Heterogeneous impacts of temperature extremes on climate attitudes and Green voting

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Abstract

In the past decade, the public in Europe has become more concerned about climate change and expresses stronger pro-environmental policy preferences. Based on data from the European Social Survey (2012-2022, 25 countries), we show that the increased exposure to temperature extremes has contributed to the observed changes in climate change attitudes and electoral support for environmentalist policy platforms. For each additional degree of excess temperature experienced during warm spells measured over the previous 12 months, we find that the probabilities of being worried about climate change, of feeling responsible for climate change, and of voting for green parties and green coalitions increase by 4.0 [CI95: 2.5, 5.5], 2.5 [CI95: 1.1, 3.9], and 2.8 [CI95: 0.9, 3.7] percentage points respectively. We also document significant heterogeneity across individuals, based on gender and education, particularly between highly educated women and low-educated men. While the latter group consistently exhibits the lowest pro-environmental attitudes and voting, it is this group that shows the strongest increases when exposed to temperature extremes, converging towards the levels of their more educated counterparts. Further regional heterogeneity analyses reveal that the effects of warm temperature extremes are smaller in less prosperous or economically disadvantaged regions, as well as in regions with greenhouse gas emission levels above the median. The findings suggest a nuanced interplay between individual factors and contextual influences in shaping climate attitudes of European citizens and their motivations or reservations towards greater climate action.

Keywords: Climate change | Extreme temperature | Climate attitudes | Green voting | Heterogeneity

1 Introduction

Climate change affects populations worldwide in the form of more frequent and intense extreme weather events, increased heat stress, rising sea levels, and the gradual degradation of ecosystems and biodiversity (1). A growing body of evidence documents how the experience of climatic stress affects attitudes, policy preferences, and political behavior, including environmental concerns, beliefs about climate change, public support for climate action, and pro-environmental voting behavior (2–8). Recent studies from Switzerland and the US, respectively, showed an impact of floods and forest fires on referendum votes on environmental matters (9, 10). In Australia, having been affected by bushfires increased support for the Greens in state elections, and decreased support for the left Australian Labor Party (ALP) (11); in Germany, the 2021 floods increased support for the Greens in affected areas (12) [1]. Hilbig and Riaz (14) fail to find localized effects of the exposure to floods on Green voting, but provide evidence of those same floods on Green support nationwide; and in the UK, vote shares for parties that took more environmentally-minded stances increased in areas that experienced floods (15). Extreme weather events, including heat and drought episodes, have also been shown to positively affect environmental concerns and Green party voting in European Parliament elections (16).

Different theoretical explanations exist for why the direct experience of climatic stress translates into changes in environmental concerns and ultimately Green voting. Being exposed to climatic events can reduce the psychological distance to climate change and its impacts, and increase the willingness to take action (5). Green parties are central in turning environmentalist preferences into action since this party family has issue ownership over environmental policy topics (17). Major generational and social differences can be observed in environmental concerns and Green voting behavior (6, 18–21): younger, higher-income and higher-educated voters tend to express more concern and more support for environmental policies. Furthermore, climate change beliefs are ideologically polarized (22) and support for environmental policies is driven both by economic interest and by altruism or reciprocity (23), suggesting that both personal interests and norms matter.

In earlier papers the consequences of climatic events on voting were studied using official election returns measured aggregately at a given geographic location (9–12, 16). Here, we analyze the effects of temperature extremes on climate change attitudes and vote choices using individual-level European Social Survey (ESS) data for 25 European countries over ten years. Geographic information on place of residence and date of the election is used to assign region- and time-specific measures of temperature anomalies and heat episodes to each individual respondent. We find a robust association between exposure to extreme weather and climate change concerns, the feeling of responsibility for the climate, and voting for Green parties across European countries. We estimate

[1] The results are corroborated by the findings in Holub and Schündeln (13).

that one additional extremely warm day per week in the previous 52 weeks increases the probability of being worried about climate change by 7.3 pp [CI95: 4.7, 9.9]; of feeling responsible by 3.2 pp [CI95: 0.8, 5.6]; and of voting for green coalitions by 5.0 pp [CI95: 3.3, 6.7]. Similarly, one additional degree of excess temperature during warm spells over the same time window is estimated to lead to a 4.0 pp [CI95: 2.5, 5.5], 2.5 pp [CI95: 1.1, 3.9], and 2.8 pp [CI95: 0.9, 3.7] increase in the three outcomes, respectively.

As our models account for place- and time-based unobserved confounders and due to the plausibly exogenous timing of extreme temperatures conditional on geographic location, our models provide causal estimates of the impacts of temperature extremes on attitudes and voting patterns. Given that the ESS provides detailed information on individual characteristics, we can further explore heterogeneity in the impacts . Complementing the existing literature, we focus on both the role of individual and contextual-level factors as moderators. In particular, here we are interested in differences between demographic groups and the role of local economic contexts.

Previous studies have suggested that extreme weather events have stronger effects on environmental concern and Green voting in more affluent areas of Europe (16); that environmental issues are neglected in areas negatively affected by globalization (24) and in time periods of economic disruptions, such as in the aftermath of the Great Recession (25); and that they are considered more important under good economic conditions (26–28). Competition for limited attention or a direct tension between economic and environmental priorities might explain these patterns, which result in a major heterogeneity in climate change attitudes and Green voting across Europe both between and within countries (Fig. 1).

Indeed, there are direct policy trade-offs, where reducing emissions – or transitioning to a greener economy – might come at a loss of economic activity and employment, at least in the short run and for some occupational groups during an adjustment phase, or even in the long run in a "degrowth" perspective (29). Accordingly, at the individual level, studies have shown that more privileged, better educated individuals are more in support of degrowth policies (30) and that ideological predispositions (in terms of Democratic vs. Republican leaning of US municipalities) affect the relationship between experiencing of an extreme environmental event and support for environmental policies (10). The observed heterogeneity in terms of policy priorities might reflect differences in material conditions and the share of the burden of adjustment individuals expect to bear, e.g., because more educated voters have transferable skills that would allow them to quickly change occupations, and thrive also in a greener economy.

By presenting evidence on which voters are inclined to support parties prioritizing environmental issues after experiencing temperature extremes, and which on the other hand are impervious, we can identify demographic groups that are more responsive. Within the constraints of survey analysis, we can explore why direct experience might have a more profound influence on certain voters. This enables us to delve deeper into this relationship, documenting how demographic and other individual characteristics shape the link between exposure to extreme events and political behavior across different contexts. As individuals are nested in environments rich with information exchange, and the political consequences of an individual experience might be affected by the context itself, this requires a multi-level perspective as employed in our analysis.

[FIGURE 1 ABOUT HERE]

2 Results

2.1 Temperature extremes affect climate attitudes and increase Green voting

Our analysis relies on five ESS waves (2012-2022) which include detailed information about respondents' attitudes towards climate change and voting behavior. Attitudes are captured using two items measuring whether respondents are worried about climate change and feel responsible for it. Green voting was operationalized using information on respondents' voting behavior in the last national parliamentary election. Respondents are counted as Green voters if they voted either for a Green party or a party that announced a coalition with a Green party prior to the election. Two-way fixed effects panel models are used to estimate the impacts of two temperature anomaly measures: the excess temperature during warm spells; and the number of days classified as warm spells[2].

In the baseline specification, warm spells are defined as at least three consecutive days with daily mean temperature above the 95th percentile of the distribution in the respective region-week of the previous ten years (Section A.2). The weekly sums of the number of days classified as warm spells and of the excess temperatures on these days are then averaged over 4, 52, and 104 weeks prior to the interview and election dates. Variables are normalized to allow for comparisons across different time windows. The models are estimated at the individual level controlling for sub-national region, year, and month of interview/month of election fixed effects. Given that temperature anomalies occur independently of the interview or election timing, location, and intensity, the reported coefficients provide an estimate of a causal effect.

Figure 2 shows the results of our baseline models estimating the impacts of temperature extremes on the probability of being worried about climate change, of feeling responsible for it, and of voting for Green coalitions. Across models, we find evidence of a positive effect of the temperature anomaly measures on climate attitudes and Green voting. The effects are smaller for the shortest time interval (4 weeks): this might arguably be a too short time to result in changes in climate change worries, feelings of responsibility, and vote choices. In line with previous work (16), stronger effects are

[2]The regression models and its assumptions are described in detail in Section 4.

found when longer time windows are considered. One additional extremely warm day in the previous 52 weeks is estimated to increase the probability of being worried about climate change by 7.3 pp [CI95: 4.7, 9.9]; of feeling responsible by 3.2 pp [CI95: 0.8, 5.6]; and of voting for green coalitions by 5.0 pp [CI95: 3.3, 6.7]. Similarly, one additional degree of excess temperature during warm spells over the same time window is estimated to lead to a 4.0 pp [CI95: 2.5, 5.5], 2.5 pp [CI95: 1.1, 3.9], and 2.8 pp [CI95: 0.9, 3.7] increase in the three outcomes, respectively.

[FIGURE 2 ABOUT HERE]

These findings are robust to a number of sensitivity analyses (Supplementary Figures S1-S3), employing different temperature anomaly measures, using alternative outcome variables, adding further controls to the specification, and removing individual countries, survey rounds or election years from the analysis, corroborating that the baseline estimates reflect a genuine causal relationship. In addition, we perform placebo tests, using as predictors the lead values of temperature anomalies: these capture temperatures *after* the interview (for attitudinal items) or the election (for the vote choice variable). Reassuringly, the lead values are never significantly correlated with the outcome measures [3]. Hence, the evidence implies that recent past experiences with temperature extremes are driving the estimated effects and not any underlying time trends or correlations between residual geographic characteristics and public opinion.

The effects of exposure to climate extremes on Green voting may come from three channels: i) individuals who would otherwise not have voted turn out and vote for the Greens in response to extreme temperature exposure; ii) voter turnout is overall unaffected, but individuals predisposed towards the Greens are more likely to turn out in response to extreme temperatures while turnout decreases among voters who are less environmentally predisposed; iii) votes for Green parties come from individuals who would have otherwise cast a vote for other parties in the absence of temperature anomalies.

In SI Section C.3, we provide evidence suggesting that the third channel is behind the effect on green voting. In Table C.12 we show the results of a regression model in which the outcome is self-reported turnout in the last national election, while the main predictors are the anomaly measures used in the baseline models. The effects of extreme temperatures on voter turnout is small in magnitude and statistically not significant. We can therefore exclude that the effect of green voting comes mainly from new voters who would have otherwise abstained. In Table C.11, we furthermore regress the extreme temperature measures on a set of individual characteristics of respondents who cast a vote in the last election. If anything, there are only minor differences in the composition of the group of voters across all models. These results suggest that not only overall electoral turnout did not change, but also that there were no compositional changes in the electorate in response to extreme temperatures. Accordingly, we conclude that the

[3]Robustness and placebo analyses are detailed in Sections 2.4 and B

effect on Green voting can be mainly attributed to voter flow from other parties to Green parties and coalitions.

2.2 Demographic factors shape differences in climate attitudes and Green voting

Figure 3 shows the predicted probability of being worried about climate change, feeling responsible about it, and voting for Green coalitions as a function of the intensity of the temperature anomalies experienced. Here, we use interaction models allowing us to distinguish the temperature effects by the level of education and gender of the respondent. Increased educational attainment could enhance climate change literacy and consequently foster pro-environmental attitudes and behaviors later in life. Studies using schooling reforms for identification have shown the causal impact of education on pro-environmental behaviors (31, 32). Similarly, research consistently reveals that women tend to exhibit higher levels of concern about climate change (33), are more likely to support environmental legislation (34), and are more likely to vote for left-leaning parties possibly due to socio-structural conditions (35) .

[FIGURE 3 ABOUT HERE]

In Figure 3, we report average predicted values for female and male, low- and highly educated along the distribution of excess temperature values. At 0, individuals experience no exposure to extreme warm weather, while at 100 they experience the highest exposure observable in the data. This analysis allows us to understand how baseline levels and differences across groups change with the exposure to extreme temperatures.

We find considerable differences in climate attitudes and Green voting between the demographic groups. Highly educated women have, on average, higher values across all outcomes, relative to any other groups. In the absence of temperature anomalies (x-axis = 0), differences across groups are large. Low-educated men have a 6.4%, 12.0%, 17.3% percentage points lower probability of feeling responsible for climate change, 6.8% 8.9%, 15.4% percentage points lower probability of worrying about climate change, and 1.1% 4.0%, 6.8% percentage points lower probability of voting for a Green coalition than low-educated women, highly educated men, and highly educated women, respectively. As excess temperatures increase, low-educated men exhibit a stronger reaction compared to both highly educated men and low-educated women. Under the most extreme recorded temperature anomalies (x-axis = 100), low-educated men now have only a 3.1% (11.4%, 18.2%) percentage points lower probability of feeling responsible for climate change, 4.1% (4.4%, 9.1%) percentage points lower probability of worrying about climate change, and 1.1% (1.8%, 6.2%) percentage points lower probability of voting for a Green coalition than low-educated women, highly educated men and highly educated women, respectively. The experiences of extreme temperatures hence induces members of the groups with the lowest levels of climate change concern and of environmentalist voting to converge towards the level of the more educated groups in the sample. For the low-educated female population, we do not observe a similar catch up effect, possibly because this group already expresses higher pro-environmental attitudes and voting patterns in the absence of experiencing an extreme event compared to both low- and highly educated men.

Additional heterogeneity analyses reveal further interesting patterns in the data (Supplementary Figure C.7). Without temperature anomalies, individuals residing in urban areas are more concerned about climate change and are more likely to vote for green coalitions. Under strong temperature anomalies, however, these divides seem to largely disappear and the urban-rural difference in climate change worries and Green voting decreases from 4.3 to 3.0, and from 3.3% to 0.9%, respectively (the difference for the feeling of responsibility towards climate change increases in urban areas from 0.3% to 3.1%). Likewise, older individuals – especially higher educated men – react more strongly to temperature anomalies and eventually catch up with younger individuals in their probability of voting for Green coalitions following direct experience of strong temperature anomalies.

2.3 Individual and regional economic conditions moderate the impact of temperature anomalies

Economic factors have been shown to be important in influencing climate change attitudes and voting behavior. Here, we examine the role of both individual- and regional-level economic factors and their interplay. Figure 4 shows the predicted probability of supporting Green coalitions for different occupational groups and distinguishing by whether respondents' region lies above or below the European median in terms of different macro-level characteristics: In the top panel, we split regions by their GDP per capita; in the center panel by unemployment rate; and in the bottom panel by level of greenhouse gas emissions per capita. Here, we focus on Green voting as our primary outcome of interest since data for this variable are available across all regions for several time periods, allowing us to explore some of the underlying heterogeneities in greater detail. While the distinction by GDP per capita and unemployment levels allows us to investigate the relationships between Green voting and regional economic conditions, we use the information on local emissions to explore how the presence of more or less emission intensive industries affects the results.

[FIGURE 4 ABOUT HERE]

At the individual level, we find that different occupational groups express differential concerns for the environment and tendencies to vote for Green party coalitions (Figure 4c). Irrespective of temperature anomalies, those employed in the service industry are more likely to vote for Green coalitions compared to both manufacturing and agricultural employees. With increasingly strong temperature anomalies, however, these divides largely disappear.

Contextual influences also play an important role in shaping voting behavior. The effects of temperature anomalies are considerably smaller in less affluent region, with lower GDP per capita, or regions experiencing economic distress, with higher unemployment levels. Across all groups, the average increase in Green voting in response to temperature anomalies is 5.3% in regions with a low unemployment level as opposed to 4.3% in high-unemployment regions (Figure 4a) and 4.2% in regions with a high GDP as opposed to 0.7% in those with a low GDP (Figure 4b). We also find that the experience of temperature anomalies is less consequential for individuals who reside in areas with greater greenhouse gases emissions . The average increase in green voting is 7.2% in low-emission regions and 2.5% in high-emission regions.

These findings indicate that economic incentives, along with other factors related to the occupational structure and prosperity of a region, as well as the potential consequences of climate change policies, may play a crucial role in moderating the observed relationship. We also observe major interactions between the regional level variables and the individual characteristics, with specific occupational groups, such as agricultural workers, showing a lower tendency to catch up with other groups in wealthier regions. There seems to be a nuanced interplay between socioeconomic factors, regional characteristics, and the impact of temperature anomalies on climate attitudes and voting behavior, underscoring the importance of jointly considering the different aspects in one analytical framework.

2.4 Robustness and placebo analysis

We test the robustness of our baseline estimates in several ways (Supplementary Section B [4]). All robustness and placebos are reported for both measures of extreme warm weather, i.e., excess days and excess temperatures. Supplementary Figure C.1 reports estimates from alternative specifications where i) we adjust the definition of extreme weather to be more or less restrictive, ii) instead of 10 years rolling windows we use a fixed year range (from 1970 to 2000) to compute the distribution of average daily temperatures on which the definition of extreme weather is based, iii) we add additional individual controls (employment status, months elapsed between the last national election and the ESS survey) and iv) we add month-of-interview fixed effects.

Reassuringly, all alternative estimates are similar in magnitude and not statistically different from our baseline estimate. In Supplementary Figure C.2 we report estimates from regression models in which we exclude either one country, one ESS round or one election survey at a time to test for the role of compositional effects on our estimates. The estimated coefficients of temperature anomalies on green voting do not change across

[4]For the sake of brevity, we discuss robustness and placebo results only for green voting and only for the 52 weeks of exposure. Results for alternative weeks of exposure (4 or 104) and for climate attitudes are also robust to alternative specifications and placebo test, and are reported in the Supplementary Material, Tables C.21 and C.22 and Figures C.4, C.5 and C.6

specifications, suggesting that the baseline results are not driven by any specific group of countries, survey years or election rounds.

In addition to these robustness checks, we also run two types of placebo analyses. First, we use as predictors the lead values of extreme warm measures. We therefore assign to each election date the excess days and excess temperatures from the year after or the two years after, using 52 weeks of exposure. Results reported in Supplementary Table C.13, show that coefficients are zeros with the two years lead, while they are similar in magnitude but opposite in sign for the one year lead. This result is directly related to the construction of the extreme weather measure.

We also randomly assign extreme weather measures to European regions and use these placebo measures as predictors, repeating the procedure three hundred times. The distribution of estimated coefficients – reported in Figure C.3 – is centered exactly around zero, corroborating that the estimated effects in the main models are not an artifact of the fixed effects structure we employ.

3 Discussion

In the setting of a representative democracy, it is key that the arguably urgently needed policies to address climate change are adopted through transparent legislative procedures and negotiation among representatives of citizens. Hence, political parties advocating for environmental policies must secure legislative representation. Importantly, the strongest support for ambitious environmental policy is arguably found among those who value participatory governance and freedom of expression (21, 36–38). Hence top-down technocratic policies would run the risk of alienating exactly the social constituencies that support climate mitigation policies the most (39).

Public opinion and public salience of environmental issues are found to influence the climate agenda of mainstream parties (40). Understanding how political behavior is affected by direct experience of climate-change related events thus plays a key role in identifying mechanisms underlying public support for climate action, which is fundamental for tackling climate change. Previous studies have documented how exposure to extreme temperatures and climatic events influence attitudes and beliefs about climate change including pro-environmental behavior (41, 42). Effectively addressing climate change however requires – at both the national and international levels – policies specifically aimed at substantial emissions reduction. By analyzing actual vote choices in legislative elections, not only do we identify a robust and tangible pro-environmental initiative from an individual, we can also capture *revealed preferences* (43).

Voter decision-making involves trade-offs. Opting for Party A entails forgoing support for Party B and necessitates a comparison of entire policy bundles offered by competing parties. In a nutshell, unlike ultimately inconsequential support for actual or hypothetical policies expressed in a survey, vote choice is a costly behavior: in order to choose, for instance, a Green party, voters have to forgo the opportunity to support other parties they might find appealing. In addition, voters act as if their individual vote affected the final outcome, hence as if it directly increased the probability of representation of Green politicians in the legislature. The composition of the legislature in turn affects the environmental content of legislation that might be introduced, and possibly also executive decisions.

The evidence on the impact of exposure to climate extremes on voting behavior is limited. Existing large-scale cross-national studies (16) are based on regional averages of Eurobarometer survey responses and vote shares from official European Parliament election returns which have no immediate legislative consequences on national level. We extend beyond the current knowledge by using individual-level survey data which also capture how the respondents voted in the last election. Direct experience of temperature anomalies likely plays a causal role both on preferences for environmental policy, as revealed by vote choice in national legislative elections, and on attitudes about concern and responsibility regarding climate change. The effects are substantively significant with each additional extremely warm day per week and each one degree of excess temperature in the past 52 weeks leading to a 2.8 and 5.0 percentage points increase in voting for green coalition, respectively.

Additionally, by leveraging the individual-level features of the survey data used, coupled with uniquely merged regional data, we can identify distinctive patterns of heterogeneity driven by individual and regional characteristics. First of all, direct experience has a stronger effect on the demographic groups (less educated, and male, respondents) that have in general the lowest level of climate concern and the lowest support for environmentally-oriented political parties. A similar catching up effect is observed among those living in a rural area and older age groups. One simple and plausible interpretation is that the experience, for instance, of a heat wave constitutes a "wake-up call" for individuals who are not predisposed to support environmentalist policy platforms or to express concern with climate change on more ideological or lifestyle grounds. Firsthand experience of extreme weather events has a powerful symbolic significance, making climate change more salient because it enables individuals to grasp its otherwise abstract effects – a concept referred to as "experiential learning" (44). In particular, it is documented that "bad is stronger than good": experiencing negative events has a greater and longer lasting impact than experiencing positive events (45). As a consequence, personal experiences play an important role in fostering concern about climate change and promoting action, especially among individuals who were previously less engaged in climate-related issues. Given that the share of women and the highly educated who vote for Green political options is already high, exposure to extremely warm temperatures does not substantially alter their voting patterns. This is plausibly due to ceiling effects, where at high levels there is less room for further increases.

Yet, the evidence about the regional heterogeneity provides one further indication that material interest and support for environmental policies might be in tension. In fact, in less prosperous regions, in regions with higher unemployment levels, and in regions with an economy more reliant on greenhouse-gas emitting industries, direct experience with temperature anomalies has a muted effect on attitudes and political behavior. This indicates that economic concerns might overwhelm concerns with the environment, in line with the aggregate-level findings of (16). One corollary is that policies that overlook the genuine economic concerns of some sectors of society might be dangerous, as they might lead to a backlash. Recent work documents that environmental policies that inflict concentrated costs might lead to an increase of support for climate-skeptic parties, like the radical right League in Italy (46); at the same time, climate agreements that promote a fair distribution of costs find larger support (47). Policies that balance economic and environmental issues are feasible: a study using a scenario approach demonstrates that reducing income inequality both within- and between-country can go hand-in-hand with emission reduction because at higher income levels consumption and production are less carbon-intensive (48); ambitious and effective policies, if designed with attention to cost distribution, can generate increasing popular support (49).

Our study faces some limitations which are important for the interpretation of the results. First, the climate attitudes and Green voting measures considered as outcomes in our analysis may be prone to measurement issues and inaccuracies, potentially introducing noise into our estimation. For example, respondents may be affected by recall biases when asked in the ESS about their voting decisions in the last election. We account for this by including month of interview fixed effects and by controlling for the time between the interview and the last election. Second, while the estimates of the baseline models have a causal interpretation under the assumption that, conditional on place (and time), prior extreme events are exogenous to individual climate attitudes and voting decisions, our heterogeneity analyses are descriptive, and explorative, in nature, given that heterogeneity might be driven by unobserved variables. Thus, in spite of the plausibly causal estimates of the effects of weather anomalies, any claim about heterogeneity based on pre-treatment characteristics cannot be causal (and therefore has to be merely descriptive) because the pre-treatment characteristics, e.g., education of an individual or economic structure of a region, are themselves not randomly assigned.

The analyses nevertheless reveal important descriptive patterns showing how anomalies affect the outcomes differently for various demographic groups and in different regional contexts. Finally, while we are able to provide reduced form estimates of the relationships, a more detailed exploration of the relevant mechanisms driving the effects is beyond the scope of this paper. There are different theoretical explanations for why people show attitudinal and behavioral responses to extreme events, including due to psychological effects after experiencing an event, as well as indirect effects mediated for example by peer groups and the media. A further exploration of these channels could yield important insights into public perceptions of environmental stress and their role in political decision-making processes.

This is the first study to present large-scale evidence at the individual level spanning 25 countries over a decade on how firsthand experiences of temperature extremes influence climate change attitudes and voting behavior. In particular, we underline the importance of demographic, economic and regional characteristics and the interplay among them in shaping differential responses to exposure to temperature shocks. That personal experience contributes to bridging the gaps between the groups less engaged and more engaged in climate-related issues suggests that effective communication strategies about the threat of climate change may help increase awareness and public support for climate policy. Furthermore, the findings underscore the importance of integrating climate policies with broader social and economic policies aimed at addressing welfare and inequalities.

4 Material and Methods

Data

We rely on rounds 6 to 10 of the European Social Survey (50–54) which span national elections that were held between 2012 and 2022 in 25 European countries. The total number of respondents in our sample is 151,366, among which 109,108 (72%) voted in the last national election.

To measure support for Green parties, we create an indicator variable that takes the value of one if the respondent reports to have voted for a Green party or a pre-electoral coalition that includes a Green party. In the SI Section C.2 we discuss alternative measures that rely exclusively on Green parties (excluding support for parties that run in a pre-electoral coalition with Green parties) and on a score of environmental policy stance derived from Manifesto Project data (55). Further details about the coding of political parties and coalitions are provided in the SI Section A.1.1.

The survey item about vote choice in the ESS asks how the respondent voted in the last general election. Based on the date of the interview, we back out the date of the election to which the question refers. For instance, a respondent interviewed in Germany in January 2021 is answering a question about their vote choice in the prior election, which was held in September 2017. The weather data attributed to this respondent in the voting behavior models refers to conditions in a window before that election, not before the interview itself. The elections covered in our data span the period from January 2012 to January 2022.

The attitudinal items about worry and responsibility regarding climate change come from rounds 8 and 10 of the European Social Survey. The outcome variables are binary indicators that take the value of one if the respondent reported a score above seven on the ten-point scale on which the personal responsibility item is measured, and declared to be "very" or "extremely" worried about climate change on the worry item. When we analyze attitudes as an outcome variable, we attribute to the respondent the temperature data calculated for windows before the exact interview date reported in the survey.

Further information and descriptive statistics on climate attitudes are provided in SI Section A.1.2.

Measures of extreme temperature are constructed from the ERA5-Land 0.1° grids (56), aggregated to the NUTS regions reported for ESS respondents. The weather predictors used in the regressions are defined based on the distribution of daily values in region r and calendar week w in the 10 years prior to the election or interview. Warm (cold) spells are defined as at least three consecutive days in which the daily mean temperature does not fall below (exceed) an extreme percentile of the historical region-week distribution. We then compute the sum of degree Celsius in excess of the threshold used to classify spells and the number of days classified as warm (cold) spells. These measures are then averaged over 4, 52, and 104 weeks prior to the interview or prior to the last national election. We compute both area- and population-weighted variants of the temperature measures to test whether the results are sensitive to the weighting scheme. Further details on the construction of the weather variables are found in SI Section A.2.

For the regional heterogeneity analysis, we rely on Eurostat data on unemployment rate, ARDECO data on GDP per capita, and EDGAR data on greenhouse gas emissions. We split the sample of respondents according to whether their region falls below or above the median value of each regional characteristic. The median value comes from the distribution of average regional characteristics across the period 2012-2022. Further details on the construction of regional variables are found in SI Section A.3.

Empirical approach

We estimates models of the general form

$$y_{it} = \alpha_{r(i)} + \beta X_{r(i)t} + \gamma Z_{it} + \eta_{c(i)t} + \epsilon_{it} \tag{1}$$

where y is the voting or attitudinal item of interest, α_r are fixed effects for NUTS regions and η_{ct} are fixed effects for country-year combinations. The pre-treatment covariates Z are gender, age [5], level of education, and an indicator variable for respondents born in the country of residence. Post-stratification weights are used in all models. X_{rt} is the weather shock variable. Functions $r(i)$ and $c(i)$ map each respondent respectively to their region and their country of residence.

The identifying assumption relies on the quasi-random occurrence of climate events relative to the timing of survey interviews or election dates. That is, the occurrence of climate events is not influenced by the timing of elections or surveys and is not dependent on the characteristics of the affected population. While it is unlikely that the timing of the survey implementation or of *national* elections is changed as a consequence of *regional* weather events, it may occur that the groups of respondents or voters refuse to

[5] We use age at election for voting outcomes, and age at interview for environmental attitudes

being interviewed or vote under adverse weather conditions (e.g., heat wave). To test this assumption, we show in Tables C.9 to C.11 that weather shocks are conditionally independent from the pre-treatment observable characteristics of survey respondents and voters.

Importantly, it has to be made clear that our unit of analysis is the individual, not the region. Yet, the "treatment assignment" mechanism is clustered at the NUTS-year level, in that all individuals within a region at a given point in time are exposed to the same intensity of the weather anomaly measure. This is unproblematic from the point of view of bias, given that, as we discuss above, the weather anomalies, and their timing, are as good as randomly assigned, and particularly so when we condition on geographic location with region fixed effecs. These region fixed effects account for all regional features that are time-invariant, including climatic, institutional, and cultural characteristics.

Fixed effects for country-election year combinations account for all the features specific to a given election in a given country: this includes supply-side effects, e.g. credibility of the Green party, as well as other characteristics of the country at the time of a given election, e.g. popularity of the incumbent administration or national-level economic conditions. The country-interview year fixed effects capture any time-varying shock that affects the entire country in that year. While causal identification does not hinge on these time fixed effects, their inclusion increases precision by removing the effects of shocks shared by all regions within a country at a given point in time. Given the fixed-effects structure, the coefficient on temperature anomaly is identified from variation in exposure during the time window conditional on geographic location (region). In particular, the timing of a warm or cold spell plays a key role.

The standard errors reported are clustered at the NUTS-year level. This accounts for the fact that individual respondents within a region at a given point in time are all exposed to the same intensity of the weather shock. (57). It also conservatively accounts for the multi-stage sampling scheme adopted by the ESS surveys. It is important to note that the ESS headquarters requires surveys in each individual country to adopt a strict random probability sampling at every stage, with no quotas and no substitutions. Whenever possible, full population registers are used as sampling frames. At the same time, the sampling schemes are multi-stage and this fact needs to be accounted for in inference.

In the baseline model, we use warm and cold spells defined as either the excess days or temperatures based on the extreme 5% at the top and bottom of the distribution. Warm and cold spells are included together in the regression models. In order to investigate the temporal dynamics of the effects, we estimate separate models for the mean of the weather indicators in the 4 weeks, 52 weeks and 104 weeks before the election or interview day. The weather shocks are measured prior to the occurrence of the outcome, i.e. election day for green voting and the interview for the attitudinal measures.

The descriptive estimates of individual heterogeneity are based on a series of interaction models, where the temperature anomaly measure is interacted with demographic characteristics. This allows us to estimate the effect of the weather anomaly separately for each group defined by observable characteristics. Specifically, we estimate models of the form

$$y_{it} = \alpha_{r(i)} + \beta_1 X_{r(i)t} + \beta_2 X_{r(i)t} \dot{z}'_{it} + \beta_3 z'_{it} + \gamma Z_{it} + \eta_{c(i)t} + \epsilon_{it} \tag{2}$$

for a given individual trait z'_{it}. To describe heterogeneity based on regional characteristics we adopt the more flexible approach of splitting the sample by (time-varying) regional characteristics. In the main analysis, these are GDP per capita, unemployment level, and greenhouse gas emissions. We split the sample at the median of the respective variable and then estimate models like Eq. 1 and 2 on the split samples.

Significance Statement

Firsthand encounters with temperature extremes resulting from climate change not only influence attitudes toward climate issues but also foster backing of political parties that advocate environmental policies. Social groups that initially exhibit lower likelihood of endorsing pro-environmental perspectives e.g., men and lower educated individuals are more strongly influenced by direct experiences, converging towards the levels observed in groups with initially higher pro-environmental attitudes and a greater tendency to vote for parties manifesting green policies. The impact of direct experiences is diminished in less affluent regions and in areas with a more pollutant-intensive economy, suggesting tension between economic interests and support for climate mitigation policies.

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Figure captions

1. Average regional vote share for green coalitions 2012–2022 (percent).

2. Estimated effects of temperature anomalies on the probability of feeling responsible for climate change, worrying about climate change, and voting for a green coalition. Temperature anomalies are measured as number of days classified as warm spells in the region of residence, and the average excess temperature during the warm spells. Warm spells are defined as at least three consecutive days with mean temperature exceeding the 95th percentile of the calendar week distribution of the previous 10 years in the respective region. The horizontal axis shows the estimated effect sizes for the different outcomes distinguishing the effects of temperature anomalies measured over 4, 54, and 104 weeks prior to the attitude measurement or the last national election. The full model results are shown in Supplementary Tables C.4–C.6.

3. Predicted probabilities of feeling responsible for climate change, worrying about climate change, and voting for a Green coalition by education level and gender. The x-axis shows the percentile of excess temperature during warm spells observed in respondents' region of residence. Warm spells are defined as at least three consecutive days with mean temperature exceeding the 95th percentile of the calendar week distribution of the previous 10 years in the respective region. Higher values reflect stronger heat anomalies. The predicted probabilities are reported separately for respondents with a high (light blue) and low (dark blue) education as well as for women (continuous line) and men (dashed line).

4. Predicted probabilities of voting for a Green coalition by sector of occupation, on split samples based on regional GDP per capita, regional unemployment, and regional greenhouse gas emissions per capita. The horizontal axis shows the percentile of excess temperature during warm spells observed in the respondent's region of residence. Warm spells are defined as at least three consecutive days with mean temperature exceeding the 95th percentile of the calendar week distribution of the previous 10 years in the respective region. Higher values reflect stronger heat anomalies. The predicted probabilities are reported separately for respondents working in the agriculture (solid line), industry (small dashed line) and service (large dashed line) sectors.

Supplementary Information

A Data and variables

The data used for the analysis come from three main sources, the European Social Survey (ESS), the ERA5-Land reanalysis, and Eurostat and the Annual Regional Database of the European Commission (ARDECO), which is also largely based on Eurostat databases. In this section we describe the main features of each dataset, while in the following sections we explain in detail the construction of our outcomes variables – green voting, climate change worry, and climate change responsibility – based on ESS waves 6–10 (50–54) as well as our independent variables – temperature extremes – based on the ERA5-Land reanalysis (56) and regional characteristics.

A.1 European Social Survey

The ESS is a cross-sectional cross-country representative survey covering 39 countries running bi-annually since 2002. It collects a wide range of information on attitudes, beliefs, political orientation, voting behavior, as well as demographic characteristics. For the analysis on green voting we use all individuals who voted in the last national election. For our analysis we use all observations between wave 6 and 10 for which the last national election falls between 2012 and 2022. The decision to restrict to national elections in the last decade has different reasons. First, in the first decade of the 2000s, the number of green parties was extremely small, and so were the votes for green parties in most European regions. Second, and related to this, extreme warm spells have become more frequent 2012–2022 compared to the previous decade (Figure C.11), which has increased the salience of global warming on the individual and societal level. Finally, we want to avoid the inclusion in the analysis of periods before and after the Great Recession. For both the analysis on green attitudes and green voting we restrict our sample to EU/EEA countries.

Most questions on green attitudes were only asked in the ESS Round 8, and only a subset was included also in the survey of ESS Round 10. To maximize our sample size, we only make use of the variables that were asked in both surveys. We therefore include all individuals from ESS rounds 8 and 10 with non-missing values on the outcome variables. The COVID-19 pandemic caused changes in ESS10 which have implications for longitudinal comparisons with previous survey waves (54). 9 countries switched to a self-completion approach from the usual face-to-face interviews in ESS10. Those countries that maintained the personal interviews partly switched to video calls. Furthermore, ESS10 was carried out over a longer time period than previous survey waves.

As explained in the next section, our main predictor are extreme weather events in the region of residence before being interviewed or having voted in national elections.

Region of residence is available for the vast majority of ESS respondents. Nonetheless, the definition of NUTS region codes varies within countries across time, as well as across countries. For some countries only NUTS1 are available, while for other NUTS2. We harmonize regions within countries by assigning to the same region the most updated NUTS classification to which it belongs. If the NUTS classification changed the NUTS boundaries – NUTS regions merged, separated or disappeared – we treat regions belonging to subsequent classifications as separate regions. The total number of unique regions is 335. The average regional sample size is 455 respondents.

The total sample size is 151,366 individuals. Among these, 109,108 voted in the last national election (72.1%). Table C.2 summarizes the ESS sample composition by demographic, regional, and political characteristics for the full sample of respondents for election years 2012-2022, for the sample of voters in national elections between 2012 and 2022, for the sample of respondents in ESS Round 8 and 10. Table C.3 reports observation counts by country and ESS round for both voters (used in the analysis on green voting) and respondents (used in the analysis on climate attitudes). An overview of number of observations and elections by country, year, and month is given in Figure C.8.

A.1.1 Green voting

To construct the green voting outcome we first assign the correct national election in which respondents voted. We do this by assigning the date of the last election relative to the precise day in which individuals responded to the ESS survey. We then use the information on the party or electoral coalition voted in the last national election, as provided in the ESS data. Respondents are first asked "Did you vote in the last [country] national election in [month/year]?". If they voted, they are asked to select the party or electoral coalition they voted for, choosing from a predefined list of parties and electoral coalitions. Taking these pieces of information together, we manually code green parties and green coalitions based on their party description and historical information, and create a dummy variable which takes value 1 if individuals voted for a green party or green coalition and 0 if they voted for any other party. Individuals who did not vote are coded as missing. Only electoral coalitions which include green parties are considered green coalitions, while government coalitions are not. One example of electoral green coalition is the *Coligação Democrática Unitária* (CDU) in Portugal, traditionally formed by the *Partido Comunista Português* (PCP) and the *Partido Ecologista "Os Verdes"* (PEV). The CDU is coded as green coalition in our data, so that votes for any of the two parties are given a 1. One example of government coalition is the 2021 *traffic light coalition* between SPD, FPD and Alliance90/The Greens. The *traffic light coalition* is not coded as green coalitions and only votes to the Alliance90/The Greens party are coded as 1.

While our main outcome is voting for green parties and green coalitions together, in Section B we show the results from models where the outcome is voting for green party. Moreover, in an alternative model we abstract from the definition of green party and estimate our model using a score from the Manifesto Project (58) which captures the amount of pro-environmental statements in each party's electoral agenda. Data from the Manifesto Project are linked to the ESS through party names.

Table C.1 provides a list of parties that we classify as green parties or part of green coalitions. Figure C.10a shows the average share of respondents that reported to have voted for a party that entered a green coalition over the time period 2012–2022, broken down by age and education, gender and education, and age and gender.

A.1.2 Climate change worry and responsibility

We define two variables that capture attitudes towards climate change. The first is whether respondents are worried about climate change. Respondents are asked the following question: "How worried are you about climate change?". They may express their worries using a scale from 1 (not worried at all) to 5 (extremely worried). We create a dummy variable that gives value 1 if individuals are very worried (4) or extremely worried (5) and 0 otherwise. The second attitude towards climate change captures the degree to which respondents feel responsible for climate change. Respondents are asked the following question: "To what extent do you feel a personal responsibility to try to reduce climate change?". They are asked to give a score between 0 (not at all) and 10 (a great deal). We construct a dummy variable that takes value 1 if the score is between 7 and 10, and 0 otherwise.

Figure C.9 gives an overview of the regional population share that reported to worry about climate change and feel personally responsible for it, respectively, in ESS rounds 8 and 10. Respondents in eastern and southern Europe tend to feel less responsible for climate change than those in continental Europe. This division is not as clear cut for climate change concern, however. Both measures increased in most regions across Europe between the two survey rounds.

Figure C.10b and c additionally break down the variables by age, education, and region. On average, both feeling responsible and worrying about climate change increases with age and education. Overall, the feeling of climate change responsibility is highest in continental Europe, while the climate change concern is highest in the South.

A.2 Extreme weather

Measures of temperature extremes are computed with daily means from the ERA5-Land reanalysis (56). ERA5 combines meteorological observations with a global climate model to produce a 0.1° grid. The cells are aggregated to NUTS regions as their mean, weighted by area or population. Population weights are derived from LandScan Global 2017 data (59). The measures are then defined based on the distribution of daily values in region i and calendar week w in the reference period which characterizes the regional climate. The reference periods are the 10 years prior to the interview or election date.

Warm (cold) spells are defined as at least three consecutive days with temperatures T_{it}^{spell} that fall above (below) the 90th, 95th, or 97.5 th (10th, 5th, 2.5th) percentile $\tau_{iw}^{10\text{yr}}$. Using these thresholds, we calculate number of days during warm and cold spells as well as the excess temperature. The positive excess temperature is defined as

$$T_{it}^{\text{excess,warm}} = \begin{cases} T_{it}^{\text{spell}} - \tau_{iw}^{10\text{yr}}, & \text{if } T_{it}^{\text{spell}} > \tau_{iw}^{10\text{yr}} \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

and the negative excess temperature as

$$T_{it}^{\text{excess,cold}} = \begin{cases} \mid T_{it}^{\text{spell}} - \tau_{iw}^{10\text{yr}} \mid, & \text{if } T_{it}^{\text{spell}} < \tau_{iw}^{10\text{yr}} \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

so that higher values of both cold and warm spell measures indicate more extreme events. The daily values are then summed up to weekly values and averaged over rolling multi-week periods.

Figure C.11 presents boxplots of weekly, regional warm and cold spells by region, comparing 2002–2012 with 2012–2022. The distributions indicate that cold spells become less common, in particular in east and south Europe, with more extreme cold spells becoming outliers. At the same time, warm spells have become more common in the recent decade, mostly in continental and southern Europe. Here outliers at the bottom of the distribution have become more frequent. Both developments are indicative of global warming.

A.3 Regional data

In Section 2.3 of the manuscript, we analyze how regional characteristics mediate the effects of extreme weather for different population groups. We mainly focus on the role of unemployment rate, GDP per capita, and greenhouse gas emissions per capita. Annual data on regional unemployment rate come from Eurostat, while data on GDP per capita are collected and harmonized in the Annual Regional Database of the European Commission (ARDECO).

Based on the Eurostat definition, regional (NUTS level 2) unemployment rate represents unemployed persons as a percentage of the economically active population (i.e. labour force or sum of employed and unemployed). The indicator is based on the EU Labour Force Survey. Unemployed persons comprise persons aged 15-74 who were (all three conditions must be fulfilled simultaneously): 1) without work during the reference week; 2) currently available for work; 3) actively seeking work or who had found a job to start within a period of at most three months. The employed persons are those aged 15-64, who during the reference week did any work for pay, profit or family gain for at least one hour, or were not at work but had a job or business from which they were temporarily absent. GDP per capita is computed as total GDP at current prices * 1'000'000 / total population (from regional accounts).

Greenhouse gas emissions annual regional data come from the Emission Database for Global Atmospheric Research (EDGAR). The database collects and harmonizes the emissions of different types of greenhouse gas, standardizing the emission measure to CO2 equivalents (60). Greenhouse gases are CO2, CH4, N20 and F-gases. We sum all types of GHG-emissions in each year and region to obtain the total of GHG-emissions and then divide by the total annual population in each region to obtain GHG-emissions per capita.

In Figure C.12 we show the distribution of unemployment rate, GDP per capita and emissions per capita across NUTS2 regions, as well as the regions that fall below or above the median split. The median split samples are obtained by first computing the median of the distribution across all NUTS2 and election years available and then assigning a 1 to all regions with a value of unemployment rate, GDP per capita or GHG-emissions per capita above the median and 0 to all regions with a value below the median. Results on splitted samples are robust to using a time-invariant distribution of mean regional unemployment rate, GDP per capita and GHG-emissions per capita. In Figure C.13, we additionally display correlations across regional characteristics, highlighting that GDP strongly negatively correlates with the unemployment rate, GHG emissions per capita, as well as the industrial GHG intensity.

B Robustness analysis

B.1 Robustness checks

In this section we detail the robustness checks that we performed on our baseline estimates of the effects of exposure to extremely warm weather (in the year before national elections) on voting for green coalitions. First, we vary the definition of extremely warm weather (as excess days or excess temperatures during heat waves). We redefine warm (cold) spells as at least three consecutive days with temperatures T_{it}^{spell} that fall above (below) the 90th or 97.5th (10th, 2.5th), instead of 95th (5th). The first and second coefficients in Figure C.1 report the estimated coefficients. These are close in magnitude and not statistically different from our baseline results, suggesting that the choice of the cut-off percentiles for the definition of warm and cold spells does not affect our main findings. Additionally, we change the temperature distribution underlying our climate measures. The third coefficient refers to regression models in which the distribution of daily temperatures – on which our extreme weather measures are based on – is computed using a fixed time window from 1970 to 2000 instead of 10-year rolling time windows. Again, the estimated coefficients are not different from the baseline. Finally, in Tables C.16-C.20 we show that our results are robust to an alternative definition of extreme temperatures which weights the temperature measures by the population size (instead of the area).

As a second step, we show that our baseline are robust to the inclusion of additional controls and fixed effects in our baseline model. The forth coefficient results from a regression model in which we control for current employment status and months between interview and last national election. By including the distance in months between interview and the last national election we are controlling for possible memory bias in recalling the vote cast in the previous election. Finally, we run models in which we include month of interview fixed effects, as heat exposure before the interview may affect how respondents recall their last vote in national elections. The estimated coefficients show up last in the figure. The vertical red line indicates the baseline estimate (0.050 for the excess days and 0.028 for the excess degrees). For both specifications the estimated coefficient is not statistically different from the baseline estimate and similar in magnitude.

Third, we show that our baseline results are not driven by any particular group of observations. The panels in Figure C.2 report estimated coefficients for regression models in which we exclude one country, one survey round and one election year at a time. The Y axis displays the excluded category. The red line indicates the baseline estimate. Also in this case, for all models estimated coefficients are not statistically different from our baseline estimate so that we can exclude the possibility that our results are driven by specific countries, survey rounds or election years.

B.2 Placebo estimations

In Table C.13 we display results from placebo estimations where we assign to each election the extreme weather measures of the following one or two years, computing the placebo one year exposure. As example, consider one election taking place in June 2015. The one-year lead model averages the excess weather measures over the period July 2015 and June 2016, the two-years lead model averages the excess weather measures over the period July 2016 and June 2017. Our results show a strong negative effect – similar in magnitude but opposite in sign to our baseline result – for the one-year lead model. This is a mechanical effect of how the baseline climate extremes are computed and is expected to precisely counterbalance the baseline coefficients (i.e., they sum to zero). The two-years lead mode shows extremely small and not statistically significant effects on green voting, confirming that future temperatures are not correlated with present green voting outcomes.

As a second placebo estimation, we randomly re-assign 300 times the extreme weather measures therefore estimating the effects of 300 placebo extreme weather exposures on green voting. Importantly, we constrain the random assignment of climate measures to occur within the same country and the same survey year. Figure C.3 displays the distribution of the 300 placebo coefficients as well as the true coefficient (the red vertical line). Placebo coefficients for both excess warm days and temperatures are normally distributed, and the average coefficient size is not different from 0. These results corroborate that the estimated effects in the main models are not an artifact of the fixed effects structure we employ.

C Additional results

C.1 Average marginal effects

In Figure 3 of Section 2 in the main text and Figure C.7 of the SI, we displayed average predicted probabilities of being worried for climate change, feeling responsible for it and voting for green parties and green coalitions for subgroups based on sex and education, age and education, age and sex, urban-rural, and individual employment sector. In Figure 4 we additionally displayed average predicted probabilities of voting for green parties and green coalitions for different employment sector, splitting the sample according to regional unemployment rate, GDP per capita and GHG emissions per capita. Average predicted probabilities have the advantage that they account for the baseline differences in outcome across subgroups and allow to show results along the distribution of the our climate predictors. In this section we complement these results reporting - in Table C.14 and Table C.15 the average marginal effects of extreme warm temperatures for the different subgroups and sample median splits. In the full sample results show that average marginal effects of extreme temperatures are higher for groups with lower baseline levels of green voting and worries about climate change: low-educated men, older individuals, rural inhabitants and employees in the industry sector. The marginal effects of extreme temperatures on feeling responsible for climate change follow a different pattern. They are significant only for low-educated and young male, high-educated women and urban residents. In the regional split samples, average marginal effects are close to zero and not statistically significant in regions with high uemployment, low GDP per capita, and high GHG-emissions per capita, while they are strong and significant in regions with low unemployment, high GDP per capita, and low GHG-emissions per capita.

C.2 Additional outcomes

Alternatively to our main outcome, we display results for two additional measures of green voting. First, we use voting for green parties as outcome. This outcome codes as 1 only green parties, while parties which belong to an electoral coalition that includes green parties are coded as zero. We therefore estimate the effect of extreme weather on casting votes for green parties specifically. Second, we use the Manifesto Project score that captures the amount of pro-environment statements in each party's political agenda. The pro-environmental scores allows to abstract from the formal definition of green parties and capture shifts in voting behaviors towards parties which do not define themselves as green parties but have nonetheless a green agenda. Tables C.6-C.8 display our results for green parties and green coalitions (our baseline results), green parties only and the pro-environment score. All outcomes convey a similar message. Short-term exposure has no effect on green voting, while one-year and two-year exposures to extreme warm spells significantly increases all green voting outcomes. In detail, considering 1 year of exposure before the national election, one additional day (degree) of extremely hot weather increases vote for green parties by 4.3 (2.3) percentage points and raises the environmental score by 13.7% (12.8%). When we consider a period of two years of exposure, results are similar. One additional day (degree) of extremely hot weather increases vote for green parties by 3.1 (1.6) percentage points and raises the environmental score by 17.0% (12.9%).

C.3 Voter turnout and characteristics

In this section we detail the analysis on the channels that may drive our green voting results, in terms of voters' turnout and voters' flow. As explained in Section 2.1 our main results on green voting may be explained by either - or a combination of - a change in voters' turnout, a change in voters' demographics or a reshuffle of votes towards Green parties and green coalitions. To gauge which channel prevails, we run two types of analysis. First, we estimate our baseline model using voter turnout as outcome. Before being asked about the parties they voted for, respondents are asked whether they voted in the last national election. We assign a 1 to respondents who voted and 0 otherwise. Results on voters' turnout, reported in Table C.12, display no statistically significant effects of extreme warm spells. For the 52 weeks exposure, the estimated coefficients are 0.04 and 0.01 respectively for excess days and excess temperatures. Given a mean turnout of 70%, the effect of our extreme warm measures on voters' turnout is virtually zero. We can therefore exclude that the effects on green voting are driven by either new voters showing up to the ballot box. Second, we test whether - even without a change in turnout - extreme temperatures affect the demographics of voters and, in turn, the probability of voting green. We run a regression model in which extreme warm indicators are the outcomes, while the characteristics of voters are the predictors, therefore testing the joint significance of these demographics. Results are reported in Table C.11 displays the estimated coefficients. Depending on the models, part of the estimated coefficients are statistically significant. Older individuals and women are less likely to vote if exposed to warm spells, while respondents with no migration background are more likely. Nonetheless, given the size of the coefficients and the share of respondents in each of the categories, as reported in Table C.2, the magnitude of the estimated differences is negligible. We therefore conclude that the increase in green voting is driven by voters who changed their previous voting preferences in favor of green parties and green coalitions.

Supplementary Tables

Table C.1: List of green parties and green coalitions by country

Country	Green parties	Green coalitions
AT	Grüne, PILZ	
BE	Agalev/Groen!, Ecolo	
CH	Green Party, Green Liberal Party	
CZ	SZ	
DE	Bündnis 90/Die Grünen	
DK	Enhedslisten	Socialistisk Folkeparti
EE	Erakond Eestimaa Rohelised, Tulevikuerakond	
ES	Iniciativa per Catalunya-Verds (ICV)	Compromís - EQUO, Junts per Catalunya/PDeCAT, Izquierda Unida (IU) - (ICV en Cataluña), PACMA, CUP, Unidos Podemos, En Comù Podem, Compromís-Podemos-EUPV. Partido Socialista Obrero Español - PSOE (2016), Teruel Existe, EAJ-PNV
FI	Green League	Left Alliance
FR	Les Verts, Europe Ecologie Les Verts (EELV), Autres mouvements écologistes	UMP
GB	Green Party, Green Liberal Party	
GR	Greens, The Ecological Greens,	25, SYRIZA, ANTARSYA,
HR		Možemo, Zagreb je naš, NLJ, RF, Orah
HU	Párbeszéd (Párbeszéd Magyarországért Párt)	LMP (Lehet Más A Politika)
IE	Green Party, Green Liberal Party	
IT	Verdi e SDI (Girasole), Sinistra Ecologia e Libertà (SEL)	Partito Democratico (2018), Potere al popolo, +Europa, Italia Europa Insieme, Liberi e Uguali
LT	Lithuanian Peasant and Greens Union (LVZS), Lithuanian Greens Party (LZP)	Lithuanian Social Democratic Party (LSDP)
LV	Zaļo un Zemnieku savienība, Greens and Farmers Union	Progresīvie
NL	Green Left	Party for the Animals
NO	Miljøpartiet De Grønne	Sosialistisk Venstreparti
PL	Zjednoczona Lewica	Koalicja Obywatelska, Sojusz Lewicy Demokratycznej, Socjaldemokracja Polska
PT		PCP-PEV, PCP-PEV-CDU, Bloco de Esquerda (BE), PAN, LIVRE
SE	Miljöpartiet de gröna	Socialdemokraterna, Vänsterpartiet
SI	ZL	SD, SMS

Table C.2: Descriptive statistics

	Full sample		Voters		ESS8-10	
	Mean	SD	Mean	SD	Mean	SD
Demographic characteristics						
Age at election	48.13	18.62	51.33	17.08	47.81	18.63
Age at election: < 35	0.27	0.44	0.20	0.40	0.28	0.45
Age at election: 35-54	0.33	0.47	0.35	0.48	0.33	0.47
Age at election: 35-54	0.40	0.49	0.45	0.50	0.39	0.49
Male	0.47	0.50	0.47	0.50	0.47	0.50
Female	0.53	0.50	0.53	0.50	0.53	0.50
Natives	0.91	0.29	0.95	0.22	0.91	0.29
1st generation migrants	0.09	0.29	0.05	0.22	0.09	0.29
Low Educated	0.24	0.42	0.19	0.39	0.23	0.42
Mid Educated	0.39	0.49	0.38	0.49	0.38	0.49
High Educated	0.38	0.48	0.43	0.49	0.39	0.49
Regional characteristics						
Continental Europe	0.50	0.50	0.53	0.50	0.48	0.50
Southern Europe	0.14	0.35	0.14	0.35	0.18	0.39
Eastern Europe	0.36	0.48	0.33	0.47	0.34	0.47
Hot	0.59	0.49	0.58	0.49	0.59	0.49
Temperate	0.11	0.32	0.12	0.32	0.15	0.35
Cold	0.30	0.46	0.31	0.46	0.27	0.44
Unenmployment rate	7.41	4.10	7.37	4.19	7.35	4.45
GDP per capita (thousands)	30.09	15.51	30.70	15.15	30.85	15.72
GHG emissions per capita	0.02	0.04	0.02	0.03	0.02	0.04
Incumbent government						
Government: Left-center	0.52	0.50	0.51	0.50	0.52	0.50
Government: Balance Left-right	0.26	0.44	0.28	0.45	0.26	0.44
Government: Right	0.22	0.41	0.21	0.41	0.22	0.41
Government: no green seats	0.49	0.50	0.47	0.50	0.50	0.50
Government: at least 1 green seat	0.51	0.50	0.53	0.50	0.50	0.50
Observations	151366		109108		80369	

Table C.3: Descriptive statistics for the sample of voters

	Voters					Respondents	
	ESS6	ESS7	ESS8	ESS9	ESS10	ESS8	ESS10
AT		1287	1585	1989	1588	1976	1874
BE		1430	1389	1348		1764	
CH			846	727	840	1502	1477
CZ		1177	1201	1459	1487	2255	2459
DE		2338	2112	1858	6828	2836	7929
DK				1332			
EE			1249	1166	1033	2015	1533
ES			1398	1116	1695	1817	2121
FI			1503	1381	1265	1918	1572
FR	1401	1155	1198	1172	1023	2002	1918
GB		254	1398	1641		1916	
GR					2300		2710
HR				1186	1029		1513
HU		1171	1108	1148	1294	1587	1839
IE			1913	1608		2704	
IT	714		1675	1968	1769	2476	2526
LT	1133	1156	1117	1224	1105	2081	1646
LV				591			
NL	1241	1422	1263	1283	1251	1671	1463
NO		1126	1202	1131	1119	1540	1403
PL			1176	967	1580	1673	1958
PT		247	922	736	1237	1260	1816
SE		1051	1354	1396	1931	1540	2246
SI		793	858	827	824	1254	1227
SK	1365			704	1012		1352
N	5854	14607	26467	29958	32210	37787	42582

Table C.4: Worried about climate change

	1 month		1 year		2 years	
	(1)	(2)	(3)	(4)	(5)	(6)
Extreme cold (days)	-0.007*		-0.091***		-0.202***	
	(0.004)		(0.031)		(0.063)	
Extreme warm (days)	0.013***		0.073***		0.060*	
	(0.004)		(0.026)		(0.034)	
Extreme cold (C°)		-0.003*		-0.045***		-0.095***
		(0.002)		(0.014)		(0.028)
Extreme warm (C°)		0.007***		0.040***		0.039**
		(0.002)		(0.015)		(0.018)
N	78584	78584	78584	78584	78584	78584
R^2	0.09	0.09	0.09	0.09	0.09	0.09
Mean of outcome	0.36	0.36	0.36	0.36	0.36	0.36
SD of outcome	0.48	0.48	0.48	0.48	0.48	0.48

Note: Outcome is worried about climate change, recoded as binary variable. A value of 1 is assigned to respondents who state that they are either "very worried" or "extremely worried" on a scale from 1 to 5. Extreme weather spells are computed relative to the distribution of temperatures over a 10 year rolling window from the day of the interview. Warm (cold) spells are defined as at least three consecutive days with temperatures T_{it}^{spell} that fall above (below) the 95th (5th) percentile $\tau_{iw}^{10\text{yr}}$. Individual controls include: age at interview, migration background, educational level, gender. Fixed effects: Country by interview year, interview month, NUTS. Standard errors clustered at the NUTS x ESS round. Significance levels are indicated by $* < .1$, $** < .05$, $*** < .01$.

Table C.5: Feel personal responsibility for climate change

	1 month		1 year		2 years	
	(1)	(2)	(3)	(4)	(5)	(6)
Extreme cold (days)	-0.007*		0.002		0.020	
	(0.004)		(0.033)		(0.063)	
Extreme warm (days)	0.015***		0.032		0.067**	
	(0.005)		(0.024)		(0.026)	
Extreme cold (C°)		-0.002		0.008		0.004
		(0.002)		(0.017)		(0.032)
Extreme warm (C°)		0.007***		0.025*		0.049***
		(0.003)		(0.014)		(0.014)
N	77611	77611	77611	77611	77611	77611
R^2	0.12	0.12	0.12	0.12	0.12	0.12
Mean of outcome	0.49	0.49	0.49	0.49	0.49	0.49
SD of outcome	0.50	0.50	0.50	0.50	0.50	0.50

Note: Outcome is feeling responsible for climate change, recoded as binary. A value of 1 is assigned to respondents who report a score between 7 and 10 on a scale 0-10. Extreme weather spells are computed relative to the distribution of temperatures over a 10 year rolling window from the day of the interview. Warm (cold) spells are defined as at least three consecutive days with temperatures T_{it}^{spell} that fall above (below) the 95th (5th) percentile τ_{iw}^{10yr}. Individual controls include: age at interview, migration background, educational level, gender. Fixed effects: Country by interview year, interview month, NUTS. Standard errors clustered at the NUTS x ESS round. Significance levels are indicated by $* < .1$, ** $< .05$, *** $< .01$.

Table C.6: Voting for green parties and green coalitions

	1 month		1 year		2 years	
	(1)	(2)	(3)	(4)	(5)	(6)
Extreme cold (days)	-0.038***		-0.018		-0.084***	
	(0.006)		(0.021)		(0.033)	
Extreme warm (days)	0.005		0.050***		0.042**	
	(0.005)		(0.017)		(0.018)	
Extreme cold (C°)		-0.017***		-0.001		-0.017
		(0.004)		(0.010)		(0.016)
Extreme warm (C°)		-0.001		0.028***		0.020**
		(0.004)		(0.009)		(0.010)
N	109096	109096	109096	109096	109096	109096
R^2	0.11	0.11	0.11	0.11	0.11	0.11
Mean of outcome	0.10	0.10	0.10	0.10	0.10	0.10
SD of outcome	0.30	0.30	0.30	0.30	0.30	0.30

Note: Outcome is voting for green parties and green coalitions. Parties that are not classified as green parties but are in electoral coalitions with green parties are given value 1. Extreme weather spells are computed relative to the distribution of temperatures over a 10 year rolling window from the day of the last national election. Warm (cold) spells are defined as at least three consecutive days with temperatures T_{it}^{spell} that fall above (below) the 95th (5th) percentile $\tau_{iw}^{10\text{yr}}$. Individual controls include: age at election, migration background, educational level, gender. Fixed effects: Country by election year, election month, NUTS. Standard errors clustered at the NUTS x ESS round. Significance levels are indicated by $* < .1$, ** $< .05$, *** $< .01$.

Table C.7: Voting for green parties

	1 month		1 year		2 years	
	(1)	(2)	(3)	(4)	(5)	(6)
Extreme cold (days)	-0.025***		-0.020		-0.073***	
	(0.005)		(0.018)		(0.028)	
Extreme warm (days)	0.005		0.043***		0.031**	
	(0.005)		(0.013)		(0.014)	
Extreme cold (C°)		-0.009***		-0.003		-0.014
		(0.003)		(0.009)		(0.012)
Extreme warm (C°)		0.000		0.023***		0.016**
		(0.003)		(0.008)		(0.008)
N	109096	109096	109096	109096	109096	109096
R^2	0.10	0.10	0.10	0.10	0.10	0.10
Mean of outcome	0.07	0.07	0.07	0.07	0.07	0.07
SD of outcome	0.25	0.25	0.25	0.25	0.25	0.25

Note: Outcome is voting for green parties. Parties that are not classified as green parties but are in electoral coalitions with green parties are given value 0. Extreme weather spells are computed relative to the distribution of temperatures over a 10 year rolling window from the day of the last national election. Warm (cold) spells are defined as at least three consecutive days with temperatures T_{it}^{spell} that fall above (below) the 95th (5th) percentile $\tau_{iw}^{10\text{yr}}$. Individual controls include: age at election, migration background, educational level, gender. Fixed effects: Country by election year, election month, NUTS. Standard errors clustered at the NUTS x ESS round. Significance levels are indicated by $* < .1$, ** $< .05$, *** $< .01$.

Table C.8: Pro-environment score

	1 month		1 year		2 years	
	(1)	(2)	(3)	(4)	(5)	(6)
Extreme cold (days)	-0.070***		0.091		0.150	
	(0.025)		(0.066)		(0.113)	
Extreme warm (days)	-0.002		0.137*		0.170*	
	(0.025)		(0.074)		(0.088)	
Extreme cold (C°)		-0.036*		0.113***		0.139**
		(0.021)		(0.037)		(0.056)
Extreme warm (C°)		0.006		0.128***		0.129***
		(0.015)		(0.039)		(0.042)
N	89022	89022	89022	89022	89022	89022
R^2	0.53	0.53	0.53	0.53	0.53	0.53
Mean of outcome	4.50	4.50	4.50	4.50	4.50	4.50
SD of outcome	1.43	1.43	1.43	1.43	1.43	1.43

Note: Outcome is a pro-environment score based on the Manifesto Project data. The score is based on the amount of pro-environment statements the party's agenda contains. Extreme weather spells are computed relative to the distribution of temperatures over a 10 year rolling window from the day of the last national election. Warm (cold) spells are defined as at least three consecutive days with temperatures T_{it}^{spell} that fall above (below) the 95th (5th) percentile $\tau_{iw}^{10\text{yr}}$. Individual controls include: age at election, migration background, educational level, gender. Fixed effects: Country by election year, election month, NUTS. Standard errors clustered at the NUTS x ESS round. Significance levels are indicated by $* < .1$, ** $< .05$, *** $< .01$.

Table C.9: Covariate balance for the sample of respondents in ESS rounds 8 and 10

	Excess warm days			Excess warm temperatures		
	(1) 1 month	(2) 1 year	(3) 2 years	(4) 1 month	(5) 1 year	(6) 2 years
Age at interview: 35-54	0.008	0.001	-0.001**	0.019*	0.001	-0.003**
	(0.005)	(0.001)	(0.001)	(0.010)	(0.001)	(0.001)
Age at interview: 55+	0.011**	0.004***	-0.000	0.023**	0.007***	-0.001
	(0.005)	(0.001)	(0.001)	(0.009)	(0.001)	(0.001)
Migration background	-0.002	-0.001	-0.000	0.001	-0.001	0.000
	(0.008)	(0.001)	(0.001)	(0.014)	(0.002)	(0.001)
Female	0.010**	0.001*	-0.000	0.020***	0.001	-0.001*
	(0.004)	(0.001)	(0.000)	(0.007)	(0.001)	(0.001)
Education: Mid	-0.005	-0.000	0.000	-0.012	-0.000	-0.001
	(0.006)	(0.001)	(0.001)	(0.012)	(0.001)	(0.001)
Education: High	-0.003	0.001	0.001**	-0.007	0.001	0.002
	(0.007)	(0.001)	(0.001)	(0.014)	(0.002)	(0.001)
N	78839	78839	78839	78839	78839	78839
R^2	0.25	0.84	0.86	0.26	0.88	0.89
Mean of outcome	0.26	0.35	0.39	0.38	0.57	0.66
SD of outcome	0.59	0.20	0.17	1.07	0.38	0.35

Note: The table reports the coefficients from a regression model with extreme warm spells (days or temperatures) as outcomes and demographic characteristics as explanatory variables. Extreme weather spells are computed relative to the distribution of temperatures over a 10 year rolling window from the day of the last national election. Warm (cold) spells are defined as at least three consecutive days with temperatures T_{it}^{spell} that fall above (below) the 95th (5th) percentile $\tau_{iw}^{10\text{yr}}$. Fixed effects: Country by election year, election month, NUTS. Standard errors clustered at the NUTS x ESS round. Significance levels are indicated by $* < .1$, ** $< .05$, *** $< .01$.

Table C.10: Covariate balance for the sample of voters and non-voters in national elections between 2012 and 2022

	Excess warm days			Excess warm temperatures		
	(1) 1 month	(2) 1 year	(3) 2 years	(4) 1 month	(5) 1 year	(6) 2 years
Age at election: 35-54	-0.001	-0.001	-0.000	-0.001	-0.001	-0.000
	(0.001)	(0.000)	(0.000)	(0.002)	(0.001)	(0.001)
Age at election: 55+	-0.001	-0.001**	-0.000	-0.003	-0.002***	-0.001*
	(0.001)	(0.000)	(0.000)	(0.002)	(0.001)	(0.001)
Migration background	0.002	0.001	0.001***	0.001	0.003**	0.003***
	(0.002)	(0.001)	(0.000)	(0.002)	(0.001)	(0.001)
Female	0.000	-0.001*	-0.000	-0.001	-0.001	-0.001
	(0.001)	(0.000)	(0.000)	(0.002)	(0.001)	(0.000)
Education: Mid	0.001	0.000	0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.000)	(0.002)	(0.001)	(0.001)
Education: High	0.001	-0.000	0.000	0.000	-0.000	0.000
	(0.002)	(0.001)	(0.000)	(0.003)	(0.001)	(0.001)
N	152831	152831	152831	152831	152831	152831
R^2	0.90	0.91	0.91	0.93	0.92	0.90
Mean of outcome	0.27	0.36	0.35	0.43	0.58	0.55
SD of outcome	0.54	0.22	0.17	1.10	0.39	0.30

Note: The table reports the coefficients from a regression model with extreme warm spells (days or temperatures) as outcomes and demographic characteristics as explanatory variables. Extreme weather spells are computed relative to the distribution of temperatures over a 10 year rolling window from the day of the survey. Warm (cold) spells are defined as at least three consecutive days with temperatures T_{it}^{spell} that fall above (below) the 95th (5th) percentile $\tau_{iw}^{10\text{yr}}$. Fixed effects: Country by year, month, NUTS. Standard errors clustered at the NUTS x ESS round. Significance levels are indicated by $* < .1$, ** $< .05$, *** $< .01$.

Table C.11: Covariate balance for the sample of voters in national elections between 2012 and 2022

	Excess warm days			Excess warm temperatures		
	(1) 1 month	(2) 1 year	(3) 2 years	(4) 1 month	(5) 1 year	(6) 2 years
Age at election: 35-54	-0.001	-0.001*	-0.000	-0.000	-0.001	-0.000
	(0.001)	(0.001)	(0.000)	(0.002)	(0.001)	(0.001)
Age at election: 55+	0.000	-0.001**	-0.000	-0.002	-0.002***	-0.001*
	(0.001)	(0.001)	(0.000)	(0.003)	(0.001)	(0.001)
Migration background	0.003	0.004***	0.002**	0.007**	0.007***	0.005***
	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)
Female	-0.002*	-0.001**	-0.000	-0.003*	-0.001	-0.000
	(0.001)	(0.000)	(0.000)	(0.002)	(0.001)	(0.001)
Education: Mid	0.003	-0.001*	-0.000	0.003	-0.002	-0.000
	(0.002)	(0.001)	(0.000)	(0.003)	(0.001)	(0.001)
Education: High	0.002	-0.001	-0.000	0.002	-0.001	-0.000
	(0.002)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)
N	109096	109096	109096	109096	109096	109096
R^2	0.90	0.91	0.91	0.93	0.91	0.90
Mean of outcome	0.25	0.36	0.34	0.40	0.58	0.55
SD of outcome	0.52	0.22	0.17	1.05	0.39	0.30

Note: The table reports the coefficients from a regression model with extreme warm spells (days or temperatures) as outcomes and demographic characteristics as explanatory variables. Extreme weather spells are computed relative to the distribution of temperatures over a 10 year rolling window from the day of the last national election. Warm (cold) spells are defined as at least three consecutive days with temperatures T_{it}^{spell} that fall above (below) the 95th (5th) percentile $\tau_{iw}^{10\text{yr}}$. Fixed effects: Country by election year, election month, NUTS. Standard errors clustered at the NUTS x ESS round. Significance levels are indicated by $* < .1$, ** $< .05$, *** $< .01$.

Table C.12: Voted in last national election

	1 month		1 year		2 years	
	(1)	(2)	(3)	(4)	(5)	(6)
Extreme cold (days)	-0.008		-0.028		-0.035	
	(0.008)		(0.020)		(0.034)	
Extreme warm (days)	0.004		-0.004		0.035	
	(0.008)		(0.017)		(0.024)	
Extreme cold (C°)		-0.002		0.006		-0.005
		(0.006)		(0.012)		(0.015)
Extreme warm (C°)		-0.004		-0.001		0.006
		(0.005)		(0.011)		(0.014)
N	151351	151351	151351	151351	151351	151351
R^2	0.26	0.26	0.26	0.26	0.26	0.26
Mean of outcome	0.70	0.70	0.70	0.70	0.70	0.70
SD of outcome	0.46	0.46	0.46	0.46	0.46	0.46

Note: Outcome is voting in the last national election. Extreme weather spells are computed relative to the distribution of temperatures over a 10 year rolling window from the day of the last national election. Warm (cold) spells are defined as at least three consecutive days with temperatures T_{it}^{spell} that fall above (below) the 95th (5th) percentile $\tau_{iw}^{10\text{yr}}$. Individual controls include: age at election, migration background, educational level, gender. Fixed effects: Country by election year, election month, NUTS. Standard errors clustered at the NUTS x ESS round. Significance levels are indicated by $* < .1$, ** $< .05$, *** $< .01$.

Table C.13: Leads for voting for green parties and green coalitions

	1 year		2 years	
	(1)	(2)	(3)	(4)
Extreme cold (days)	-0.033		-0.033	
	(0.026)		(0.027)	
Extreme warm (days)	-0.048**		0.006	
	(0.019)		(0.017)	
Extreme cold (C°)		-0.001		0.012
		(0.013)		(0.016)
Extreme warm (C°)		-0.034***		-0.003
		(0.011)		(0.008)
N	108980	108980	100148	100148
R^2	0.11	0.11	0.12	0.12
Mean of outcome	0.10	0.10	0.10	0.10
SD of outcome	0.30	0.30	0.30	0.30

Note: Outcome is voting for green parties and green coalitions. Parties that are not classified as green parties but are in electoral coalitions with green parties are given value 1. Extreme weather spells are computed relative to the distribution of temperatures over a 10 year rolling window from the day of the last national election, plus 1 year or 2 years. Warm (cold) spells are defined as at least three consecutive days with temperatures T_{it}^{spell} that fall above (below) the 95th (5th) percentile $\tau_{iw}^{10\text{yr}}$. Results reported in the table are for 52 weeks of exposure. Individual controls include: age at election, migration background, educational level, gender. Fixed effects: Country by election year, election month, NUTS. Standard errors clustered at the NUTS x ESS round. Significance levels are indicated by $* < .1$, ** $< .05$, *** $< .01$.

Table C.14: Average marginal effects of excess warm temperatures on climate attitudes and green voting by socio-demographic group

	Feel responsible for CC	Worried about CC	Green voting
LowEdu#Male	0.031*	0.056***	0.031***
HighEdu#Male	0.027	0.029	0.017*
LowEdu#Female	0.01	0.04**	0.031***
HighEdu#Female	0.035*	0.018	0.028**
LowEdu#<40	0.030	0.064***	0.011
HighEdu#<40	0.036	0.031	0.011
LowEdu#40+	0.014	0.039*	0.038***
HighEdu#40+	0.029	0.02	0.031***
<40#Male	0.039*	0.06***	0.01
40+#Male	0.025	0.04**	0.034***
<40#Female	0.029	0.045**	0.014
40+#Female	0.014	0.026	0.038***
Rural	0.021	0.043***	0.032***
Urban	0.038**	0.035*	0.017
Agriculture	-0.033	0.053**	0.036**
Industry	0.027	0.053***	0.036***
Service	0.011	0.035*	0.020**

Note: the table reports average marginal effects for different demographic subgroups. Coefficients come from a regression model in which the extreme weather measures - our key predictors - are interacted with individual characteristics (gender and education, age and education, gender and age, rural-urban and employment sector). Average marginal effects are marginal effects of extremely high temperatures on the probability of feeling responsible for climate change. feeling worried about climate change and voting for a green party or a green coalition. All fixed effects and controls are the same as in the baseline specification. Significance levels are indicated by $* < .1$, ** $< .05$, *** $< .01$.

Table C.15: Average marginal effects of excess warm temperatures on green voting by NACE and regional characteristics

	Unemployment rate		GDP per capita		GHG emissions per capita	
	BelowMedian	AboveMedian	BelowMedian	AboveMedian	BelowMedian	AboveMedian
Agriculture	0.025	0.039	0.027	0.001	0.036	0.030
Industry	0.049***	0.029	0.001	0.048***	0.064***	0.012
Service	0.031***	0.018	-0.013	0.028**	0.041***	0.008

Note: The table reports average marginal effects for different demographic subgroups and by different levels of regional characteristics. Coefficients come from a regression model in which the extreme weather measures - our key predictors - are interacted with individual characteristics (gender and education, age and education, gender and age, rural-urban and employment sector) for subsamples splitted based on the regional value of unemployment rate, GDP per capita and GHG emissions per capita. Average marginal effects are marginal effects of extremely high temperatures on the probability of feeling responsible for climate change, feeling worried about climate change and voting for a green party or a green coalition. All fixed effects and controls are the same as in the baseline specification. Significance levels are indicated by $* < .1$, $** < .05$, $*** < .01$.

Table C.16: Worried about climate change

	1 month		1 year		2 years	
	(1)	(2)	(3)	(4)	(5)	(6)
Extreme cold (days)	-0.007*		-0.089***		-0.185***	
	(0.004)		(0.031)		(0.061)	
Extreme warm (days)	0.014***		0.086***		0.096**	
	(0.004)		(0.028)		(0.038)	
Extreme cold (C°)		-0.003*		-0.037**		-0.078***
		(0.002)		(0.015)		(0.029)
Extreme warm (C°)		0.008***		0.040**		0.048**
		(0.002)		(0.016)		(0.019)
N	78584	78584	78584	78584	78584	78584
R^2	0.09	0.09	0.09	0.09	0.09	0.09
Mean of outcome	0.36	0.36	0.36	0.36	0.36	0.36
SD of outcome	0.48	0.48	0.48	0.48	0.48	0.48

Note: Outcome is worried about climate change, recoded as binary variable. A value of 1 is assigned to respondents who state that they are either "very worried" or "extremely worried" on a scale from 1 to 5. Extreme weather spells are computed relative to the distribution of temperatures over a 10 year rolling window from the day of the interview. Warm (cold) spells are defined as at least three consecutive days with temperatures T_{it}^{spell} that fall above (below) the 95th (5th) percentile $\tau_{iw}^{10\text{yr}}$. Temperature measures are weighted by the population size. Individual controls include: age at interview, migration background, educational level, gender. Fixed effects: Country by interview year, interview month, NUTS. Standard errors clustered at the NUTS x ESS round. Significance levels are indicated by $* < .1$, ** $< .05$, *** $< .01$.

Table C.17: Feel personal responsibility for climate change

	1 month		1 year		2 years	
	(1)	(2)	(3)	(4)	(5)	(6)
Extreme cold (days)	-0.009**		0.001		0.032	
	(0.004)		(0.033)		(0.063)	
Extreme warm (days)	0.013***		0.037		0.098***	
	(0.005)		(0.026)		(0.029)	
Extreme cold (C°)		-0.002		0.007		-0.001
		(0.002)		(0.018)		(0.033)
Extreme warm (C°)		0.007**		0.020		0.046***
		(0.003)		(0.015)		(0.015)
N	77611	77611	77611	77611	77611	77611
R^2	0.12	0.12	0.12	0.12	0.12	0.12
Mean of outcome	0.49	0.49	0.49	0.49	0.49	0.49
SD of outcome	0.50	0.50	0.50	0.50	0.50	0.50

Note: Outcome is feeling responsible for climate change, recoded as binary. A value of 1 is assigned to respondents who report a score between 7 and 10 on a scale 0-10. Extreme weather spells are computed relative to the distribution of temperatures over a 10 year rolling window from the day of the interview. Warm (cold) spells are defined as at least three consecutive days with temperatures T_{it}^{spell} that fall above (below) the 95th (5th) percentile $\tau_{iw}^{10\text{yr}}$. Temperature measures are weighted by the population size. Individual controls include: age at interview, migration background, educational level, gender. Fixed effects: Country by interview year, interview month, NUTS. Standard errors clustered at the NUTS x ESS round. Significance levels are indicated by $* < .1$, ** $< .05$, *** $< .01$.

Table C.18: Voting for green parties and green coalitions

	1 month		1 year		2 years	
	(1)	(2)	(3)	(4)	(5)	(6)
Extreme cold (days)	-0.044***		-0.019		-0.075**	
	(0.007)		(0.018)		(0.031)	
Extreme warm (days)	0.006		0.071***		0.058***	
	(0.005)		(0.015)		(0.020)	
Extreme cold (C°)		-0.016***		-0.006		-0.023
		(0.004)		(0.010)		(0.017)
Extreme warm (C°)		0.001		0.032***		0.021*
		(0.004)		(0.009)		(0.011)
N	109096	109096	109096	109096	109096	109096
R^2	0.11	0.11	0.11	0.11	0.11	0.11
Mean of outcome	0.10	0.10	0.10	0.10	0.10	0.10
SD of outcome	0.30	0.30	0.30	0.30	0.30	0.30

Note: Outcome is voting for green parties and green coalitions. Parties that are not classified as green parties but are in electoral coalitions with green parties are given value 1. Extreme weather spells are computed relative to the distribution of temperatures over a 10 year rolling window from the day of the last national election. Warm (cold) spells are defined as at least three consecutive days with temperatures T_{it}^{spell} that fall above (below) the 95th (5th) percentile $\tau_{iw}^{10\text{yr}}$. Temperature measures are weighted by the population size. Individual controls include: age at election, migration background, educational level, gender. Fixed effects: Country by election year, election month, NUTS. Standard errors clustered at the NUTS x ESS round. Significance levels are indicated by $* < .1$, ** $< .05$, *** $< .01$.

Table C.19: Voting for green parties

	1 month		1 year		2 years	
	(1)	(2)	(3)	(4)	(5)	(6)
Extreme cold (days)	-0.032***		-0.030*		-0.086***	
	(0.006)		(0.016)		(0.026)	
Extreme warm (days)	0.001		0.038***		0.030**	
	(0.004)		(0.012)		(0.013)	
Extreme cold (C°)		-0.010***		-0.006		-0.018
		(0.003)		(0.009)		(0.012)
Extreme warm (C°)		0.001		0.023***		0.016**
		(0.003)		(0.007)		(0.008)
N	109096	109096	109096	109096	109096	109096
R^2	0.10	0.10	0.10	0.10	0.10	0.10
Mean of outcome	0.07	0.07	0.07	0.07	0.07	0.07
SD of outcome	0.25	0.25	0.25	0.25	0.25	0.25

Note: Outcome is voting for green parties. Parties that are not classified as green parties but are in electoral coalitions with green parties are given value 0. Extreme weather spells are computed relative to the distribution of temperatures over a 10 year rolling window from the day of the last national election. Warm (cold) spells are defined as at least three consecutive days with temperatures T_{it}^{spell} that fall above (below) the 95th (5th) percentile $\tau_{iw}^{10\text{yr}}$. Temperature measures are weighted by the population size. Individual controls include: age at election, migration background, educational level, gender. Fixed effects: Country by election year, election month, NUTS. Standard errors clustered at the NUTS x ESS round. Significance levels are indicated by $* < .1$, ** $< .05$, *** $< .01$.

Table C.20: Pro-environment score

	1 month		1 year		2 years	
	(1)	(2)	(3)	(4)	(5)	(6)
Extreme cold (days)	-0.060**		0.134**		0.205*	
	(0.027)		(0.062)		(0.111)	
Extreme warm (days)	-0.008		0.240***		0.242**	
	(0.024)		(0.071)		(0.094)	
Extreme cold (C°)		-0.028		0.098**		0.127**
		(0.020)		(0.043)		(0.060)
Extreme warm (C°)		0.000		0.112***		0.113**
		(0.016)		(0.041)		(0.046)
N	89022	89022	89022	89022	89022	89022
R^2	0.53	0.53	0.53	0.53	0.53	0.53
Mean of outcome	4.50	4.50	4.50	4.50	4.50	4.50
SD of outcome	1.43	1.43	1.43	1.43	1.43	1.43

Note: Outcome is a pro-environment score based on the Manifesto Project data. The score is based on the amount of pro-environment statements the party's agenda contains. Extreme weather spells are computed relative to the distribution of temperatures over a 10 year rolling window from the day of the last national election. Warm (cold) spells are defined as at least three consecutive days with temperatures T_{it}^{spell} that fall above (below) the 95th (5th) percentile $\tau_{iw}^{10\text{yr}}$. Temperature measures are weighted by the population size. Individual controls include: age at election, migration background, educational level, gender. Fixed effects: Country by election year, election month, NUTS. Standard errors clustered at the NUTS x ESS round. Significance levels are indicated by $* < .1$, ** $< .05$, *** $< .01$.

Table C.21: Leads for worried about climate change

	1 year		2 years	
	(1)	(2)	(3)	(4)
Extreme cold (days)	0.062		-0.133	
	(0.039)		(0.099)	
Extreme warm (days)	-0.044		-0.055	
	(0.047)		(0.059)	
Extreme cold (C°)		0.034**		-0.010
		(0.016)		(0.047)
Extreme warm (C°)		-0.064**		-0.027
		(0.027)		(0.032)
N	69955	69955	37843	37843
R^2	0.09	0.09	0.08	0.08
Mean of outcome	0.35	0.35	0.29	0.29
SD of outcome	0.48	0.48	0.45	0.45

Note: Outcome is worried about climate change. Extreme weather spells are computed relative to the distribution of temperatures over a 10 year rolling window from the day of the interview, plus 1 year or 2 years. Warm (cold) spells are defined as at least three consecutive days with temperatures T_{it}^{spell} that fall above (below) the 95th (5th) percentile τ_{iw}^{10yr}. Results reported in the table are for 52 weeks of exposure. Individual controls include: age at interview, migration background, educational level, gender. Fixed effects: Country by year, NUTS. Standard errors clustered at the NUTS x ESS round. Significance levels are indicated by $* < .1$, ** $< .05$, *** $< .01$.

Table C.22: Leads for feeling responsible about climate change

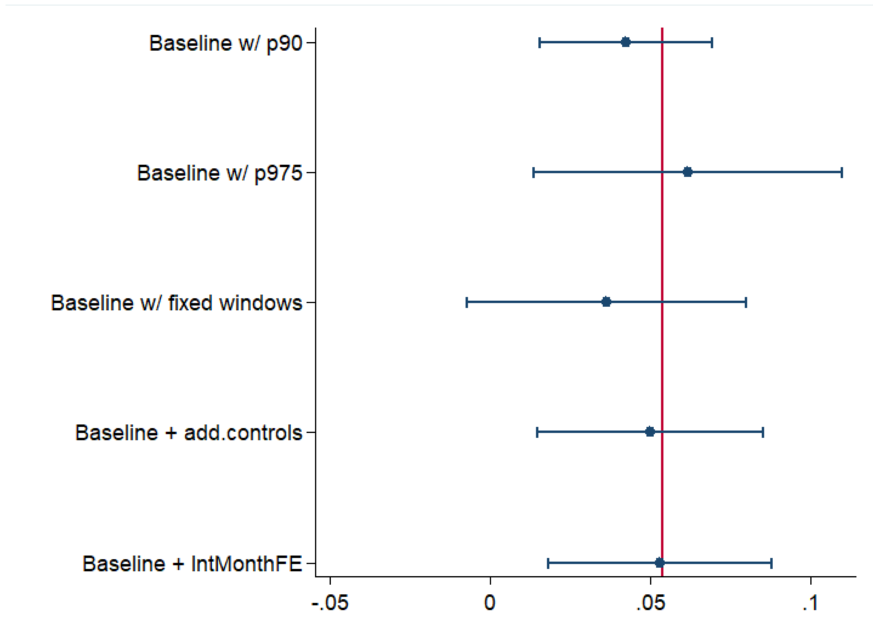
	1 year		2 years	
	(1)	(2)	(3)	(4)
Extreme cold (days)	0.069*		-0.074	
	(0.041)		(0.105)	
Extreme warm (days)	-0.028		0.015	
	(0.037)		(0.065)	
Extreme cold (C°)		0.041**		-0.064
		(0.017)		(0.060)
Extreme warm (C°)		-0.038*		-0.014
		(0.021)		(0.034)
N	69021	69021	37299	37299
R^2	0.12	0.12	0.12	0.12
Mean of outcome	0.48	0.48	0.44	0.44
SD of outcome	0.50	0.50	0.50	0.50

Note: Outcome is feeling responsible for climate change. Extreme weather spells are computed relative to the distribution of temperatures over a 10 year rolling window from the day of the interview, plus 1 year or 2 years. Warm (cold) spells are defined as at least three consecutive days with temperatures T_{it}^{spell} that fall above (below) the 95th (5th) percentile $\tau_{iw}^{10\text{yr}}$. Results reported in the table are for 52 weeks of exposure. Individual controls include: age at interview, migration background, educational level, gender. Fixed effects: Country by year, NUTS. Standard errors clustered at the NUTS x ESS round. Significance levels are indicated by $* < .1$, ** $< .05$, *** $< .01$.

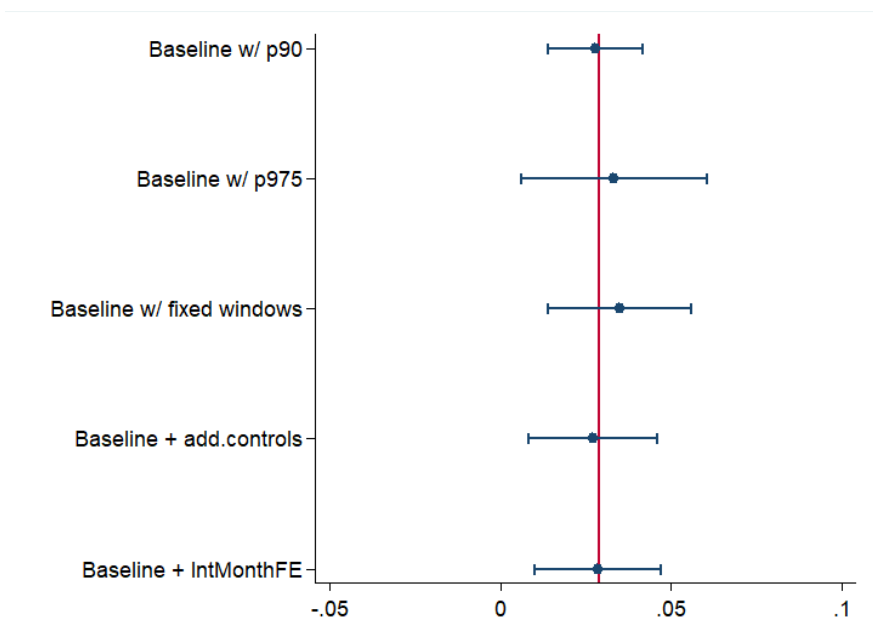
Supplementary Figures

Figure C.1: Robustness to alternative specifications

(a) Days

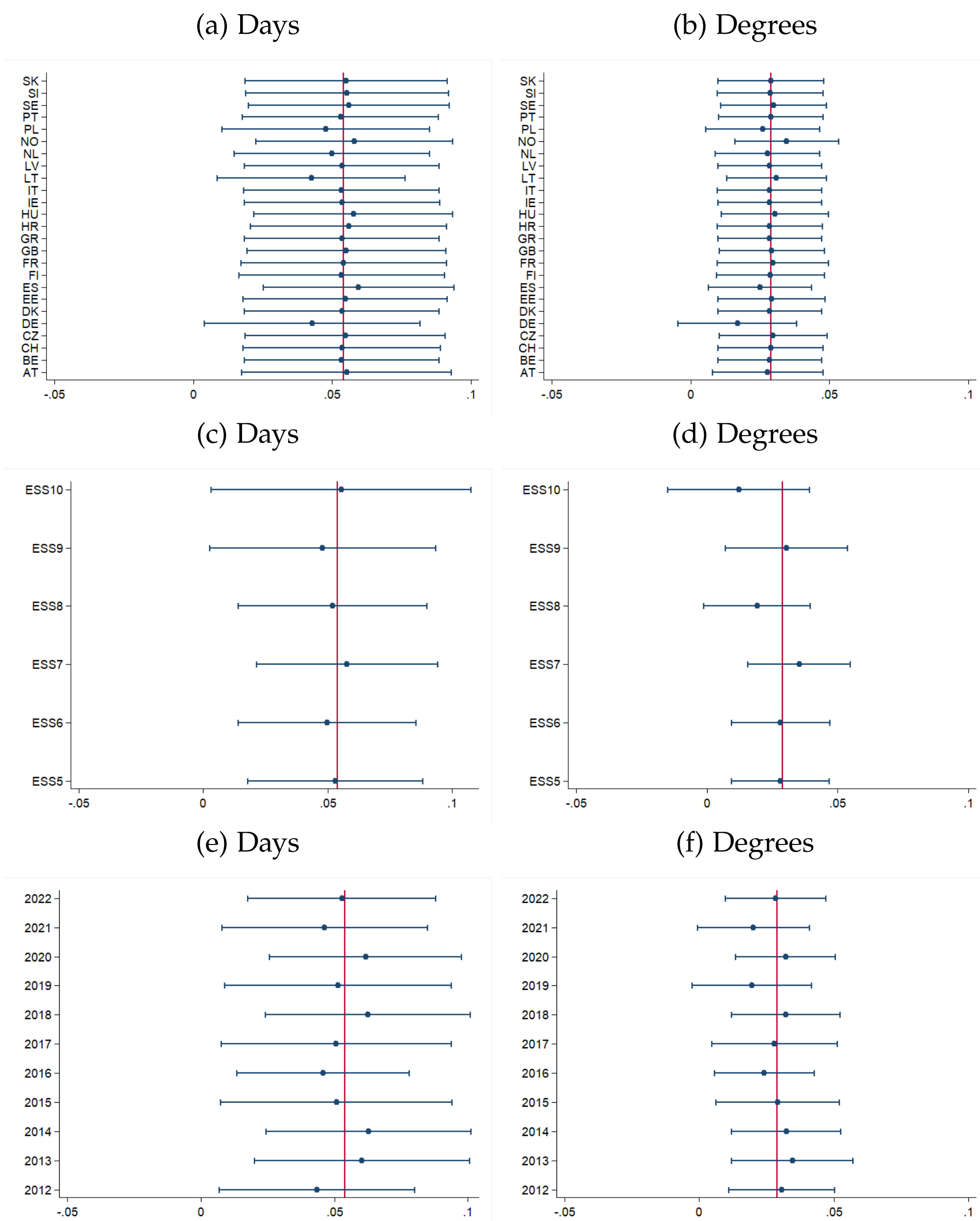


(b) Degrees



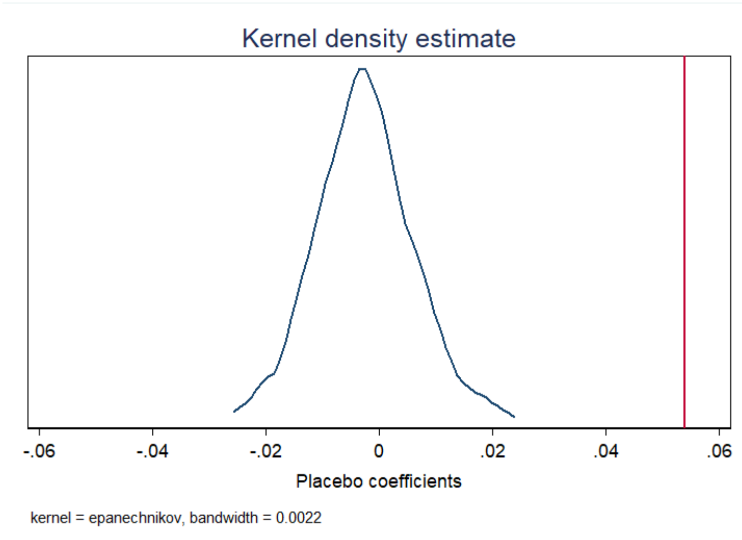
Notes: The figure displays estimated coefficients for alternative specifications of the baseline model. In Panel a) the main predictor is excess days of extremely high temperatures, while in Panel b) is excess temperatures. The red line indicates the baseline estimated coefficient.

Figure C.2: Robustness to the exclusion of countries, survey rounds and election years

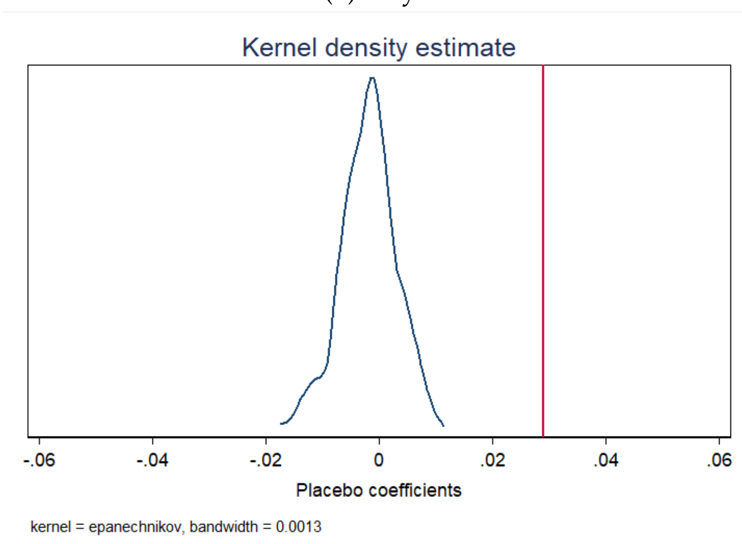


Notes: The figure displays estimated coefficients for alternative specifications of the baseline model excluding one country at a time (panels a and b), one survey round at a time (panels c and d), one election year at a time (panels e and f). In panels a,c,e) the main predictor is excess days of extremely high temperatures, while in panels b,d,f) the main predictor is excess hot temperatures. The red line indicates the baseline estimated coefficient.

Figure C.3: Placebo estimations: random assignment of excess warm days and temperatures within country and survey round



(a) Days

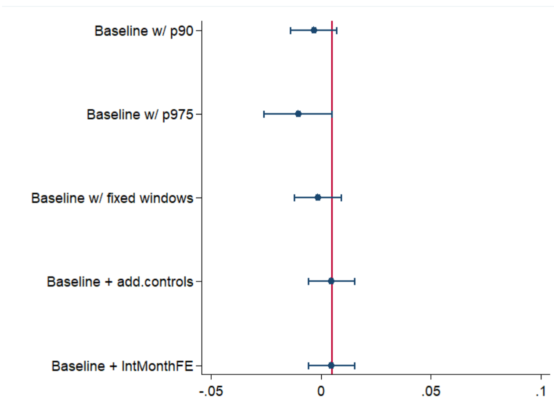


(b) Degrees

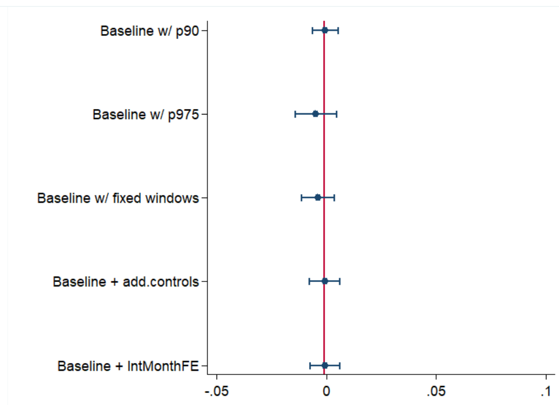
Notes: The figure displays the distribution (kernel density) of estimated coefficients for 300 regressions models in which climate measures are reshuffled. Reshuffling of climate measures is performed across regions, and within country and election year. In Panel a) the main predictor is excess days of extremely high temperatures, while in Panel b) is excess temperatures. The red line indicates the baseline estimated coefficient.

Figure C.4: Robustness to alternative specifications: 4 and 104 weeks exposure

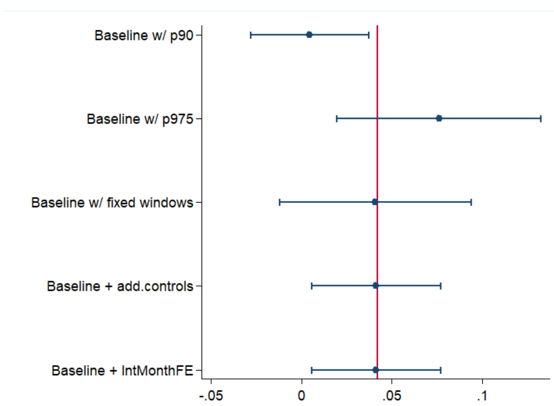
(a) Days - 1 month exposure



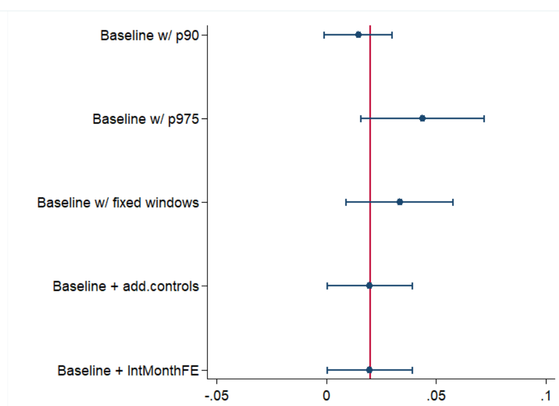
(b) Degrees - 1 month exposure



(c) Days - 2 years exposure



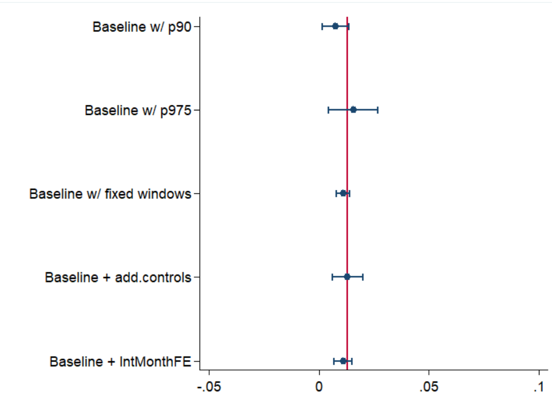
(d) Degrees - 2 years exposure



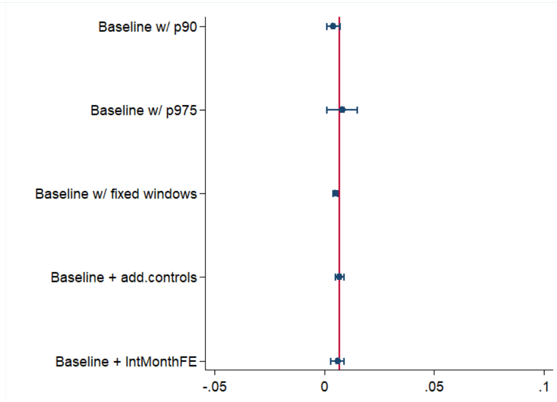
Notes: The figure displays estimated coefficients for alternative specifications of the baseline model. In Panels a) and c) the main predictor is excess days of extremely high temperatures, while in Panels b) and d) is excess temperatures. The red line indicates the baseline estimated coefficient. Outcomes is voting for green parties or green coalitions.

Figure C.5: Worried about climate change: robustness to alternative specifications: 1 month, 1 year, 2 years of exposure

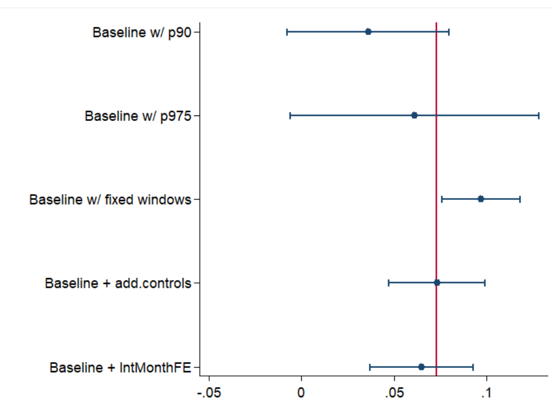
(a) Days - 1 month exposure



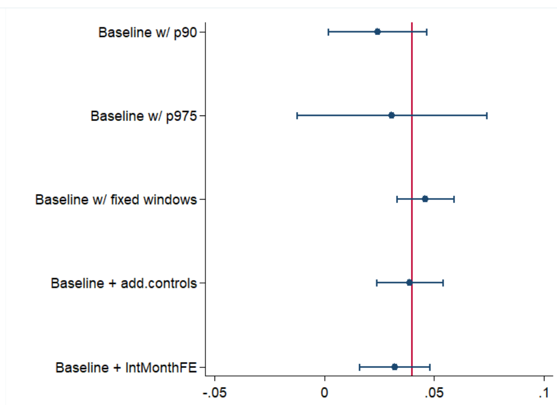
(b) Degrees - 1 month exposure



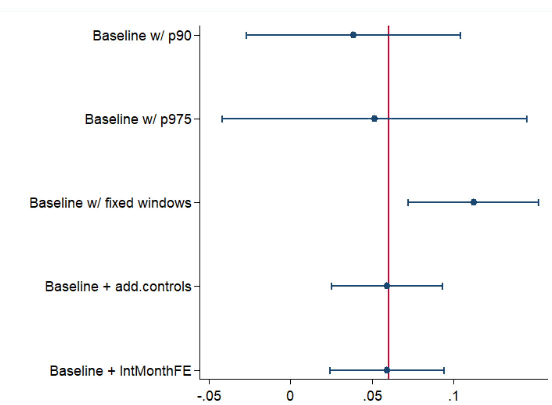
(c) Days - 1 year exposure



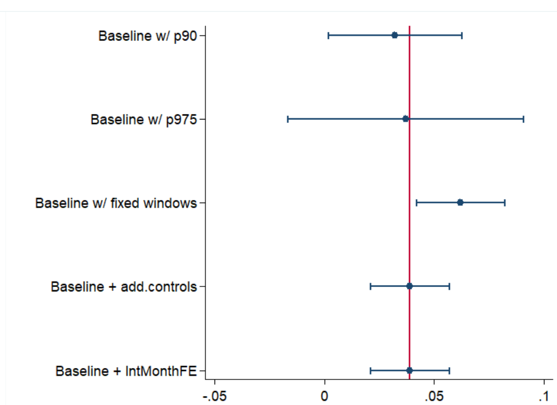
(d) Degrees - 1 year exposure



(e) Days - 2 years exposure



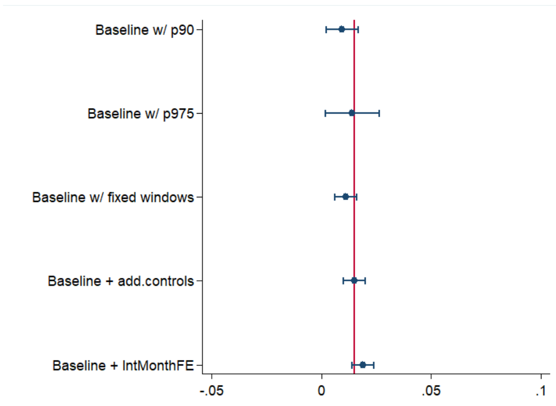
(f) Degrees - 2 years exposure



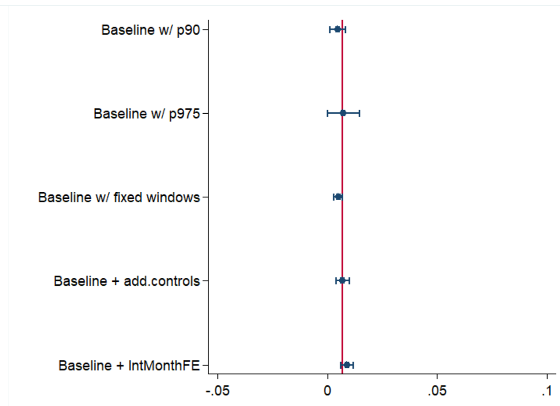
Notes: The figure displays estimated coefficients for alternative specifications of the baseline model. In Panel a), c) and e) the main predictor is excess days of extremely high temperatures, while in Panel b), d) and f) is excess temperatures. The red line indicates the baseline estimated coefficient.

Figure C.6: Feel personally responsible for climate change: robustness to alternative specifications: 1 month, 1 year, 2 years of exposure

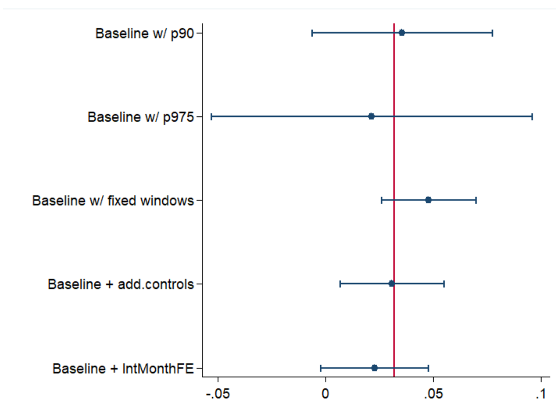
(a) Days - 1 month exposure



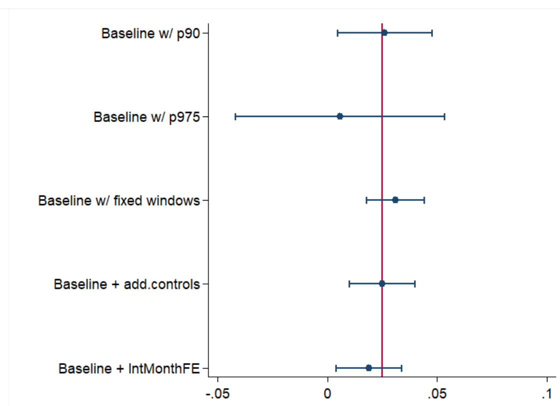
(b) Degrees - 1 month exposure



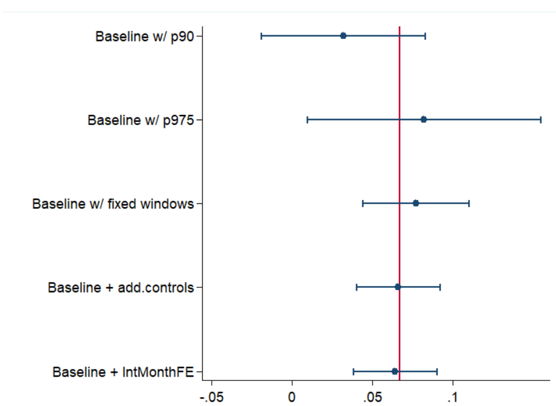
(c) Days - 1 year exposure



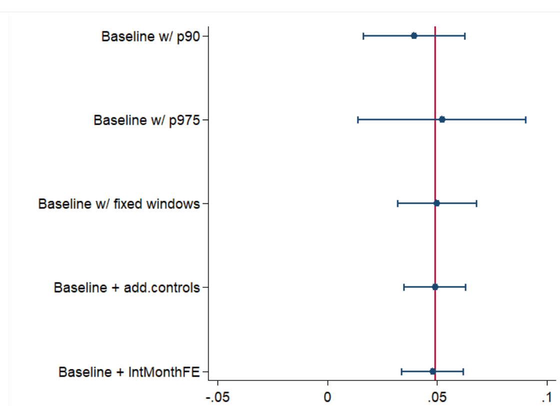
(d) Degrees - 1 year exposure



(e) Days - 2 years exposure

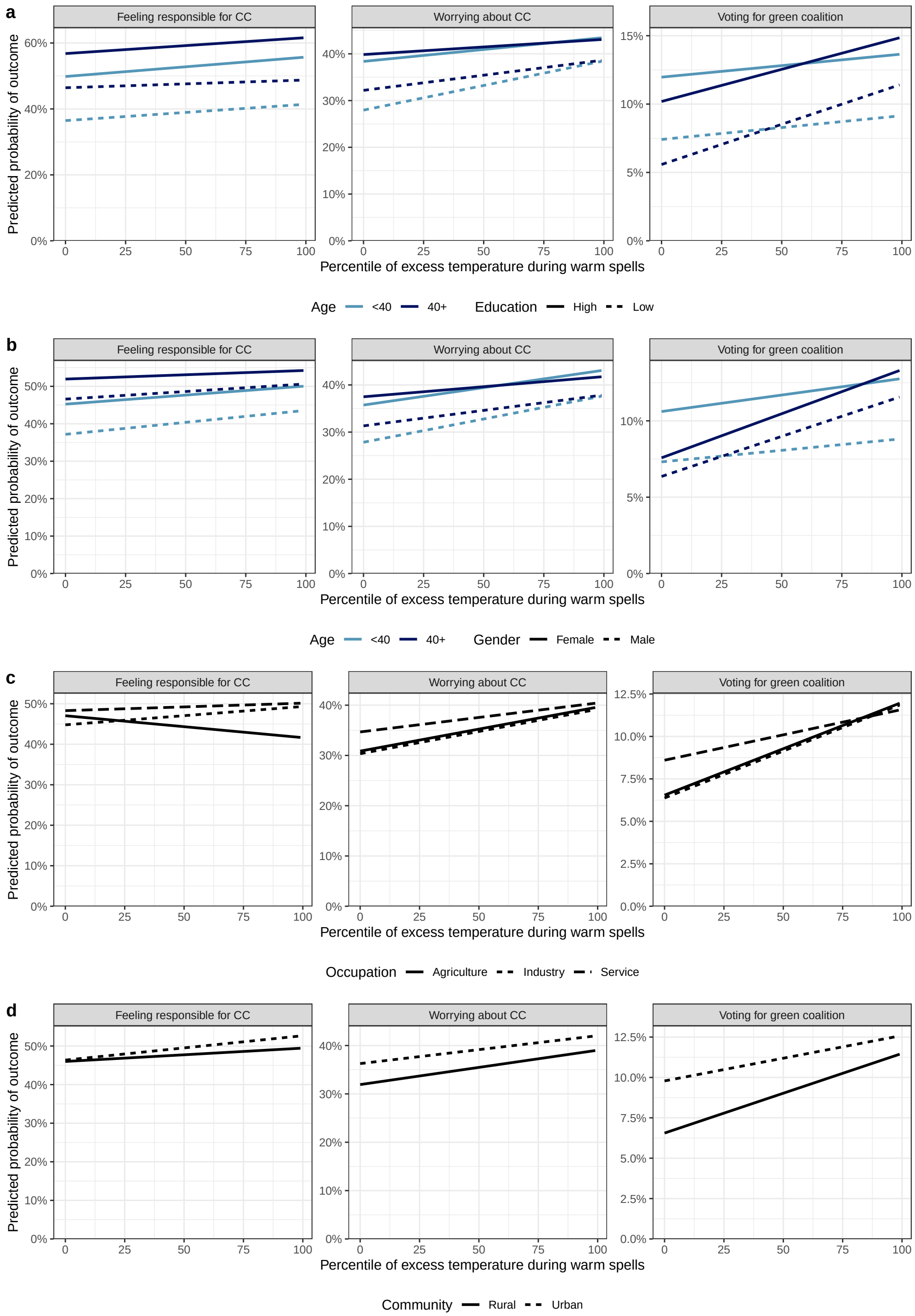


(f) Degrees - 2 years exposure



Notes: The figure displays estimated coefficients for alternative specifications of the baseline model. In Panel a), c) and e) the main predictor is excess days of extremely high temperatures, while in Panel b), d) and f) is excess temperatures. The red line indicates the baseline estimated coefficient.

Figure C.7: Heterogeneous predictions by (a) education and age, (b) gender and age, (c) occupation, and (d) community type.



Notes: the figure displays average predicted probabilities of feeling responsible for climate change, being worried about climate chance and voting for green parties and green coalitions for different demographic subgroups. The y-axis indicates the size of the average predicted probability, the x-axis indicates the distribution (in percentiles) of the extremely warm temperatures. Panel a) reports results for the interaction between age and education panel b) for age and gender, panel c) for employment sector and panel d) for urban-rural.

Figure C.8: Number of observations and elections by country, year, and month.

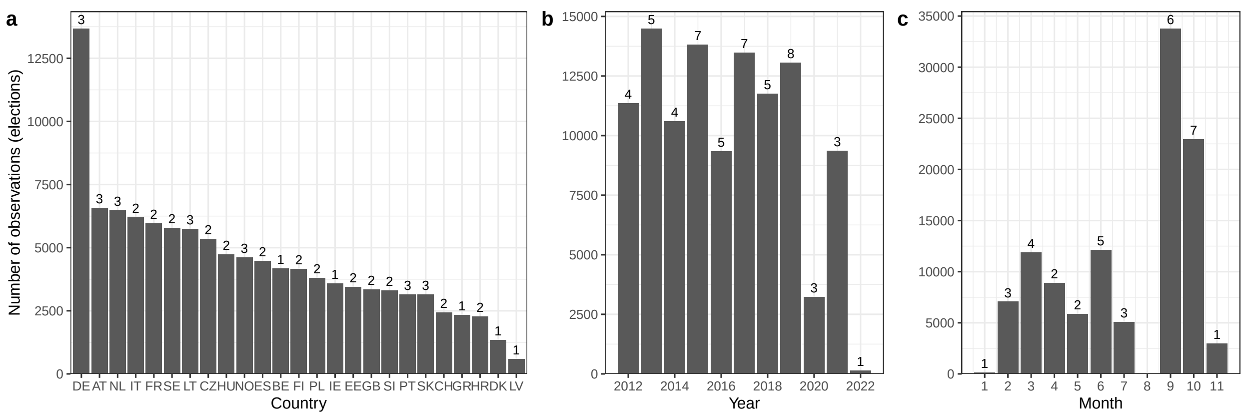


Figure C.9: Average regional share that worries about climate change and that feels personally responsible for climate change by ESS round (percent).

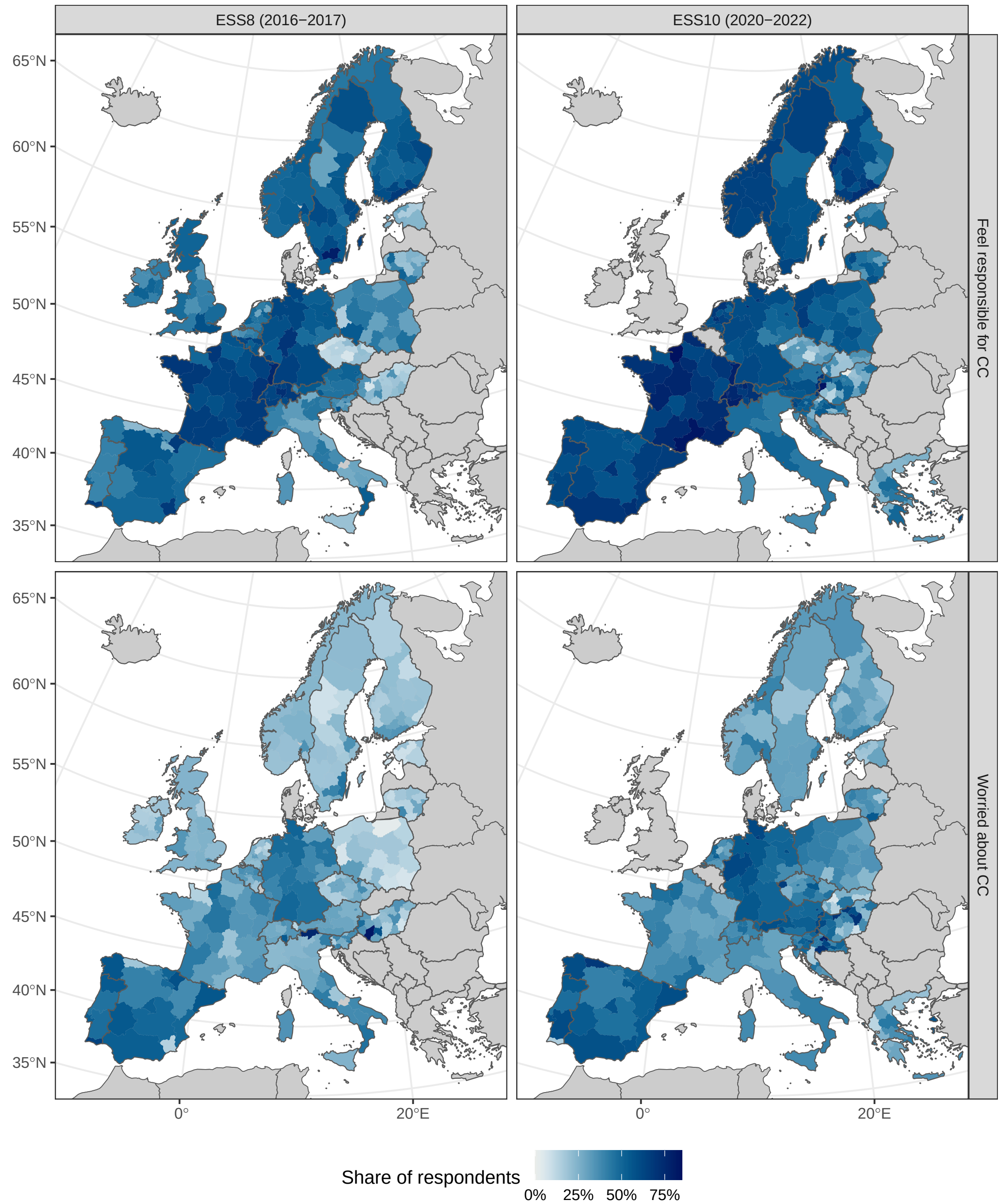
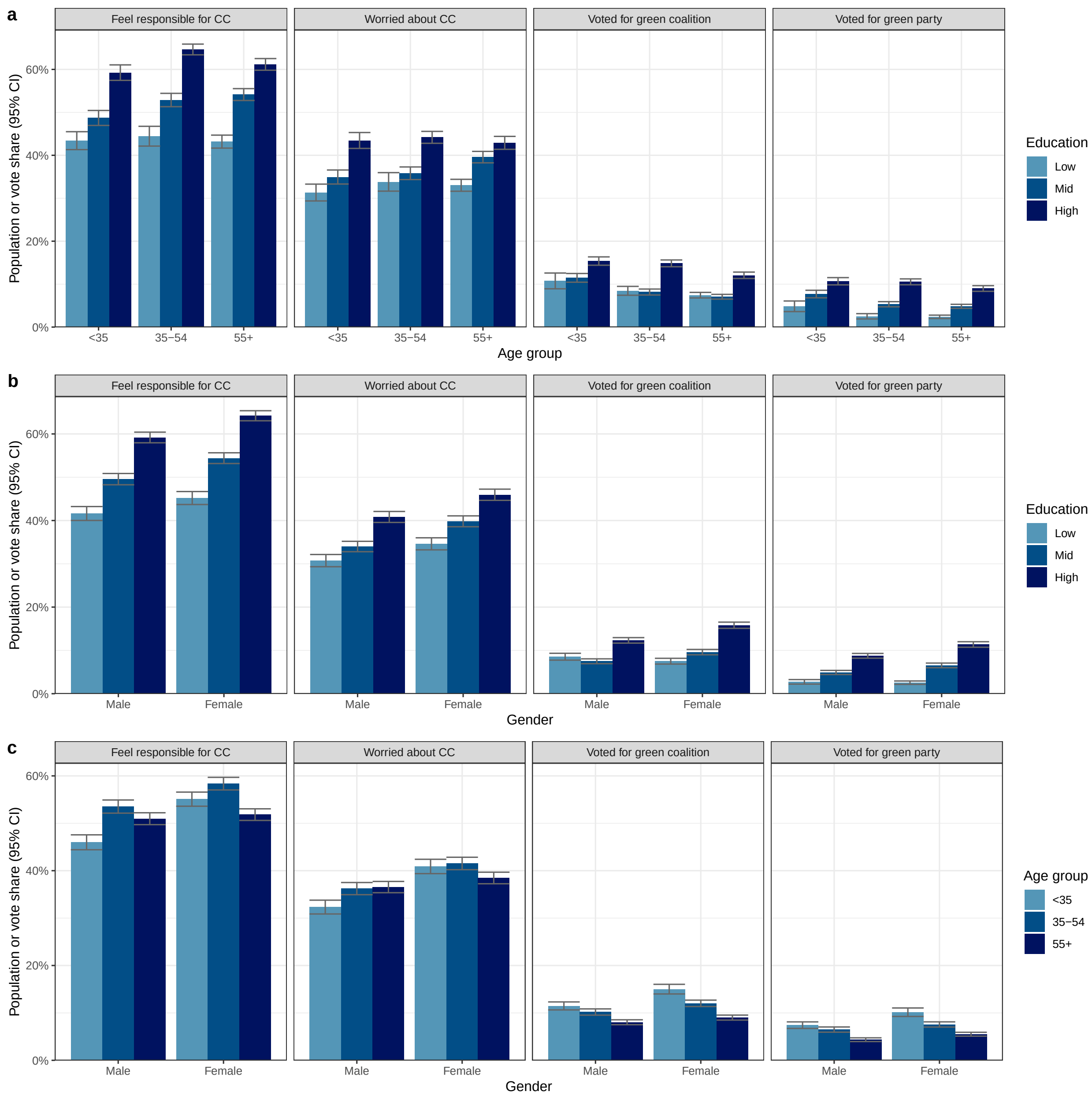
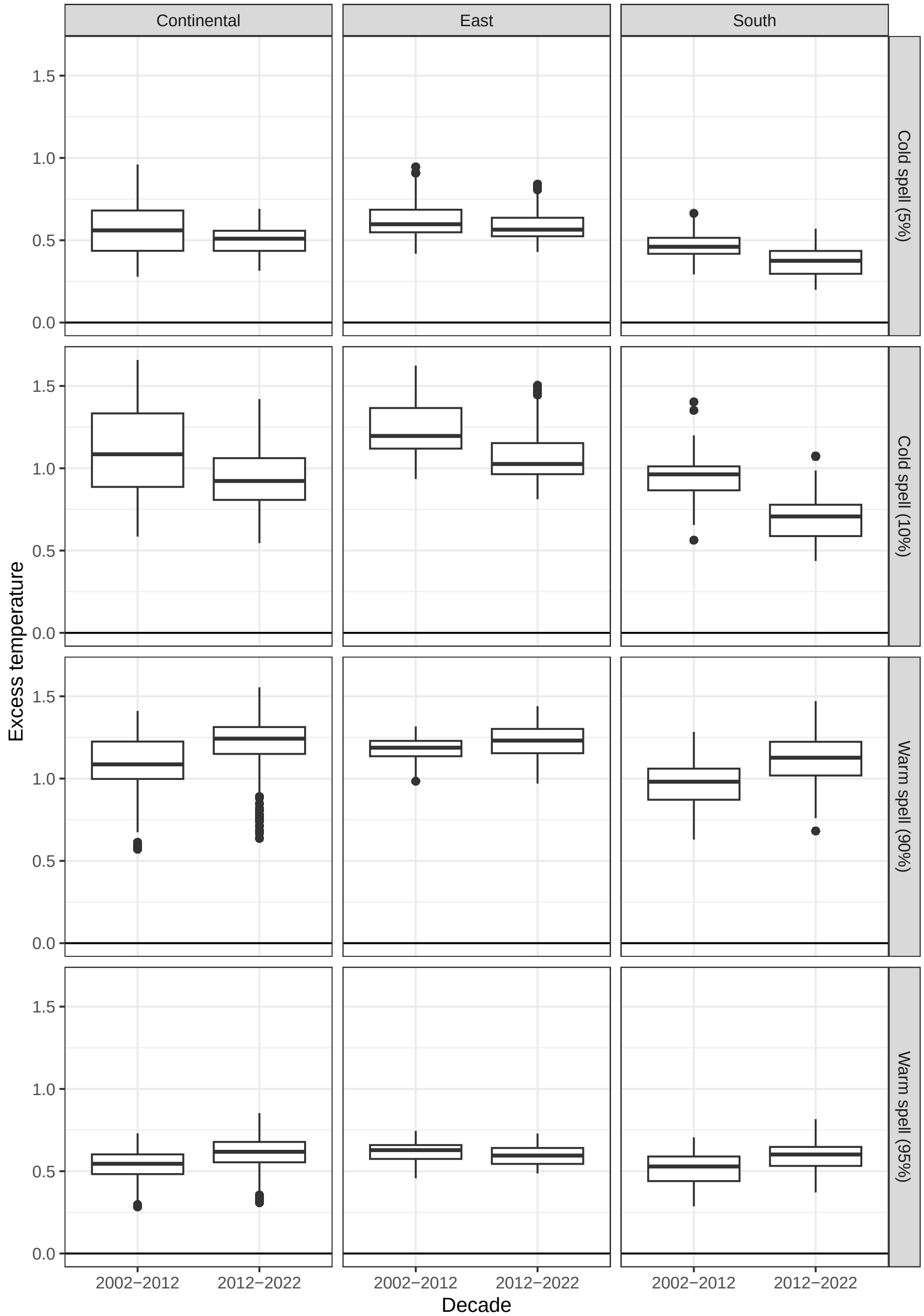


Figure C.10: Average shares by (a) age and education, (b) gender and education, and (c) gender and age (2012–2022).



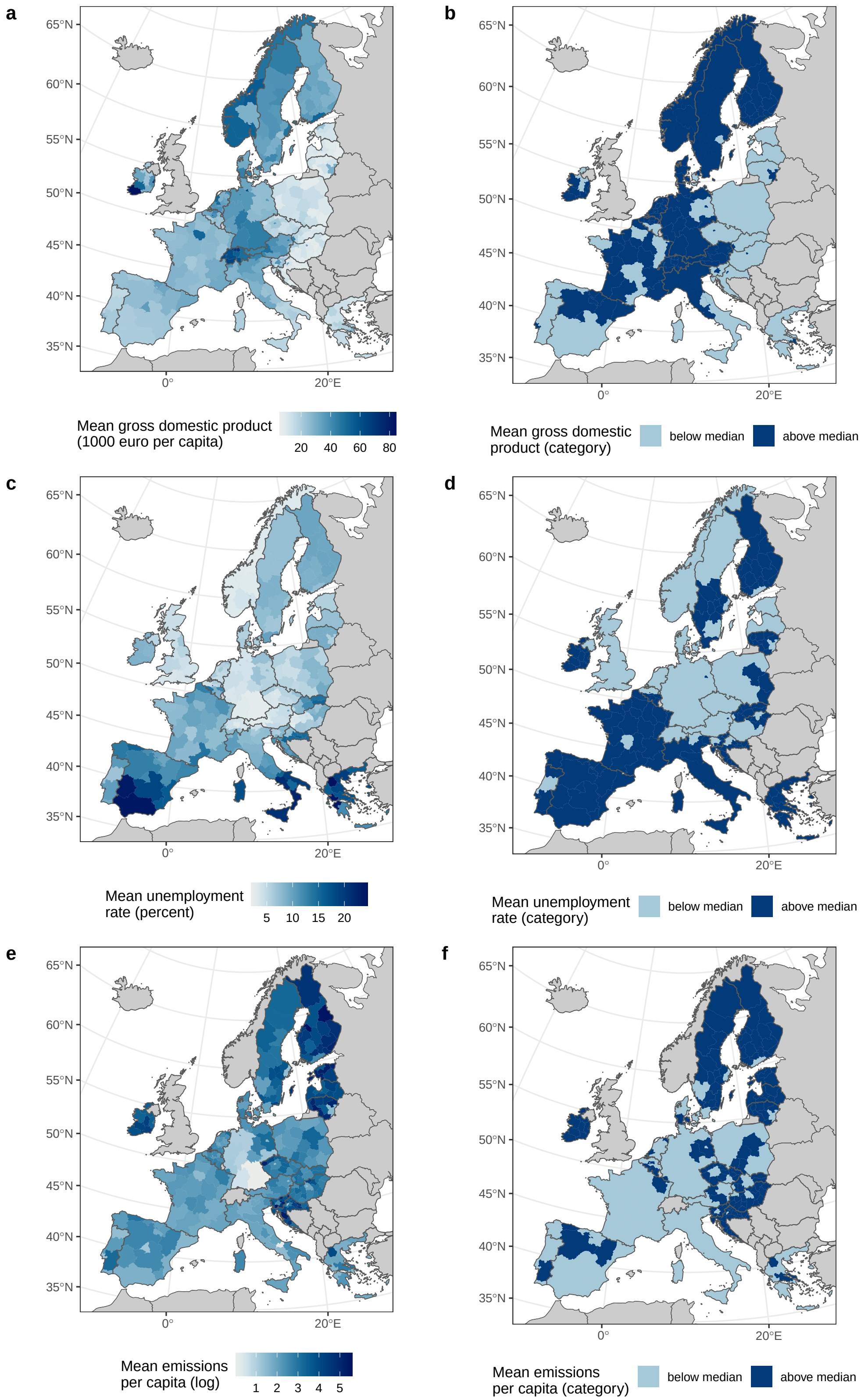
Notes: Average share that feels personally responsible for climate change, that is worried about climate, that voted for a green coalition, and that voted for a green party (percent). Attitudes are shown as share of the whole population and voting outcomes as shares of votes. Range indicates 95% confidence interval.

Figure C.11: Boxplots of weekly, regional warm and cold spells by region



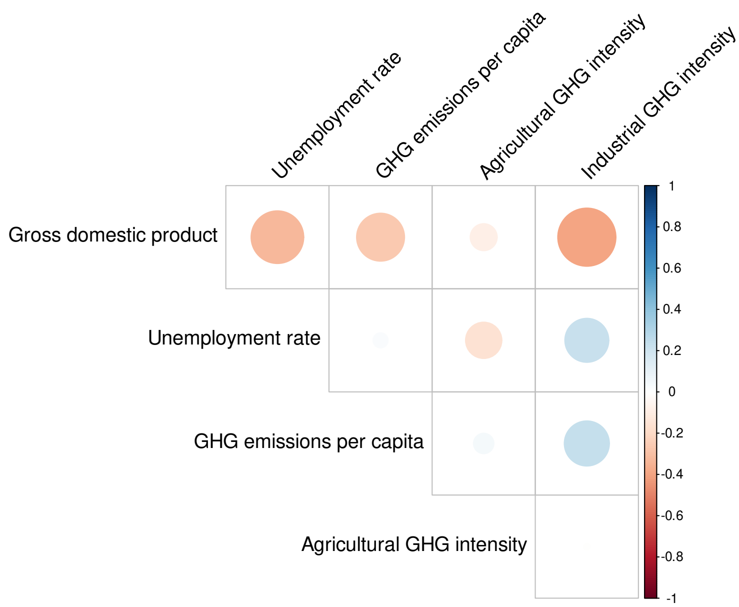
Notes: Variables are defined by the extreme 5% and 10% of the weekly, regional distribution of daily temperature means in the previous 10 years. The boxes indicate the first, second, and third quartile and the vertical lines the largest and smallest value within a distance from the box of 1.5 × the interquartile range. Any observations outside of this range are classified as outliers and shown as points.

Figure C.12: Maps of regional characteristics.



Notes: Values are averages over the time span 2012–2022. Figure (e) shows GHG emissions in CO_2 equivalents per 1000 capita, applying a log transformation to improve readability of the scale.

Figure C.13: Pearson correlation coefficients of regional characteristics.



Notes: Positive correlations are indicated in blue, negative correlations in red. The absolute value of the coefficients is shown by circle area and color saturation.