

Heat and well-being in the Old Continent*

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Abstract

Climate change is bringing abnormally high temperatures to Europe. With them comes a substantial physical and mental health burden, especially for older populations. We expand the individual longitudinal Survey on Health, Ageing and Retirement (SHARE) on the 50+ population in Europe, with temperature exposure information from gridded datasets and derived household location. We estimate that heat negatively affects well-being: ten extra days in a year at 31° (an increase predicted for many European regions under current climate forecasting exercises), without AC, increases by 2 - 5 p.p. the probability of reporting fatigue, by 2 - 6 p.p. of reporting reduced appetite, by 2 - 4 of reporting irritability and by 1 - 3 of reporting issues sleeping. Taking into account several possible biases in estimating the mitigating effect of AC ownership, we find that it constitutes an effective adaptation strategy against reduced appetite and particularly against fatigue. We do not find evidence of such protection against irritability nor sleeping difficulties. We estimate the effects of heat and the protection provided by AC accrue over time. To put results in context, future research shall estimate the protective effect of other, less energy-intensive and more equitable, adaptation strategies. Such climate adaptation research questions can be further explored through the developed dataset.

JEL Classification: D12, O13, Q41, Q5

Keywords: Climate Adaptation, Air Conditioning, Heat, Well-being, Climate Change

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1 Introduction

Record-breaking high temperatures are now frequently making the headlines and heat exposure is rising in most places. Climate change is bringing abnormally hot winters and summers to the European old continent, the fastest-warming region in the world¹. These trends, combined with the aging of the European population, imply an accentuated vulnerability to heat impacts compared to other regions (Falchetta et al., 2024b). Globally, 37% (range 20.5–76.3%) of warm-season heat-related deaths observed between 2000 and 2020 have been attributed to anthropogenic climate change (Vicedo-Cabrera et al., 2021). In Europe, despite the growing number of heat-health action plans, the number of premature deaths attributed to record-hot summer of 2022 remains substantial. Significant associations have also been found between rising temperatures and hospital admissions (Adélaïde et al., 2022), mental health issues (Mullins and White 2019, Thompson et al. 2018), suicide attempts (Burke et al., 2018), respiratory and infectious diseases (VanDaalen et al., 2022), cognitive performance (Martin et al., 2019), criminality (Stevens et al., 2024) and broader social conflicts (Helman and Zaitchik 2020, Hsiang et al. 2013).

Following the unprecedented temperatures experienced in Europe, air-conditioning (AC) has been spreading. While recent studies examined how air-conditioning can put pressure on the electricity load (Colelli et al., 2023) and on energy expenditure (Randazzo et al., 2020), to what extent AC can sustain human well-being is less known, and its protective effect has mostly been assessed in relation to mortality (Barreca et al. 2016, Sera et al. 2020). Whether AC adaptation brings benefits also in terms of sub-clinical outcomes in Europe remains largely unexplored.

In this paper, we use a longitudinal survey augmented with climate information to causally estimate how heat impacts the 50+ population in Europe. We look into four measures of well-being: fatigue, reduced appetite, irritability, and trouble sleeping, and evaluate how AC ownership can mitigate the negative effects of heat on these outcomes. These are of interest themselves but also as precursors to physical and mental health deterioration. We focus on the effect of heat exposure over a year as opposed to acute effects. Our interest is not on how, when an interview takes place in a hot day/week, individuals might indicate they are more tired. Our interest instead is whether accumulated heat exposure over a certain period of time will result in worse well-being outcomes throughout old age. We believe this is the relevant approach to draw parallels to climate change.

We transform and merge two different sources of publicly available data to obtain a novel dataset, SHARE-ENV. Our starting points are 1) the SHARE survey, an individual longitudinal survey on health and ageing for European residents aged 50 and above and 2) gridded climate data. We retrieve lifetime information on the location of all houses where each individual has lived since he was born, from the dedicated module of the SHARE survey. By merging lifetime locations with environmental information, we are able to measure not only present climate exposure but also lifetime exposure to different climate conditions.

We find that exposure to heat has a negative effect on well-being, measured by the four outcome variables of fatigue, reduced appetite, irritability, and trouble in sleeping. We show that 10 extra Cooling Degree Days (CDDs) over a year, for individuals without AC, increase by 0.2 - 0.5 p.p. the probability of reporting fatigue, by 0.2 - 0.6 p.p. the probability of reporting reduced appetite, by 0.2 - 0.4 p.p. the probability of reporting irritability and by up to 0.3 p.p. the probability of reporting issues sleeping. An extra 10 CDDs in a year occur when, for example, there is an extra day with 31°, i.e., with average mean temperature exceeding 21° by 10. Current climate forecasts estimate for the majority of European regions more than 100 extra CDDs per year by

¹<https://www.eea.europa.eu/publications/european-climate-risk-assessment>

2041-2070, even under optimistic climate scenarios.

We find AC ownership provides substantial protection against the negative effects of heat on fatigue, regardless of the specification considered. Our IV estimates indicate that AC provides full protection against some outcomes (fatigue and reduced appetite) and, in fact, there might be positive effects of (moderate) heat exposure when individuals have AC in their home. We confirm these results by restricting our sample to individuals for whom endogeneity concerns are minimized and by using an alternative measure of heat exposure, which considers long-standing regional climate adaptation (anomalies in CDDs).

Our paper contributes to the literature in several ways. The first contribution is to illustrate the importance of advancements in data accessibility to study the effectiveness of climate adaptation strategies. The proposed dataset, by combining the longitudinal personal history of individuals with environmental information, makes it possible to trace exposure, vulnerability, and, therefore, risk, over time and across space. We consider this paper a demonstration of the potential of such dataset to answer research questions on adaptation. We expect follow-up analyses building on this dataset and illustrate ways in which it can be used.

The second contribution of this paper is to evaluate the impacts of heat and high temperatures on sub-clinical, well-being outcomes, which, unlike mortality, have only rarely been considered, especially in Europe. High temperatures are associated with excess mortality ([Gasparrini et al. 2015](#)), have negative impacts on mental health ([Thompson et al. 2018](#)), and influence subjective well-being ([Noelke et al. 2016](#)) and life satisfaction ([Barrington-Leigh and Behzadnejad 2017](#)). Well-being is a complex concept ([Lamb and Steinberger 2017](#)), but physical and mental health are part of its defining dimensions, and presence of fatigue, reduced appetite, irritability, and trouble sleeping are certainly precursors of health deterioration.

The third contribution is to provide new empirical evidence on the protective effect of a specific form of adaptation in Europe. Papers on the mitigating role of AC for such outcomes are almost absent. Some assessments have been conducted in relation to mortality ([Sera et al. 2020](#)). [Park et al. \(2020\)](#) is the only study examining protection from AC against an outcome other than morbidity or mortality: high school test scores. Moreover, considering well-being outcomes is fundamental to account for the total cost of climate change and allow for comprehensive policy analysis. We provide such estimates for Europe, whereas the great majority of studies so far have focused on the United States. AC ownership in Europe is far from the norm, including in warmer regions. We consider a representative sample of the 50+ population in Europe, an expanding portion of the population with high heat vulnerability.

The fourth contribution is to provide causal evidence on adaptation effectiveness, while accounting for the potential confounding effect of other mediating factors. Numerous epidemiological studies have investigated the direct relationship between mortality/morbidity and environmental stressors (such as air pollution and extreme temperatures). Nonetheless, the methods and the data from the biomedical science literature do not allow for causal identification of the effect of people's adaptive behaviours. Importantly, they are often unable to consider the mediating effect of socioeconomic confounders ([Zivin and Neidell 2016](#)). We highlight there might be important omitted variable biases in non-causal estimates of the protective effect of residential AC. Such biases are problematic whenever estimates are used to forecast the health-burden of climate change or to estimate impacts of adaptation policy. We propose an Instrumental Variable (IV) approach to instrument for residential AC ownership, where we exploit individuals who have moved between regions. This goes in the direction of paving the way for a new stream of literature on policy evaluation of adaptation policies and actions.

The remainder of the paper is organized as follows. Section 2 summarizes the existing literature on the effects of heat on well-being and on the protective effect of AC. Section 3 presents our dataset. Section 4 introduces our econometric approach and identification strategy and section 5 presents our results. Section 6 concludes the paper.

2 Background

2.1 Effects of heat on well-being

There is ample evidence on the effects of heat on mortality (see [Sheridan and Allen 2018](#) for a review), and numerous meta-analyses are also being published, especially by the biomedical literature (see, among others, [Moghadamnia et al. 2017](#) and [Hu et al. 2022](#)). Empirical assessments of the effects of heat on morbidity are more sparse but have increased in recent years, and meta-analyses summarizing the existing literature have also been published ([Wu et al. 2022](#)), mostly with a focus on hospital admissions. A 2018 review ([Thompson et al. 2018](#)) shows the literature finds heat to be associated with increased admissions due to mental illness (namely, depression, bipolar disorder and schizophrenia), as well as to increased suicide frequency. While mental health outcomes are not analogous to well-being measures, they are related. In fact, questions about feeling fatigued or on lack of energy are part of both depression scales and well-being scales.

Negative self-assessment of well-being can also be seen as a precursor of deterioration in mental state and ultimately a predictor of mental illness. [Mullins and White \(2019\)](#) look at self-reported mental state and find a significant negative effect of heat². Through the same self-reported data, they find evidence that heat impacts negatively quality of sleep, a likely explanatory mechanism to reduced mental well-being. Thermoregulation is fundamental for sleep and the possible sleep loss associated with climate change has been singled out as an important health concern, especially for the elderly (see [Obradovich et al. 2017](#)). Their heat exposure is built at the county-level and associated to respondents, but when they perform the same analysis with state-level temperature variation, they obtain similar results (our regions are substantially smaller than U.S. states, since we work, as we explain ahead, with 5 subregions within each NUTS2/NUTS3 region). We also consider self-reported outcomes, specifically on whether individuals report troubles sleeping and irritability.

Our paper is also similar to [Noelke et al. \(2016\)](#), who look into the effect of heat on a well-being index, built from self-reported well-being outcomes. The underlying self-reported outcomes include fatigue - an outcome we also look into - as well as stress and anger, which relate to our irritability outcome. [Barrington-Leigh and Behzadnejad \(2017\)](#) have a similar underlying dataset as well - an individual longitudinal survey for Canada - and consider the effect of weather on reports of life satisfaction. The paper mostly focuses on the effects of weather on the day of the interview, finding that worse weather leads to lower reports of life satisfaction. While this is not the same research question, it informs our decision to, as a robustness check, divide the period of exposure into the month of preceding the interview - to which the questions on well-being relate - and the previous 11 months (we include temperature exposure during the month preceding the interview, since that is the most granular information we have about its timing). While the study is not focused on yearly exposure, [Barrington-Leigh and Behzadnejad \(2017\)](#) do find that the yearly difference between average maximum and minimum temperatures, with individual fixed effects, is associated with lower self-reported life satisfaction.

²"Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?"

2.2 Protective Effects of AC

Most of the existing assessments on the protective effect of AC have focused on mortality or hospital admission outcomes, and have been conducted in the United States. [Ostro et al. \(2010\)](#) perform logistic regressions relating hospital admissions from California to temperatures in the preceding days. Through separate regressions for several 25km radius regions (buffers), they obtain an estimate for the effect of AC by doing a random effect meta-regression on the coefficients. AC ownership is aggregated at the buffer level and thus it captures differences in AC penetration at the regional level, as opposed to individual. Socio-demographic characteristics were included alongside regional AC prevalence (analogous to including interactions beyond AC in a regression setting). They find AC reduces by about 50% admissions related to cardiovascular disease.

[Bobb et al. \(2014\)](#) look into heat-related mortality for 79 U.S. cities. They firstly perform Poisson regressions of the count of daily deaths, separately for each city, and estimate the effect of daily temperatures. They allow the coefficient of daily temperatures to change linearly yearly. They then test whether the city-specific estimates of change (decrease) in mortality risk are associated to the city-specific changes in AC prevalence through Bayesian hierarchical models. They, however, do not find a statistically significant effect. [Barreca et al. \(2016\)](#) consider the evolution through time in U.S. state-level heat-related mortality. They find heat mortality reduced by 75% and attribute the decrease almost entirely to the penetration of AC. The impact of AC is estimated through interactions of the temperature variables with the state's rate of residential AC prevalence. They consider also the interaction of temperature variables with doctors per capita and electrification and still find a protective effect of AC.

Outside the United States, [Sera et al. \(2020\)](#) is the only multi-country longitudinal study (considering Japan, US, Spain and Canada). They show that AC has had an attenuating effect on heat-related mortality, but that several other unidentified factors, correlated with increases in AC penetration, account for a larger part of adaptation. They estimate reductions in mortality attributable to AC in the range of 14 to 20%. Similarly to [Ostro et al. \(2010\)](#) and [Bobb et al. \(2014\)](#), they calculate place-specific quasi-Poisson regressions and then aggregate estimates through a meta-regression. This is the only paper we have found which includes estimates on Europe, though only on capital cities in Spain.

Although [Mullins and White \(2019\)](#) consider a self-reported outcome in investigating the impacts of heat, they do not study AC's mitigation potential for said variable. They do investigate AC's role in preventing heat related suicides and mental health hospital admissions, but find no statistically significant effect. [Burke et al. \(2018\)](#), similarly, do not find evidence that AC reduces the impact of heat on suicide. Both papers include an interaction term, as [Barreca et al. \(2016\)](#). They then study differences in trends and conclude there is no significant difference in the association between heat and suicide through time.

Our paper is most similar to [Park et al. \(2020\)](#), which look at high school test results (PSATs) and at how heat affects them negatively. They consider the mitigating effect of AC in schools, focusing on an outcome outside of mortality and morbidity, and find that, without air conditioning, a 1 degree F hotter school reduces learning outcomes by 1 percent. The heat exposure variable of interest, is, like ours, exposure to heat accumulated over the year preceding observation. The endogeneity concerns around the estimation of the interaction term are also very similar; an important possible confounder is AC outside school (AC protection elsewhere) as well as sociodemographic characteristics. As we do, they expand the initial model (of the simple interaction between AC and heat exposure) with interactions with the possibly meaningful confounders. Recognizing such approach is not yet causal they provide a triple-difference estimate. We, in-

stead, propose an Instrumental Variable (IV) approach, as detailed in the Econometric Approach section.

3 Data

3.1 The individual survey SHARE

We use the Survey of Health, Ageing, and Retirement in Europe (SHARE), which is a dataset on a wide range of individual-level socio-economic, demographic characteristics and health information. SHARE is a longitudinal stratified sample representative of European residents aged 50+ for 27 European countries and Israel. The SHARE survey interviews approximately 120,000 individuals every two years since 2004 (wave 1). We use waves 1 to 7, which was conducted in 2017³. The regular panel waves of SHARE follow individuals (respondents and their spouses) over time. In addition, two specific interviews, conducted in the third and seventh waves (2008/2009 and 2017), called SHARELIFE, reconstruct retrospective life history, providing year on year information on respondents' life conditions, health history, healthcare use, and working lives. They include information on every house where the individual has lived since they were born, namely their region and the degree of urbanization of their surrounding area⁴.

3.1.1 Well-being measures

The SHARE database contains numerous variables that can be used to characterize the impacts of climate change on an array of morbidity types, subjective health indicators and clinical and subclinical health outcomes. We consider four self-reported outcomes - fatigue, reduced appetite, irritability and issues sleeping - for which there is evidence, in the clinical literature, of negative impacts due to exposure to excess heat; see, for example, [González-Alonso et al. \(1999\)](#), [Richardson et al. \(2018\)](#), [Anderson \(2001\)](#) and [Obradovich et al. \(2017\)](#), respectively. Below we report the explicit questions that are posed to those being interviewed:

1. **Fatigue:** In the last month, have you had too little energy to do the things you wanted to do? (No=0, Yes=100)
2. **Reduced appetite:** What has your appetite been like? (No diminution in desire for food=0, Diminution in desire for food=100)
3. **Irritability:** Have you been irritable recently? (No=0, Yes=100)
4. **Issues Sleeping:** Have you had trouble sleeping recently? (No=0, Yes=100)

Table 1 summarizes the descriptive statistics for the key variables used in this paper. Individuals report fatigue and trouble sleeping on more than 30% of answers, while they report feeling irritable for 25% and having reduced appetite only for 9%. In 14% of answers, individuals had been hospitalized at least once over the preceding 12 months. On average, they rate themselves as 3.1 health-wise, which is coded from 1 (poor health) until 5 (excellent health). Considering all waves, between 20 and 30% individuals change status between two consecutive waves, i.e., they either start reporting a negative state or stop reporting a negative state. There is considerable variation in the outcomes considered.

³Wave 8 conducted in 2019 has not been considered in this study since no detailed location information is available.

⁴In our analysis we require information at wave 1 or 2 in order to construct AC availability, as well as detailed regional information, which restricts our analysis to 12 countries instead of 27.

3.1.2 Air conditioning

Air conditioning (AC) is a binary variable that takes value 1 in case the household possesses an air conditioner, 0 otherwise. Information on whether a household owns AC in their main residence is reported in waves 1 (2004) and 2 (2006/2007), but not in the subsequent waves. When we consider the 11 countries for which there is AC information on both waves, AC ownership is 11% in both wave 1 and wave 2, hinting that at least for the 50+ population, the penetration of AC was not yet significantly increasing at the time. According to the European Environmental Agency, in 2010, household ownership of AC was 14%, having increased to 20% by 2019⁵. On average, today, this share has increased above 30% (Falchetta et al., 2024a).

Out of the final individuals in our sample, 9,861 individuals never have AC throughout the period and 1,801 individuals always have AC. Only 49 individuals change their AC status between wave 1 and wave 2. The AC ownership rate is 13% for the responses used in our analysis.

Figure 1 map the percentage of individuals with AC in wave 2 for each of the NUTS1 region of SHARE. As expected, they are mostly located in southern Europe, though high prevalence rates are also observed in Nordic countries. We do not have information on the type of air conditioner, nor whether they can also be used as electric heater in winter time. This could well be the case in countries like Sweden and Norway, which have a prevailing share of electricity as heating source, and a relatively high share of AC despite the low value of CDDs (see Table S3).

⁵<https://www.eea.europa.eu/publications/cooling-buildings-sustainably-in-europe>

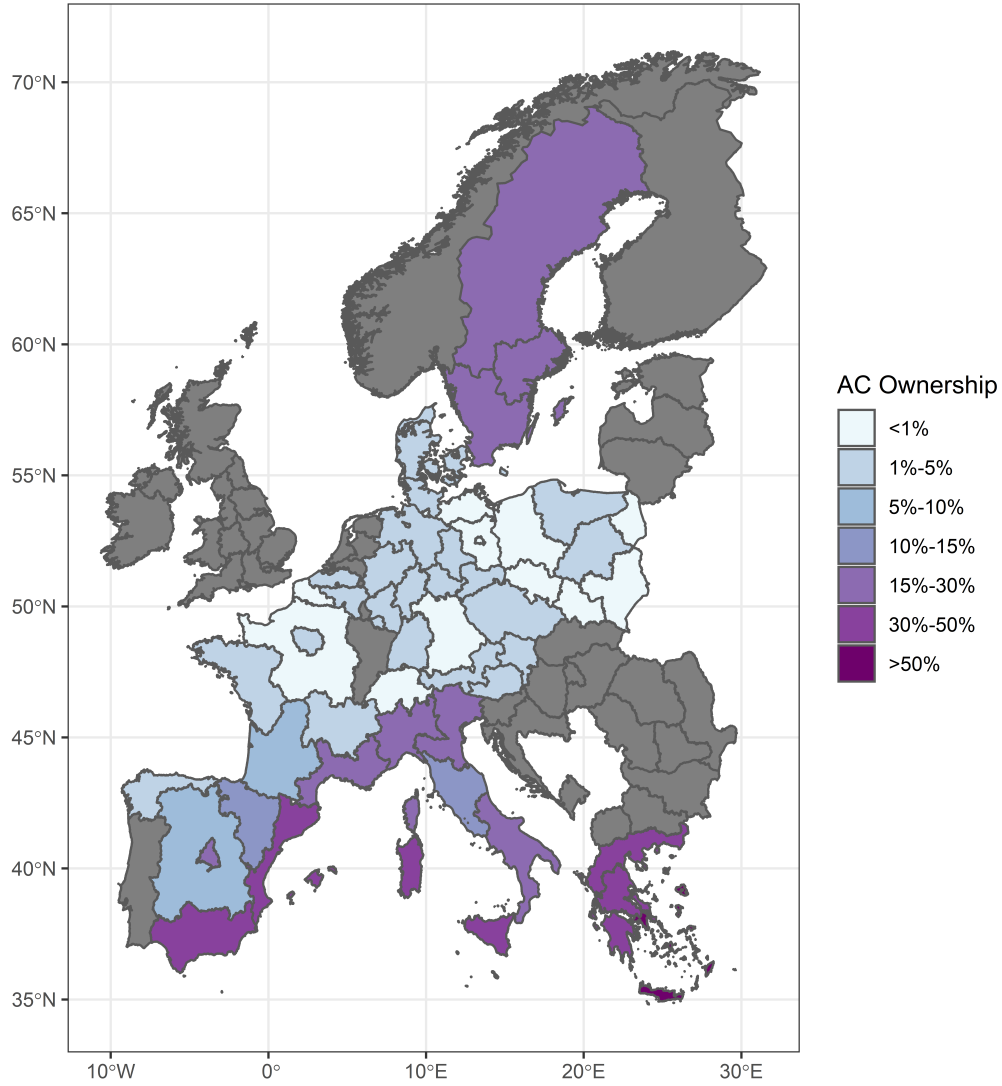


Figure 1: AC Ownership in SHARE survey weighted with SHARE cross-sectional weights. Only regions for which there are at least 10 observations are plotted

3.2 Heat exposure

This study builds upon the SHARE-ENV dataset (Midões et al. 2024), which expands on SHARE by creating variables on individual-specific yearly and cumulative exposure to different environmental and meteorological indicators. SHARE-ENV combines a high-resolution gridded dataset of daily meteorological variables over Europe, E-OBS, with information on where individuals have lived in each year of their lives, from birth until last survey participation, from the retrospective accommodation modules of SHARELIFE and the regular wave⁶.

The E-OBS is a daily gridded observational dataset of daily meteorological variables over Europe. It resorts to data collected from the meteorological station network of the European Climate Assessment & Dataset (ECA&D). It has a geographic resolution of 0.1 degrees, which means that each grid cell is roughly the size of 10 kilometers by 10 kilometers⁷. From gridded daily datasets of temperature we build bins of maximum temperature (i.e., number of days

⁶The regions are cantons in the case of Luxembourg and NUTS regions (Nomenclature of territorial units for statistics) for the remaining EU countries, in their majority NUTS2 (see the Appendix in Midões et al. (2024) for more details).

⁷10km x 10km at the equator

per month where the maximum temperature exceeds 30°C) and Cooling Degree Days (CDDs), the main exposure variable used throughout this paper.

Cooling Degree Days (CDDs) is a measure of the need for indoor cooling. Degree-days have been routinely used by building designers and engineers to estimate indoor space cooling energy consumption and by policy makers and researchers for forecasting energy demand, consumption patterns and associated carbon emissions. This is partly rooted in their simplicity but yet powerful capability to represent a relationship between climate and cooling or heating requirements. We use the EUROSTAT definition of CDDs, where 24°C is considered the temperature threshold above which indoor cooling is required⁸. Specifically, in a given day d where the mean temperature is above 24°C, a degree day is the difference from the mean temperature to 21°C. For example, a day with a mean temperature of 27°C registers 6 CDDs. A day with a mean temperature of 22°C, or with any mean temperature below 24°C, registers 0 CDDs:

$$CDD_d = (TAVG_d - 21) * 1[TAVG_d \geq 24]$$

Degree-days are defined as the monthly or annual sum of the difference between a base temperature and daily mean outdoor air temperature. We aggregate daily CDDs to monthly CDDs by summing daily CDDs for each month.

$$CDD_m = \sum_{d=1}^{d=M} CDD_d$$

where M is the last day of the month, $M \in [28, 29, 30, 31]$.

Heating Degree Days, which we include as a control variable, are defined in a similar way, with the EUROSTAT threshold set at 15°C:

$$HDD_d = (18 - TAVG_d) * 1[TAVG_d \leq 15]$$

$$HDD_m = \sum_{d=1}^{d=M} HDD_d$$

The effect on indoor heat of the same level of atmospheric heat will depend on factors such as urban planning and building insulation. Regions whose climate is warmer might have long standing climate adapted street and building structure (building orientation and materials, street organization, to name a few examples). In order to account for these region-specific characteristics, we consider as a third exposure variable the anomaly in CDDs, which is the difference between the value of CDDs and the 30-year average CDDs in that same region.

3.2.1 Regional aggregation

Resorting to the Degree of Urbanization DEGURBA methodology (the EU/OECD standard for urbanization classification), we classify each gridcell from the monthly CDDs/HDDs as being either part of a city, of towns and suburbs, or of a rural area. Using a historical annual population 0.1° gridded dataset⁹, we compute for each SHARE region-DEGURBA region pair a population-weighted average of the gridded monthly CDDs. Each SHARE region thus has three sub-regions, for which we construct population-weighted average monthly CDDs.

With estimated country-specific weights, we then transform the averages of SHARE region-DEGURBA regions into averages for the five regions indicated by SHARE respondents. Specifically, individuals report they live in one of the following: i) a big city; ii) the suburbs of a big city; iii) a large town; iv) a small town or v) a rural area or village. Appendix A gives full details

⁸https://ec.europa.eu/eurostat/cache/metadata/en/nrg_chdd_esms.htm

⁹ISIMIP Population, available at: <https://data.isimip.org/datasets/fc1e4a06-bd4a-4044-b8e6-46ce86346489/>

on how the we map the three categories of DEGURBA into the five urbanization categories of SHARE. We merge on interview month, SHARE region, and urbanization category, the monthly CDDs and HDDs. We then obtain yearly *CDDs* (and *HDDs*) by summing the CDDs (and HDDs) in the 12 months preceding the month of the interview of each individual:

$$CDD = \sum_{m=1}^{12} CDD_m$$

$$HDD = \sum_{m=1}^{12} HDD_m$$

An analogous process is done for the alternative exposure variables (CDD anomalies and bin variables). For historical exposure, we know the SHARE region and urbanization category of the region where individuals lived for each year of their lives. We thus construct yearly CDDs and merge based on the year of the interview.

We identify a household's SHARE region through the NUTS regions reported in the retrospective accommodation waves 3 and 7, or through the NUTS in which the household was located at the moment of sampling in the regular waves¹⁰. The latter is reported in the housing modules of the regular panel waves.

3.3 Building age

We resort to the JRC LUISA Reference Scenario 2016 ([Baranzelli and Ronchi 2011](#)) for constructing age of buildings at the SHARE region level. The JRC provides data on the percentage of buildings built before 1950 at the city and Functional Urban Area (FUA) level, depending on the country, based on National Census and building stock statistics. We overlay the cities and the FUA with SHARE regions and construct area-weighted averages of the percentage of buildings built before 1950. We do not differentiate between level of urbanization, i.e., the variable constructed is constant within the SHARE region.

3.4 Summary Statistics

House ownership is quite widespread in Europe particularly for those aged 50+, and 74% of households own the dwelling in which they live. The average age of the respondents, 66.5 years, reflects the design of the survey. Average household income in euros PPP is approximately 32,900. GDP per capita, at the NUTS level, is on average 27,513 euros. On average, individuals live in regions where 32% of buildings were built before 1950.

¹⁰The NUTS regions indicated are a mix of NUTS2 and NUTS3 regions (with the exception of Germany and Belgium which report NUTS1 regions only). For Luxembourg, cantons are reported instead of NUTS regions

Table 1: Summary statistics

	N	mean	sd	min	max
AC	46,816	0.134	0.341	0	1
Fatigue	46,816	33.81	47.31	0	100
Reduced appetite	42,344	8.877	28.44	0	100
Irritability	46,771	25.09	43.35	0	100
Trouble sleeping	46,799	32.59	46.87	0	100
Health (perceived)	40,682	3.099	1.077	1	5
Hospitalized in the last 12 months	46,800	14.40	35.11	0	100
Household income	46,816	32900	42900	0	4,242,000
Household network	46,816	252900	368,900	-479,000	31,210,000
Age	46,816	66.47	9.855	50	104
Education	46,816	0.613	0.487	0	1
Owner	46,816	0.736	0.441	0	1
GDP_{pc}	46,816	27,513	11,948	5,000	93,800
Historical individual CDD	46,815	72.7	116	0	633.3
CDD	46,816	102.4	154.5	0	642.6
HDD	46,816	2638.2	1003.3	0	6219.2
CDD anomalies	46,816	23.6	72.8	-478.9	382
Bins (# days ≥ 30 °C)	46,816	22.1	25.5	0	110.7
% buildings built before 1950	38,901	0.319	0.158	0.0243	0.654

Notes: Household income refers to the SHARE imputed variable *thinc*, which sums the income across all components, converted to euros PPP (purchasing power parity). Household network refers to the SHARE imputed variable *hnetw*, converted to euros PPP. Household education level has been coded as 1 if the highest educated member of the household has at least upper secondary education, as 0 otherwise. GDP per capita comes from EUROSTAT series [nama.10r.3gdp].

Figure 2 shows the gridded exposure to CDDs and bins of maximum temperature in waves 1 and 7. The well-known North-South gradient is evident for both CDDs and days with daily average temperature above 30 degrees Celsius. Between the two waves, 2004 and 2017, 50% of the EU NUTS regions have experienced an increase in CDDs greater than 10. In about 35% (10%) of them, CDDs have increases by more than 18% (58%).

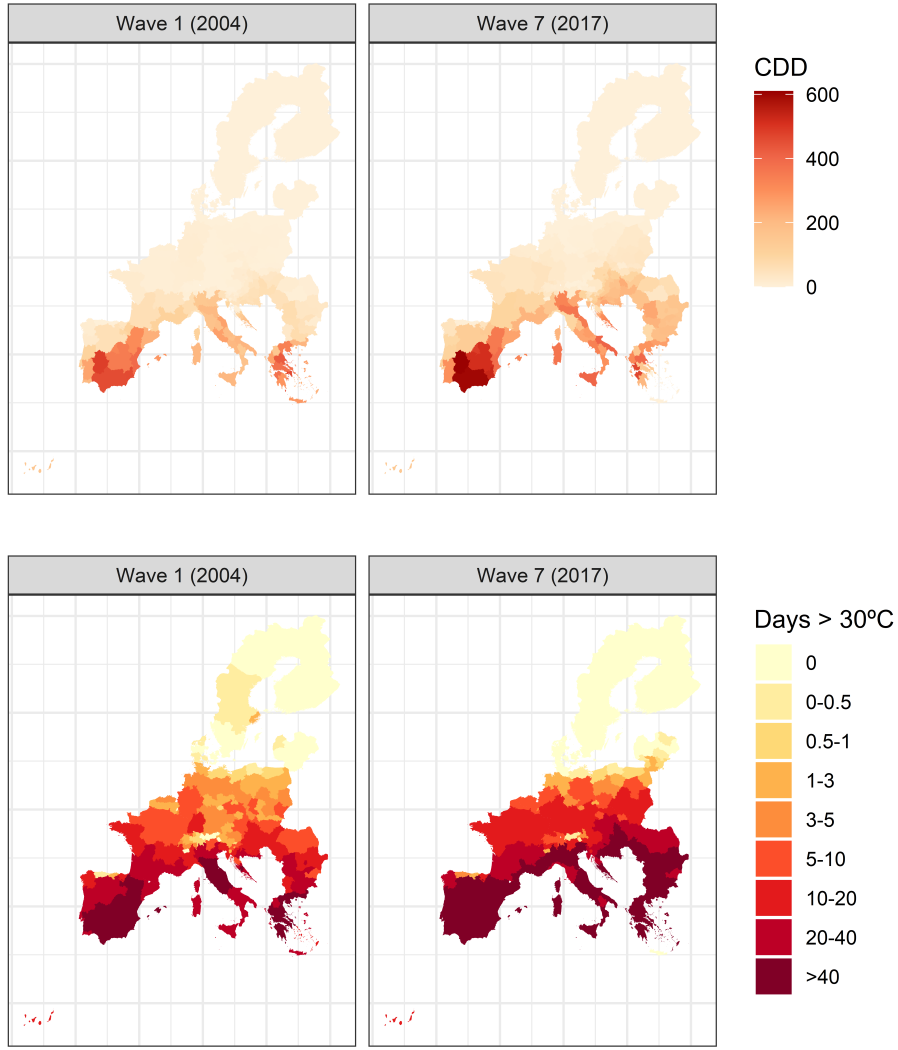


Figure 2: Exposure variables

4 Econometric Approach

The main objective of our empirical analysis is to investigate the effectiveness of AC at mitigating the impacts of extreme temperatures on a number of selected health outcomes. We model in a linear way the relationship between high temperatures experienced by each individual i at a given point in time t , CDD_{it} , and well-being outcomes for each individual at time t , y_{it} :

$$y_{it} = \beta_1 CDD_{it} + x_{it}\gamma + z_{rt}\phi + \eta_i + \epsilon_{it} \quad (1)$$

i : individual; t : year; r : region where individual i is living at time t .

y_{it} are well-being outcomes, specifically fatigue, reduced appetite, irritability and difficulty sleeping ('Yes'=100,'No'=0)

CDD_{it} is the number of CDDs over the last 12 months preceding the month of the interview in the area where the individual i has lived

x_{it} is a vector of individual-level, time-varying controls, specifically, household income, age, age^2 , Heating Degree Days (HDDs), and month of interview

\mathbf{z}_{rt} is a vector of region-level, time-varying controls, namely GDP per capita.

Our identification strategy relies on the randomness of interannual weather variation by region and year. Exploiting the randomness of interannual variation in weather for identification is routinely done in the literature (e.g., [Barreca et al., 2016](#), [Deschenes, 2018](#)). We include individual-level fixed effects in all specifications considered and cluster standard errors at the individual level.

The most direct way to obtain an estimate of how AC can protect against heat is to add an interaction of our heat exposure measure with AC:

$$y_{it} = \beta_1 CDD_{it} + \beta_2 CDD_{it} \times AC_i + \mathbf{x}_{it}\gamma + \mathbf{z}_{rt}\phi + \eta_i + \epsilon_{it} \quad (2)$$

AC_i is a dummy variable:

1: individual has AC at the beginning of the period.

0: individual does not have AC at the beginning of the period.

We expect the coefficient β_2 to be negative, reflecting the protective effect of AC. Given there is only AC information on waves 1 and waves 2, we use as a variable AC ownership in the first period of participation in SHARE.

In that short time window, only 49 individuals changed AC status, which does not allow us to rely on within-individual variation for identification of the effect of AC. Moreover, this information limitation implies that we can only consider individuals who participated in wave 1 and/or wave 2. Yet, we do not use only waves 1 and 2, but also subsequent waves in which those individuals participated. While it is true that between 2004 and 2007 there were very few changes in AC ownership, AC penetration in Europe has increased since. Though this trend accelerated mainly after 2019 (see section 3.1.2), we cannot be sure that the AC status of individuals did not change until wave 7, which takes place in 2017. In our main specification, we drop waves if the individual has since changed house. In fact, in our final sample, the result is only 33% of observations are from waves after wave 2 - 14% in wave 4, 9% in wave 5, 10% in wave 6 and only 0.2% in wave 7. It is not likely for individuals to remove AC from their accommodation. As an additional robustness check, for individuals who do not have AC, we consider their answers only until wave 4 even if they did not move house, as they might have installed AC since.

Our primary econometric problem is selection into treatment, i.e., selection into AC, which, if correlated with heat impacts, is a source of omitted variable bias. Considerable underestimation of the effect of AC is likely, since individuals who are most affected by heat are more likely to select into AC ownership (Table 2, second column). Our control group, thus, will be composed of individuals who are less vulnerable to heat, making our counterfactual lower than it should be. This issue of underestimation from sample selection is common across studies of the effectiveness of protective behaviours. For an illustrative example, pertaining to flood damages and the adoption of mitigation behaviours, see [Endendijk et al. \(2023\)](#).

Vulnerability to heat is however unobservable. To address the issue, we propose an Instrumental Variable (IV) approach. We instrument AC ownership exploiting individuals who move regions and focus on a subsample for which the exclusion restriction is more likely to hold. There are, nonetheless, other factors influencing AC ownership whose omission could lead to instead some overestimation of the impacts of heat, as described in Table 3 (first column). These include income, past exposure to heat, house ownership, and education. Income is highly associated with AC ownership ([De Cian et al., 2019](#)). But income is also associated with being able to access

better healthcare, including preventive healthcare (Mielck et al., 2009). Past exposure to heat, as described by the climate conditions in the area an individual lives in, can also be a central determinant of AC ownership. Yet, it also leads to biological adaptation, where an individual becomes better equipped to deal with high temperatures physiologically (Dong et al., 2022). Home owners are more likely to have AC, but also to invest in other ways in thermal comfort (Ameli and Brandt, 2015). Finally, more educated individuals might choose to purchase AC to defend against heat, and also to adopt behaviours which reduce their exposure and protect their health (Terraneo, 2015). We introduce additional modifier variables which could induce positive bias (an overestimation of the protective effect of AC) in our basic model described in Equation (2).

Other adaptation measures might be responsible for biases, but of uncertain direction (Table 2, third column). Fans, house insulation and other adaptation measures will lead to an over or an underestimation of the protective effect of AC, depending on whether they are, respectively, complements or substitutes to AC.

Table 2: Examples of possibly meaningful omitted variables

+ (Overestimation)	- (Underestimation)	Uncertain direction
Higher income	Higher vulnerability	Fans
Past exposure		House insulation
House ownership		Other adaptation measures
Higher education		

4.1 Augmented model

A first strategy to address these potential sources of bias would be to add all omitted variables in the regression. Park et al. (2020) when estimating the mitigating potential of AC, likewise, expand their model with additional interactions. However, how well an individual handles heat, i.e., his heat vulnerability, is unobservable. Concerning the variables in Table 3, column 3, their impact is uncertain and data are not available. We focus on the factors in column 1, which could lead to an overestimation of the effect of AC.

We firstly confirm that the variables listed in the first column of Table 2 influence the decision of a household to adopt AC. We estimate a linear probability model with AC (No=0, Yes=1) as dependent variable. We exploit variation across individuals. We use one observation per individual from either wave 2 or, when no AC answer exists in wave 2, from wave 1:

$$AC_i = \beta_1 own_i + \beta_2 income_i + \beta_3 edu_i + \beta_4 \overline{CDD}_i + \beta_5 size_i + a_k + \gamma_c + \rho date_i$$

c : country of region r .

own_i : indicator of whether the individual owns their house (1=Yes, 0=No)

$income_i$: household income at first wave of participation in SHARE

edu_i : indicator of whether the most educated individual in the household has at least upper secondary education (1=Yes, 0=No)

$\overline{CDD}_i : \frac{\sum_{t=t_b}^{T_m-1} CDD_{i,t}}{(T_m-1-t_b)}$ past average exposure to heat of individual i , measured by the average annual CDDs experienced from birth (t_b) until the year before the wave of interview ($T_m - 1$)

$size_i$: number of individuals in the household

a_k : area of urbanization fixed effects (1:big city, 2:suburbs, 3:large town, 4:small town, 5:rural area, 999: undefined.)

$date_i$: date of the interview (time trend, expressing the association between having AC and the interview taking place one day later)

Table S5 in the Appendix shows our results. We find, as in the literature, that income and home ownership are positively related with AC ownership, as are higher levels of education. Regarding heat exposure, we find that higher average exposure to CDD through life is positively associated with AC ownership. The augmented model, expressed in Equation (3), adds to Equation (2) these individual-level modifiers we identified:

$$y_{it} = \beta_1 CDD_{it} + \beta_2 CDD_{it} \times AC_i + \beta_4 CDD_{it} \times own_{it_0} + \beta_5 CDD_{it} \times income_{it_0} + \beta_3 CDD_{it} \times edu_i + \beta_6 CDD_{it} \times \overline{CDD}_{it-1} + x_{it}\gamma + z_{rt}\phi + \eta_i + \epsilon_{it} \quad (3)$$

where:

$\overline{CDD}_{it-1} = \frac{\sum_{t=t_b}^{(T_m-1)} CDD_{i,t}}{((T_m-1)-t_b)}$ is the past average exposure to heat of individual i , measured by the average annual CDDs experienced from birth (t_b) until the year before the wave of interview ($T_m - 1$);

$t = t_0$ is the year preceding first participation in the SHARE normal waves.

Our expectation is for the coefficient β_2 from the augmented model in Equation (3) to be smaller compared to the basic model of Equation (2).

We also consider whether AC still has an attenuating effect once we explicitly consider interactions of heat exposure with region-specific linear and quadratic trends. While intuitively, these could represent a measure of regional adaptation, they also partly capture individual adaptation, particularly physiological adaptation. In such a model, we see AC as a proxy of behavioural adaptation. Since other individual confounders remain, we run analysis with interactions with both individual confounders and region-specific trends, adding region-specific trend interactions to Equation (3), $\rho_r \times t$:

$$y_{it} = \beta_1 CDD_{it} + \beta_2 CDD_{it} \times AC_i + \beta_4 CDD_{it} \times own_{it_0} + \beta_5 CDD_{it} \times income_{it_0} + \beta_3 CDD_{it} \times edu_i + \beta_6 CDD_{it} \times \overline{CDD}_{it-1} + \beta_r CDD_{it} \times \rho_r \times t + x_{it}\gamma + z_{rt}\phi + \eta_i + \epsilon_{it} \quad (4)$$

This should give a lower bound of the protective effect of AC, since we address only possible sources of overestimation.

4.2 IV approach

The previous estimate of the protective effect of AC cannot be considered causal. We cannot fully augment our model since we cannot control for unobserved modifiers, such as insulation and fans, nor for unobservable modifiers, such as vulnerability to heat. Park et al. (2020), after expanding their model with additional interactions, take a triple-difference approach. We take an Instrument Variable (IV) approach, and choose as instrument a variable that is related to AC ownership, but not to the other unobserved and unobservable individual-specific mitigating

factors.

In search for a causal estimate, we propose an IV that exploits individuals who have moved across regions. Whether an individual lives in a house with AC, especially in Europe at the time these answers were recorded, also depends on the availability of houses with AC in the region. For individuals who have moved to a new region, their individual exposure to past high temperatures - possibly affecting biological adaptation and behaviours - differs from the new region's exposure to past high temperatures. It is the individual exposure which determines individual physiological/behavioural "readiness" to handle extreme temperatures, but it is only the region's exposure to past high temperatures which determines regional-level supply of houses with AC.

We choose as an instrument a determinant of AC prevalence in the **region** where the individual i currently lives, namely the 1-year-lagged CDD average in that region, \overline{CDD}_{rt-1} : where

$$\overline{CDD}_{rt-1} = \frac{\sum_{t=t_0}^{(T_m-1)} CDD_{r,t}}{((t-1) - t_0)}$$

is the lifetime average heat exposure of region r , measured by the average annual CDDs experienced in region r since birth (t_0) and until the year before he moved to his current region of residence (T_m). We add as a control the 1-year-lagged CDD average experienced by the **individual**, \overline{CDD}_{it-1} , where:

$$\overline{CDD}_{it-1} = \frac{\sum_{t=t_0}^{(T_m-1)} CDD_{i,t}}{((t-1) - t_0)}$$

is the lifetime average heat exposure of individual i , measured by the average annual CDDs experienced from birth (t_0) until the year before the wave of interview ($T_m - 1$). These two variables only differ from each other for individuals who have moved at some point in their lives. Identification relies on the regional 1-year-lagged CDD average \overline{CDD}_{rt-1} being conditionally (on the individual CDD average \overline{CDD}_{it-1}) exogenous. Both averages are taken over the entire life of the individual (or for the maximum number of years of their life for which we have location information).

We use a two-stage least squares (2SLS) approach and model the interaction of AC_i with CDD_{it} in a first-stage regression as follows:

$$CDD_{it} \times AC_i = \rho_0 CDD_{it} \times \overline{CDD}_{rt-1} + \rho_1 CDD_{it} + \rho_2 CDD_{it} \times \overline{CDD}_{it-1} + \rho_3 \overline{CDD}_{it-1} + x_{it}\lambda + x_{rt}\theta + \omega_i + v_{it} \quad (5)$$

Our final estimation equation thus reads as follows:

$$y_{it} = \beta_1 CDD_{it} + \beta_2 CDD_{it} \times AC_i + \beta_3 CDD_{it} \times \overline{CDD}_{it-1} + \beta_4 \overline{CDD}_{it-1} + x_{it}\gamma + x_{rt}\phi + \eta_i + \epsilon_{it} \quad (6)$$

Importantly, we are not exploiting mainly individuals who moved during our window of observation, but, instead, those who have moved at any point during their lives. The relevance of the instrument is widely supported by other modelling exercises, which take long-term averages of previous temperatures as predictors of AC prevalence. In our own model of AC ownership, the regional average CDD is statistically significant (p-value=0.000) for AC ownership when controlling for individual exposure and country-specific time trends (see Table S5).

Exclusion restriction

Since there is the risk that, after a certain age, individuals move because of temperatures - choosing a retirement location due to weather - we restrict our IV sample to individuals who moved while in employment and before 60 years of age.

Another threat to exogeneity would come from the regional CDD average affecting other strategies of regional adaptation. Individual adaptation is not a concern, since we explicitly add such a control. We believe there have been very few regional adaptation measures which could have safeguarded individuals from the impacts of heat. Following the 2003 heatwave, a few countries implemented heat adaptation plans and heat warning systems between 2004 and 2010. Green areas have also changed over time, but changes are quite slow and changes in surface temperature are captured by our exposure variable itself, which does also disaggregate regions by their level of urbanization. The type of buildings might, however, affect insulation and thus the effects of higher outdoor temperatures. We add to the IV model an interaction of temperature exposure with the percentage of buildings built before 1950 in each NUTS2/NUTS3 region (*building_r*). The rationale is that the type of buildings in a region (and thus, their insulation ability) has been mostly driven by the historical period in which they were built and the type of construction taking place at the time. The final estimation equation at the second-stage thus includes an additional interaction variable:

$$y_{it} = \beta_1 CDD_{it} + \beta_2 CDD_{it} \times AC_i + \beta_3 CDD_{it} \times \overline{CDD}_{it-1} + \beta_4 \overline{CDD}_{it-1} + \beta_5 CDD_{it} \times building_r + x_{it}\gamma + x_{rt}\phi + \eta_i + \epsilon_{it} \quad (7)$$

5 Results

5.1 The effects of heat and AC's protective effect

We firstly examine the impact of heat (in terms of estimated marginal effect of an extra CDD) on the prevalence of fatigue, reduced appetite, irritability, and trouble sleeping without considering AC ownership. We thus use the full (50+) SHARE sample, which contains many more individuals than when we require reporting AC information (specifically, we can include individuals who joined the survey after wave 2 for which no AC information exists). We find evidence of a strong association between heat and higher prevalence of all the negative states but trouble sleeping (Table S4). Note that our main variables of interest are binary variables and yet our main specifications are linear. This is for two main reasons: the first, to consider individual fixed effects; and the second, because although linear probability model are necessarily misspecified, they yield similar average marginal effects to probit or logit models (averaged across the distribution of the covariates) (Wooldridge, 2010). We confirm, as Table S4 and Figure S2 show, that the estimated marginal effects are very similar when using instead the (Mundlak) probit specification, i.e., a pooled probit model with averages of the time-varying covariates (Mundlak, 1978).

We find evidence that one extra CDD increases the probability of feeling fatigued by 0.005 percentage points (p.p.), the probability of experiencing reduced appetite by 0.0234 percentage points, and the probability of feeling irritable by 0.0135 percentage points. This means that, an extra day at 31°, which corresponds to 10 extra CDDs, brings an increase in the probability of reporting each of the states from 0.05 p.p. for fatigue to 0.234 p.p. for reduced appetite. A rise in CDDs by 100 - a value that has been experienced by some EU regions between 2004 and 2017 - leads to more significant numbers, from 0.5 p.p. to 2.3 p.p. for fatigue and reduced appetite and 1.35 for irritability. The probability of being fatigued, having reduced appetite, or being irritable, at mean values of the covariates in the full sample is 30%, 9%, and 26% respectively.

When the effect of heat is estimated on the sub-sample of individuals with AC information (Table 4), we find that, for individuals who do not own AC, heat is always associated with higher prevalence of all the negative states, in this case, also trouble sleeping. An extra day at 31°, i.e., 10 extra CDDs, bring an increase between 0.1 p.p. (trouble sleeping) and 0.2 p.p. (reduced appetite) in the probability of reporting each of the states. The probability of being fatigued, having reduced appetite, being irritable, or having trouble sleeping at mean values of the covariates in the reduced sample is 30%, 7%, 25%, and 32% respectively.

Our results for fatigue and irritability echo in sign and magnitude Noelke et al. (2016)'s results on temperature and subjective well-being for American residents. Baylis (2020) looks at the relationship between social media language content and heat. They consider a metric of aggressive profanity intended to capture the association between expressed verbal aggression and temperature. They find an increase in the percentage of tweets with aggressive profane content when temperature rises above 30 °C. Hou et al. (2023) find a significant statistical association between six symptoms of depressions (feeling frustrated, nervous, hopeless, perceiving life as difficult or meaningless) and days with temperature above 30 degree Celsius across 25 provincial administrative units in China. Our results are also consistent with (Mullins and White, 2019), which consider mental health outcomes of different severity, including self-reported mental health in relation to stress, depression, and problems with emotions. Taken together, our results corroborate the robust evidence between high temperatures and well-being related outcomes.

Individuals who own AC (Table 4, Columns 1-4) experience considerably smaller effects. AC appears to fully cancel the negative effects of CDD on fatigue and difficulty sleeping and partly for reduced appetite. If we consider only waves 1 through 4 for individuals who do not own AC

- to minimize concerns on AC status changing -, results are qualitatively and quantitatively similar (not shown). Figure S2 compares how the average marginal effects of heat change with AC across the (Mundlak) probit specification and the fixed effects. We find once more similar results across the linear and the non-linear specification, this time in what regards the protective effects of AC. No impact is found on the outcome of irritability, a result that aligns with Mullins and White (2019), who measure hospitalization due to mental health. It is in contrast with Hou et al. (2023), who consider a mental health score, but the effect of short-term temperatures instead.

Under our augmented model (Table 4, Columns 5-8), as expected, we find smaller protective effects of AC, but still significant for fatigue and reduced appetite. In this model, lifetime exposure to CDD is associated with lower effects of heat (see negative coefficient on $CDD \times \overline{CDD_{it-1}}$), possibly highlighting individual adaptation and potentially regional adaptation through mechanisms other than AC. When we add interactions with region-specific trends, we still find a significant protective effect of AC but only for fatigue (see Tables S9 through S12).

The IV specification's impact estimates of heat are bigger in magnitude (between 0.2 and 0.7 p.p. for 10 additional CDDs) and so is the protective effect of AC for fatigue and reduced appetite. An extra day at 31° (10 extra CDDs), bring an increase between 0.2 p.p. (irritability) and 0.6 p.p. (reduced appetite) in the probability of reporting each of the states. AC appears to provide protection against reduced appetite and particularly against fatigue, allowing individuals to feel tired less often when experiencing moderate heat. AC does not seem to, however, ameliorate individuals' troubles at sleeping and irritability, as previously demonstrated by Mullins and White (2019). Considering that sleeping deprivation strongly correlates with mental health (Löhms 2018), the evidence for significant residual impacts, net of AC private adaptation, call for more research on alternative adaptation measures. Results from the first-stage regression match the expectations of a strong and positive association between our instrument and the interaction of heat with AC exposure (see Table S6). In our model of AC ownership, likewise, the regional average temperature is statistically significant when controlling for individual average exposure and country-specific time trends (see Table S5). Based on Montiel-Pflueger (Olea and Pflueger, 2013) the instrument is not overtly strong: we reject at the 5% level that the IV bias is above 30% of the worst case scenario, but not that is above 20% (see Table S7).

For the IV estimates we present results considering only individuals who moved to their current region during their working lives. The concern is that otherwise, some individuals - those less vulnerable to heat - might choose to move to warmer regions and thus select into AC ownership, resulting in an overestimation of AC's protection (the opposite situation to the simple FE, where it is the most vulnerable who select into AC, leading to underestimation). When we consider the full sample for our IV we do indeed find a higher protective effect of AC (see Table S8). This is consistent with our sample restriction in fact reducing this source of endogeneity. Table 3 reports the average marginal protective effect of AC, computed as the average difference in the probability of each given outcome to occur, without and with AC.

Table 3: Average Marginal Effect of AC (in p.p.)

	O1	O2	O3	O4
BAS	-2.1656***	-1.670***	-0.3133	-1.3679*
AUG	-1.4834*	-0.9727*	0.0273	-0.6365
IV	-10.1067*	-5.2125*	-2.1171	-0.9536

Notes: O1=Fatigue; O2=Reduced appetite; O3=Irritability; O4=Trouble sleeping; No=0, Yes=100. Average Marginal Effects are the average difference in predicted probability when AC=0 and AC=1 from the models in Table 4. Predicted probabilities were censored into the 0-1 range. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 4: Main results

	Basic				Augmented				IV (working life movers)			
	(O1)	(O2)	(O3)	(O4)	(O1)	(O2)	(O3)	(O4)	(O1)	(O2)	(O3)	(O4)
CDD	0.0211*** (0.0063)	0.0240*** (0.0050)	0.0212*** (0.0059)	0.0122** (0.0057)	0.0484*** (0.0129)	0.0407*** (0.0099)	0.0505*** (0.0127)	0.0336*** (0.0118)	0.0723*** (0.0263)	0.0628*** (0.0187)	0.0387* (0.0207)	0.0584*** (0.0194)
CDD \times AC	-0.0212*** (0.0079)	-0.0176*** (0.0056)	-0.0031 (0.0075)	-0.0134* (0.0071)	-0.0147* (0.0088)	-0.0109* (0.0062)	0.0003 (0.0085)	-0.0063 (0.0080)	-0.2359** (0.1098)	-0.1273* (0.0662)	-0.0382 (0.0818)	-0.0170 (0.0716)
CDD \times own					-0.0139 (0.0107)	0.0024 (0.0073)	-0.0189* (0.0103)	-0.0064 (0.0087)				
CDD \times income					-0.0192 (0.0126)	-0.0082 (0.0073)	-0.0240* (0.0135)	0.0059 (0.0112)				
CDD \times edu					0.0098 (0.0082)	0.0073 (0.0057)	-0.0089 (0.0080)	0.0031 (0.0075)				
CDD \times \overline{CDD}_{it-1}					-0.0001* (0.0000)	-0.0001*** (0.0000)	-0.0000 (0.0000)	-0.0001*** (0.0000)				
\overline{CDD}_{it-1}									-0.0185 (0.1276)	0.0159 (0.0841)	0.0420 (0.1142)	0.0011 (0.1065)
CDD \times \overline{CDD}_{it-1}									0.0003 (0.0002)	0.0001 (0.0001)	0.0000 (0.0001)	-0.0001 (0.0001)
CDD \times building									-0.1417** (0.0654)	-0.0333 (0.0429)	-0.0608 (0.0520)	-0.0838* (0.0485)
Total Avg. Marg. Effect of CDD	0.0182***	0.0216***	0.0208***	0.0104**	0.0308***	0.0368***	0.0213***	0.0271***	0.0103	0.0365***	0.0156*	0.0188**
Avg. Marg. Effect of CDD when AC = 0	0.0211***	0.0240***	0.0212***	0.0122**	0.0327***	0.0383***	0.0212***	0.0280***	0.0529***	0.0606***	0.0225	0.0219
Avg. Marg. Effect of CDD when AC = 1	-0.0001	0.0065	0.0181***	-0.0012	0.0180*	0.0274***	0.0215**	0.0217**	-0.1830**	-0.0667	-0.0157	0.0050
Observations	46816	42387	46808	46849	45818	41533	45810	45847	27402	24454	27393	27410

Notes: All models include individual fixed effects and month of interview fixed effects, as well as the following controls: HDD, home ownership, household income, age, age^2 and GDP per capita. O1=Fatigue (No=0, Yes=100); O2=Reduced appetite (No=0, Yes=100); O3=Irritability (No=0, Yes=100); O4=Trouble sleeping (No=0, Yes=100). Std. errors clustered at the individual level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

5.2 Acute and non-acute effects

High temperatures have a contemporaneous effect on thermal comfort and thus on the outcomes we consider. [Noelke et al. \(2016\)](#) show a positive association between higher temperatures in a certain day and reporting having felt fatigued on that same day, alongside associations with lower aggregate well-being and less (more) pronounced positive (negative) feelings. Physiologically this is also the case, with higher temperatures leading to faster onset of fatigue. The same is true for irritability, as direct physical discomfort from hot temperatures is accepted to cause violence and aggression (for example, [Stechemesser et al. 2022](#) show that in days with hot temperature extremes, hate speech in the forms of tweets is more than 20% higher).

In the SHARE survey, respondents are asked about a recent time period ("previous month" or the more vague "recently"). A contemporaneous effect is expected, i.e., individuals are likely to report having felt more fatigued if the period of reference was hotter. We consider this to be an acute effect of heat: a possibly transitory period where well-being is diminished due to ambient temperatures. Yet, we are interested on whether individuals who experience higher temperatures are more likely to feel fatigued any given point in time, highlighting a persistent or cumulative negative effect of heat on mental state. In other words: for the same temperature exposure in the previous month, is well-being in the previous month related to earlier temperature exposure?

Due to the two different reference periods used in SHARE - "last month" and "recently" - we build two different specifications to distinguish between acute and non-acute effects of heat. In the first, we divide exposure over the previous 12 months into exposure in the previous month and in the 11 months before; in the second, we divide exposure into the previous three months and the 9 months before. We find that CDD^1 , i.e., the CDDs in the month preceding the interview, increase the probability of reporting all negative states except for trouble sleeping. Importantly however, when including CDD^1 in our specification, the CDDs experienced before this more recent month remain significant, signalling effects are not purely acute. Individuals who own AC are partly protected from these longer-term effects from heat, yet, we do not find evidence of protection against its acute effects. If we divide effects into the 3 months preceding the interview (CDD^3) and the preceding 9 months ($CDD - CDD^3$), we confirm the protective effects of AC takes place mostly over the longer term.

Table 5: Different horizons

	1 month				3 months			
	(O1)	(O2)	(O3)	(O4)	(O1)	(O2)	(O3)	(O4)
CDD^1	0.0596*** (0.0149)	0.0432*** (0.0107)	0.0536*** (0.0135)	-0.0001 (0.0131)				
$CDD^1 \times AC$	-0.0234 (0.0181)	-0.0233* (0.0123)	0.0117 (0.0171)	0.0264 (0.0164)				
$CDD - CDD^1$	0.0168*** (0.0064)	0.0219*** (0.0051)	0.0174*** (0.0061)	0.0128** (0.0058)				
$(CDD - CDD^1) \times AC$	-0.0234*** (0.0081)	-0.0171*** (0.0058)	-0.0068 (0.0078)	-0.0180** (0.0074)				
CDD^3					0.0418*** (0.0094)	0.0331*** (0.0068)	0.0366*** (0.0083)	0.0112 (0.0080)
$CDD^3 \times AC$					-0.0200* (0.0118)	-0.0218*** (0.0082)	-0.0041 (0.0110)	0.0023 (0.0104)
$CDD - CDD^3$					0.0168*** (0.0063)	0.0223*** (0.0051)	0.0181*** (0.0060)	0.0112* (0.0057)
$(CDD - CDD^3) \times AC$					-0.0247*** (0.0080)	-0.0173*** (0.0057)	-0.0052 (0.0076)	-0.0160** (0.0072)
Observations	46,816	42387	46808	46849	46816	42387	46808	46849

Notes: All models include individual fixed effects and month of interview fixed effects, as well as the following controls: HDD, home ownership, household income, age, age^2 and GDP per capita. O1=Fatigue (No=0, Yes=100); O2=Reduced appetite (No=0, Yes=100); O3=Irritability (No=0, Yes=100); O4=Trouble sleeping (No=0, Yes=100). Std. errors clustered at the individual level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

5.3 Alternative exposure variables

We consider two alternative exposure variables: the number of days over the previous 12 months where the maximum temperature was above 30°C and anomalies in CDD, i.e., the deviation from CDD to the 30-year local CDD average. The estimated impact of the anomalies are, across all specifications, higher than those of the CDD, indicating that some adaptation to regional temperatures is taking place. When considering anomalies, our IV approach delivers estimates of similar magnitude of the protective effect of AC (see Table 7). This further minimizes concerns of endogeneity of our IV, which could arise if the CDD regional average was related to meaningful local forms of adaptation, minimizing the effect of heat inside people's homes. The estimated impact of one extra day with maximum temperature above 30° are about 6 times the estimated impact of one extra CDD, regardless of the specification considered (see Table 6).

5.4 Alternative outcomes

We consider two other outcomes: one subjective - self-perceived health - and one objective - whether individuals were ever hospitalized in the preceding 12 months, in Table 8. We find consistently negative effects of heat. One extra CDD decreases self-perceived health. Both in the basic and in the augmented specification we find evidence that AC decreases this effect. One extra CDD also increases the probability of hospitalization, by 0.01 to 0.02 percentage points. This effect is about half the effect on the incidence of fatigue. We do not find statistically significant evidence for AC decreasing this effect. Although the IV estimates are larger in magnitude as would be expected, the protective effect is not statistically significant.

Table 6: Alternative exposure variable: No. of days with max. temperature $\geq 30^\circ\text{C}$

	Basic				Augmented				IV (working life movers)			
	(O1)	(O2)	(O3)	(O4)	(O1)	(O2)	(O3)	(O4)	(O1)	(O2)	(O3)	(O4)
# days max $\geq 30^\circ\text{C}$	0.1107*** (0.0390)	0.1824*** (0.0320)	0.0305 (0.0398)	0.0808** (0.0366)	0.2508*** (0.0862)	0.2297*** (0.0620)	0.1457* (0.0840)	0.1936*** (0.0751)	0.1619 (0.1273)	0.2748*** (0.0908)	-0.1079 (0.1078)	0.0972 (0.0977)
# days max $\geq 30^\circ\text{C} \times \text{AC}$	-0.1524** (0.0663)	-0.1549*** (0.0473)	0.0919 (0.0657)	-0.1135* (0.0598)	-0.1171 (0.0737)	-0.1329** (0.0524)	0.0706 (0.0741)	-0.0625 (0.0655)	-2.4828* (1.3592)	-1.5896 (1.0310)	0.1335 (1.0454)	0.6525 (1.0028)
# days max $\geq 30^\circ\text{C} \times \text{owner}_{it_0}$					-0.0985 (0.0796)	-0.0157 (0.0547)	-0.1176 (0.0797)	0.0352 (0.0681)				
# days max $\geq 30^\circ\text{C} \times \text{income}_{it_0}$					-0.1672** (0.0831)	-0.0786 (0.0533)	-0.1121 (0.0740)	-0.1220* (0.0646)				
# days max $\geq 30^\circ\text{C} \times \text{education}$					0.0721 (0.0637)	0.0548 (0.0461)	0.0002 (0.0637)	-0.0490 (0.0579)				
# days max $\geq 30^\circ\text{C} \times \overline{\text{CDD}}_{it_0}$					-0.0002 (0.0002)	-0.0002 (0.0002)	0.0002 (0.0002)	-0.0004** (0.0002)				
$\overline{\text{CDD}}_{it-1}$									-0.0903 (0.1514)	-0.0662 (0.1078)	0.0589 (0.1316)	0.0840 (0.1244)
# days max $\geq 30^\circ\text{C} \times \overline{\text{CDD}}_{it-1}$									0.0038* (0.0022)	0.0021 (0.0017)	0.0005 (0.0017)	-0.0016 (0.0016)
# days max $\geq 30^\circ\text{C} \times \text{building}$									-0.0486 (0.0537)	0.0066 (0.0360)	0.0370 (0.0450)	0.0128 (0.0422)
Total Marginal Effect of # days max $\geq 30^\circ\text{C}$	0.0903**	0.1609***	0.0428	0.0656**	0.1251**	0.1866***	0.0383	0.1035***	0.0566	0.1831***	-0.0281	0.0648
Avg. Marg. Effect of # days max $\geq 30^\circ\text{C}$ when AC = 0	0.1107***	0.1824***	0.0305	0.0808**	0.1407***	0.2045***	0.0289	0.1119***	0.5045*	0.4841**	-0.0522	-0.0530
Avg. Marg. Effect of # days max $\geq 30^\circ\text{C}$ when AC = 1	-0.0417	0.0275	0.1223**	-0.0326	0.0236	0.0721	0.0995	0.0493	-1.978*	-1.1055	0.0813	0.6000
Observations	46816	42387	46808	46849	45818	41533	45810	45847	27402	24454	27393	27410

Notes: All models include individual fixed effects and month of interview fixed effects, as well as the following controls: HDD, home ownership, household income, age, age² and GDP per capita. O1=Fatigue (No=0, Yes=100); O2=Reduced appetite (No=0, Yes=100); O3=Irritability (No=0, Yes=100); O4=Trouble sleeping (No=0, Yes=100). Std. errors clustered at the individual level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 7: Alternative exposure variable: CDD anomalies

	Basic				Augmented				IV (working life movers)			
	(O1)	(O2)	(O3)	(O4)	(O1)	(O2)	(O3)	(O4)	(O1)	(O2)	(O3)	(O4)
ΔCDD	0.0230*** (0.0062)	0.0248*** (0.0049)	0.0213*** (0.0060)	0.0139** (0.0057)	0.0463*** (0.0132)	0.0375*** (0.0099)	0.0446*** (0.0131)	0.0340*** (0.0120)	0.0371 (0.0246)	0.0477*** (0.0165)	0.0063 (0.0200)	0.0417** (0.0189)
$\Delta CDD \times AC$	-0.0222*** (0.0078)	-0.0177*** (0.0055)	-0.0014 (0.0076)	-0.0131* (0.0071)	-0.0177** (0.0089)	-0.0119* (0.0062)	-0.0014 (0.0087)	-0.0070 (0.0080)	-0.2206* (0.1156)	-0.0963 (0.0645)	0.0088 (0.0872)	0.0240 (0.0794)
$\Delta CDD \times own$					-0.0143 (0.0107)	0.0045 (0.0074)	-0.0215** (0.0105)	-0.0064 (0.0089)				
$\Delta CDD \times income$					-0.0179 (0.0123)	-0.0060 (0.0068)	-0.0215 (0.0131)	0.0026 (0.0106)				
$\Delta CDD \times edu$					0.0056 (0.0082)	0.0064 (0.0056)	-0.0110 (0.0081)	0.0040 (0.0076)				
$\Delta CDD \times \overline{CDD}_{it-1}$					-0.0000 (0.0000)	-0.0001*** (0.0000)	0.0000 (0.0000)	-0.0001** (0.0000)				
\overline{CDD}_{it-1}									0.1204 (0.1211)	0.0841 (0.0792)	0.0644 (0.1056)	-0.0026 (0.0970)
$\Delta CDD \times \overline{CDD}_{it-1}$									0.0003* (0.0002)	0.0001 (0.0001)	0.0000 (0.0001)	-0.0001 (0.0001)
$\Delta CDD \times building$									-0.0499 (0.0611)	0.0016 (0.0381)	0.0125 (0.0500)	-0.0405 (0.0468)
Total Marginal Effect of ΔCDD	0.0200***	0.0223***	0.0211***	0.0121**	0.0275***	0.0354***	0.0156**	0.0270***	0.0123	0.0358***	0.0148*	0.0200**
Avg. Marg. Effect of ΔCDD at AC=0	0.0230***	0.0248***	0.0213***	0.0139**	0.0298***	0.0371***	0.0157**	0.0280***	0.0521**	0.0540***	0.0132	0.0156
Avg. Marg. Effect of ΔCDD at AC=1	0.0008	0.0070	0.0200***	0.0007	0.0121	0.0252***	0.0144	0.0210**	-0.1685*	-0.0423	0.0148	0.0396
Observations	46816	42387	46808	46849	45818	41533	45810	45847	27402	24454	27393	27410

Notes: All models include individual fixed effects and month of interview fixed effects, as well as the following controls: HDD, home ownership, household income, age, age^2 and GDP per capita. O1=Fatigue (No=0, Yes=100); O2=Reduced appetite (No=0, Yes=100); O3=Irritability (No=0, Yes=100); O4= Trouble sleeping (No=0, Yes=100). Std. errors clustered at the individual level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 8: Different outcome variables

	Basic		Augmented		IV (working life movers)	
	(O5)	(O6)	(O5)	(O6)	(O5)	(O6)
CDD	0.0004*** (0.0001)	0.0129*** (0.0045)	0.0014*** (0.0002)	0.0165* (0.0097)	0.0010** (0.0004)	0.0214 (0.0153)
CDD \times AC	-0.0007*** (0.0001)	-0.0046 (0.0053)	-0.0004** (0.0002)	-0.0031 (0.0060)	-0.0016 (0.0015)	-0.0531 (0.0505)
CDD \times own			-0.0003* (0.0002)	0.0012 (0.0067)		
CDD \times income			-0.0005** (0.0002)	0.0081 (0.0084)		
CDD \times edu			-0.0002 (0.0001)	0.0011 (0.0053)		
CDD \times \overline{CDD}_{it-1}			-0.0000*** (0.0000)	-0.0000 (0.0000)		
\overline{CDD}_{it-1}					0.0008 (0.0022)	-0.1223 (0.0768)
CDD \times \overline{CDD}_{it-1}					-0.0000 (0.0000)	0.0001 (0.0001)
CDD \times building					-0.0004 (0.0010)	-0.0367 (0.0375)
Total Marginal Effect of CDD	0.0003***	0.0122***	0.0007***	0.0189***	0.0006***	0.0073
Avg. Marg. Effect of CDD when AC=0	0.0004***	0.0129***	0.0007***	0.0193***	0.0008***	0.0169*
Avg. Marg. Effect of CDD when AC=1	-0.0003***	0.0083**	0.0004*	0.0162**	-0.0007	-0.0363
Observations	41048	47171	40020	46143	24420	27583

Notes: All models include individual fixed effects and month of interview fixed effects, as well as the following controls: HDD, home ownership, household income, age, age^2 and GDP per capita. O5= Health (self-perceived), 1 = excellent, 2 = very good, 3=good, 4=fair and 5=poor. O6 = Hospitalized in the previous 12 months (No=0, Yes=100). Std. errors clustered at the individual level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

5.5 Heterogeneity analysis

We investigate whether populations with different baseline conditions present a different susceptibility to temperature. We look at preexisting health conditions and at socio-economic affluence. We first divide our sample into two groups based on whether, at the beginning of the period, their perceived reported health is fair or poor (bad status) or good, very good or excellent (good status). Figure 3 shows that individuals who report poor or fair health at the start of the period are more negatively affected by heat. For both groups, having AC results in a smaller impact from heat.

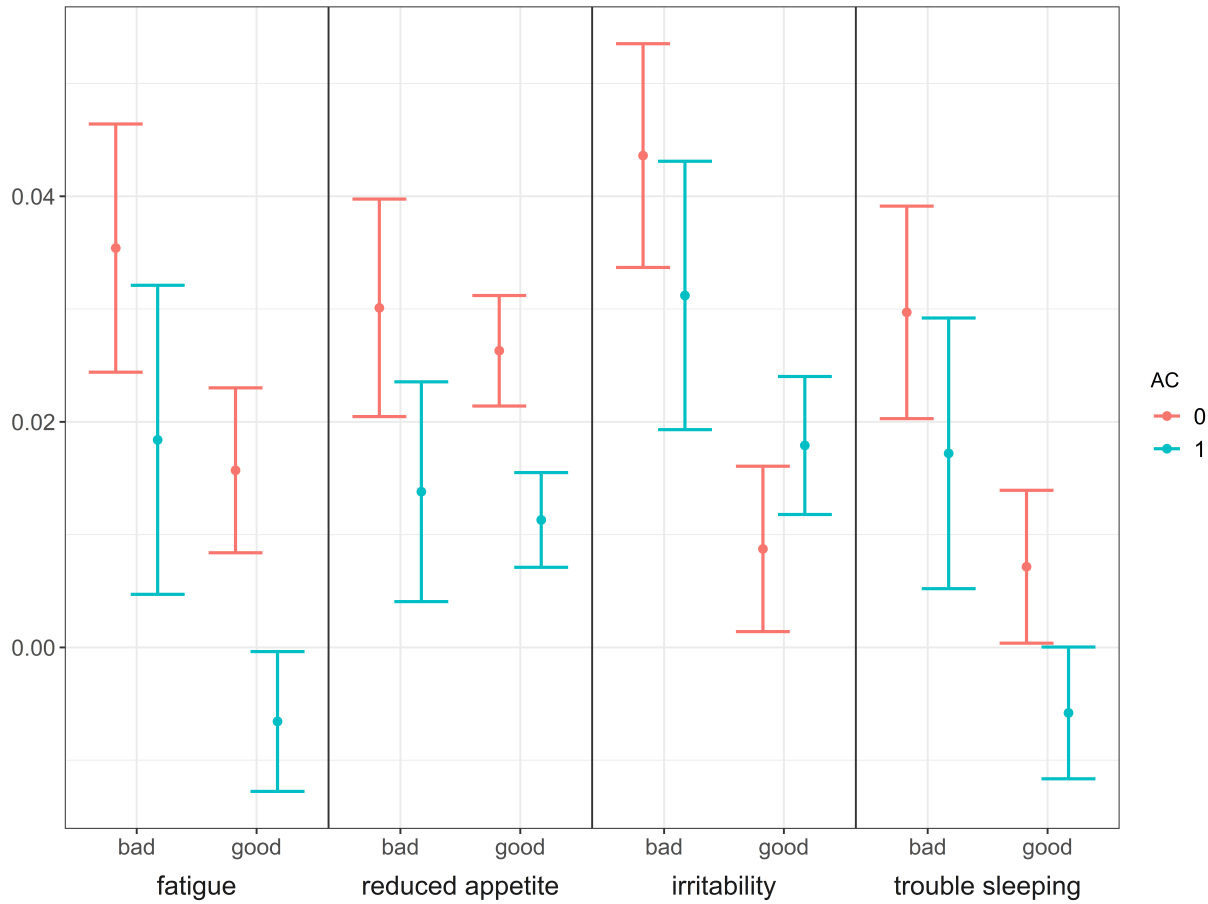


Figure 3: Marginal effect (in p.p.) of one extra CDD, by health status at the start of the period (Basic model)

We then divide our sample into four groups based on wealth quartiles, computed at the country level, based on household network¹¹. We chose wealth to consider a single variable but which correlates with both income levels and home ownership, two different mechanisms which favour adaptation (as seen in the augmented model regressions in Table 4).

We find that, for individuals without AC, larger wealth is associated with lower impacts of extreme temperature, signaling the possibility to undertake perhaps other adaptation actions, as also found by [Obradovich et al. 2018](#). On the other hand, for individuals who own AC, wealth status does not seem to provide additional protection. However, this could be exactly because individuals who own AC are wealthier, thus budget constraints are not relevant for them. Another way of looking at this results is that AC provides particularly meaningful protection for poorer individuals who cannot easily afford alternative adaptation responses, such as higher quality housing.

¹¹Using the the SHARE variable hnetw, on first wave of participation. On average, for our sample, household network is approximately 42,000 euros PPP for the first quartile, 135,000 euros PPP for the second quartile, 261,000 for the third quartile and 590,000 for the fourth quartile, but with substantial country variation (average network for the first quartile ranges from 6,000 euros PPP in Poland to 90,000 in Spain, and for the fourth quartile from 151,000 in Poland again to 713,000 in France).

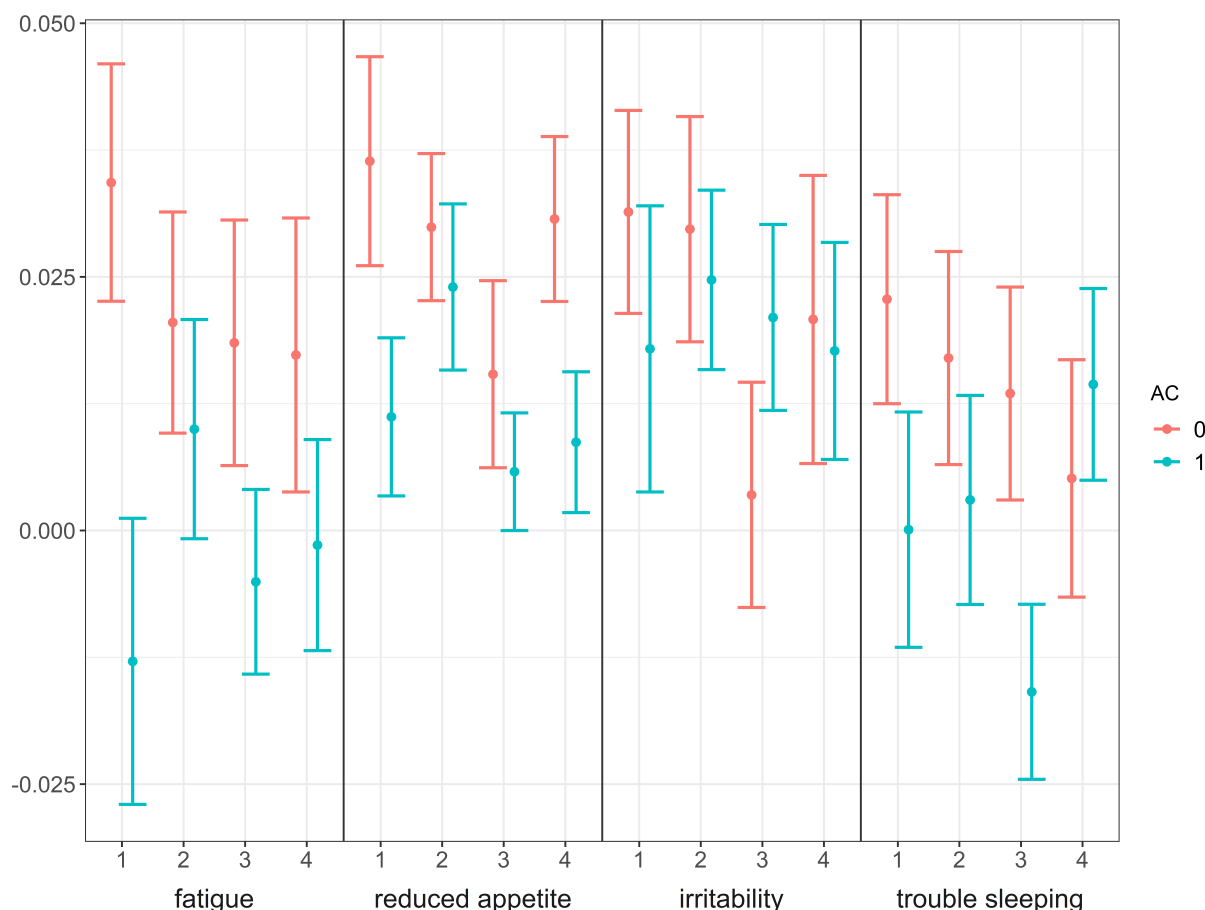


Figure 4: Marginal effect (in p.p.) of one extra CDD, by wealth quartile at the start of the period (Basic model)

6 Discussion and conclusions

In Europe, the rising risks posed by heat will compound with socio-demographic trends and expose a growing fraction of households to deteriorating living conditions, making the challenge of adaptation even more urgent. Thermal comfort inside buildings is fundamental, as Europeans spend approximately 80% to 90% of their time indoors¹². Here we investigate the protective effect of AC after documenting the negative impact of heat on four self-reported well-being metrics. We find that 10 extra CDDs over a year (an extra day at 31°), for individuals without AC, increases by 0.2 - 0.5 p.p. the probability of reporting fatigue, by 0.2 - 0.6 p.p. the probability of reduced appetite, by 0.2 - 0.4 the probability of reporting irritability and by 0.1 - 0.3 the probability of reporting issues sleeping. We find that heat also relates to negative outcomes in terms of perceived health and increases the likelihood of hospitalization (0.1 to 0.2 p.p.).

Climate forecasts for 2041-2070 predict that the majority of regions of Europe will experience an increase of at least 100 CDDs per year (compared to 1980-2010), even under optimistic climate scenarios (Spinoni et al., 2018). Thus, our results would indicate that for a great part of Europe, there would be at least an increase in the order of 2 - 6 percentage points in the prevalence of the negative states we consider.

The negative effects of heat are not purely acute, i.e., once we consider most recent exposure (1 or 3 months) versus exposure over the remaining months of the year, most of the negative effects

¹²<https://www.eea.europa.eu/publications/cooling-buildings-sustainably-in-europe>

come from this second, mid-run, exposure. AC also seems to provide value over the mid-run as opposed to during the month of the interview.

We find AC ownership provides substantial protection against the negative effects of heat on fatigue, regardless of the specification considered. When considering our IV estimates, we find protection against both fatigue and reduced appetite. Our IV estimates point to AC providing full protection against these two outcomes and, in fact, we estimate there might lower levels of fatigue from (moderate) heat exposure for individuals who AC in their home. Positive effects from heat seem to accrue in terms of improved sleeping whenever baseline health conditions are good, based on the heterogeneity analysis. It is conceivable that with AC, especially fragile individuals might actually benefit from (moderate) exposure to heat. This might be because, while they usually face difficulties thermoregulating, when there is both outdoor heat and AC they can manage to adapt. Individuals might for example be able to enjoy sunlight without sacrificing thermal comfort. A 2019 review of the scientific literature ([Larriva and García 2019](#)) shows that on average, those above 65 need higher temperatures for thermal comfort.

Our results indicate that AC does not seem to work as effectively to reduce irritability nor on average difficulties sleeping. It is worth remembering our AC variable pertains to ownership, not use, of AC. Households might refrain from using AC during the night, or its noise may disturb sleep. That AC appears to, on average, provide considerable protection against fatigue, and that it provides particularly meaningful protection for poorer individuals, might signal that utilization and ownership, at least in the day time, are not too far apart in the population we consider. [Ostro et al. \(2010\)](#) show this to be the case in California (USA), suggesting that budget-constrained individuals are willing to forego other expenses to keep cooling on. This also means that AC bears the risk of introducing a new source of inequalities, much more than other policies.

If we consider irritability and difficulties at sleeping the outcomes most directly related to mental health, these results align with studies conducted in the US on temperature-mental health relationships ([Mullins and White, 2019](#)). Differently from ([Mullins and White, 2019](#)), our analyses reveal the existence of groups that are particularly at risk. AC is more effective if people are in good health and it provides particularly meaningful protection for poorer individuals, who cannot easily afford alternative adaptation responses.

The three specifications considered (basic model, augmented, IV) point to robust negative effects of heat as well as to a protective effect of AC across self-reported health outcomes. The range in the estimated magnitude of the coefficients indicates that the augmented models might not be able to capture hidden vulnerabilities that go beyond individual factors - which we control for - as well as the multiplicity of intended and unintended adaptation strategies that might be available in a different way across regions and over time and that can complement the effectiveness of AC. The model that considers the anomalies in CDDs as exposure variable attempts to account for some of these region-specific characteristics and shows similar results. AC protects individuals from CDD anomalies when it comes to fatigue and to a lower extent reduced appetite. Regional characteristics might affect not only the availability of adaptation options (e.g. air-conditioned malls, blue areas) but also the accessibility to them (e.g. public transportation). While some threats to the exogeneity of our instrument might remain unaddressed, we find a substantially larger protective effect of AC under the IV approach as opposed to the simple FE, which is expected given the issue of selection into adaptation by the most vulnerable, and in line with similar papers.

Our results overall show AC is effective as a protective measure against some outcomes only, and that important well-being subjective indicators that have been related to more severe mental health issues - irritability and trouble sleeping - are not as effectively protected. Moreover,

we have not performed any cost-effectiveness analysis. It should not be inferred that AC and particularly residential AC is an ideal adaptation strategy. It might be that building insulation, for example, is similarly effective and at lower cost, and in fact, we find an association between older buildings and lower negative effects of heat. AC availability at work and in public spaces are relevant too, and possibly more cost-effective as policy measures. The idea of providing for cooling common spaces in cities is already a reality. For example, Paris provides maps of all cooling locations to citizens, where these include air-conditioned libraries and museums. In the US Pacific Northwest, cooling centers were open in 2021 ahead of record-breaking temperatures¹³.

This same dataset can be used to estimate the potential of other adaptation strategies. This can be done by looking, for example, into exogenous policy interventions around building insulation or heat warning systems. Another angle which deserves further consideration is individual adaptation versus regional adaptation outside the specific topic of AC ownership. In our models with additional interactions, we find that individuals who have experienced higher average exposure to heat since birth are less impacted by additional CDD. The dynamics of accumulated exposure to heat through life - to what extent/until what stage it provides protection and when does it become a burden on health - are a fundamental topic to understand the overall impacts of climate change on human health.

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Author contributions

C.M and E.D.C. designed the analysis. C.M. gathered, processed, and harmonized the data, performed the analysis, and wrote the first draft. C.M and E.D.C. contributed to analysis of the results and the writing of the paper.

Competing interests

The authors declare no competing interests.

Data and materials availability

The final dataset is available from the authors upon request.

¹³<https://www.reuters.com/world/us/cooling-centers-open-us-pacific-northwest-ahead-life-threatening-heat-2021-06-25/>

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Appendix

A Regional Aggregation

We build monthly exposure variables at the SHARE region - urbanization level, i.e., for each SHARE region, there are five subregions - big cities, suburbs, large towns, small towns and rural areas. The starting point for this process are daily gridded datasets of temperature and an yearly gridded dataset of population, which we use for weighing and for constructing urbanization levels. We provide a step by step example for the NUTS2 region of Veneto. Starting with a daily gridded dataset of E-OBS on average temperatures we build CDD_{day} as described in the main text.

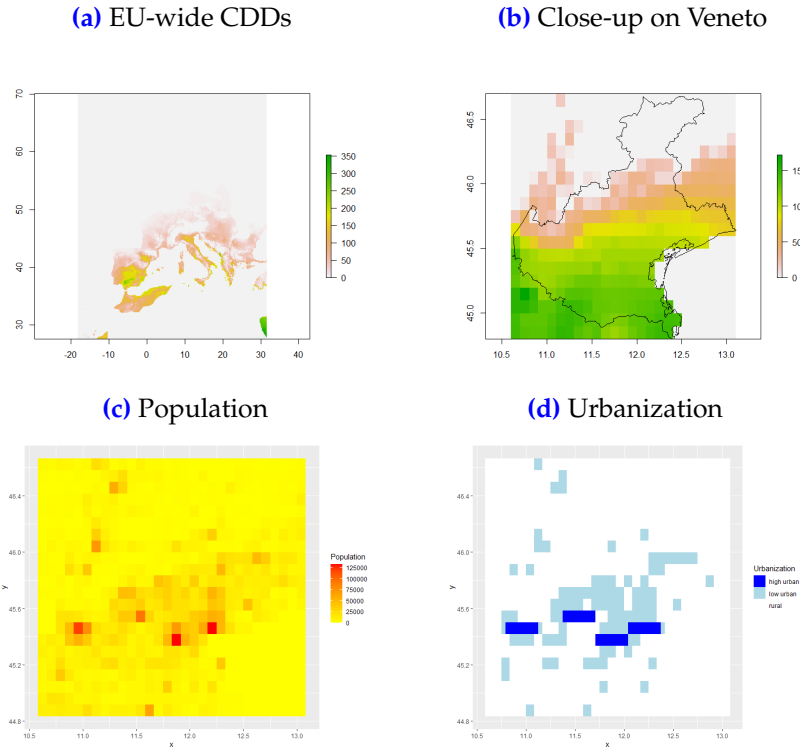
$$CDD_d = (TAVG_d - TAVG^*) * 1[TAVG_d \geq 24]$$

We aggregate daily CDDs to monthly CDDs by summing daily CDDs for each month.

$$CDD_m = \sum_{d=1}^{d=M} CDD_d$$

At this stage we have monthly CDDs for each grid (see Figure S1). We overlay these datasets with shapefiles of the SHARE regions, as exemplified for Veneto in Figure S1. Resorting to a 50+ population gridded dataset from ISIMIP¹⁴, we follow the DEGURBA Manual by the [European Union \(2021\)](#) and classify regions into rural, semi-urban and highly urban. This allows us to calculate CDDs for three subregions within each NUTS, which we calculate as a population-weighted average of CDDs. Table S1 shows us this intermediate result.

Figure S1: Aggregation and weighting procedure: illustration for August 2011 CDDs and the Veneto region



¹⁴ISIMIP Population, available at: <https://data.isimip.org/datasets/fc1e4a06-bd4a-4044-b8e6-46ce86346489/>

Table S1: Example: CDDs by urbanization level in the Veneto region by DEGURBA aggregates

area	08/2011 CDDs
High urban	104.48
Low Urban	88.13
Rural Area	84.29

To add extra variability and a plausible merge to SHARE, we transform these three subregions into the five self-reported SHARE subregions - big city, suburbs, large town, small town and rural areas - using data motivated, country-specific weights.

For all countries, we assume that individuals who in SHARE report living in a big city live in (DEGURBA-classified) highly urban areas, and that individuals who report living in a rural area or village live in (DEGURBA-classified) rural areas. We then estimate, for each country, for the remaining, intermediate, areas - suburbs, large towns, and small towns - the percentage which live in each of the three DEGURBA regions. We start by assuming certain values to be zero: for individuals who report living in the suburbs of a big city, we assume they do not live in rural areas, but are divided between highly urbanized and low urbanized areas; for those living in a small town, we assume they do not live in a highly urban area, and thus are divided in low urbanized area and rural areas. For those in a large town, we assume they might live in any of the three region types.

We estimate the non-zero percentages by approximating the population distribution of SHARE subregions to the population distribution of DEGURBA areas. From our gridded population dataset, we compute, for each NUTS region, what percentage of the 50+ population lives in rural, low urban, and high urban areas. From SHARE, we compute the percentage of respondents who report living in each of the five regions. We then choose the country-specific percentages that minimize the squared distance between the proportion of individuals living in a rural/low-urban/high-urban area according to the gridded dataset and according to SHARE.

Table S2: Example: CDDs by urbanization level in the Veneto region by SHARE aggregates

area within Veneto	08/2011 CDDs
1. Big city	104.48
2. Suburbs of a big city	95.06
3. A large town	91.15
4. A small town	87.11
5. A rural area or village	84.29

We identify the household location, i.e., their SHARE region, through the NUTS regions reported in the retrospective accommodation waves 3 and 7, or through the NUTS in which the household was located at the moment of sampling in the regular waves¹⁵. The latter is reported in the housing modules of the regular panel waves.

¹⁵The NUTS regions indicated are a mix of NUTS2 and NUTS3 regions (with the exception of Germany and Belgium which report NUTS1 regions only). For Luxembourg, cantons are reported instead of NUTS regions

B Summary Statistics

Table S3: Summary statistics, by country

		AC				Year CDDs: CDD^{12}			
	n	mean	sd	min	max	mean	sd	min	max
Austria	2,534	0.03	0.16	0	1	39.50	39.11	0	171.87
Belgium	6,904	0.02	0.14	0	1	19.67	14.21	0	60.26
Czechia	3,692	0.03	0.17	0	1	35.22	22.23	0	165.72
Denmark	4,526	0.01	0.11	0	1	0.68	1.33	0	7.36
France	908	0.02	0.15	0	1	28.17	19.00	9.05	54.15
Germany	5,092	0.02	0.13	0	1	29.38	22.17	0	136.71
Greece	4,653	0.60	0.49	0	1	349.13	170.41	0	642.60
Italy	5,398	0.21	0.41	0	1	235.48	104.05	15.11	626.45
Poland	3,387	0.01	0.07	0	1	26.39	23.32	0	97.60
Spain	3,962	0.22	0.41	0	1	317.34	172.96	0.01	637.34
Sweden	5,749	0.17	0.37	0	1	1.34	2.73	0	13.50
Switzerland	11	0.00	0.00	0	0	5.07	5.56	0.05	14.91

C Effects of heat

Table S4: Average Marginal Effects of heat, linear and non-linear model

	FE fatigue	(Mundlak) Probit fatigue	FE reduced appetite	(Mundlak) Probit reduced appetite	FE irritability	(Mundlak) Probit irritability	FE trouble sleeping	(Mundlak) Probit trouble sleeping
CDD	0.0050* (0.0029)	0.0044 (0.00336)	0.0234*** (0.0025)	0.0201*** (0.0026)	0.0135*** (0.0027)	0.0121*** (0.0031)	-0.0012 (0.0027)	-0.0025 (0.0034)
HDD	-0.0006 (0.0005)	-0.0001 (0.0006)	0.0061*** (0.0005)	0.0057*** (0.0005)	0.0011** (0.0005)	0.0013** (0.0006)	0.0001 (0.0005)	0.0006 (0.0006)
age	-4.8102*** (0.3780)	0.7293*** (0.0844)	-1.8302*** (0.2931)	0.9800** (0.0616)	-0.7162** (0.3537)	0.1926** (0.0798)	-1.2125*** (0.3528)	0.2916*** (0.0857)
age ²	0.0422*** (0.0028)		0.0217*** (0.0021)	0.0070*** (0.0009***)		0.0117*** (0.0026)		
wealth	0.0598 (0.0551)	-0.258*** (0.0003)	-0.0009 (0.0483)	-0.0009*** (0.0002)	0.0991* (0.0515)	-0.0328 (0.0225)	-0.0242 (0.0514)	-0.1550*** (0.0327)
income	-0.0410 (0.4133)	-0.0866 (0.5730)	-0.8995*** (0.3349)	-0.8374** (0.3495)	0.5443 (0.3869)	0.6095 (0.4735)	0.4770 (0.3860)	0.5555 (0.5057)
owner	-2.5495*** (0.7623)	-2.0471** (0.8895)	-0.8988 (0.6554)	-0.6646 (0.680)	-1.2970* (0.7131)	-1.1399 (0.8461)	-2.4044*** (0.7110)	-2.1888** (0.8942)
GDP pc	-0.0002*** (0.0001)	-0.0002** (0.0001)	-0.0006*** (0.0001)	-0.0005*** (0.0001)	-0.0003*** (0.0001)	-0.0004*** (0.0001)	-0.0002*** (0.0001)	-0.0003*** (0.0001)
Observations	133,534	133,534	103,592	103,592	133,532	133,532	133,636	133,636

Notes: The FE models include individual fixed effects and month of interview fixed effects, as well as the following controls: HDD, home ownership, household income, age, age² and GDP per capita. The (Mundlak) Probit models include individual-averages of all covariates (average marginal effects were omitted) and the average marginal effects reported are those of the time-varying covariates, meant to be compared with the FE average marginal effects. O1=Fatigue (No=0, Yes=100); O2=Reduced appetite (No=0, Yes=100). O3=Irritability (No=0, Yes=100); O4= Trouble sleeping (No=0, Yes=100). Std. errors clustered at the individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

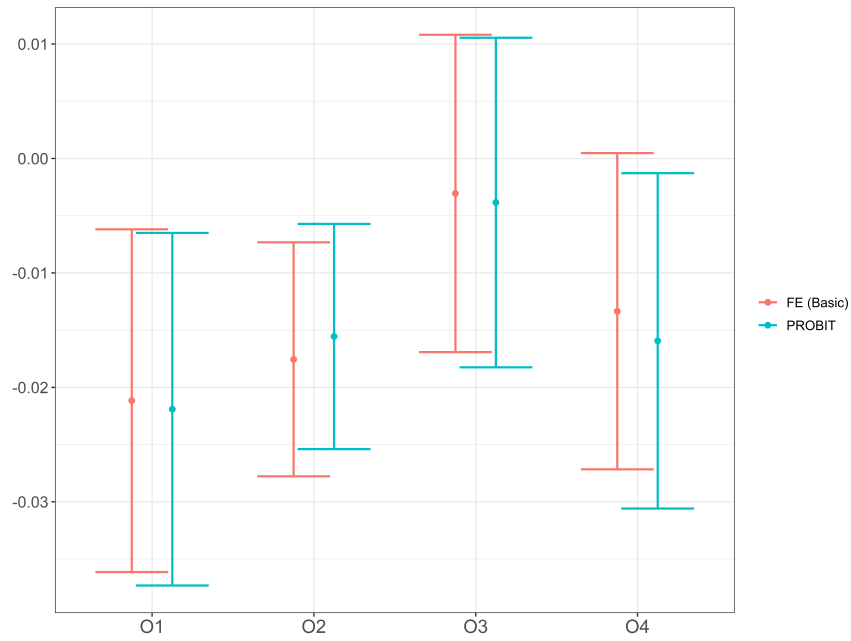


Figure S2: Basic model versus pooled Mundlak probit: Moderating effect of AC on the marginal effect of CDD. O1=Fatigue (No=0, Yes=100); O2=Reduced appetite (No=0, Yes=100). O3=Irritability (No=0, Yes=100); O4=Trouble sleeping (No=0, Yes=100).

D Selection into AC

Table S5: AC Ownership

	AC			
\overline{CDD}_i	0.000620*** (3.67e-05)	0.000662*** (3.71e-05)	4.24e-05 (0.000160)	8.48e-05 (0.000160)
\overline{CDD}_r			0.000582*** (0.000155)	0.000581*** (0.000155)
age	-0.000330* (0.000193)	-0.000341* (0.000193)	-0.000328* (0.000193)	-0.000338* (0.000193)
owner	0.00719* (0.00387)	0.00747* (0.00387)	0.00706* (0.00387)	0.00734* (0.00387)
income	0.0186*** (0.00660)	0.0185*** (0.00654)	0.0185*** (0.00656)	0.0185*** (0.00651)
education	0.0554*** (0.00454)	0.0544*** (0.00453)	0.0556*** (0.00454)	0.0546*** (0.00453)
household size	0.00188 (0.00177)	0.00201 (0.00177)	0.00170 (0.00177)	0.00184 (0.00177)
areatype=2	-0.0334*** (0.00917)	-0.0348*** (0.00918)	-0.0310*** (0.00919)	-0.0324*** (0.00919)
areatype=3	-0.0242*** (0.00780)	-0.0240*** (0.00779)	-0.0197** (0.00780)	-0.0195** (0.00779)
areatype=4	-0.0307*** (0.00741)	-0.0314*** (0.00739)	-0.0275*** (0.00741)	-0.0281*** (0.00739)
areatype=5	-0.0563*** (0.00681)	-0.0558*** (0.00679)	-0.0523*** (0.00681)	-0.0518*** (0.00679)
areatype=999	-0.0567*** (0.00689)	-0.0591*** (0.00689)	-0.0538*** (0.00688)	-0.0561*** (0.00689)
time trend	2.09e-05*** (5.12e-06)	4.42e-06 (1.03e-05)	2.08e-05*** (5.12e-06)	4.39e-06 (1.03e-05)
Country FE	Yes	No	Yes	No
Country \times time trend	No	Yes	No	Yes
Observations	26,524	26,524	26,504	26,504
R-squared	0.314	0.317	0.315	0.318

Notes: Household size: number of individuals in the household. Time trend corresponds to the month and year of interview. White std. errors. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

E IV details

Table S6: IV, first stage regression for fatigue

	$AC \times CDD$
$CDD \times \overline{CDD}_{rt-1}$	0.00113*** (0.000322)
\overline{CDD}_{it-1}	-0.0543 (0.183)
$CDD \times \overline{CDD}_{it-1}$	0.000471 (0.000368)
CDD	0.0249 (0.0281)
$HDD12$	0.00313*** (0.000816)
wealth	Y
income	Y
owner	Y
GDP_{pc}	Y
age	Y
age^2	Y
Observations	23,868

Table S7: Montiel-Pflueger robust weak instrument test

	Fatigue	
Effective F-statistic	12.258	
% of Worst Case Bias	CV TSLS ($\alpha=5\%$)	CV TSLS ($\alpha=10\%$)
$\tau = 5\%$	37.418	33.105
$\tau = 10\%$	23.109	19.748
$\tau = 20\%$	15.062	12.374
$\tau = 30\%$	12.039	9.650
Observations	23,868	

Table S8: IV (no moving age restriction)

	(O1)	(O2)	(O3)	(O4)	(O1)	(O2)	(O3)	(O4)
CDD	0.0372*** (0.0108)	0.0522*** (0.0091)	0.0212** (0.0099)	0.0240** (0.0095)	0.0797*** (0.0291)	0.0596*** (0.0198)	0.0445* (0.0232)	0.0387* (0.0206)
CDD \times AC	-0.2004** (0.0958)	-0.1362** (0.0682)	-0.0571 (0.0822)	0.0718 (0.0781)	-0.2671** (0.1304)	-0.1327* (0.0762)	-0.0911 (0.1015)	0.0295 (0.0849)
\overline{CDD}_{it-1}	-0.1214** (0.0558)	-0.0407 (0.0429)	-0.0612 (0.0505)	0.0222 (0.0475)	-0.1348** (0.0624)	-0.0351 (0.0419)	-0.0700 (0.0522)	0.0088 (0.0450)
CDD $\times \overline{CDD}_{it-1}$	0.0003* (0.0002)	0.0001 (0.0001)	0.0001 (0.0001)	-0.0002 (0.0001)	0.0003* (0.0002)	0.0001 (0.0001)	0.0001 (0.0001)	-0.0001 (0.0001)
CDD \times <i>building</i>					-0.1617** (0.0743)	-0.0281 (0.0473)	-0.0861 (0.0592)	-0.0401 (0.0525)
AME CDD	0.0301***	0.0428***	0.0208**	0.0198**	0.0116	0.0386***	0.0137*	0.0194**
AME CDD at AC = 0	0.0569***	0.0617***	0.0284*	0.0102	0.0532***	0.0600***	0.0284*	0.0154
AME CDD at AC = 1	-0.1435***	-0.0745	-0.0286	0.0820	-0.2091*	-0.0705	-0.0642	0.0403
Observations	46815	42387	46807	46848	38901	35153	38892	38921

Notes: All models include individual fixed effects and month of interview fixed effects, as well as the following controls: HDD, home ownership, household income, age, age^2 and GDP per capita. O1=Fatigue (No=0, Yes=100); O2=Reduced appetite (No=0, Yes=100); O3=Irritability (No=0, Yes=100); O4=Trouble sleeping (No=0, Yes=100). Std. errors clustered at the individual level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

F Regional interactions

Table S9: Regional Interactions: fatigue and reduced appetite

	O1	O1	O1	O1	O1	O2	O2	O2	O2	O2
CDD	0.0211*** (0.00625)	0.0283 (0.0474)	3.411 (10.88)	-0.00409 (0.0592)	-13.11 (13.79)	0.0240*** (0.00500)	0.00418 (0.0308)	-9.350 (11.58)	-0.0564 (0.0365)	-31.43** (15.62)
CDD x AC	-0.0212*** (0.00785)	-0.0177** (0.00876)	-0.0167* (0.00874)	-0.0160* (0.00886)	-0.0160* (0.00884)	-0.0176*** (0.00559)	-0.00945 (0.00624)	-0.0101 (0.00627)	-0.00786 (0.00639)	-0.00758 (0.00634)
CDD x country x year	NO	YES	NO	NO	NO	NO	YES	NO	NO	NO
CDD x country x year x year	NO	NO	YES	NO	NO	NO	NO	YES	NO	NO
CDD x NUTS1 x year	NO	NO	NO	YES	NO	NO	NO	NO	YES	NO
CDD x NUTS1 x year x year	NO	NO	NO	NO	YES	NO	NO	NO	NO	YES
Observations	46,816	46,816	46,816	46,816	46,816	42,387	42,387	42,387	42,387	42,387

Notes: All models include individual fixed effects and month of interview fixed effects, as well as the following controls: HDD, home ownership, household income, age, age^2 and GDP per capita. O1=Fatigue (No=0, Yes=100); O2=Reduced appetite (No=0, Yes=100). Std. errors clustered at the individual level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table S10: Regional Interactions + individual confounders: fatigue and reduced appetite

	O1	O1	O1	O1	O1	O1	O2	O2	O2	O2	O2	O2
CDD	0.0484** (0.0129)	0.0418 (0.0484)	4.5285 (10.9284)	0.0056 (0.0601)	-12.6482 (13.8736)	0.0407** (0.0099)	-0.0001 (0.0316)	-8.9633 (11.5798)	-31.2650* (15.6082)	0.0505** (0.0127)		
CDD x AC	-0.0147* (0.0088)	-0.0161* (0.0091)	-0.0155* (0.0091)	-0.0156* (0.0091)	-0.0159* (0.0091)	-0.0109* (0.0062)	-0.0104 (0.0063)	-0.0097 (0.0064)	-0.0086 (0.0064)	0.0003 (0.0085)		
CDD x country x year	NO	YES	NO	NO	NO	NO	YES	NO	NO	NO		
CDD x country x year x year	NO	NO	YES	NO	NO	NO	NO	YES	NO	NO		
CDD x NUTS1 x year	NO	NO	NO	YES	NO	NO	NO	NO	YES	NO		
CDD x NUTS1 x year x year	NO	NO	NO	NO	YES	NO	NO	NO	NO	YES		
Observations	46,816	46,816	46,816	46,816	46,816	42,387	42,387	42,387	42,387	42,387		

Notes: All models include individual fixed effects and month of interview fixed effects, as well as the following controls: HDD, home ownership, household income, age, age^2 and GDP per capita. O1=Fatigue (No=0, Yes=100); O2=Reduced appetite (No=0, Yes=100). Std. errors clustered at the individual level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table S11: Regional Interactions: irritability and trouble sleeping

	O3	O3	O3	O3	O3	O4	O4	O4	O4	O4	O4
CDD	0.0212*** (0.00592)	-0.0195 (0.0434)	-1.095 (10.45)	-0.0287 (0.0525)	-3.965 (14.04)	0.0122** (0.00566)	0.0471 (0.0519)	3.214 (13.27)	0.0846 (0.0630)	-1.229 (17.80)	0.0212*** (0.00592)
CDD x AC	-0.00306 (0.00750)	-0.00792 (0.00827)	-0.00594 (0.00820)	-0.00527 (0.00858)	-0.00457 (0.00853)	-0.0134* (0.00710)	-0.00527 (0.00773)	-0.00521 (0.00768)	-0.00799 (0.00786)	-0.00806 (0.00781)	-0.00306 (0.00750)
CDD x country x year	NO	YES	NO	NO	NO	NO	YES	NO	NO	NO	NO
CDD x country x year x year	NO	NO	YES	NO	NO	NO	NO	YES	NO	NO	NO
CDD x NUTS1 x year	NO	NO	NO	YES	NO	NO	NO	NO	YES	NO	NO
CDD x NUTS1 x year x year	NO	NO	NO	NO	YES	NO	NO	NO	NO	YES	NO
Observations	46,808	46,808	46,808	46,808	46,808	46,849	46,849	46,849	46,849	46,849	46,808

Notes: All models include individual fixed effects and month of interview fixed effects, as well as the following controls: HDD, home ownership, household income, age, age^2 and GDP per capita. O3=Irritability (No=0, Yes=100); O4=Trouble sleeping (No=0, Yes=100). Std. errors clustered at the individual level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table S12: Regional Interactions + individual confounders: irritability and trouble sleeping

	O3	O3	O3	O3	O3	O4	O4	O4	O4	O4
CDD	0.0505*** (0.0127)	0.0111 (0.0444)	-0.6981 (10.4907)	0.0004 (0.0534)	-3.2233 (14.1660)	0.0336*** (0.0118)	0.0451 (0.0526)	2.9454 (13.2984)	0.0805 (0.0637)	-1.3466 (17.8704)
CDD x AC	0.0003 (0.0085)	-0.0038 (0.0088)	-0.0027 (0.0087)	-0.0022 (0.0089)	-0.0017 (0.0089)	-0.0063 (0.0080)	-0.0060 (0.0081)	-0.0058 (0.0081)	-0.0078 (0.0081)	-0.0078 (0.0081)
CDD x country x year	NO	YES	NO	NO	NO	NO	YES	NO	NO	NO
CDD x country x year x year	NO	NO	YES	NO	NO	NO	NO	YES	NO	NO
CDD x NUTS1 x year	NO	NO	NO	YES	NO	NO	NO	NO	YES	NO
CDD x NUTS1 x year x year	NO	NO	NO	NO	YES	NO	NO	NO	NO	YES
Observations	46,808	46,808	46,808	46,808	46,808	46,849	46,849	46,849	46,849	46,849

Notes: All models include individual fixed effects and month of interview fixed effects, as well as the following controls: HDD, home ownership, household income, age, age^2 and GDP per capita. O3=Irritability (No=0, Yes=100); O4=Trouble sleeping (No=0, Yes=100). Std. errors clustered at the individual level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.