859	4.44
Elementary (Outdoor)	2441	9.11	2441	3.17	2441	10.57	2441	6.02
Manual (Indoor)	8853	8.35	8853	2.80	8853	6.22	8853	3.26
Manual (Outdoor)	5617	8.77	5617	3.02	5617	7.90	5617	4.36
Clerical (Indoor)	21375	8.40	21375	2.87	21375	5.58	21375	3.03
Clerical (Outdoor)	1181	8.48	1181	2.74	1181	5.05	1181	2.42
Abstract (Indoor)	21443	8.54	21443	2.90	21443	4.18	21443	2.05
Abstract (Outdoor)	948	8.24	948	2.66	948	4.35	948	2.13
Total	68717	8.53	68717	2.92	68717	5.80	68717	3.09

A.3 Occupational and Sectoral Exposure

Table A10: Exposed Occupations and Sectors by Country of Residence

	Sectors			*Occupations*		
	Not-Exposed	Exposed	Total	Not-Exposed	Exposed	Total
Austria	3713	2240	5953	4318	941	5259
Belgium	6537	3307	9844	8055	930	8985
Czech Republic	1522	1499	3021	2455	478	2933
Denmark	5922	3632	9554	7191	918	8109
France	4455	2476	6931	5364	926	6290
Germany	3117	1562	4679	3651	636	4287
Greece	908	549	1457	1119	284	1403
Italy	4657	3323	7980	6333	1404	7737
Poland	1131	984	2115	1300	532	1832
Portugal	823	577	1400	861	242	1103
Slovenia	596	516	1112	696	198	894
Spain	2393	2227	4620	3420	1092	4512
Sweden	5374	2849	8223	7355	761	8116
Switzerland	5786	2417	8203	6709	849	7558
Total	46934	28158	75092	58827	10191	69018

Table A11: Exposed Occupations and Sectors by Earnings Percentile

	Sectors			*Occupations*		
	Not-Exposed	Exposed	Total	Not-Exposed	Exposed	Total
0–5th percentile	2284	1468	3752	2790	650	3440
5th–10th percentile	2306	1454	3760	2796	634	3430
10th–20th percentile	4600	2913	7513	5784	1171	6955
20th–30th percentile	4708	2792	7500	5762	1143	6905
30th–40th percentile	4727	2776	7503	5837	1086	6923
40th–50th percentile	4810	2692	7502	5899	1051	6950
50th–60th percentile	4757	2757	7514	5915	1055	6970
60th–70th percentile	4697	2814	7511	5999	919	6918
70th–80th percentile	4771	2734	7505	5990	828	6818
80th–90th percentile	4706	2814	7520	5992	845	6837
90th–95th percentile	2311	1445	3756	3056	374	3430
95th–100th percentile	2257	1499	3756	3007	435	3442
Total	46934	28158	75092	58827	10191	69018

Table A12: Exposed Occupations by Sector and Occupation Group

	Indoor	Outdoor	Total
	By Sector Group		
Financial, Real Estate and Business	3376	62	3438
Agriculture & Fishing	528	2329	2857
Construction	1884	3256	5140
Industry	12829	1418	14247
Wholesale and Retail Trade	7901	656	8557
Transport, Hospitality & Storage	5033	967	6000
Public & Other Services	27157	1496	28653
Total	58708	10184	68892
	By Occupation Group		
Elementary	6859	2441	9300
Manual	8853	5617	14470
Clerical	21375	1181	22556
Abstract	21443	948	22391
Total	58530	10187	68717

B Validation of the Identifying Assumption

Table B.13: Testing for Covariates' Imbalance in Heatwave Exposure

	T_{MAX} > 95th perc >5 consecutive days		T_{MAX} > 95th perc >2 consecutive days	
	(1)	(2)	(3)	(4)
Age	0.000302		0.000823	
	(0.0016)		(0.0009)	
Gender × Age	-0.00195	-0.00370	-0.00244***	-0.00204
	(0.0013)	(0.0028)	(0.0007)	(0.0019)
Age Squared	-0.00000925	-0.0000327	-0.00000430	-0.0000250
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Gender × Age Squared	0.0000290*	0.0000508	0.0000352***	0.0000314
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Lower Seconday Edu	-0.00737		0.00186	
	(0.0063)		(0.0037)	
Upper Seconday Edu	0.000936		0.00620*	
	(0.0052)		(0.0032)	
Tertiary Edu	-0.00540		0.00421	
	(0.0059)		(0.0038)	
One shelf of books (at age 10)	0.00195		-0.00127	
	(0.0049)		(0.0026)	
One bookcase (at age 10)	0.00759		0.00133	
	(0.0047)		(0.0028)	
Two bookcases (at age 10)	0.0101*		0.000212	
	(0.0060)		(0.0034)	
More than two bookcases (at age 10)	0.00784		0.00325	
	(0.0061)		(0.0036)	
Health loss	0.00000148	0.00000550	0.000000779	0.00000531*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Always Part-time	0.0159***	0.0119	0.00139	-0.0122
	(0.0059)	(0.0156)	(0.0030)	(0.0082)
From part- to full-time	-0.00382	0.0180	0.00477	-0.0149
	(0.0110)	(0.0259)	(0.0076)	(0.0196)
From full- to part-time	-0.0146	-0.109**	0.00732	-0.0236
	(0.0152)	(0.0447)	(0.0102)	(0.0297)
Changed multiple time part-/full-time	0.0156	-0.00185	-0.0133	-0.0527
	(0.0156)	(0.0494)	(0.0099)	(0.0378)
Self Employed	0.00337	0.0193	0.00351	0.00506
	(0.0064)	(0.0168)	(0.0039)	(0.0098)
Experience	-0.000317	-0.00389*	0.0000887	-0.00126
	(0.0007)	(0.0023)	(0.0004)	(0.0013)
Experience Squared	0.0000104	0.0000513**	-0.00000356	0.0000180
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Seniority	-0.000616	-0.00244*	-0.000888**	-0.00111
	(0.0006)	(0.0014)	(0.0004)	(0.0009)
Seniority Squared	0.0000274*	0.0000782**	0.0000181**	0.0000134
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Location, Generation,Year FE	✓	✓	✓	✓
Country-Year Linear Trends	✓	✓	✓	✓
Individual FE		✓		✓
Individual by Occupation (isco1) FE				
Individuals	32337	15580	32337	15580
Observations	73577	44271	73577	44271
Adjusted R^2	0.29645	0.28196	0.21827	0.17257

Notes. 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 B.14: Testing for Serial Correlation in Heatwave Occurrence

	(1)	(2)	(3)	(4)
Shock (T_{MAX} > 95th perc, >5 consecutive days) t-1	-0.0188*	-0.0133		
	(0.0113)	(0.0162)		
Shock (T_{MAX} > 95th perc, >2 consecutive days) t-1			0.0310**	0.0208
			(0.0156)	(0.0196)
Precipitation control	✓	✓	✓	✓
Location, Generation,Year FE	✓	✓	✓	✓
Covariates	✓	✓	✓	✓
Country-Year Linear Trends	✓	✓	✓	✓
Individual FE		✓		✓
Individual by Occupation (isco1) FE				
Individuals	32188	15399	32188	15399
Observations	72674	43590	72674	43590
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 heatwave occurs, and 0 otherwise. The manin regressor is a dummy for the occurence 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 * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

C Complementary Results: Temperature Impact on Earnings

Table C.15: Effect of Heat Waves on Earnings, Without Country-Year Linear Trends

	(1)	(2)	(3)	(4)	(5)
Days of HW (T_{MAX} > 95th perc)	-0.00612***	-0.00601***	-0.00615***	-0.00511***	-0.00485***
	(0.0013)	(0.0013)	(0.0015)	(0.0019)	(0.0019)
Precipitation control	✓	✓	✓	✓	✓
Location, Generation, Year FE	✓	✓	✓	✓	✓
Main Covariates	✓	✓	✓	✓	✓
Extended Covariates		✓	✓	✓	✓
Country-Year Linear Trends					
Individual FE				✓	✓
Individual × Occupation (ISCO1) FE					✓
Individuals	32782	32337	15580	15580	15580
Observations	75258	73577	44271	44271	44271
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). Days of HW count the number of days spent in a heatwave (T_{MAX} > 95th 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 C.16: Effect of Heat Waves on Earnings, with NUTS1-Year Linear Trends

	(1)	(2)	(3)	(4)	(5)
Days of HW (T_{MAX} > 95th perc)	-0.00311***	-0.00327***	-0.00314***	-0.00242*	-0.00254*
	(0.0009)	(0.0009)	(0.0011)	(0.0013)	(0.0014)
Precipitation control	✓	✓	✓	✓	✓
Location, Generation, Year FE	✓	✓	✓	✓	✓
Main Covariates	✓	✓	✓	✓	✓
Extended Covariates		✓	✓	✓	✓
NUTS1-Year Linear Trends	✓	✓	✓	✓	✓
Individual FE				✓	✓
Individual × Occupation (ISCO1) FE					✓
Individuals	31671	31232	15455	15455	15455
Observations	73977	72305	43997	43997	43997
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). Days of HW count the number of days spent in a heatwave (T_{MAX} > 95th 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 C.17: Effect of Heat Waves on Earnings, Short Heat Waves

	(1)	(2)	(3)	(4)	(5)
Days of HW (T_{MAX} > 95th perc)	-0.00239***	-0.00258***	-0.00237***	-0.00173**	-0.00180**
	(0.0005)	(0.0005)	(0.0006)	(0.0008)	(0.0009)
Precipitation control	✓	✓	✓	✓	✓
Location, Generation, Year FE	✓	✓	✓	✓	✓
Main Covariates	✓	✓	✓	✓	✓
Extended Covariates		✓	✓	✓	✓
Country-Year Linear Trends	✓	✓	✓	✓	✓
Individual FE				✓	✓
Individual × Occupation (ISCO1) FE					✓
Individuals	32782	32337	15580	15580	15580
Observations	75258	73577	44271	44271	44271
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). Days of HW count the number of days spent in a heatwave (T_{MAX} > 95th 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 C.18: Effect of Heat Waves on Earnings, by Period

	1960-1990	1975-2005	1990-2020
	(1)	(2)	(3)
Days of HW (T_{MAX} > 95th perc)	-0.00320*	-0.00188**	-0.00208**
	(0.0018)	(0.0009)	(0.0008)
Precipitation control	✓	✓	✓
Location, Generation,Year FE	✓	✓	✓
Main Covariates	✓	✓	✓
Extended Covariates	✓	✓	✓
Country-Year Linear Trends	✓	✓	✓
Individual FE			
Individual by Occupation (isco1) FE			
Individuals	18654	19754	25897
Observations	35252	33000	38313
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). Days of HW count the number of days spent in a heatwave (T_{MAX} > 95th 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 C.19: Effect of Heat Waves on Earnings, Leave-One-Country-Out Estimates

	(1) Austria	(2) Belgium	(3) Czech Republic	(4) Denmark	(5) France	(6) Germany	(7) Greece
Days of HW (T_{MAX} > 95th perc)	-0.00259***	-0.00321***	-0.00335***	-0.00411***	-0.00281***	-0.00320***	-0.00306***
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
	(8) Italy	(9) Poland	(10) Portugal	(11) Slovenia	(12) Spain	(13) Sweden	(14) Switzerland
	-0.00156*	-0.00328***	-0.00282***	-0.00334***	-0.00347***	-0.00301***	-0.00299***
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Precipitation control	✓	✓	✓	✓	✓	✓	✓
Geo id, Generation,Year FE	✓	✓	✓	✓	✓	✓	✓
Covariates	✓	✓	✓	✓	✓	✓	✓
Country-Time Trends	✓	✓	✓	✓	✓	✓	✓
Individual FE							
Individual by Occupation (isco1) FE							
Individuals	30001	28260	30250	29225	29511	29466	31059
	28871	30909	31702	31444	30112	29280	30291
Observations	67619	63701	70568	64024	66661	68900	72102
	65604	71461	72179	72467	68967	65322	66926
Adjusted R^2	0.48832	0.52717	0.49552	0.50444	0.53049	0.51819	0.52025
	0.54430	0.50744	0.52540	0.51887	0.53998	0.50806	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). Days of HW count the number of days spent in a heatwave (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 C.20: Effect of Heat Waves on Earnings, Full-Time Workers

	(1)	(2)	(3)	(4)	(5)
Days of HW (T_{MAX} > 95th perc)	-0.00280***	-0.00292***	-0.00311***	-0.00211	-0.00218
	(0.0009)	(0.0009)	(0.0011)	(0.0014)	(0.0014)
Precipitation control	✓	✓	✓	✓	✓
Location, Generation, Year FE	✓	✓	✓	✓	✓
Main Covariates	✓	✓	✓	✓	✓
Extended Covariates		✓	✓	✓	✓
Country-Year Linear Trends	✓	✓	✓	✓	✓
Individual FE				✓	✓
Individual × Occupation (ISCO1) FE					✓
Individuals	29934	29540	13262	13262	13262
Observations	64788	63567	36628	36628	36628
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). Days of HW count the number of days spent in a heatwave (T_{MAX} > 95th 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 C.21: Effect of Heat Waves on Earnings, with Location by Occupation FE

	(1)	(2)	(3)	(4)
Days of HW (T_{MAX} > 95th perc)	-0.00583***	-0.00559***	-0.00576***	-0.00525***
	(0.0014)	(0.0014)	(0.0015)	(0.0019)
Precipitation control	✓	✓	✓	✓
Location, Generation, Year FE	✓	✓	✓	✓
Main Covariates	✓	✓	✓	✓
Extended Covariates		✓	✓	✓
Country-Year Linear Trends	✓	✓	✓	✓
Individual FE				✓
Individuals	30360	29916	16929	16929
Observations	68309	66653	53450	53450
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). Days of HW count the number of days spent in a heatwave (T_{MAX} > 95th 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 * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

D Complementary Results: Absolute Temperature Measures

In this section of the Appendix, we re-estimate our main results using absolute temperature thresholds, defining heatwave days as those with $T_{\mathrm{MAX}} \geq 30°\mathrm{C}$ for at least five consecutive days (Tables D.22 and D.23). We also explore the effects of temperature across the full distribution by modeling exposure through temperature bins (Tables D.24, D.25, and Figure A2), 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 heatwave 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 D.22, column 2), an additional day in a heat wave of at least five consecutive days lowers income by approximately 1 percent, while Table D.24 shows that each additional day above 30°C reduces earnings by about 1.3 percent. These magnitudes are consistent with, though somewhat larger than, those obtained using relative thresholds.

When we include country-year linear trends (Tables D.23 and D.25), the estimated effects largely disappear, highlighting that much of the variation in absolute threshold measures is driven by long-term local trends rather than short-term heat shocks.

This pattern is consistent with recent evidence on binning bias in nonlinear temperature regressions (Jones et al., 2025). Global warming mechanically increases the number of very hot days in already warm countries and decreases the number of very cold days in cooler ones. When long-run income dynamics also differ systematically with baseline climate—as is likely across European countries—regressions may conflate these parallel trends with causal temperature shocks. The fact that the estimated effects disappear even when we include country-year linear trends suggests that much of the identifying variation in absolute temperature measures reflects these cross-country differences in baseline climate rather than genuine short-run heat shocks. In other words, the attenuation of effects likely indicates the removal of spurious "trends-on-trends" correlations, rather than the absence of any short-run temperature impacts, which may not be adequately captured by our absolute temperature thresholds.

Table D.22: Effect of Heat Waves (Absolute Measures, T_{MAX} > 30 ° C) on Earnings, Without Country-Year Linear Trends

	(1)	(2)	(3)	(4)	(5)
Days of HW (T_{MAX} > 30 ° C)	-0.0111***	-0.0108***	-0.0107***	-0.00993***	-0.00976***
	(0.0016)	(0.0016)	(0.0018)	(0.0021)	(0.0021)
Precipitation control	✓	✓	✓	✓	✓
Location, Generation, Year FE	✓	✓	✓	✓	✓
Main Covariates	✓	✓	✓	✓	✓
Extended Covariates		✓	✓	✓	✓
Country-Year Linear Trends					
Individual FE				✓	✓
Individual × Occupation (ISCO1) FE					✓
Individuals	32782	32337	15580	15580	15580
Observations	75258	73577	44271	44271	44271
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). Days of HW count the number of days spent in a heatwave (T_{MAX} > 95th 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 D.23: Effect of Heat Waves (Absolute Measures, T_{MAX} > 30 ° C) on Earnings, With Country-Year Linear Trends

	(1)	(2)	(3)	(4)	(5)
Days of HW (T_{MAX} > 30 ° C)	0.000220	0.000186	0.00132	0.00202	0.00217
	(0.0009)	(0.0008)	(0.0011)	(0.0015)	(0.0015)
Precipitation control	✓	✓	✓	✓	✓
Location, Generation, Year FE	✓	✓	✓	✓	✓
Main Covariates	✓	✓	✓	✓	✓
Extended Covariates		✓	✓	✓	✓
Country-Year Linear Trends	✓	✓	✓	✓	✓
Individual FE				✓	✓
Individual × Occupation (ISCO1) FE					✓
Individuals	32782	32337	15580	15580	15580
Observations	75258	73577	44271	44271	44271
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). Days of HW count the number of days spent in a heatwave (T_{MAX} > 95th 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 D.24: Effect of Temperature Bins on Earnings, Without Country-Year Linear Trends

	(1)	(2)	(3)	(4)	(5)
T_{AVG} < -5 °C	0.00380***	0.00342***	0.00475***	0.00409***	0.00309*
	(0.0013)	(0.0013)	(0.0014)	(0.0015)	(0.0016)
-5 °C $\geq T_{AVG} <$ 0°C	0.000328	-0.000114	0.000893	0.00132	0.00104
	(0.0011)	(0.0011)	(0.0011)	(0.0013)	(0.0013)
0 °C $\geq T_{AVG} <$ 5°C	-0.000261	-0.000419	0.0000820	-0.000323	-0.000724
	(0.0010)	(0.0010)	(0.0011)	(0.0012)	(0.0012)
5 °C $\geq T_{AVG} <$ 10°C	0.000139	-0.0000106	0.000355	0.000148	0.000140
	(0.0007)	(0.0007)	(0.0008)	(0.0009)	(0.0009)
15 °C $\geq T_{AVG} <$ 20°C	-0.000936*	-0.000852	-0.000813	-0.00107	-0.00112
	(0.0005)	(0.0005)	(0.0006)	(0.0007)	(0.0007)
20 °C $\geq T_{AVG} <$ 25°C	0.00312***	0.00312***	0.00348***	0.00387***	0.00355***
	(0.0008)	(0.0007)	(0.0008)	(0.0010)	(0.0010)
25 °C $\geq T_{AVG} <$ 30°C	-0.0115***	-0.0112***	-0.00942***	-0.00894***	-0.00884***
	(0.0017)	(0.0017)	(0.0018)	(0.0022)	(0.0023)
T_{AVG} >30 °C	-0.0137***	-0.0136***	-0.0211***	-0.0150**	-0.0154**
	(0.0044)	(0.0044)	(0.0051)	(0.0065)	(0.0068)
Precipitation control	✓	✓	✓	✓	✓
Location, Generation, Year FE	✓	✓	✓	✓	✓
Main Covariates	✓	✓	✓	✓	✓
Extended Covariates		✓	✓	✓	✓
Country-Year Linear Trends					
Individual FE				✓	✓
Individual × Occupation (ISCO1) FE					✓
Individuals	32779	32334	15580	15580	15580
Observations	75255	73574	44271	44271	44271
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°C $\geq T_{AVG} <$ 10°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 D.25: Effect of Temperature Bins on Earnings, With Country-Year Linear Trends

	(1)	(2)	(3)	(4)	(5)
T_{AVG} < -5 °C	0.000270	0.000486	0.00116	0.000860	0.000280
	(0.0008)	(0.0008)	(0.0010)	(0.0012)	(0.0013)
-5 °C $\geq T_{AVG} <$ 0°C	-0.000519	-0.000214	0.000645	0.00143	0.00111
	(0.0006)	(0.0006)	(0.0008)	(0.0009)	(0.0009)
0 °C $\geq T_{AVG} <$ 5°C	-0.000560	-0.000294	0.000250	0.000756	0.000299
	(0.0005)	(0.0006)	(0.0007)	(0.0008)	(0.0008)
5 °C $\geq T_{AVG} <$ 10°C	-0.000467	-0.000450	-0.000137	0.000626	0.000508
	(0.0005)	(0.0005)	(0.0006)	(0.0007)	(0.0007)
15 °C $\geq T_{AVG} <$ 20°C	-0.000975**	-0.00101**	-0.000619	-0.000636	-0.000774
	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0006)
20 °C $\geq T_{AVG} <$ 25°C	-0.00235***	-0.00240***	-0.00194***	-0.00206***	-0.00217***
	(0.0005)	(0.0005)	(0.0006)	(0.0007)	(0.0007)
25 °C $\geq T_{AVG} <$ 30°C	-0.00177**	-0.00172**	0.000260	0.000928	0.000998
	(0.0008)	(0.0008)	(0.0010)	(0.0014)	(0.0014)
T_{AVG} >30 °C	-0.00303	-0.00289	-0.000174	0.00344	0.00217
	(0.0029)	(0.0029)	(0.0057)	(0.0051)	(0.0051)
Precipitation control	✓	✓	✓	✓	✓
Location, Generation, Year FE	✓	✓	✓	✓	✓
Main Covariates	✓	✓	✓	✓	✓
Extended Covariates		✓	✓	✓	✓
Country-Year Linear Trends	✓	✓	✓	✓	✓
Individual FE				✓	✓
Individual × Occupation (ISCO1) FE					✓
Individuals	32779	32334	15580	15580	15580
Observations	75255	73574	44271	44271	44271
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°C $\geq T_{AVG} <$ 10°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 * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

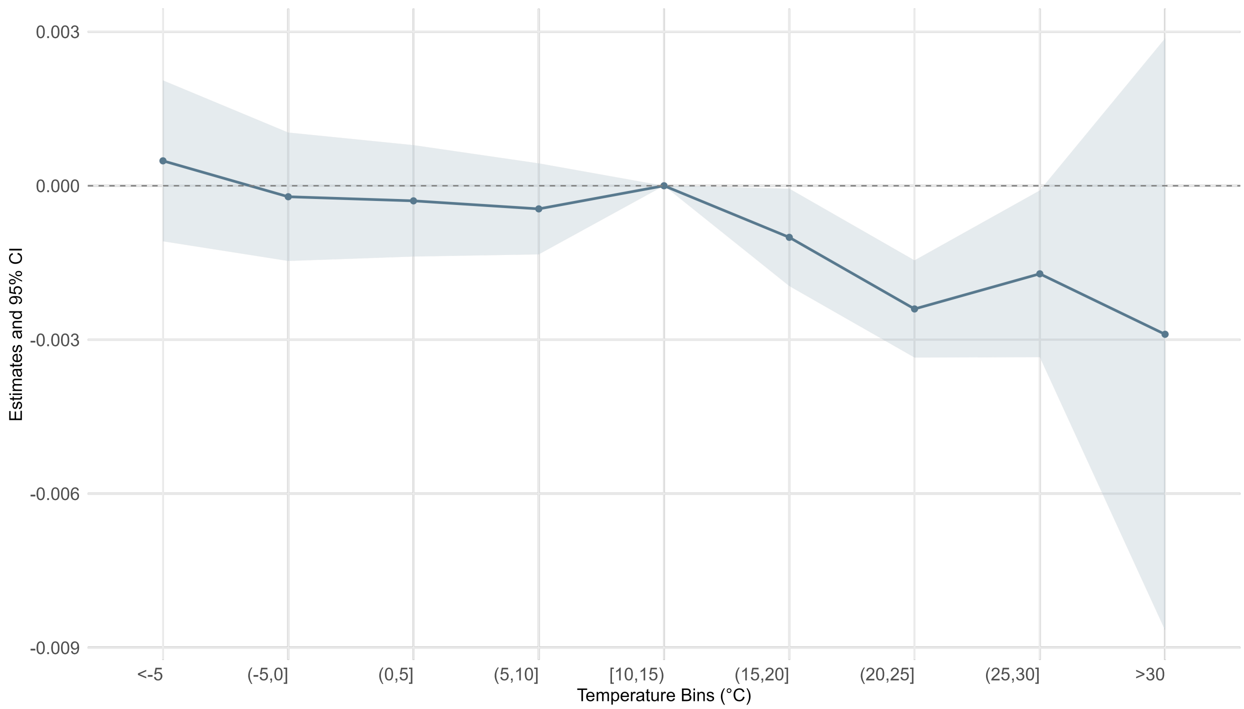

Figure A2: Temperature Impact on Earnings - Temperature Bins

Notes. The dependent variable is the log transformation of earnings expressed in dollars (base year 2010). The omitted temperature bin is $5°C \geq T_{\text{AVG}} < 10°C$. 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 Complementary Results: Distributional and Heterogeneous Effects of Heat Waves

Table E.26: Effect of Heat Waves on Earnings, Heterogeneity by Occupation and Sector

	(1)	(2)	(3)	(4)
Days of HW (T_{MAX} > 95th perc)	-0.00263***	-0.000138	-0.00219***	-0.00343*
	(0.0009)	(0.0024)	(0.0008)	(0.0019)
Panel A: By Exposed Sectors				
Exposed Sectors x HW (T_{MAX} > 95th perc)	-0.00120			
	(0.0011)			
Panel B: By Sector				
Agriculture & Fishing x HW (T_{MAX} > 95th perc)		-0.00967**		
		(0.0048)		
Construction x HW (T_{MAX} > 95th perc)		-0.00161		
		(0.0034)		
Industry x HW (T_{MAX} > 95th perc)		-0.00264		
		(0.0027)		
Wholesale & Retail Trade x HW (T_{MAX} > 95th perc)		-0.00482		
		(0.0031)		
Transport, Hospitality & Storage x HW (T_{MAX} > 95th perc)		-0.00316		
		(0.0029)		
Public & Other Services x HW (T_{MAX} > 95th perc)		-0.00248		
		(0.0026)		
Panel C: By Exposed Occupations				
Outdoor Exposed Occupations x HW (T_{MAX} > 95th perc)			-0.00353*	
			(0.0018)	
Panel D: By Occupations				
Elementary (Outdoor) x HW (T_{MAX} > 95th perc)				0.00163
				(0.0031)
Manual (Indoor) x HW (T_{MAX} > 95th perc)				0.00346
				(0.0024)
Manual (Outdoor) x HW (T_{MAX} > 95th perc)				-0.00424
				(0.0029)
Clerical (Indoor) x HW (T_{MAX} > 95th perc)				0.00121
				(0.0021)
Clerical (Outdoor) x HW (T_{MAX} > 95th perc)				-0.00833*
				(0.0047)
Abstract (Indoor) x HW (T_{MAX} > 95th perc)				0.000962
				(0.0022)
Abstract (Outdoor) x HW (T_{MAX} > 95th perc)				0.00719
				(0.0052)
Precipitation control	✓	✓	✓	✓
Location, Generation,Year FE	✓	✓	✓	✓
Restricted Covariates	✓	✓	✓	✓
Extended Covariates	✓	✓	✓	✓
Country-Year Linear Trends	✓	✓	✓	✓
Individual FE				
Individual by Occupation (isco1) FE				
Individuals	32269	32269	30318	30218
Observations	73413	73413	67355	67057
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). Days of HW count the number of days spent in a heatwave (T_{MAX} > 95th perc) $>$ 5 consecutive days. The reference category is Not Outdoor Exposed Occupations in column (1); Armed Forces, Managers, Professionals in column (2); Not Exposed Sectors in column (3); and Financial, Real Estate and Business in column (4). Restricted 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 E.27: Effect of Heat Waves on Earnings, Heterogenity by Institutional Setting

	(1)
Days of HW (T_{MAX} > 95th perc)	-0.000163
	(0.0014)
Sectoral Regulation x HW (T_{MAX} > 95th perc)	-0.00353**
	(0.0014)
Large Deregulation x HW (T_{MAX} > 95th perc)	-0.00359
	(0.0026)
Precipitation control	✓
Location, Generation,Year FE	✓
Restricted Covariates	✓
Extended Covariates	✓
Country-Year Linear Trends	✓
Individual FE	
Individual by Occupation (isco1) FE	
Individuals	32337
Observations	73577
Adjusted R^2	0.51756

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} > 95th perc) longer than 5 consecutive days. The reference category is centralized bargaining system countries in column (1) and Alpine Regions in column (2). Restricted 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 * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table E.28: Effect of Heat Waves on Earnings, Heterogenity by Socio-demographic factors

	(1)	(2)	(3)	(4)	(5)
Days of HW (T_{MAX} > 95th perc)	-0.00303***	-0.00112	-0.00302***	-0.00513***	-0.00505***
	(0.0010)	(0.0020)	(0.0009)	(0.0015)	(0.0012)
			By Gender		
Female x HW (T_{MAX} > 95th perc)	-0.000216				
	(0.0011)				
			By Age		
$25 \leq$ Age<45 x HW (T_{MAX} > 95th perc)		-0.00293			
		(0.0024)			
Age $\geq$ x HW (T_{MAX} > 95th perc)		-0.00247			
			By Health Condition		
Health Loss x HW (T_{MAX} > 95th perc)			-0.00177		
			(0.0022)		
			By Education		
Lower Secondary Edu x HW (T_{MAX} > 95th perc)				0.000746	
				(0.0020)	
Upper Secondary Edu x HW (T_{MAX} > 95th perc)				0.00285*	
				(0.0017)	
Tertiary Edu x HW (T_{MAX} > 95th perc)				0.00404**	
				(0.0018)	
			By Parental Background		
One shelf of books (at age 10) x HW (T_{MAX} > 95th perc)					0.00304**
					(0.0014)
One bookcase (at age 10) x HW (T_{MAX} > 95th perc)					0.00244
					(0.0018)
Two bookcases (at age 10) x HW (T_{MAX} > 95th perc)					0.00498***
					(0.0019)
More than two bookcases (at age 10) x HW (T_{MAX} > 95th perc)					0.00516**
					(0.0021)
Precipitation, Geo id, Generation,Year FE	✓	✓	✓	✓	✓
Restricted Covariates	✓	✓	✓	✓	✓
Extended Covariates	✓	✓	✓	✓	✓
Country-Year Linear Trends	✓	✓	✓	✓	✓
Individual FE					
Individual by Occupation (isco1) FE					
Individuals	32337	32337	32390	32337	32337
Observations	73577	73577	73661	73577	73577
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). Days of HW count the number of days spent in a heatwave (T_{MAX} > 95th perc) $>$ 5 consecutive days. The reference category is Male in column (1); Age <25 in column (2); Good Health (Health Loss <95th percentile) in column (3); No education in column (4); None or very few books (at age 10) in column (5). Restricted 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 * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

F Complementary Results: Unconditional Quantile Regression

Table F.29: Unconditional Quantile Regression

	q5	q10	q20	q30	q40	q50
Days of HW (T_{MAX} > 95th perc)	-0.0131***	-0.00235	-0.00165	-0.000147	-0.00169	-0.00261**
	(0.004)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
	q60	q70	q80	q90	q95	
	-0.00164	-0.00167	-0.000253	-0.00268**	-0.00409***	
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	
Precipitation, Geo id, Generation,Year FE	✓	✓	✓	✓	✓	✓
Retricted Covariates	✓	✓	✓	✓	✓	✓
Extended Covariates	✓	✓	✓	✓	✓	✓
Country-Year Linear Trends	✓	✓	✓	✓	✓	✓
Individual FE						
Individuals	32364	32364	32364	32364	32364	32364
	32364	32364	32364	32364	32364	
Observations	73514	73514	73514	73514	73514	73514
	73514	73514	73514	73514	73514	
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). Days of HW count the number of days spent in a heatwave (T_{MAX} > 95th perc) longer than 5 consecutive days. Restricted 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 F.30: Unconditional Quantile Regression, Heterogeneity by Sector

	q5	q10	q20	q30	q40	q50
Days of HW (T_{MAX} > 95th perc)	-0.00917**	0.000810	-0.000199	-0.000315	-0.00180	-0.00261**
	(0.004)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)
Outdoor Exposed Sectors x HW (T_{MAX} > 95th perc)	-0.00965	-0.00795**	-0.00362	0.000216	0.000203	-0.0000840
	(0.006)	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)
	q60	q70	q80	q90	q95	
	-0.00153	-0.00154	0.000292	-0.00319**	-0.00364**	
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	
	-0.000319	-0.000313	-0.00143	0.00114	-0.00138	
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	
Precipitation control	✓	✓	✓	✓	✓	✓
Geo id, Generation,Year FE	✓	✓	✓	✓	✓	✓
Restricted Covariates	✓	✓	✓	✓	✓	✓
Extended Covariates	✓	✓	✓	✓	✓	✓
Country-Year Linear Trends	✓	✓	✓	✓	✓	✓
Individuals	32296	32296	32296	32296	32296	32296
	32296	32296	32296	32296	32296	
Observations	73347	73347	73347	73347	73347	73347
	73347	73347	73347	73347	73347	
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). Days of HW count the number of days spent in a heatwave (T_{MAX} > 95th perc) longer than 5 consecutive days. Restricted 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 F.31: Unconditional Quantile Regression, Heterogeneity by Occupation

	q5	q10	q20	q30	q40	q50
Days of HW (T_{MAX} > 95th perc)	-0.00691*	0.000494	-0.000357	0.000490	-0.000687	-0.00155
	(0.004)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
Outdoor Exposed Occupations x HW (T_{MAX} > 95th perc)	-0.0251***	-0.0118***	-0.00537*	-0.00173	-0.00197	-0.000886
	(0.009)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)
	q60	q70	q80	q90	q95	
	-0.00157	-0.00163	0.0000776	-0.00207	-0.00367**	
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	
	0.00163	-0.000144	-0.00217	-0.00408*	-0.00296	
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	
Precipitation control	✓	✓	✓	✓	✓	✓
Geo id, Generation,Year FE	✓	✓	✓	✓	✓	✓
Restricted Covariates	✓	✓	✓	✓	✓	✓
Extended Covariates	✓	✓	✓	✓	✓	✓
Country-Year Linear Trends	✓	✓	✓	✓	✓	✓
Individuals	30347	30347	30347	30347	30347	30347
	30347	30347	30347	30347	30347	
Observations	67288	67288	67288	67288	67288	67288
	67288	67288	67288	67288	67288	
Adjusted R^2	0.16377	0.24784	0.35750	0.42146	0.44062	0.43152
	0.40569	0.36079	0.28514	0.19773	0.14238	

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). Days of HW count the number of days spent in a heatwave (T_{MAX} > 95th perc) longer than 5 consecutive days. Restricted 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 Quantification of the Impacts

Table G.32: 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***	2070.14	2.91	-159.63	-0.64
Not-Exposed Sectors	-0.00263**	2101.29	2.91	-137.47	-0.55
Exposed Sectors	-0.00383***	1852.06	2.99	-181.30	-0.82
Financial, Real Estate & Business	-0.00014	2592.06	2.96	-9.18	-0.03
Agriculture & Fishing	-0.00981**	1632.89	3.03	-414.89	-2.12
Construction	-0.00175	2310.44	2.97	-102.65	-0.37
Industry	-0.00278**	2016.21	2.88	-137.99	-0.57
Wholesale & Retail Trade	-0.00496**	1804.34	2.79	-213.44	-0.99
Transport, Hospitality & Storage	-0.00329*	2091.06	2.95	-173.48	-0.69
Public & Other Services	-0.00262**	2111.81	2.92	-138.10	-0.54
Not-Exposed Occupations	-0.00219**	2101.29	2.91	-114.47	-0.45
Exposed Occupations	-0.00572**	1852.06	3.01	-272.57	-1.23
Elementary (Indoor)	-0.00343*	1360.52	3.20	-127.65	-0.78
Elementary (Outdoor)	-0.00247*	1470.11	3.17	-98.39	-0.56
Manual (Indoor)	0.00376	1774.35	2.80	159.68	0.75
Manual (Outdoor)	-0.00767**	1896.88	3.02	-375.58	-1.65
Clerical (Indoor)	-0.00223*	1825.07	2.87	-99.85	-0.46
Clerical (Outdoor)	-0.01176**	1786.97	2.74	-492.19	-2.30
Abstract (Indoor)	-0.00247*	2744.70	2.90	-168.06	-0.51
Abstract (Outdoor)	0.00376	2645.02	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***	7540.31	2.73	-1127.90	-1.25
Exposed Sectors (5th perc)	-0.01358***	128.05	2.63	-39.09	-2.54
Exposed Sectors (95th perc)	-0.00691***	7509.56	2.48	-1100.03	-1.22
Exposed Occupations (5th perc)	-0.02387***	128.05	2.63	-68.71	-4.47
Exposed Occupations (95th perc)	-0.00880***	7509.56	2.48	-1400.91	-1.55
Highly Centralized	-0.00016	2047.43	2.17	-6.08	-0.02
Sectorally Regulated	-0.00369***	2240.94	3.34	-236.08	-0.88
Largely Deregulated	-0.00375	637.05	2.45	-50.03	-0.65
Age <25 y/o	-0.00112	1553.75	2.25	-33.47	-0.18
Age 25-44 y/o	-0.00406**	2297.53	3.04	-242.39	-0.88
Age >44 y/o	-0.00359***	2241.37	3.22	-221.48	-0.82
Male	-0.00303***	2464.74	2.93	-187.04	-0.63
Female	-0.00324***	1652.43	2.88	-131.80	-0.66
No/Primary Edu	-0.00513***	1695.29	3.40	-252.76	-1.24
Lower Secondary Edu	-0.00438**	1675.33	3.05	-191.31	-0.95
Upper Secondary Edu	-0.00228*	1962.75	2.74	-104.81	-0.45
Tertiary Edu	-0.00109	2688.15	2.78	-69.63	-0.22
Health Good/Moderate Healthy	-0.00302***	2053.81	2.92	-154.81	-0.63
Health Sick	-0.00479*	1964.24	3.20	-257.36	-1.09
None/few books (at age 10)	-0.00505***	1749.62	3.12	-235.64	-1.12
One shelf (at age 10)	-0.00201	1959.81	2.86	-96.30	-0.41
One bookcase (at age 10)	-0.00261	2205.99	2.77	-136.33	-0.51
Two bookcases (at age 10)	-0.00007	2422.66	2.81	-4.07	-0.01
More than two bookcases (at age 10)	0.00011	2625.52	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 heatwave days for that subgroup. The final column expresses the implied loss as a percentage of annual earnings.

FONDAZIONE ENI ENRICO MATTEI WORKING PAPER SERIES

Our Working Papers are available on the Internet at the following address:
https://www.feem.it/pubblicazioni/feem-working-papers/

"NOTE DI LAVORO" PUBLISHED IN 2024

1. A. Sileo, M. Bonacina, The automotive industry: when regulated supply fails to meet demand. The Case of Italy
2. A. Bastianin, E. Mirto, Y. Qin, L. Rossini, What drives the European carbon market? Macroeconomic factors and forecasts
3. M. Rizzati, E. Ciola, E. Turco, D. Bazzana, S. Vergalli, Beyond Green Preferences: Alternative Pathways to Net-Zero Emissions in the MATRIX model
4. L. Di Corato, M. Moretto, Supply contracting under dynamic asymmetric cost information
5. C. Drago, L. Errichiello, Remote work admist the Covid-19 outbreak: Insights from an Ensemble Community-Based Keyword Network Analysis
6. F. Cappelli, Unequal contributions to CO2 emissions along the income distribution within and between countries
7. I. Bos, G. Maccarrone, M. A. Marini, Anti-Consumerism: Stick or Carrot?
8. M. Gilli, A. Sorrentino, The Set of Equilibria in Max-Min Two Groups Contests with Binary Actions and a Private Good Prize
9. E. Bachiocchi, A. Bastianin, G. Moramarco, Macroeconomic Spillovers of Weather Shocks across U.S. States
10. T. Schmitz, I. Colantone, G. Ottaviano, Regional and Aggregate Economic Consequences of Environmental Policy
11. D. Bosco, M. Gilli, Effort Provision and Incentivisation in Tullock Group-Contests with Many Groups: An Explicit Characterisation
12. A. Drigo, Environmental justice gap in Italy: the role of industrial agglomerations and regional pollution dispersion capacity
13. P. I. Rivadeneyra García, F. Cornacchia, A. G. Martínez Hernández, M. Bidoia, C. Giupponi, Multi-platform assessment of coastal protection and carbon sequestration in the Venice Lagoon under future scenarios
14. T. Angel, A. Berthe, V. Costantini, M. D'Angeli, How the nature of inequality reduction matters for CO2 emissions
15. E. Bacchiocchi, A. Bastianin, T. Kitagawa, E. Mirto, Partially identified heteroskedastic SVARs
16. B. Bosco, C. F. Bosco, P. Maranzano, Income taxation and labour response. Empirical evidence from a DID analysis of an income tax treatment in Italy
17. M. M. H. Sarker, A. Gabino Martinez-Hernandez, J. Reyes Vásquez, P. Rivadeneyra, S. Raimondo, Coastal Infrastructure and Climate Change adaptation in Bangladesh: Ecosystem services insights from an integrated SES-DAPSIR framework
18. P. Maranzano, M. Pelagatti, A Hodrick-Prescott filter with automatically selected jumps
19. M. Bonacina, M. Demir, A. Sileo, A. Zanoni, The slow lane: a study on the diffusion of full-electric cars in Italy
20. C. Castelli, M. Castellini, C. Gusperti, V. Lupi, S. Vergalli, Balancing Climate Policies and Economic Development in the Mediterranean Countries
21. M. Gilli, A. Sorrentino, Characterization of the Set of Equilibria in Max-Min Group Contests with Continuous Efforts and a Private Good Prize
22. P. Pakrooh, M. Manera, Causality, Connectedness, and Volatility Pass-through among Energy-Metal-Stock-Carbon Markets: New Evidence from the EU
23. F. F. Frattini, F. Vona, F. Bontadini, Does Green Re-industrialization Pay off? Impacts on Employment, Wages and Productivity
24. A. Drigo, Breathing Inequality? Income, Ethnicity and PM2.5 Exposure in Bologna, Italy
25. D. Bosco, M. Gilli, A. Sorrentino, A Max-Min Two-Group Contest with Binary Actions and Incomplete Information à la Global Games
26. C. Amadei, C. Dosi, F. J. Pintus, Energy Intensity and Structural Changes: Does Offshoring Matter?
27. E. Ciola, E. M. Turco, M. Rizzati, D. Bazzana, S. Vergalli, Taking the green pill: Macro-financial transition risks and policy challenges in the MATRIX model
28. P. Agnolin, I. Colantone, P. Stanig, In Search of the Causes of the Globalization Backlash: Methodological Considerations on Post-Treatment Bias
29. I. Colantone, G. I. P. Ottaviano, K. Takeda, Trade and Intergenerational Income Mobility: Theory and Evidence from the U.S.
30. L. Muñoz-Blanco, F. F. Frattini, Vaccines on the Move and the War on Polio
31. M. Kuntze, F. F. Frattini, F. Vona, I. Brunetti, A. Ricci, Exploring Skills in the Green Transition: New Insights from Italian Data

Fondazione Eni Enrico Mattei
Corso Magenta 63, Milano – Italia

Tel. +39 02 403 36934

E-mail: letter@feem.it
www.feem.it

Fondazione Eni Enrico Mattei