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Essays on climate-change impacts, adaptation and mitigation policy

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Chapter 1.

Introduction

In 2015, 196 countries signed the Paris Agreement, committing to efforts to limit the increase in global average temperature to 1.5°C above pre-industrial levels. Over 140 countries pledged to reach net-zero emissions by 2030 or 2040. Numerous policies have been put in place around the world to achieve those targets. However, the implemented and planned policies are not sufficient to meet the mitigation commitments. The commitments, in turn, are not sufficient to limit warming to 1.5°C, the global goal for averting far more severe consequences of climate change.

Partly due to our own failures — or, more optimistically, delays — in implementing mitigation policies, climate impacts and adaptation strategies have moved to the forefront. Temperatures are rising rapidly, and damages are no longer just a problem of the future. The summer of 2024 has been the hottest on record. From a policy standpoint, addressing climate change requires an integrated approach that considers impacts, adaptation, and mitigation policy.

These are three incredibly broad and continuously expanding areas of research, reflecting the scale of the challenge we face. Climate change, as an existential threat, has far-reaching consequences that touch every aspect of (human) life. Countless other essays on impacts, adaptation, and mitigation policy must be written; this thesis is another piece of this extra-large puzzle. Through it, I address important gaps in the literature of these three subfields. At the same time, I strive to open new research avenues by, whenever possible, providing new data and demonstrating its potential to answer other research questions.

When considering the impacts of climate change on health, most studies focuses on mortality, and, to a lesser extent, hospitalization rates. Considering subclinical outcomes is fundamental to account for the total cost of climate change and allow for comprehensive policy analysis. I thus look at the effects of high temperatures on four well-being indicators in the 50+ population: fatigue, reduced appetite, irritability and difficulty sleeping. I provide such estimates for Europe, whereas the great majority of studies so far have focused on the United States. Europe is actually, with climate change, the fastest-warming region in the world[1].

As impacts take their toll, individuals, and governments, try to adapt in multiple ways. Yet, quantitative studies on the effectiveness of adaptation strategies are lacking. A recent review (Berrang-Ford et al. 2021) shows that, out of 1,628 papers on climate adaptation

[1] See the EEA European Climate Risk Assessment.

reviewed, only 30 articles present primary quantitative evidence on the effectiveness of adaptation, and only 15 articles provide quantitative estimates. The existing evidence in the empirical economic literature is still piecemeal and confined mostly to the United States.

I address this gap by providing new empirical evidence on the protective effect of a specific form of adaptation, Air Conditioning (AC). Papers on the mitigating role of AC for subclinical outcomes are almost absent. Some assessments have been conducted in relation to mortality (Sera et al. 2020). Moreover, AC ownership in Europe is far from the norm, including in warmer regions. I consider a representative sample of the 50+ population in Europe, an expanding portion of the population with high heat vulnerability. I consider mediating factors, namely lifetime exposure to high temperatures, building characteristics, health status and wealth. I then strive to provide causal estimates for the protective effect of AC, a very challenging task which I can undertake thanks to the granular nature of our dataset. I am able to disentangle individual exposure to temperature from regional exposure to temperature, and thus distinguish individual vulnerability from regional adaptation.

Individuals will undoubtedly be negatively affected by climate change, particularly in the absence of well-designed policies. Yet the population does not necessarily perceive this risk (Capstick and Pidgeon, 2014). Being concerned about climate change is a precondition for supporting the climate action and policies which are fundamental to tackle the climate crisis. This is a topic where impacts spill over to policy. I look at whether in Europe individuals more exposed to temperature anomalies are more likely to express concern about climate change. In tandem, I look at the impact of the United Nations Climate Change Conferences of Parties (COP meetings) on climate change concern. The goal is to study factors behind the recent increase in climate change concern in the EU, considering both long-term, slow moving factors - temperature anomalies - and short-term factors such as increased media and political attention.

While similar exercises have been undertaken in the literature, I use a cross-national, EU- wide, representative, individual survey, which allows us to take into consideration numerous important confounding factors. I consider heterogeneity of respondents across the right-left ideological spectrum to identify whether drivers of climate change concern differ depending on political orientation, which, to the best of my knowledge, has not yet been done. Alongside concern about climate change, I consider beliefs about effective government action on the matter, a topic which is under explored in the literature.

Designing effective climate policy is fundamental, and can possibly increase confidence among individuals on the capability of governments to coordinate and tackle the climate crisis. Carbon pricing counts on most support from economists, yet, renewable-energy support is the most frequent climate policy in practice. They often co-exist, despite microeconomic arguments suggesting their combination brings no additional emissions reduction in the case of cap-and-trade, while in the case of a carbon tax only potentially but at a social cost. Under a renewable-energy target, a certain volume of emissions is abated in the energy sector. Yet, this means in the case of emissions trading there is scope for higher emissions elsewhere while staying within the emissions cap, the so-called 'waterbed effect'. Therefore, overall emissions will not go down. Moreover, costs of meeting the cap will be higher whenever the cheapest abatement opportunities are not in the energy sector. In the case of a carbon tax, a renewable-energy target or subsidy might contribute to additional emissions reduction, if the marginal abatement cost of renewable energy is higher than the tax. But in that case, provided the carbon tax is optimal, the marginal cost will be higher than the marginal benefit of abatement, meaning that the extra abatement comes at a net social welfare loss.

To identify possible reasons why implementation differs from the simpler theoretical rationale, I collect quantitative estimates of any synergistic effects in emissions reduction between carbon pricing and renewable-energy policies in ex-ante economic modelling studies. This is the contribution of this thesis to the field of mitigation policy. No systematic analysis had yet been done on the matter, despite the prevalence of these policies. I consider not only synergy in terms of emissions, but also potential welfare gains in the form of higher consumer utility, addressing other market and government failures, innovation externalities and environmental co-benefits. This exercises is consistent with the overarching goal of informing climate policy by aggregating and analysing pre-existing data.

Through this thesis, I also make available EU-wide, representative, datasets, derived from two pre-existing surveys, the Survey on Health, Ageing, and Retirement in Europe (SHARE) and the European Social Survey (ESS). This new data allows for the study of varied impacts of climatic variables. The main outcomes of interest pertain to health and to political/social attitudes, respectively. The exercise is simple: I link pre-existing, publicly available, individual level surveys with different environmental exposure variables. I build the latter from publicly available gridded datasets of climatic variables, pollution, and floods. To link exposure to individuals, I explore the most granular information possible on location. I use simultaneously the regions where individuals report living in and how urbanized their surroundings are and calculate population-weighted averages.

This strategy can, hypothetically, be used for any survey which provides such location information. I strive to show robust analyses can be built, especially in what pertains to climatic variables, even without information on postal codes or exact coordinates. At the same time, I hope these essays, by demonstrating the potential of individual surveys for climate change research, motivate data providers to make more detailed location information available (while respecting privacy concerns). More granular location information would reduce measurement error. Moreover, concerning the impacts of pollution, this would reduce biases compared to the current approach.

Taken together, these essays tackle several important aspects related to climate change and climate change policy in Europe: health impacts and adaptation strategies, evolving public opinion and, finally, the design of mitigation policy. I create and make available new datasets and illustrate their potential. I hope new studies will build on this work and tackle quantitatively other, closely-related, open research questions on climate changes impacts and adaptation.

In the next chapter, I introduce SHARE-ENV, a dataset obtained by expanding the EU representative, individual-level, longitudinal dataset SHARE, with environmental exposure information on temperature, radiation, precipitation, pollution, and flood events. In the third chapter, I study the impacts of climate change on well-being indicators for the 50+ population in the EU. I then consider the effectiveness of an adaptation strategy, Air-Conditioning, in mitigating these negative effects. I do so through a first empirical application of SHARE-ENV. In the fourth chapter, through the ESS, I look into the impacts of climate change and of global political initiatives on public opinion. I consider how concerned with the topic individuals are in the EU and how much they trust the government to enact effective action. In the fifth chapter, I turn to mitigation policy, focusing on renewable-energy support and carbon pricing, specifically, conducting a meta-analysis of the synergy between these two instruments in ex-ante economic modelling studies.

Chapter 2.

SHARE-ENV: a dataset to advance our knowledge of the environment-wellbeing relationship

Abstract

Climate change interacts with other environmental stressors and vulnerability factors. Some places and, owing to socioeconomic conditions, some people, are far more at risk. The data behind current assessments of the environment-wellbeing nexus is coarse and regionally aggregated, when considering multiple regions/groups; or, when granular, comes from ad hoc samples with few variables. To assess the impacts of climate change, we require data that is granular and comprehensive, both in the variables and population studied. We build a publicly accessible dataset, the SHARE-ENV dataset, which fulfils these criteria. We expand on EU representative, individual-level, longitudinal data (the SHARE survey), with environmental exposure information on temperature, radiation, precipitation, pollution, and flood events. We illustrate through four simplified multilevel linear regressions, cross-sectional and longitudinal, how full-fledged studies can use SHARE-ENV to contribute to the literature. Such studies would help assess climate impacts and could then estimate the effectiveness and fairness of several climate adaptation policies. Other surveys can be expanded with environmental information to unlock different research avenues.

Keywords: climate change risk, environmental impacts, climate adaptation, population health, longitudinal data
JEL codes: I1, I31, D10, Q54

Note: The contents of this chapter have been published in Environment & Health as a joint work with Enrica de Cian, Giacomo Pasini, Sara Pesenti and Malcolm M. Mistry.

2.1. Introduction

The Glasgow Climate Pact adopted at the 26th United Nations Conference of Parties (COP26) climate conference calls for an improved understanding of the geography of climate change impacts, related adaptation needs, and response options. Climate and environmental risks affect people in different ways, depending on the context in which they live and on their individual characteristics (see, for example, Hsiang et al. 2013 or Vona 2021).

Analyses conducted at the territorial level provide important insights into the regional dimensions of climate and environmental impacts, but even subnational studies do not address how environmental risk affects the wellbeing of different groups within wider geographies over time and across generations (Mitchell and Norman 2012). Moreover, they cannot create the quasi-experimental settings needed to evaluate the effectiveness of adaptive behaviors. A recent review on the climate adaptation literature underscores the lack of quantitative assessments of climate adaptation (Berrang-Ford et al. 2021). Out of 1,628 papers on climate adaptation reviewed, only 30 articles present primary quantitative evidence on the effectiveness of adaptation, and only 15 articles provide quantitative estimates. At least three reasons can explain the paucity of studies in climate adaptation evaluation: the lead time between actions and effects; the difficulty in causally linking exposure with the outcome; and the difficulty in measuring outcome variables. The existing evidence in the empirical economic literature is still piecemeal and confined mostly to the United States; and, moreover, to a few outcome and adaptation variables, namely, mortality and air-conditioning (Barreca et al. 2016), and learning and air-conditioning (Park et al. 2020). In the epidemiology field, a few studies provide conflicting evidence on the ability of air-conditioning to reduce mortality (Sera et al. 2020, Ostro et al. 2010).

Wellbeing is a complex and contested concept (Lamb and Steinberger 2017). Health-related dimensions that incorporate physical health and mental health, perceived and objectively measured, are, unambiguously, some of its defining dimensions. Vulnerability links to numerous individual characteristics, among them age, gender, education, and socioeconomic status, and to many health-related dimensions, such as pre-existing health conditions, lifestyles, and awareness of risk. Individuals can act to reduce the impacts of climate change only if they have access to safe housing, access to appropriate healthcare, and the ability to devote resources to unforeseen expenses in times of need.

We argue that granular, individual-level, representative longitudinal survey data, can be expanded with variables on environmental hazards, to advance the causal assessment of both environmental impacts and adaptation interventions. This strategy can provide the much-needed information for evaluation of climate actions and the pursuit of climate justice (Breil et al. 2021). Longitudinal studies, following individuals over long periods, can uncover causal relationships between exposure, vulnerability, and policy interventions and actions. Built to represent populations of interest and providing a wide wealth of data, these studies also hold more promise than current causal inference studies, which resort to ad-hoc samples.

We show the potential of this strategy by expanding on the longitudinal Survey on Health, Ageing and Retirement in Europe (SHARE), a European Union (EU)-funded initiative. The SHARE survey interviews approximately 120,000 individuals every two years since 2004 and is representative of 50+ EU-27 residents (plus Israel). Importantly, two specific interviews, conducted in the third and seventh waves (2008, 2016), called SHARELIFE, reconstruct retrospective life history, providing year on year information on respondents' life conditions, health history, healthcare use, and working lives. We expand on SHARE by building variables on individual-specific yearly and cumulative exposure to different environmental hazards. The result is the SHARE-ENV dataset (currently available in an online repository). We demonstrate that these data can be used to study relationships between environment and wellbeing, and ultimately, to advance the climate adaptation and climate policy literatures. The data can uncover links between climate change and human health that are usually hidden in purely regional analyses.

We use the SHARE-ENV dataset and develop several illustrative analyses as proof of concept of its potential to shed light on the heterogeneity and ramifications of climate change impacts. The remainder of the paper is organized as follows. Section 2 describes the data sources and the construction of SHARE-ENV. Section 3 provides examples of the type of relationships that can be explored with SHARE-ENV through cross-sectional and longitudinal multilevel regressions. We consider impacts on labor productivity, whose reduction is a well-established climate change impact, and on health and wellbeing, on which SHARE provides extensive information. In section 4, we discuss in more detail the advantages of SHARE-ENV which become visible through our illustrating examples. We describe why and how full-fledged analyses based on SHARE-ENV could give substantive contributions to the literature. In section 5, we discuss the potential of SHARE-ENV for future research, focusing on its potential to study adaptation.

2.2. Methods: SHARE-ENV dataset

Our database combines a set of environmental hazards - extreme temperatures, solar radiation exposure, heavy precipitation, average and/or high concentration of ozone, nitrogen dioxide, and two particulate matter measurements $PM_{2.5}$ and PM_{10} and flood events - with a comprehensive set of variables on individual-level health, on behavioral risks and on risk-averting behaviors at different points in life in Europe, from the SHARE database.

SHARE is a longitudinal stratified sample representative of 50+ EU-27 residents (plus Israel). It contains approximately 120,000 individuals and 300,000 interviews (Börsch-Supan et al. 2013). The regular panel waves (2004-2019) of SHARE follow individuals (and their spouses) over time. Respondents are interviewed every two years. In addition, the SHARE-LIFE modules (waves 3 and 7 in 2008 and 2016) reconstruct the retrospective life history of respondents. These histories include key focal points, such as the age at which a person left school, the dates when the person started and ended any given job, the dates of the onset of any illness, and details about changes in housing circumstances and family composition. Importantly, the retrospective accommodation models provide information on all regions where individuals have lived throughout their lives, which we explore to build exposure variables.

2.2.1. Main outcomes of interest

The SHARE database contains numerous variables which 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. SHARE quantifies perceived health status at the individual level, from poor to excellent. Clinical objective health indicators can be retrieved through questions on whether an individual has ever been diagnosed or bothered by a disease, whether he or she is taking drugs for certain illnesses, and the age of the onset for a range of illnesses, such as heart attack, stroke, high blood pressure, asthma, lung disease, cancer, diabetes, arthritis, Alzheimer, Parkinson, mental disorders/depression amongst others.

Respondents provide information on up to three periods of prolonged ill health throughout life, with a start and an end year, and what health conditions were responsible for such periods. Questions about the severity of illness include whether they brought on negative consequences at work, whether they limited social life and leisure activities or whether they otherwise impacted the family negatively. From this SHARE primary data, we generate additional health variables to facilitate the analysis of environmental factors. We describe them in Table S3 in the Appendix.

There are also clinically measured health outcomes, some targeted to older age individuals. These include depression scores, cognitive scores for different cognitive functions, physical health measures (difficulties with Activities of Daily Living (ADL) and difficulties with Instrumental Activities of Daily Living (IADL), lung functioning, walking speed, grip strength and dried blood spots).

Childhood health is considered separately. Beyond perceived childhood health status (variable takes values from 1 to 5, excellent to poor), other questions measure possible severity of health conditions during childhood . Respondents answer whether they had any of a list of illnesses, of note, infectious diseases, asthma, respiratory problems other than asthma, allergies, severe diarrhea, severe headaches, emotional problems, childhood diabetes and heart trouble. Respondents provide information on illness onset and duration .

In addition to morbidity and health outcomes, a wide range of other individual and household-level characteristics are available. These include, for example, quality of housing, location of dwelling (big city, the suburbs or outskirts of a big city, a large town, a small town, a rural area or village), type of housing situation (e.g., owner versus renter), occupation including ISCO coding, education including ISCED codes and job conditions. Information commonly collected in longitudinal surveys about income, wealth, material wellbeing and migration is likewise available. Some variables of particular relevance for health outcomes are also available, namely, variables on behavioral risks (e.g., smoking, drinking; stress levels; parental behavioral risks). Several other research questions, outside the health/wellbeing framework, can be tackled using the wealth of information provided by SHARE, namely those related to labor supply and labor productivity.

2.2.2. Construction of environmental variables

To generate variables on exposure to environmental hazards we resort to high-resolution gridded datasets and the information derived from SHARE on where individuals have lived in each year of their lives, from birth until last survey participation. Individual location is provided in the retrospective accommodation modules of SHARELIFE and through the region in which the household was located at the moment of sampling in the regular waves. The 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 Appendix for more details on the NUTS classifications used).

With gridded datasets of temperature, radiation, precipitation, pollutant concentrations and emissions, and flood events, we generate, first at the grid cell level, yearly variables on environmental hazards. From the high-resolution, daily, near-surface temperature, precipitation and radiation gridded-observational data E-OBS, made available by the European Climate Assessment & Dataset (ECA&D) at 0.1° X0.1° resolution (Cornes et al. 2018), we generate: bins of daily mean, minimum, and maximum temperature, average seasonal temperature, heating degree days and cooling degree days, yearly and seasonal average radiation and number of days with precipitation above 10 and 20 mm.

From the Dartmouth Flood Observatory (DFO) database (Brakenridge 2021) we build variables on number of flood events and flood intensity. From the Copernicus Atmosphere Monitoring Service (CAMS) global reanalysis (EAC4) monthly averaged fields on pollutant concentration (Inness et al. 2019), we build average yearly concentration of $PM_{2.5}$, PM_{10}, and NO_2, and yearly and summer average concentration of ozone. From the Emissions Database for Global Atmospheric Research (EDGAR, ver 5.0), made available by the European Commission Joint Research Centre (JRC) (Crippa et al. 2019), we build yearly emissions of $PM_{2.5}$ and PM_{10}. We elaborate on the choice and construction of variables in the Appendix. We aggregate these variables from grid cells to the regions reported by SHARE respondents, using unweighted and population-weighted means. The next maps show average yearly bins of average temperature, specifically, the average number of days per year where average temperature was above 27.5°C and below 0°C for each SHARE region. We show one map for the average between 1980-2009 and one for the average between 2010 and 2019:

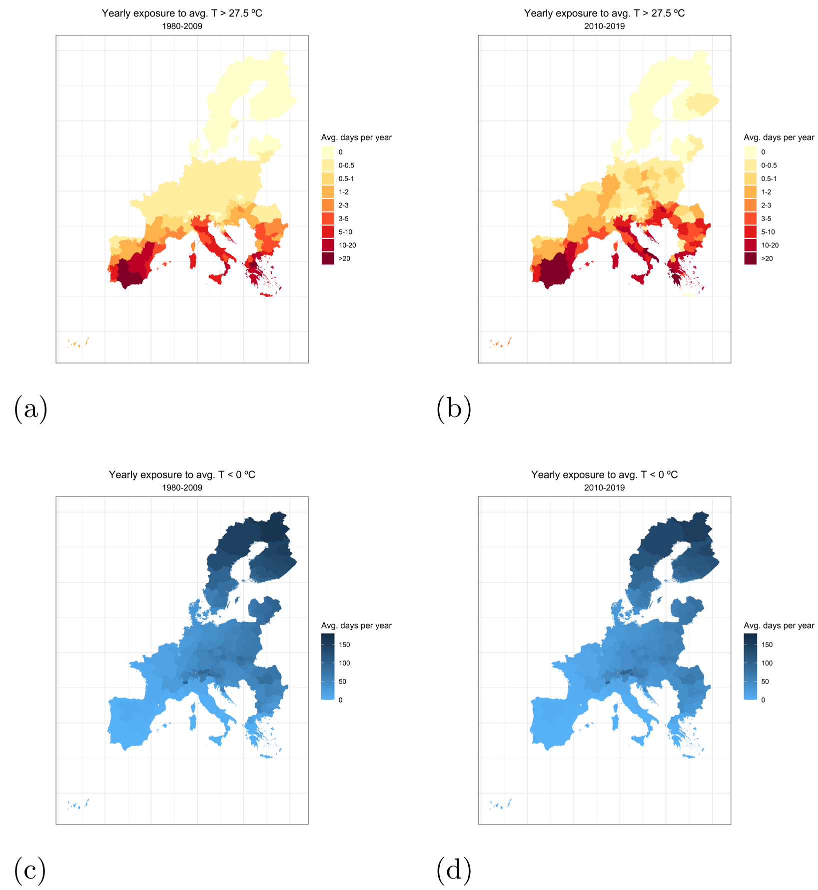

Figure 1: Selected environmental variables: Number of average annual days with daily average temperature above 27.5°C (top) and with daily average temperature below 0° (bottom)

We merge these aggregate variables to SHARE respondents, based on yearly information on their residence, from birth until the last SHARE wave. From yearly variables, we construct cumulative variables, measuring exposure that had occurred from the time an individual was born until the wave in question and in critical periods, namely childhood. This process is summarized in Figure 2. A second version of the dataset, to be released after additional robustness checks, provides more granular geographical information. In such a version we divide each NUTS region into five subregions and provide population-weighted average environmental exposure in big cities, suburbs, large towns, small towns and rural areas of every NUTS region. This brings additional, within region, variation.

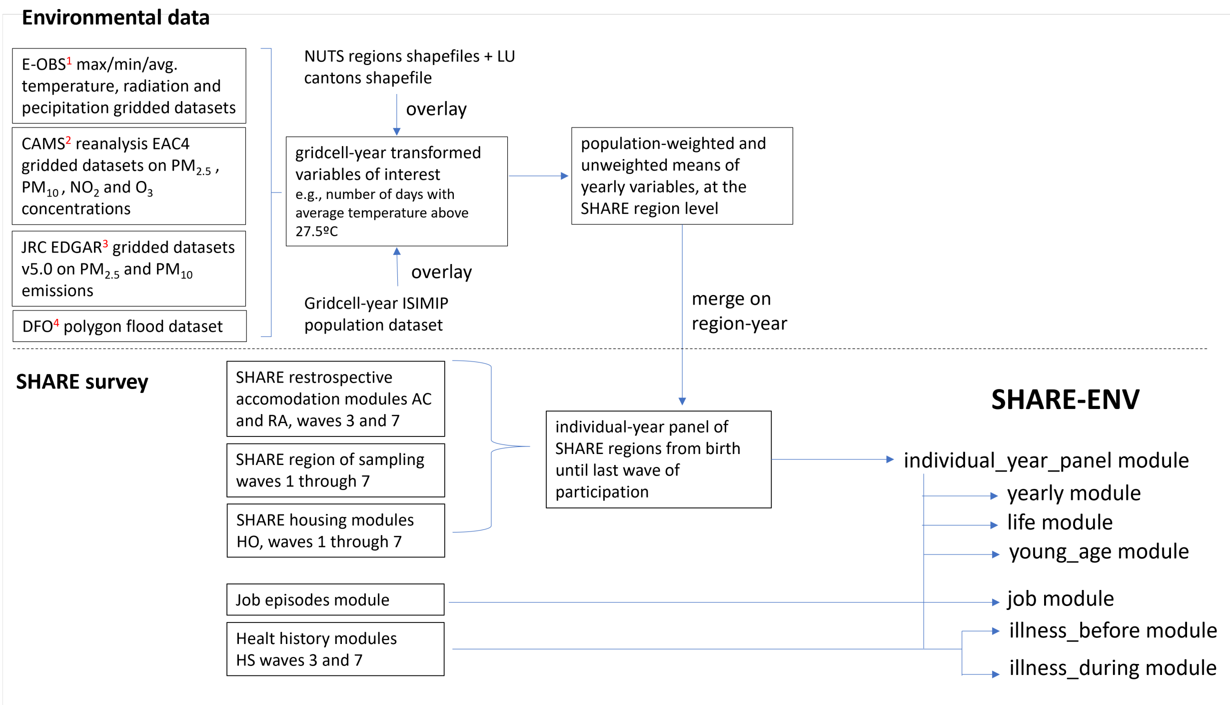

Figure 2: SHARE-ENV construction. Environmental data available at: [1]European Climate Assessment & Dataset (ECA&D); [2]Copernicus Atmosphere Monitoring Service (CAMS); [3]JRC EDGAR v5.0 Global Air Pollutant Emissions; [4]Dartmouth Flood Observatory (upon request).

2.2.3. Data structure

The construction of the SHARE-ENV database is illustrated in Figure 2. The resulting SHARE-ENV database consists of seven modules, all of which are available in an online repository. The following table provides a short description of each of them:

Four of these modules, the individual_year_panel, the yearly module, the life module and the illness_during module, are longitudinal. The first module, individual_year_panel, refers to yearly variables (i.e., environmental-hazard exposure in a specific year, as opposed to cumulative exposure or averages over longer time periods). It is not merged with current-wave information, and, instead, provides a full individual-year panel for the period from birth until most recent participation in SHARE. This dataset can be of particular interest when merged with other retrospective modules of SHARE, such as the jobs-episode module. A long-term longitudinal analysis is then feasible. The second module, the yearly module, has the same variables, but merged with wave-on-wave information. For each individual-wave observation, we report environmental-hazard exposure in the year of that wave, in the year before, and in the year two years before, signaled by suffixes "t0", "t_1bf," and "t_2bf," respectively. Such module only provides information on the waves in which respondents participated (alongside the information from one year and two years immediately prior to those waves). This module is most suited for longitudinal analysis on short-term effects, exploiting wave on wave variation in exposure and outcomes. The life module is in all similar

Table 1: SHARE-ENV modules

Module	**Description**	**Unique ID**	**Main purpose**
individual_year_panel module	yearly exposure in years since birth up to the most recent participation in SHARE	Individual, year	Long-term effects
yearly module	yearly exposure in year of wave (and one and two years before the wave)	individual, wave	Short-term effects
life module	rolling exposure throughout life	individual, wave	Cumulative effects
young_age module	cumulative exposure over the first five, ten and fifteen years of life	individual	Effects of critical period exposure
job module	cumulative exposure during the years at one's most recent job	individual	Effects on labor supply and labor productivity
illness_before module	cumulative exposure during one-, three-, and five-year periods before the onset of illness	individual, illness-period	Effects on disease onset
illness_during module	rolling exposure during periods of illness	individual, wave	Effects on disease progression

except it provides cumulative and average exposure variables instead of yearly variables, to study cumulative effects of environmental factors.

The illness_before and illness_during modules include own-generated variables on illness length and intensity. These are best suited to study, respectively, how environmental factors might trigger/accelerate disease onset and how they might affect disease progression. In the illness_during module, variables differ between waves only for individuals for whom the illness period intersects with the SHARE interview period. The young_age module is designed to study the impact of environmental factors during critical life periods. The job module is designed to study outcomes related to labor supply and labor productivity, known to be adversely affected by climate change.

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2.3. Illustrative analyses

We use the SHARE-ENV dataset to illustrate relationships between environmental stressors and four types of subjective and objective outcomes. These examples use four of the seven different modules of SHARE-ENV: the life module, the young_age module, the job module and the yearly module respectively. The exact estimation equations are listed below, as well as the definition of the variables used. Analysis i), ii) and iii) are cross-sectional analysis, where we keep only one observation per individual – the last wave of participation in SHARE unless stated otherwise -, while analysis iv) on cognitive decline explores the panel component of the dataset. We consider individual-level confounders. All cross-sectional analyses include country fixed effects. We estimate all regressions through Ordinary Least Squares (OLS) except for the analysis on cognitive decline where we also resort to fixed effects estimation. To ensure estimates are robust to heteroskedasticity, we use White standard errors in the cross-sectional analyses and cluster at the individual level in the panel analysis (White 1980, Stock and Watson 2008).

Health/wellbeing is one of the areas in which SHARE has a competitive advantage vis-à-vis other surveys. Three of our illustrative analyses use such outcomes, which are directly connected to environmental damages: i) the prevalence of breathlessness; ii) perceived health status through life and iv) cognitive decline. These examples are far from an encompassing analysis of possible research questions. Several other research questions can be tackled by using the wealth of information provided by SHARE. We provide a quick illustration, analysis iii), where we consider the effect of temperature on an outcome connected to labor productivity: perceived comfort at one's job. Results are summarized in Table 2 and presented in more detail in Tables A4, A5 and A6 in the Appendix.

2.3.1. The empirical model

Cross-sectional analysis

Our generic estimation equation for analysis i), ii) and iii) is a multilevel cross-sectional linear regression between y_i, an indicator of health/wellbeing outcomes observed for a given individual i in the wave of participation in the survey, and K average environmental variables ENV^k_{seq}, averaged over a sequence seq of regions where the individual has lived until the wave of participation:

$$y_i = \alpha + \beta_1 ENV^1_{seq} + ... + \beta_k ENV^k_{seq} + \mathbf{x_i}\gamma + \theta_c$$

where y_i is measured with selected illustrative health/wellbeing outcomes:

1. Ever experienced breathlessness (100 if yes, 0 otherwise);
2. Perceived reported health (1= poor, until 5=excellent) at different points during the lifetime – 15 years of age, first wave of participation and last wave of participation;
3. Uncomfortable job (100 if yes, 0 otherwise).

and $ENV^k_{seq} = \frac{1}{T}\sum_{t=t_0}^{T} ENV^k_{rt}$, where:

ENV^k_{rt} is the environmental variable k in year t for the smallest region r the individual reports living in in year t, from the beginning of the relevant period ($t = t_0$) until wave of participation ($t = T$). Our ENV^k_{seq} variables are rolling averages, following individuals throughout the regions they move to during their life. For these illustrative relationships, various indicators of environmental and climate risk have been chosen in relation to the specific outcome variable. We consider only one observation per individual. The period of interest determines the precise sequence seq considered for the rolling averages:

1. Episodes of breathlessness are related to average $PM_{2.5}$ concentration, average number of days with temperatures above 30°C and average number of days with temperatures below 0°C. In this case, the sequence seq pertains to the period since birth until last wave of participation.
2. Perceived health status is related to the average number of days with temperatures above 30°C, the average number of days with temperatures below 0°C, and, in the case of childhood perceived health, average radiation. When we consider childhood health, the sequence seq pertains to the period since birth until 15 years of age. We consider two different periods for old age health, with t_0 being birth and T either the first or the last wave of participation in SHARE.
3. Perceptions about whether one's job is uncomfortable is related to average winter temperatures, average summer temperatures and average radiation. In this case, t_0 is the year when the individual started the job and T is the last wave of participation while employed.

All specifications include a vector ($\mathbf{x_i}$) of individual level variables, which are possible confounders, specifically: age, household income and other measures of material deprivation, whether an individual had any illness at birth, Body Mass Index (BMI), whether an individual ever smoked, frequency with which the individual practices sports and whether the individual's job is uncomfortable . In the case of childhood health, we also include indicators of parental education, childhood abuse/neglect and time spent living in urban areas. All specifications include country-specific fixed effects, θ_c. In analysis iii), we demonstrate how to assess heterogeneity across groups by interacting certain variables with our environmental exposure variables. Specifically, we interact $physical_i$, a binary indicator of whether the job of individual is physically demanding, with the ENV^k_{seq} variables (summer and winter temperatures and radiation). We resort to the following estimation equation:

$$\begin{aligned} y_i = \alpha + \gamma_p physical_i + \beta_1 ENV^1_{seq} + \beta'_1 physical_i \times ENV^1_{seq} \\ +... + \beta_k ENV^k_{seq} + \beta'_k physical_i \times ENV^k_{seq} + \mathbf{x_i}\gamma + \theta_c \end{aligned}$$

Panel analysis

For analysis iv), we consider the relationship between the rate of cognitive decline and the exposure to $PM_{2.5}$. This analysis illustrates two different ways to use the panel nature of the yealy_module. The first equation is estimated through pooled OLS, and includes lagged individual level variables, which we use to isolate factors commonly related to the rate of cognitive decline, such as general health, income, or education levels. The second equation represents an individual fixed effects model, which we estimate through the within estimator. We can only estimate the impact of time-varying variables, and include household income, age, exercise frequency and a measure of depression.

We use two different estimation equations:

$$1[\Delta y_{it} \leq -0.15] = \alpha + \beta_1 \Delta ENV^1_{rt} + \beta_2 \Delta ENV^2_{rt} + \mathbf{x_{it-1}}\gamma + \theta_c$$

and

$$\Delta y_{it} = \alpha + \beta_1 ENV^1_{rt} + \beta_2 ENV^2_{rt} + \mathbf{x_{it-1}}\gamma + \eta_i$$

where:

$1[\Delta y_{it} \leq -0.15]$ is an indicator function taking value 100 if the annual decline in the cognitive score y_{it} was higher than 15% and taking value 0 otherwise;

y_{it} is the cognitive score of respondent i, from the words list learning cognitive test;

η_i are individual fixed effects;

ENV^1_{rt} is the concentration of $PM_{2.5}$ in region r in year t;

ENV^2_{rt} are heating degree days (HDD) in region r in year t.

2.3.2. Results

Having ever experienced breathlessness in one's lifetime is positively related to average exposure to pollution (concentration of fine particulate matter, $PM_{2.5}$), and the relative impact of actual exposure grows once one accounts for the relevant individual-level variables x_i. A 10 µg/m^3 higher daily average exposure to $PM_{2.5}$ through life (an increase of approximately 2 standard deviations) is associated with a 1.9 percent point (p.p.) higher probability of experiencing breathlessness; for comparison, having ever smoked is associated with a 3.9 p.p. higher probability of breathlessness.

We find that perceived health in childhood is positively related to exposure to more frequent high temperatures. Such a relationship remains equally strong once we consider the significant positive effect of average solar radiation (positively correlated with high temperature extremes). If we consider an ordered probit model (as opposed to a liner regression) we find the same positive associations, as measured through average marginal effects (AME, not shown). Higher temperature and higher radiation increase the probability of reporting excellent health and decrease the probability of reporting poor, fair or good health (not shown). A possible channel through which frequent high temperatures might have a positive impact on young age health is by allowing children to engage in more activities outdoors, a behavior we do not observe.

Cumulative exposure to extreme temperatures affects one's perceived health status differently depending on when in one's lifetime the question is posed. Exposure to both extremely high and extremely low temperatures is associated with worse perceived physical health in old age, unlike in childhood. When we consider only the information provided in the first wave of individual interviews, only extremely low temperatures are significantly associated with worse health. By contrast, when we consider the most recent wave, in which individuals are considerably older (69 years old on average, 6 years older than the average age in their first wave), only extremely high temperatures are significantly associated with worse health status (see Supplementary Table A5). Ordered probit models, as opposed to linear regressions, confirm these variables increase the probability of reporting poor and fair health, and decrease the probability of reporting good, very good, or excellent health (in terms of AME, not shown).

We show that, for jobs which are physical, higher summer temperatures and higher summer radiation averages are associated with a higher probability of stating that one's job is uncomfortable. For each additional degree in average summer temperature, individuals working physical jobs are 0.56 (0.831-0.268) p.p. more likely to report having an uncomfortable job. For this same type of job, in winter, milder/less cold temperatures are associated with a lower probability of having a job perceived as uncomfortable – each additional degree in winter temperature is associated with a -0.43 (0.748-1.18) p.p. change in the probability of feeling one's job as uncomfortable. For non-physical jobs, radiation does not have a significant effect, while a higher summer temperature reduces the probability of considering one's job uncomfortable.

In our analysis regarding cognitive scores, in both specifications, we consider differences instead of levels of cognitive scores since a deterioration of from one wave to another is expected; we are thus interested in differences in the rate of deterioration. We find that the higher the exposure, the higher the cognitive decline. An increase of 10 µg/m^3 in the average daily exposure to $PM_{2.5}$ is associated with a 3.7 p.p. increase in the probability of showing large cognitive decline. We find a meaningful protective effect of several factors such as better general health and educational levels – for example, having primary school education instead of no schooling is associated with a 3.5 p.p. decrease in the probability of high cognitive decline (see Table A4). The same 10 µg/m^3 increase in $PM_{2.5}$, as estimated through the fixed effects model, is associated with an average decrease of 7 p.p. in cognitive scores (see Table A6 in the Appendix).

2.4. Discussion

The simplified analyses above show some of the characteristics of the SHARE-ENV dataset which full-fledged analyses can explore to give meaningful contributions to the literature.

A first characteristic is that the outcomes of analyses i), ii) and iv) on health and wellbeing are not the most commonly found in the literature. Regarding the association between health and pollutant concentration, a great part of the literature focuses on mortality (Sheridan and Allen 2015). The same is true for the effects of extreme temperatures, focusing either on mortality or hospitalization rates (Deschenes 2014). Using pre-clinical outcomes such as breathlessness has two main advantages. The most obvious is definitional: one can assess impacts that arise at an earlier stage. The second advantage, by comparison to healthcare data, is minimizing sample selection. Individuals who resort to healthcare are wealthier and sicker on average. Information on early-stage cognitive decline is especially difficult to collect through healthcare data, as many individuals only resort to medical care in later stages of disease progression. We find statistically significant results in the three analyses conducted, showing associations between environmental hazards and non-acute negative health outcomes.

The literature on the relationship between pollution and cognitive decline is more limited than that on effects of pollution or temperature on morbidity or perceived health, though recent years have seen an increase in contributions. A recently published study (Zare Sakhvidi et al. 2022) contributes to the literature by considering multiple pollutants, multiple outcomes regarding cognitive capacity, and a large sample of individuals aged 45+

Table 2: Association between environmental hazards, health outcomes, and risk-avoiding behaviors

	1. Ever experienced breathlessness (0=no, 100= yes)		**2.Young age (15) perceived reported health (1=poor; 5= excellent)**		**3. Uncomfortable job (0=no, 100= yes)**		**4. High cognitive decline (0=no, 100= yes)**	
Exposure	Avg. $PM_{2.5}$ conc. median (µg/m3)	0.19***	Avg. first 15 years exposure	0.0002	Avg. winter temperature	0.748***	Δ $PM_{2.5}$	0.374***
	conc. median (µg/m3)	(0.001)	to temp. below 0	(0.0004)		(0.131)		(0.075)
	Avg. lifetime exposure	0.000442	Avg. first 15 years exposure	0.003*	Avg. summer temperature	-0.268***	Δ HDD	-7.11e-04***
	to temperature (# days)	(0.0091)	to temperature 30°C	(0.0015)		(0.100)		(0.0000531)
	Avg. lifetime exposure	-0.044*	Avg. first 15 years	0.002*	Average radiation	0.015		
	to temperature 30°C (# days)	(0.024)	solar radiation (W/m2)	(0.001)		(0.037)		
Exposure					Job is physical	-1.18***		
$\times$ **individual**					x avg. winter temperature	(0.156)		
characteristics				Job is physical	0.831***			
					x avg. summer temperature	(0.136)		
					Job is physical	0.135***		
					x avg. radiation	(0.026)		
Individual confounders		Y		Y		Y		Y
Country FE		Y		Y		Y		Y

Notes: Model 1 includes fixed effects of the International Standard Classification of Occupations (ISCO) (at the one-digit level). Model 3 includes fixed effects for the ISCO (at the one-digit level), the International Standard Classification of Education (ISCED), and the country. The corresponding questions to outcome variables 1 to 3 are the answers to the following questions or statement. Ever experienced breathlessness: “For the past six months at least, have you been bothered by any of the health conditions of breathlessness or difficult breathing?” Responses indicate whether they selected this symptom in any survey wave. Young age perceived health: “Would you say that your health during your childhood was in general excellent, very good, good, fair, or poor?” Responses were coded as follows: excellent 5, very good 4, good 3, fair 2, poor 1. ”My immediate work environment was uncomfortable (for example, because of noise, heat, crowding).” Answers were coded as follows: one ((has an uncomfortable job) for “Strongly Agree” or “Agree;” zero (does not have an uncomfortable job) for “Disagree” and “Strongly Disagree.” Model 4 outcome variable is whether the cognitive score of the list learning test decreased by more than 15% on a yearly basis between waves (other thresholds yield similar qualitatively results). It includes controls for the type of area of the house – whether a big city, the suburbs of such a city, a large town, a small town or a rural area. Exposure variables are unweighted, but weighted variables yield very similar results.

in metropolitan France, which "contrasts with most available studies which compare populations with relatively high exposure with those living in rural areas or small cities". Through SHARE-ENV, a full-fledged analysis could likewise consider multiple pollutant and cognitive measures, but with an even more extensive sample, spanning multiple EU countries and time periods.

In fact, the simplified analysis of high cognitive decline in the previous section already uses the multiple time periods, i.e., the panel component of the longitudinal SHARE-ENV modules. We firstly exploit year-on-year variation on pollution concentration, finding a significant effect of pollution concentration on the likelihood of large cognitive decline. In that same analysis, we consider some possible risk factors for higher cognitive decline and find, as in the literature, that higher education levels and higher level of physical activity are protective against cognitive deterioration. It is commonly assumed in the literature that year-on-year temperature variation is as good as random (Deschenes 2018). Variation on pollution instead is only partly driven by as-good-as-random atmospheric conditions. While individuals are less likely to sort into regions based on yearly variation than on average values, we reduce this possible sorting bias by considering individual fixed effects. We find, once more, meaningful associations between variation in $PM_{2.5}$ and faster cognitive decline, while controlling for time variation in regional and individual factors.

Individual level analysis, even if cross-sectional, has great potential to advance the literature on the impacts of pollution and temperature on health outcomes whenever we can consider additional confounders. Important behavioral risk variables, such as whether an individual has ever smoked, are not easily found in regionally aggregated analysis nor in hospital admissions datasets, one of the most granular sources of data used in epidemiology literature. Socioeconomic variables, such as household income, are also not available at the individual level in such datasets and are often, at best, proxied by postal code indicators. Such datasets are thus still less granular and provide fewer variables than SHARE. Moreover, instead of being publicly available, they are usually licensed on a study-by-study basis due to their sensitive nature. The importance of these confounders is clear in analysis i), relating exposure to pollution and breathlessness: smoking behavior and household income are highly significant and correlated with regional level pollution. Once included, the impact of pollution become statistically significant. Additional variables, if important confounders, must be included to ensure unbiased estimation of effects. Even if they are not related with the environmental variables of interest, their inclusion can reduce unexplained variance and increase the power of the analysis.

Another advantage of using individual-level variables is to put environmental hazards into perspective. As observed in analysis ii), the magnitude of the association between higher temperatures/higher average solar radiation and improved childhood health is two orders of magnitude smaller than the association between childhood health and material deprivation (see Table S4 in Appendix). In analysis ii) we looked at three different points – childhood, first wave of participation in the SHARE and last wave of participation. High temperatures are associated with better health in childhood and worse health only in the last wave of participation, when individuals are on average 69 years old. Such differences demonstrate the importance of considering different age groups separately for assessing vulnerability and ultimately to design adaptation policies.

Other longitudinal surveys span a few decades of data collection as well but do not provide detailed retrospective life histories. A particularly unique feature of the SHARE-ENV dataset is the ability to look at very early periods of life and at cumulative variables of exposure to hazards. Early life exposure is extremely relevant; for example, extreme temperatures are shown to have negative impacts on birth weight, which are then related to several negative health outcomes later in life (Deschenes et al. 2009). Disentangling the effects of short-term and long-term exposure to extreme temperature is also fundamental, as they have been shown to differ (Zivin et al. 2018).

Often studied climate change impacts other than reductions in wellbeing can also be revisited through SHARE-ENV, as the analysis on job comfort shows. Reductions of labor productivity are one of the most widely discussed climate change impacts. The empirical literature on the topic is extensive, yet, even when at the micro-level, is not without its issues. SHARE-ENV, given its detailed information about the sectors where individuals work, allows studying heterogeneity of effects by sector. This differs from many micro-level analyses which are based on ad hoc samples (for instance, considering a sample of factories) and focus only on certain sectors, particularly agriculture or manufacturing.

The literature mostly considers aggregate measures of labor productivity, looks at one specific component of it, or, more rarely, considers jointly the number of hours worked and productivity during those hours together (Dasgupta et al. 2021). With SHARE-ENV, it becomes possible to disaggregate specific mechanisms explaining why productivity is lower in the hours worked - comfort at the job is one example, but we can also consider attitudes towards work. It is also possible to look at channels driving the overall reduction in hours worked, such as early retirement and illness onset.

In this quick example, we interacted exposure with whether a job is physical, finding such driver determines how temperatures and radiation affect comfort. Through SHARE-ENV, numerous similar heterogeneity analyses can be conducted to identify vulnerable groups.

2.5. Conclusions

The existing evidence in the empirical economic literature regarding adaptation is limited and focused on the United States. In the epidemiology field, a few studies provide conflicting evidence on the ability of air-conditioning to reduce mortality (Sera et al. 2020,Ostro et al. 2010). As of now, only one study (Park et al. 2020) considers the mitigating effects of AC on learning outcomes in a quasi-experimental setting. SHARE-ENV, which provides information on AC ownership, can be used to study the mitigating effect of AC on varied health outcomes, encompassing dimensions of both mental and physical health. A forthcoming paper investigates this research question in detail.

Quasi-experimental evidence on heat alert systems, another adaptation policy, could also be expanded through SHARE-ENV. Reviewing the literature on the topic, we found only two papers which look at the effectiveness of heat warning systems in reducing morbidity (and 22 in reducing mortality) by considering hospitalizations (Marinacci et al. 2009,Weinberger et al. 2021). Comparatively, a study using SHARE-ENV could consider different outcomes or consider hospitalizations while adding more confounders on behavioral risk and economic conditions. Unlike for AC, the treatment variable must be constructed, that is, a variable on where and when heat alert systems were implemented and/or triggered must be built and merged with SHARE-ENV. A similar policy which requires additional quantitative evidence is the availability of climate refuges.

The quality of building insulation is thought to be an important and cost-effective strategy for climate adaptation. Yet, again, quantitative assessments are lacking. Variables on building stock can be merged to the SHARE-ENV dataset, such as those provided in EU-BUCCO(Milojevic-Dupont et al. 2023). Other potential treatment variables would relate to retrofitting policy interventions.

Other regional level adaptation measures whose effectiveness can be estimated through SHARE-ENV are the availability of green and blue spaces. Treatment variables must be built, yet they are easily attained through the same aggregation process we applied to our gridded datasets. Time-varying, gridded information on land use and cover is easily transformed into regional time-varying variables capturing the extension of public parks and public water bodies. The literature on the effects of green spaces on mental health generally (not as an adaptation channel specifically) is primarily qualitative. However, some quantitative studies exist. One to which a SHARE-ENV based analysis would resemble is Astell-Burt et al. (2014), who use the British Household Panel Survey (BHPS) and consider the relationship between general health and green space availability through longitudinal representative samples.

A great part of the adaptation literature focuses on econometric techniques to disentangle climate and weather effects and estimate adaptation by comparing the two (Bento et al. 2023). Yet, estimation is almost always conducted at the regional level. While some adaptation is place-based (city-wide initiatives of climate refuges being an example), individuals greatly adapt to climate conditions. They do so physiologically and behaviorally. In SHARE-ENV, we know when individuals move to a new region – and what temperatures that region has been exposed to - as well as their cumulative life exposure to extreme temperatures. How much individuals who recently moved to new regions are affected by extreme temperatures compared to individuals who have always been there, can help make inferences about the importance of behavioral and individual factors versus place-specific infrastructure and adaptation policies.

Merging environmental information with geographically localized, individual-level, longitudinal survey data can open new research avenues. We have demonstrated that is the case for the SHARE-survey. The wealth of variables in SHARE and its representative, extensive, EU samples, allow researchers to disentangle heterogeneity of impacts of climate change and of effectiveness of adaptation policies. Moreover, it can help determine if policies favor specific socioeconomic groups, a crucial endeavor to design fair policies, both national and EU-wide. SHARE-ENV can help respond to the mission of climate justice by considering such factors. Better research on the connection between climate and health, which SHARE-ENV unlocks, is more important than ever, as the COP28 Climate Change Conference moves to feature a Health Day for the first time since conception.

Chapter 3.

Heat and wellbeing in the old continent

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 31º (an increase predicted for many European regions under current climate forecasting exercises), without Air-Conditioning (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 that 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

Note: This chapter is joint work with Enrica de Cian.

3.1. 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 world[1]. 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

[1] `https://www.eea.europa.eu/publications/european-climate-risk-assessment`

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 31º, i.e., with average mean temperature exceeding 21º by 10. Current climate forecasts estimate for the majority of European regions more than 100 extra CDDs per year by 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.

3.2. Background

3.2.1. 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 being 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 heat[2]. 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,

[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?""

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.

3.2.2. Protective effects of Air-Conditioning

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

3.3. Data

3.3.1. 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 2017[3]. 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

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

urbanization of their surrounding area[4].

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, Gonzàlez-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.

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 2019[5]. 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

[4]In 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.

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

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 A3).

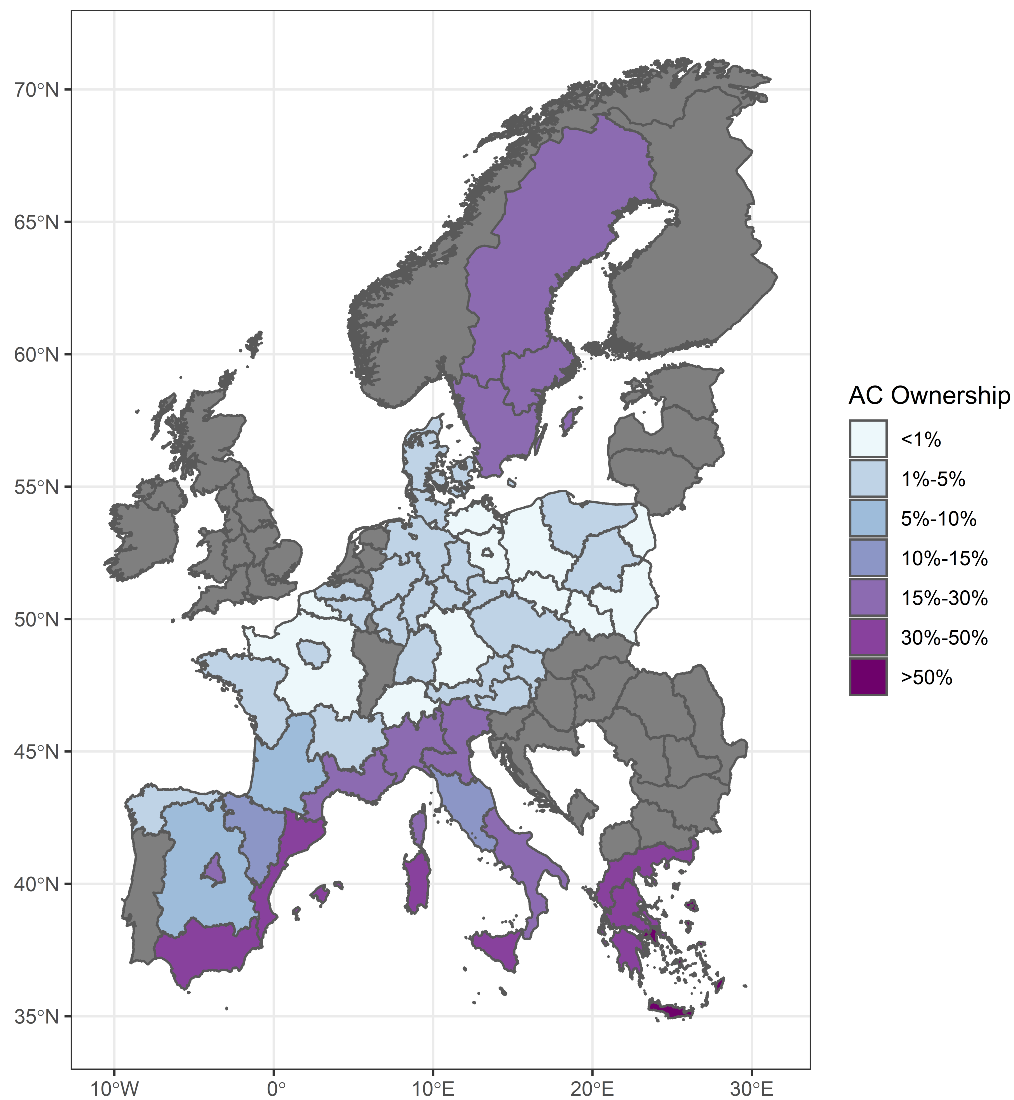


Figure 1: AC Ownership in SHARE survey weighted with SHARE cross-sectional weights. Only regions for which there are at least 10 observations are plotted

3.3.2. 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 wave[6].

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 kilometers[7]. From gridded daily datasets of temperature we build bins of maximum temperature (i.e., number of days per month where the maximum temperature exceeds 30ºC) 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 24ºC is considered the temperature threshold above which indoor cooling is required[8]. Specifically, in a given day d where the mean temperature is above 24ºC, a degree day is the difference from the mean temperature to 21ºC. For example, a day with a mean temperature of 27ºC registers 6 CDDs. A day with a mean temperature of 22ºC, or with any mean temperature below 24ºC, 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 15ºC:

[6] The 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).

[7] 10km x 10km at the equator

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

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

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

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.

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 0.1º gridded dataset[9], 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 B1. gives full details 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.

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

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 waves[10]. The latter is reported in the housing modules of the regular panel waves.

3.3.3. 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 buldings 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.

3.3.4. 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 househoold 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.

[10]The 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 networth	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 $\geq$ 30)	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 networth 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%).

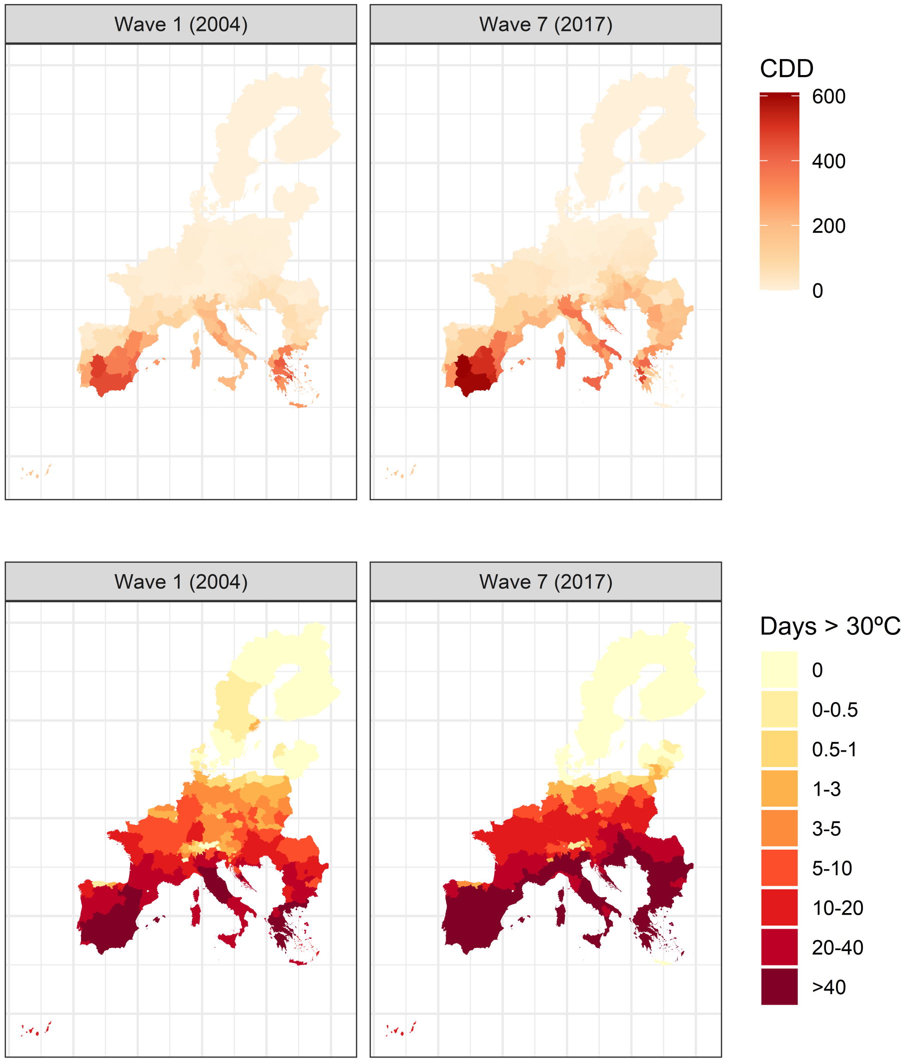


Figure 2: Exposure variables

3.4. 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}:

$$y_{it} = \beta_1 CDD_{it} + \boldsymbol{x_{it}}\boldsymbol{\gamma} + \boldsymbol{z_{rt}}\boldsymbol{\phi} + \eta_i + \epsilon_{it} \tag{3..1}$$

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

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

$\boldsymbol{z_{rt}}$ 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:

$$y_{it} = \beta_1 CDD_{it} + \beta_2 CDD_{it} \times AC_i + \boldsymbol{x_{it}\gamma} + \boldsymbol{z_{rt}\phi} + \eta_i + \epsilon_{it} \qquad (3..2)$$

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 3.3.1.), 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		

3.4.1. 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 A5 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:

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

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), $\rho_r \times t$:

$$
\begin{aligned}
y_{it} = \beta_1 CDD_{it} + \beta_2 CDD_{it} \times AC_i + \beta_4 CDD_{it} \times own_{it_0} + \\
\beta_5 CDD_{it} \times income_{it_0} + \beta_3 CDD_{it} \times edu_i + \beta_6 CDD_{it} \times \overline{CDD}_{it-1} + \beta_r CDD_{it} \times \rho_r \times t + \\
\boldsymbol{x_{it}\gamma} + \boldsymbol{z_{rt}\phi} + \eta_i + \epsilon_{it}
\end{aligned}
\tag{3..4}
$$

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

3.4.2. Instrumental variable 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:

$$\begin{aligned} CDD_{it} \times AC_i = \rho_0 CDD_{it} \times \overline{CDD}_{rt-1} + \rho_1 CDD_{it} + \\ \rho_2 CDD_{it} \times \overline{CDD}_{it-1} + \rho_3 \overline{CDD}_{it-1} + \boldsymbol{x_{it}\lambda} + \boldsymbol{x_{rt}\theta} + \omega_i + \upsilon_{it} \end{aligned} \tag{3..5}$$

Our final estimation equation thus reads as follows:

$$\begin{aligned} y_{it} = \beta_1 CDD_{it} + \beta_2 CDD_{it} \times AC_i + \\ \beta_3 CDD_{it} \times \overline{CDD}_{it-1} + \beta_4 \overline{CDD}_{it-1} + \boldsymbol{x_{it}\gamma} + \boldsymbol{x_{rt}\phi} + \eta_i + \epsilon_{it} \end{aligned} \tag{3..6}$$

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 A5).

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 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:

$$\begin{aligned} y_{it} = \beta_1 CDD_{it} + \beta_2 CDD_{it} \times AC_i + \\ \beta_3 CDD_{it} \times \overline{CDD}_{it-1} + \beta_4 \overline{CDD}_{it-1} + \beta_5 CDD_{it} \times building_r + \\ \boldsymbol{x_{it}\gamma} + \boldsymbol{x_{rt}\phi} + \eta_i + \epsilon_{it} \end{aligned} \tag{3..7}$$

3.5. Results

3.5.1. The effects of heat and the protection awarded by Air-Conditioning

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 A4). 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 A4 and Figure 2 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 31º, 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 ha 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 31º, 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 . 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 2 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 A9 through A12).

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 31º (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 (Lõhmus 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 A6). 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 A5). 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 A7).

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 A8). 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***	0.0240***	0.0212***	0.0122**	0.0484***	0.0407***	0.0505***	0.0336***	0.0723***	0.0628***	0.0387*	0.0584***
	(0.0063)	(0.0050)	(0.0059)	(0.0057)	(0.0129)	(0.0099)	(0.0127)	(0.0118)	(0.0263)	(0.0187)	(0.0207)	(0.0194)
CDD × AC	-0.0212***	-0.0176***	-0.0031	-0.0134*	-0.0147*	-0.0109*	0.0003	-0.0063	-0.2359**	-0.1273*	-0.0382	-0.0170
	(0.0079)	(0.0056)	(0.0075)	(0.0071)	(0.0088)	(0.0062)	(0.0085)	(0.0080)	(0.1098)	(0.0662)	(0.0818)	(0.0716)
CDD × own					-0.0139	0.0024	-0.0189*	-0.0064				
					(0.0107)	(0.0073)	(0.0103)	(0.0087)				
CDD $\times income$					-0.0192	-0.0082	-0.0240*	0.0059				
					(0.0126)	(0.0073)	(0.0135)	(0.0112)				
CDD × edu					0.0098	0.0073	-0.0089	0.0031				
					(0.0082)	(0.0057)	(0.0080)	(0.0075)				
CDD $\times\overline{CDD}_{it-1}$					-0.0001*	-0.0001***	-0.0000	-0.0001***				
					(0.0000)	(0.0000)	(0.0000)	(0.0000)				
$\overline{CDD}_{it-1}$									-0.0185	0.0159	0.0420	0.0011
									(0.1276)	(0.0841)	(0.1142)	(0.1065)
CDD $\times\overline{CDD}_{it-1}$									0.0003	0.0001	0.0000	-0.0001
									(0.0002)	(0.0001)	(0.0001)	(0.0001)
CDD $\times building$									-0.1417**	-0.0333	-0.0608	-0.0838*
									(0.0654)	(0.0429)	(0.0520)	(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. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

3.5.2. 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 diminshed 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)	(04)	(O1)	(02)	(O3)	(O4)
CDD^1	0.0596***	0.0432***	0.0536***	-0.0001				
	(0.0149)	(0.0107)	(0.0135)	(0.0131)				
$CDD^1 \times$ AC	-0.0234	-0.0233*	0.0117	0.0264				
	(0.0181)	(0.0123)	(0.0171)	(0.0164)				
$CDD - CDD^1$	0.0168***	0.0219***	0.0174***	0.0128**				
	(0.0064)	(0.0051)	(0.0061)	(0.0058)				
$(CDD - CDD^1) \times$ AC	-0.0234***	-0.0171***	-0.0068	-0.0180**				
	(0.0081)	(0.0058)	(0.0078)	(0.0074)				
CDD^3					0.0418***	0.0331***	0.0366***	0.0112
					(0.0094)	(0.0068)	(0.0083)	(0.0080)
$CDD^3 \times$ AC					-0.0200*	-0.0218***	-0.0041	0.0023
					(0.0118)	(0.0082)	(0.0110)	(0.0104)
$CDD - CDD^3$					0.0168***	0.0223***	0.0181***	0.0112*
					(0.0063)	(0.0051)	(0.0060)	(0.0057)
$(CDD - CDD^3) \times$ AC					-0.0247***	-0.0173***	-0.0052	-0.0160**
					(0.0080)	(0.0057)	(0.0076)	(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. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

3.5.3. 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 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 30º are about 6 times the estimated impact of one extra CDD, regardless of the specification considered (see Table 6).

3.5.4. 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 ≥ 30

	Basic				Augmented				IV (working life movers)			
	(O1)	(O2)	(O3)	(O4)	(O1)	(O2)	(O3)	(O4)	(O1)	(O2)	(O3)	(O4)
# days max ≥ 30	0.1107***	0.1824***	0.0305	0.0808**	0.2508***	0.2297***	0.1457*	0.1936***	0.1619	0.2748***	-0.1079	0.0972
	(0.0390)	(0.0320)	(0.0398)	(0.0366)	(0.0862)	(0.0620)	(0.0840)	(0.0751)	(0.1273)	(0.0908)	(0.1078)	(0.0977)
# days max $\geq 30 \times$ AC	-0.1524**	-0.1549***	0.0919	-0.1135*	-0.1171	-0.1329**	0.0706	-0.0625	-2.4828*	-1.5896	0.1335	0.6525
	(0.0663)	(0.0473)	(0.0657)	(0.0598)	(0.0737)	(0.0524)	(0.0741)	(0.0655)	(1.3592)	(1.0310)	(1.0454)	(1.0028)
# days max $\geq 30 \times owner_{t0}$					-0.0985	-0.0157	-0.1176	0.0352				
					(0.0796)	(0.0547)	(0.0797)	(0.0681)				
# days max $\geq 30 \times income_{t0}$					-0.1672**	-0.0786	-0.1121	-0.1220*				
					(0.0831)	(0.0533)	(0.0740)	(0.0646)				
# days max $\geq 30 \times$ education					0.0721	0.0548	0.0002	-0.0490				
					(0.0637)	(0.0461)	(0.0637)	(0.0579)				
# days max $\geq 30 \times \overline{CDD}_{it_0}$					-0.0002	-0.0002	0.0002	-0.0004**				
					(0.0002)	(0.0002)	(0.0002)	(0.0002)				
$\overline{CDD}_{it-1}$									-0.0903	-0.0662	0.0589	0.0840
									(0.1514)	(0.1078)	(0.1316)	(0.1244)
# days max $\geq 30 \times \overline{CDD}_{it-1}$									0.0038*	0.0021	0.0005	-0.0016
									(0.0022)	(0.0017)	(0.0017)	(0.0016)
# days max $\geq 30 \times building$									-0.0486	0.0066	0.0370	0.0128
									(0.0537)	(0.0360)	(0.0450)	(0.0422)
Total Marginal Effect of # days max ≥ 30	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 ≥ 30 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 ≥ 30 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, 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 7: Alternative exposure variable: CDD anomalies

	Basic				Augmented				IV (working life movers)			
	(O1)	(O2)	(O3)	(O4)	(O1)	(O2)	(O3)	(O4)	(O1)	(O2)	(O3)	(O4)
Δ CDD	0.0230***	0.0248***	0.0213***	0.0139**	0.0463***	0.0375***	0.0446***	0.0340***	0.0371	0.0477***	0.0063	0.0417**
	(0.0062)	(0.0049)	(0.0060)	(0.0057)	(0.0132)	(0.0099)	(0.0131)	(0.0120)	(0.0246)	(0.0165)	(0.0200)	(0.0189)
Δ CDD $\times$ AC	-0.0222***	-0.0177***	-0.0014	-0.0131*	-0.0177**	-0.0119*	-0.0014	-0.0070	-0.2206*	-0.0963	0.0088	0.0240
	(0.0078)	(0.0055)	(0.0076)	(0.0071)	(0.0089)	(0.0062)	(0.0087)	(0.0080)	(0.1156)	(0.0645)	(0.0872)	(0.0794)
Δ CDD $\times$ own					-0.0143	0.0045	-0.0215**	-0.0064				
					(0.0107)	(0.0074)	(0.0105)	(0.0089)				
Δ CDD $\times income$					-0.0179	-0.0060	-0.0215	0.0026				
					(0.0123)	(0.0068)	(0.0131)	(0.0106)				
Δ CDD $\times$ edu					0.0056	0.0064	-0.0110	0.0040				
					(0.0082)	(0.0056)	(0.0081)	(0.0076)				
Δ CDD $\times$ $\overline{CDD}_{it-1}$					-0.0000	-0.0001***	0.0000	-0.0001**				
					(0.0000)	(0.0000)	(0.0000)	(0.0000)				
$\overline{CDD}_{it-1}$									0.1204	0.0841	0.0644	-0.0026
									(0.1211)	(0.0792)	(0.1056)	(0.0970)
Δ CDD $\times$ $\overline{CDD}_{it-1}$									0.0003*	0.0001	0.0000	-0.0001
									(0.0002)	(0.0001)	(0.0001)	(0.0001)
Δ CDD $\times$ $building$									-0.0499	0.0016	0.0125	-0.0405
									(0.0611)	(0.0381)	(0.0500)	(0.0468)
Total Marginal Effect of Δ CDD	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 Δ CDD 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 Δ CDD 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***	0.0129***	0.0014***	0.0165*	0.0010**	0.0214
	(0.0001)	(0.0045)	(0.0002)	(0.0097)	(0.0004)	(0.0153)
CDD × AC	-0.0007***	-0.0046	-0.0004**	-0.0031	-0.0016	-0.0531
	(0.0001)	(0.0053)	(0.0002)	(0.0060)	(0.0015)	(0.0505)
CDD × own			-0.0003*	0.0012		
			(0.0002)	(0.0067)		
CDD × *income*			-0.0005**	0.0081		
			(0.0002)	(0.0084)		
CDD × edu			-0.0002	0.0011		
			(0.0001)	(0.0053)		
CDD × $\overline{CDD}_{it-1}$			-0.0000***	-0.0000		
			(0.0000)	(0.0000)		
$\overline{CDD}_{it-1}$					0.0008	-0.1223
					(0.0022)	(0.0768)
CDD × $\overline{CDD}_{it-1}$					-0.0000	0.0001
					(0.0000)	(0.0001)
CDD × *building*					-0.0004	-0.0367
					(0.0010)	(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. 06 = Hospitalized in the previous 12 months (No=0, Yes=100). Std. errors clustered at the individual level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

3.5.5. Analysis of heterogeneity by wealth and health status

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.

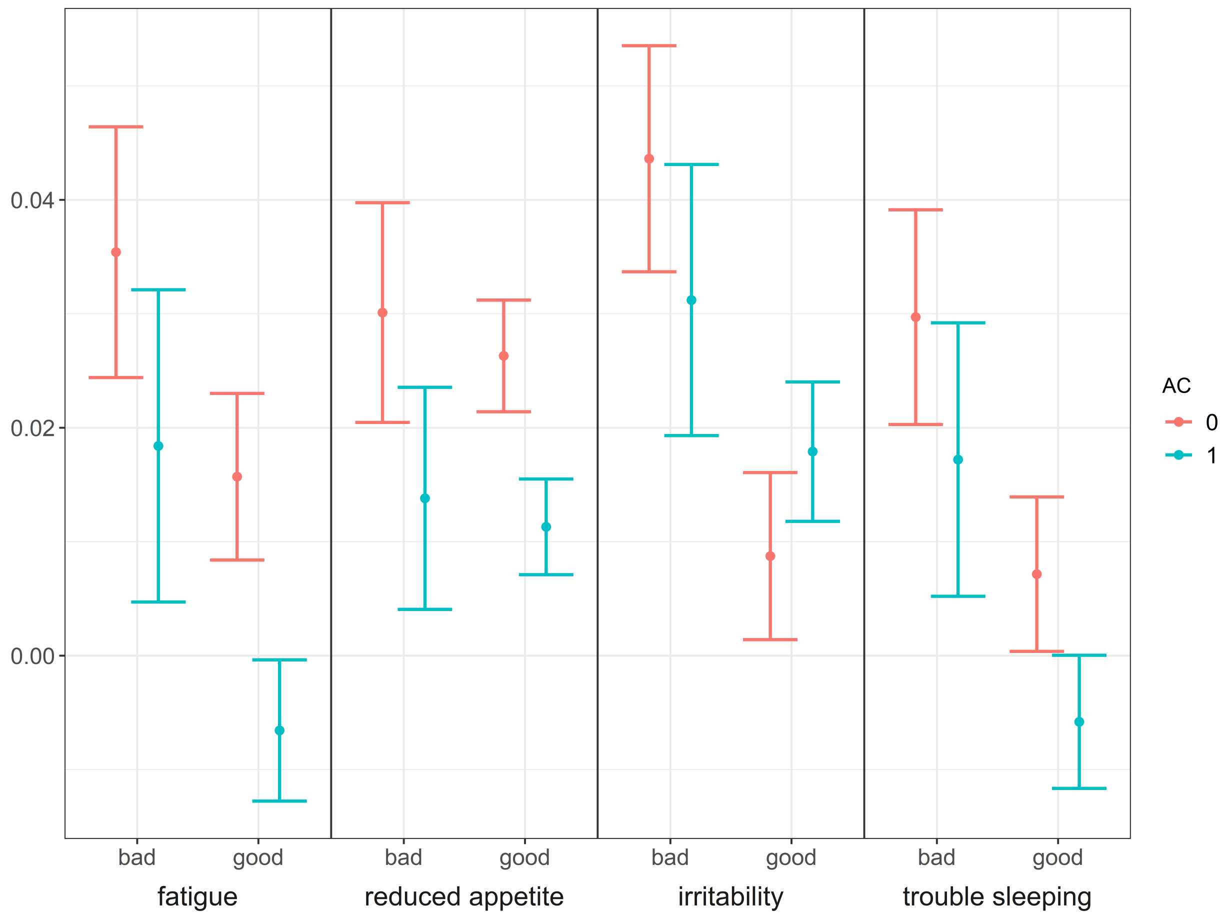


Figure 3: Marginal effect (in p.p.) of one extra CDD, by health status at the start of the period (Basic model)

We then divide our sample into four groups based on wealth quartiles, computed at the country level, based on household networth[11]. 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

[11]Using the the SHARE variable hnetw, on first wave of participation. On average, for our sample, household networth 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 and 590,000 for the fourth quartile, but with substantial country variation (average networth for the first quartile ranges fom 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).

responses, such as higher quality housing.

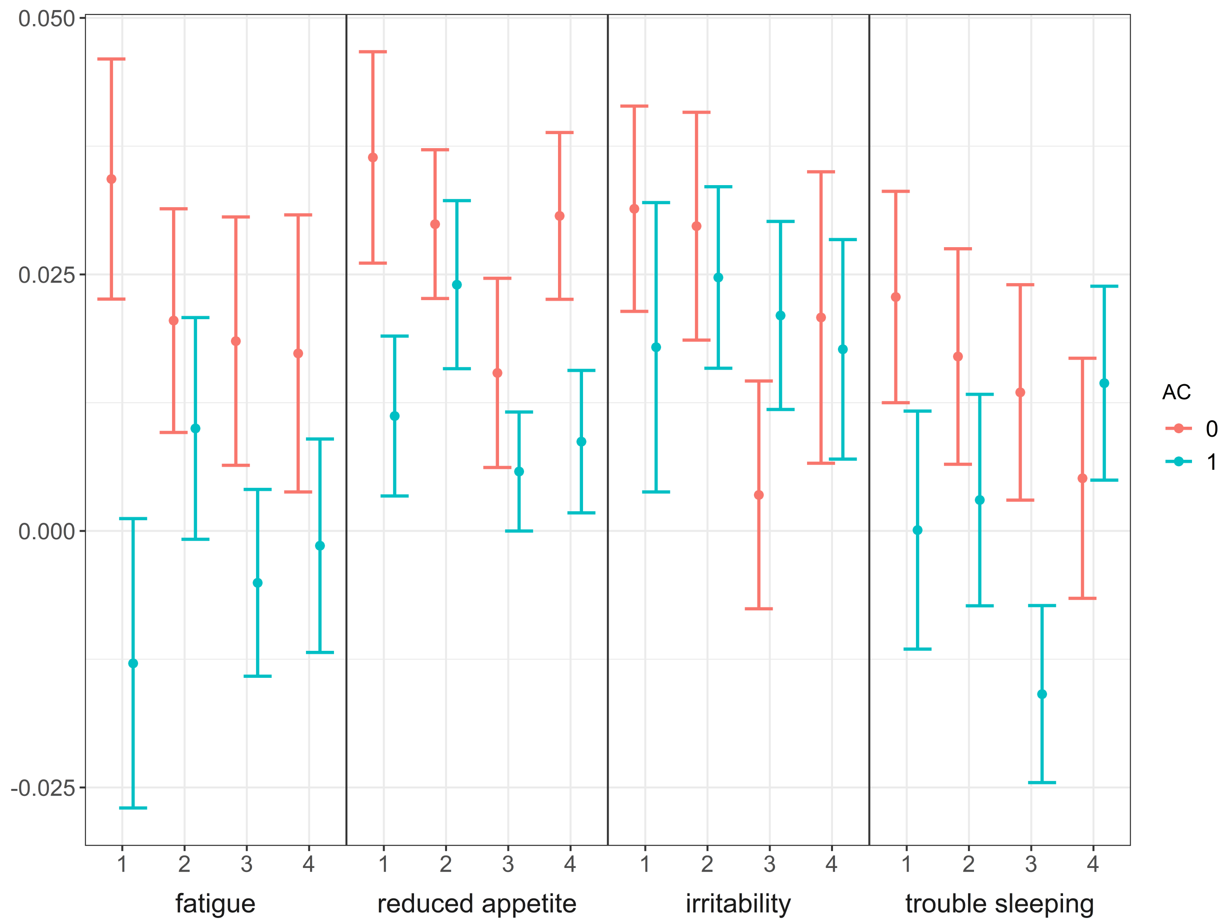


Figure 4: Marginal effect (in p.p.) of one extra CDD, by wealth quartile at the start of the period (Basic model)

3.6. 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 indoors[12]. 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 31º), 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.).

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

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 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 temperatures[13].

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.

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

Chapter 4.

Concern about climate change in Europe: ideology, temperature anomalies and global political initiatives

Abstract

Climate change concern is a precondition for supporting climate action. Concern is becoming more widespread in Europe, yet, it remains polarized along ideological lines. Both temperature anomalies and political initiatives have been found to shape attitudes towards Climate Change. I merge responses to Waves 8 and 10 of the European Social Survey with daily gridded temperature data. I find that respondents exposed to upwards temperature anomalies are more likely to be concerned about climate change, regardless of their left-right ideological position. They also reveal concern more often as anomalies accumulate. Yet, those on the right and center are also prone to attributing to climate change single events. I then study two global, bipartisan, political initiatives, 2021's COP26 in Glasgow and 2016's COP22 in Marrakech, which took place during the ESS interviews. Respondents interviewed throughout Glasgow's COP26 — but not COP22 — were more likely to express concern about climate change. In this case, it is center and particularly right-wing respondents who express increased concern. The latter also report a higher belief in the anthropogenic origins of climate change. Despite these changes, ideological barriers to policy support might remain: those on the right remain equally skeptical that governments will act, while the remaining respondents, when exposed to climate anomalies and to COP26, become more confident action will take place.

JEL Classification:
Keywords: Climate Change, COP26, COP22, Climate Action, Public Opinion.
Note: This chapter is solo work. An earlier version was joint work with Riccardo di Leo.

4.1. Introduction

Climate change skepticism remains non-negligible in Europe, even if it is substantially lower than in the US.[1] This is an urgent problem, given it reduces support and willingness to pay for climate policies (Gaikwad et al., 2022, Kotchen et al., 2013), and is positively associated with greenhouse gas emissions (Tjernström and Tietenberg, 2008). On a positive note, climate change concern has been increasing in the Old Continent, the fastest-warming region in the world[2]. Possible explanations are that individuals are experiencing climate change and that climate-related political initiatives are increasing in importance and media coverage. Exposure to upward temperature anomalies has been found to increase climate change concern (Bergquist and Warshaw, 2019, Egan and Mullin, 2012, Hoffmann et al., 2022) and so have extreme events (Hoffmann et al., 2022, Konisky et al., 2016). Studies on the United Nations Climate Change Conferences (hereafter, *COPs*) have found they increase climate change-related internet searches (Sisco et al., 2021), and that news on COP20 increased climate change awareness for US citizens (Bakaki and Bernauer, 2017).

Attitudes towards climate change are however entangled in political tones. Several authors have investigated the role of social norms (Bechtel et al., 2019) and individual socio-political factors (Lubell et al., 2007). It is not surprising that the interpretation of political initiatives depends on ideology. For example, Valentim (2023) finds that in Germany, the Fridays for Future protests increased concern with climate change for those on the left, but decreased it for those on the right.

Yet, also the interpretation of atypical, climate change related, weather patterns, can depend on ideology. Climate is "intangible" (Moser and Ekstrom, 2010), and vulnerability factors linked to climate change are not perceived as such by the population (Capstick and Pidgeon, 2014). Climate attribution, i.e., determining to what extent an event was made more likely by climate change, is a scientific field in and of itself, reflecting the difficulty in inferring climate change from single events. Biases are thus likely to transpire for individuals. Citizens, possibly due to their preconceived ideas, might on one hand erroneously use single events to believe or not in climate change and on the other, not be able to identify climate change effects despite repeated, anomalous, patterns.

The paper studies how individual climate change concern responds to i) temperature anomalies and ii) global, bi-partisan, and (mostly) economically impact-free political initiatives — COP meetings. I use a EU-wide, individual-level, representative survey, the European Social Survey (ESS). I make use of the fact that two COP meetings took place during the interview dates: COP26, taking place in Glasgow in 2021, and COP22, held in Marrakech five years earlier. I then study whether the effects of anomalies and of COP meetings differ across the political spectrum. I consider, besides likelihood to be concerned about climate change, likelihood to believe in anthropogenic climate change and the degree of confidence in effective government action on the matter. I also consider whether actual temperatures at the time of the interview, from which one should not infer climate change, influence the responses of individuals.

COP26 led 197 countries to sign the Glasgow Climate Pact, reaffirming the emissions

[1]See for example the Report on International Public Opinion on Climate Change.
[2]See the EEA European Climate risk Assessment

goals stated in the Paris Agreement. It was significantly more successful than its predecessors in intensifying global attention towards climate change (Figure 1a), arguably due to the grassroots protests that accompanied the Conference, culminating in the Global Day of Action for Climate Justice.[3] I argue that the bipartisan nature of the Conference, its high media salience (Figure 1b), and the lack of immediate repercussions on citizens' life of the Glasgow Climate Pact[4] make COP26 an ideal proxy for a pure increase in climate change salience.

I contribute to the literature in several ways. First, I expand on the European Social Survey (ESS) by adding exposure to temperature and temperature anomalies. I show this dataset can be used to consider climate change attitudes, but it could also answer numerous other questions, such as the impact of temperatures on perceived well-being. Second, I study the effect of both temperature anomalies and of COP meetings via a cross-national, EU-wide, representative, individual survey, which allows to take into consideration numerous important confounding factors. Third, I focus on heterogeneity in Europe across the political spectrum regarding the effect of temperature anomalies, which, to the best of my knowledge, has not yet been done.

I find that a one-standard deviation increase in temperature anomalies is associated with a 0.9 percentage point increase in the probability of being concerned with climate change, with no significant differences across the political spectrum. I also find that lower temperatures during the interview make those on the center and right less likely to worry, while having no effect on left-wing respondents. The first finding suggests individuals are able to update their beliefs appropriately; while the second indicates some confirmation biases might lead individuals to erroneously infer climate change patterns from single events. COP26 increases the likelihood of expressing belief in the anthropogenic origins of climate change for those on the right. Yet, these individuals are substantially less likely than those on the left to believe in effective government action on climate change following COP meetings or temperature anomalies. This could indicate that the ideological barrier is thick: certain individuals might be convinced of the urgency of the climate crisis but still not support policy due to skepticism towards the government.

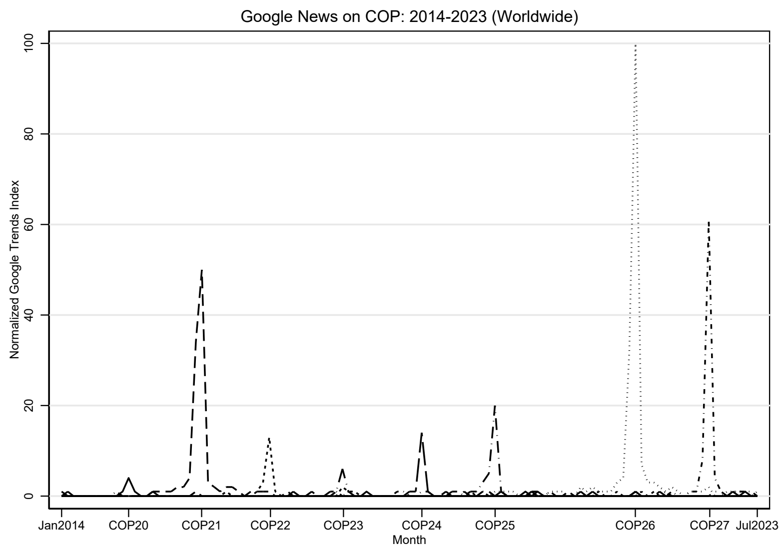
I estimate a 3 percentage points increase in the likelihood of expressing concern over climate change relative to the pre-COP26 week. COP26 was particularly successful in raising climate change concern among right-wing respondents, as well as in reducing their skepticism on human responsibility behind climate change. The fact that I do not estimate a comparable effect of 2016's COP22 is compatible with an increased overall "attention" of the European public to climate change, as confirmed by the growing media coverage of COP worldwide. The effect of COP26 appears short-lived, though possibly enduring slightly longer (up to three weeks) for right-wing respondents.

The paper is organized as follows. Section 2 provides additional background on the literature on the effects of climate change experience and of political events on attitudes towards the matter. Section 3 gives details on the data. I describe response variables, control variables, and the construction of temperature data (temperature anomalies and average temperatures). Section 4 describes the methods. Section 5 provides the main

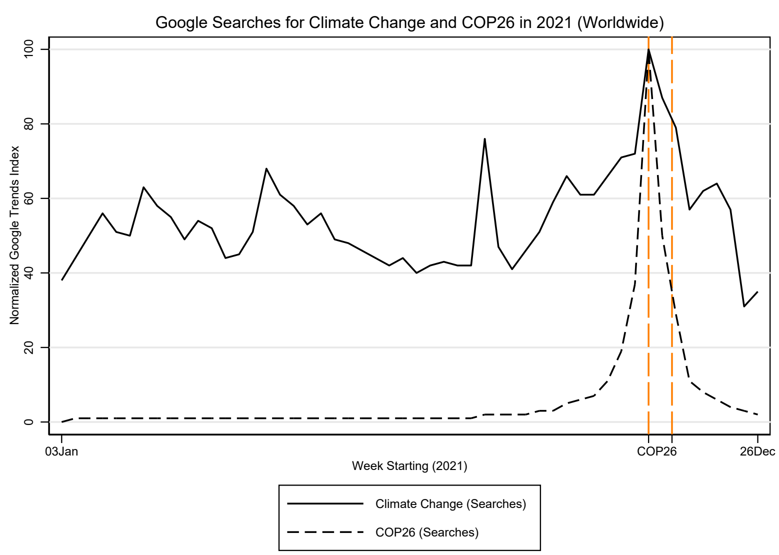
[3] The Guardian (06/11/2021). Online resources were last accessed on: September 24, 2024.

[4] Nature (14/11/21).

results. Section 6 provides robustness checks. Section 7 discusses the results and concludes.



(a) **Google News on COP (2014-2023)**



(b) **Google Searches (2021)**

Notes: Source: Google Trends. Panel 1a: worldwide *Google News* on each COP taking place between 2014 (COP20) and 2022 (COP27). The score is normalized to take values between 0 and 100, relative to the most covered outcome, i.e., COP26. Panel 1b: worldwide *Google searches* on Climate Change and COP26 in 2021. The search score is normalized separately for each outcome to take values between 0 and 100. The dashed vertical lines capture, respectively, the start (Oct31) and end (Nov13) date of COP26 in Glasgow.

Figure 1: Internet search activity and news relating to Climate Change and COP

4.2. Background

Notwithstanding the important role played by socio-economic conditions (Poortinga et al., 2011), gender differences (Bush and Clayton, 2023), information (Kellstedt et al., 2008, Krosnick et al., 2006) , institutional trust (Lubell et al., 2007) and values (Leiserowitz, 2006), direct exposure to extreme events — including unusually high temperatures (Donner and McDaniels, 2013, Zaval et al., 2014) — has been found to affect the salience of climate change, and attitudes towards it (Baccini and Leemann, 2021, Konisky et al., 2016).

A significant strand of research has focused on how increasingly frequent exposure to extreme weather might change attitudes towards climate change. (Konisky et al., 2016). Yet, natural events exhibit an inherently political nature: ideological preconceptions and partisan affiliations mediate their impact on individual attitudes (Capstick and Pidgeon, 2014), and, in turn, in the voting booth (Healy and Malhotra, 2009). As a result, most studies have struggled to disentangle the effect caused by the source of increased climate change salience, from that of the political response to it.[5]

To overcome this issue, a possible approach is to consider temperature anomalies, i.e., how much temperature differ from long-term averages. This is, like extreme events, a measure which increases, and will keep increasing, as the effects of climate change transpire. The seminal paper on the matter of the effects of climate change experience on environmental concern in Europe, Hoffmann et al. (2022), considers both types of events, and their impact on the percentage of individuals within a region who are concerned about the environment, through Eurobarometer data. In terms of heterogeneity, they focus on heterogeneity across socioeconomic conditions. They find that in wealthier regions, support for climate action is more responsive to temperature anomalies. Other papers have also confirmed that exposure to upward temperature anomalies raises climate change concern (Bergquist and Warshaw, 2019, Egan and Mullin, 2012).

I decide to focus on anomalies, which, if not extreme, do not require a political response. Some evidence for the US has been collected on the issue, but with somewhat contradicting results. Hamilton and Stampone (2013), for example, find that - in the US - belief in anthropogenic climate change is indeed predicted by temperature anomalies, but only among Independents, i.e., not Democrats or Republicans. On the contrary, Deryugina (2013) identifies an impact of (longer-run) temperature fluctuations on climate change beliefs, only among Republicans.

Temperature anomalies can be one factor behind the increased concern about climate change in Europe. They are, however, a slow-moving phenomenon. Another possibility for the increased concern in recent years is increased political and media attention. This might affect concern too, but in the short-term. Elite cues (Carmichael and Brulle, 2017, Constantino et al., 2021), contested legislative actions (Stokes, 2016, Colantone et al., 2022), grassroots participation (Sisco et al., 2021, Barrie et al., 2023, Valentim, 2023) and media coverage (Bell, 1994, Wilson, 2000) are indeed all important in the formation of the public opinion on climate change. So are less visible, but possibly as substantial, political decisions on budget allocation (Cohen and Werker, 2008, Neumayer et al., 2014), and on the legislative

[5] Gasper and Reeves (2011) represent a notable exception, yet their data does not allow for individual-level analyses.

framing of climate policies (Druckman, 2001, Lakoff, 2010).

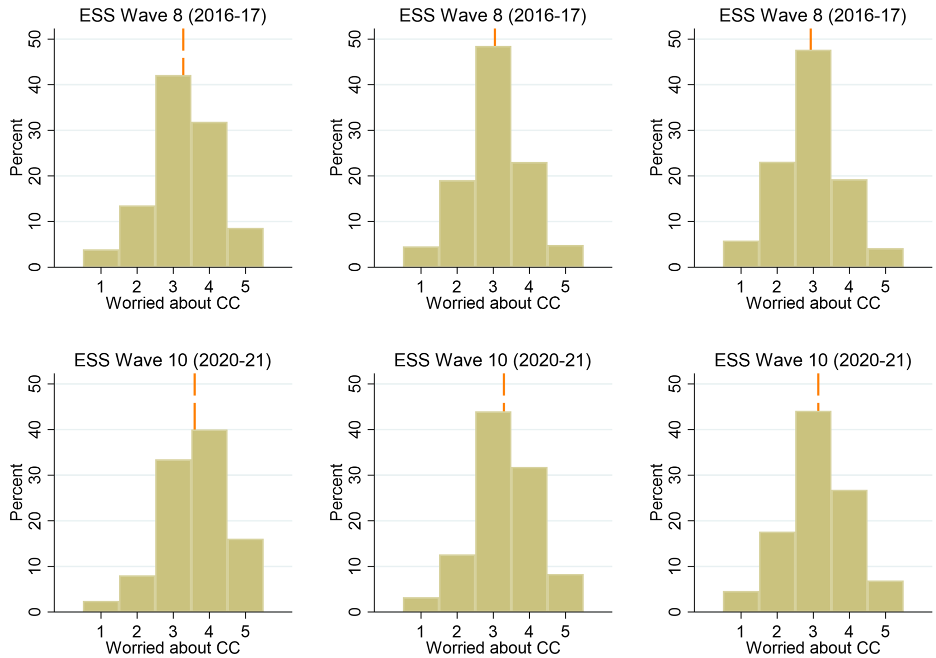
4.3. Data

I gather individual-level attitudes towards Climate Change from the European Social Survey (ESS), covering nationally representative samples across 24 European countries. I focus on Waves 8 (conducted in 2016-17) and 10 (2020-21), since these are the only waves which included questions about climate change. They happen to overlap with, respectively, the 2016 COP22 in Marrakech and the 2021 COP26 in Glasgow.

I construct a proxy for climate change concern from the question asking: "How worried are you about climate change?". Respondents could answer on a scale from 1 ("Not at all") to 5 ("Extremely worried"). I classify individuals as Left, Center and Right based on their self-reported position on a spectrum defined as (0 "Left-wing" - 10 "Right-wing"), building a categorical variable with three levels: 'Left' coming from 0-3, 'Center' from 4-6 and 'Right' from 7-10.

The ESS data confirms findings from other surveys (namely, the Pew Research Center Global Attitudes survey and the Edelman Trust Barometer[6]): there is an increase in climate change concern from Wave 8 to Wave 10. As expected, concerns decreases as individuals report being more right-wing. Interestingly, regardless of whether they are on the left, center, or right, on average, there has been an increase in climate change concern (see Figure 2).

[6]As summarised in the following Clean Energy Wire report.



Notes: Source: *ESS* Wave 8 (2016-17) and 10 (2020-21). The dashed vertical line captures the mean value for each sub-figure.

Figure 2: Distribution of climate change concern in 2016-17 and 2020-21.

Climate change attitudes are captured by questions covering beliefs in anthropogenic climate change and optimism towwards government action on climate change. These come, respectively, from the following questions: "Do you think that climate change is caused by natural processes, human activity, or both? (1 "Entirely by natural processes" - 5 "Entirely by human activity"" and "And how likely do you think it is that governments in enough countries will take action that reduces climate change?" (0 "Not at all likely" - 10 "Extremely likely")". In the same way as with climate change concern, those on the left are more likely to believe that climate change has important anthropogenic origins.

4.3.1. Control variables

Among the independent variables, I include: age of the respondent, years of completed full-time or part-time schooling, domicile (big city; suburbs; town; village; countryside). I include variables for perceived household income (0 "Very hard to cope" - 3 "Living comfortably"), interest in politics (0 "Not at all" - 3 "Very interested"), and ideology (0 "Left-wing" - 10 "Right-wing"). Finally, I employ a number of indicator variables equal to one if the respondent's self-reported gender was "male", if they were born in the country, if they were unemployed at the time of the interview, and if they had any child living in their household. Descriptive statistics for both dependent and independent variables are provided in Table A1.

4.3.2. Temperature data

I build temperature and temperature anomalies starting from a gridded dataset of average temperatures, the E-OBS. E-OBS is a gridded observational dataset gathering daily meteorological variables across Europe, resorting to information collected from the meteorological station network of the *European Climate Assessment & Dataset* (ECA&D).[7] The data has a geographic resolution of 0.1 degrees (i.e., each grid cell is roughly 10×10 kilometers at the equator).

I then merge the computed indicators with the ESS by using the most detailed location information provided in the survey (Midões et al., 2024, perform a similar exercise employing SHARE data). First, I identify an approximate location for each ESS respondent by the NUTS region where their interview took place. The regions provided in the ESS are either NUTS2 — Austria, Belgium, Switzerland, Denmark, Greece, Spain, France, Croatia, Italy, Norway, Poland, Portugal, Sweden — or NUTS3 — Bulgaria, Czech Republic, Estonia, Finland, Croatia, Hungary, Ireland, Iceland, Lithuania, Latvia, Macedonia, Sweden, Slovenia and Slovakia. Germany and the United Kingdom (and, in some waves, Italy) provide NUTS1 identifiers only.

Second, I resort to the Degree of Urbanization (*DEGURBA*) methodology — the EU/OECD standard for urbanization classification — to classify each gridcell in the E-OBS average temperature dataset as part of either: (1) a city; (2) a town or suburb; (3) a rural area. Each NUTS region is therefore subdivided into three sub-regions. Using a historical annual population 0.1º-gridded dataset — *ISIMIP Population*[8] — I compute, for each NUTS-DEGURBA regional couplet, a population-weighted average temperature.

Finally, I exploit the ESS item asking respondents about their domicile, i.e., whether they live in a big city, a suburb, a town, a village, or in the countryside. Each ESS-defined region can therefore be divided into five — as opposed to three, for the temperature data — sub-regions. To obtain the average daily temperature in each of the five ESS sub-regions, I compute a weighted average across the three, DEGURBA-defined, sub-regions, applying country-specific weights. In doing so, I consider how perceptions of living in a 'small town' or in a 'suburb' vary across countries.

From daily temperatures, I build (positive) temperature anomalies following Hoffmann et al. (2022). For each day of the year, I subtract the long-term average temperature (30 year average from 1980 to 2010) for that same day. I standardize this deviation. At that point, I have a daily indicator of temperature anomalies. I then take the average of that indicator over the 365 days preceding the two days before the interview.

Tables A2 and A3 display descriptive statistics for: (a) mean temperatures experienced by ESS respondents, averaged between the day of the interview and the previous one; (b) upward temperature anomalies — relative to the long-run local climate mean (1980-2010) — . In both cases, statistics are computed across all ESS respondents interviewed in Wave 8 and 10, coming from countries covered by the E-OBS data.[9]

[7] For more information, see: E-OBS.

[8] Available online.

[9] Following the literature, standardized deviations below 0.5 are set to 0, i.e., not considered for the rolling average.

4.4. Methods

In the main specifications, I choose to code climate change concern (CC_i) as a binary indicator, taking value 1 if the respondent is somewhat, very, or extremely worried about climate change (else 0). This shrewdness is employed for a twofold reason. First, to resemble Hoffmann et al. (2022), the existing study which is closest to ours. Second, to increase the comparability of the findings to the literature studying the impact of temperature anomalies on climate change attitudes (as opposed to climate change concern). The majority of existing survey studies tend in fact to aggregate answers into indicators capturing whether individuals believe (or not), in climate change (see: Howe et al., 2019, for a review). Arguably, if someone does not believe in climate change, she is bound to be not at all concerned about it. Nonetheless, given the ordered nature of the variable, I reproduce the analysis with ordered probit models in section 4.6.3.

When considering the anthropogenic origins of climate change, I likewise use a binary indicator, 'CC Anthropogenic'. This variable takes value 1 if individuals consider that climate change is either caused about equally by natural processes and human activity ('3' in the original variable), mainly by human activity ('4' in the original variable) or entirely by human activity ('5' in the original variable). When looking into belief in government action, I resort to the original variable, taking values 0 ("Not at all likely") to 10 ("Extremely likely") from responses to 'How likely do you think it is that governments in enough countries will take action that reduces climate change?'.

I focus on the full sample of interviews taking place in Waves 8 and 10 of the ESS — when questions about climate change were asked. I estimate the following regression:

$$\text{CC}_i = \alpha + \delta_1 \text{ Temp. Anom}_{rt-2} + \delta_2 \text{ Temp. Interview}_{rt} + \rho\, \mathbf{Z}_i + \sigma_c + \theta_s + \lambda_c \tau_t + \epsilon_i \quad (4..1)$$

Temp. Anom.$_{rt-2}$ captures average positive temperature anomalies in the respondent i's region r in the 365 days preceding the second day before the interview $(t-2)$, relative to the 30-years average (1980-2010). I also acount for the average temperature experienced by the respondent on the interview day and in the previous one — Temp. Interview$_{rt}$ — as this may impact climate change concern (Joireman et al., 2010). Standard errors are clustered at the country-by-wave level.[10]

I include country fixed effects (σ_c) and a vector of individual predictors of climate change attitudes ($\mathbf{Z}_i$): self-reported gender, nationality and age of the respondent (both in level and squared), education level, domicile, children living in the household, unemployment status, perceived household income, political interest and ideology. Standard errors clustered at the country-by-wave level. I include seasonal fixed effects (θ_s) and either country specific time-trends ($\lambda_c \tau_t$) or a time-trend common across countries ($\lambda_c = \lambda$). Descriptive statistics are presented in SI C1.

To study the effect on climate change attitudes coming from global climate conferences — controlling for exposure to temperature anomalies and for temperature at the time of the

[10]In a second specification, displayed in Columns 3 and 4 of Table A5, I employ **Temp. Anom.**$_{r,t-1}$: the average upward temperature anomalies in the 365 days preceding the first — rather than second — day before i's interview $(t-1)$, relative to the usual 30-years average. In this second specification, I do not control for average temperature levels, following Hoffmann et al. (2022).

interview — I focus on the subset interviewed during, respectively, COP22 (Nov7-Nov11, 2016) and COP26 (Oct31-Nov13, 2021). I estimate the following specification, via an OLS regression:

$$\mathrm{CC}_i = \alpha + \beta\,\mathrm{COP}_t + \delta_1\,\mathrm{Temp.\ Anom.}_{rt-2} + \delta_2\,\mathrm{Temp.\ Interview}_{rt} + \rho\,\mathbf{Z}_i + \sigma_c + \epsilon_i \quad (4..2)$$

where CC_i captures climate change attitudes of respondent i, from region r, in country c, interviewed on day t. COP_t is an indicator taking value 1 if the respondent was interviewed during COP26 (or COP22), 0 if during the previous week (see Figure 3). I include numerous control variables, addressing possible imbalances between the treatment and control groups. In Section 4.6.1. I instead increase comparability via Propensity Score Matching (PSM).

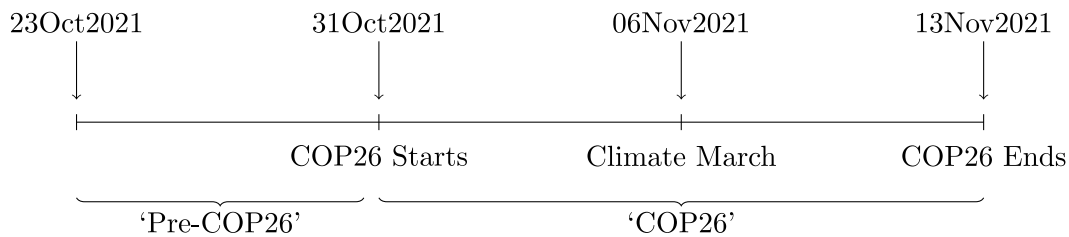


Figure 3: Timeline and construction of the 'COP26' and 'pre-COP26' groups.

In studying the effect of COP22 and COP26, the variables on temperature serve as control variables, in case the event coincided with a particularly anomalous period in terms of temperature. These become potentially relevant once I extend the period of analysis further, from two to four weeks, in the analysis of the duration of effects in section 4.5.2..

The heterogeneity analysis adds interactions between the coefficients of interest - δ_1, δ_2 and β - and the categorical variable of political ideology (Left, Right or Center).

4.5. Results

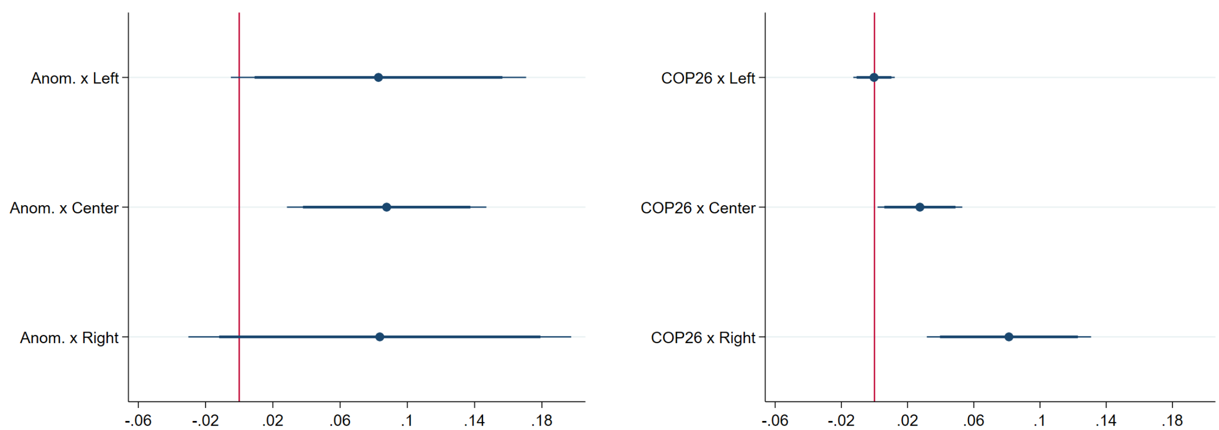
The estimates support the consensus in the literature: exposure to upward temperature anomalies is associated with a 9.3 percentage points increase in the likelihood to express concern about Climate Change. For better interpretation of the magnitude, it is worth noting that the temperature anomaly variable has a standard deviation of 0.1, meaning one additional standard deviation in anomalies increases the probability of being concerned by approximately 0.9 percentage points. I also find evidence of an effect of the temperature (but not of the temperature anomaly) felt during the day of the interview and the day before (Table A5 provides full details).

Regarding COP26, I estimate a 3 p.p. increase in the likelihood of expressing some concern over climate change (see Table A6 for full details). This likely represents a downward estimate of the effect, given that COP26 was already on the news in the weeks preceding the Conference. I do not recover any statistically significant effect of 2016's COP22. In Figures 3 and 4, I show how the estimates for the impact of temperature anomalies and of

COP26 on climate change concern do not vary significantly in magnitude when I iteratively remove respondents from a specific country. Regressions are reported in full in SI C4.

4.5.1. Heterogeneity based on ideology

I test whether experiencing upward temperature anomalies prior to the interview date affects climate change concern differently among self-identified left-, center- and right-leaning respondents. The results, plotted in Figure 4, suggest that, although the latter two groups report lower levels of concern ex ante, their attitudes do not respond differently to the experience of temperature anomalies compared to left-wing respondents (Table A13 shows full results). The right panel shows that instead, in what pertains to COP26, respondents who self-identified as right-wing are significantly more affected. I consider this is not simply a result of 'ceiling' effects on the left (there is still a substantial proportion of left-wing individuals with minimal climate change concern). COP22 does not reveal any statistically significant effect across ideological positioning (not shown in Figure 4, but estimates are presented in Table A14).

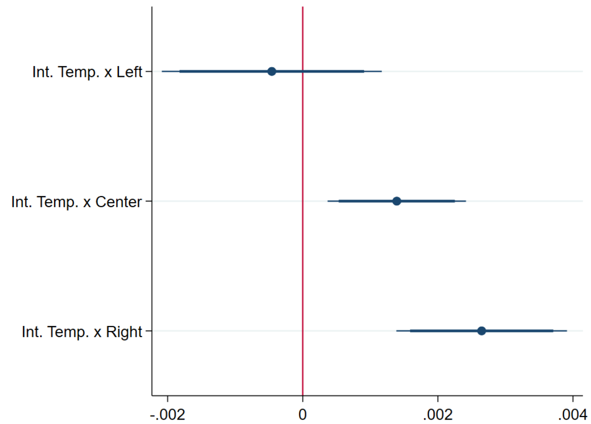


(a) **Temp. Anomalies** (b) **COP26 (Glasgow, 2021)**

Notes. Source: *ESS*. Thick (thin) lines signify the 90% (95%) confidence interval. Full regression tables are reported in Tables A13-A14.

Figure 4: Ideology heterogeneity of Temperature Anomalies (left-panel) and of COP26 (right panel).

I also find evidence of heterogeneity of the effects of temperature during the interview, with respondents on the center and right being less (more) likely to express concern if temperatures are colder (warmer), as plotted in Figure 5:

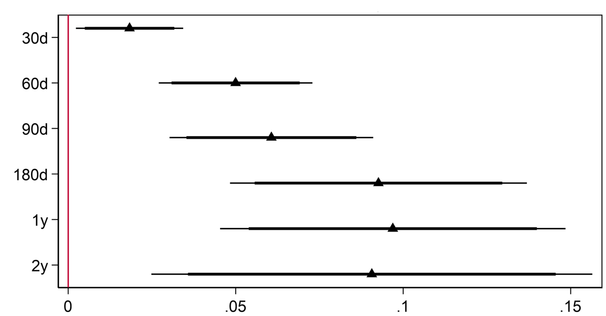


Notes. Source: *ESS*. Thick (thin) lines signify the 90% (95%) confidence interval. Full regressions are reported in Table A13.

Figure 5: Ideology heterogeneity of temperature during interview.

4.5.2. Duration of effects

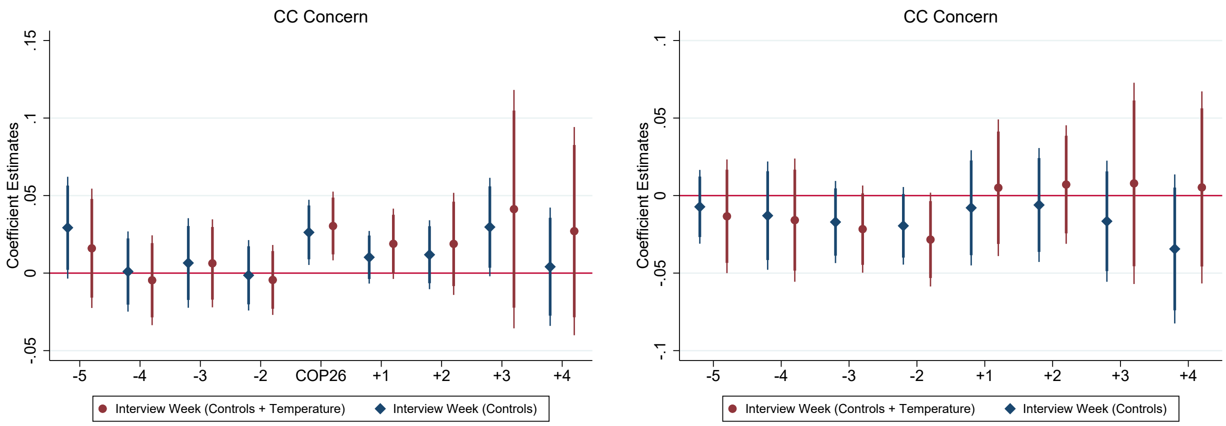
Temperature anomalies are argued to increase climate change concern through both recency and threshold factors (Hoffmann et al., 2022). To confirm this pattern in the novel dataset, I consider different time horizons for the anomalies. Small effects transpire when considering anomalies over the previous month (but not in shorter time periods), and grow steadily until one-year. This finding is compatible with Deryugina (2013) who studies beliefs about global warming and only finds effects of fluctuations experienced over at least 1 month. As in Hoffmann et al. (2022), the strongest effect comes from anomalies recorded over the previous year. Results are summarized in Figure 6, with full details in Table A8.



Notes. Source: *ESS* and $E-OBS$. Thick (thin) lines signify the 90% (95%) confidence interval. Full regressions are reported in Table A8. The window starts counting backwards from 2 days before the interview. 30d is 30 days before, 60d is 60 days before, 90d is 90 days before, 180d is 180 days before, 1y is 365 days - the standard specification across the paper - and 2y is 730 days.

Figure 6: Alternative reference windows for Temperature Anomalies

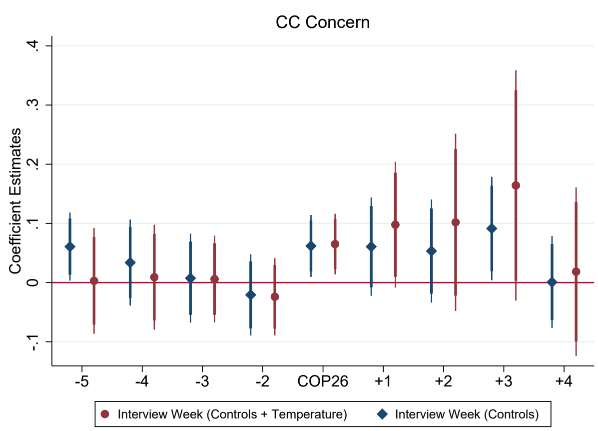
I then turn to the duration of the effect of the COP meetings. I extend the treatment group to individuals interviewed 1,2,3 and 4 weeks after the end of COP. I no longer find statistically significant effects, hinting that the effect of COP is on average short lived. For right-wing respondents, substantially more affected by COP26, the effect of COP26 might last slightly more, with statistically significant effects (at the 10% level) still present at the three-week mark as show in Figure 8.



(a) **COP26 (Glasgow, 2021)** (b) **COP22 (Marrakech, 2016)**

Notes. Source: *ESS*. In 7a, in each column I shift the date of COP26 in Glasgow (Oct31-Nov13, 2021) by 5 weeks from the original one, and estimate Equation 4..2 keeping the same control group, i.e., respondents interviewed during the week preceding COP26. In 7b, I replicate the analysis for COP22 in Marrakech (Nov7-Nov11, 2016). Country fixed effects apply, standard errors clustered at country-by-wave. Thick (thin) lines signify the 90% (95%) confidence interval. Full regression tables are reported in Tables A9-A12.

Figure 7: Climate change concern before and after COP26 (left-panel) and COP22 (right panel).

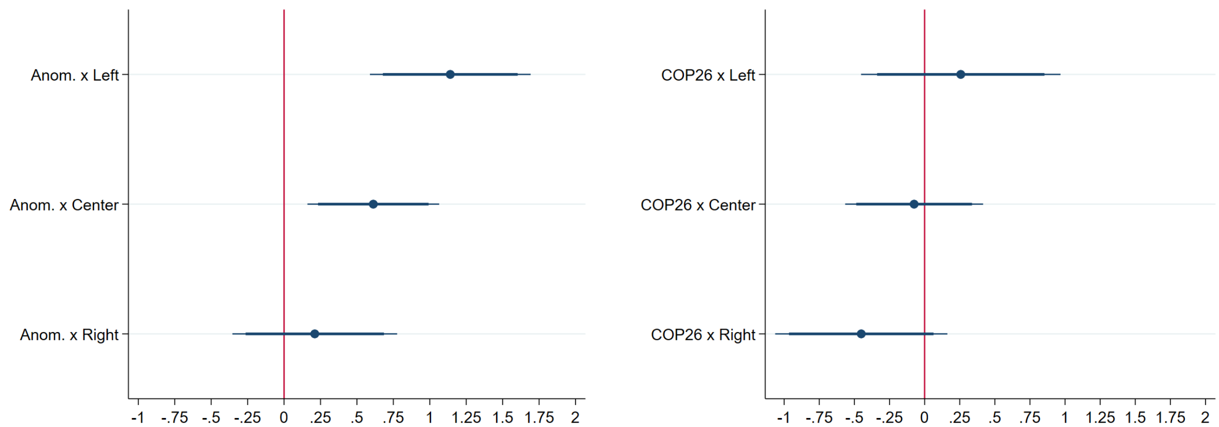


Notes. Source: *ESS*. In each column I shift the date of COP26 in Glasgow (Oct31-Nov13, 2021) by 5 weeks from the original one, and estimate Equation 4..2 keeping the same control group, i.e., respondents interviewed during the week preceding COP26. I subset the sample to consider only right-wing respondents. Country fixed effects apply, standard errors clustered at country-by-wave. Thick (thin) lines signify the 90% (95%) confidence interval.

Figure 8: Climate change concern in the weeks before and after COP26 for right-wing respondents

4.5.3. Climate change beliefs beyond concern

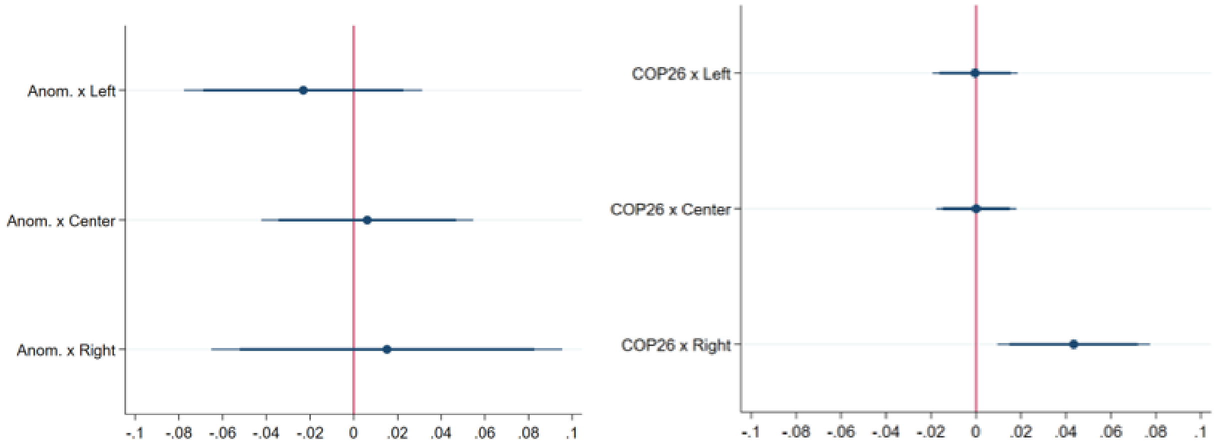
Interestingly, increased anomalies do not only increase the concern about climate change but also the belief that governments will act on the matter (coded as 1 to 10, an additional anomaly is associated with a 0.6 increase in the belief in government action, see Table A7). Such an effect is exclusive to center and left-wing respondents (Figure 9, left panel). COP26, despite increasing concern, does not on average bring such an effect. I identify an increased belief in anthropogenic climate change but only for right-leaning respondents interviewed during COP26 (Figure 10). Once again, 2016's COP22 does not exert a significant impact on the attitudes of either group of respondents (results not shown). In a nutshell, despite right-wing respondents becoming more concerned about climate change and expressing less climate skepticism during COP26, their skepticism towards effect government action on the matter remains. Their skepticism is also not reduced by temperature anomalies.



(a) **Temp. Anomalies** (b) **COP26 (Glasgow, 2021)**

Notes. Source: *ESS*. Thick (thin) lines signify the 90% (95%) confidence interval. Full regression tables are reported in Tables A13 and A14.

Figure 9: Ideology heterogeneity of Temperature Anomalies (left-panel) and of COP26 (right panel) on belief in government action.



(a) **Temp. Anomalies** (b) **COP26 (Glasgow, 2021)**

Notes. Source: *ESS*. Thick (thin) lines signify the 90% (95%) confidence interval. Full regression tables are reported in Tables A13 and A14.

Figure 10: Ideology heterogeneity of Temperature Anomalies (left-panel) and of COP26 (right panel) on belief in anthropocentric origin of climate change.

4.5.4. Specific events within COP26

While I have considered COP26 as a whole, effects might be driven by specific events related to it. I first ask whether the highly-debated marches co-organized by Greta Thunberg's *Fridays for Future* and taking place worldwide during the Global Day of Action for Climate Justice on November 6, 2021 (during COP26), might have played a role in shaping climate change concern, as suggested by the literature (Sisco et al., 2021). Second, I check whether, rather than the Conference itself, it was the contested Glasgow Climate Pact, signed on the final day of the event, that drove the boost in climate change debates.

As illustrated in the timeline in Figure 11, to study the effect of the Climate Action March, I restrict the sample to respondents interviewed during COP26, and define the broadly-defined 'treatment' ('control') group as interviewees during Nov7-Nov12, 2021 (Oct31-Nov5). When the focus is on the end of COP26, the 'treatment' ('control') group is composed of individuals interviewed after (during) the conference, hence between Nov14 and Nov21, 2021 (Oct31-Nov12). Estimates presented in Figure 12 suggest that, if anything, the end of COP26, coinciding with the approval of the Glasgow Climate Pact, led to a slight decrease in the probability of being concerned about climate change. There is some evidence that, instead, Fridays for Future might have increased this probability, over and above COP26 as a whole.

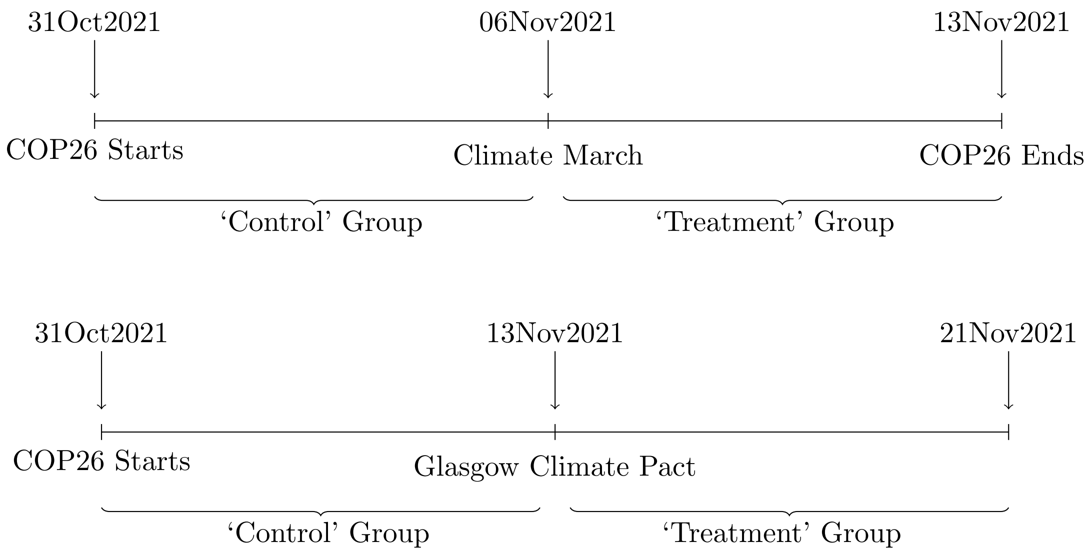
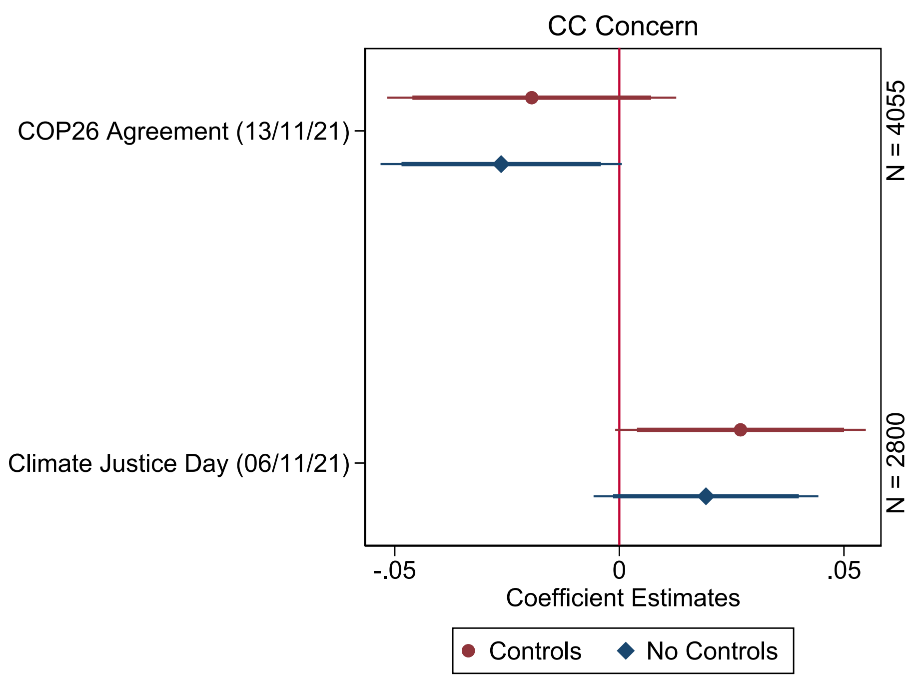


Figure 11: Timeline and construction of the 'treatment' and 'control' groups.



Notes: Source: *ESS*. The outcome variable is climate change concern. Country fixed effects apply, standard errors clustered at country-by-wave. Thick (thin) lines signify the 90% (95%) confidence interval. Full regressions are reported in Table A15.

Figure 12: Concern about climate change: Glasgow Climate Pact and Climate Justice Day.

4.6. Robustness checks

4.6.1. Propensity score matching

In this section, I check the comparability in observable characteristics between ESS respondents interviewed right before and during COP26, and try to reduce the imbalance in covariates across the two groups, by means of a Propensity Score Matching (PSM) algorithm. This exercise yields an estimate of the effect of COP26 on climate change concern that is consistent in magnitude and significance with the non-PSM specification.

To increase the comparability of the two groups, I match respondents interviewed during and before COP26 based on their observable characteristics, using a PSM algorithm with replacement. After estimating the Propensity Score (PS) through a logistic regression, respondents within both groups are randomly sorted from a uniform distribution, and each individual interviewed during COP26 is compared to its closest PS-based match among those contacted in the week preceding the Conference. As shown in Figure 1, the two groups are relatively comparable. Figure 2 confirms how, when matched on observables, the two groups are de facto indistinguishable from each other: the B-statistic is 12.2, and the R-statistic of 1.05 (Rubin (2001) recommends the former to be below 25, and the latter between 0.5 and 2, for the samples to be considered as balanced).

I retrieve again a statistically significant effect of being interviewed during COP26, rather than just before, on climate change concern. I estimate an Average Treatment Effect of 0.032, with AI-robust Standard Error 0.0139, significant at 5% (p-value = 0.018, z-stat=2.37, N=5,107), only slightly higher than those estimated in the OLS setting (see Table A6). This exercise — whilst not addressing potential selection on unobservables — is reassuring about the robustness of the findings across an increasingly similar set of respondents.

4.6.2. Subset on the same set of countries

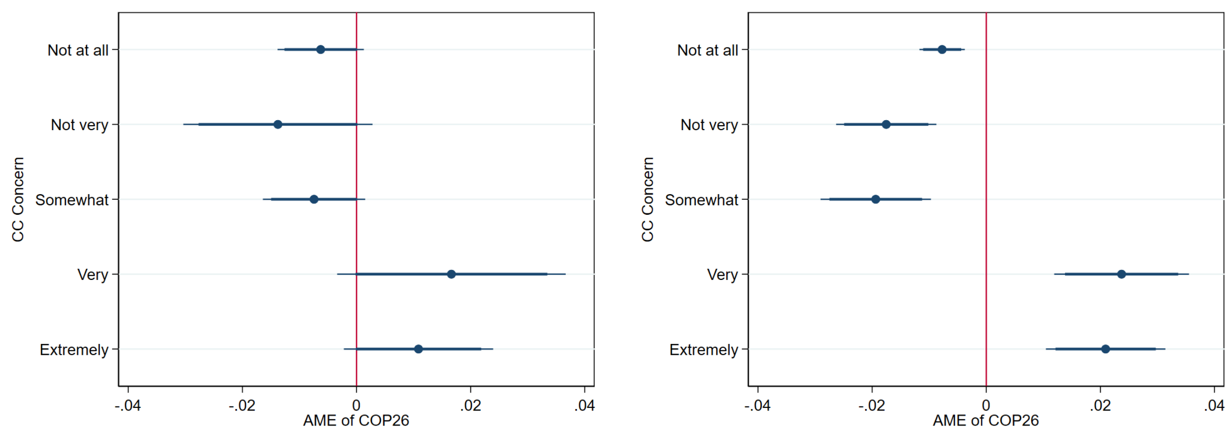
In this section, I restrict the sample to the intersection of countries used in the three analyses (temperature anomalies, COP26 and COP22). The goal is to confirm the contrasting results on ideology - playing a role in the impact of COP26, but not in the impact of anomalies - is not driven by this difference in sample composition.

When using only the 14 countries present across both COP analyses, I find that anomalies bring the probability to report concern up, but the effect is only statistically significant for those on the left, the only group for which the effect is not statistically significant. Results for COP26 are similar to using the full sample available: the likelihood of reporting climate change concern during COP26 is highest among the right and then the center than on the left (statistically significant differences at the 5% and 10% level respectively). The magnitude of the effect of both COP26 and anomalies is very close to those previously reported. Full results are presented in Table A16.

It seems that COP26 showing effect only on individuals on the right is not driven by a ceiling effect, i.e., from the possibly already generalized concern about climate change for left-wing individuals. In fact, resorting to this new subset, those on the left are not affected by COP26 but they still are affected by anomalies, showing there are possible increases in climate concern for respondents who are not right-wing.

4.6.3. Alternative coding of outcome: ordered probit models

In this section I estimate ordered probit models, keeping the original coding of climate change concern as provided by ESS. I report Average Marginal Effects (AME) of the variables of interest on the probability of reporting each of the five levels of concern about climate change. For both temperature anomalies and COP26, individuals are more likely to report being very or extremely concern about climate change; they are instead less likely to report being not at all, not very or only somewwhat concerned. Results on Temperature Anomalies are however not statistically significant under this specification (p-value=0.104).



(a) **Temp. Anomalies** (b) **COP26 (Glasgow, 2021)**

Notes. Source: *ESS*. Thick (thin) lines signify the 90% (95%) confidence interval. Average Marginal Effects from an ordered probit model.

Figure 13: AME of Temperature Anomalies (left-panel) and COP26 (right panel).

4.7. Discussion

I confirm the finding in the literature that exposure to upward temperature anomalies raises climate change concern (Bergquist and Warshaw, 2019, Egan and Mullin, 2012, Hoffmann et al., 2022). A one-standard deviation increase in temperature anomalies is associated with approximately a 0.9 percentage point increase in the probability of being concerned with climate change. At the same time, I also find that warmer temperatures during the interview increase climate concern (as found in Risen and Critcher 2011 and Joireman et al. 2010). The impact of temperature anomalies on climate change concern does not differ based on ideology. The impact of temperature during the interview, however, does, with center and right-wing respondents being less (more) likely to be concerned with climate change if temperatures are lower (higher) than usual.

Whilst "there is an elemental quality to the personal witnessing of such manifestations of natural forces, [...] a direct encounter with contrary or supportive first-hand evidence can initiate powerful rationalising defenses for some, as well as confirmation and validation for others" (Reser et al., 2014, 530-31). Indeed, I find both. It appears respondents, regardless of political orientation, on average are more likely to be concerned about climate change after experiencing temperature anomalies. Moreover, they react to recent anomalies, but only over one month, and, as they accumulate up to one-year, the effect on concern increases. This would mean individuals are correctly updating their beliefs. However, individuals on the center and right appear influenced also by single events, which can be argued is part of a confirmation bias.

I then focus on a global political initiative which was bi-partisan in nature, and did not impact the citizens' lives (and pockets) in the short-run. This should overcome the challenge of separating "events beyond the control of a politician (e.g., a natural disaster)" from "areas where politicians can take action (e.g., the response to a natural disaster)" (Gasper and Reeves, 2011, 340). This sets this paper apart from existing research on contested policy-making (Colantone et al., 2022), contextual disaster management (Bechtel and Hainmueller, 2011), and costly investments (Cohen and Werker, 2008).

I find respondents are 3 percentage points more likely to be concerned about climate change during COP26, but find no similar effect for COP22. This could signal an increased sensitivity of the European public opinion to political and media stimuli on climate change over the years (supported by Figure 2). It could also simply be a result of the magnitude of the media attention, which was much higher during COP26 than during any other COP to that date (see Figure 1a). The findings are in line with the online survey experiment conducted by Bakaki and Bernauer (2017), who find that climate change awareness increased among US-based respondents exposed to slanted news about 2014's COP20, especially among the less engaged. I cannot distinguish the effects of COP26 from those of Fridays for Future, as the events overlap. I do find an even larger increase in reported concern (compared to pre-COP26 weeks) after the Fridays for Future Climate March.

The findings indicate that more right-leaning respondents, on average less worried about climate change and more doubtful about its anthropocentric origin, not only respond to temperature anomalies, but were also the most affected by COP26. They were more likely to express concern and less likely to be skeptic about human-caused climate change. This finding could suggest that global, bi-partisan political initiatives may help convince the skeptical segments of the European population about the urgency of climate change. I gather some evidence that these effects might last up until three weeks before the end of the event.

Nonetheless, individuals on the right did not become more confident that governments would act effectively on the matter of climate change upon experiencing climate anomalies, while those on the center and on the left did. They were also significantly less likely than those on the left to believe in such government action during COP26. This could indicate that such individuals might not support additional government measures, even if they were to change their mind on the seriousness of the climate crisis.

Chapter 5.

A meta-analysis of synergy between carbon pricing and renewable energy policies

Abstract

Microeconomic arguments suggest that combining carbon pricing with renewable-energy policies will bring no additional emissions reduction in the case of cap-and-trade, while in the case of a carbon tax only potentially but at a social cost. Yet, implemented policy in many countries combines carbon pricing with renewable-energy incentives. To go beyond theory and assess the evidence, we systematically collect quantitative estimates of any synergistic effects in emissions reduction between carbon pricing and renewable-energy policies. On average, combining the two instruments leads to 6.5% more emissions reduction. In 50% of cases, the two instruments are found to be more effective in reducing emissions than either one alone. Additional reduction is more common when a carbon tax is in place, as predicted by the theoretical literature. However, additional abatement is also found for cap-and-trade. In 70% of studies, there is either additional emissions reduction or a positive welfare outcome due to combining the two instruments. The deviation of these outcomes from theoretical predictions is due to particular model choices, notably: welfare metrics limited to consumer utility; incomplete emissions coverage by one or both instruments (e.g., some sectors exempted); lagged, intermittent or otherwise constrained policy implementation; or additional market and government failures, such as fossil fuel subsidies, innovation externalities, learning-by-doing, and environmental co-benefits.

Keywords: Instrument interaction, carbon tax, carbon market, cap-and-trade, renewable-energy target

Note: This article is joint work with Jeroen van den Bergh and Ivan Savin and has received a R&R from a top field journal.

5.1. Introduction

Among potential instruments of climate policy, carbon pricing can count on most support from economists[1]. Nonetheless, renewable-energy support is the most frequent policy in practice. As of December 2022, 47 national and 36 subnational jurisdictions have introduced carbon pricing[2]. In comparison, 156 countries have renewable subsidies – feed-in-tarifs/premiums or net metering - or renewable mandates – implemented through targets or tenders -in place.

Worldwide, whenever carbon pricing is in place, it often co-exists with renewable-energy targets or subsidies. This holds true, for example, for many countries in Europe, several states in the USA, Japan and China. However, such overlap defies microeconomic arguments on the expected direction of synergy of instrument combinations, as summarised by, for example, Fankhauser et al. (2010). Theory predicts that combining carbon pricing with renewable-energy policies will bring no additional emissions reduction in the case of cap-and-trade, and only potentially, and at a social cost, in the case of a carbon tax. Under a renewable-energy target, a certain volume of emissions is abated in the energy sector. Yet, this means in the case of emissions trading there is scope for higher emissions elsewhere while staying within the emissions cap, the so-called 'waterbed effect'. Therefore, overall emissions will not go down. Moreover, costs of meeting the cap will be higher whenever the cheapest abatement opportunities are not in the energy sector. In the case of a carbon tax, a renewable-energy target or subsidy might contribute to additional emissions reduction, if the marginal abatement cost of renewable energy is higher than the tax. But in that case, provided the carbon tax is optimal, the marginal cost will be higher than the marginal benefit of abatement, meaning that the extra abatement comes at a net social welfare loss.

The review by van den Bergh et al. (2021) provides a framework to assess and classify synergy in emissions reduction. Such synergy is judged by comparing the effects on emissions of each instrument separately with those of the policy mix. We build on this review in four main ways. First, we expand the classification of synergy, distinguishing additional outcomes. Second, we collect quantitative evidence on instrument synergy and compare it to theoretical expectations. Third, we assess welfare outcomes and their association with synergy. Fourth, through meta-regressions and case-by-case analysis of model assumptions, we identify factors influencing synergy and welfare outcomes.

The remainder of the paper is organized as follows. Section 2 describes the search procedure undertaken to identify papers suitable for meta-regressions. Section 3 explains how we obtain synergy estimates from the selected papers and classify them into categories. Section 4 provides descriptive information about the estimates, such as policy instruments used, model type, category and magnitude of estimates, and welfare effects. Section 5 undertakes regression analysis to assess the factors associated with higher (positive) synergy and welfare outcomes. Section 6 discusses, on a case-by-case basis, the empirical regularities

[1]As an example, the European Association of Environmental and Resource Economists" Statement of 2019 (https://www.eaere.org/statement/), "proposed for endorsement to the whole community of economists in Europe and worldwide" reads: 'Economists encourage the emergence of a global carbon price", as 'carbon price is the most cost-effective lever to reduce carbon emissions'.

[2]REN21 Renewables Global State Report, available at https://www.ren21.net/wp-content/uploads/2019/05/GSR2022_Full_Report.pdf

and modelling assumptions that lead to deviations from theoretical predictions. Section 7 concludes.

5.2. Search and selection of studies

For the literature review, we first undertake a snowball search, starting with the studies collected in the recent review by van den Bergh et al. (2021); we complement this with a systematic search in Web of Science. The first strategy ensures we identify a set of papers directly relevant to the theme, which informs the search terms for the systematic search. The second step is required to ensure completeness, also as new papers might have been published in the meantime, and because the original review did not have the exact same scope as the current one. While the previous review was geared towards papers addressing instrument interactions in general, here we intend to capture all studies that assess or simulate a combination of the two specific instruments (carbon pricing and renewable-energy policies), even if that is not always their main objective. Another reason for a systemic search is that there are numerous ways to denote carbon pricing and renewable-energy instruments. By expanding the terminology in the search process, we can find a wider set of potentially suitable studies.

As a starting point for the snowball search, we took the papers that reported on the combination of carbon pricing and renewable-energy policy in van den Bergh et al. (2021). We skimmed the reference lists of all these papers. Lehmann and Gawel (2013) stood out as it provided 11 references with quantitative estimates of synergy, divided by the type of model employed. We then proceeded with the snowball approach by searching for any papers citing Lehmann and Gawel (2013) or any of the 11 references it provided. Through this strategy we found a total of 23 suitable papers.

Next, we undertook a systematic search in Web of Science. We structured the search terms to return any article in which carbon pricing instruments and renewable-energy instruments are mentioned in the article title or abstract, while terms hinting at empirical or quantitative results and policy combinations or mixes were referred to anywhere in the text. This strategy is similar to Capstick et al. (2015) whose search term considers certain words as a prerequisite in the title while others can be present anywhere in the text. The search term was informed by the findings of the snowball approach[3]. This specific structure of the search terms allows us to identify studies relevant to our aim, while limiting the total number of papers.

To understand our approach, note that we combined four groups of terms, E (identifying carbon pricing instruments), R (identifying renewable-energy instruments), N (identifying quantitative results) and C (identifying combination of instruments). Table D2 in Appendix A lists all the elements of each group E, R, N and C. The search terms comprise all possible combinations of the elements from these groups, named **e, r, n** and **c**. In formal terms, the search procedure can be described as:

In abstract[(**e**) AND (**r**)] AND [Anywhere in the text [(**n**) AND (**c**)]]

[3]For example, papers identified often reported quantitative estimates and looked at a combination of instruments but without explicit mention of these in the abstract.

As an example, the following two combinations are included in our search terms:

In abstract[("ETS") AND ("green certificate")] AND [Anywhere in the text [("numeric") AND ("interaction")]]

In abstract[("carbon tax") AND ("renewable target")] AND [Anywhere in the text [("general equilibrium") AND ("combination")]]

This search uncovered 277 papers, including 18 of the 23 papers obtained through the snowball approach. From the 5 not detected in the Web of Science search, 3 are unpublished papers (Abrell and Weigt 2008, Morris 2009, and Böhringer and Rosendahl 2011). One paper, van den Bergh et al. (2013), by what appears to be a technical error, does not have a searchable full text in Web of Science. The fifth paper, Boeters and Koornneef (2011), uses the unusual expression 'carbon policy' to refer to carbon pricing instruments and thus was not captured by our search.

From the 277 papers found through the Web of Science search, we excluded 228. The exclusion criteria are as follows:

1. 'Different topic' refers to papers which are not about policy instruments. Examples include papers where the ETS acronym stands for something other than Emissions Trading Scheme.

2. 'No simulation of policy instrument scenarios' refers to papers which speak of policy instruments and their interaction, but do not simulate specific scenarios with numeric results. These papers are discursive or use theoretical microeconomic models. While they cannot be included in the meta-analysis, we do consider them in the discussion of Section 5.6..

3. 'Another instrument combination' and 'more than 2 instruments' refers to, respectively, papers which are focused on interaction between policy instruments other than carbon pricing and renewable-energy instruments, and papers on combinations of more than two instruments.

4. 'Insufficient scenarios' means a paper did not cover sufficient policy scenarios with quantitative results, to allow for a conclusion on the synergy between carbon pricing and the renewable-energy instrument.

5. 'Neither emissions nor welfare outcomes' means a paper did not have emissions outcomes nor welfare outcomes. While our primary focus is on emissions, we also keep papers which look at welfare under different instrument combinations even if emissions are exogenously fixed. These are not used for our synergy analysis, but allow to say something about the trade-off between effectiveness and welfare

6. 'Included in another paper' refers to multiple papers reporting the same results with respect to policy synergy[4].

[4]For example, Kalkuhl et al. (2015), extending Kalkuhl et al. (2013), includes additional results on carbon capture and storage but no new results regarding the interaction of interest to us. Verma and Kumar (2013) results had been previously published as conference proceedings in Verma and Kumar (2012) (both versions were identified by Web of Science).

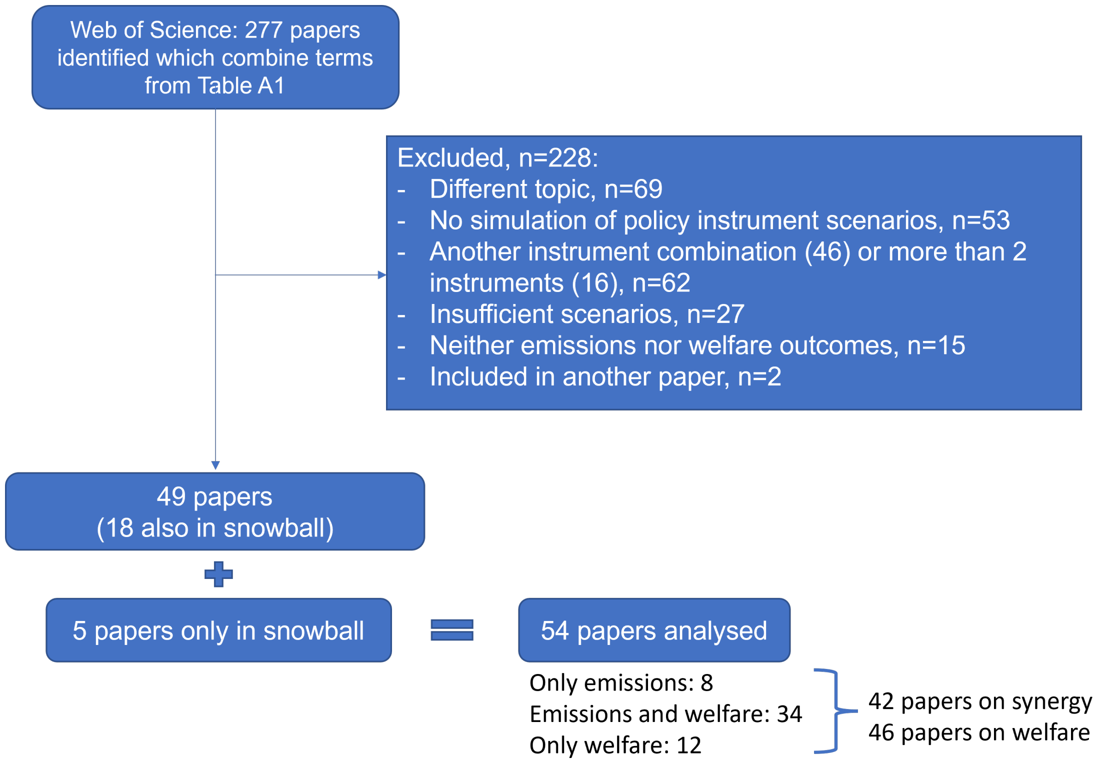


Figure 1: Sample construction

Note that the same paper might provide more than one estimate of the interaction between instruments. This explains why 42 papers generate 55 synergy estimates.[5]

5.3. Synergy estimates

The review by van den Bergh et al. (2021) proposed four categories of synergy: 'positive synergy', 'no synergy', 'negative synergy' and 'backfire'. We suggest two additional categories, as illustrated in Figure 2. The boundary between 'negative synergy' and 'backfire' becomes a category of its own, called 'border of backfire'. This is handy as we will refer a lot to it later. 'Border of backfire' means the combination is redundant. This distinction determines whether there is any advantage in terms of emissions in piling instruments, i.e., any additional abatement. 'Negative synergy' denotes that the combination of instruments

[5]For example, Böhringer et al. (2009) generate three synergy estimates, using three different computable general equilibrium models. Choi and Thomas (2012) provide two estimates of synergy, one where the emission cap is implemented with emission allowances and one without. Fagiani et al. (2014) also provide two estimates of synergy, one where the renewable-energy incentive is a green certificate market and one where it is an feed-in tariff. Liu et al. (2018), De Jonghe et al. (2009) and van den Bergh et al. (2013) provide two estimates of synergy, one with a carbon tax and another with a carbon quota. Liu and Wei (2016) provide two estimates of synergy, one where the emissions trading schemes implemented by two regions are independent and one where they are integrated. Arnette (2017) and Arnette and Zobel (2011) undertake multi-objective linear optimization and generate multiple synergy estimates (3 and 5, respectively) using distinct sets of weights for objectives.

achieves more emissions reduction than either instrument alone but excludes the case of backfire. We divide backfire into 'single backfire' and 'double backfire': the first denotes that the combination of instruments reduces emissions less than the most, but more than the least, effective instrument; the second indicates that the combination of instruments reduces emissions even less than the least effective instrument.

To assess the exact synergy between two instruments, four scenarios are needed: no instrument, one instrument only (instrument 1 with abatement A), the other instrument only (instrument 2 with abatement B), and the two together (combination of instruments 1 and 2 with abatement effect A&B).

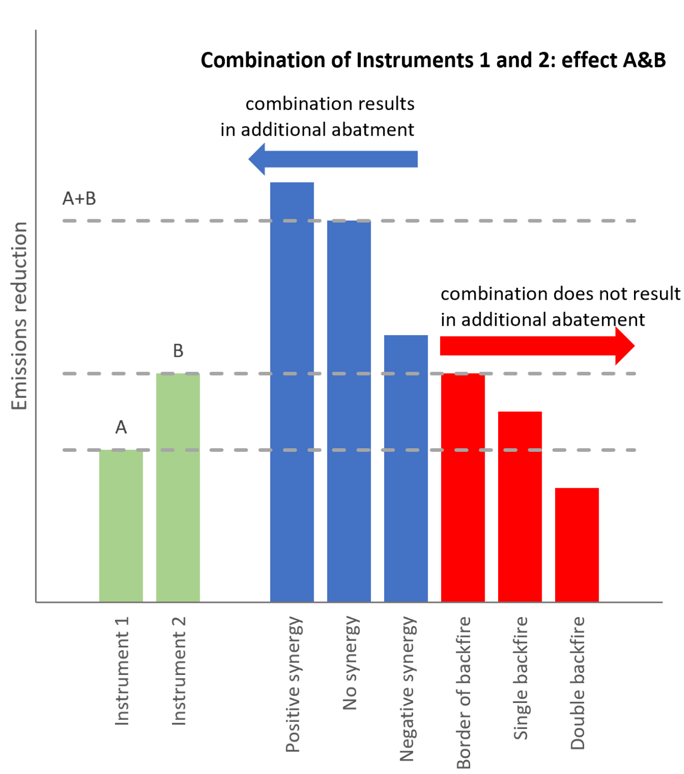


Figure 2: Synergy categories

We have found only 31 estimates that are based on simulations covering all four scenarios. We decided to keep 24 additional estimates coming from simulations with only three scenarios - no instrument, one instrument, and their combination. Of these, 19 involve simulation of a carbon pricing instrument alone, but not of the renewable-energy instrument alone (Table 1).

Table 1: Number of estimates by the number of scenarios simulated

Scenarios	**No. of estimates**
all four scenarios	31
missing 'renewable-energy instrument alone'	19
missing 'carbon pricing instrument alone'	5
Total	55

If one scenario is missing, we cannot categorize the synergy with certainty and must instead provide a range. To aid deriving insights from studies with only three scenarios, we classify papers where one scenario with one of the instruments alone is missing into three types:

- Type I: The combination of instruments 1 and 2 has the same effect as instrument 1 (A& B equals A);
- Type II: The combination of instruments 1 and 2 has a larger effect than instrument 1 (A&B is larger than A);
- Type III (not found in our sample): The combination of instruments 1 and 2 has a smaller effect than instrument 1 (A&B is smaller than A).

We now determine, using Figure 3, the range of synergy effects for papers of Type I and of Type II by varying the (unknown) effect B. We start in Figure 3a, where B ¿ A&B for papers of Type II, and reduce B step by step, until we reach Figure 3f. We highlight the changes in the synergy categories in bold.

The range of possible synergy effects for Type I results is limited, from backfire (cases 3a, 3b and 3c) to border of backfire (cases 3d, 3e and 3f). The range of possible synergy for Type II results, instead, is broader, namely from single backfire (cases 3a) until positive synergy (case 3f). In all cases, studies of Type II have better synergy outcomes. We will also make use of the distinction between Type I and Type II in the descriptive results and statistical analysis in subsequent sections.

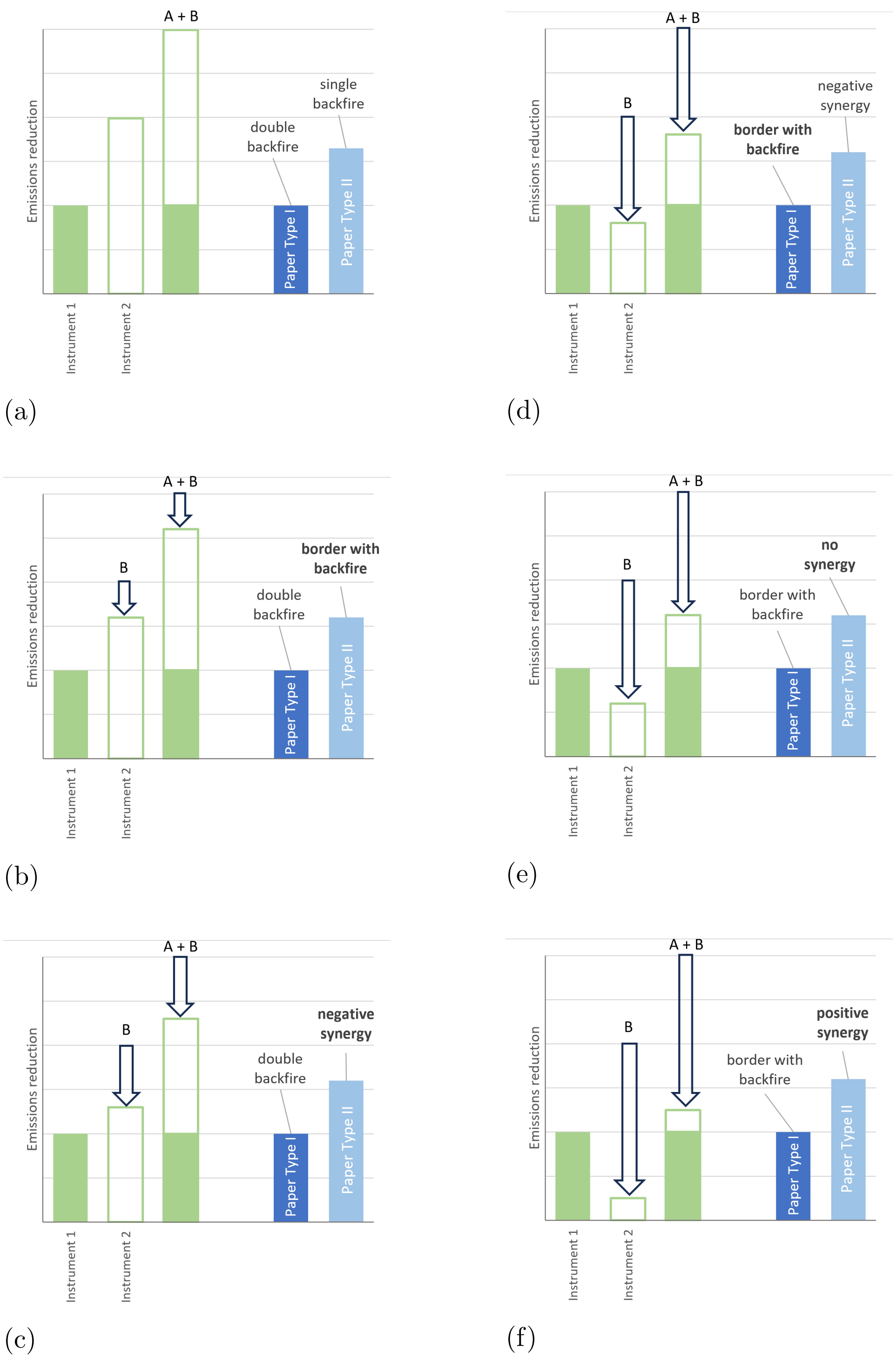


Figure 3: Possible synergy categories when instrument 2 is missing (in bold when there is an improvement in the synergy category)

5.4. Descriptive results

5.4.1. Policy instruments

The estimates we collect cover four instruments - carbon caps, carbon taxes, renewable-energy targets (RET) and renewable-energy subsidies (RES). The term 'carbon cap' encompasses mandated ceilings on emissions without tradable certificates and carbon markets. The RETs are likewise either mandated and modelled as constraints in a model, or represented by a Green Tradable Certificates market. Most estimates (33/53) come from models with carbon caps instead of carbon taxes. RETs are more common than RES (34 vs. 19). Table 2 provides more details on the instrument combination.

Table 2: Type of instrument interaction

Type of Interaction	**No. of estimates**	
Carbon cap	33	
of which, with RES		11
of which, with RET		22
Carbon tax	20	
of which, with RES		8
of which, with RET		12
generic carbon price*	2	
Total	55	

*Estimates come from models with an exogenously set carbon price.

5.4.2. Model type

All models considered in the review represent ex-ante assessments, as opposed to empirical ex-post studies of synergy. The synergy estimates thus come from model simulations and not from observational or experimental data. However, models use empirical data (to different extents) to calibrate model parameters.

Most estimates derive from partial equilibrium models (17), followed by models optimizing the power sector (16) and general equilibrium (GE) models (16). The first consider endogenous demand when maximizing profits for the energy sector, while the second fix demand and minimize the cost of energy provision.

Partial equilibrium models can be classified by the level of detail of the energy engineering system compared to that of the economic system. Out of 17 estimates, 7 come from 'energy system models', several of which are based on the MARKAL framework. The remaining models have a stylized energy dispatch system, but higher economic complexity. Some consider energy providers to have market power (instead of assuming perfecting competition), others include innovation, investment, environmental externalities other than

CO2-related or a social planner.

One paper, Rezai and van der Ploeg (2017), uses an integrated assessment model (IAM). Two papers (three estimates) use agent-based modelling (ABM) - Fagiani et al. (2014) and Richstein et al. (2015). Two papers use the 3EME modelling framework (Mercure et al. 2014 and Knobloch et al. 2019), a self-designated macro-econometric approach. These use structural equations with econometrically estimated parameters, and do not impose equilibrium conditions.

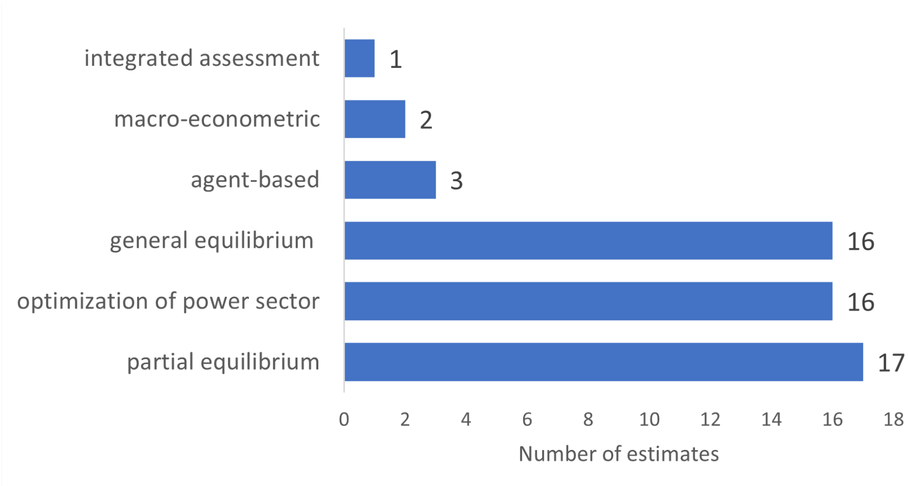


Figure 4: Types of model used

5.4.3. Estimates of synergy

As explained in Section 5.3., we know with certainty the synergy from 31 estimates. Of these, 16 estimates indicate that the combination of instruments results in additional abatement. In one of these, the synergy is positive, but, in all the remaining cases, it is negative.

For the 24 estimates for which the synergy is not known with certainty we provide a range, following the approach of section 5.3.. We find 12 estimates of Type I – where the combination of instruments achieves no additional abatement, with the possible synergy ranging from double backfire to border of backfire. The remaining 12 are of Type II and the combination of instruments might deliver additional abatement, with possible outcomes ranging from single backfire to positive synergy.

These results do not indicate striking differences between papers with four and three scenarios (compare Tables 3 and 4). In the latter group, we know 12/24 do not result in additional abatement (papers of Type I). If we assume that for most papers of Type II the combination of instruments contributes some additional emissions reduction - arguably a realistic assumption[6] -, we would end up with similar shares of papers with an emissions

[6] As shown in Figure **??**, in 4 out of 6 cases, papers of Type II are better than 'border of backfire'. Moreover, the two cases where they are not - 3a and 3b - require the missing instrument to provide substantially more abatement than the instrument analysed. The instrument most often missing is the renewable-energy one (in 9 out of the 12 Type II estimates), which, accordingly to the literature, is highly unlikely to provide substantially more abatement than carbon pricing on its own.

reduction in terms of piling instruments.

Table 3: Synergy category when four scenarios are present

Synergy category	No. of estimates
backfire	1
border of backfire	14
negative, no border of backfire	15
positive	1
Total	**31**

Table 4: Synergy range when three scenarios are present

Synergy range	No. of estimates
at best border of backfire (Type I)	12
at best positive synergy (Type II)	12
Total	**24**

We express additional abatement as the increase (or decrease) in emissions reduction when implementing both instruments versus implementing only the most effective one. This means in the 'border of backfire' case – 14 out of 31 estimates - additional abatement is 0. In the single backfire case, emissions reduction is -3.2%. In the single positive synergy case, additional abatement is between 4% and 10%. Of those with negative synergy, the additional emissions reduction is on average 13.8%, with a maximum increase of 38.5% (and a median of 10.7%). If we take the average of all estimates, the additional reduction in emissions is 6.5%.

5.4.4. Welfare benefits from instrument combination

We now look at whether there are any positive effects of implementing two instruments as opposed to only one, apart from the emission impact. Studies in which emissions are exogenously fixed were omitted from the analysis on emission synergy, but are included here if they present welfare outcomes.

The definition of 'welfare' varies widely across papers. Some papers, for example, exclusively look at generation costs of the energy system or at producer surplus, while others consider GDP, or focus only on consumers. A total of 32 estimates provide information on consumer-focused metrics, namely, Hicksian equivalent variation , consumer surplus, discounted consumption and lower retail electricity prices. For 33 out of the 58 estimates we find some advantage in terms of welfare when implementing both instruments instead of only one (see Table 5).

Table 5: Welfare effects of two instruments versus only one

Welfare effects	**No. of estimates**
Negative	22
Zero	3
Positive	33
Total	58

5.5. Regression analysis

Next we undertake a meta-regression of theoretical models, similar to Patuelli et al. (2005). We construct binary variables, as done in the meta-regression by Anderson (2020). We run several logistic and Tobit regressions to identify factors explaining positive results of a policy interaction, in terms of abatement or welfare. For abatement, we consider two binary independent variables: carbon tax, i.e., taking a value of 1 if the carbon pricing instrument is a tax (and 0 if it is a market), and GE model, taking value 1 if the model is a general equilibrium model and 0 otherwise. We consider carbon tax as a variable of interest, given the literature predicts additional abatement for taxes but not markets. We choose to look at GE models separately since the 'waterbed effect' would require considering also markets other than energy.

If we consider only estimates from papers with four scenarios, we find through a logistic regression that GE models are associated with lower probability of additional abatement. We do not find any significant effect regarding carbon taxation (see Table D3 in Appendix B). To increase statistical power, we combine the synergy estimates from models with four and three scenarios, and use two different specifications: an ordered logistic model and a Tobit model. We also include an indicator variable signalling whenever estimates come from models with four scenarios. Using the terminology of Section 5.3., for papers with three scenarios, we know that those of Type I have a zero probability of additional abatement. Papers of Type II, instead have a probability of additional abatement of 16/31 (as shown in Table 3). We thus can treat our variable on the probability of additional abatement as a continuous variable, bounded between 0 and 1, and resort to Tobit regressions.

The combination of instruments is more likely to bring additional abatement with a carbon tax rather than with a cap. However, this result is only significant in the Tobit model when the variable 'four scenarios' is omitted, and only at the 10% level. In the ordered logistic models in Appendix, described in Tables D4 and D5, the variable is also only significant at the 10% level, regardless of whether we consider the number of scenarios simulated. We find that GE models are less likely to find additional abatement from the instrument combination, regardless of the specification.

Regarding welfare impacts, through a logistic regression, we find that models where the welfare function explicitly considers environmental damages are 50% more likely to find positive welfare outcomes. The association between consumer-focused welfare metrics and positive welfare effects is not statistically significant. Likewise, we do not find any evidence of a trade-off between emission synergy and welfare effects - the association between positive

Table 6: Tobit of the probability of additional abatement from an instrument combination

	Probability of additional abatement	
Carbon tax	0.377*	0.364
	(0.223)	(0.230)
GE model	−0.531**	−0.501*
	(0.257)	(0.291)
Four scenarios		0.055
		(0.257)
Constant	0.110	0.078
	(0.172)	(0.228)
Observations	53	53

welfare outcomes and non-redundant emission outcomes is not significant (and positive).

Table 7: Average marginal effects of logistic regression of positive welfare outcomes

	Positive welfare outcomes	
Positive probability of additional abatement	0.0707	
	(0.143)	
Consumer metric	0.1808	0.1809
	(0.1383)	(0.1432)
Damages	0.5017***	0.5031***
	(0.0727)	(0.0728)
Carbon tax	0.1812	0.1957
	(0.1383)	(0.1322)
GE model	0.1646	0.1331
	(0.1969)	(0.1862)
Four scenarios	-0.2120	-0.2330
	(0.1806)	(0.1732)
Observations	45	58

5.6. Discussion

5.6.1. Additional emissions reduction

We find that papers with a carbon tax, as opposed to a carbon cap, are more likely to find additional abatement from the instrument combination. Nonetheless, this association is only weakly significant (at the 10% level). Furthermore, some papers go against what the theory predicts and find additional emissions reduction even with cap-and-trade. In our sample, this is a result of either: i) partial coverage of policies or ii) intermittent, lagged, or otherwise constrained climate policy. We expand on these two cases below.

In the case of partial coverage, one of the policy instruments does not cover all regions or sectors. In Fais et al. (2015) and Weigt et al. (2013), the FIT only covers Germany, while the cap is the EU-ETS. Weigt et al. (2013) not only find additional emissions reduction, but actually positive synergy. Liu and Wei (2016) find that when a China ETS and a EU-ETS are set up independently – each only covers one of the regions-, renewable-energy policy results in additional emissions reduction.

In terms of constrained carbon pricing , Lecuyer and Quirion (2013,2019) find that intermittent or non-dynamic carbon pricing implies combining it with a renewable-energy subsidy results in additional abatement. Intermittent carbon pricing means that in certain periods carbon pricing might be suspended. Non-dynamic carbon pricing, instead, reflects that the carbon price might not be easily adjusted upwards . Political constraints can lead to both situations. Shahnazari et al. (2017) similarly argue that RET leads to a reduction of political uncertainty compared to a carbon tax. Under the RET, a signal is sent to the market which makes investment into renewable-energy less risky. Through a real options model, they conclude abatement will be less costly for private investors under the instrument combination than with either instrument alone. They refer to Australia as a case study, where a carbon tax was implemented, and a posteriori removed.

Yi et al. (2019) present a case for China where carbon pricing only has meaningful effects after several years. This is because carbon pricing triggers the construction of nuclear energy infrastructure which takes considerably more time to build than renewable alternatives. They estimate that due to learning by doing and lock-in effects, the combination of the policies leads to higher abatement in the short-run.

5.6.2. Welfare effects

Whenever the welfare function explicitly includes environmental damages - in 6 estimates - we find a positive welfare effect from the instrument combination. Clancy and Moschini (2018) find, under a carbon tax, additional abatement from the combination and simultaneously higher welfare. They include innovation externalities and co-benefits (pollution reduction). Silva et al. (2021), with the same instrument types, finds additional abatement from the combination, and higher welfare.

Even though this association is not statistically significant, measures which focus on consumers more often find gains in our sample. All papers which consider as the only outcome retail electricity prices find lower prices under the combination than with carbon pricing alone. Often, using the renewable-energy instrument alone reduces consumer costs (Jensen and Skytte (2003) expand on the issue). However, in several instances, the existence of emissions trading makes the introduction of renewable energy more beneficial to consumers as well (see Linares et al. (2008) for a stylized example based on the Spanish electricity market).

Other papers find lower financial costs for consumers namely, Fagiani et al. (2014), who report it alongside additional abatement, and Huang et al. (2013). Kalkuhl et al. (2013) also find benefits in terms of retail electricity prices from the policy combination. Knobloch et al. (2019) find additional emissions reduction and, simultaneously, a reduction in consumer costs. One of the three computable general equilibrium estimates provided in Böhringer et al. (2009) reports slightly higher welfare as measured by Hicksian equivalent variation (with a carbon cap) due to 'prior distortions in the energy market', specifically, fossil fuel subsidies. Bauer et al. (2012), also focusing on consumption, find higher welfare of the combination of instruments when carbon pricing policy lags. This is explained through a learning by doing externality[7].

Including environmental damages or focusing on consumers are not a necessary condition for welfare gains, however. Rausch and Reilly (2015) find GDP gains from the instrument combination, alongside emissions reduction. This is explained by avoiding adjustment costs of energy capacity expansion. Similarly, Rezai and van der Ploeg (2017), focusing on a carbon tax, obtain higher GDP from the instrument combination due to learning by doing in renewable-energy technologies alongside emissions reduction[8].

Fischer et al. (2017) and Hirth and Ueckerdt (2013) find that the combination leads to higher consumer surplus, but much lower producer surplus, than carbon pricing alone. Whether the policy mix is advisable, given carbon pricing is first-best in terms of total surplus, depends on whether redistribution – in the previous cases, from producers to consumers - is feasible. A flagrant example of possibly limited redistribution is Liu and Wei (2016), who find that the combination brings higher consumer welfare for both the EU and China under the instrument combination but only higher total welfare in China. Implementing carbon pricing is first-best in terms of allocative efficiency, yet, it would require transfers across borders. Several papers such as Kalkuhl et al. (2013) and Kalkuhl et al. (2015) analyse the policy mix from this second-best perspective, admitting that a global carbon tax is infeasible due to limits to social transfers between countries.

5.7. Conclusions

We have collected quantitative results from the literature on the synergy effects in emissions reduction from a combination of carbon pricing and renewable-energy policies. All estimates come from ex-ante assessments. Indeed, ex-post studies cannot easily estimate a synergy effect. Doing so would require a region to have alternated carbon pricing and renewable-energy policy, before finally overlapping the two.

In about 50% of cases, the two instruments are more effective in reducing emissions than either one alone. There is scope for additional emissions reduction, albeit admittedly small:

[7] The model keeps emissions fixed.

[8] Likely reduction, simulations has three scenarios and is of Type II

we find that combining a carbon pricing and a renewable-energy instrument on average leads to 6.5% more emissions reduction than using only the most effective instrument. Among cases with additional abatement, we find the mean (median) additional abatement is 13.8% (10.7%).

An important finding from this review is the lack of complete information in many papers. Typically, model simulations omit a scenario with only a renewable-energy instrument. We collect 24 additional estimates from studies which omit one scenario. We cannot classify the synergy with absolute certainty, but are able to provide range. We find similar results, with about 50% of estimates likely reflecting additional abatement.

Additional abatement, according to theoretical arguments, should not be found if a carbon cap (as opposed to a tax) is in place. We find such an association, but it is only weakly statistically significant. Some studies do find additional abatement, due to either: i) partial coverage of policies or ii) intermittent, lagged, or otherwise constrained carbon pricing. The partial coverage of carbon pricing will endure while policy is not coordinated at the global scale. Even at the national level, due to political constraints, carbon pricing might become intermittent – in certain periods applied, in other periods removed. Its adoption might lag, i.e., be substantially slower than the more popular renewable-energy policies. It might also lose its stringency due to changing market conditions, which, if the instrument is not fully dynamic, can require new lengthy political negotiations. Under these conditions, adding renewable-energy policy gives a stable price signal and locks in investments, triggering earlier the construction of energy infrastructure which will not be a posteriori disposed of. This can bring increases in total welfare by providing an "assured" minimum level of abatement. It is largely a matter of political economy if it is feasible to reduce these long-standing constraints and thus improve carbon pricing, or if, instead, combining the two instruments is the best workable option.

Regarding welfare, we find gains in 57% of cases. Whenever co-benefits are considered, there is a welfare gain from the instrument combination. Measures focused on the consumer, such as Hicksian equivalent variation, consumption, and, particularly, retail electricity prices, also often find advantages in combining the instruments, yet this association is not statistically significant in the meta-regressions. Some studies find gains in GDP, alongside additional abatement, thanks to learning by doing in renewable-energy technologies and lower adjustment costs in the energy system. In these cases, similarly to the co-benefits case, there is a market failure which renewable-energy policy tackles. Innovation externalities might be better targeted by R&D subsidies (Fischer et al. 2017). We do not find evidence of a trade-off between additional abatement and welfare gains. In 70% of studies, there is either additional emissions reduction or a positive welfare outcome due to combining the two instruments.

Regarding limitations of our study, some remarks are in order. Firstly, a meta-regression, compared to primary studies, can achieve considerable statistical power by combining statistical estimates. In our case, the estimates are deterministic (conditional on the assumptions of the models). It is important to clarify what is the interpretation of the meta-regressions: the papers collected should be seen as a sample of the population of all ex-ante assessments of synergy which could be constructed. Our meta-regressions thus allow us to make inferences about ex-ante assessments of synergy in general. The direction of a possible sample selection bias is unknown. It is not clear which results are more likely to be published: those confirming, or those deviating, from a theoretical base case. Furthermore, to extrapolate from ex-ante assessments to reality, we must examine, for any given situation, which assumptions are likely to hold and to what extent. Our review, in fact, reveals that specific modelling assumptions - for example, in terms of externalities considered or emissions coverage by a policy instrument - might co-determine the type of synergy.

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Appendix A

Chapter 2 appendix

A1. Details on environmental variables

A1.1. Climate data

The E-OBS gridded datasets (Cornes et al. 2018) on temperature, radiation and precipitation, are the starting point for the climate data generated.

Temperature Bins

For yearly measures of the full temperature distribution, we focus on bins of temperature, i.e., the number of days in a year where the minimum (TN variable in E-OBS), mean (TG variable in E-OBS) and maximum (TX variable in E-OBS) temperature fall in one of the sixteen 2.5°C temperature intervals: ¡-5, -5 to -2.5, -2.5 to 0, 0 to 2.5, 2.5 to 5, 5 to 7.5, 7.5 to 10, 10 to 12.5, 12.5 to 15, 15 to 17.5, 17.5 to 20, 20 to 22.5, 22.5 to 25, 25 to 27.5, 27.5 to 30 and ≥ 30, computed at the grid cell level. The use of temperature bins allows flexibility in considering the non-linear impacts of temperature on health and other variables of interest. We then assign the grid cells to the SHARE regions by employing a shapefile of the SHARE regions and geospatial routines from R packages sf and raster. We constructed a shapefile of the SHARE regions by resorting to EUROSTAT NUTS shapefiles (downloadable from EUROSTAT) and to a shapefile of Luxembourg cantons (downloadable from data.public.lu). Once the bins are computed at grid cell level and georeferenced to a SHARE region, we aggregate them into two regional measures: median and mean. We also calculate the standard deviation between the cells of a SHARE region, given that, especially for larger regions, spatial variability might be substantial. Accordingly, the variable names end with ‘_median’, ‘_mean’ or ‘_std’.

Average (seasonal) temperature

We calculate the average annual temperature and the average seasonal temperatures – spring, summer, fall and winter - in the SHARE region where the respondent lived in a certain year. These are calculated for each grid cell as the average of the mean temperature (TG variable in E-OBS) in all days of the year, or in the days pertaining to each season (December, January and February were allocated to winter; March, April and May to spring;

June, July and August to summer; and September, October and November to fall). These grid cells values are aggregated to the SHARE region through both the median and the mean.

Heating and Cooling Degree days

Following the EUROSTAT definitions[1], at each grid cell we calculate the number of heating degree days (HDD) and cooling degree days (CDD) using the average temperature from the E-OBS dataset (TG variable). Thus, for HDD, we sum over a year, for each grid cell, the differences between 18ºC and the recorded mean daily temperatures, for every day when the temperature in that grid cell was equal or below 15ºC (average temperature coming from TG variable of E-OBS). For CDD, the process is analogous, except we sum the differences between the recorded mean daily temperature and 21ºC, only for those days where the mean temperature was above 24ºC. Each grid cell thus has, for each year, an HDD and a CDD index. These are aggregated to the SHARE regions through both the median and the mean, as with the remaining variables.

Radiation

The 0.1° gridded E-OBS dataset provides data on daily radiation starting in 1950 through variable QQ. For each grid cell, we calculate for any given year, the average of the radiation over all the days in that year, or in the days pertaining to each season. These grid cell values are aggregated to the SHARE region through both the median and the mean.

Precipitation

For precipitation we likewise provide yearly variables and cumulative variables calculated from them, starting from the E-OBS dataset, resorting to daily near-surface precipitation (E-OBS variable RR). At each grid cell, we calculate the number of days in each year where the sum of precipitation exceeds 10 mm and 20 mm - heavy and very heavy precipitation days-, as defined in the Agroclimatic indicators datasets part of the C3S Global Agriculture Sectoral Information Systems (SIS). As with temperature variables, these are georeferenced to SHARE regions, and aggregated using the median and mean, alongside the standard deviation to analyze intra-region variation.

A1.2. Pollution data

The variables considered for pollution relate to the four most explored pollutants in the context of health: particulate matter 2.5 microns (in diameter) ($PM_{2.5}$), particulate matter 10 microns (PM_{10}), ozone (O_3) and nitrogen dioxide (NO_2) (as put forward in the WHO Review of evidence on health aspects of air pollutionS1).

[1]https://ec.europa.eu/eurostat/cache/metadata/en/nrg_chdd_esms.htm)

Concentration

For $PM_{2.5}$, PM_{10} and NO_2, there is limited evidence for the existence of a threshold below which health effects are negligible. Negative health outcomes have been found at very low concentrations (WHO 2014). We therefore resort to yearly average exposures, starting from the dataset CAMS global reanalysis (EAC4) on monthly averaged fields whose first year is 2003.

The original CAMS EAC4 monthly dataset resolution is 0.75° X 0.75°. We disaggregate the dataset into 0.1° X 0.1° through bilinear interpolation, and, at the grid cell level, take the average of the 12 months of each year. As done with the temperature dataset, each grid cell is associated with the SHARE region when its centroid falls within the region boundary, and the three variables, mean, median and standard deviation, are then constructed.

For O3, the literature documents mixed evidence on the existence of thresholds. Several papers find an association between health outcomes and summer ozone concentration, but not winter season concentration; a finding attributed to the existence of a threshold by some studies or due to confounding effects or seasonal behavioral differencesS2. Other studies that specifically analyze the threshold question arrive to different conclusions (e.g., evidence of thresholds is found in some studiesS3 but not in othersS4). We follow the recent literature on long-term effects of ozone exposure and operate with yearly averages of daily maxima and warm-season averages of daily maximaS5, S6, S7. The dataset used is CAMS EAC4 (Inness et al. 2019), from which we use the average O3 concentration at 3-hour intervals of each day at the surface level, whose first year is 2004. For each day, we keep the maximum of the 6 observations reported, at the grid cell level (after disaggregating the spatial resolution from the gridded 0.75° to 0.1° as mentioned above). We then take either the yearly average or the warm months average (April to September) of the daily maxima, for each grid cell. The grid cells are overlapped with the SHARE regions, as with the temperature datasets, and we calculate the mean, median, and standard deviation at the SHARE region level.

Emissions

The datasets on pollution concentration mentioned begin in 2003 (or in 2004 for O_3), thus, enabling coverage for the regular SHARE waves (which start in 2004), but not for the cumulative exposure. To allow us to go further back in time we use a dataset not on pollution concentration, but on pollutant emissions, the EDGAR v5.0 Global Air Pollutant Emissions dataset, which covers the period 1970-201513. The relevant variable for direct health effects is concentration, thus, the health impacts of emissions will be different across regions, depending, namely, on meteorological conditions and topography. Even so, especially given that emissions are the variables which can be affected policy-wise, considering their (indirect) effects on other variables can be of interest. The variables obtained from EDGAR are estimates of yearly emissions of $PM_{2.5}$ and PM_{10} at the grid cell level which we overlap with SHARE regions to obtain the yearly mean, median and standard deviation at the region level. Information on concentration could also be derived from the EDGAR dataset if combined with advanced chemical transport models (CTMs). The original dataset is available a 0.1° X 0.1° resolution.

A1.3. Flood events data

For floods, we resort to the DFO dataset (Brakenridge 2021), which provides information on flood events from 1985 until the present. We report 6 variables: the number of flood events, the number of casualties, the number of displaced individuals, a weighted number of flood events (weighted by an indicator 1, 1.5 or 2, representing the severity of the flood event), the total days during which there were floods events, and the weighted total days (weighted by an indicator 1, 1.5 or 2 representing the severity of the flood event).

The variables correspond to whether the individual was living in a region considered in the dataset to be affected by the flood event (more specifically, if the region where the individual was living overlaps with the region provided as 'affected' in the DFO dataset). Since depending on the country, individuals might report a NUTS2 or NUTS1 region, other 12 variables are created. The first 6 refer to whether the NUTS1 region where the individual resided was affected by flood events and the latter 6 to whether the NUTS2 region where the individual resided was affected by flood events.

A1.4. Regional aggregation and population weighting

We identify households' location through the SHARE 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 waves. The latter is reported in the housing modules of the regular panel waves. We use information from the housing modules on whether individuals changed house to expand forward regional information.

SHARE regions are mostly NUTS2 (Austria, Bulgaria, Croatia, Czechia, Denmark, Finland, Greece, Hungary except for Budapest and Pest, which are reported together as the NUTS1 region of Central Hungary, Italy, Latvia, Lithuania, Poland, Portugal, Romania, Slovakia, Slovenia, Spain and Sweden) with a few countries reporting NUTS1 only (Belgium, France, Germany and one region of Hungary, Central Hungary).

Whenever individuals lived in a country different to that in which they were now sampled, we do not know in which region they lived, but only the country. Country-level information is considered too aggregate to provide useful environmental exposure measures. Thus, for periods where respondents were outside the country, we do not have any environmental information. Cumulative exposure variables, therefore, do not consider such years. Averages which explicitly consider this fact can be calculated by dividing cumulative exposures by the number of years for which there is information (which excludes the years when individuals were abroad). We provide the variables necessary for users to build said averages.

From gridded raw datasets, we generate transformed variables at the grid cell level, as explained in the previous sections. We finally aggregate them to the SHARE regions: we detect in which SHARE region the grid cells are located by overlaying them with a shapefile of the SHARE regions, constructed resorting to EUROSTAT NUTS shapefiles (downloadable from EUROSTAT) and to a shapefile of Luxembourg cantons (downloadable from data.public.lu, see SI for more details on the NUTS classifications used.) For climate and pollution variables we provide unweighted variables and population-weighted variables. For population-weighted variables, we resort to the historical gridded population dataset from ISIMIP , which provides annual population estimates for 1901-2020. Weighting is done at the moment of regional aggregation.

A second version of the dataset, currently undergoing further robustness checks, explores more granular geographical data. Resorting to the Degree of Urbanization DEGURBA methodology (the EU/OECD standard for urbanization classification), we classify each grid cell within a SHARE region as being either part of a city, of towns and suburbs, or of a rural area. We compute for each SHARE region-DEGURBA region pair population-weighted exposure variables. With estimated country-specific weights, we transform these into averages for the five regions indicated by SHARE respondents - big cities, suburbs, large towns, small towns and rural areas.

A1.5. Cumulative variables

The SHARE dataset is a panel dataset. Environmental hazards might have a cumulative impact on health. Situations which took place at a young age might also only later transpire into health consequences. We therefore construct cumulative variables of exposure to environmental hazards, reflecting not the exposure to for instance extreme temperatures in the year of a wave, but instead exposure since an individual was born until the wave in question, amongst other cumulative indicators.

If a variable has no prefix, it refers to the exposure to the environmental hazard in the year of the wave. Prefixes starting with 's' correspond to a rolling sum of exposure, with the simple 's_' corresponding to the rolling sum of exposure from birth (or from the oldest year available) up until the year of the wave in question.

The prefixes starting with 'y' are simple sums instead of rolling sums; they correspond to total exposure during certain, relevant, years. For early age exposure, 'y5_', 'y10_' and 'y15_' correspond to total exposure during the first 5, 10 and 15 years of age. 'yjob_' corresponds to exposure during the years at current job or at the most recent job. We also generate variables for exposure to environment in the years preceding periods of ill health during adulthood. Respondents indicate up to 3 periods where they experienced ill health, specifying the start and end (more details in Appendix 2). For individuals indicating illness periods, we construct variables with prefix 'yill1_', 'yill2_' and 'yill3_' denoting exposure during the years of illness periods 1,2 and 3 respectively. We construct variables with prefix 'y1bf_', 'y3bf_' and 'y5bf_' to represent exposure to hazards during the 1 year, the 3 years and the 5 years preceding the start of each illness period.

We generate cumulative variables since birth for 6 of the 16 temperature bins, on the low extremes and on the high extremes, i.e., for temperatures below 5ºC, between -5ºC and -2.5 ºC and between -2.5 ºC and 0 ºC; and for temperatures between 25 ºC and 27.5 ºC, between 27.5 ºC and 30 ºC, and above 30 ºC. Other bins can be made available on request. On the temperature variables, we report cumulative exposure since birth for CDD and HDD. Cumulative variables since birth are also available for precipitation. We report cumulative variables for flood variables as well.

As auxiliary variables, we report the rolling sum of the number of years for which cumulative measures were computed. We choose to provide both cumulative exposures and years for which cumulative exposure is available, instead of only averages, since even for the same variable, the information for the same number of years for all individuals is not available. This is for two reasons: i) individuals who were born before the years where the environmental variables start and ii) periods in which individuals were outside their country of interview. By providing both cumulative and years available, averages can be readily computed through their ratio, if averages are the variables of interest, and simultaneously, subsets of the sample based on the number of years available (e.g., necessarily all years since birth) can be analyzed separately.

We report as well average spring, summer, fall, winter, and yearly temperatures and average radiation, since birth and during the first 5, 10 and 15 years of life. For these, we directly provide these averages alongside the rolling sum of the number of years, instead of cumulative exposure as we do for the remaining (count) variables.

The cumulative variables are created using the yearly variables; therefore, their names are the same, but with added prefixes which indicate over what period are the cumulative measures taken.

Table A1: Environmental variables list

Variable name	Variable description
Temperature Variables	
Bins	
[tn/tg/tx]_neg5_[median/mean/w][none/_t1bf/_t2bf] (3*2*3 vars)	No. days [min/avg/max] temp. below -5^{o}C ([median/mean/population weighted mean] grid cells) at [year wave/year before/2years before]
[tn/tg/tx]_neg5_neg2p5_[median/mean/w][none/_t1bf/_t2bf] (3*2*3 vars)	No. days [min/avg/max] temp. bt -5 and -2.5^{o}C ([median/mean/population weighted mean] grid cells) at [year wave/year before/2years before]
[tn/tg/tx]_neg2p5_0_[median/mean/w][none/_t1bf/_t2bf] (3*2*3 vars)	No. days [min/avg/max] temp. bt -2.5 and 0^{o}C ([median/mean/population weighted mean] grid cells) at [year wave/year before/2years before]
[tn/tg/tx]_0_2p5_[median/mean/w][none/_t1bf/_t2bf] (3*2*3 vars)	No. days [min/avg/max] temp. bt 0 and 2.5^{o}C ([median/mean/population weighted mean] grid cells) at [year wave/year before/2years before]
[tn/tg/tx]_2p5_5_[median/mean/w][none/_t1bf/_t2bf] (3*2*3 vars)	No. days [min/avg/max] temp. bt 2.5 and 5^{o}C ([median/mean/population weighted mean] grid cells) at [year wave/year before/2years before]
[tn/tg/tx]_5_7p5_[median/mean/w][none/_t1bf/_t2bf] (3*2*3 vars)	No. days [min/avg/max] temp. bt 5 and 7.5^{o}C ([median/mean/population weighted mean] grid cells) at [year wave/year before/2years before]
[tn/tg/tx]_7p5_10_[median/mean/w][none/_t1bf/_t2bf] (3*2*3 vars)	No. days [min/avg/max] temp. bt 7.5 and 10^{o}C ([median/mean/population weighted mean] grid cells) at [year wave/year before/2years before]
[tn/tg/tx]_10_12p5_[median/mean/w][none/_t1bf/_t2bf] (3*2*3 vars)	No. days [min/avg/max] temp. bt 10 and 12.5^{o}C ([median/mean/population weighted mean] grid cells) at [year wave/year before/2years before]
[tn/tg/tx]_12p5_15_[median/mean/w][none/_t1bf/_t2bf] (3*2*3 vars)	No. days [min/avg/max] temp. bt 12.5 and 15^{o}C ([median/mean/population weighted mean] grid cells) at [year wave/year before/2years before]
[tn/tg/tx]_15_17p5_[median/mean/w][none/_t1bf/_t2bf] (3*2*3 vars)	No. days [min/avg/max] temp. bt 15 and 17.5^{o}C ([median/mean/population weighted mean] grid cells) at [year wave/year before/2years before]
[tn/tg/tx]_17p5_20_[median/mean/w][none/_t1bf/_t2bf] (3*2*3 vars)	No. days [min/avg/max] temp. bt 17.5 and 20^{o}C ([median/mean/population weighted mean] grid cells) at [year wave/year before/2years before]
[tn/tg/tx]_20_22p5_[median/mean/w][none/_t1bf/_t2bf] (3*2*3 vars)	No. days [min/avg/max] temp. bt 20 and 22.5^{o}C ([median/mean/population weighted mean] grid cells) at [year wave/year before/2years before]
[tn/tg/tx]_22p5_25_[median/mean/w][none/_t1bf/_t2bf] (3*2*3 vars)	No. days [min/avg/max] temp. bt 22.5 and 25^{o}C ([median/mean/population weighted mean] grid cells) at [year wave/year before/2years before]
[tn/tg/tx]_25_27p5_[median/mean/w][none/_t1bf/_t2bf] (3*2*3 vars)	No. days [min/avg/max] temp. bt 25 and 27.5^{o}C ([median/mean/population weighted mean] grid cells) at [year wave/year before/2years before]
[tn/tg/tx]_27p5_30_[median/mean/w][none/_t1bf/_t2bf] (3*2*3 vars)	No. days [min/avg/max] temp. bt 27.5 and 30^{o}C ([median/mean/population weighted mean] grid cells) at [year wave/year before/2years before]
[tn/tg/tx]_g30_[median/mean/w][none/_t1bf/_t2bf] (3*2*3 vars)	No. days [min/avg/max] temp. above 30^{o}C ([median/mean/population weighted mean] grid cells) at [year wave/year before/2years before]
Average temperatures	
temperature_[median/mean/w][none/_t1bf/_t2bf] (2*3 vars)	Avg. daily mean temperature ([median/mean/population weighted mean] grid cells) at [year wave/year before/2years before]
summer_[median/mean/w][none/_t1bf/_t2bf] (2*3 vars)	Avg. summer daily mean temperature ([median/mean/population weighted mean]] grid cells) at [year wave/year before/2years before]
spring_[median/mean/w][none/_t1bf/_t2bf] (2*3 vars)	Avg. spring daily mean temperature ([median/mean/population weighted mean] grid cells) at [year wave/year before/2years before]
fall_[median/mean/w][none/_t1bf/_t2bf] (2*3 vars)	Avg. fall daily mean temperature ([median/mean/population weighted mean] grid cells) at [year wave/year before/2years before]
winter_[median/mean/w][none/_t1bf/_t2bf] (2*3 vars)	Avg. winter daily mean temperature ([median/mean/population weighted mean] grid cells) at [year wave/year before/2years before]
CDD/HDD	
CDD_[median/mean/w][none/_t1bf/_t2bf] (2*3 vars)	EUROSTAT Cooling degree days index ([median/mean/population weighted mean] grid cells) at [year wave/year before/2years before]
HDD_[median/mean/w][none/_t1bf/_t2bf] (2*3 vars)	EUROSTAT Heating degree days index ([median/mean/population weighted mean] grid cells) at [year wave/year before/2years before]
Radiation Variables	
radiation_[median/mean/w][none/_t1bf/_t2bf] (2*3 vars)	Average daily radiation ([median/mean/population weighted mean] grid cells) at [year wave/year before/2years before]
radiation_spring_[median/mean/w][none/_t1bf/_t2bf] (2*3 vars)	Average daily radiation in spring months ([median/mean/population weighted mean] grid cells) at [year wave/year before/2years before]
radiation_summer_[median/mean/w][none/_t1bf/_t2bf] (2*3 vars)	Average daily radiation in summer months ([median/mean/population weighted mean] grid cells) at [year wave/year before/2years before]
radiation_fall_[median/mean/w][none/_t1bf/_t2bf] (2*3 vars)	Average daily radiation in fall months ([median/mean/population weighted mean] grid cells) at [year wave/year before/2years before]
radiation_winter_[median/mean/w]_[t0/t_1bf/t_2bf] (2*3 vars)	Average daily radiation in winter months ([median/mean/population weighted mean] grid cells) at [year wave/year before/2years before]

Precipitation Variables	
prec10_[median/mean/w][none/_t1bf/_t2bf]	No. days total precipitation above 10mm ([median/mean/population weighted mean] grid cells)
(2*3 vars)	at [year wave/year before/2years before]
prec20_[median/mean/w][none/_t1bf/_t2bf]	No. days total precipitation above 20mm ([median/mean/population weighted mean] grid cells)
(2*3 vars)	at [year wave/year before/2years before]

Flood Variables	
fl_no_floods_[SHARE/NUTS1/NUTS2] [none/_t1bf/_t2bf]	No. flood events in SHARE region / NUTS1 region / NUTS2 region
(3*3 vars)	at [year wave/year before/2years before]
fl_tot_dead_[SHARE/NUTS1/NUTS2] [none/_t1bf/_t2bf]	No. casualties of flood events in SHARE region / NUTS1 region / NUTS2 region
(3*3 vars)	at [year wave/year before/2years before]
fl_tot_displaced_[SHARE/NUTS1/NUTS2] [none/_t1bf/_t2bf]	No. displaced by flood events in SHARE region / NUTS1 region / NUTS2 region
(3*3 vars)	at [year wave/year before/2years before]
fl_weighted_floods_[SHARE/NUTS1/NUTS2] [none/_t1bf/_t2bf]	Weighted No. of flood events in SHARE region / NUTS1 region / NUTS2 region
(3*3 vars)	at [year wave/year before/2years before]
fl_tot_days_[SHARE/NUTS1/NUTS2] [none/_t1bf/_t2bf]	No. days of flood events in SHARE region / NUTS1 region / NUTS2 region
(3*3 vars)	at [year wave/year before/2years before]
fl_weighted_[days_SHARE/NUTS1/NUTS2] [none/_t1bf/_t2bf]	Weighted No. days of flood events in SHARE region / NUTS1 region / NUTS2 region
(3*3 vars)	at [year wave/year before/2years before]

Pollution vars	
Concentration	
conc_pm2p5_[median/mean/w][none/_t1bf/_t2bf]	Avg monthly concentration $PM_{2.5}$ ([median/mean/population weighted mean] grid cells)
(2*3 vars)	at [year wave/year before/2years before]
conc_pm10_[median/mean/w][none/_t1bf/_t2bf]	Avg monthly concentration PM_{10} ([median/mean/population weighted mean] grid cells)
(2*3 vars)	at [year wave/year before/2years before]
conc_no2_[median/mean/w][none/_t1bf/_t2bf]	Avg monthly concentration NO_2 ([median/mean/population weighted mean] grid cells)
(2*3 vars)	at [year wave/year before/2years before]
conc_yearly_o3_[median/mean/w][none/_t1bf/_t2bf]	Avg daily max O_3 concentration ([median/mean/population weighted mean] grid cells)
(2*3 vars)	at [year wave/year before/2years before]
conc_warm_o3_[median/mean/w][none/_t1bf/_t2bf]	Avg daily max O_3 concentration in warm months ([median/mean/population weighted mean] grid cells)
(2*3 vars)	at [year wave/year before/2years before]
Emissions	
emissions_pm2p5_[median/mean/w][none/_t1bf/_t2bf]	Yearly emissions of $PM_{2.5}$ ([median/mean/population weighted mean] grid cells)
(2*3 vars)	at [year wave/year before/2years before]
emissions_pm10_[median/mean/w][none/_t1bf/_t2bf]	Yearly emissions of PM_{10} ([median/mean/population weighted mean] grid cells)
(2*3 vars)	at [year wave/year before/2years before]

Table A2: Cumulative environmental variables list

Cumulative variable prefix	Prefix meaning	Yearly Variables for which the cumulative measure is calculated	Module
s_	Rolling sum since birth (or earliest available year) until present wave	Bin variables (1920), HDD (1920), CDD (1920), Precipitation Variables (1920), Flood Variables (1985)	life$_{m}odule$
avg	Rolling average since birth (or earliest available year) until present wave	Average temperature variables (1920), Radiation Variables (1950), Concentration Variables (2003/2004), Emissions Variables (1970)	life$_{m}odule$
y5$_{/}y10_{/}y_{1}5$	Cumulative exposure during the first 5/10/15 years of life	Bin variables, HDD, CDD, Precipitation Variables[2]	young$_{a}ge_{m}odule$
avg5$_{/}avg10_{/}avg15$	Average during the first 5/10/15 years of life	Average temperatures variables, Radiation Variables, (no concentration variables), Emission Variables	young$_{a}ge_{m}odule$
yjob	Cumulative exposure during the most recent job	Bin variables, HDD, CDD, Precipitation Variables, (no flood variables)	job$_{m}odule$
avgjob	Average exposure during the most recent job	Average temperature variables (1920), Radiation Variables (1950), Concentration Variables (2003/2004), Emissions Variables (1970),	job$_{m}odule$
yill[1/2/3]	Cumulative exposure during illness period 1/2/3	Bin variables, HDD, CDD, Precipitation Variables, Flood variables	illness$_{d}uring_{m}odule$
avgill[1/2/3]	Average exposure during illness period [1/2/3]	Average temperature variables (1920), Radiation Variables (1950), Concentration Variables (2003/2004), Emissions Variables (1970)	illness$_{d}uring_{m}odule$
y[1/3/5]bf$_{[}$1/2/3]	Cumulative exposure during the [1/3/5] year(s) preceding illness period [1/2/3]	Bin variables, HDD, CDD, Precipitation Variables, Flood variables	illness$_{b}efore_{m}odule$
avg[1/3/5]bf$_{[}$1/2/3]	Average exposure during the [1/3/5] year(s) preceding illness period [1/2/3]	Average temperature variables (1920), Radiation Variables (1950), Concentration Variables (2003/2004), Emissions Variables (1970)	illness $_{b}efore_{m}odule$

Auxiliary variables (denominator for averages)			
rol_years_exposure [*temp/prec/rad/* fl[SHARE/NUTS1/ NUTS2]/ conc_noto3/conc_o3/emissions]	Rolling sum of non-empty years of [temperature/ / precipitation/radiation / floods pertaining to [SHARE region /NUTS1 region/NUTS2 region] / non-O_3 concentration/ O_3 concentration/emissions] variables	All variables	life_module
tot_years_exposure_[temp/prec/ rad/fl[SHARE/ NUTS1/NUTS2]/conc_noto3/conc_o3/emissions]	Maximum of rol_years_exposure_[temp/prec/ rad/fl[SHARE/ NUTS1/NUTS2]/conc_noto3/conc_o3/emissions]	All variables	life_module
years_present_[temp/prec/rad/emissions] _outof[5/10/15]	Years for which there is information on [temperature /precipitation/radiation/emissions] variables out of the first [5/10/15] years of life	All variables except flood and concentration variables [a]	young_age_module
job_years_exposure [*temp/prec/rad/emissions/* con_noto3/conc_o3]	Years in which individual was at most recent job for which there is information on [temperature /precipitation /radiation/emissions/ non-ozone concentration/ozone concentration] variables	All variables except flood variables [b]	job_module
Ill_years_exp_dur[1/2/3] [*temp/prec/rad/emissions/fl[SHARE/NUTS1/NUTS2]/* NUTS2 level]/conc_noto3/conc_o3/emissions]	Years for which during period of illness [1/2/3] there is info on [temperature/precipitation/radiation/emissions/floods at [SHARE level/NUTS1 level/ non-ozone concentration/ozone concentration/emissions] variables	All variables	illness_during_module
ill_y_exp_[1/3/5]_bf_[1/2/3] [*temp/prec/rad/emissions/fl[SHARE/NUTS1/NUTS2]/* conc_noto3/conc_o3/emissions]	Years for which there is info. out of the [1/3/5] years before illness period [1/2/3] on [temperature/precipitation/radiation/floods at [SHARE level/ NUTS1 level /NUTS2 level]/not-ozone concentration/ozone concentration/emissions] variables	All variables	illness_during_module

[a] do not go back in time sufficiently to catch the first 15 years of life of respondents
[b] flood events during years at most recent job not considered a variable of interest

A2. Details on illness variables

Table A3: Generated morbidity variables

Variable	Variable Description
ill_length_[1/2/3]	Length of illness period 1/2/3
ill_age_onset_[1/2/3	Age of onset of illness period 1/2/3
ill_start_[1/2/3]	Year when illness period 1/2/3 started
ill_end_[1/2/3]	Year when illness period 1/2/3 ended
ill_any_issue[1/2/3]	Any issue in period 1/2/3
Ill_any_env_related_issue[1/2/3]	Any environment-related issue in period 1/2/3
[environment-related illness name][1/2/3]	Whether it was [angina or heart attack/ stroke/asthma/other respiratory problems/ migraines/emotional distress/fatigue/ infectious diseases/allergies] (one of) the issue(s) responsible for illness period 1/2/3

Notes: Environment-related issues are angina or heart attack, stroke, asthma, (other) respiratory problems, migraines, emotional distress, fatigue, infectious diseases and allergies. These variables are provided as part of the 'illness_before_module' and 'illness_during_module'. Respondents report on only up to three periods of illness, coded as 1/2/3 respectively.

Table A4: Extensive regression results of Table 2

Bothered by breathlessness		Young age health		Uncomfortable job		High cognitive decline	
Avg. $PM_{2.5}$ concentration	0.0019***	Avg. first 15 years exposure to	0.0002	Avg. winter temp.	0.00748***	Δ Avg. $PM_{2.5}$ conc.	0.00374***
(µg/m3)	(0.0007)	temp. ≤ 0 (# days)	(0.0004)		(0.00131)		(0.000747)
Avg. lifetime exposure to	0.0000	Avg. first 15 years exposure to	0.0028*	Avg. summer temp.	-0.00268***	Δ HDD	-7.11e-06***
temp. ≤ 0 (# days)	(0.0001)	temp. ≥ 30°C (days)	(0.0015)		(0.000989)		(5.31e-07)
Avg. lifetime exposure to	-0.0004*	Avg. first 15 years solar	0.0022	Avg. solar radiation (W/m2)	0.000148	Depression score (lagged)	0.00953***
temp. ≥ 30°C (# days)	(0.0002)	radiation (W/m2)	(0.0013)		(0.0004)		(0.00107)
Born with an illness	0.1291***	Rooms/people at 10 years old	0.0333*	Job is physical ×	-0.0118***	Δ depression score	0.0107***
	(0.0276)		(0.0201)	Avg. winter temp.	(0.00156)		(0.00102)
Job is uncomfortable [disagree]	0.0188***	Mother ISCED educ. level	0.0154	Job is physical ×	0.00831***	Cognitive score (lagged)	0.0177***
	(0.0047)		(0.0094)	Avg. summer temp.	(0.00136)		(0.000601)
Job is uncomfortable [agree]	0.0392***	Father ISCED educ. level	0.0171**	Job is physical ×	0.00135***	Health status: 2 (lagged)	-0.000424
	(0.0057)		(0.0083)	Avg. solar radiation	(0.0003)		(0.00598)
Job is uncomfortable [strongly agree]	0.0623***	House at 15 years had	-0.1192***	Job is physical	-0.00143	Health status: 3 (lagged)	0.00854
	(0.0072)	no basic amenities	(0.0277)		(0.0302)		(0.00577)
Total household income	-0.0000***	% of time in urban area	-0.0091	Total household income	-3.72e-07***	Health status: 4 (lagged)	0.0212***
	(0.0000)		(0.0217)		(1.11e-07)		(0.00657)
Current age	0.0048***	Year of birth	0.0105***	ISCO codes (1digit)	Y	Health status: 5 (lagged)	0.0512***
	(0.0002)		(0.0011)				(0.00934)
Ever smoked	0.0391***	Parental ISCO codes	Y	ISCED educ. level 2	-0.0145	ISCED educ. level 2	-0.0346***
	(0.0039)		Y		(0.00895)		(0.00623)
BMI	0.0097***	Physical harm in childhood	-0.1019***	ISCED educ. level 3	-0.0435***	ISCED educ. level 3	-0.0633***
	(0.0005)		(0.0163)		(0.00839)		(0.00573)
Sports [once a week]	0.0001	Ever lonely in childhood	-0.2809***	ISCED educ. level 4	-0.0622***	ISCED educ. level 4	-0.0620***
	(0.0057)		(0.0205)		(0.0124)		(0.0112)
Sports [one to three times a month]	0.0097	Ever poor in childhood	-0.1648***	ISCED educ. level 5	-0.0802***	ISCED educ. level 5	-0.0938***
	(0.0062)		(0.0210)		(0.00922)		(0.00620)
	(0.00620)						
Sports [hardly ever, or never]	0.0802***	Born with an illness	-0.6605***	ISCED educ. level 6	-0.121***	ISCED educ. level 6	-0.123***
	(0.0048)		(0.0906)		(0.0207)		(0.0150)
						Age (lagged)	0.00633***
							(0.000209)
						Female	-0.0314***
							(0.00359)
						Ever moved	-0.0129***
							(0.00393)
Urbanization level Fixed Effects	N		N		N		Y
Country Fixed Effects	Y		Y		Y		Y
Observations	33,482		16,040		43,717		40,050
R-squared	0.080		0.081		0.205		0.064

Table A5: Effect of temperature exposure on old age health at first wave of participation (younger age) and at last wave of participation (older age)

	Old age (≥50) perceived reported health (1=poor; 5= excellent)	
	First wave of participation	Last wave of participation
Exposure		
Avg. exposure to temp. ≥ 27.5°C (# days)	-0.0005	-0.0018***
	(0.0005)	(0.0005)
Avg. exposure to temp. ≤ 0°C (# days)	-0.0008***	-0.0002
	(0.0003)	(0.0002)
Occupation and educational effects		
ISCED educ. level 2	0.0809***	0.0582***
	(0.0160)	(0.0154)
ISCED educ. level 3	0.2071***	0.1382***
	(0.0149)	(0.0141)
ISCED educ. level 4	0.3274***	0.1689***
	(0.0296)	(0.0255)
ISCED educ. level 5	0.3992***	0.2493***
	(0.0164)	(0.0159)
ISCED educ. level 6	0.3911***	0.2897***
	(0.0515)	(0.0468)
Job is uncomfortable [disagree]	-0.1036***	-0.0903***
	(0.0116)	(0.0110)
Job is uncomfortable [agree]	-0.1887***	-0.1707***
	(0.0136)	(0.0130)
Job is uncomfortable [strongly agree]	-0.2310***	-0.2284***
	(0.0170)	(0.0162)
Total household income	0.0000***	0.0000***
	(0.0000)	(0.0000)
Household net worth	0.0000***	0.0000***
	(0.0000)	(0.0000)
Behavioural effects		
Ever smoked daily	-0.0788***	-0.0651***
	(0.0094)	(0.0090)
Body mass index	-0.0304***	-0.0285***
	(0.0011)	(0.0010)
Sports [once a week]	-0.1365***	-0.0667***
	(0.0135)	(0.0157)
Sports [one to three times a month]	-0.1729***	-0.0884***
	(0.0155)	(0.0168)
Sports [hardly ever, or never]	-0.4852***	-0.3778***
	(0.0113)	(0.0126)
Year of birth	0.0152***	0.0206***
	(0.0005)	(0.0005)
Female	-0.0049	0.0561***
	(0.0097)	(0.0094)
Depression score	-0.4179***	-0.4476***
	(0.0098)	(0.0118)
Country Fixed Effects	Y	Y
Year Fixed Effects	Y	Y
Observations	41,133	45,123
R-squared	0.272	0.223

Table A6: Effect of $PM_{2.5}$ concentration on cognitive decline, fixed effects regression

	Difference in cognitive score
avg. $PM_{2.5}$ conc. median (µg/m3)	-0.0067***
	(0.0011)
Heating degree days	-0.0000
	(0.0000)
Age	0.0010
	(0.0008)
Depression score	-0.0077***
	(0.0011)
Total household income	0.0000
	(0.0000)
Sports [once a week]	-0.0030
	(0.0049)
Sports [one to three times a month]	0.0025
	(0.0060)
Sports [hardly ever, or never]	-0.0108**
	(0.0044)
Individual Fixed Effects	Y
Observations	98,861
R-squared	0.005

A3. Extended regression results

A4. Summary statistics

Table A7: Summary statistics of variables in Table A4

VARIABLES	N	mean	s.d.	min	max
Young age health					
Young age ($\leq$ 15) perceived health (1=poor; 5= excellent)	90,103	3.853	1.035	1	5
Avg. first 15 years solar radiation (W/m2)	59,602	136.9	24.14	58.52	222.2
Avg. first 15 years exposure to temperature $\geq$ 30°C (# days)	71,230	10.87	15.79	0	86.07
Avg. first 15 years exposure to temperature $\leq$ 0°C (# days)	71,230	87.87	45.77	0	237.4
Loneliness in childhood	61,212	0.203	0.402	0	1
Physical harm in childhood	56,245	0.401	0.49	0	1
Ever poor in childhood	59,183	0.309	0.462	0	1
House at 15 years had no basic amenities	89,747	0.321	0.467	0	1
Rooms / people when 10 years old	88,139	0.714	0.441	0	16.67
Born with an illness	90,103	0.0104	0.101	0	1
Father ISCED educ. level	41,006	2.371	1.331	1	6
Mother ISCED educ. level	40,414	1.965	1.096	1	6
% of time in urban area	69,825	0.183	0.373	0	1
Parental ISCO codes (1digit)	90,103	6.748	3.107	1	11
Year of Birth	90,078	1,947	10.54	1910	1995
Ever experienced breathlessness					
Ever experienced breathlessness	84,171	0.165	0.371	0	1
Avg. $PM_{2.5}$ conc. median (µg/m3)	108,460	15.93	4.825	3.059	36.87
Avg. lifetime exposure to temperature $\geq$ 30°C (# days)	108,464	14.4	16.93	0	115
Avg. lifetime exposure to temperature $\leq$ 0°C (# days)	108,464	79.48	43.83	0	227.1
Household Income (average)	139,010	25,384	41,728	0	5.04E+06
Born with an illness	206,725	0.00993	0.0991	0	1
BMI (Body Mass Index, average)	136,226	27.66	4.885	12.4	99.09
Current Age	124,812	68.82	11.07	22	111
Job is uncomfortable	77,373	2.253	0.987	1	4
Frequency of exercise	119,412	3.023	1.247	1	4
Ever smoked	118,381	0.461	0.498	0	1
Uncomfortable job					
Uncomfortable job	57,617	0.393	0.489	0	1
Average radiation	66,337	135.1	24.53	40.37	223.5
Average summer temperature	66,451	16.41	3.746	-5.867	33.74
Average winter temperature	66,451	4.67	3.716	-12.7	25.77
Physical job	57,657	0.582	0.493	0	1
Household Income (average)	139,010	25,384	41,728	0	5.04E+06
Cognitive decline					
High cognitive decline	144,107	0.162	0.368	0	1
Difference avg. $PM_{2.5}$ (µg/m3)	134,644	3.135	2.389	0.255	23.52
Difference in average summer temperature	133,376	2,608	985.8	21.5	6,489
Lagged cognitive score	216,992	8.913	3.696	0	20
Age (lagged)	206,047	66.77	10.18	15	106
ISCED education level	206,473	2.873	1.418	1	6
Lagged health status	203,727	1.823	1.086	0	4
Lagged depression score	209,283	2.435	2.267	0	12
Diff. in depression score	122,660	0.018	2.135	-12	12
Gender	523,291	0.529	0.499	0	1
Type of area	216,109	3.441	1.443	1	5
Ever moved region	296,090	0.277	0.448	0	1

Table A8: Summary statistics of variables in Table A5

VARIABLES	N	mean	s.d.	min	max
Constant across all observations					
Gender	81,806	1.554	0.497	0	1
Year of birth	81,806	1,946	10.28	1,902	1,980
Job is uncomfortable	55,468	2.177	0.977	1	4
First observation					
Old age (>49) perceived reported health (1=poor; 5= excellent)	81,806	2.885	1.092	1	5
Avg. lifetime exposure to negative temperature (# days)	63,929	74.65	42.75	0	228
Avg. lifetime exposure to temperature >27.5°C (# days)	63,929	28.79	26.73	0	147
Ever smoked	80,652	0.455	0.498	0	1
Sports frequency	81,590	2.533	1.335	1	4
BMI (current)	78,946	26.89	4.592	12.76	86.59
Depression score (EUROD)	80,780	0.398	0.49	0	1
Household Income (current)	81,806	34,360	50,546	0	3.71E+06
Household Net worth	81,806	261,255	533,757	-718,856	3.63E+07
Last observation					
Old age (>49) perceived reported health (1=poor; 5= excellent)	81,806	2.687	1.069	1	5
Avg. lifetime exposure to negative temperature (# days)	67,454	75.13	42.71	0	227.1
Avg. lifetime exposure to temperature >27.5°C (# days)	67,454	28.65	26.59	0	147
Ever smoked	81,093	0.454	0.498	0	1
Sports frequency	38,609	2.832	1.311	1	4
BMI (current)	78,683	26.88	4.664	12.46	74.05
Depression score (EUROD)	36,901	0.397	0.489	0	1
Household Income (current)	81,806	15,027	69,562	0	1.00E+07
Household Net worth	81,806	124,386	325,012	-7.24E+06	1.50E+07

Table A9: Summary statistics of variables in Table A6

VARIABLES	N	mean	s.d.	min	max
Sports frequency	98,861	2.683	1.323	1	4
Household income	98,861	30,845	67,542	0	1.00E+07
Depression score (EUROD)	98,861	2.371	2.244	0	12
Age	98,861	68.26	9.774	26	103
Diff. in cognitive score (annualized)	98,861	0.0435	0.3	-1	7.5
Cumulative HDD	98,861	169,268	95,738	0	599,069
Avg. $PM_{2.5}$ conc. median (µg/m3)	98,861	14.38	5.334	0	36.87

Appendix B

Chapter 3 appendix

B1. 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 1). We overlay these datasets with shapefiles of the SHARE regions, as exemplified for Veneto in Figure 1. Resorting to a 50+ population gridded dataset from ISIMIP[1], 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 A1 shows us this intermediate result.

[1]ISIMIP Population, available at: https://data.isimip.org/datasets/fc1e4a06-bd4a-4044-b8e6-46ce86346489/

Figure 1: Aggregation and weighting procedure: illustration for August 2011 CDDs and the Veneto region

(a) EU-wide CDDs (b) Close-up on Veneto

(c) Population (d) Urbanization

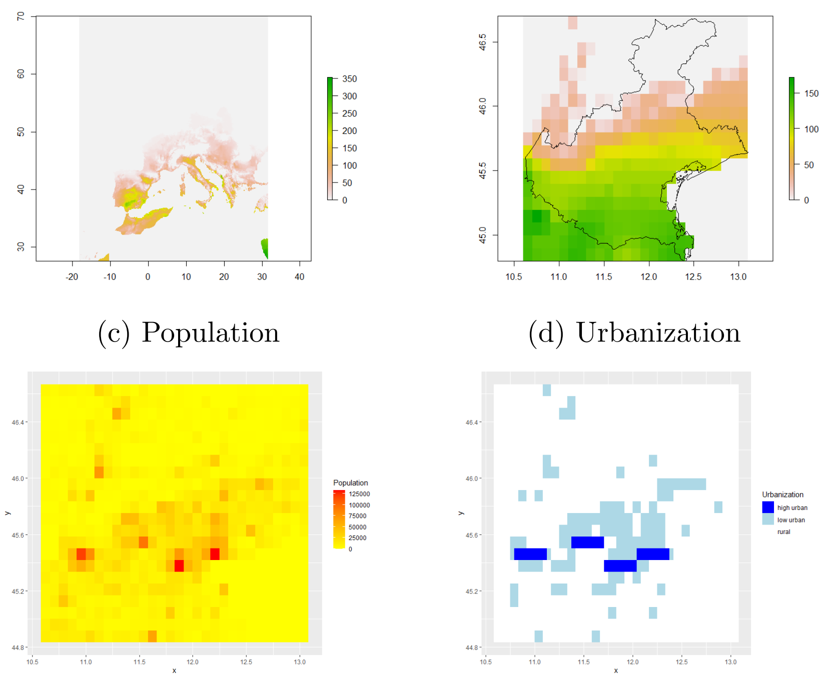


Table A1: Example: CDDs by urbanization level in the Veneto region by DEGURBA aggregates

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 A2: 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 waves[2]. The latter is reported in the housing modules of the regular panel waves.

B2. Summary statistics

Table A3: 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

[2]The 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

B3. Effects of heat

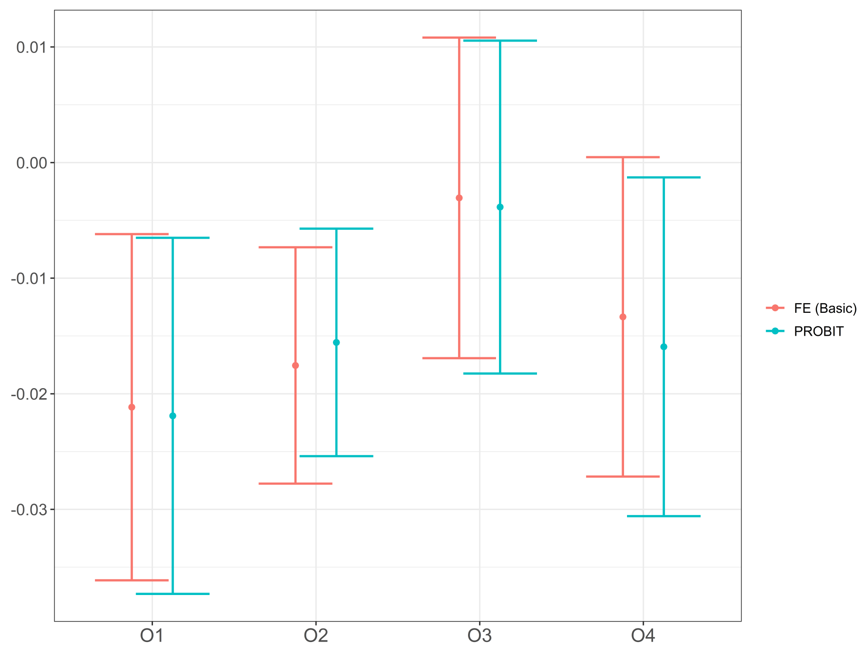


Figure 2: Basic model versus pooled Mundlak probit: Moderating effect of AC on the marginal effect of CDD. O1=Fatigue (No=0, Yes=100); O2=Reduced appetite (No=0, Yes=100). O3=Irritability (No=0, Yes=100); O4=Trouble sleeping (No=0, Yes=100).

Table A4: 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*	0.0044	0.0234**	0.0201**	0.0135**	0.0121**	-0.0012	-0.0025
	(0.0029)	(0.00336)	(0.0025)	(0.0026)	(0.0027)	(0.0031)	(0.0027)	(0.0034)
HDD	-0.0006	-0.0001	0.0061sym**	0.0057**	0.0011*	0.0013*	0.0001	0.0006
	(0.0005)	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0005)	(0.0006)
age	-4.8102**	0.7293**	-1.8302**	0.9800**	-0.7162*	0.1926*	-1.2125**	0.2916**
	(0.3780)	(0.0844)	(0.2931)	(0.0616)	(0.3537)	(0.0798)	(0.3528019)	(0.0857)
age^2	0.0422199**		0.0217183**		0.0069868**		0.0116577**	
	(0.0027615)		(0.0021346)		(0.0025837)		(0.0025768)	
wealth	0.0597877	-0.0025757**	-0.0006876	-0.0008653**	0.0990702*	-0.0003277	-0.0242473	-0.0015449**
	(0.0550522)	(0.0003081)	(0.0483337)	(0.0002042)	(0.0515326)	(0.0002250)	(0.0514077)	(0.0003268)
income	-0.0410071	-0.0008656	-0.8995074**	-0.0083741*	0.5442820	0.0060954	0.4770039	0.0055547
	(0.4133201)	(0.0057299)	(0.3348839)	(0.0034945)	(0.3869281)	(0.0047345)	(0.3859781)	(0.0050569)
owner	-2.5495050**	-0.0204705*	-0.8987541	-0.0066461	-1.2970389*	-0.0113989	-2.4044475**	-0.0218882*
	(0.7623268)	(0.0088946)	(0.6554716)	(0.0067980)	(0.7130690)	(0.0084616)	(0.7109875)	(0.0089424)
GDP pc	-0.0002410**	-0.0000024*	-0.0005641**	-0.0000046**	-0.0003033**	-0.0000036**	-0.0002207**	-0.0000028**
	(0.0000904)	(0.0000011)	(0.0000754)	(0.0000008)	(0.0000846)	(0.0000010)	(0.0000844)	(0.0000011)
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, age^2 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. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

B4. Selection into AC

Table A5: AC Ownership

	AC			
$\overline{CDD_i}$	0.000620***	0.000662***	4.24e-05	8.48e-05
	(3.67e-05)	(3.71e-05)	(0.000160)	(0.000160)
$\overline{CDD_r}$			0.000582***	0.000581***
			(0.000155)	(0.000155)
age	-0.000330*	-0.000341*	-0.000328*	-0.000338*
	(0.000193)	(0.000193)	(0.000193)	(0.000193)
owner	0.00719*	0.00747*	0.00706*	0.00734*
	(0.00387)	(0.00387)	(0.00387)	(0.00387)
income	0.0186***	0.0185***	0.0185***	0.0185***
	(0.00660)	(0.00654)	(0.00656)	(0.00651)
education	0.0554***	0.0544***	0.0556***	0.0546***
	(0.00454)	(0.00453)	(0.00454)	(0.00453)
household size	0.00188	0.00201	0.00170	0.00184
	(0.00177)	(0.00177)	(0.00177)	(0.00177)
areatype=2	-0.0334***	-0.0348***	-0.0310***	-0.0324***
	(0.00917)	(0.00918)	(0.00919)	(0.00919)
areatype=3	-0.0242***	-0.0240***	-0.0197**	-0.0195**
	(0.00780)	(0.00779)	(0.00780)	(0.00779)
areatype=4	-0.0307***	-0.0314***	-0.0275***	-0.0281***
	(0.00741)	(0.00739)	(0.00741)	(0.00739)
areatype=5	-0.0563***	-0.0558***	-0.0523***	-0.0518***
	(0.00681)	(0.00679)	(0.00681)	(0.00679)
areatype=999	-0.0567***	-0.0591***	-0.0538***	-0.0561***
	(0.00689)	(0.00689)	(0.00688)	(0.00689)
time trend	2.09e-05***	4.42e-06	2.08e-05***	4.39e-06
	(5.12e-06)	(1.03e-05)	(5.12e-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. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

B5. IV details

Table A6: 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 A7: Montiel-Pflueger robust weak instrument test

	Fatigue	
Effective F-statistic	12.258	
% of Worst Case Bias	CV TSLS (α=5%)	CV TSLS (α=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 A8: IV (no moving age restriction)

	(O1)	(O2)	(O3)	(O4)	(O1)	(O2)	(O3)	(O4)
CDD	0.0372***	0.0522***	0.0212**	0.0240**	0.0797***	0.0596***	0.0445*	0.0387*
	(0.0108)	(0.0091)	(0.0099)	(0.0095)	(0.0291)	(0.0198)	(0.0232)	(0.0206)
CDD × AC	-0.2004**	-0.1362**	-0.0571	0.0718	-0.2671**	-0.1327*	-0.0911	0.0295
	(0.0958)	(0.0682)	(0.0822)	(0.0781)	(0.1304)	(0.0762)	(0.1015)	(0.0849)
$\overline{CDD}_{it-1}$	-0.1214**	-0.0407	-0.0612	0.0222	-0.1348**	-0.0351	-0.0700	0.0088
	(0.0558)	(0.0429)	(0.0505)	(0.0475)	(0.0624)	(0.0419)	(0.0522)	(0.0450)
CDD $\times\overline{CDD}_{it-1}$	0.0003*	0.0001	0.0001	-0.0002	0.0003*	0.0001	0.0001	-0.0001
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
CDD × *building*					-0.1617**	-0.0281	-0.0861	-0.0401
					(0.0743)	(0.0473)	(0.0592)	(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. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

B6. Regional interactions

Table A9: Regional Interactions: fatigue and reduced appetite

	O1	O1	O1	O1	O1	O2	O2	O2	O2	O2
CDD	0.0211***	0.0283	3.411	-0.00409	-13.11	0.0240***	0.00418	-9.350	-0.0564	-31.43**
	(0.00625)	(0.0474)	(10.88)	(0.0592)	(13.79)	(0.00500)	(0.0308)	(11.58)	(0.0365)	(15.62)
CDD x AC	-0.0212***	-0.0177**	-0.0167*	-0.0160*	-0.0160*	-0.0176***	-0.00945	-0.0101	-0.00786	-0.00758
	(0.00785)	(0.00876)	(0.00874)	(0.00886)	(0.00884)	(0.00559)	(0.00624)	(0.00627)	(0.00639)	(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 A10: Regional Interactions + individual confounders: fatigue and reduced appetite

	O1	O1	O1	O1	O1	O2	O2	O2	O2	O2
CDD	0.0484**	0.0418	4.5285	0.0056	-12.6482	0.0407**	-0.0001	-8.9633	-31.2650*	0.0505**
	(0.0129)	(0.0484)	(10.9284)	(0.0601)	(13.8736)	(0.0099)	(0.0316)	(11.5798)	(15.6082)	(0.0127)
CDD x AC	-0.0147*	-0.0161*	-0.0155*	-0.0156*	-0.0159*	-0.0109*	-0.0104	-0.0097	-0.0086	0.0003
	(0.0088)	(0.0091)	(0.0091)	(0.0091)	(0.0091)	(0.0062)	(0.0063)	(0.0064)	(0.0064)	(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 A11: Regional Interactions: irritability and trouble sleeping

	O3	O3	O3	O3	O3	O4	O4	O4	O4	O4	O4
CDD	0.0212***	-0.0195	-1.095	-0.0287	-3.965	0.0122**	0.0471	3.214	0.0846	-1.229	0.0212***
	(0.00592)	(0.0434)	(10.45)	(0.0525)	(14.04)	(0.00566)	(0.0519)	(13.27)	(0.0630)	(17.80)	(0.00592)
CDD x AC	-0.00306	-0.00792	-0.00594	-0.00527	-0.00457	-0.0134*	-0.00527	-0.00521	-0.00799	-0.00806	-0.00306
	(0.00750)	(0.00827)	(0.00820)	(0.00858)	(0.00853)	(0.00710)	(0.00773)	(0.00768)	(0.00786)	(0.00781)	(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 A12: Regional Interactions + individual confounders: irritability and trouble sleeping

	O3	O3	O3	O3	O3	O4	O4	O4	O4	O4
CDD	0.0505**	0.0111	-0.6981	0.0004	-3.2233	0.0336**	0.0451	2.9454	0.0805	-1.3466
	(0.0127)	(0.0444)	(10.4907)	(0.0534)	(14.1660)	(0.0118)	(0.0526)	(13.2984)	(0.0637)	(17.8704)
CDD x AC	0.0003	-0.0038	-0.0027	-0.0022	-0.0017	-0.0063	-0.0060	-0.0058	-0.0078	-0.0078
	(0.0085)	(0.0088)	(0.0087)	(0.0089)	(0.0089)	(0.0080)	(0.0081)	(0.0081)	(0.0081)	(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. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Appendix C

Chapter 4 appendix

C1. Descriptive statistics

Table A1: Descriptive statistics: Dependent and Independent Variables

	Mean	Std. Dev.	Min.	Max.	N.
Dependent Vars.					
CC Concern (1-5)	3.20	0.94	1	5	87624
Some CC Concern (0-1)	0.80	0.40	0	1	87624
CC Anthropogenic (1-5)	3.49	0.80	1	5	86643
Feel Responsib. reducing CC (0-10)	5.97	2.67	0	10	86558
People limit energy: reduce CC (0-10)	4.46	2.32	0	10	47955
People limit energy: how likely (0-10)	5.33	2.36	0	10	47741
Govt's act against CC: how likely (0-10)	4.64	2.24	0	10	47578
Scientists deceive public (1-5)	2.56	1.20	1	5	44816
Important Environment Care (0-5)	3.81	1.05	0	5	72383
Subjective income (0-3)	2.10	0.81	0	3	88299
Trust: Science (0-10)	7.09	2.24	0	10	42704
Trust: EU Parliament (0-10)	4.51	2.56	0	10	84816
Trust: United Nations (0-10)	5.16	2.57	0	10	83832
Time on current news (0-2)	0.38	0.54	0	2	88349
Subjective Health (1-5)	3.80	0.90	1	5	89390
Happiness (0-10)	7.32	1.93	0	10	89210
Temperature					
Avg. temperature: int. day	9.73	7.15	-23	32	89507
Avg. temperature: int. day-1	9.79	7.14	-22	32	89507
Avg. temperature: int. day and -1	9.76	7.07	-22	31	89507
Upward temp. anomalies: prev. 365 days (Int. Day-1)	0.47	0.10	0	1	89507
Upward temp. anomalies: prev. 365 days (Int. Day-2)	0.47	0.10	0	1	89507
Control Vars.					
Domicile type (1-5)	2.93	1.20	1	5	89507
Years of education	13.14	4.04	0	76	87753
Age	50.08	18.58	15	100	89507
Male (0-1)	0.47	0.50	0	1	89507
Child living at home (0-1)	0.46	0.50	0	1	88147
Born abroad (0-1)	0.09	0.29	0	1	89420
Currently unemployed (0-1)	0.04	0.19	0	1	89507
Subjective income (0-3)	2.10	0.81	0	3	88299
Political interest (0-3)	1.40	0.91	0	3	89288
Political interest: quite/very interested (0-1)	0.47	0.50	0	1	89288
Ideology (0-10)	5.05	2.32	0	10	79148
Ideology: Left (0-3)	0.23	0.42	0	1	79148
Ideology: Center (4-6)	0.51	0.50	0	1	79148
Ideology: Right (7-10)	0.25	0.43	0	1	79148

Notes. We report here the descriptive statistics for all the variables employed in our analysis. Data for the dependent and independent variables comes from Wave 8 and 10 of the European Social Survey. Daily gridded data on temperature comes from E-OBS.

Table A2: Country averages: avg. temperature (°C), interview day and previous day.

	Wave 8			Wave 10		
Country	Mean (°C)	Std. Dev.	N.	Mean (°C)	Std. Dev.	N.
Austria	5.89	4.537	2001	9.41	3.556	1852
Belgium	9.29	5.036	1766	10.40	5.220	1027
Bulgaria				22.01	4.126	2695
Croatia				18.38	5.063	1545
Czech Republic	3.55	3.428	2269	18.58	2.747	2472
Estonia	0.35	3.726	2019	11.30	7.207	1542
Finland	0.11	4.957	1923	4.96	6.271	1577
France	5.89	3.875	2069	13.91	5.575	1974
Germany	7.93	7.373	2849	8.57	2.602	8021
Greece				6.46	3.702	1363
Hungary	22.19	2.895	1614	22.52	3.439	1844
Iceland	1.85	3.245	499	7.96	3.911	734
Ireland	8.16	2.451	2714	11.33	3.278	924
Italy	14.63	4.014	2610	8.45	3.837	2591
Lithuania	5.67	3.461	2105	9.00	8.425	1656
Macedonia				5.21	4.473	1412
Montenegro				6.23	4.721	1259
Netherlands	9.00	6.002	1681	7.71	3.004	1460
Norway	6.80	6.007	1542	7.60	6.942	1409
Poland	1.43	4.603	1687	4.36	4.883	1904
Portugal	13.74	4.065	1268	14.18	4.508	1835
Slovak Republic	14.18	4.508	1835	18.89	4.764	1366
Slovenia	9.15	4.103	1304	15.81	5.266	1250
Spain	12.53	3.415	1947	10.88	2.676	2237
Sweden	7.75	6.141	1542	5.11	5.081	2224
Switzerland	9.18	6.508	1519	9.87	6.523	1512
United Kingdom	10.64	4.315	1923	10.31	4.040	971
Total	8.18	4.485	40686	11.09	4.661	50656

Notes. Source: E-OBS. Country averages computed, respectively, in Wave 8 (2016-17) and 10 (2020-21) of the *ESS*.

Table A3: country averages: Standardized Upward Temperature anomalies in the 365 days before the interview date-2.

	Wave 8			**Wave 10**		
Country	Mean (°C)	Std. Dev.	N.	Mean (°C)	Std. Dev.	N.
Austria	0.53	0.033	2001	0.41	0.021	1852
Belgium	0.54	0.075	1766	0.39	0.058	1027
Bulgaria				0.53	0.076	2695
Croatia				0.50	0.036	1545
Czech Republic	0.51	0.027	2269	0.42	0.030	2472
Estonia	0.46	0.037	2019	0.62	0.053	1542
Finland	0.50	0.044	1923	0.59	0.044	1577
France	0.43	0.053	2069	0.44	0.032	1974
Germany	0.50	0.050	2849	0.38	0.029	8021
Greece				0.49	0.152	1363
Hungary	0.43	0.031	1614	0.51	0.041	1844
Iceland	0.53	0.035	499	0.62	0.102	734
Ireland	0.43	0.062	2714	0.55	0.045	924
Italy	0.57	0.175	2610	0.49	0.237	2591
Lithuania	0.33	0.021	2105	0.53	0.056	1656
Macedonia				0.50	0.072	1412
Montenegro				0.59	0.039	1259
Netherlands	0.54	0.054	1681	0.38	0.022	1460
Norway	0.45	0.040	1542	0.50	0.052	1409
Poland	0.49	0.032	1687	0.42	0.037	1904
Portugal	0.41	0.064	1268	0.33	0.061	1835
Slovak Republic	0.33	0.061	1835	0.50	0.038	1366
Slovenia	0.49	0.038	1304	0.51	0.079	1250
Spain	0.44	0.099	1947	0.40	0.070	2237
Sweden	0.50	0.057	1542	0.56	0.042	2224
Switzerland	0.49	0.049	1519	0.37	0.054	1512
United Kingdom	0.52	0.070	1923	0.42	0.060	971
Total	0.47	0.055	40686	0.48	0.061	50656

Notes. Source: E-OBS. Country averages computed, respectively, in Wave 8 (2016-17) and 10 (2020-21) of the *ESS*.

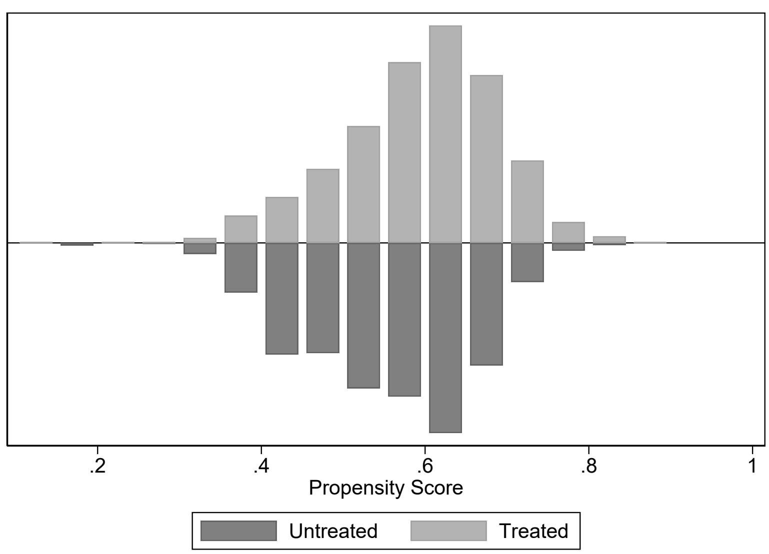
C2. Propensity score matching details

Table A4: Covariates balance: respondents interviewed during and before COP26.

	Mean (pre-COP26)	Mean (during-COP26)	Diff.	p-value
Years of education	13.65	13.50	0.15	0.176
Age	51.14	51.56	-0.42	0.426
Age^2	2967.81	2997.52	-29.71	0.584
Male (0-1)	0.48	0.47	0.00	0.779
Child living at home (0-1)	0.57	0.56	0.01	0.582
Born abroad (0-1)	0.10	0.09	0.00	0.819
Currently unemployed (0-1)	0.02	0.03	-0.01	0.003
Subjective income (0-3)	2.32	2.22	0.11	0.000
Political interest (0-3)	1.71	1.62	0.08	0.000
Ideology (0-10)	4.84	4.79	0.05	0.477
Domicile: Big City	0.18	0.19	-0.01	0.601
Domicile: Suburbs	0.15	0.13	0.02	0.074
Domicile: Town	0.31	0.30	0.01	0.488
Domicile: Village	0.28	0.32	-0.04	0.002
Domicile: Countryside	0.08	0.06	0.02	0.005
Upward temp. anomalies: prev. 365 days (Int. Day-2)	0.46	0.43	0.03	0.000
Avg. temperature: int. day and -1	8.21	7.83	0.37	0.000
Observations	2156	2951	5107	

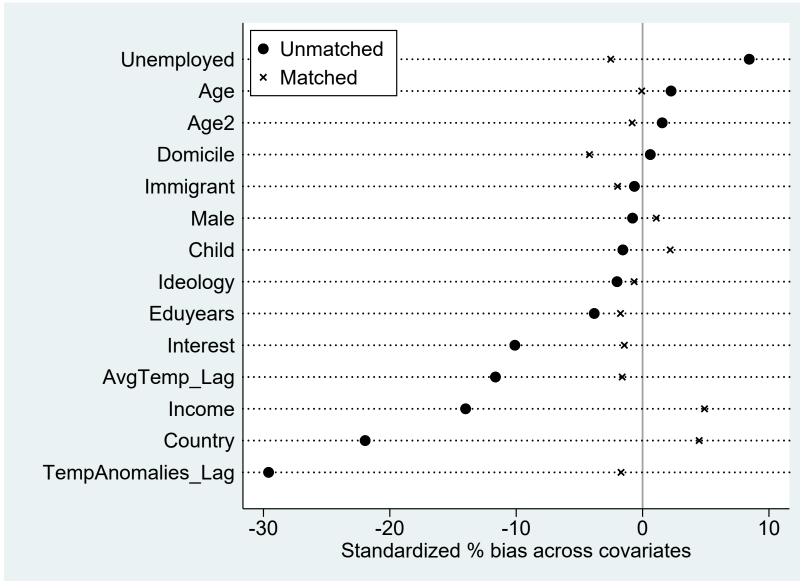
Notes. We report here the covariate balance for respondents interviewed during COP26 (Oct31-Nov13, 2021), and in the week prior (Oct23-Oct30, 2021). Data comes from Wave 8 and 10 of the European Social Survey and E-OBS.

Figure 1: Common support for the Propensity Score.



Notes. Source: *ESS*. We plot here the density of the Propensity Score (PS) across interviews taking place during COP26 (Oct31-Nov13, 2021), and in the week prior (Oct23-Oct30, 2021). The PS captures the probability of being interviewed during COP26, rather than before, and is estimated via a logistic regression, without replacement.

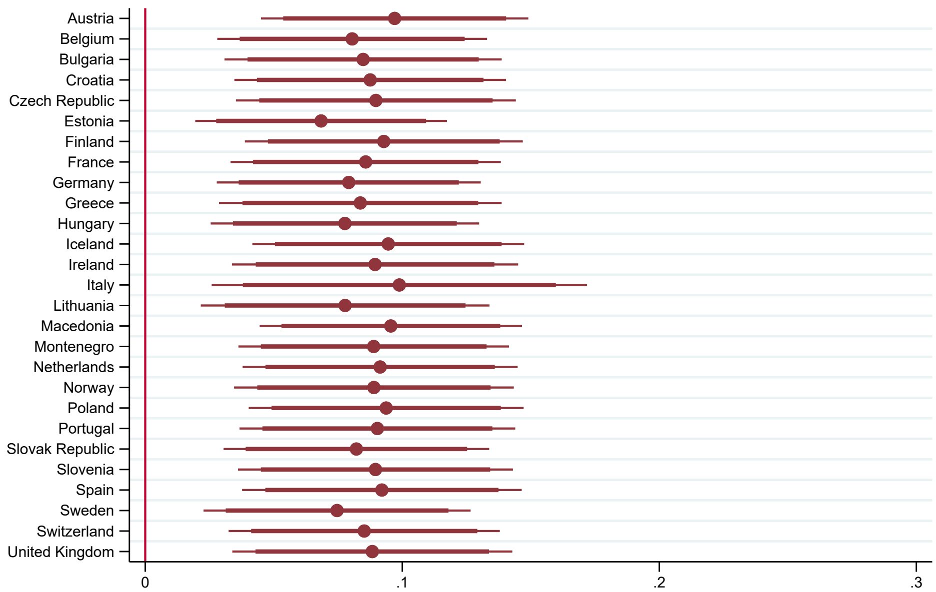
Figure 2: Covariate bias: pre and post propensity score matching.



Notes. Sources: ESS and E-OBS. In each row, crosses (dots) indicate the post-matching (pre-matching) between respondents interviewed during COP26 (Oct31-Nov13, 2021), and in the week prior (Oct23-Oct30, 2021).

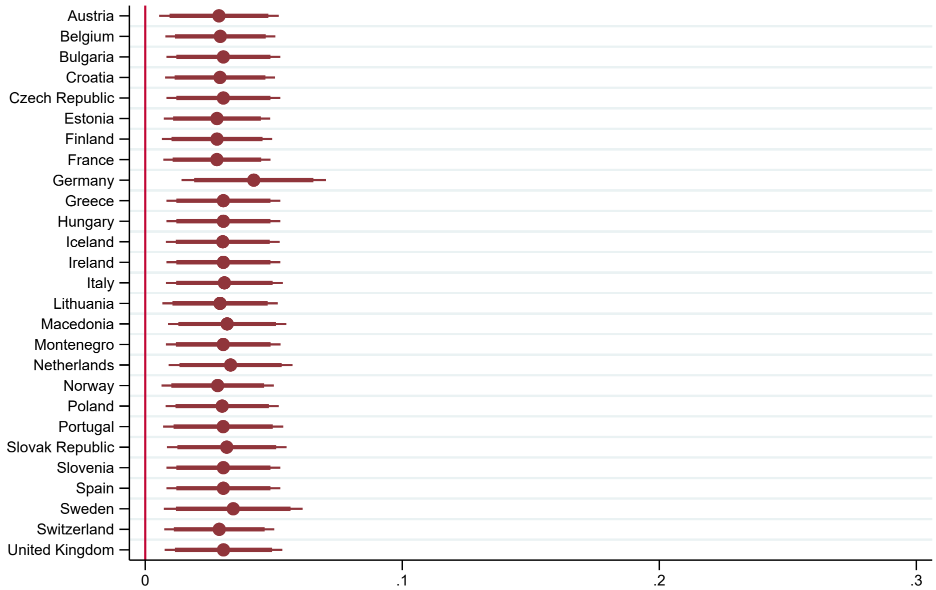
C3. One-country out

Figure 3: Preoccupation about CC and Temp. Anom., removing one country from the sample.



Notes. Source: *ESS*. Each sub-figure's title indicates the country which is removed from the sample when the estimation is performed. Country fixed effects apply, standard errors clustered at country-by-wave. Thick (thin) lines signify the 90% (95%) confidence interval. Full regression tables are reported here.

Figure 4: Preoccupation about climate change and COP26, removing one country from the sample.



Notes. Source: *ESS*. Each sub-figure's title indicates the country which is removed from the sample when the estimation is performed. Country fixed effects apply, standard errors clustered at country-by-wave. Thick (thin) lines signify the 90% (95%) confidence interval. Full regression tables are reported here.

C4. Full regression tables

Table A5: Climate change concern and Temperature Anomalies: full sample (Wave 8 and 10).

	(1) Some CC Concern (0-1)	(2) Some CC Concern (0-1)	(3) Some CC Concern (0-1)	(4) Some CC Concern (0-1)
Temp. Anom. (t-2)	0.087***	0.093***		
	(0.026)	(0.028)		
Temp. Interview	0.001**	0.001***		
	(0.001)	(0.001)		
Temp. Anom. (t-1)			0.097***	0.104***
			(0.026)	(0.027)
Years of education	0.005***	0.005***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Age	0.002***	0.002***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
Age^2	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Male (0-1)	-0.072***	-0.072***	-0.072***	-0.072***
	(0.006)	(0.006)	(0.006)	(0.006)
Child living at home (0-1)	0.017***	0.018***	0.018***	0.018***
	(0.006)	(0.006)	(0.006)	(0.006)
Born abroad (0-1)	0.001	0.001	0.001	0.001
	(0.008)	(0.008)	(0.008)	(0.008)
Currently unemployed (0-1)	-0.015	-0.014	-0.014	-0.014
	(0.010)	(0.010)	(0.010)	(0.010)
Subjective income (0-3)	-0.001	-0.001	-0.001	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)
Political interest (0-3)	0.041***	0.041***	0.041***	0.041***
	(0.004)	(0.004)	(0.004)	(0.004)
Ideology (0-10)	-0.013***	-0.013***	-0.013***	-0.013***
	(0.002)	(0.002)	(0.002)	(0.002)
Domicile: Suburbs	0.015*	0.015*	0.015*	0.015*
	(0.008)	(0.008)	(0.008)	(0.008)
Domicile: Town	-0.003	-0.003	-0.003	-0.003
	(0.007)	(0.007)	(0.007)	(0.007)
Domicile: Village	-0.006	-0.006	-0.007	-0.006
	(0.007)	(0.007)	(0.007)	(0.007)
Domicile: Countryside	-0.038***	-0.038***	-0.038***	-0.038***
	(0.010)	(0.010)	(0.010)	(0.010)
Constant	-0.080	0.689***	-0.089	0.698***
	(0.090)	(0.026)	(0.091)	(0.026)
Controls	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Season FE	Yes	Yes	Yes	Yes
Time Trends	Yes	No	Yes	No
Country-Specific Time Trends	No	Yes	No	Yes
Observations	74980	74980	74980	74980
R-squared	0.078	0.078	0.078	0.078
No. of Clusters	48	48	48	48

Notes. ${}^{*}p < 0.10, {}^{**}p < 0.05, {}^{***}p < 0.01$. We report here the estimates of the effect on CC Concern of temperature anomalies experienced by respondents interviewed during Waves 8 and 10 of the *ESS*. Coefficients are estimated using an OLS regression with country fixed-effects and individual controls. Standard errors are clustered at the country-by-wave level. Sources: *ESS* and $E - OBS$.

Table A6: Climate change concern and COP meetings

	(1) Concerned about CC (Yes/No)	(2) Concerned about CC (Yes/No)	(3) Concerned about CC (Yes/No)	(4) Concerned about CC (Yes/No)
COP26 (2021)	0.029***	0.030***		
	(0.009)	(0.011)		
COP22 (2016)			-0.008	-0.005
			(0.015)	(0.022)
Years of completed education		0.006***		0.007***
		(0.001)		(0.002)
Age		0.001		0.002
		(0.001)		(0.002)
Age, squared		-0.000		-0.000*
		(0.000)		(0.000)
Male		-0.074***		-0.096***
		(0.009)		(0.012)
Children in the hh		0.011		0.017
		(0.018)		(0.018)
Immigrant		0.017		0.011
		(0.020)		(0.018)
Unemployed		-0.038		0.006
		(0.029)		(0.049)
Subjective household income		0.012		-0.023**
		(0.008)		(0.009)
Interest in Politics		0.027***		0.072***
		(0.005)		(0.014)
Left - Right Scale		-0.018***		-0.011***
		(0.003)		(0.002)
Suburbs		-0.015		-0.017
		(0.012)		(0.024)
Town		-0.006		-0.016
		(0.010)		(0.014)
Village		-0.019		-0.047**
		(0.015)		(0.016)
Countryside		-0.040		-0.024
		(0.025)		(0.044)
Temp. Anom.		0.271*		0.176
		(0.152)		(0.319)
Temp. interview		0.001		0.002
		(0.002)		(0.002)
Constant	0.841***	0.654***	0.695***	0.585***
	(0.005)	(0.080)	(0.010)	(0.170)
Country FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Observations	5987	5107	5452	4973
R-squared	0.031	0.069	0.066	0.104
No. of Clusters	20	20	16	16

Notes. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$. We report here the estimates of the effect on Climate change concern — coded as a 1/0 indicator — of being interviewed during COP26 in Glasgow (Oct31-Nov13, 2021) and COP22 in Marrakech (Nov7-Nov11, 2016), rather than in the previous week. Coefficients are estimated using an OLS regression with country fixed-effects and individual controls. Standard errors are clustered at the country-by-wave level. Source: *ESS*.

Table A7: Climate change beliefs

	(1) CC Anthropogenic	(2) CC Anthropogenic	(3) CC Anthropogenic	(4) CC Gov. Action	(5) CC Gov. Action	(6) CC Gov. Action
Temp. Anom.	0.002	-0.076	-0.092	0.633***	3.544**	-0.176
	(0.024)	(0.190)	(0.138)	(0.183)	(1.273)	(1.423)
Temp. interview	0.000	0.002	-0.001	-0.005	0.005	0.011
	(0.000)	(0.002)	(0.001)	(0.003)	(0.040)	(0.010)
COP26 (2021)		0.009			-0.132	
		(0.009)			(0.166)	
COP22 (2016)			-0.006			-0.071
			(0.012)			(0.088)
Years of completed education	0.003***	0.002**	0.005***	-0.017***	0.000	-0.022*
	(0.000)	(0.001)	(0.001)	(0.005)	(0.024)	(0.011)
Age	-0.000	0.000	-0.001	-0.012**	-0.054***	-0.013
	(0.000)	(0.001)	(0.002)	(0.005)	(0.016)	(0.008)
Age, squared	-0.000	-0.000	0.000	0.000***	0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	-0.028***	-0.034***	-0.031***	-0.050*	-0.249	-0.027
	(0.003)	(0.005)	(0.010)	(0.026)	(0.189)	(0.065)
Children in the hh	0.009***	-0.010	0.006	0.030	0.761***	-0.020
	(0.002)	(0.008)	(0.017)	(0.032)	(0.233)	(0.068)
Immigrant	-0.019***	-0.028	0.012	0.239***	0.471	0.027
	(0.005)	(0.021)	(0.014)	(0.082)	(0.275)	(0.219)
Unemployed	-0.010	-0.030	0.019	0.023	0.247	0.029
	(0.006)	(0.036)	(0.021)	(0.060)	(0.367)	(0.122)
Subjective household income	0.003	0.004	-0.006	0.118***	0.288*	0.108
	(0.002)	(0.005)	(0.004)	(0.028)	(0.158)	(0.090)
Interest in Politics	0.003*	0.007*	-0.000	0.074***	0.030	0.078
	(0.002)	(0.004)	(0.005)	(0.024)	(0.134)	(0.050)
Left - Right Scale	-0.006***	-0.007***	-0.005**	0.048***	0.052	0.029
	(0.001)	(0.002)	(0.002)	(0.010)	(0.065)	(0.024)
Suburbs	0.007*	0.006	0.001	-0.051	0.089	-0.067
	(0.004)	(0.011)	(0.016)	(0.060)	(0.288)	(0.099)
Town	0.001	0.000	0.013	-0.018	0.144	-0.040
	(0.004)	(0.014)	(0.009)	(0.044)	(0.219)	(0.095)
Village	-0.001	0.009	-0.007	-0.024	-0.028	-0.058
	(0.003)	(0.013)	(0.011)	(0.066)	(0.258)	(0.079)
Countryside	-0.018**	-0.006	0.017	-0.147**	-0.319	-0.139
	(0.008)	(0.024)	(0.025)	(0.060)	(0.194)	(0.136)
spring	0.009			-0.031		
	(0.005)			(0.068)		
summer	0.003			0.020		
	(0.006)			(0.089)		
winter	0.007			-0.035		
	(0.005)			(0.033)		
Trend	0.000***			0.000**		
	(0.000)			(0.000)		
Constant	0.828***	0.952***	0.978***	2.669***	3.062***	4.860***
	(0.039)	(0.101)	(0.083)	(0.651)	(0.918)	(0.973)
Country FE						
Controls						
Observations	74476	5093	4946	41458	716	4896
R-squared	0.026	0.035	0.023	0.041	0.094	0.041
No. of Clusters	48	20	16	43	16	16

Notes. $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$. We report here the estimates of the effect on climate change concern — coded as a 1/0 indicator — of temperature anomalies, and of being interviewed during COP26 in Glasgow (Oct31-Nov13, 2021) and COP22 in Marrakech (Nov7-Nov11, 2016), rather than in the previous week. Coefficients are estimated using an OLS regression with country fixed-effects and individual controls. Standard errors are clustered at the country-by-wave level. Source: *ESS*.

Table A8: Climate change concern and Temperature Anomalies: alt. reference windows.

	(1) Some CC Concern (0-1)	(2) Some CC Concern (0-1)	(3) Some CC Concern (0-1)	(4) Some CC Concern (0-1)	(5) Some CC Concern (0-1)	(6) Some CC Concern (0-1)
Anomalies: prev. 30d	0.018**					
	(0.008)					
Prev. 60 days		0.050***				
		(0.011)				
Prev. 90 days			0.061***			
			(0.015)			
Prev. 180 days				0.093***		
				(0.022)		
Prev. 365 days					0.097***	
					(0.026)	
Prev. 24 months						0.091***
						(0.033)
Years of education	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age^2	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male (0-1)	-0.072***	-0.072***	-0.072***	-0.072***	-0.072***	-0.072***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Child living at home (0-1)	0.018***	0.018***	0.018***	0.018***	0.018***	0.018***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Born abroad (0-1)	0.001	0.001	0.001	0.001	0.001	0.001
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Currently unemployed (0-1)	-0.013	-0.014	-0.014	-0.014	-0.014	-0.014
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Subjective income (0-3)	-0.001	-0.002	-0.002	-0.001	-0.001	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Political interest (0-3)	0.041***	0.041***	0.041***	0.040***	0.041***	0.041***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Ideology (0-10)	-0.013***	-0.013***	-0.013***	-0.013***	-0.013***	-0.013***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Domicile: Suburbs	0.015*	0.015*	0.015*	0.015*	0.015*	0.015*
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Domicile: Town	-0.002	-0.003	-0.003	-0.003	-0.003	-0.003
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Domicile: Village	-0.006	-0.006	-0.006	-0.006	-0.007	-0.006
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Domicile: Countryside	-0.038***	-0.039***	-0.039***	-0.039***	-0.038***	-0.038***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Constant	-0.018	-0.033	-0.058	-0.058	-0.089	-0.016
	(0.090)	(0.088)	(0.087)	(0.086)	(0.091)	(0.088)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Season FE	Yes	Yes	Yes	Yes	Yes	Yes
Time Trends	Yes	Yes	Yes	Yes	Yes	Yes
Observations	74980	74980	74980	74980	74980	74980
R-squared	0.078	0.078	0.078	0.079	0.078	0.078
No. of Clusters	48	48	48	48	48	48

Notes. $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$. We report here the estimates of the effect on CC Concern of temperature anomalies experienced by respondents interviewed during Waves 8 and 10 of the *ESS*. Coefficients are estimated using an OLS regression with country fixed-effects and individual controls. Standard errors are clustered at the country-by-wave level. Sources: *ESS* and $E - OBS$.

Table A9: Concern about Climate Change in the four weeks before COP26.

	(1) Concerned about CC (Yes/No)	(2) Concerned about CC (Yes/No)	(3) Concerned about CC (Yes/No)	(4) Concerned about CC (Yes/No)	(5) Concerned about CC (Yes/No)	(6) Concerned about CC (Yes/No)	(7) Concerned about CC (Yes/No)	(8) Concerned about CC (Yes/No)
COP26-5 Weeks	0.029*	0.016						
	(0.016)	(0.019)						
-4 Weeks			0.001	-0.005				
			(0.012)	(0.014)				
-3 Weeks					0.007	0.006		
					(0.014)	(0.014)		
-2 Weeks							-0.001	-0.004
							(0.011)	(0.011)
Years of completed education	0.007***	0.008***	0.007***	0.007***	0.003*	0.003*	0.005***	0.005***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age	0.001	0.001	-0.000	-0.000	0.002	0.002	0.001	0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age, squared	-0.000	-0.000	0.000	0.000	-0.000	-0.000*	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	-0.091***	-0.091***	-0.076***	-0.076***	-0.071***	-0.071***	-0.094***	-0.094***
	(0.012)	(0.012)	(0.008)	(0.008)	(0.019)	(0.019)	(0.016)	(0.016)
Children in the hh	0.022	0.022	0.025**	0.025**	0.012	0.012	0.023**	0.023**
	(0.015)	(0.015)	(0.011)	(0.011)	(0.011)	(0.011)	(0.009)	(0.009)
Immigrant	0.011	0.011	-0.026	-0.024	-0.016	-0.017	0.003	0.004
	(0.028)	(0.027)	(0.017)	(0.017)	(0.012)	(0.013)	(0.022)	(0.023)
Unemployed	-0.015	-0.019	-0.042	-0.044	-0.010	-0.010	-0.020	-0.022
	(0.049)	(0.050)	(0.029)	(0.029)	(0.035)	(0.035)	(0.035)	(0.035)
Subjective household income	0.009	0.010	0.014	0.014	0.015	0.015	0.014*	0.014**
	(0.007)	(0.007)	(0.010)	(0.010)	(0.010)	(0.010)	(0.007)	(0.007)
Interest in Politics	0.022***	0.022***	0.024***	0.024***	0.022***	0.022***	0.027***	0.027***
	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
Left - Right Scale	-0.025***	-0.025***	-0.024***	-0.024***	-0.026***	-0.026***	-0.028***	-0.028***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Suburbs	-0.019	-0.020	0.005	0.005	0.000	0.001	-0.006	-0.005
	(0.016)	(0.016)	(0.007)	(0.007)	(0.009)	(0.009)	(0.009)	(0.010)
Town	-0.027	-0.026	-0.003	-0.003	-0.015*	-0.013	-0.013	-0.010
	(0.019)	(0.019)	(0.012)	(0.011)	(0.007)	(0.008)	(0.011)	(0.011)
Village	-0.035	-0.033	-0.008	-0.007	-0.027***	-0.025**	-0.029**	-0.025**
	(0.021)	(0.022)	(0.009)	(0.009)	(0.009)	(0.009)	(0.011)	(0.012)
Countryside	-0.047	-0.045	-0.036**	-0.035**	-0.048***	-0.046***	-0.058*	-0.055*
	(0.030)	(0.030)	(0.016)	(0.016)	(0.016)	(0.015)	(0.030)	(0.030)
Temp. Anom.		0.246		0.254***		-0.084		0.050
		(0.152)		(0.076)		(0.138)		(0.190)
Temp. interview		0.003		0.001		0.001		0.004
		(0.003)		(0.002)		(0.001)		(0.003)
Constant	0.827***	0.686***	0.833***	0.710***	0.859***	0.882***	0.868***	0.813***
	(0.045)	(0.074)	(0.039)	(0.053)	(0.052)	(0.047)	(0.028)	(0.089)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temperatures	No	Yes	No	Yes	No	Yes	No	Yes
Observations	3082	3082	4837	4837	6591	6591	5064	5064
R-squared	0.087	0.088	0.076	0.077	0.089	0.089	0.100	0.100
No. of Clusters	22	22	20	20	19	19	19	19

Notes. $^{*}p < 0.10$,$^{**}p < 0.05$,$^{***}p < 0.01$. Keeping the control group constant, we artificially shift the COP26 dates by 4 weeks around the real one. Coefficients are estimated using an OLS regression with country fixed-effects and individual controls. Standard errors are clustered at the country-by-wave level. Source: *ESS*.

Table A10: Concern about Climate Change in the four weeks after COP26.

	(1) Concerned about CC (Yes/No)	(2) Concerned about CC (Yes/No)	(3) Concerned about CC (Yes/No)	(4) Concerned about CC (Yes/No)	(5) Concerned about CC (Yes/No)	(6) Concerned about CC (Yes/No)	(7) Concerned about CC (Yes/No)	(8) Concerned about CC (Yes/No)	(9) Concerned about CC (Yes/No)	(10) Concerned about CC (Yes/No)
COP26	0.026**	0.030***								
	(0.010)	(0.011)								
+1 Week			0.010	0.019*						
			(0.008)	(0.011)						
+2 Weeks					0.012	0.019				
					(0.011)	(0.016)				
+3 Weeks							0.030*	0.041		
							(0.015)	(0.037)		
+4 Weeks									0.004	0.027
									(0.018)	(0.032)
Years of completed education	0.006***	0.006***	0.005***	0.005***	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age	0.001	0.001	0.002	0.002	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age, squared	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	-0.074***	-0.074***	-0.080***	-0.080***	-0.088***	-0.088***	-0.088***	-0.088***	-0.082***	-0.081***
	(0.009)	(0.009)	(0.013)	(0.013)	(0.015)	(0.015)	(0.013)	(0.013)	(0.011)	(0.010)
Children in the hh	0.010	0.011	0.010	0.010	0.022	0.022	0.020*	0.019	0.030*	0.032*
	(0.017)	(0.018)	(0.014)	(0.014)	(0.013)	(0.013)	(0.011)	(0.011)	(0.017)	(0.018)
Immigrant	0.017	0.017	0.015	0.016	0.030	0.030	0.008	0.009	0.007	0.007
	(0.021)	(0.020)	(0.023)	(0.022)	(0.026)	(0.026)	(0.027)	(0.027)	(0.030)	(0.029)
Unemployed	-0.035	-0.038	0.016	0.014	-0.009	-0.011	-0.036	-0.038	-0.081	-0.086
	(0.029)	(0.029)	(0.052)	(0.052)	(0.037)	(0.037)	(0.043)	(0.043)	(0.060)	(0.060)
Subjective household income	0.011	0.012	0.023***	0.024***	0.009	0.009	0.011	0.011	-0.001	0.001
	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.011)	(0.011)
Interest in Politics	0.027***	0.027***	0.033***	0.033***	0.043***	0.043***	0.027***	0.027***	0.027***	0.026***
	(0.005)	(0.005)	(0.008)	(0.008)	(0.007)	(0.007)	(0.006)	(0.005)	(0.007)	(0.006)
Left - Right Scale	-0.018***	-0.018***	-0.020***	-0.020***	-0.022***	-0.022***	-0.021***	-0.021***	-0.023***	-0.023***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Suburbs	-0.014	-0.015	-0.027	-0.028	-0.002	-0.003	0.006	0.005	0.001	-0.003
	(0.012)	(0.012)	(0.016)	(0.017)	(0.015)	(0.015)	(0.016)	(0.016)	(0.023)	(0.022)
Town	-0.005	-0.006	-0.005	-0.006	0.016	0.016	-0.008	-0.009	-0.010	-0.016
	(0.010)	(0.010)	(0.012)	(0.012)	(0.011)	(0.012)	(0.015)	(0.016)	(0.027)	(0.024)
Village	-0.020	-0.019	-0.032*	-0.031*	-0.010	-0.010	-0.030*	-0.030	-0.024	-0.030
	(0.015)	(0.015)	(0.016)	(0.017)	(0.012)	(0.012)	(0.017)	(0.018)	(0.026)	(0.023)
Countryside	-0.040	-0.040	-0.062**	-0.062**	-0.014	-0.013	-0.056*	-0.056*	-0.056	-0.061
	(0.025)	(0.025)	(0.026)	(0.026)	(0.028)	(0.029)	(0.029)	(0.029)	(0.042)	(0.041)
Temp. Anom.		0.271*		0.225**		0.081		0.146*		0.389***
		(0.152)		(0.093)		(0.125)		(0.071)		(0.126)
Temp. interview		0.001		0.001		0.001		0.001		0.001
		(0.002)		(0.003)		(0.002)		(0.003)		(0.003)
Constant	0.788***	0.654***	0.750***	0.637***	0.762***	0.718***	0.810***	0.736***	0.843***	0.657***
	(0.048)	(0.080)	(0.059)	(0.058)	(0.055)	(0.064)	(0.046)	(0.048)	(0.067)	(0.092)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temperatures	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	5107	5107	3441	3441	3107	3107	3020	3020	2932	2932
R-squared	0.068	0.069	0.088	0.089	0.085	0.085	0.080	0.081	0.088	0.091
No. of Clusters	20	20	20	20	21	21	21	21	22	22

Notes. $^{*}p < 0.10$,$^{**}p < 0.05$,$^{***}p < 0.01$. Keeping the control group constant, we artificially shift the COP26 dates by 4 weeks around the real one. Coefficients are estimated using an OLS regression with country fixed-effects and individual controls. Standard errors are clustered at the country-by-wave level. Source: *ESS*.

Table A11: Concern about Climate Change in the four weeks before COP22.

	(1) Concerned about CC (Yes/No)	(2) Concerned about CC (Yes/No)	(3) Concerned about CC (Yes/No)	(4) Concerned about CC (Yes/No)	(5) Concerned about CC (Yes/No)	(6) Concerned about CC (Yes/No)	(7) Concerned about CC (Yes/No)	(8) Concerned about CC (Yes/No)
COP22-5 Weeks	-0.007	-0.013						
	(0.011)	(0.017)						
-4 Weeks			-0.013	-0.016				
			(0.016)	(0.018)				
-3 Weeks					-0.017	-0.022		
					(0.012)	(0.013)		
-2 Weeks							-0.019	-0.028*
							(0.012)	(0.014)
Years of completed education	0.007***	0.006***	0.007**	0.006**	0.008***	0.008***	0.009***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age	0.000	0.000	0.002	0.002	0.001	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Age, squared	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	-0.075***	-0.075***	-0.084***	-0.084***	-0.083***	-0.083***	-0.091***	-0.091***
	(0.010)	(0.010)	(0.015)	(0.015)	(0.010)	(0.010)	(0.010)	(0.010)
Children in the hh	0.026	0.027	0.034*	0.035*	0.030*	0.030*	0.043**	0.043**
	(0.018)	(0.018)	(0.018)	(0.018)	(0.016)	(0.016)	(0.018)	(0.018)
Immigrant	-0.004	-0.005	-0.008	-0.008	-0.017	-0.018	0.023	0.021
	(0.023)	(0.023)	(0.025)	(0.025)	(0.039)	(0.039)	(0.034)	(0.033)
Unemployed	-0.004	-0.002	-0.062	-0.062	-0.008	-0.009	-0.008	-0.006
	(0.029)	(0.029)	(0.036)	(0.036)	(0.033)	(0.034)	(0.037)	(0.037)
Subjective household income	-0.015	-0.015	-0.041***	-0.040***	-0.038***	-0.038***	-0.033***	-0.033***
	(0.012)	(0.013)	(0.009)	(0.010)	(0.006)	(0.006)	(0.009)	(0.009)
Interest in Politics	0.066***	0.066***	0.069***	0.068***	0.062***	0.062***	0.075***	0.075***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.012)	(0.012)	(0.009)	(0.009)
Left - Right Scale	-0.012***	-0.012***	-0.009**	-0.009**	-0.009**	-0.009**	-0.012***	-0.013***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Suburbs	-0.026	-0.027	-0.004	-0.004	-0.014	-0.014	0.005	0.002
	(0.029)	(0.030)	(0.025)	(0.024)	(0.027)	(0.026)	(0.031)	(0.031)
Town	-0.035*	-0.036*	-0.048**	-0.048**	-0.038**	-0.039**	-0.008	-0.007
	(0.019)	(0.019)	(0.018)	(0.017)	(0.016)	(0.016)	(0.021)	(0.018)
Village	-0.026	-0.027	-0.032	-0.031	-0.029**	-0.028**	-0.033*	-0.031*
	(0.019)	(0.019)	(0.021)	(0.021)	(0.012)	(0.012)	(0.016)	(0.015)
Countryside	-0.038*	-0.039*	-0.095***	-0.094***	-0.070	-0.070	-0.029	-0.027
	(0.019)	(0.018)	(0.025)	(0.024)	(0.042)	(0.042)	(0.021)	(0.021)
Temp. Anom.		0.211		0.219		0.254		0.431**
		(0.253)		(0.186)		(0.154)		(0.177)
Temp. interview		0.001		0.002		0.001		0.004
		(0.002)		(0.004)		(0.003)		(0.004)
Constant	0.722***	0.605***	0.745***	0.622***	0.751***	0.611***	0.694***	0.448***
	(0.062)	(0.143)	(0.044)	(0.098)	(0.059)	(0.094)	(0.049)	(0.101)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temperatures	No	Yes	No	Yes	No	Yes	No	Yes
Observations	3310	3310	3291	3291	3290	3290	3344	3344
R-squared	0.095	0.095	0.101	0.102	0.095	0.095	0.105	0.106
No. of Clusters	14	14	14	14	14	14	14	14

Notes. $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$. Keeping the control group constant, we artificially shift the COP26 dates by 4 weeks around the real one. Coefficients are estimated using an OLS regression with country fixed-effects and individual controls. Standard errors are clustered at the country-by-wave level. Source: *ESS*. The full set of fixed effects is available here.

Table A12: Concern about Climate Change in the four weeks after COP22.

	(1) Concerned about CC (Yes/No)	(2) Concerned about CC (Yes/No)	(3) Concerned about CC (Yes/No)	(4) Concerned about CC (Yes/No)	(5) Concerned about CC (Yes/No)	(6) Concerned about CC (Yes/No)	(7) Concerned about CC (Yes/No)	(8) Concerned about CC (Yes/No)	(9) Concerned about CC (Yes/No)	(10) Concerned about CC (Yes/No)
COP22	-0.018	-0.005								
	(0.017)	(0.022)								
+1 Week			-0.008	0.005						
			(0.017)	(0.021)						
+2 Weeks					-0.006	0.007				
					(0.017)	(0.018)				
+3 Weeks							-0.017	0.008		
							(0.018)	(0.031)		
+4 Weeks									-0.034	0.005
									(0.023)	(0.029)
Years of completed education	0.007***	0.007***	0.009***	0.008***	0.010***	0.010***	0.010***	0.009***	0.007***	0.007**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age	0.002	0.002	0.002	0.002	0.005**	0.005**	0.001	0.001	0.005**	0.005*
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Age, squared	-0.000*	-0.000*	-0.000	-0.000	-0.000**	-0.000**	-0.000*	-0.000*	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	-0.096***	-0.096***	-0.066***	-0.066***	-0.064***	-0.064***	-0.067***	-0.066***	-0.084***	-0.083***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.019)	(0.019)	(0.011)	(0.012)	(0.012)	(0.012)
Children in the hh	0.017	0.017	0.039**	0.039**	0.029	0.029	0.025	0.025	0.033*	0.033*
	(0.018)	(0.018)	(0.017)	(0.016)	(0.018)	(0.018)	(0.019)	(0.018)	(0.017)	(0.017)
Immigrant	0.010	0.011	-0.022	-0.022	-0.043	-0.044	-0.018	-0.019	-0.021	-0.021
	(0.018)	(0.018)	(0.025)	(0.024)	(0.029)	(0.028)	(0.036)	(0.035)	(0.044)	(0.044)
Unemployed	0.005	0.006	0.024	0.026	-0.059*	-0.058*	-0.032	-0.031	0.001	0.005
	(0.048)	(0.049)	(0.037)	(0.037)	(0.031)	(0.031)	(0.038)	(0.037)	(0.030)	(0.031)
Subjective household income	-0.023**	-0.023**	-0.030***	-0.030***	-0.035***	-0.035***	-0.027***	-0.027***	-0.039***	-0.038***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
Interest in Politics	0.072***	0.072***	0.063***	0.063***	0.055***	0.055***	0.079***	0.080***	0.073***	0.072***
	(0.014)	(0.014)	(0.015)	(0.015)	(0.013)	(0.013)	(0.011)	(0.011)	(0.013)	(0.013)
Left - Right Scale	-0.011***	-0.011***	-0.014***	-0.014***	-0.010***	-0.010***	-0.007***	-0.008***	-0.009**	-0.009**
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
Suburbs	-0.017	-0.017	0.027	0.027	0.007	0.008	-0.009	-0.011	0.014	0.016
	(0.024)	(0.024)	(0.033)	(0.033)	(0.029)	(0.029)	(0.023)	(0.023)	(0.032)	(0.032)
Town	-0.018	-0.016	-0.023	-0.022	-0.007	-0.008	-0.019	-0.021	-0.025	-0.021
	(0.014)	(0.014)	(0.018)	(0.017)	(0.024)	(0.025)	(0.023)	(0.021)	(0.021)	(0.021)
Village	-0.049***	-0.047**	-0.040*	-0.040*	-0.012	-0.013	-0.002	-0.004	-0.029	-0.024
	(0.016)	(0.016)	(0.021)	(0.020)	(0.020)	(0.021)	(0.021)	(0.019)	(0.019)	(0.018)
Countryside	-0.026	-0.024	-0.065**	-0.065**	-0.051**	-0.051*	-0.073**	-0.074**	-0.024	-0.022
	(0.044)	(0.044)	(0.027)	(0.027)	(0.024)	(0.024)	(0.026)	(0.027)	(0.037)	(0.037)
Temp. Anom.		0.176		0.344		0.311		0.410		0.267
		(0.319)		(0.303)		(0.232)		(0.267)		(0.270)
Temp. interview		0.002		0.003		0.000		-0.000		0.007**
		(0.002)		(0.002)		(0.003)		(0.003)		(0.003)
Constant	0.691***	0.585***	0.689***	0.493***	0.578***	0.414***	0.635***	0.420**	0.646***	0.468***
	(0.043)	(0.170)	(0.070)	(0.148)	(0.055)	(0.101)	(0.060)	(0.147)	(0.055)	(0.157)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temperatures	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	4973	4973	3781	3781	3657	3657	3273	3273	2959	2959
R-squared	0.104	0.104	0.105	0.105	0.100	0.100	0.104	0.105	0.111	0.112
No. of Clusters	16	16	16	16	17	17	17	17	17	17

Notes. $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$. Keeping the control group constant, we artificially shift the COP26 dates by 4 weeks around the real one. Coefficients are estimated using an OLS regression with country fixed-effects and individual controls. Standard errors are clustered at the country-by-wave level. Source: *ESS*. The full set of fixed effects is available here.

Table A13: Climate change concern and temperature: Ideological Bias

	(1) CC Concern	(2) CC Concern	(3) CC Concern	(4) CC Concern
Temp. Anom. (t-2)	0.083*	0.061		
	(0.045)	(0.042)		
Center × Temp. Anom. (t-2)	0.005	-0.007		
	(0.040)	(0.040)		
Right × Temp. Anom. (t-2)	0.001	-0.009		
	(0.083)	(0.084)		
Temp. Anom. (t-1)			0.085*	0.062
			(0.045)	(0.043)
Center × Temp. Anom. (t-1)			0.014	0.001
			(0.042)	(0.042)
Right × Temp. Anom. (t-1)			0.019	0.009
			(0.088)	(0.089)
Temp. Interview	-0.000	-0.001		
	(0.001)	(0.001)		
Center × Temp. Interview	0.002**	0.002**		
	(0.001)	(0.001)		
Right × Temp. Interview	0.003***	0.003***		
	(0.001)	(0.001)		
Ideology: Center	-0.052***	-0.044**	-0.038*	-0.032
	(0.018)	(0.019)	(0.020)	(0.020)
Ideology: Right	-0.115***	-0.108**	-0.093**	-0.088**
	(0.040)	(0.040)	(0.043)	(0.044)
Years of education	0.005***	0.005***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Age	0.002***	0.002***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
Age^2	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Male (0-1)	-0.072***	-0.072***	-0.072***	-0.072***
	(0.006)	(0.006)	(0.006)	(0.006)
Child living at home (0-1)	0.018***	0.017***	0.018***	0.016***
	(0.006)	(0.006)	(0.006)	(0.006)
Born abroad (0-1)	0.001	0.001	0.001	0.001
	(0.008)	(0.008)	(0.008)	(0.008)
Currently unemployed (0-1)	-0.015	-0.015	-0.014	-0.015
	(0.010)	(0.010)	(0.010)	(0.009)
Subjective Income (0-3)	-0.001	-0.001	-0.001	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)
Political Interest (0-3)	0.041***	0.041***	0.041***	0.041***
	(0.004)	(0.004)	(0.004)	(0.004)
Domicile: suburbs	0.015*	0.015*	0.015*	0.015*
	(0.008)	(0.008)	(0.008)	(0.008)
Domicile: town	-0.003	-0.003	-0.004	-0.003
	(0.007)	(0.007)	(0.007)	(0.007)
Domicile: village	-0.006	-0.006	-0.007	-0.007
	(0.007)	(0.007)	(0.007)	(0.007)
Domicile: Countryside	-0.038***	-0.039***	-0.039***	-0.039***
	(0.010)	(0.010)	(0.010)	(0.010)
Constant	-0.097	-0.488***	-0.124	-0.535***
	(0.093)	(0.060)	(0.095)	(0.062)
Country FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Trend	Y	N	Y	N
Country Trends	N	Y	N	Y
Observations	74980	74980	74980	74980
R-squared	0.079	0.082	0.079	0.082
No. of Clusters	48	48	48	48

Notes. $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$. We report here the estimates of the effect on CC Concern of temperature anomalies experienced by respondents interviewed during Waves 8 and 10 of the *ESS*. Coefficients are estimated using an OLS regression with country fixed-effects and individual controls. Standard errors are clustered at the country-by-wave level. Sources: *ESS* and $E - OBS$.

Table A14: Climate change concern and COP meetings: Ideological Bias

	(1) CC Concern	(2) CC Concern	(3) CC Anthropogenic	(4) CC Anthropogenic	(5) CC Gov. Action	(6) CC Gov. Action	(7) CC Concern	(8) CC Concern	(9) CC Anthropogenic	(10) CC Anthropogenic	(11) CC Gov. Action	(12) CC Gov. Action
COP26 (2021)	-0.001	-0.000	-0.001	-0.000	0.112	0.279						
	(0.008)	(0.006)	(0.010)	(0.010)	(0.347)	(0.364)						
COP26 × Center	0.031**	0.028**	-0.001	0.000	-0.224	-0.387						
	(0.012)	(0.013)	(0.013)	(0.012)	(0.492)	(0.525)						
COP26 × Right-Wing	0.070***	0.082***	0.047**	0.044**	-0.703	-0.698						
	(0.023)	(0.024)	(0.017)	(0.017)	(0.492)	(0.512)						
COP22 (2016)							-0.012	-0.015	0.018	0.011	-0.187	-0.205
							(0.020)	(0.022)	(0.018)	(0.018)	(0.118)	(0.176)
COP22 × Center							0.023	0.029	-0.016	-0.015	0.167	0.226
							(0.031)	(0.035)	(0.024)	(0.025)	(0.147)	(0.161)
COP22 × Right							-0.036	-0.025	-0.036	-0.035	0.019	0.060
							(0.027)	(0.034)	(0.025)	(0.027)	(0.121)	(0.162)
Ideology: Center (4-6)	-0.073***	-0.053***	-0.021*	-0.019*	0.402	0.598	-0.055**	-0.047	0.006	0.006	-0.072	-0.105
	(0.011)	(0.013)	(0.011)	(0.009)	(0.356)	(0.420)	(0.026)	(0.031)	(0.017)	(0.016)	(0.158)	(0.175)
Ideology: Right (7-10)	-0.177***	-0.173***	-0.076***	-0.067***	0.981**	0.982*	-0.077***	-0.069**	-0.015	-0.010	0.188	0.154
	(0.018)	(0.015)	(0.014)	(0.014)	(0.385)	(0.462)	(0.025)	(0.030)	(0.018)	(0.020)	(0.168)	(0.178)
Years of completed education		0.006***		0.002**		-0.001		0.007***		0.006***		-0.023*
		(0.002)		(0.001)		(0.025)		(0.002)		(0.001)		(0.011)
Age		0.001		0.000		-0.058***		0.002		-0.001		-0.013
		(0.001)		(0.001)		(0.015)		(0.002)		(0.002)		(0.008)
Age, squared		-0.000		-0.000		0.001***		-0.000*		0.000		0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Male		-0.073***		-0.034***		-0.257		-0.095***		-0.030***		-0.030
		(0.009)		(0.005)		(0.191)		(0.012)		(0.010)		(0.063)
Children in the hh		0.009		-0.011		0.754***		0.018		0.006		-0.021
		(0.017)		(0.008)		(0.227)		(0.017)		(0.017)		(0.070)
Immigrant		0.015		-0.029		0.470		0.011		0.012		0.029
		(0.019)		(0.021)		(0.281)		(0.017)		(0.014)		(0.219)
Unemployed		-0.039		-0.032		0.240		0.005		0.019		0.030
		(0.029)		(0.035)		(0.361)		(0.049)		(0.021)		(0.126)
Subjective household income		0.012		0.004		0.282*		-0.022**		-0.006		0.108
		(0.008)		(0.005)		(0.159)		(0.010)		(0.004)		(0.091)
Interest in Politics		0.029***		0.007*		0.043		0.073***		0.000		0.075
		(0.005)		(0.004)		(0.142)		(0.014)		(0.005)		(0.052)
Suburbs		-0.016		0.006		0.095		-0.018		0.001		-0.066
		(0.012)		(0.011)		(0.297)		(0.024)		(0.017)		(0.100)
Town		-0.007		-0.000		0.140		-0.016		0.013		-0.038
		(0.010)		(0.014)		(0.225)		(0.014)		(0.009)		(0.097)
Village		-0.022		0.007		-0.030		-0.048***		-0.008		-0.056
		(0.016)		(0.013)		(0.257)		(0.015)		(0.011)		(0.083)
Countryside		-0.041		-0.007		-0.322		-0.026		0.016		-0.147
		(0.026)		(0.024)		(0.216)		(0.044)		(0.025)		(0.139)
Temp. Anom.		0.249		-0.086		3.775***		0.183		-0.094		-0.160
		(0.153)		(0.190)		(1.278)		(0.322)		(0.139)		(1.436)
Temp. interview		0.002		0.002		0.005		0.002		-0.001		0.010
		(0.002)		(0.002)		(0.039)		(0.002)		(0.001)		(0.010)
Constant	0.917***	0.632***	0.965***	0.945***	4.533***	2.743***	0.758***	0.564***	0.913***	0.948***	4.692***	5.033***
	(0.010)	(0.083)	(0.009)	(0.101)	(0.260)	(0.779)	(0.019)	(0.170)	(0.013)	(0.081)	(0.137)	(0.973)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	5456	5107	5436	5093	742	716	5039	4973	5016	4946	4964	4896
R-squared	0.049	0.073	0.028	0.036	0.059	0.098	0.070	0.106	0.014	0.023	0.038	0.042
No. of Clusters	20	20	20	20	16	16	16	16	16	16	16	16

Notes. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors are clustered at the country-by-wave level. Sources: ESS and $E-OBS$. The full set of fixed effects is available here.

Table A15: Climate change concern and specific events within COP26

	(1) CC Concern	(2) CC Concern	(3) CC Concern	(4) CC Concern
Glasgow Pact	-0.026*	-0.019		
	(0.013)	(0.015)		
Climate March			0.019	0.027*
			(0.012)	(0.013)
Years of education		0.004*		0.006**
		(0.002)		(0.002)
Age		0.002		0.001
		(0.002)		(0.002)
Age^2		-0.000		0.000
		(0.000)		(0.000)
Male (0-1)		-0.066***		-0.064***
		(0.010)		(0.009)
Child living at home (0-1)		0.004		0.005
		(0.018)		(0.023)
Born abroad (0-1)		0.022		0.019
		(0.017)		(0.021)
Currently Unemployed (0-1)		0.022		-0.025
		(0.038)		(0.028)
Subjective income (0-3)		0.025***		0.017
		(0.007)		(0.012)
Interest in Politics (0-3)		0.032***		0.025***
		(0.008)		(0.009)
Domicile: Suburbs		-0.033**		-0.032*
		(0.016)		(0.017)
Domicile: Town		-0.012		-0.013
		(0.016)		(0.015)
Domicile: Village		-0.023		-0.018
		(0.019)		(0.021)
Domicile: Countryside		-0.064**		-0.046
		(0.025)		(0.029)
Temp. Anom.		0.174		0.214
		(0.142)		(0.295)
Temp. Interview		0.003*		0.004*
		(0.002)		(0.002)
Constant	0.873***	0.668***	0.864***	0.641***
	(0.004)	(0.097)	(0.005)	(0.141)
Country FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Observations	4784	4055	3307	2800
R-squared	0.031	0.066	0.029	0.060
No. of Clusters	20	20	20	20

Notes. $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$. We report here the estimates of the effect on CC Concern of temperature anomalies experienced by respondents interviewed during Waves 8 and 10 of the *ESS*. Coefficients are estimated using an OLS regression with country fixed-effects and individual controls. Standard errors are clustered at the country-by-wave level. Sources: *ESS* and $E - OBS$.

Table A16: Climate change concern: same countries across Temp. Anomalies and COP analyses

	(1) CC Concern	(2) CC Concern	(3) CC Concern
COP22 (2016)		-0.019	
		(0.035)	
COP22 × Center		0.004	
		(0.047)	
COP22 × Right		-0.038	
		(0.049)	
COP26	0.002		
	(0.005)		
COP26 × Center	0.029^{*}		
	(0.013)		
COP26 × Right	0.075^{**}		
	(0.026)		
Temp. Anom. (t-2)	0.405^{*}	-0.076	0.155^{**}
	(0.195)	(0.307)	(0.073)
Temp. Anom. (t-2) × Center			-0.080^{*}
			(0.045)
Temp. Anom. (t-2) × Right			-0.051
			(0.123)
Temp. Interview	0.002	0.003	0.001
	(0.002)	(0.003)	(0.001)
Temp. Interview × Center			0.000
			(0.001)
Temp. Interview × Right			0.001
	(0.109)	(0.194)	(0.119)
Center	-0.058^{***}	-0.020	-0.009
	(0.012)	(0.039)	(0.021)
Right	-0.179^{***}	-0.048	-0.097^{*}
	(0.015)	(0.043)	(0.055)
Country FE	Y	Y	Y
Time trend	N	N	Y
Controls	Y	Y	Y
Observations	4507	3434	46840
R-squared	0.076	0.093	0.077
No. of Clusters	14	14	28

Notes. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$. We report here the estimates of the effect on Climate change concern of COP26, COP22 and temperature anomalies, considering ideology heterogeneity. We resort to 14 countries only for the three regressions, those present for all analyses. Coefficients are estimated using an OLS regression with country fixed-effects and individual controls. Standard errors are clustered at the country-by-wave level. Sources: ESS and $E - OBS$.

Appendix D

Chapter 5 appendix

D1. Papers included in the meta-analysis

D1.1. On emission synergy (42)

Abrell, J. and Weigt, H. (2008). Economics of Global Warming The Interaction of Emissions Trading and Renewable Energy Promotion Jan Abrell and Hannes Weigt Renewable Energy Promotion. *Renewable Energy*, (December)

Anke, C. P. and Möst, D. (2021). The expansion of RES and the EU ETS – valuable addition or conflicting instruments? *Energy Policy*, 150(June 2020)

Arnette, A. N. and Zobel, C. W. (2011). The role of public policy in optimizing renewable energy development in the greater southern Appalachian mountains. *Renewable and Sustainable Energy Reviews*, 15(8):3690–3702

Arnette, A. N. (2017). Renewable energy and carbon capture and sequestration for a reduced carbon energy plan: An optimization model. *Renewable and Sustainable Energy Reviews*, 70(October 2015):254–265

Bird, L., Chapman, C., Logan, J., Sumner, J., and Short, W. (2011). Evaluating renewable portfolio standards and carbon cap scenarios in the U.S. electric sector. *Energy Policy*, 39(5):2573–2585

Boeters, S. and Koornneef, J. (2011). Supply of renewable energy sources and the cost of EU climate policy. *Energy Economics*, 33(5):1024–1034

Böhringer, C., Rutherford, T. F., and Tol, R. S. (2009). THE EU 20/20/2020 targets: An overview of the EMF22 assessment. *Energy Economics*, 31(SUPPL. 2):S268–S273

Choi, D. G. and Thomas, V. M. (2012). An electricity generation planning model incorporating demand response. *Energy Policy*, 42:429–441

Clancy, M. S. and Moschini, G. (2018). Mandates and the incentive for environmental innovation. *American Journal of Agricultural Economics*, 100(1):198–219

Dai, H., Xie, Y., Liu, J., and Masui, T. (2018). Aligning renewable energy targets with carbon emissions trading to achieve China's INDCs: A general equilibrium assessment. *Renewable and Sustainable Energy Reviews*, 82(March 2016):4121–4131

De Jonghe, C., Delarue, E., Belmans, R., and D'haeseleer, W. (2009). Interactions between measures for the support of electricity from renewable energy sources and CO2 mitigation. *Energy Policy*, 37(11):4743–4752

Delarue, E. and Van den Bergh, K. (2016). Carbon mitigation in the electric power sector under cap-and-trade and renewables policies. *Energy Policy*, 92:34–44

Fagiani, R., Richstein, J. C., Hakvoort, R., and De Vries, L. (2014). The dynamic impact of carbon reduction and renewable support policies on the electricity sector. *Utilities Policy*, 28:28–41

Fais, B., Blesl, M., Fahl, U., and Voß, A. (2015). Analysing the interaction between emission trading and renewable electricity support in TIMES. *Climate Policy*, 15(3):355–373

Feng, C. C., Chang, K. F., Lin, J. X., Lee, T. C., and Lin, S. M. (2022). Toward green transition in the post Paris Agreement era: The case of Taiwan. *Energy Policy*, 165(April):112996

Flues, F., Löschel, A., Lutz, B. J., and Schenker, O. (2014). Designing an EU energy and climate policy portfolio for 2030: Implications of overlapping regulation under different levels of electricity demand. *Energy Policy*, 75(2010):91–99

Nelson, H. T. (2008). Planning implications from the interactions between renewable energy programs and carbon regulation. *Journal of Environmental Planning and Management*, 51(4):581–596

Knobloch, F., Pollitt, H., Chewpreecha, U., Daioglou, V., and Mercure, J. F. (2019). Simulating the deep decarbonisation of residential heating for limiting global warming to 1.5 °C. *Energy Efficiency*, 12(2):521–550

Lecuyer, O. and Quirion, P. (2013). Can uncertainty justify overlapping policy instruments to mitigate emissions? *Ecological Economics*, 93:177–191

Lecuyer, O. and Quirion, P. (2019). Interaction between CO2 emissions trading and renewable energy subsidies under uncertainty: feed-in tariffs as a safety net against over-allocation. *Climate Policy*, 19(8):1002–1018

Li, A., Peng, D., Wang, D., and Yao, X. (2017). Comparing regional effects of climate policies to promote non-fossil fuels in China. *Energy*, 141:1998–2012

Linares, P., Santos, F. J., and Ventosa, M. (2008). Coordination of carbon reduction and renewable energy support policies. *Climate Policy*, 8(4):377–394

Liu, Y. and Wei, T. (2016). Linking the emissions trading schemes of Europe and China - Combining climate and energy policy instruments. *Mitigation and Adaptation Strategies for Global Change*, 21(2):135–151

Liu, X., Du, H., Brown, M. A., Zuo, J., Zhang, N., Rong, Q., and Mao, G. (2018). Low-carbon technology diffusion in the decarbonization of the power sector: Policy implications. *Energy Policy*, 116(February):344–356

Mercure, J. F., Pollitt, H., Chewpreecha, U., Salas, P., Foley, A. M., Holden, P. B., and Edwards, N. R. (2014). The dynamics of technology diffusion and the impacts of climate policy instruments in the decarbonisation of the global electricity sector. *Energy Policy*, 73:686–700

Morris, J. F. (2009). Combining a Renewable Portfolio Standard with a Cap-and-Trade Policy : A General Equilibrium Analysis, A Thesis submitted to Engineering System Division, Massachusetts Institute of Technology (MIT), USA

Oderinwale, T. and van der Weijde, A. H. (2017). Carbon taxation and feed-in tariffs: evaluating the effect of network and market properties on policy effectiveness. *Energy Systems*, 8(3):623–642

Pothen, F. and Hübler, M. (2018). The interaction of climate and trade policy. *European Economic Review*, 107:1–26

Rathmann, M. (2007). Do support systems for RES-E reduce EU-ETS-driven electricity prices? *Energy Policy*, 35(1):342–349

Rausch, S. and Reilly, J. (2015). Carbon taxes, deficits, and energy policy interactions. *National Tax Journal*, 68(1):157–178

Ren, S., Wang, P., Lin, Z., and Zhao, D. (2022). The Policy Choice and Economic Assessment of High Emissions Industries to Achieve the Carbon Peak Target under Energy Shortage—A Case Study of Guangdong Province. *Energies*, 15(18)

Rezai, A. and van der Ploeg, F. (2017). Second-Best Renewable Subsidies to De-carbonize the Economy: Commitment and the Green Paradox. *Environmental and Resource Economics*, 66(3):409–434

Richstein, J. C., Chappin, É. J., and de Vries, L. J. (2015). Adjusting the CO2 cap to subsidised RES generation: Can CO2 prices be decoupled from renewable policy? *Applied Energy*, 156:693–702

Silva, S., Soares, I., and Afonso, O. (2021). Assessing the double dividend of a third-generation environmental tax reform with resource substitution. *Environment, Development and Sustainability*, 23(10):15145–15156

Song, J., Yang, W., Higano, Y., and Wang, X. (2015). Introducing renewable energy and industrial restructuring to reduce GHG emission: Application of a dynamic simulation model. *Energy Conversion and Management*, 96:625–636

Traber, T. and Kemfert, C. (2009). Impacts of the german support for renewable energy on electricity prices, emissions, and firms. *Energy Journal*, 30(3):155–178

van den Bergh, K., Delarue, E., and D'haeseleer, W. (2013). Impact of renewables deployment on the CO2 price and the CO2 emissions in the European electricity sector. *Energy Policy*, 63(2013):1021–1031

Verma, Y. P. and Kumar, A. (2013). Potential impacts of emission concerned policies on power system operation with renewable energy sources. *International Journal of Electrical Power and Energy Systems*, 44(1):520–529

Weigt, H., Ellerman, D., and Delarue, E. (2013). CO2 abatement from renewables in the German electricity sector: Does a CO2 price help? *Energy Economics*, 40:S149–S158

Yan, Y., Sun, M., and Guo, Z. (2022). How do carbon cap-and-trade mechanisms and renewable portfolio standards affect renewable energy investment? *Energy Policy*, 165(November 2021):112938

Mu, Y., Wang, C., and Cai, W. (2018). The economic impact of China's INDC: Distinguishing the roles of the renewable energy quota and the carbon market. *Renewable and Sustainable Energy Reviews*, 81(November 2016):2955–2966

Yi, B. W., Xu, J. H., and Fan, Y. (2019). Coordination of policy goals between renewable portfolio standards and carbon caps: A quantitative assessment in China. *Applied Energy*, 237(August 2018):25–35

D1.2. Only welfare (12)

Bauer, N., Baumstark, L., and Leimbach, M. (2012). The REMIND-R model: The role of renewables in the low-carbon transformation-first-best vs. second-best worlds. *Climatic Change*, 114(1):145–168

Böhringer, C. and Rosendahl, K. E. (2011). Greening Electricity More Than Necessary: On the Cost Implications of Overlapping Regulation in EU Climate Policy. *Schmollers Jahrbuch*, 131(3):469–492

Hindsberger, M., Nybroe, M. H., Ravn, H. F., and Schmidt, R. (2003). Co-existence of electricity, TEP, and TGC markets in the Baltic Sea Region. *Energy Policy*, 31(1):85–96

Huang, J., Xue, F., and Song, X. (2013). Simulation analysis on policy interaction effects between emission trading and renewable energy subsidy. *Journal of Modern Power Systems and Clean Energy*, 1(2):195–201

Kalkuhl, M., Edenhofer, O., and Lessmann, K. (2013). Renewable energy subsidies: Second-best policy or fatal aberration for mitigation? *Resource and Energy Economics*, 35(3):217–234

Lehmann, P., Sijm, J., Gawel, E., Strunz, S., Chewpreecha, U., Mercure, J. F., and Pollitt, H. (2019). Addressing multiple externalities from electricity generation: a case for EU renewable energy policy beyond 2020? *Environmental Economics and Policy Studies*, 21(2):255–283

Oh, I., Yoo, W. J., and Kim, K. (2020). Economic effects of renewable energy expansion policy: Computable general equilibrium analysis for Korea. *International Journal of Environmental Research and Public Health*, 17(13):1–21

Tsao, C. C., Campbell, J. E., and Chen, Y. (2011). When renewable portfolio standards meet cap-and-trade regulations in the electricity sector: Market interactions, profits implications, and policy redundancy. *Energy Policy*, 39(7):3966–3974

Unger, T. and Ahlgren, E. O. (2005). Impacts of a common green certificate market on electricity and CO2-emission markets in the Nordic countries. *Energy Policy*, 33(16):2152–2163

Wang, L. and Li, K. (2022). Research on renewable energy consumption and emission reduction in power market based on bi-level decision making in China. *Energy*, 260(March)

Wu, J., Fan, Y., and Xia, Y. (2017). How can China achieve its nationally determined contribution targets combining emissions trading scheme and renewable energy policies? *Energies*, 10(8)

Wu, J., Fan, Y., Timilsina, G., Xia, Y., and Guo, R. (2020). Understanding the economic impact of interacting carbon pricing and renewable energy policy in China. *Regional Environmental Change*, 20(3)

Table D1: Distribution of sample by journal

Journal	No. of papers
American journal of agricultural economics	1
Applied energy	2
Climate policy	3
Climatic change	1
Ecological economics	1
Energies	2
Energy	2
Energy conversion and management	1
Energy economics	3
Energy efficiency	1
Energy policy	15
Energy systems-optimization modeling simulation and economic aspects	1
Environment development and sustainability	1
Environmental & resource economics	1
Environmental economics and policy studies	1
European economic review	1
International journal of electrical power & energy systems	1
International journal of environmental research and public health	1
Journal of environmental planning and management	1
Journal of modern power systems and clean energy	1
Mitigation and adaptation strategies for global change	1
National tax journal	1
Regional environmental change	1
Renewable & sustainable energy reviews	2
Renewable and Sustainable Energy Reviews	2
Resource and Energy Economics	1
The energy journal	1
Utilities policy	1
Working Paper	3
Total	54

D2. Search terms for the meta-analysis

D3. Alternative specifications for synergy regression

When we restrict our sample to cases with four scenarios, we find through a logistic regression that GE models are more likely to find additional abatement. However, we do not find any statistically significant association regarding implementation of a carbon tax instead of a cap.

Table D2: Groups of terms

E: group of terms identifying the carbon pricing instrument
*ETS, cap*trade, emission* pric*, emission* tax*, emission* trad*, emission* permit*, emission* market, emission* quota, emission* ceiling, emission* reduction*, emission* target*, emission* cut*, carbon pric*, carbon tax*, carbon trad*, carbon permit*, carbon market, carbon quota, carbon ceiling, carbon reduction*, carbon target*, carbon cut*, CO*2 pric*, CO*2 tax*, CO*2 trad*, CO*2 permit*, CO*2 market, CO*2 quota, CO*2 ceiling, CO*2 reduction*, CO*2 target*, CO*2 cut*
R: group of terms identifying the renewable-energy instrument
renewable* certificate*, renewable* quota*, renewable* ceiling, renewable* target*, renewable* standard*, renewable* floor, renewable* polic*, renewable* subsid*, renewable* support, green * certificate*, green energy quota*, green energy ceiling, green energy target*, green energy standard*, green energy floor, green energy polic*, green energy subsid*, green energy support, green electricity quota*, green electricity ceiling, green electricity target*, green electricity standard*, green electricity floor, green electricity polic*, green electricity subsid*, green electricity support, green power quota*, green power ceiling, green power target*, green power standard*, green power floor, green power polic*, green power subsid*, green power support, clean energy quota*, clean energy ceiling, clean energy target*, clean energy standard*, clean energy floor, clean energy polic*, clean energy subsid*, clean energy support, clean electricity quota*, clean electricity ceiling, clean electricity target*, clean electricity standard*, clean electricity floor, clean electricity polic*, clean electricity subsid*, clean electricity support, clean power quota*, clean power ceiling, clean power target*, clean power standard*, clean power floor, clean power polic*, clean power subsid*, clean power support,
N: group of terms identifying quantitative results
model, numeric*, empirical, CGE, general equilibrium, partial equilibrium, simulations(s), counterfactual, optimi*ation, agent*based, ABM, quanti*, estimat*,result*
C: group of terms identifying the combination of instruments
interact*, comb*, align*, overlap*, joint effect, joint impact, total effect, total impact, simultaneous effect, simultaneous impact, policy portfolio, policy mix*, policy coordination, policy choice*, policy design, instrument portfolio, policy mix*, instrument coordination, instrument choice*, instrument design, synergy, co*existence, additionality

Table D3: Average marginal effects of logistic regression of the probability of additional abatement from an instrument combination (papers with four scenarios)

	Prob. of additional abatement
Carbon tax	0.0489
	(0.1760)
GE model	-0.5737***
	(0.0976)
Observations	29

In an attempt to increase statistical power, we combine estimates from papers with four and three scenarios. In the main text, we show results from a Tobit specification, where the probability of additional abatement is not a binary variable but instead, estimates of Type II are given the empirically estimated probability of additional abatement (16/31). This resulted in a continuous variable, bounded between 0 and 1. Next, we implement an ordered logistic model, which involves aggregating synergy results into categories. We choose three categories: 0: no additional abatement ('backfire', 'border of backfire', and estimates of Type I when only three scenarios area available), 1: possible additional abatement (estimates of Type II when only three scenarios area available), and 2: certain additional abatement ('negative synergy' and 'positive synergy'). While the categories are in increasing order in terms of expected synergy, they are not entirely separate, since category 1, or estimates of Type II, can be in category 0 or in category 2, depending on what the real (unknowable) synergy is. We find that carbon taxes are associated with higher probability of additional abatement (at the 10% level), both without and with an indicator variable for papers with four scenarios (Tables D4 and D5, respectively).

Table D4: Average marginal effects of ordered logistic model

	0: no additional abatement	1: possible additional abatement	2: certain additional abatement
Carbon tax	-0.254*	0.04	0.214*
	(0.131)	(0.033)	(0.120)
GE model	0.308**	-0.087	-0.221**
	(0.135)	(0.058)	(0.095)
n		53	

Table D5: Average marginal effects of ordered logistic model, considering the number of scenarios

	0: no additional abatement	1: possible additional abatement	2: certain additional abatement
Carbon tax	-0.229*	0.035	0.194
	(0.136)	(0.032)	(0.123)
GE model	0.266*	-0.071	-0.195*
	(0.152)	(0.059)	(0.105)
Four scenarios	-0.115	0.024	0.091
	(0.151)	(0.034)	(0.121)
n		53	