Climate Change Concerns and Information Spillovers from Socially-Connected Friends*

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Abstract

This paper studies the role of social connections in shaping individuals' concerns about climate change. I combine granular climate data, region-level social network data and survey responses for 24 European countries in order to document large information spillovers. Individuals become more concerned about climate change when their geographically distant friends living in socially-connected regions have experienced large increases in temperatures since 1990. Exploring the heterogeneity of the spillover effects, I uncover that the learning via social networks plays a central role. Further, results illustrate the important role of social values and economic preferences for understanding how information spillovers affect individual concerns.

Keywords: Information Spillovers, Climate Change, Beliefs, Social Networks

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1. Introduction

Battling the adverse consequences of climate change and global warming is one of the most momentous challenges for generations to come and is expected to impose high costs on virtually everyone. Accepting these challenges will be vital for implementing effective policies today that mitigate negative consequences that only materialize in the future (Nordhaus, 2019). Studying how awareness of these challenges and costs is formed, particularly for those not (yet) suffering from the consequences, is important.[1] The goal of this paper is, therefore, to understand the role of social interactions in shaping this process.

In particular, this paper studies how exposure to visible changes in climatic conditions transmits via social networks and creates spillover effects on the concerns of individuals about climate change who themselves are not (yet) exposed to adverse effects of global warming. This follows an extensive literature dating back to Katz and Lazarsfeld (1955) highlighting the importance of networks, and in particular weak ties (Granovetter, 1973), in shaping individual behavior and the associated literature on issues of identification going back to Manski's (1993) formulation of the *reflection problem.* Building on extensive global climate data and social network data, I find that having socially-connected—hereafter *distant*— friends connected via social networks who are already more exposed to the consequences of climate change today leads to individuals being increasingly concerned about climate change as a global problem. In particular, by exploring heterogeneity across individual responses, I establish that estimated spillover effects are consistent with individuals learning about the negative consequences of climate change through indirect exposure via distant friends. Hence, social networks, in particular social ties to regions exposed to climate change, serve as a powerful substitute for direct exposure to climate change. Further results highlight the important role of social values in the propagation of experiences via social networks.

This paper operates under the premise that while consequences of climate change might only be felt in the future, effective actions have to be taken today in order to prevent these adverse consequences from materializing. This is aggravated by the fact that Western countries, while not yet suffering under the consequences of climate change as other developing countries are, have historically been and currently remain a large contributor to global CO2 emissions.[2] Beliefs and, in particular, concerns about climate change are an important prerequisite for effective policies against climate change (Falk et al., 2021). Figure 1 plots the relationship

1 Related, recent literature (Falk et al., 2018; D'Acunto et al., 2022; Bernard et al., 2022) study individuals' willingness to take actions against climate change and highlight the role of peers and higher-order beliefs about the willingness of their peers to fight climate.

2 Around 10% of global emissions are still emitted by EU27 countries (Crippa et al., 2019) of that, around 20% are emitted by private households (Ivanova et al., 2017).

between climate change concerns and changes in CO2 emissions as a broadly available measure of first successes and future commitments in fighting climate change. Data on CO2 emissions are obtained for 24 European countries either at the regional level (Panel (a)) or country level (Panel (b)). While Panel (a) shows that individual concerns about climate change correlate with larger decreases in CO2 emissions between 2013 and 2018, Panel (b) highlights that those countries with a higher share of respondents concerned about climate change have also committed themselves to more considerable reductions in CO2 emissions over the next years.[3] Together, these correlations illustrate that concerns about climate change could be an important contributing factor to explaining the willingness to adopt policies against climate change. Understanding the drivers of these concerns is, therefore, an important question.

In order to identify spillover effects on concerns about climate change via distant friends, I construct a high-resolution dataset on global temperatures to compute the change in the maximum monthly average temperature from 1990 to 2010 as a measure of exposure to climate change. While temperature changes are only an imperfect measure for the effects of climate change, this measure has the advantage of being firstly easily observable for individuals and secondly available at a highly granular regional resolution, unlike, for example, natural disasters, which are typically available at a more aggregated level.[4]

I combine the temperature data with granular regional data on social network connections between regions worldwide obtained from the *Social Connectivity Index* (SCI) to measure the indirect exposure to temperature changes experienced by distant friends in connected regions. The SCI constitutes a unique measure for worldwide social interactions via the social media platform *The Facebook* at a regional level. For one, Facebook's market penetration is global and it is widely used across socioeconomic groups. Secondly, Facebook friendships can be considered a valid measure for actual social interactions across regions as friendship requests have to be mutually accepted, and a single user is limited to at most 5000 friendship connections (Bailey et al., 2018b). As such, the SCI has demonstrated its validity in a wide range of contexts.[5] I then leverage this highly dis-aggregated regional data in combination with individual survey responses on climate change beliefs for a wide variety of European countries from the *Eurobarometer* public opionion polls to address the question at hand.

In the baseline specification, I regress a dummy variable indicating whether respondents

3 These reductions are part of the agreed policies at the supra-national European level in order to meet the goals outlined in the Paris agreement. See Regulation No 2018/842.

4 See, e.g., Bharath and Cho (2021) or Hu (2022) for applications with disaster data.

5 Social connections, as measured by the SCI, have explanatory power for the trade between countries (Bailey et al., 2021), migration patterns (Bailey et al., 2018b), assimilation of migrants (Bailey et al., 2022) or beliefs about things like house prices (Bailey et al., 2018a) the spread of COVID 19 (Bailey et al., 2020c).

are concerned about climate change on the respondents' indirect exposure to temperature change via their distant friends in connected regions, as well as direct exposure to changes in temperatures in their own region. I find consistent evidence of positive spillover effects via social networks. Estimates reveal that a one standard deviation increase in indirect exposure via distant friends is about 50% larger relative to a similar increase in direct exposure to changes in temperature. This result is robust to the inclusion of different sets of individual characteristics and regional controls.

One concern regarding identification is that both measures of indirect and direct exposure are time-invariant, and hence identification exploits regional variation within countries while pooling across survey waves. Identification is, therefore, possibly subject to reverse causation at a lower regional level as social networks form due to assortative matching across regions with similar beliefs or socioeconomic characteristics. To address these concerns, I first restrict the sample to include only regions available in the *Eurobarometer* at a more granular level (both metropolitan areas and counties) and allow for unobserved heterogeneity at the county or state level, respectively. Allowing for unobserved heterogeneity at more granular regional levels yields estimates of the spillover effects that are at least as large as the baseline effect. Next, I leverage recent machine learning techniques (Athey and Imbens, 2019; McCaffrey et al., 2013) to flexibly estimate generalized propensity scores and construct a matched sample of individuals with similar observable characteristics and living in regions with different indirect exposure to increases in temperatures via their distant friends. As long as individuals with similar observed characteristics are also more similar in terms of unobserved heterogeneity, this approach controls for any reverse causation due to assortative matching in social networks. Results based on the matched sample confirm the baseline results. Lastly, I also show evidence of the positive spillover effects on climate change concerns via social networks by exploiting time variation within narrowly defined regions while allowing for unobserved heterogeneity at the most granular regional level. To this end, I use data on natural disasters and construct, as before, measures of direct exposure to natural disasters as well as indirect exposure to natural disasters that occur in socially connected regions of distant friends. Data on disasters are only available for broad regional categories, yet the different exposure to these disasters in connected regions over time enables the inclusion of granular region fixed effects. Results based on natural disasters largely confirm the existence of positive spillover effects of distant friends' experiences. In addition, these findings are indicative of the fact that results are indeed not driven by reverse causality, as social networks form endogenously at lower regional levels.

Next, I investigate the forces behind the positive spillover effects by exploiting heterogeneity across observable background characteristics at the individual level as well as across regions that display different social values and economic preferences. The positive spillover effects are consistent with a *learning channel*. I find that spillover effects of indirect exposure to climate change via distant friends are particularly large for respondents who live in regions that have experienced only moderate changes in temperatures. This indicates that social networks and shared experiences of distant friends can serve as an essential source of information in order to learn about the consequences of climate change and act as a substitute for individuals' own experiences.

I further corroborate the learning channel by documenting an *inverse-u* shaped relationship between estimated spillovers and respondents' age and education, respectively. Additionally, I find that the effects are stronger for individuals using social media more frequently and individuals reporting to trust in stories published on social networks. The fact that individuals more likely to interact via social networks and trust information gathered through these interactions grow more concerned about climate change is indicative that social networks indeed propagate experiences. Further, since estimated spillovers scale with the salience of using social networks despite the fact that social connections are identified only at the regional level is reassuring that similar effects would likely persist when using more granular de-identified social network data at the individual level.

To dig deeper into the role of social and economic preferences, I further leverage data from the *Global Value Survey* (Falk et al., 2021) aggregated to the regional level. Spillover effects are predominantly present in regions characterized by higher altruism and lower patience. While the positive effect of altruism is an intuitive finding, the negative effect of higher levels of patience is interesting and provides further evidence of the learning channel. As more patient individuals place an ex-ante higher weight on future events, they likely spend more effort learning about potential future risks and, as such, more patient individuals respond less to the exposure via distant friends. By contrast, for less patient individuals who ex-ante care less about future events, spillovers via social networks are large as they constitute a source of new and no-cost information, which they would not have acquired otherwise.

Lastly, I assess the potential effects on economic decision-making. To this end, I use questions from the *Eurobarometer* regarding whether respondents have taken personal actions against climate change. While the share of respondents having taken actions against climate change is associated, as expected, with larger decreases in CO2 emissions between 2013 and 2018, I find no evidence of spillover effects. I, do however, document a strong and robust positive spillover effect for individuals characterized by more altruistic behavior, highlighting the importance of social norms for battling climate change as a global problem.

Literature This paper adds to a growing literature on climate-change-related beliefs and the role of social norms. Closely related is the paper by Falk et al. (2021), who study the willingness to fight climate change. Similar to this paper, they first document the importance of patience, altruism, and moral values for predicting climate preferences. They establish causal evidence on how misperceptions about climate-friendly behaviors and norms of peers affect the willingness to fight climate change. By contrast, I show the importance of information about climate change transmitted via friendship networks for explaining individuals' concerns about climate change and the substantial heterogeneity in these spillover effects across regions with different social values. This also contributes to a growing literature on the role of social values and economic preferences, mostly in terms of energy efficiency (Newell and Siikamäki, 2015; Schleich et al., 2019; Fischbacher et al., 2021; Costa and Kahn, 2013), as well as pro-environmental behavior, Lades et al. (2021), collective action against global warming (Bolsen et al., 2014).

More broadly, this paper is related to the substantial literature on peer effects and spillovers via social networks in a wide array of contexts, most prominently education (see, e.g. Sacerdote, 2011, for a review in the context of education) with a recent focus on personality (see, e.g., Golsteyn et al., 2021), and more generally the role of networks for the transmission of information. Closely related is the paper by Bailey et al. (2020a), who apply the dis-aggregated social network data used at the regional level in this paper to study house price beliefs in the US.

More specifically, this paper contributes to the literature on peer effects and climate change. Bernard et al. (2022) study individuals' willingness to pay to offset carbon emissions in an information provision experiment. They document the greater importance of the information provided by peers relative to scientific/government sources of information for individuals' willingness to pay. Relatedly, D'Acunto et al. (2022) study beliefs about an alternative for financing abatement policies and show how support for certain policies very much depends on which populations stand to gain or lose from certain policies. In that sense, this results suggest targeting individuals more likely not yet to know about the consequences of climate change in order to raise awareness for policy interventions and point to potential multiplier effects via social networks. Similarly, Hu (2022) uses social network data from the SCI and provides evidence of social networks as an important transmission channel for information dissemination and attention triggering in the context of flood experiences; he shows for the US how following the flooding experiences of distant friends and public information campaigns for flood insurance in connected areas lead to increased demand for flood insurance in the peer network. This paper similarly shows spillover effects of natural disasters via social networks but focuses instead on individual beliefs.

This paper additionally relates to a growing literature that instead studies firms' beliefs about climate regulation and abatement activities (Ramadorai and Zeni, 2021) as well as the effects of climate-related news and climate risk on asset prices both in equity markets (Alok et al., 2020; Engle et al., 2020) and bond markets (Huynh and Xia, 2021).

Roadmap The paper proceeds as follows: Section 2 describes the data construction and estimation strategy. Section 3 contains the empirical results and explores channels behind those results. Section 4 concludes.

2. Data and Empirical Strategy

2.1. Data Description

The main results of this paper use social network data and high-resolution global temperature data in combination with individual survey responses from the Eurobarometer. I also collect data on natural disasters worldwide, regional socioeconomic controls, and regional economic preferences for further robustness tests. Details on the data, matching and variable construction are described below.

Social Network Connections I obtain data on social networks between regions across the globe from the *Social Connectedness Index* (SCI) as described in Bailey et al. (2020b, 2018b, 2020a, 2021). The SCI is based on a one-time snapshot in April 2016 of friendship links between active users of *The Facebook*. The de-identified user data is mapped to each user's respective region and country using place-related information stated on users' profiles and activities on the platform.[6] Based on the regional linkages, the SCI captures the relative probability of a Facebook friendship link between any Facebook user in location r and any other user in location u:

$$SCI_{r,u} = \frac{\#\text{ Facebook Connections}_{r,u}}{\#\text{ Facebook Users}_r \times \#\text{ Facebook Users}_u}, \tag{1}$$

6 For large countries, data is aggregated to regions equivalent to US counties (i.e., GADM2 level and NUTS3 level for Europe). In contrast, smaller countries are dis-aggregated to regional levels that correspond to US states (GADM1 and NUTS2). Data from countries with less than 1 million are not further disaggregated. Countries dis-aggregated to the highest resolution (i.e., NUTS3 and GADM2) are all European countries, the main focus here, as well as The United States, Canada, Bangladesh, India, Nepal, Pakistan, and Sri Lanka.

where # Facebook Connections$_{r,u}$ is the number of friendship links between region r and u and # Facebook User$_r$ is the total number of active Facebook users in location r. To guarantee that the links are active, only links among Facebook users who had an interaction in the 30 days prior to the snapshot are used (Bailey et al., 2018b). I use the SCI aggregated to a granular regional level that allows for tracking friendship networks between regions worldwide.

Temperature Data I construct a high-resolution dataset of global temperature changes at a granular regional level by leveraging several sources: First, I obtain comparable and consistent global data on monthly average temperatures on a 0.5°× 0.5°grid from the *University of Delaware Air Temperature & Precipitation* dataset (UDAT; see Willmott and Matsuura, 2001, for details). Second, whenever regions fall outside these gridpoints, I use data from the individual weather stations underlying the UDAT and augment this with additional data from European weather stations supplied by the *European Climate Assessment & Dataset* (Klein Tank et al., 2002) and NASA's *Daymet* gridded (1km × 1km) temperature dataset for the US (Thornton et al., 1997, 2021).

The resulting geospatial data are matched to regions using the shapefiles from Bailey et al. (2020b), and I aggregate temperatures to the regional level by averaging across all observations (grid points or stations) contained within a region. Figure 2a and Figure 2b display the maximum monthly average temperatures in 1990 and 2010, respectively.

In order to identify information spillovers to concerns about climate change that are transmitted via social networks, I combine the temperature data with the social network data to construct a proxy for the exposure of distant friends to changes in climatic conditions. More specifically, for individuals living in region r, I consider the percentage change in maximum monthly average temperature from 1990 to 2010 in regions $u \neq r$ connected via Facebook friendships. Then I compute for each region r the weighted 75th percentile of temperature changes in connected regions u using the *SCI* as relative weights; this is the primary measure of the empirical analysis.

Figure 2c plots the spatial distribution of the exposure of distant friends at the regional level for all countries included in the *Eurobarometer*, a repeated cross-sectional survey in European countries, and at the regional resolution used in the *Eurobarometer* as this eventually determines the granularity of variation used for identification.[7] Figure 3 plots the temperature change of distant friends (on the y-axis) against the temperature change in the region of respondents itself; histograms show the distribution of both variables. Indirect exposure to changes in the climate of distant friends living in connected regions and their own

7 Note that white regions are missing either temperature data or have no respondent in the Eurobarometer.

direct experiences is negatively correlated. Hence, exposure to distant friends can potentially serve as an information device for individuals who have not yet experienced any significant temperature changes. Further, the observation that individuals' direct exposure is more dispersed and, on average, larger relative to their indirect exposure, reflects that using the entire distribution of temperature changes in connected regions u helps to attenuate concerns about measurement error and noise in the data.

By using the 75th percentile, I account for the assumption that friends with exposure to more extreme changes in temperatures are also more likely to share these experiences, so connections to these individuals should thereby play a more prominent role in the transmission of climate change-related information. Variation in the distant friends' exposure across regions originates from using the SCI as weights that reflect the relative likelihood of friendship connections and hence exchanges about personal experiences between two regions. The choice of the year 2010 as an endpoint is motivated by using only information available before any of the survey waves eliciting the beliefs about climate change. Secondly, by focusing on a relatively short time frame (i.e., 20 years), I ensure that the measured temperature change has a reasonable overlap with the lifetime experience of Facebook users, who tend to be younger.[8]

To avoid any confounding influence from individuals' direct exposure to changes in average temperatures, I exclude any connections to regions u located in the same country and similarly exclude any regions u in a 100km perimeter of the region r to parsimoniously address discontinuities in border regions. The concern with including the exposure of geographically close regions or regions in the same country is that information transmission might not only occur via social networks, the object of interest, but instead reflect spurious attribution with personal experiences at a national level or other underlying spatial correlations of changes in climatic conditions.[9] Instead, I control for the direct exposure of individuals living in the region r by including the percentage change in maximum average monthly temperatures from 1990 to 2010 in the region r as a control variable in the estimation.

Survey Data I obtain data on individual concerns about climate change for a broad set of European regions and over several years from the Eurobarometer survey. The Eurobarometer is a repeated cross-sectional survey fielded across 24 countries (see Table 1) in Europe since 1978. I use responses from surveys fielded in 2013, 2015, 2017, and 2019 that elicit respondents' concerns about climate change. Specifically, I use items in each Eurobarometer wave that record whether respondents consider climate change a global problem when asked: *"Which*

8 See country-specific data from `https://napoleoncat.com/`.

9 Changes in temperature in regions in the same country are likely more present on national news and hence exposure to these experiences is not only driven via information transmitted through the social network.

of the following do you consider to be the single most serious problem facing the world as a whole? Which others do you consider to be serious problems?". Respondents can choose from a list of ten options[10] and are asked successively about each option and whether they consider it a serious problem. For this paper, I do not distinguish whether climate change is mentioned as the single most serious or a serious problem and instead pool answers to elicit whether respondents believe climate change to be a serious problem. In addition, to measure changes in actual economic behavior, I rely on survey items asking respondents whether they have taken any personal actions against climate change.

In the *Eurobarometer*, respondents' locations are reported at the regional level and are used to match individuals with data on their social networks and local temperatures. The regional information is at different regional resolutions for different countries. Table 1 reports the regional level for each country as well as the number of regions by country, and the average number of observations in each region and survey wave. The exposure to temperature changes of distant friends and individuals' direct exposure is aggregated to the corresponding lowest possible regional level available from the Eurobarometer.

Further, I collect respondents' characteristics from the Eurobarometer; these include respondents' age in years, gender, marital status, a dummy whether an individual has kids, education aggregated into six categories according to years of education, and employment/occupational status and income proxy.[11] Summary statistics are reported in Table 2.

In addition, I use questions fielded only in certain waves of the survey to explore the channels behind the main results. In particular, I use items about the frequency of internet use fielded only in 2013-2017, and items on social networks and trust in social networks contained in the 2017 wave.

Disasters Additional data on natural disasters comes from the *International Disasters Database*.[12] To assign the disasters from EM-DAT to a given region, I rely on the geolocations provided by the *Geocoded Disasters dataset* (GDIS)[13] and match the geocoded disaster data with regional data using the *SCI* shapefiles as before (Bailey et al., 2020b). The

10 These are: Climate change, International Terrorism, Poverty, hunger and lack of drinking water, the spread of infectious diseases, the economic situation, proliferation of nuclear weapons, armed conflicts, increasing global population, other, or none.

11 Education groups are up to 14 years, 15-17 years, 18-20 years, more than 21 years of education, students, and individuals without full-time education. Employment/occupational status comprises the following categories: self-employed, managers, other white-collar jobs, manual workers, house persons, unemployed, retired, and students. Eurobarometer, unfortunately, does not collect detailed income information but instead asks about individuals' difficulties with paying bills with the following answer categories: "most of the time", "from time to time", and "almost never/never".

12 EM-DAT, DREC/UCLouvain, Brussels, Belgium (Guha-Sapir et al., 2015); downloaded 08.03.2022

13 See Rosvold and Buhaug (2021); Rosvold (2020)

Eurobarometer survey records the interview time, and I only consider disasters that occurred at least a month before the earliest interview of each survey wave. I pool all disaster categories (climatological, geophysical, hydrological, and meteorological) and additionally show results for individual disaster types.[14] I compute the exposure to disasters as the number of previous (before each survey wave) disasters in a given region. Similarly, the exposure to natural disasters of distant friends is computed as the weighted average of experienced disasters across connected regions u using, as before, the $SCI_{r,u}$ as relative weights. Summary statistics for the number of all disasters are reported in Table 2.

Regional Controls To control for socioeconomic differences at the regional level, I further obtain additional control variables at the regional level from *Eurostat*. These include the population density and demographic structure and gross domestic output, unemployment rate, and the number of heating degree days, all measured the year before each survey wave. Summary statistics are reported in Table 2.

2.2. Empirical Strategy

I estimate the following equation at the level of individual survey respondents i using OLS:

$$\begin{aligned} \textit{Climate Change Concerns}_{it} = & \beta \left(\Delta \textit{Temperature - Distant Friends}_{r(i)} \right) + \\ & \gamma \left(\Delta \textit{Temperature - Own Exposure}_{r(i)} \right) + \\ & \mathbf{c} X_{i,t} + \mathbf{d} W_{r(i),t-1} + \delta_t + \rho_{c(i)} + \epsilon_{i,t}. \end{aligned} \tag{2}$$

The dependent variable is a dummy variable that takes on the value one if respondent i is concerned that climate change is a serious world problem in survey wave t.
Δ *Temperature - Distant Friends*$_{r(i)}$ is the indirect exposure to changes in climate via distant friends and Δ *Temperature - Direct Exposure*$_{r(i)}$ is the change in temperature in region r of respondent i. The vector of individual controls X includes respondents' age, marital status, income, education, information on employment status and occupation, as well as a dummy variable if the respondent has children; W denotes a set of control variables at the regional level $r(i)$ and measured the year before a given survey wave, these include population density, GDP, unemployment rate, heating-degree days, population below 15 and above 65. δ_t and $\rho_{c(i)}$ denote time fixed effects and country fixed effects, respectively, where c denotes the country of respondent i. All continuous variables are winsorized at 1%. ϵ denotes the error term, and standard errors are clustered at the regional level r at the highest possible granularity.

14 I consider in particular droughts, extreme temperature events, floods, and storms.

The coefficient of interest β captures information spillovers via social network connections. The parameter is identified by the variation in distant friends' exposure across regions within the same country. For example, Figure 2c illustrates the substantial heterogeneity across regions within countries as well as across countries that stem from differences in social network connections and the related differential indirect exposure of distant friends to changes in climate. At the regional level, distant friends' exposure is time-invariant and prevents the inclusion of fixed effects at more granular regional levels. The inclusion of country fixed-effects absorbs any confounding correlation between concerns about climate change and national economic trends or preferences. Similarly, awareness about climate change may be spuriously correlated across regions within the same country for political reasons or due to national news media.

A remaining concern regarding the identification is possible reverse causation at a lower regional level, as social networks form due to assortative matching across regions with similar beliefs or socioeconomic characteristics. I address these concerns in three ways: First, I show that restricting the sample to countries where regions are reported at a higher resolution, i.e., NUTS3 regions, and correspondingly including more granular regional fixed-effects yields comparable results. Secondly, to address potential confounding influences from observable differences across respondents in different regions, I use machine learning techniques, i.e., boosted regression trees (Athey and Imbens, 2019), to estimate generalized propensity scores for individuals living in regions with differential indirect exposure to changes in climatic conditions via their distant friends. Based on the estimated scores, I construct a matched sample of individuals with similar observable characteristics that live in regions connected to distant friends that have different experiences with changes in climate. To the extent that individuals with similar observed characteristics are also more similar in terms of their unobserved heterogeneity, this poses a more stringent test of the underlying hypothesis. Thirdly, I leverage data on natural disasters available only at a supra-regional level and exploit time-variation in exposure to natural disasters within regions while controlling for unobserved heterogeneity at a granular regional level. I establish that social connections to distant friends with higher disaster experience yield qualitatively similar results.

3. Results

3.1. Baseline Results

Main results from estimating Equation (2) are presented in Table 3. The coefficient on Δ *Temperature - Distant Friends* is positive and statistically significant across all specifications. This is consistent with the existence of information spillovers from regions more exposed to climate changes via social networks. Including respondents' direct exposure to changes in temperatures in column 2 marginally increases the effect of indirect exposure via distant friends. Both effects are statistically significant at the 5% level. Unsurprisingly, the effect of direct exposure is estimated to be larger (20.87 vs. 10.98). Yet, comparing the relative magnitudes of direct and indirect exposure effects on climate change beliefs demonstrates that the estimated effect of a one standard deviation increase in exposure via distant friends is about 50% larger than an equivalent increase in direct exposure (both evaluated at the respective means).[15] This attests to the important role of positive information spillovers for beliefs about climate change.

These coefficients are robust to including all control variables (column 3) or controlling for regional characteristics to account for any observable economic differences across regions (column 4). Coefficients on control variables are, for brevity, reported in Table A1 and Table A2, but are largely as expected. On average, women, older, more educated, employed, and richer respondents are more concerned about climate change. Similarly, respondents living in regions that are more densely populated and have lower unemployment rates are more likely to report concerns about climate change. The effect of age is ambiguous at the regional level.

3.2. Robustness

The challenge with identifying the spillover effects from distant friends is that the measure of exposure to climate change is time-invariant at the regional level. Hence, including regional fixed effects at the highest regional resolution would wash out the coefficient of interest. I next establish that the main result is robust to restricting the sample to regions at a higher resolution and including more granular fixed effects or restricting the analysis to a matched sample to effectively control for observed heterogeneity across regions with different indirect exposure to climate change via their distant friends. Lastly, I show that using other time-varying measures of exposure to climate change yields similar results.

15 Indirect Exposure: $\frac{(0.057+0{,}081)\times 10.98-0.057\times 10.98}{0.057\times 10.98}$ and Direct Exposure: $\frac{(0.111+0{,}110)\times 20.867-0.110\times 20.867}{0.110\times 20.867}$

Granular Regional Fixed Effects The *Eurobarometer* reports respondents' locations for different countries at different regional levels (see Table 1). The main results use data on social connections and temperatures at the most granular regional level possible and allow for country-specific unobserved heterogeneity by including country fixed effects. Results in columns 1 to 3 of Table 4 are estimated by restricting the sample to the most granular regional level (NUTS3 in column 2) while allowing for unobserved heterogeneity at the NUTS2-level, which comprises regional clusters with a population between 800,000 and 3MM and roughly corresponds to the *Metropolitan Statistical Areas* for the US. Column 3 restricts the sample to respondents for whom locations are reported at the NUTS2 or NUTS3 level and include fixed effects at the NUTS1 level, which roughly correspond to US states. The baseline specification (all regions, country fixed effects) is displayed in Column 1 for comparison. Results reveal that allowing for unobserved heterogeneity at more granular regional levels tends to yield larger estimates of the spillover effects of climate change exposure of distant friends. Therefore, the baseline estimate seems to be a conservative estimate of the spillover effects. Interestingly, the effect of direct exposure to changes in temperature is less precisely estimated and even smaller relative to the indirect effect via distant friends when including fixed effects at the NUTS2 level (column 2).

Matched Sample To overcome the limitations imposed by the cross-sectional nature of the Eurobarometer, I next explore the role of observed and unobserved heterogeneity at the individual level. To this end, I construct a matched sample of individuals with comparable observable characteristics living in regions that are differently exposed to direct and indirect experiences with changes in climatic conditions. To the extent that individuals with similar observed characteristics are also more similar in terms of unobserved heterogeneity, this poses a more stringent test of the underlying hypothesis.

I begin by assigning respondents to treatment groups for each survey wave based on quartiles of indirect exposure to temperature changes via distant friends to end up with 16 treatment groups (four quartiles and four survey waves). Assigning regions that belong to the same quartile of indirect exposure to different treatment groups for each survey wave allows to parsimoniously control for any demographic changes over time across regions differently exposed to climate change. To estimate the propensity scores, I build on the literature of generalized propensity scores (Hirano and Imbens, 2001, 2004) and leverage recent machine learning methods to handle a large number of treatment groups by estimating so-called boosted regression models. This method is an iterative fitting algorithm building on regression trees, where each iteration starts with a simple regression tree and adds a new tree at each iteration aimed at fitting the residuals of the tree from the previous iteration (see, e.g., Athey and Imbens, 2019; McCaffrey et al., 2013, for further explanation). I use individual characteristics described above and quartiles of direct exposure to temperature changes as observables when fitting the model.

Diagnostics on the matching are displayed in Figure 4. Panel (a) plots the standardized difference, defined as the difference in means of standardized observable characteristics between two treatment groups, for all possible pairs of treatment groups. The unweighted difference on the y-axis corresponds to the differences in means for the raw sample. In contrast, the differences in weighted means are plotted on the x-axis, where the estimated propensity scores serve as weights. The weighted mean differences across groups are much smaller relative to their unweighted counterparts, therefore mitigating any concerns about confounding observable differences. This is further corroborated in Panel (b) of Figure 4, which plots p-values corresponding to the t-test of mean differences across the treatment groups for each observable characteristic. While the majority of p-values associated with differences in unweighted group means (on the x-axis) fall below the threshold of 5% significance (red crosses), only a few p-values below the critical value of 5% significance remain once the propensity scores are used to compute the weighted means (on the y-axis).[16]

Results from the weighted counterpart of the baseline regression using the propensity scores as weights are in column 4 of Table 4. The estimated coefficient on the spillover effects is larger than the baseline (11.86 vs. 10.98) and of similar significance (t-statistic 2.27 vs. 2.33). Additionally, including regional control variables in the weighted regression in column 5 has little effect, and only slightly reduces the estimated coefficient but is similarly estimated to be larger than its counterpart in Table 3. Overall, controlling for unobserved heterogeneity by constructing a matched sample to address differences in observable characteristics across regions with differential exposure to climate change, either indirectly via distant friends or directly, or using more granular fixed effects delivers qualitatively similar results. Results indicate that the baseline effect is likely a conservative estimate of the spillover effects via social connections between regions with different exposure to changes in climate.

Exploiting Time-Variation in Disaster Experience Next, I explore whether the results are robust to using time-variation within regions to identify the spillover effects of distant friends' exposure to climate change while allowing for unobserved regional heterogeneity at the most granular level. In particular, I exploit variation in distant friends' exposure to natural disasters within narrowly defined regions across time as disasters occur between the different survey waves. However, unlike the temperature data, the disaster locations are geocoded at a

16 Roughly 53% of pairwise group comparisons are significantly different from zero at the 5% level and, in contrast, only roughly 6% after weighing by the estimated propensity scores.

much lower resolution. Hence they are often only assigned to states or even countries rather than the granular regional resolution to counties of the *SCI* and temperature data.

Results are in Table 5, where the number of disasters corresponds to the disasters that have happened in a respondent's region $r(i)$ since 1990, and the number of disasters of distant friends is the weighted average of the number of disasters that happened in a friend's region u since 1990 using the *SCI* between region r and u as weights. All regressions, importantly, allow for unobserved heterogeneity at the most granular regional level as reported in Table 1.

Estimates in column 1 confirm the existence of positive spillovers of distant friends' exposure to climate change, as measured by disaster experiences, to individual beliefs or concerns about climate change. The coefficient on disaster experience of distant friends is highly significant and large relative to the effect of direct disaster exposure, which is also estimated less precisely (t-statistic of 1.87 vs. 3.99). While column 1 uses all types of natural disasters, columns 3, 5, 7, and 9 decompose the effect for different disaster categories (extreme temperatures, droughts, floods, storms). Estimated coefficients on the spillover effects of distant friends' disaster experiences are all positive and mostly significant (except floods), but interestingly the effects are substantial for events associated with extreme temperatures or droughts, which are most closely reflected in the main measure of exposure to climate change used in this paper and can most easily be related to climate change. Overall, results are therefore also robust to a different measure of exposure—direct or indirect—to changes in climate and, importantly, remain large and significant when including very granular regional fixed effects.

Adding flexible interactions between disaster experiences and direct and indirect exposure to temperature changes (columns 2, 4, 6, 8, and 10) has little effect on estimates. These specifications, unlike before, include fixed effects at the most granular level as variation in disaster experience across time differs across regions with different, time-invariant exposure to changes in temperatures. Closer inspection and interpretation of the interaction terms are relegated to Section 3.3.

3.3. Channels

Next, I explore potential channels behind the observed positive spillovers from distant friends' exposure to temperature changes to concerns about climate change. To this end, I explore the heterogeneity of the spillover effects by re-estimating Equation (2) and including interaction terms between the indirect exposure via distant friends and several observable individual characteristics and indicators of the salience of certain economic and social preferences at the regional level. All regressions also control for individuals' direct exposure to temperature changes (even if not shown for brevity), individual controls, and country fixed effects. Standard errors are clustered at the regional level. Results are plotted in Figure 5 to Figure 7, where for each figure, Panel (a) displays estimated coefficients (blue dots) and associated standard errors (horizontal red capped bars) and Panel (b) plots marginal effects implied by the linear model. The marginal effects are the predicted effect of changes in distant friends' temperatures implied by the linear model computed for each respondent holding fixed their individual characteristics (including fixed effects) and varying the variable of interest; i.e., their age, education etc. The marginal effect is then obtained by averaging the predicted effect across each respondent. Blue dots denote the point estimate of the implied predicted effect and standard errors obtained from the delta-method are plotted as vertical capped bars in red.

Use of and trust in social networks I first test how the salience of using the internet and social networks impacts the spillover effects. At the same time, this addresses a remaining concern that stems from the fact that social connections are identified only at the regional level, and indirect exposure is measured as temperature changes in connected regions rather than experiences of connected friends. While the current data does not allow for going beyond the regional level, I nevertheless show that spillovers scale at the individual level with the likelihood of using social networks and having distant friends in connected regions. For that reason, I begin by adding interactions between the indirect exposure to climate change via distant friends and respondents' frequency of using the internet or social media, respectively. Results are in Table 6; in column 1, I add a dummy that takes on the value one if a respondent uses social media at least once a week (fielded only in 2017). The coefficient is, as expected, positive (beta: 7.42) but imprecisely estimated (t-statistic: 1.11). In column 2, I add interaction with a dummy taking on the value one if a respondent reports using the internet daily.[17] Surprisingly at first, the estimated coefficient is negative and statistically significant (t-statistic: 2.07). This is, however, potentially explained by the fact that internet use might correlate with having access to a wide range of information sources that might mute any learning about climate change and belief-updating from distant friends. To make more sense of these results, I again consider how the spillover effects scale with the frequency of using social media and split the sample into individuals using the internet daily (column 3) and less frequently (column 4). As expected, spillover effects increase with the use of social media, in the sample of daily internet users, and estimated coefficients are statistically significant at the 10% level. However, while larger, the effect in the model of less-frequent internet users is less precisely estimated.

Column 5 leverages further question eliciting the trust in social networks fielded in the 2017 wave of the *Eurobarometer*. More specifically, respondents are asked whether they consider a

17 This variable was fielded from 2013 to 2017 and includes internet use in the job context as well as privately.

story published on an online social network trustworthy because based on whether they trust the social network where the story is published or not. I construct a dummy variable taking on the value one if a respondent trusts the social network and zero otherwise and interact this dummy with the indirect exposure to temperature changes through social connections. Results highlight the critical role of trust in the transmission of climate change-related information on individual concerns. The spillover effect is roughly 6 times larger for individuals trusting social networks (31.8) relative to individuals not trusting social networks and statistically significant different from the no-trust reference groups at the 5% level.

Overall, these results indicate that the spillover effects are driven by individuals who use social media or the internet more frequently and are hence who are more likely to be exposed to and trusting of experiences of distant friends. This is further suggestive evidence that using individual-level social network data would deliver similar evidence of positive spillover effects on climate change beliefs.

Learning One crucial aspect is whether positive spillovers allow individuals to learn about climate beyond their own exposure and experiences with changes in climatic conditions. I begin by testing whether indirect exposure to climate change via distant friends can substitute for direct exposure of respondents. I start by including interactions in terms of temperature changes in regions of distant friends with quartiles of the temperature changes in respondents' regions. Estimated coefficients are plotted in Panel (a) of Figure 5 with the corresponding predictive marginal effect implied by the linear model in Panel (b). The spillover effects are estimated to have a significant and positive effect only for individuals living in regions that have only experienced a moderate increase in temperatures (i.e., are in the lowest quartile of direct exposure). The estimated coefficient is 23.01, i.e., more than twice as large as the baseline estimate and significant at the 5% level (t-statistic: 2.24). The predicted marginal effect implied by the linear model is similarly different from zero in regions in the lowest quartile of direct exposure. In contrast, predicted spillovers remain reassuringly positive in regions that have experienced greater temperature changes themselves but are less precisely estimated. These results are consistent with a learning channel such that experiences of distant friends serve as an essential source of information that substitutes for individual experiences with climate change.

Figure 6 and Figure 7 repeat this exercise by adding interactions with age and education groups, respectively. Results reveal that spillover effects increase with age; coefficients are 21.10 and 17.99 for respondents aged between 51-75 and above 75, respectively (both significant at the 10% level with t-statistic 1.94 and 1.7, respectively). Similarly, there is an inverted U-shaped relation between years of education and information spillovers. Effects are large and statistically significant for individuals with education up to 14 and between 15-19 years; coefficients (relative to the baseline of individuals still studying) are 27.32 and 24.78, respectively, with corresponding t-statistics of 2.34 and 2.73. Predicted effects are similarly significantly different from zero for these education groups.[18] These groups coincide with individuals that stand to benefit the most from information spillovers from their peers and highlight the important role of learning from distant friends' exposure to climate change.

I further corroborate this evidence by illustrating how respondents update their concerns about climate change following natural disasters occurring in connected regions depending on their ex-ante heterogeneous exposure, both direct and indirect, to temperature changes. I hypothesize that if respondents indeed learn about climate change and the implied risks and costs via social connections to friends exposed to larger changes in temperatures, they should, si omnino, update their beliefs about climate change less in response to experiencing natural disasters. Furthermore, this test also allows exploiting the time variation in disaster experiences across regions differently exposed to temperature changes. Therefore, I can control for unobserved heterogeneity at a granular regional level by including regional fixed effects at the most detailed level possible.

To this end, I interact individuals' direct and indirect disaster experiences, measured as the number of disasters that occurred in respondents' regions (direct) or in connected regions of distant friends (indirect), with their direct and indirect exposure to changes in temperature as defined before. Results in Table 5 are in line with the learning channel. In column 2, the interaction between respondents' direct exposure and temperature changes in connected regions is estimated to be negative (-8.68) and statistically significant (t-statistic: 2.41); while respondents generally become more concerned about climate change in response to experiencing a natural disaster, they update their beliefs by less if they have ex-ante been exposed to larger temperature changes via their distant friends. Interestingly, the learning through distant friends or direct exposure is of roughly similar magnitude (-8.68 vs. -8.625 for indirect and direct exposure, respectively). I find similar evidence on the role of learning when focusing only on droughts (column 6) or storms (column 10). Unsurprisingly, the effects are muted for floods, as there is also no evidence of spillover effects coming from distant friends' experiences with floods (columns 7 and 8) to begin with. This effect is similarly muted when considering only extreme temperatures (column 4), likely due to the positive correlation between extreme temperature events and general increases in maximum temperatures.

18 By contrast, I find no significant difference in spillover effects across income groups, gender, or social class in additional results.

Role of Social Values and Preferences Next, I explore the role of social values and economic preferences in shaping how individuals respond to distant friends' exposure to climate change. These types of values have been shown to be an important determinant for behavior choices in the context of prosocial behavior in the labor market (Kosse and Tincani, 2020), or mobility decisions during the coronavirus pandemic (Alfaro et al., 2022). Most closely related, Falk et al. (2018) apply the survey design, which forms the basis for the regionally-aggregated preference data in this paper, and study the behavioral determinants behind the willingness to fight climate change. They find a strong relationship between climate preferences and perceived social norms as well as economic preferences and, in particular, document a positive interaction between patience, altruism, positive reciprocity, and the willingness to fight global warming. In a similar fashion, I hypothesize that social values drive the responsiveness to the indirect exposure via distant friends: altruism, positive reciprocity, and trust likely lead to larger spillover effects. How risk-taking behavior and negative reciprocity influence how individuals react to information transmitted via their social network is less clear.

Table 7 displays results from re-estimating the baseline specification of equation (2), but now the indirect exposure via distant friends is interacted with dummy variables that take the value one if a respondent lives in a region for which the value of each of the measures described above is in the highest tertile and zero for the lowest tertile. Spillover effects are significantly higher in regions characterized as more altruistic (beta: 57; t-statistic 3.13) and significantly lower in areas described as more patient (-40.96; t-statistic 2.87). This follows the hypothesis that more altruistic individuals are more likely to internalize any externalities on other individuals and adjust their beliefs according to the exposure to climate change of distant friends. The negative effect for more patient respondents is an interesting confirmation of the learning channel. As more patient individuals place higher weights on future risks, they face more substantial incentives to acquire potentially costly information about the future. As such, the negative coefficient on the interaction terms indicates that more patient individuals do not adjust their beliefs in response to indirect exposure as they are already informed about climate risks that are likely to materialize in the future. By contrast, for less patient respondents, the information spillovers via their social network provides a source of new information at no cost, which they would not have acquired otherwise.

Column 2 restricts the sample to NUTS2 and NUTS3 regions to allow for unobserved heterogeneity at the state level (i.e., NUTS1). However, this naturally reduces the precision of the estimates as the regional information in the *Global Value Survey* is often only available at broader regional levels and therefore absorbed. Accordingly, although still negative, the effect of more patient regions is now imprecisely estimated (t-statistic: 1.32).[19] By contrast, spillovers in more altruistic regions are positive and highly significant. Similarly, estimating the model on the matched sample (column 3) as described in Section 3.2 delivers consistent results on the opposite effects of patience and altruistic behavior.

Interestingly, results in column 2 indicate a differential reaction to distant friends' exposure to temperature changes in regions characterized by high positive reciprocity (more concerned) and high negative reciprocity (less concerned); yet, coefficients of high reciprocity, either positive or negative, are less precisely estimated (t-statistic: 1.91) and generally inconsistent across specifications. Finally, the positive effect of trust in social networks is partially confirmed, as spillover effects are larger for individuals living in more trusting regions but are imprecisely estimated (t-statistic 1.38).

Overall, the results indicate the critical role social and time preferences have in amplifying spillover effects via social networks.

3.4. Economic Outcomes

The last section explores whether social connections to regions with more prominent exposure to temperature changes also translate to observable differences in actions.

To validate the self-reported personal actions, Figure 8 Panel (a) plots the share of respondents reporting to have taken personal actions against climate change against the percentage change in CO2 emission between 2013 and 2018 at the regional level. The negative correlation is reassuring of the fact that survey responses, at least partially truthfully, reflect actual economic actions. To give some sense of the magnitude of the observed correlation, moving from the regions in the 10th percentile of the share of respondents that have taken personal actions to areas in the 90th percentile, would imply a sizeable 3.15% reduction in CO2 emissions between 2013 and 2018.

Table 8 displays results of estimating Equation (2), where the dependent variable is now a dummy taking on the value one if a respondent reports having taken personal action against climate change. Estimates in column 1 reveal no sizeable and significant effect of distant friends' exposure to climate change on the likelihood of respondents to take personal action against climate change; interestingly, there is also, although larger, no significant effect of respondents' direct exposure to changes to temperatures in their regions.

As before, column 2 adds interactions with a set of dummy variables that take the value one if a respondent lives in a region for which the value of each of the measures contained in

19 Coefficients on the dummy variables are not shown for brevity. Note, however, that throughout predictive marginal effect for either high or low values of each dummy remain positive.

the *Global Value Survey* is in the highest tertile and zero for the lowest tertile. In line with previous results, the spillover effects are powerful in regions characterized by more altruistic preferences; the estimate is statistically significant at the 10% level (t-statistic 1.90). The effect also seems economically relevant, as a one standard deviation increase in temperatures of connected regions (evaluated at the average) implies that a respondent is about 1.5 times more likely to take personal actions against climate change than the implied effect at the average indirect exposure. As before, column 3 is based only on regions available at the NUTS2 and NUTS3 levels, while column 4 is estimated on the matched sample. Again, results confirm the positive spillover effect in more altruistic regions; the magnitude of the estimated coefficient on the corresponding interaction term increases in both specifications (95.31 and 83.71, respectively); both are highly significant at the 1% level.

By contrast, the heterogeneity I exploited to uncover the learning channel does not affect respondents' actions differently (not shown). This observation highlights the vital role of social preferences and, in particular, altruistic behavior. The strong response seems to reflect that respondents living in more altruistic regions appear not only to adjust their beliefs more strongly to the exposure of their distant friends (see Table 7), but also act more altruistically towards their distant friends.

4. Conclusion

This paper provides evidence on how concerns about climate change are shaped by distant friends' exposure to temperature changes. These information spillovers are large and consistent with individuals not yet exposed to climate risk learning about climate change risks from the experiences of their distant friends. The paper thereby provides new evidence on the importance of social networks as a source of information and confirms evidence on the importance of peers for individual beliefs and behaviors towards climate change.

I leverage extensive global climate data in combination with social network data at the regional level to measure the extent to which connected regions, i.e., distant friends, have experienced large increases in temperatures. In a baseline specification, I then regress a dummy variable reporting whether individuals are concerned about climate change on the indirect exposure to changes in climatic conditions via distant friends as well as the direct exposure. Estimated spillover effects are large and robust to the inclusion of various controls and several tests addressing concerns about endogeneity.

Exploring the heterogeneity of the results indicates that distant friends are an essential source of information from which individuals learn about climate change. Information spillovers are substantial for individuals living in regions that themselves have experienced only small increases in temperatures, as well as for older and less educated individuals. Further, I use regional variation to provide evidence on the role of social norms and time preferences in shaping the responsiveness to experiences of distant friends by showing that effects are more prominent for individuals living in regions characterized as more altruistic and less patient. Thereby this paper complements an extensive literature on the interplay between peers, social norms, and beliefs about climate change (e.g. Falk et al., 2018; D'Acunto et al., 2022; Bernard et al., 2022).

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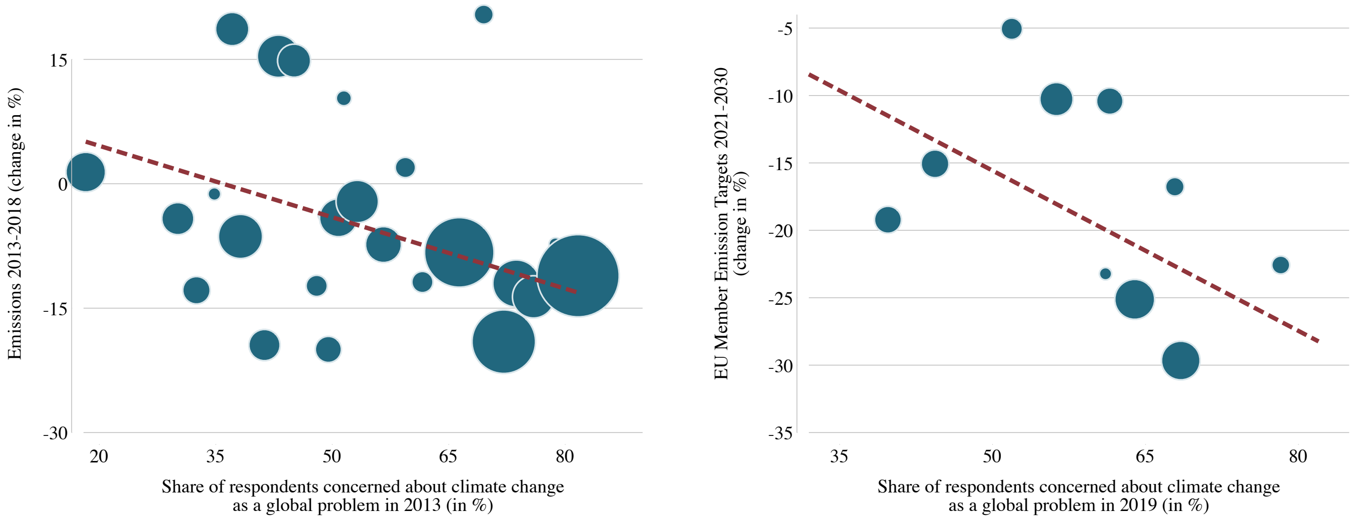
5. Figures

Figure 1
Climate Change Concerns and Co2 Emissions

Figure 1 displays the relation between climate change concerns and Co2 emissions (Panel (a)) or planned emissions (Panel (b)), respectively. The percentage change in Co2 emissions is calculated from 2013 to 2018 for regions in European countries and aggregated to the NUTS1 level and plotted against the share of respondents (at NUTS 1 level) reporting to be concerned about climate change in the 2013 wave of the Eurobarometer. The right panel plots planned reductions in Co2 emissions by EU member countries as set out in the European agreements to meet the Paris agreement (Regulation No 2018/842) against the share of respondents (at the country level) reporting to be concerned about climate change in the 2019 wave of the Eurobarometer. The size of the dots is scaled by emissions in 2013 (left panel) and 2021 (right panel).

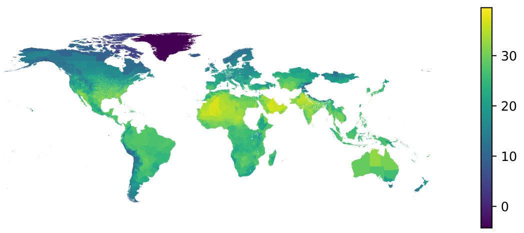


(a) Co2 Emissions and Climate Change Concerns

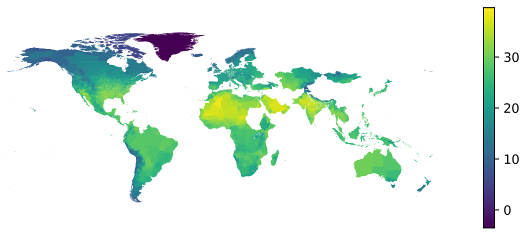
(b) Planned Reductions in Emissions and Climate Change Concerns

Figure 2
Exposure to Temperature Changes

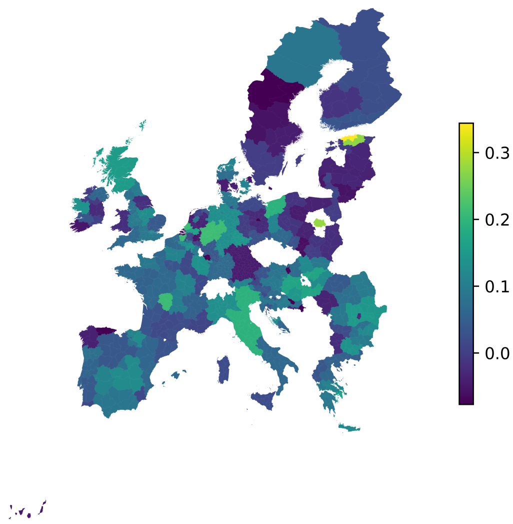
Figure 2 plots the maximum average monthly temperature in 1990 in Panel (a) and 2010 in Panel (b). Data on temperatures is obtained from the University of Delaware Air Temperature & Precipitation dataset (0.5°× 0.5°grid), the *European Climate Assessment & Dataset* (individual weather stations) and NASA's *Daymet* gridded (1km × 1km) temperature dataset for the US. Temperatures are matched to GADM and NUTS regions using shapefiles provided by Bailey et al. (2018b). Panel (c) plots the spatial distribution of distant friends' exposure to changes in climatic conditions defined as the weighted 75th percentile of the percentage change in maximum monthly average temperature from 1990 to 2010 in regions $j \neq i$ connected via Facebook friendships using the *Social Connectedness Index* between region r and u as relative weights. Distant friends' exposure is displayed for regions in countries included in the Eurobarometer survey and aggregated to the regional resolution reported in the Eurobarometer.



(a) Max. of Average Monthly Temp. - 1990



(b) Max. of Average Monthly Temp. - 2010



(c) Distant Friends' Exposure to Temperate Changes (in %)

Figure 3
Individual Exposure and Exposure of Distant Friends

Figure 3 displays a scatter plot of the percentage change in the maximum average monthly temperature from 1990 to 2010. The change in a given region r is plotted on the x-axis and exposure of distant friends' to climate changes on the y-axis, defined as the weighted 75th percentile of the percentage change in maximum monthly average temperature from 1990 to 2010 in regions $u \neq r$ connected via Facebook friendships using the *Social Connectedness Index* between region r and u as relative weights. Histograms represent the distribution of individuals' direct exposure to changes in temperature changes (in green) and exposure of their distant friends (in red).

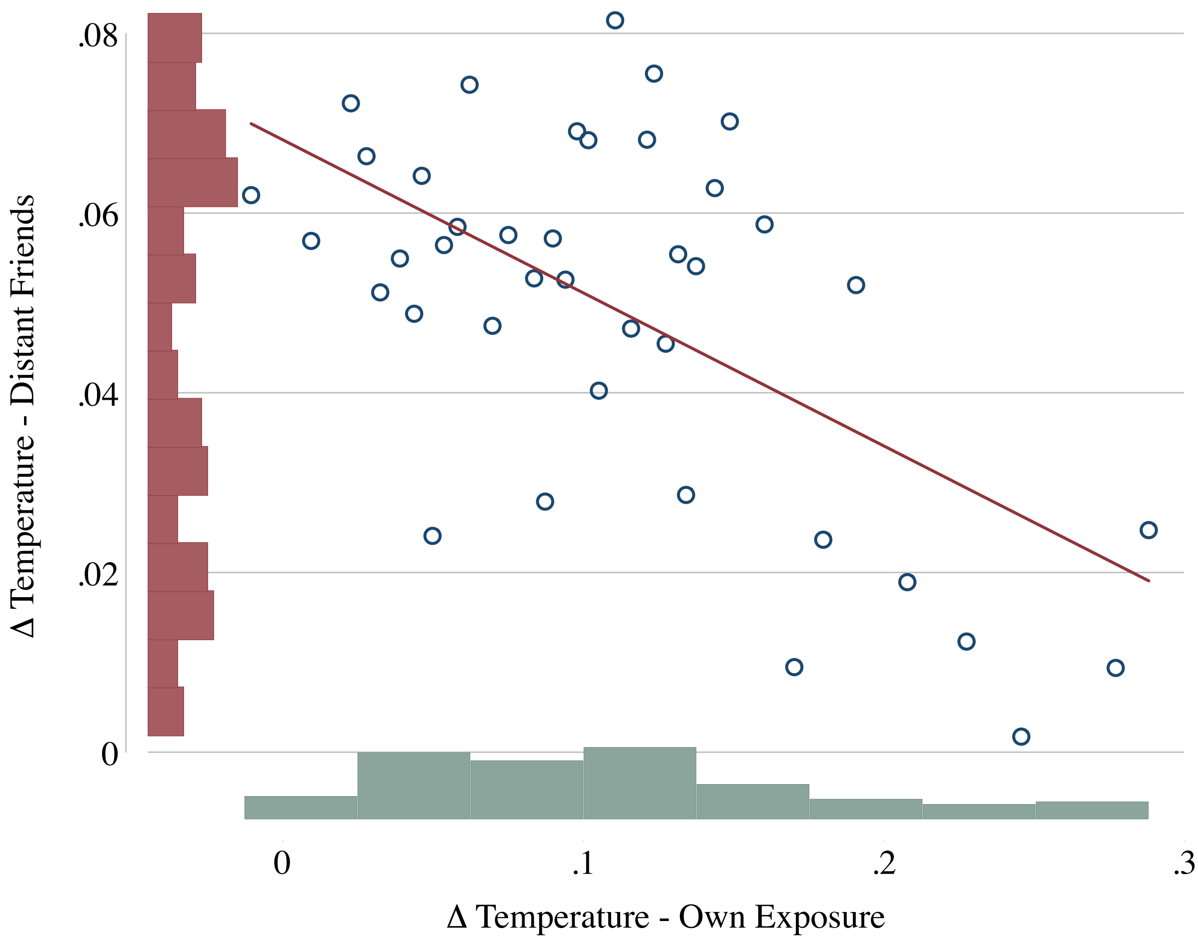
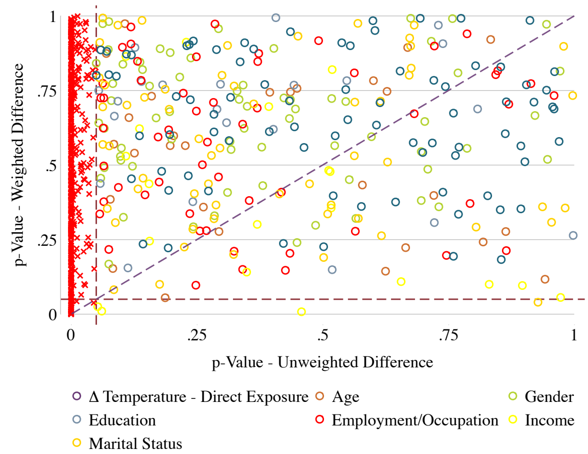


Figure 4
Standardized Bias and p-values across Treatment Groups

Figure 4 plots diagnostics on the matched sample based on generalized propensity scores. Propensity scores are estimated using boosted regression trees (McCaffrey et al., 2013) for treatment groups defined by quartiles of indirect exposure to climate change via distant friends and years. The model is fitted using the following observable characteristics: percentage change in temperature in respondents' own region, age, marital status, education, employment/occupation, income, and gender. Unweighted standardized mean differences on the y-axis in Panel (a) are the differences in group means of each observable characteristic across all quartile $\times$ year groups, and weighted mean differences are analogously computed as weighted group means using estimated propensity scores as weights. Corresponding p-values for t-tests on differences in group means are displayed in Panel (b).

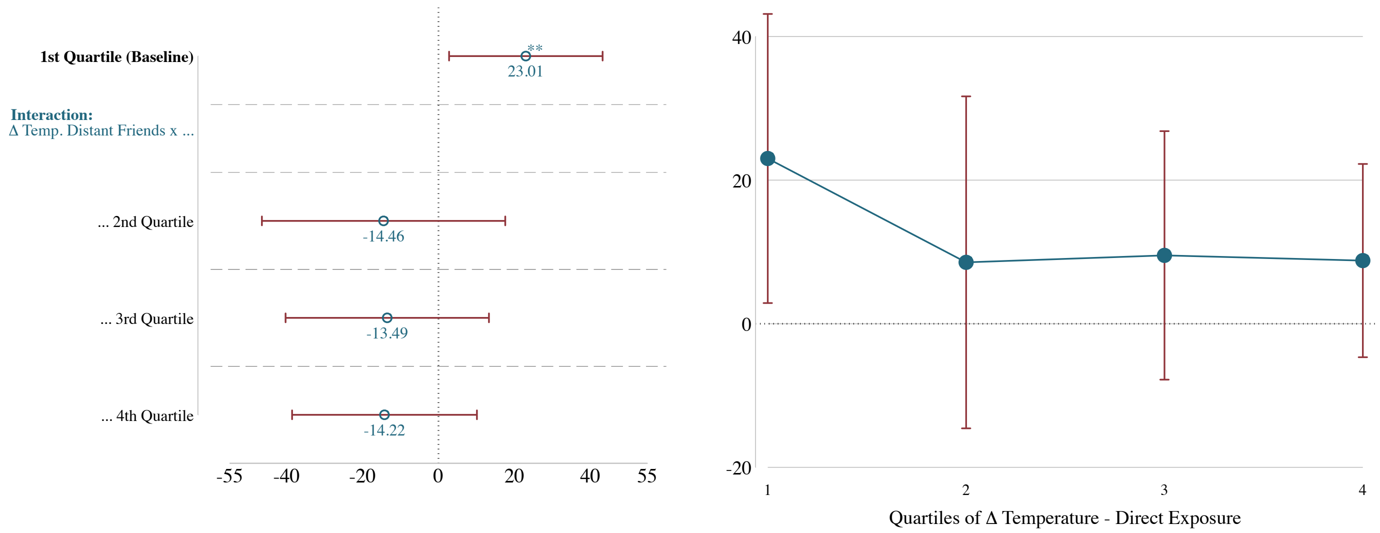
(a) Standardized Bias



(b) p-Values

Figure 5
Effect of Distant Friends' Exposure by Quartiles of Direct Exposure

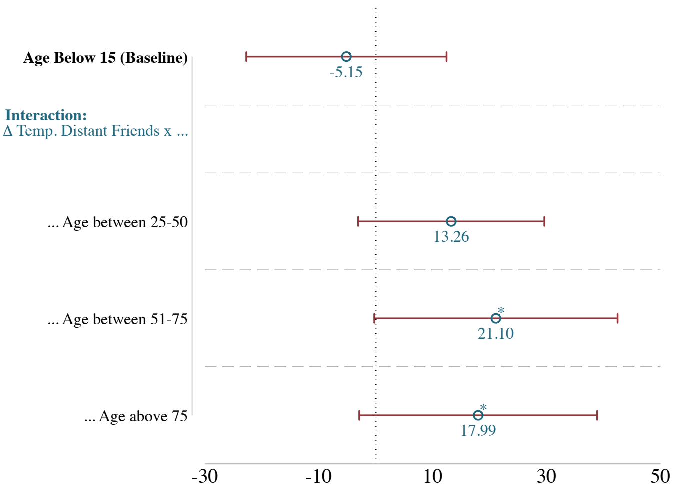
Figure 5 displays estimated interaction effects (Panel a) and implied predictive marginal effects (Panel b) from an OLS regression of respondents' concerns about climate change on respondents' indirect exposure via distant friends to changes in temperatures interacted with quartiles of respondents' direct exposure to climate change defined as the percentage changes in temperatures in respondents' region from 1990 to 2010. Δ Temperature - Distant Friends is the exposure of distant friends to changes in climate computed as the weighted 75th percentile in percentage temperature change across connected regions j from 1990 to 2010 using the $SCI_{i,j}$ as relative weights. The vector of individual controls includes respondents' age, marital status, income, education, information on employment status and occupation, and a dummy variable if the respondent has any kids. All regressions include year and region fixed effects. The dependent variable is multiplied by 100, and all continuous variables are winsorized at 1%. Standard errors are clustered at the regional level r at the highest possible granularity. ***, **, * indicate statistically different from zero at the 1%, 5% and 10% level of significance, respectively.



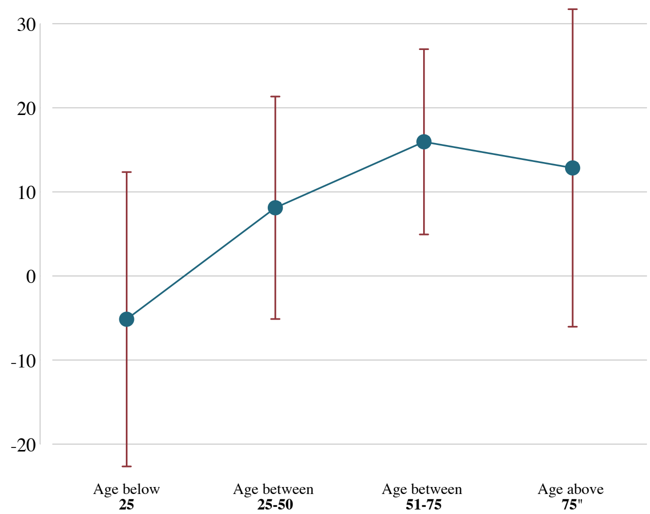
(a) Estimated Interaction Effects **(b)** Implied Predictive Marginal Effects

Figure 6
Effect of Distant Friends' Exposure to Temperate Changes by Age Groups

Figure 6 displays estimated interaction effects (Panel a) and implied predictive marginal effects (Panel b) from an OLS regression of respondents' concerns about climate change on respondents' indirect exposure via distant friends to changes in temperatures interacted with respondents' age. Δ Temperature - Distant Friends is the exposure of distant friends to changes in climate computed as the weighted 75th percentile in percentage temperature change across connected regions j from 1990 to 2010 using the $SCI_{i,j}$ as relative weights. The vector of individual controls includes respondents' age, marital status, income, education, information on employment status and occupation, and a dummy variable if the respondent has any kids. All regressions include year and region fixed effects. The dependent variable is multiplied by 100, and all continuous variables are winsorized at 1%. Standard errors are clustered at the regional level r at the highest possible granularity. ***, **, * indicate statistically different from zero at the 1%, 5% and 10% level of significance, respectively.



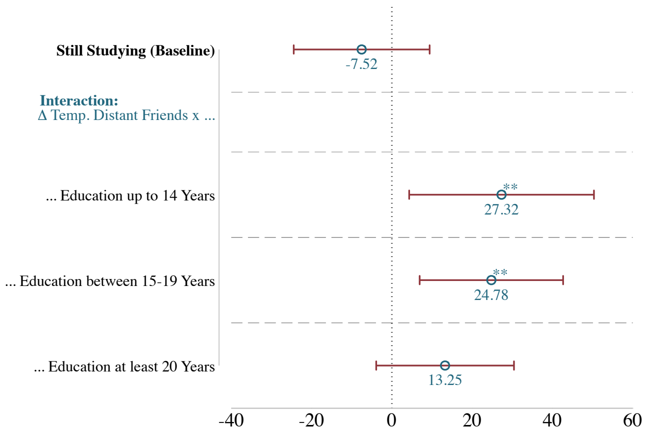
(a) Estimated Interaction Effects



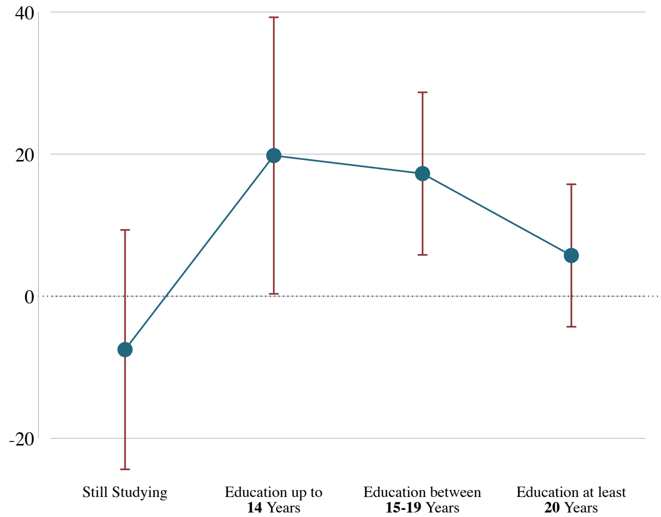
(b) Implied Predictive Marginal Effects

Figure 7
Effect of Distant Friends' Exposure to Temperate Changes by Education Groups

Figure 7 displays estimated interaction effects (Panel a) and implied predictive marginal effects (Panel b) from an OLS regression of respondents' concerns about climate change on respondents' indirect exposure via distant friends to changes in temperatures interacted with respondents' years of education. Δ Temperature - Distant Friends is the exposure of distant friends to changes in climate computed as the weighted 75th percentile in percentage temperature change across connected regions j from 1990 to 2010 using the $SCI_{i,j}$ as relative weights. The vector of individual controls includes respondents' age, marital status, income, education, information on employment status and occupation, and a dummy variable if the respondent has any kids. All regressions include year and region fixed effects. The dependent variable is multiplied by 100, and all continuous variables are winsorized at 1%. Standard errors are clustered at the regional level r at the highest possible granularity. ***, **, * indicate statistically different from zero at the 1%, 5% and 10% level of significance, respectively.



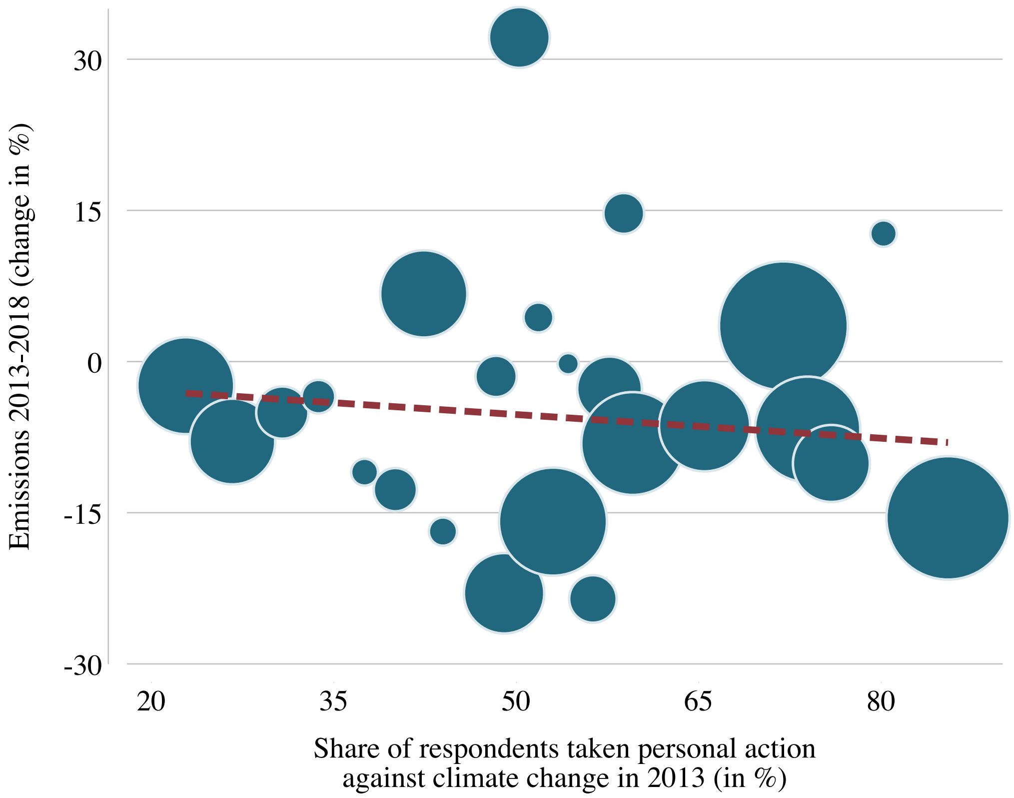
(a) Estimated Interaction Effects



(b) Implied Predictive Marginal Effects

Figure 8
Reductions in Co2 Emissions and Reported Personal Actions Against Climate Change

Figure 8 displays the relationship between the percentage change in Co2 emissions between 2013 and 2018 and the share of respondents (at NUTS 1 level) reporting to have taken personal action against climate change in the 2013 wave of the Eurobarometer. The size of each dot is scaled by the Co2 emissions in 2013.



6. Tables

Table 1
Regional Aggregation

Table 1 lists the countries included in the Eurobarometer (column 1) and whether respondents' locations are reported at the NUTS1, NUTS2 or NUTS3 level. Column 3 and 4 report the number of regions by country and the average number of respondents in each region and survey wave respectively.

Country	Aggregation	Number of Unique Regions	Average # Obs. per Region×Year
AT - Austria	NUTS level 2	9	154.71
BE - Belgium	NUTS level 2	11	113.41
BG - Bulgaria	NUTS level 2	34	156.29
DE - Germany	NUTS level 1	16	136.61
DK - Denmark	NUTS level 2	5	222.20
EE - Estonia	NUTS level 3	5	255.46
ES -Spain	NUTS level 2	17	107.37
FI - Finland	NUTS level 2	21	232.82
FR - France	NUTS level 2	21	81.10
GB - Great Britain	NUTS level 1	12	140.19
GR - Greece	NUTS level 2	10	209.37
HR - Croatia	NUTS level 3	19	95.81
HU - Hungary	NUTS level 2	7	175.29
IE - Ireland	NUTS level 3	8	161.46
IT - Italy	NUTS level 1	5	206.73
LT - Lithuania	NUTS level 3	10	139.11
LV - Latvia	NUTS level 3	5	155.64
NL - The Netherlands	NUTS level 2	12	125.00
PL - Poland	NUTS level 2	16	74.96
PT - Portugal	NUTS level 2	5	277.51
RO - Romania	NUTS level 2	8	129.17
SE - Sweden	NUTS level 2	8	175.01
SI - Slovenia	NUTS level 3	11	146.46
SK - Slovakia	NUTS level 2	4	271.75

Table 2
Summary Statistics

Table 2 reports summary statistics for the main variables used in the analysis. Data on disasters is obtained from *International Database Disaster Database.* The number of disasters in respondents' regions is computed as the number of previous (before each survey wave) disasters in a given region. The exposure to natural disasters of distant friends is computed as the weighted average across connected regions u using the $SCI_{r,u}$ as relative weights. Climate Change Concerns, Personal Actions, and individual controls (gender, age, children, marital status, education, income, and employment/occupation) are taken from the Eurobarometer survey and are pooled across survey waves from 2013, 2015, 2017, and 2019. Regional controls are taken from Eurostat. Averages on patience, risk-taking, reciprocity (positive and negative), altruism, and trust are experimentally validated measures taken from the *Global Preference Survey*(Falk et al., 2018) and aggregated to the regional level by averaging across individual responses.

	# Obs.	Mean	Median	S.D.
	(1)	(2)	(3)	(4)
Concerned about Climate Change	93,588	49.71	0.00	50.00
Personal Action Against Climate Change	90,412	0.54	1.00	0.50
# Disaster - Own Region	89,491	14.07	13.00	10.75
# Disaster - Distant Friends	89,491	19.04	18.31	4.26
Women	93,588	0.55	1.00	0.50
Age	93,588	51.04	52.00	18.15
Any Children	93,588	0.17	0.00	0.37
Marital Status:				
Unmarried	93,588	0.17	0.00	0.38
(Re-)Married/W. partner	93,588	0.64	1.00	0.48
Divorced/Separated	93,588	0.08	0.00	0.27
Widowed	93,588	0.10	0.00	0.30
Other	93,588	0.01	0.00	0.08
Education:				
Up to 14 years	93,588	0.09	0.00	0.29
15-17 years	93,588	0.20	0.00	0.40
18-20 years	93,588	0.34	0.00	0.47
More than 20 years	93,588	0.29	0.00	0.46
Still Studying	93,588	0.06	0.00	0.24
No full-time educ.	93,588	0.01	0.00	0.09
Income Proxy:				
Most of the Time	93,588	0.10	0.00	0.30
From Time to Time.	93,588	0.26	0.00	0.44
Almost Never/Never	93,588	0.64	1.00	0.48

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Table 2 ... *continued from previous page*

	(1)	(2)	(3)	(4)
Employment/Occupation:				
Self-employed	93,588	0.07	0.00	0.25
Managers	93,588	0.11	0.00	0.31
Other white collars	93,588	0.11	0.00	0.31
Manual workers	93,588	0.20	0.00	0.40
House persons	93,588	0.05	0.00	0.22
Unemployed	93,588	0.07	0.00	0.25
Retired	93,588	0.32	0.00	0.47
Students	93,588	0.06	0.00	0.24
Regional Controls:				
Population below 15	93,354	9.07	6.51	8.88
Population above 65	93,354	10.28	7.41	10.26
Heating Days p.A.	88,706	27.80	27.05	9.44
Unemployment Rate	92,215	9.21	7.70	5.45
GDP	88,706	0.03	0.03	0.03
Population Density	93,354	579.28	121.68	1216.76
Global Value Survey:				
Patience	66,744	0.24	0.20	0.48
Risk-Taking	66,744	-0.13	-0.11	0.28
Positive Reciprocity	66,744	-0.03	0.01	0.27
Negative Reciprocity	66,744	0.06	0.01	0.35
Altruism	66,744	-0.18	-0.15	0.29
Trust	66,744	0.05	0.08	0.26

Table 3
Baseline Results

Table 3 shows estimated coefficients from an OLS regression of respondents' concerns about climate change on respondents' direct and indirect exposure via distant friends to changes in climate measured as the percentage change in maximum monthly average temperatures from 1990 to 2010. Δ Temperature - Distant Friends is the exposure of distant friends to changes in climate, and Δ Temperature - Own Exposure is the change in temperature in respondents regions r of respondent i. The vector of individual controls includes respondents' age, marital status, income, education, information on employment status and occupation, and a dummy variable if the respondent has any kids. Regional controls include population density, GDP, unemployment rate, heating-degree days, and population below 15 and above 65. All regressions include country and year fixed effects. The dependent variable is multiplied by 100, and all continuous variables are winsorized at 1%. Standard errors clustered at the regional level r at the highest possible granularity are parentheses. ***, **, * indicate statistically different from zero at the 1%, 5% and 10% level of significance, respectively.

Dep. Variable	Concerned about Climate Change			
	(1)	(2)	(3)	(4)
Δ Temperature - Distant Friends	9.692**	10.984**	10.831**	9.984**
	(4.714)	(4.711)	(5.075)	(4.756)
Δ Temperature - Direct Exposure		20.867**		18.895*
		(10.464)		(11.269)
Year FE	Yes	Yes	Yes	Yes
Regional FE (NUTS 0)	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	No	Yes
Regional Controls	No	No	No	Yes
Observations	93,588	93,588	93,588	87,099
R^2	0.09	0.09	0.08	0.10

Table 4
Robustness — Fixed Effects & Matched Sample

Table 4 shows estimated coefficients from an OLS regression of respondents' concerns about climate change on respondents' direct and indirect exposure via distant friends to changes in climate measured as the percentage change in maximum monthly average temperatures from 1990 to 2010. Estimates in column 1 are based on the entire sample and include country fixed effects; column three restricts the sample to NUTS3 regions and includes fixed effects at the NUTS2 level, while column 3 contains observations at the NUTS2 and NUTS3 levels controlling for NUTS1 region fixed effects. Columns 4 and 5 are based on a matched sample. Δ Temperature - Distant Friends is the exposure of distant friends to changes in climate, and Δ Temperature - Own Exposure is the change in temperature in respondents regions r of respondent i. The vector of individual controls includes respondents' age, marital status, income, education, information on employment status and occupation, and a dummy variable if the respondent has any kids. Regional controls include population density, GDP, unemployment rate, heating-degree days, and population below 15 and above 65. All regressions include year and region fixed effects. The dependent variable is multiplied by 100, and all continuous variables are winsorized at 1%. Standard errors clustered at the regional level r at the highest possible granularity are parentheses. ***, **, * indicate statistically different from zero at the 1%, 5% and 10% level of significance, respectively.

Dep. Variable	Concerned about Climate Change				
	Baseline	Different regions		Matched Sample	
		NUTS 3	NUTS 2&3		
	(1)	(2)	(3)	(4)	(5)
Δ Temperature - Distant Friends	10.984**	18.716**	12.690***	14.488***	12.611**
	(4.711)	(9.057)	(4.096)	(5.314)	(5.385)
Δ Temperature - Direct Exposure	20.867**	11.547	24.816*	34.499***	30.795**
	(10.464)	(18.440)	(13.153)	(12.291)	(12.934)
Year FE	Yes	Yes	Yes	Yes	Yes
Regional FE	NUTS 0	NUTS 2	NUTS 1	NUTS 0	NUTS 0
Individual Controls	Yes	Yes	Yes	Yes	Yes
Regional Controls	No	No	No	No	Yes
Observations	93,588	21,479	78,889	93,588	87,099
R^2	0.09	0.07	0.10	0.09	0.09

Table 5
Information Spillovers and Disaster Experiences

Table 5 shows estimated coefficients from an OLS regression of respondents' concerns about climate change on respondents' direct and indirect exposure via distant friends to natural disasters. Data on natural disasters is from the International Disaster Database, and disasters are assigned to a given region using the Geocoded Disasters dataset (GDIS). Exposure to disasters is measured as the number of disasters since 1990 in a given region r. Similarly, the distant friends' exposure to natural disasters is computed as the weighted average of experienced disasters across connected regions u using as before the $SCI_{r,u}$ as relative weights. Δ Temperature - Distant Friends is the exposure of distant friends to changes in climate, and Δ Temperature - Own Exposure is the change in temperature in respondents regions r of respondent i. The vector of individual controls includes respondents' age, marital status, income, education, information on employment status and occupation, and a dummy variable if the respondent has any kids. The dependent variable is multiplied by 100, and all continuous variables are winsorized at 1%. All regressions include year and regional fixed effects at the highest possible resolution. Standard errors clustered at the regional level r at the highest possible granularity are parentheses. ***, **, * indicate statistically different from zero at the 1%, 5% and 10% level of significance, respectively.

Dep. Variable	Concerned about Climate Change									
	All Disaster Types		Extr. Temperatures		Droughts		Floods		Storms	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
# Disaster - Distant Friends	2.837***	2.012**	16.245***	16.352***	20.234***	27.099***	4.278	2.414	2.725***	1.592*
	(0.711)	(0.820)	(4.621)	(5.241)	(7.525)	(8.202)	(2.959)	(3.380)	(0.836)	(0.888)
# Disaster - Own Region	0.492*	1.918***	1.417	1.670	5.957***	9.706***	0.091	2.507**	1.328**	4.027***
	(0.262)	(0.572)	(1.115)	(2.228)	(1.799)	(1.617)	(0.468)	(1.192)	(0.612)	(0.927)
Δ Temperature - Distant Friends× # Disaster - Distant Friends		5.511		-17.354		-46.335		5.648		9.634**
		(4.785)		(32.218)		(53.577)		(18.855)		(4.789)
Δ Temperature - Direct Exposure× # Disaster - Distant Friends		2.925		-28.432		-111.885***		-6.552		3.486
		(3.253)		(29.779)		(42.541)		(13.682)		(2.953)
Δ Temperature - Distant Friends× # Disaster - Own Region		-8.681**		11.119		-53.950***		-8.489		-18.790***
		(3.599)		(11.819)		(16.324)		(7.096)		(6.316)
Δ Temperature - Direct Exposure× # Disaster - Own Region		-8.625*		-4.829		38.737		-24.286**		-20.415**
		(4.729)		(10.449)		(33.649)		(10.891)		(10.333)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional FE (NUTS 0)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	89,491	89,491	89,491	89,491	89,491	89,491	89,491	89,491	89,491	89,491
R^2	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10

Table 6
Internet and Social Media Use

Table 6 shows estimated coefficients from an OLS regression of respondents' concerns about climate change on respondents' direct and indirect exposure via distant friends to changes in climate measured as the percentage change in maximum monthly average temperatures from 1990 to 2010. Δ Temperature of Distant Friends is the exposure of distant friends to changes in climate. Social Media Use - Weekly is a dummy that takes on the value of one if respondents report using social media at least once a week (2017 wave of the Eurobarometer) and zero otherwise; Internet use - Daily similarly takes on the value of one if respondents' report to use the internet daily (2013-2017 waves of Eurobarometer) and zero otherwise. Social Media Trust is a dummy taking on the value one if respondents consider a story published on online social networks as trustworthy because they trust they trust the social networks the story is published on and zero otherwise. In addition, regressions include Δ Temperature - Direct Exposure, defined as the change in temperature in the region r of respondent i, respondents' age, marital status, income, education, information on employment status, and occupation, as well as a dummy variable if the respondent has any kids. All regressions include year and region fixed effects. The dependent variable is multiplied by 100, and all continuous variables are winsorized at 1%. Standard errors clustered at the regional level r at the highest possible granularity are parentheses. ***, **, * indicate statistically different from zero at the 1%, 5% and 10% level of significance, respectively.

Dep. Variable	Concerned about Climate Change				
	Social Media Use	Internet Use	Internet Use		Social Media Trust
			Daily	Infrequent	
	(1)	(2)	(3)	(4)	(5)
Δ Temperature - Distant Friends	3.093	19.891***	-5.507	5.794	5.996
	(6.708)	(7.242)	(7.774)	(9.942)	(7.418)
Socal Media Use - Weekly	1.585*		0.402	0.597	
	(0.822)		(0.946)	(2.776)	
Social Media Use - Weekly × Δ Temperature - Distant Friends	7.421		15.837*	34.394	
	(6.711)		(9.300)	(23.566)	
Use of Internet - Daily		3.786***			
		(0.726)			
Use of Internet - Daily × Δ Temperature - Distant Friends		-15.306**			
		(7.384)			
Social Media Trust					-2.301
					(1.840)
Social Media Trust × Δ Temperature - Distant Friends					34.132**
					(16.409)
Year FE	Yes	Yes	Yes	Yes	Yes
Regional FE (NUTS 0)	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes
Observations	23,529	66,299	15,967	7,562	13,394
R^2	0.10	0.09	0.10	0.06	0.10

Table 7
Social and Economic Preferences

Table 7 shows estimated coefficients from an OLS regression of respondents' concerns about climate change on respondents' direct and indirect exposure via distant friends to changes in climate measured as the percentage change in maximum monthly average temperatures from 1990 to 2010. Δ Temperature of Distant Friends is the exposure of distant friends to changes in climate and is interacted with regional levels of trust, patience, risk-taking, reciprocity (pos. and neg.), and altruism obtained from the Global Value Survey aggregated to the regional level by averaging across individual survey responses. Each variable is included as a dummy variable that takes on the value one if a measure is in the upper tertile and zero for the lower tertile. In addition, regressions include Δ Temperature - Direct Exposure, defined as the change in temperature in the region r of respondent i, respondents' age, marital status, income, education, information on employment status, and occupation, as well as a dummy variable if the respondent has any kids. Column one uses all observations, while results in column two are based on regions at the NUTS 2 and NUTS 3 levels. Column three uses the matched sample described in Section 3.2. All regressions include year and region fixed effects. The dependent variable is multiplied by 100, and all continuous variables are winsorized at 1%. Standard errors clustered at the regional level r at the highest possible granularity are parentheses. ***, **, * indicate statistically different from zero at the 1%, 5% and 10% level of significance, respectively.

Dep. Variable	Concerned about Climate Change		
	All	NUTS 2 & 3	Matched Sample
	(1)	(2)	(3)
Δ Temperature - Distant Friends	-5.802	3.420	10.630
	(13.691)	(16.787)	(18.301)
Δ Temperature - Distant Friends× High Trust	19.762	10.198	16.356
	(12.414)	(16.690)	(15.133)
Δ Temperature - Distant Friends× High Patience	-40.961***	-27.122	-50.900***
	(15.024)	(20.485)	(18.233)
Δ Temperature - Distant Friends× High Risk-Taking	4.730	-16.231	3.308
	(16.288)	(14.284)	(19.658)
Δ Temperature - Distant Friends× High Reciprocity (pos.)	-9.567	22.241*	-21.047
	(13.046)	(11.592)	(15.203)
Δ Temperature - Distant Friends× High Reciprocity (neg.)	-5.507	-21.126**	-4.214
	(11.018)	(10.076)	(12.003)
Δ Temperature - Distant Friends× High Altruism	57.005***	62.271**	62.912***
	(18.283)	(23.918)	(21.000)
Δ Temperature - Direct Exposure	19.864	29.175*	30.665**
	(12.765)	(16.278)	(14.294)
Year FE	Yes	Yes	Yes
Regional FE	NUTS0	NUTS1	NUTS0
Individual Controls	Yes	Yes	Yes
Observations	66,744	52,342	66,744
R^2	0.09	0.10	0.09

Table 8
Personal Action Against Climate Change

Table 8 shows estimated coefficients from an OLS regression of an indicator on whether respondents report having taken personal action against climate change on respondents' direct and indirect exposure via distant friends to changes in climate measured as the percentage change in maximum monthly average temperatures in from 1990 to 2010. Δ Temperature of Distant Friends is the exposure of distant friends to changes in climate and is interacted with regional levels of trust, patience, risk-taking, reciprocity (pos. and neg.), and altruism obtained from the Global Value Survey aggregated to the regional level by averaging across individual survey responses. Each variable is included as a dummy variable that takes on the value one if a measure is in the upper tertile and zero for the lower tertile. Columns 1 and 2 use all observations, while results in column three are based on regions at the NUTS 2 and NUTS 3 levels. Column four uses the matched sample described in Section 3.2. All regressions include year and region fixed effects. The dependent variable is multiplied by 100, and all continuous variables are winsorized at 1%. Standard errors clustered at the regional level r at the highest possible granularity are parentheses. ***, **, * indicate statistically different from zero at the 1%, 5% and 10% level of significance, respectively.

Dep. Variable	Personal Action Against Climate Change			
	All		NUTS 2 & 3	Matched Sample
	(1)	(2)	(3)	(4)
Δ Temperature - Distant Friends	-0.584	8.473	24.041	11.714
	(5.549)	(19.506)	(25.804)	(23.279)
Δ Temperature - Direct Exposure	14.489	1.801	-8.893	3.694
	(12.839)	(14.338)	(27.078)	(15.813)
Δ Temperature - Distant Friends× High Trust		-18.544	-35.348	-2.284
		(15.897)	(25.135)	(17.310)
Δ Temperature - Distant Friends× High Patience		-15.849	9.367	-46.120**
		(20.461)	(29.786)	(22.470)
Δ Temperature - Distant Friends× High Risk-Taking		-24.411	-30.321	-25.872
		(20.858)	(23.345)	(22.281)
Δ Temperature - Distant Friends× High Reciprocity (pos.)		-0.657	-29.168	-11.662
		(17.141)	(18.231)	(18.309)
Δ Temperature - Distant Friends× High Reciprocity (neg.)		4.673	-31.098*	2.005
		(14.209)	(16.450)	(13.760)
Δ Temperature - Distant Friends× High Altruism		53.903*	95.309***	83.706***
		(28.435)	(34.198)	(26.629)
Year FE	Yes	Yes	Yes	Yes
Regional FE	NUTS0	NUTS0	NUTS1	NUTS0
Individual Controls	Yes	Yes	Yes	Yes
Observations	90,412	64,599	50,878	64,599
R^2	0.12	0.12	0.12	0.12

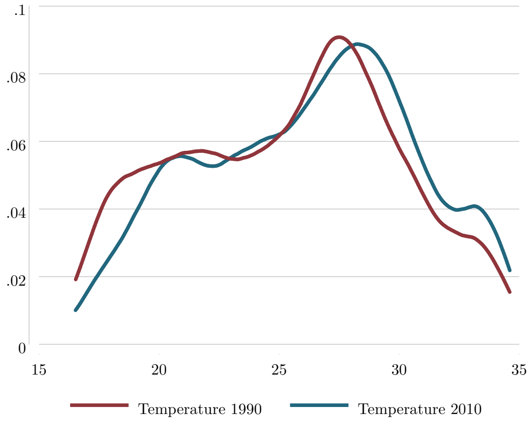
Appendix

A. Additional Results

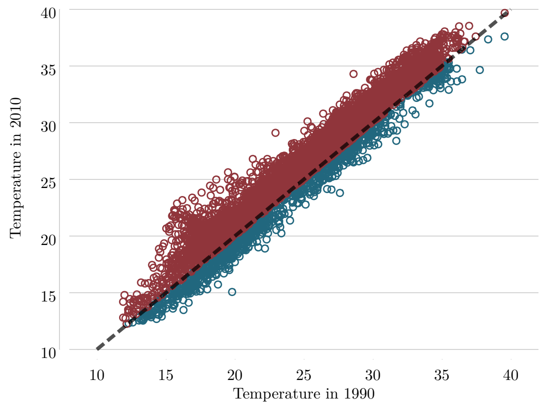
Figure A1

Temperature Changes of Maximum Average Monthly Temperature

Figure A1 displays histograms of the percentage change in the maximum average monthly temperature from 1990 to 2010. Exposure of distant friends' to climate changes defined as the weighted 75th percentile of the percentage change in maximum monthly average temperature from 1990 to 2010 in regions $j \neq i$ connected via Facebook friendships using the *Social Connectedness Index* between region i and j as relative weights.



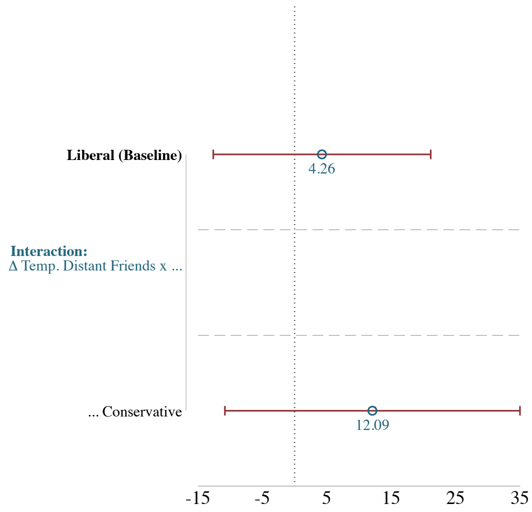
(a) Histogram



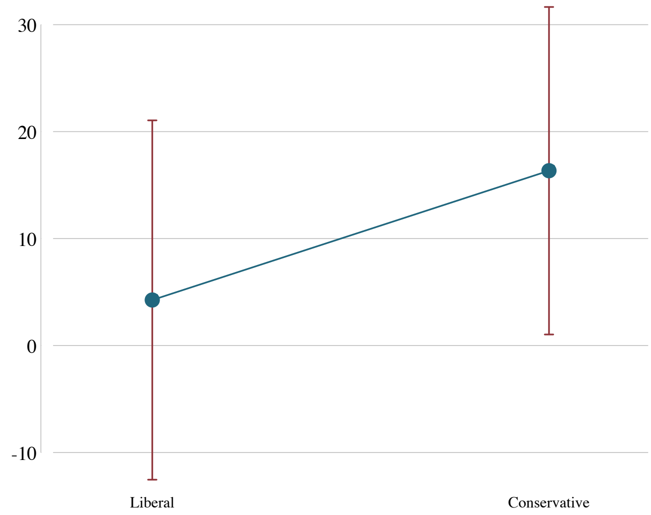
(b) Scatter Plot

Figure A2
Effect of Distant Friends' Exposure by Political Orientation

Figure A2 displays estimated interaction effects (Panel a) and implied predictive marginal effects (Panel b) from an OLS regression of respondents' concerns about climate change on respondents' indirect exposure via distant friends to changes in temperatures interacted with respondents' political orientation. Δ Temperature - Distant Friends is the exposure of distant friends to changes in climate computed as the weighted 75th percentile in percentage temperature change across connected regions j from 1990 to 2010 using the $SCI_{i,j}$ as relative weights. The vector of individual controls includes respondents' age, marital status, income, education, information on employment status and occupation, and a dummy variable if the respondent has any kids. All regressions include year and region fixed effects. The dependent variable is multiplied by 100, and all continuous variables are winsorized at 1%. Standard errors are clustered at the regional level r at the highest possible granularity. ***, **, * indicate statistically different from zero at the 1%, 5% and 10% level of significance, respectively.



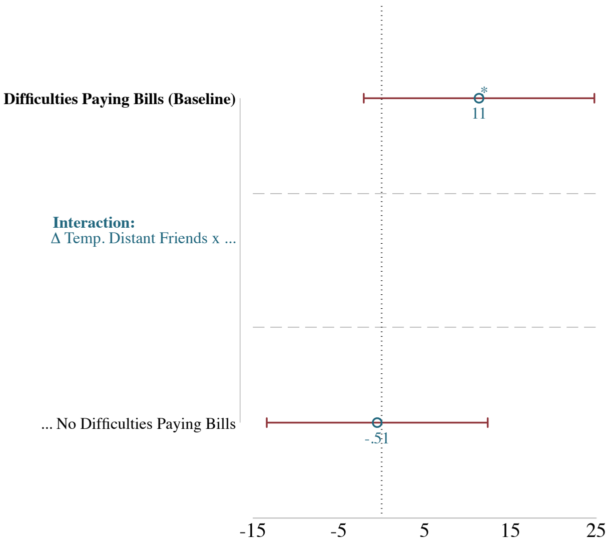
(a) Estimated Interaction Effects



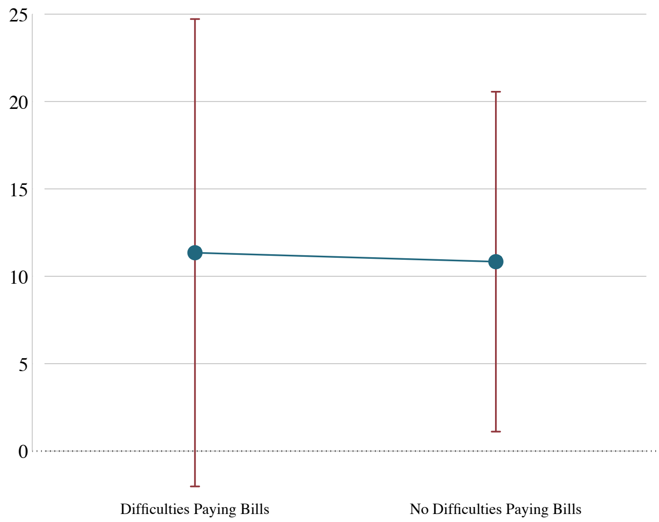
(b) Implied Predictive Marginal Effects

Figure A3
Effect of Distant Friends' Exposure by Financial Situation

Figure A3 displays estimated interaction effects (Panel a) and implied predictive marginal effects (Panel b) from an OLS regression of respondents' concerns about climate change on respondents' indirect exposure via distant friends to changes in temperatures interacted with respondents' income proxied by their difficulty paying bills as reported in the Eurobarometer. Δ Temperature - Distant Friends is the exposure of distant friends to changes in climate computed as the weighted 75th percentile in percentage temperature change across connected regions j from 1990 to 2010 using the $SCI_{i,j}$ as relative weights. The vector of individual controls includes respondents' age, marital status, income, education, information on employment status and occupation, and a dummy variable if the respondent has any kids. All regressions include year and region fixed effects. The dependent variable is multiplied by 100, and all continuous variables are winsorized at 1%. Standard errors are clustered at the regional level r at the highest possible granularity. ***, **, * indicate statistically different from zero at the 1%, 5% and 10% level of significance, respectively.



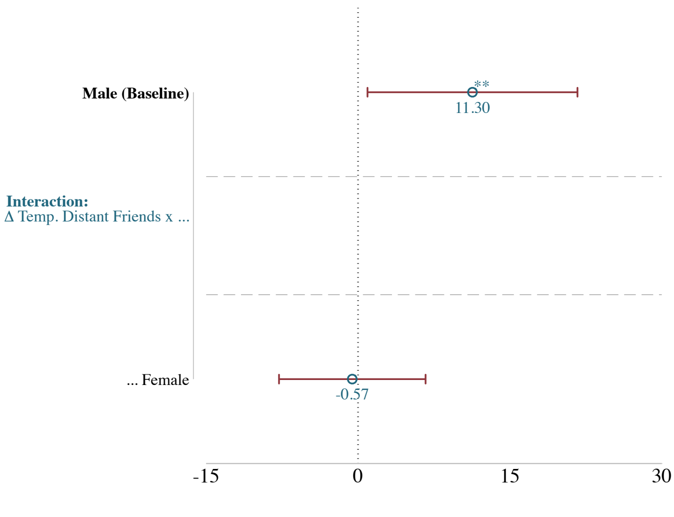
(a) Estimated Interaction Effects



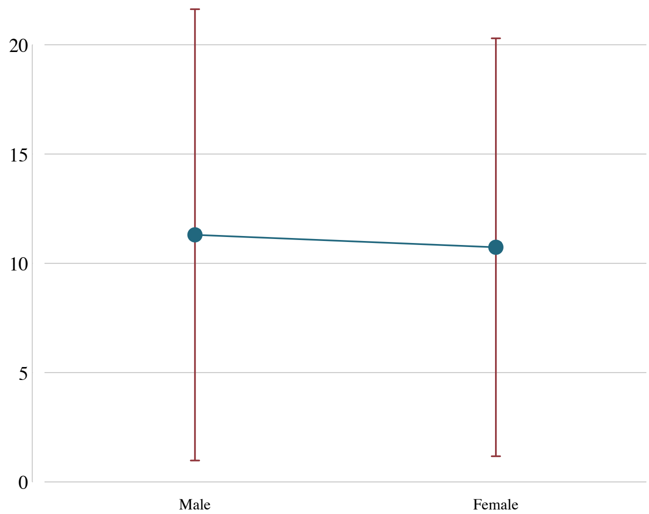
(b) Implied Predictive Marginal Effects

Figure A4
Effect of Distant Friends' Exposure by Gender

Figure A4 displays estimated interaction effects (Panel a) and implied predictive marginal effects (Panel b) from an OLS regression of respondents' concerns about climate change on respondents' indirect exposure via distant friends to changes in temperatures interacted with respondents' gender. Δ Temperature - Distant Friends is the exposure of distant friends to changes in climate computed as the weighted 75th percentile in percentage temperature change across connected regions j from 1990 to 2010 using the $SCI_{i,j}$ as relative weights. The vector of individual controls includes respondents' age, marital status, income, education, information on employment status and occupation, and a dummy variable if the respondent has any kids. All regressions include year and region fixed effects. The dependent variable is multiplied by 100, and all continuous variables are winsorized at 1%. Standard errors are clustered at the regional level r at the highest possible granularity. ***, **, * indicate statistically different from zero at the 1%, 5% and 10% level of significance, respectively.



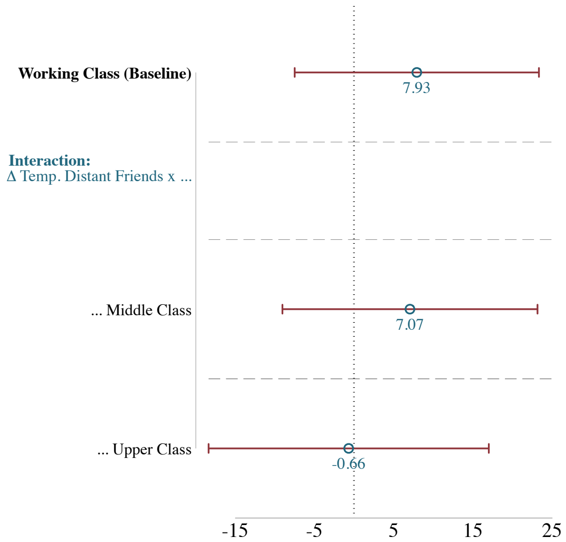
(a) Estimated Interaction Effects



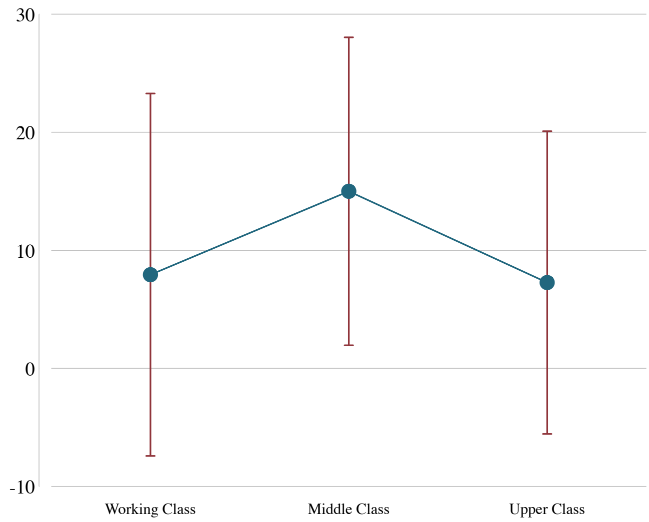
(b) Implied Predictive Marginal Effects

Figure A5
Effect of Distant Friends' Exposure by Social Class

Figure A5 displays estimated interaction effects (Panel a) and implied predictive marginal effects (Panel b) from an OLS regression of respondents' concerns about climate change on respondents' indirect exposure via distant friends to changes in temperatures interacted with respondents' self-reported social class. Δ Temperature - Distant Friends is the exposure of distant friends to changes in climate computed as the weighted 75th percentile in percentage temperature change across connected regions j from 1990 to 2010 using the $SCI_{i,j}$ as relative weights. The vector of individual controls includes respondents' age, marital status, income, education, information on employment status and occupation, and a dummy variable if the respondent has any kids. All regressions include year and region fixed effects. The dependent variable is multiplied by 100, and all continuous variables are winsorized at 1%. Standard errors are clustered at the regional level r at the highest possible granularity. ***, **, * indicate statistically different from zero at the 1%, 5% and 10% level of significance, respectively.



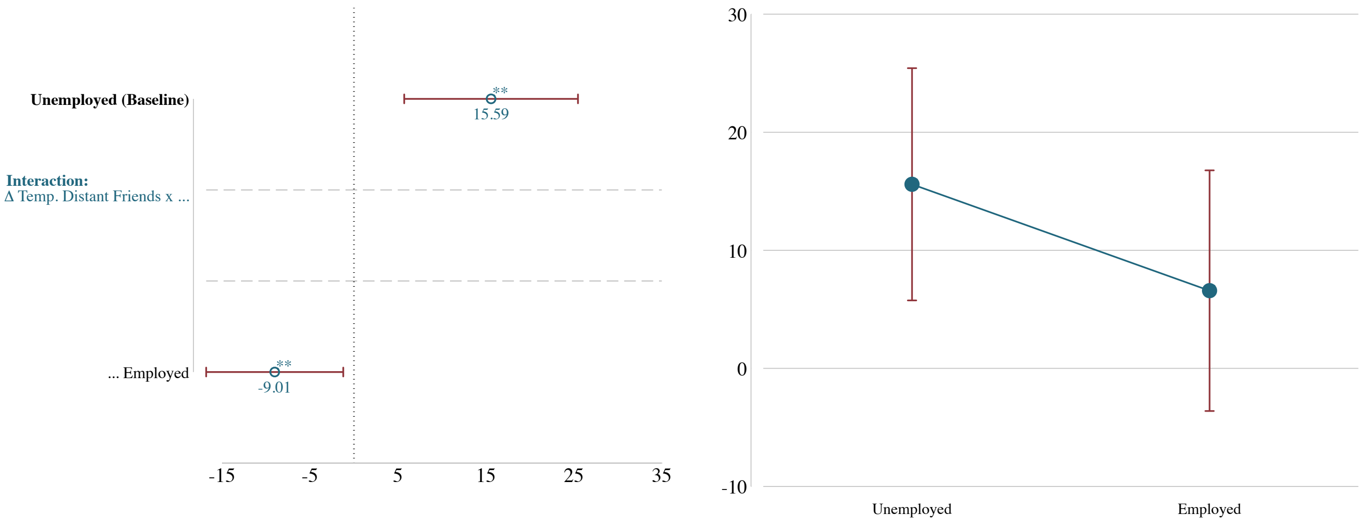
(a) Estimated Interaction Effects



(b) Implied Predictive Marginal Effects

Figure A6
Effect of Distant Friends' Exposure by Employment Status

Figure A6 displays estimated interaction effects (Panel a) and implied predictive marginal effects (Panel b) from an OLS regression of respondents' concerns about climate change on respondents' indirect exposure via distant friends to changes in temperatures interacted with respondents' years of education. Δ Temperature - Distant Friends is the exposure of distant friends to changes in climate computed as the weighted 75th percentile in percentage temperature change across connected regions j from 1990 to 2010 using the $SCI_{i,j}$ as relative weights. The vector of individual controls includes respondents' age, marital status, income, education, information on employment status and occupation, and a dummy variable if the respondent has any kids. All regressions include year and region fixed effects. The dependent variable is multiplied by 100, and all continuous variables are winsorized at 1%. Standard errors are clustered at the regional level r at the highest possible granularity. ***, **, * indicate statistically different from zero at the 1%, 5% and 10% level of significance, respectively.



(a) Estimated Interaction Effects

(b) Implied Predictive Marginal Effects

Table A1
Robustness — Individual Control Variables

Dep. Variable	Climate Change is a World Problem															
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
Δ Temperature - Distant Friends	10.98**	(4.71)	11.30**	(5.27)	11.86**	(5.08)	11.35**	(4.94)	11.99**	(4.81)	11.66**	(4.92)	11.85**	(5.06)	12.17**	(5.08)
Δ Temperature - Direct Exposure	20.87**	(10.46)	20.87**	(10.46)	22.37**	(10.95)	23.20**	(10.82)	21.19**	(10.56)	23.02**	(10.72)	22.80**	(10.86)	23.43**	(10.86)
Female	1.10***	(0.37)	1.14**	(0.44)												
Age	-0.04*	(0.02)	-0.04*	(0.02)	-0.16***	(0.01)										
Employment/Occupation (baseline self-employed):																
Managers	1.71*	(1.02)	1.71*	(1.02)			4.40***	(1.01)								
Other white collars	-1.33	(0.90)	-1.33	(0.90)			-0.64	(0.90)								
Manual workers	-2.38***	(0.89)	-2.38***	(0.89)			-4.25***	(0.90)								
House persons	-6.43***	(1.03)	-6.43***	(1.03)			-9.43***	(1.06)								
Unemployed	-2.93***	(1.03)	-2.93***	(1.03)			-5.86***	(1.00)								
Retired	-2.50***	(0.83)	-2.50***	(0.84)			-6.91***	(0.82)								
Students	12.42***	(1.58)	12.42***	(1.58)			2.61**	(1.09)								
Education (baseline ¡14):																
15-17 years	5.52***	(0.85)	5.52***	(0.85)					6.63***	(0.83)						
18-20 years	9.38***	(0.83)	9.38***	(0.83)					11.72***	(0.80)						
More than 20 years	14.77***	(0.86)	14.77***	(0.86)					18.56***	(0.81)						
No full-time educ.	0.55	(2.56)	0.55	(2.56)					0.60	(2.84)						
Still Studying									17.97***	(1.08)						
Income Proxy (baseline:)																
From Time to Time.	3.39***	(0.88)	3.39***	(0.88)							5.10***	(0.93)				
Almost Never/Never	6.49***	(0.95)	6.49***	(0.95)							9.00***	(0.95)				
Marital Status (baseline unmarried):																
(Re-)Married/W. partner	0.61	(0.48)	0.61	(0.48)									-1.20**	(0.50)		
Divorced/Separated	-0.04	(0.75)	-0.04	(0.75)									-3.05***	(0.75)		
Widowed	-2.49***	(0.70)	-2.49***	(0.70)									-8.55***	(0.77)		
Other	-1.56	(2.39)	-1.56	(2.39)									-0.05	(2.45)		
At least one Child	-0.01	(0.52)	-0.01	(0.52)											2.25***	(0.49)
Female × Δ Temperature - Distant Friends			-0.57	(3.68)												
Year FE	Yes				Yes		Yes		Yes		Yes		Yes		Yes	
Regional FE (NUTS 0)	Yes				Yes		Yes		Yes		Yes		Yes		Yes	
Observations	93,588		93,588		93,588		93,588		93,588		93,588		93,588		93,588	
R^2	0.09		0.09		0.08		0.08		0.09		0.08		0.08		0.08	

Table A2
Robustness — Regional Control Variables

Dep. Variable	Climate Change is a World Problem															
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
Δ Temperature - Distant Friends	9.37*	(4.81)	11.37**	(4.77)	11.62**	(4.81)	10.04**	(4.72)	10.59**	(4.80)	10.45**	(4.71)	10.80**	(4.70)	11.05**	(4.93)
Δ Temperature - Direct Exposure	22.07**	(10.94)	17.35	(10.97)	17.82	(10.87)	20.52**	(10.38)	22.26**	(10.58)	21.83**	(10.42)	21.97**	(10.52)	22.16**	(10.52)
Population <15	0.03	(0.13)	10.01***	(3.82)												
Population >65	-0.06	(0.12)			8.49**	(3.39)										
Heating Days p.A.	0.18	(0.14)					13.28	(13.26)								
Unemployment Rate	-0.11	(0.14)							-21.62*	(12.45)						
GDP	3.37	(12.61)									1800.64	(1133.37)				
Population Density	0.00**	(0.00)											0.08**	(0.03)		
CO2 Emissions	-0.00	(0.00)													0.01	(0.03)
Year FE	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Regional FE (NUTS 0)	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Individual Controls	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Observations	77,489		93,354		93,354		88,706		92,215		88,706		93,354		81,206	
R^2	0.10		0.09		0.09		0.10		0.09		0.10		0.09		0.09	