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# Voting for Tomorrow: Climate Change, Environmental Concern, and Green Voting

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## Abstract

In the past decade, the world has witnessed increased climate change impacts with many countries experiencing more frequent and more severe climate extremes. With public support being fundamental in scaling up climate action, here, we analyze the impact of exposure to climate extremes on environmental concern and Green voting for a large panel of European countries. Combining high-resolution climatological data with regionally aggregated and harmonized information on environmental concern (42 Eurobarometer surveys, 2002-2019, 34 countries) and European Parliamentary electoral outcomes (7 elections, 1990-2019, 28 countries) at the subnational level, we find a significant and sizeable effect of temperature anomalies, heat episodes and dry spells in the previous 12 months on green concern and voting. The effects differ significantly by region and are most pronounced in regions with a cooler Continental or temperate Atlantic climate, and weaker in regions with a warmer Mediterranean climate. The relationship is moderated by regional GDP suggesting that climate change experience increase public support for climate action only under favorable economic conditions. By empirically documenting the important role of contextual influences and regional differences on green concern and voting, our findings have important implications for the current efforts to promote and implement climate actions in line with the Paris Agreement.

## 1. Introduction

Whilst about two decades ago, climate change and associated extreme climate events were psychologically distant for many Europeans, in the past five years Europe has witnessed its warmest years on record resulting in climate-related disasters such as wildfires or droughts (WMO, 2020). In fact, the series of heatwaves in Europe since 2015 has been the most extreme in the past 2,110 years (Büntgen et al., 2021). It is evident that the impact of climate change is also being felt in Europe now. In parallel with the increasing frequency and intensity of extreme climate events, the past few years have seen a surge in climate change protests, strikes and events, notably the Friday for Futures and Extinction Rebellion movements. These social movements and media coverage have further contributed to bringing the issue of the climate crisis to the world's attention (Marris, 2019).

While individual behavioral changes are an important element of mitigation action, decarbonization of the economy requires structural reforms that bring public and macroeconomic policies, such as taxes, subsidies, and government spending, in line with the EU's ambition to move towards a climate-neutral economy. To fulfil its commitments under the Paris Agreement, the EU has pledged to cut at least 40% of its greenhouse gas emissions from 1990 levels as well as to achieve at least a 32% share for renewable energy by 2030 (European Commission, 2020). This requires radical transformations in production and consumption involving all sectors ranging from energy to land and agriculture, transport, buildings, industry and waste management. The recent rise in awareness and concern for environmental issues can contribute to achieving the transformation by catalyzing public support for climate action and inducing policy change (Egan and Mullin, 2017).

Indeed, a significant rise in the vote share of Green parties in the last European Parliamentary elections in 2019 reflects the increasing salience of the climate crisis and public concern about environmental problems and climate issues (Schumacher, 2014). Across Europe, environmental concerns and support for immediate climate action has been rising in recent years (Fig. 1). Whereas in 2002, less than 5% of Europeans agreed that environmental issues should be a priority for their country, this proportion had more than tripled in 2019 (Fig. 1 a) with Nordic countries taking a leading role (Fig. 1 b). Simultaneously, we also observe an increasing share of voters turning towards Green parties (Fig 1 c). Between 2005 and 2019 the percentage of seats held by Green parties (G-EFA group) in the European Parliament increased by 105% from merely 5.7% to 11.7%. This has a great potential to influence collective action on environmental issues as shown in recent studies about air pollution and emissions in OECD countries and the US (Dietz et al., 2015; Neumayer, 2003).

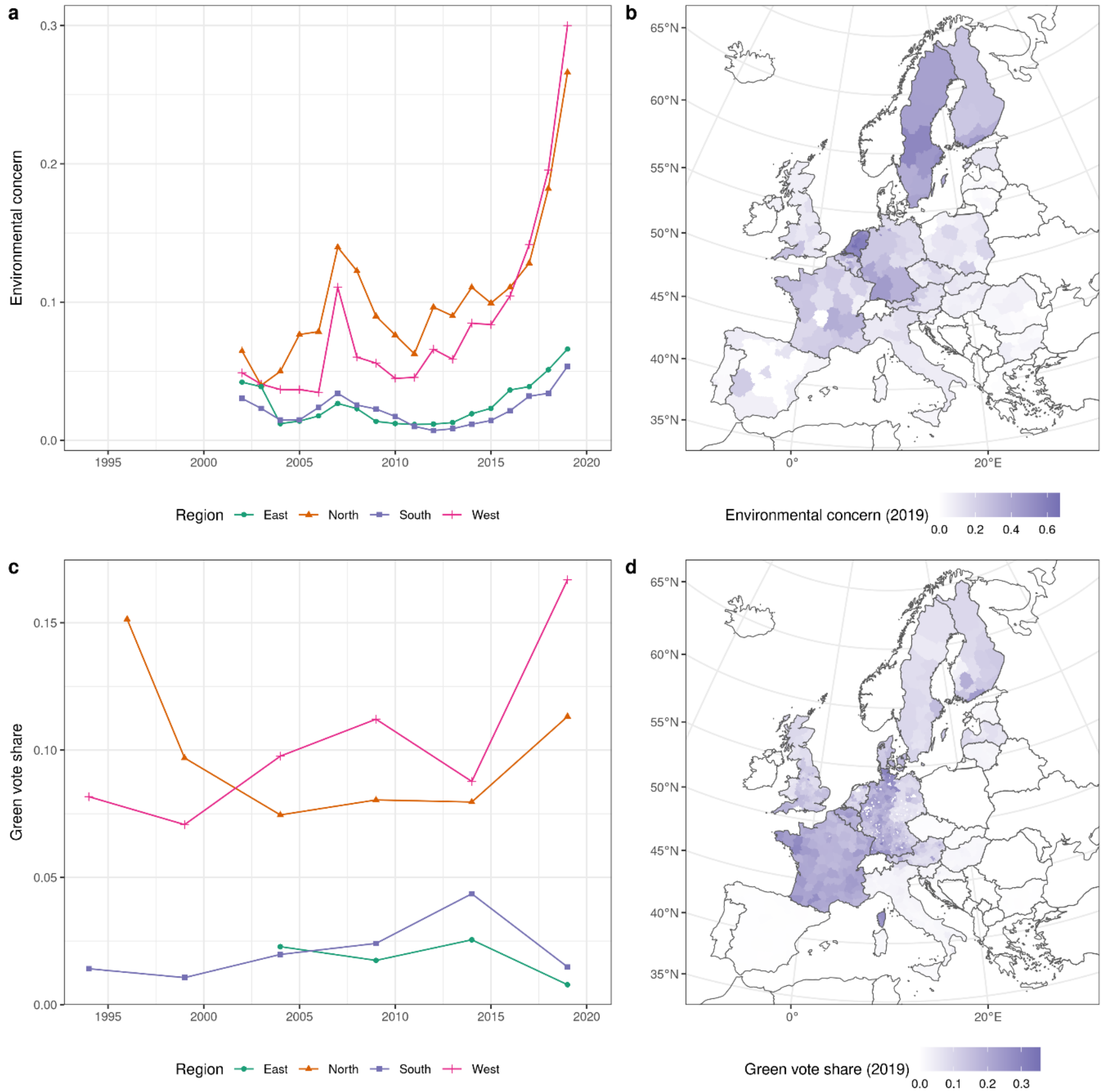


Figure 1 - Trends and patterns in environmental concerns and Green voting across European countries. a) Trends in environmental concerns from 2002 to 2019. The concern measure reflects the share of Eurobarometer respondents in a country who considered environmental issues to be important. b) Differences in environmental concern between countries in Europe for the year 2019. c) Trends in Green voting in the European Parliamentary election from 1994 to 2019. Green voting reflects the share of voters in a NUTS region who voted for a Green party (see Methods for party classification). d) Differences in Green vote shares between regions in Europe for the year 2019. Parties are classified as Green based on the party family variable in the Manifesto Project Dataset (Volkens et al., 2020) and membership in the European Green Party.

Understanding the drivers of changes in public concern and support for Green parties is important to identify the mechanisms underlying transformations towards a greener economy and more sustainable society. Previous studies showed that experiences of extreme climate events and changes are positively associated with climate change belief and environmental concern (Deryugina, 2013; Howe et al., 2013;

Bohr, 2017; Joireman et al., 2010; Konisky et al., 2016; Sisco et al., 2017; van der Linden, 2015; Arıkan and Günay, 2021; Kvaloy et al., 2012; Lorenzoni and Pidgeon, 2006). However, the overall size of the reported effects is rather small and depends on local conditions as found in a recent meta-analysis and systematic review of the literature (Hornsey et al., 2016; Howe et al., 2019). Likewise, it remains unclear whether and to what extent changes in public environmental concern affect public and political support for climate action manifested in form of voting for pro-environmental Green parties.

Exploiting time-series Eurobarometer data (42 survey waves, 2002-2019) and European Parliament election data (7 elections, 1990-2019), this study analyses for the first time how experiences of local climate extremes affect environmental concern and political support for Green parties at the subnational level across 34 and 28 European countries, respectively. The resulting regional panel dataset allows us to causally test for climatic impacts while controlling for unobserved heterogeneity and time trends via the use of fixed effects (Supplementary Table S1 and S2, Figure S2 and S3). Furthermore, in order to unpack the drivers of changes in concerns and voting behavior, we also consider how local climate and economic conditions shape the impacts of experiences allowing us to explore some of the mechanisms linking experiences and environmental attitudes and behaviors.

Our study provides three key contributions to the understanding of the underlying factors driving public opinion on environmental issues and climate change. First, we overcome the common conflation of policy preference and issue salience by directly investigating the linkages between environmental concerns and voting outcomes. Kachi et al. (2015) argue that awareness of climate change alone does not necessarily translate into support for climate policy. However, very few existing studies have considered the link between direct exposure with extreme weather events or climate anomalies on political behavior (Baccini and Leemann, 2020; Hazlett and Mildenberger, 2020). Our empirical design allows us to causally test for the effects of experiencing climate change on Green voting, which – as we show – are driven in part by changes in environmental concern. Second, exploiting European Parliament elections as well as the repeated cross-section of the Eurobarometer surveys, our study comprehensively provides insights for a broad number of countries and time periods. European Parliament elections are convenient for our purpose for several reasons: they take place approximately at the same time in all EU countries; the use of proportional rules for the allocation of seats implies that the extent to which voters engage in strategic voting (i.e., voting for the "lesser evil") is limited, and therefore vote shares provide a more accurate snapshot of the first preferences of voters; it is also convenient that electoral rules are approximately similar across countries, making the election returns more comparable across space. Third, we provide new empirical evidence on the relationship between economic conditions and public views on environmental issues, complementing previous findings in the empirical literature (Duijndam and Beukering, 2020; Kenny, 2020). Not only does covering a long series of data on concern and voting over the last two and three decades, respectively allows us to explore time variations extensively, our large cross-section of subnational regions also captures heterogeneity between units of observation. Our study thus adds important new insights into the unsettled findings on this issue.

## 2. Theoretical links between experience, concerns and voting

An increasing number of studies have considered the role experiences with climate change play for the formation of attitudes and concerns about environmental and climate issues. These have shown that people who have experienced unusual weather and extreme weather events are more likely to believe in the existence of global warming and its anthropogenic causes (Dai et al., 2015; Hamilton and Stampone, 2013), to express concern about climate change (Bergquist and Warshaw, 2019), to show willingness to engage in mitigation actions (Broomell et al., 2015), and to be in favor of climate policies (Böhmelt, 2020; Lee et al., 2018). Responses can vary with types of experience. Studies have shown differences between the effects of short-term local warming (daily to monthly) and longer-term climatic trends, whereas the latter exerts a particular strong influence on beliefs about human-caused global warming (Shao, 2017; Shao et al., 2016, 2014) and climate opinions (Howe et al., 2015; Kaufmann et al., 2017).

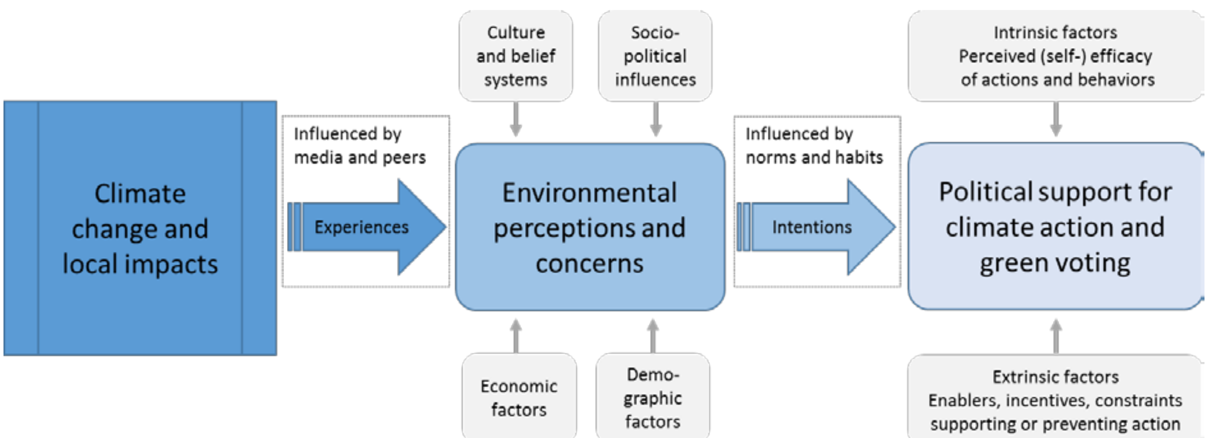


Figure 2 - Simplified conceptual model of the links between climate change experiences, environmental concerns and Green voting. Blue boxes and arrows highlight the causal pathways considered in our empirical analysis. Direct Experiences with climate change and its local impacts influence environmental perceptions and concerns together with indirect experiences shared by the media and social networks. The relationship is moderated by contextual influences, such as culture and belief systems or economic factors, which determine to what extent experiences are translated into concerns. Concerns can result in behavioral intentions, with the choice of actions being influenced by norms and habits. If different intrinsic and extrinsic conditions are met, intentions can result in behavioral changes, such as increased political support and Green vote. Illustration is adapted from Clayton et al. (2015)

While the majority of studies show that experiences matter, their relevance and the magnitude of their influence widely differ across the study contexts (Howe et al. 2019). How and whether perceived changes become relevant is influenced by a range of individual characteristics and contextual factors (Fig 2). These include economic conditions that may compete with environmental concerns, especially during times of economic uncertainty, such as in the aftermath of financial crises, when individuals may opt to prioritize economic and financial needs (Ratter et al., 2012; Scruggs and Benegal, 2012). Other influential factors are related to individual ideological predispositions, political worldviews, and belief systems (Duijndam and Beukering, 2020; Hazlett and Mildenberger, 2020), which affect perceptions about climate change. Demographic factors including age, gender and education, can play an important role for cognitive processes and can also influence the exposure and vulnerability shaping climate change awareness and attitudes (Lutz and Striessnig, 2015; Muttarak and Chankrajang, 2016; Poortinga et al., 2019).

Theoretically, experiences can help to grasp and understand the risks related to climate change and other environmental challenges, which otherwise remain abstract (Weber, 2016). With direct exposure, construal theory predicts increased levels of environmental concerns as the psychological distance between the individual and climate change impacts is reduced (McDonald et al., 2015; Schuldt et al., 2018; Spence et al., 2012). Experiences can reduce the psychological distance by making climate change and related hazards appear more certain (hypothetical distance) and temporally closer (temporal distance) as opposed to an abstract threat in a distant future. At the same time, experiences can make people understand that climate change affects them personally and their neighborhoods (spatial distance) and not a distant social group, who they have no relations to (social distance). Ample evidence from psychology and cognitive sciences confirms that risk perceptions, beliefs and concerns are particularly influenced by recent or common events such as wildfires, hurricanes and floods that are more cognitively 'available' (availability heuristics) (Barnett and Breakwell, 2001; Carlton et al., 2016; Murre and Dros, 2015; Zanocco et al., 2018). Accordingly, such experiences can contribute to an understanding of the urgency of the matter and the need to undertake climate actions.

Whether concerns are translated into behavioral intentions and ultimately actions depend on intrinsic and extrinsic factors as well as habits and norms that shape behavioral responses to external stimuli (Clayton et al., 2015). The perception of a problem and related concerns alone however are not enough to induce behavioral change. Individuals also need to perceive a sufficient self-efficacy to achieve their intention with the action and the action must be feasible (Hoffmann and Muttarak, 2020). With respect to voting, suitable policy platforms need to be available and appear sufficiently credible and trustworthy to achieve the envisioned intentions. While there is a broad literature connecting concerns, intentions and actions, only few studies have directly considered climate change impacts on voting and electoral outcomes. These studies show that climatic factors can indeed influence voting behavior such as voter turnout (Eisinga et al., 2012; Van Assche et al., 2017), votes for the incumbent party (Van Assche et al., 2017), or pro-environmental voting in climate-related ballots (Hazlett and Mildenberger, 2020). Exploiting panel data with election returns at the subnational level for most European Union countries, we are able to investigate, for the first time, the causal relationships between experiences with climate impacts, concerns and voting outcomes.

## 3. Methods and Data

We make use of a range of georeferenced data sources to measure the central outcomes of interest. Our analyses are carried out at the subnational regional level, where we connect information on changes in climatic conditions to environmental concerns and voting outcomes over time. The resulting panel dataset allows us to test for climatic impacts while controlling for unobserved heterogeneity and time trends via the use of fixed effects.

### Environmental concern data

Environmental concerns are measured using 42 waves of the Eurobarometer, which provides harmonized survey data for all EU member and EU candidate countries. The Eurobarometer is a repeated cross-sectional series of public opinion surveys based on a random, multistage sampling procedure. The surveys are carried out in regular intervals on behalf of the European Commission and other EU Institutions and cover various topics of thematic relevance for the EU (GESIS, n.d.). Here, we use information gathered in the standard Eurobarometer trend questions series about issues perceived as important problems in the respondents' own countries.

By assigning Nomenclature of Territorial Units for Statistics (NUTS) codes to the region of residence of each respondent, we construct a unique regional time series containing data for 34 countries and 277 subnational regions covering 18 years (2002–2019). The standard trend questions are typically collected in the Eurobarometer surveys three times a year during different seasons, allowing us to derive a nuanced picture of trends in environmental concerns throughout the year. All our models control for seasonal effects in form of season dummies (Supplementary Table S. 22)

As indicator for environmental concerns, we use the share of respondents in each region who consider environmental issues to be among the two most important issues facing their country at the time of survey. The answer categories to this question changed slightly over time. While until 2006 the questionnaires only listed an environment-related answer category i.e. "protecting the environment", the list was extended by adding another category: "energy related issues" afterwards. From 2011 onwards, the two separate answer categories were merged into a new category called "the environment, climate and energy issues". As our goal was to create a long, harmonized time-series for environmental concerns in Europe, we counted any responses referring to the environment as relevant irrespective of differences in the set of answer categories provided.

To account for potential difference in response behaviors by answer category types, we further tested whether any discontinuity in response behaviors was visible immediately before and after the changes in answer category types. Our results indicate no substantial changes in response behavior, suggesting that our estimation results are valid (Supplementary Table S19). We also reran our main models, restricting the data to different periods (2007–2019 and 2011–2019) in order to consistently harmonize the considered concern outcome measure (Supplementary Tables S5 and S6). All our results remain fully robust to these sampling changes providing further support to our findings on the impacts of climate change experiences on concerns over time.

### Voting outcome data

To measure voting outcomes, we collected original data on electoral returns for European Parliament (EP) elections at the NUTS-3 level from national sources. The data covers 23 countries and contains information for six EP election rounds spanning 25 years from 1994 to 2019. A few European countries (Portugal, Cyprus, Malta, and Luxembourg) and the region of Northern Ireland are not included in the data due to data availability issues. The election data were either aggregated to the NUTS-3 or to NUTS-2 level, if major boundary changes occurred in the country.

In a first step, we collected the vote shares for all parties participating in the election across sub-national regions. From this extensive list of parties, we classified parties as Green based on their party family classification in the Manifesto Project electoral program database (Merz et al., 2016), and their membership in the European Green Party, a federation of political parties across Europe supporting green politics, that within the European Parliament currently forms the G-EFA parliamentary group. Based on this information, we calculated the Green vote share as the fraction of valid votes for Green parties in each NUTS-3 region in each election round. Each observation, then, is a region-year election return (Supplementary Table S. 23).

### Climatological data

The explanatory variables are constructed from gridded datasets of temperature, precipitation, and evapotranspiration. Temperature data comes from the ERA5 reanalysis product that uses a global climate model to interpolate the observed weather station data to an even 0.1° raster (Hersbach et al., 2020). The raster is aggregated temporally to the daily means of the hourly mean temperature and then spatially to the daily regional means. In the calculation of the regional means the grid cells are weighted with the fraction which is covered by the respective region.

Based on the region-days, two measures of temperature are computed. **Temperature anomalies** capture the deviations of monthly temperatures from the long-run monthly mean. The deviations are then scaled using the long-run standard deviation in order to account for differences in variance between regions. Based on this monthly z-score, rolling means are calculated, capturing yearly fluctuations in temperature. In the calculation of the positive (negative) anomaly the negative (positive) values are set to zero before averaging. The reference period is 1971–2000, the 30 years before the start of the panel of environmental concern.

The second measure captures relative extreme temperatures. We define a **heat episode** as at least three consecutive days with a mean temperature above the 95th percentile of the monthly long-run distribution. Similarly, a **cold episode** refers to at least three consecutive days with a mean temperature below the 5th percentile of the monthly long-run distribution. For each region-month the number of days classified as heat and cold episode are counted and rolling averages are computed, similar to the temperature anomalies. Heat and cold episodes are additionally derived from the Universal Thermal Climate Index (UTCI) which represents a thermal comfort indicator by accounting for the human physiological response to temperature, humidity, wind, and solar radiation (Jendritzky et al., 2012).

Dry and wet conditions are measured using the Standardized Precipitation-Evapotranspiration Index (SPEI) based on the gridded climate data (TS4.05) from the Climate Research Unit (CRU) at the University of East Anglia (Harris et al., 2020). The SPEI is the standardized water balance, defined as the difference between precipitation and potential evapotranspiration. Evapotranspiration captures the combined water loss of evaporation and transpiration by vegetation. Accordingly, positive SPEI values indicate a larger than usual water balance (wet spell) and negative values a smaller than usual water balance (dry spell). The water balance is accumulated over a rolling period of three months in order to account for the conditions in the previous months. Standardization is done using a log-logistic distribution based on 1971–2000.

**Estimation methods**

For our analysis, we combined the georeferenced concern and voting data at the NUTS level with the gridded climatological data to study the impact of variations in climatic conditions in a region. We test whether climate extremes affect environmental concerns and Green voting with a fixed effects panel model of the following form:

$$y_{it} = \beta C_{it} + \alpha_i + \delta_t + \theta_S + \varepsilon_{it} \tag{1}$$

Where $y_{it}$ captures the share of the environmentally concerned population or Green voters in a region $i$ at time $t$. Here, $t$ refers to the month, when the Eurobarometer respondents were interviewed or when the elections were held. $C_{it}$ is a set of climatic indicators capturing weather anomalies that occurred prior to the concern and voting measurement. In our baseline, we consider the effects of temperature anomalies in the period 12 months prior, which allows us to broadly capture changes in the climatic conditions across all seasons. In additional sensitivity tests, the climate impact interval was broadened, showing slightly decreasing climatic impacts on concerns and voting with broader time intervals (Supplementary Tables S 13 – S16).

We include a region-specific intercept $\alpha_i$ in order to control for time-invariant factors (unobserved heterogeneity) that may confound the estimation. Relevant region fixed effects controlled for include the general political orientation in a region, structural economic factors, and the degree of urbanization. In addition, we include time period fixed effects $\delta_t$ (three-year periods for the concern data, elections for the voting data) and seasonal effects $\theta_S$ (only for concern data) to control for time trends and seasonal changes that are common across all regions. As the occurrence of extremes within a region over time is plausibly exogenous conditional on geographic location, time trends, and season effects, our model allows us to test for the causal impacts of climate extremes on concerns and voting

In additional models, we further extend the baseline model by including interaction terms to capture differences in climatic impacts by climate zones and economic conditions. Here, we rely on additional data provided by Beck et al (2018) for the construction of the climate zones as well as data from the Annual Regional Database of the European Commission (European Commission, 2021) for the measurement of regional incomes. Furthermore, we test for the impact of changes in concerns on voting by (i) regressing the voting outcome in year $t$ on changes in environmental concerns in the past 1 and 2 years, and (ii) by using a two-stage instrumental variable approach, where in the first stage climate variables are used as instruments to predict changes in concerns, and in the second stage the Green vote share is regressed on concern as predicted in the first stage.

Standard errors are corrected for serial and cross-sectional dependence which is assumed to decay linearly in time and space until a cutoff value is reached at which it vanishes (Conley, 1999). The choice of cutoffs is informed by tests for serial and cross-sectional correlation of the residuals (Supplementary Tables S20 and S21). Spatial autocorrelation is present on both the left- and right-hand side variables since nearby regions tend to be similar in terms of socio-economic characteristics and climate experiences (Howe et al., 2019). Serial correlation can be caused, for instance, by persistence of exogenous shocks.

Standardization makes the estimated coefficients comparable across models with different dependent and independent variables. We use the standard deviation of the fixed effects residuals for the standardization of the coefficients, accordingly capturing only the variance that is observed within regions over time. This way the results can be interpreted using changes in the weather that are possible given the historical data (Mummolo and Peterson, 2018). Further estimations using alternative standardizations are presented in the Supplement (Supplementary Table S10-S12).

**Limitations**

Our analysis comes with certain limitations, which are important for the interpretation of our results. The main purpose of our study is the estimation of impacts of climate extremes on concerns and Green voting across subnational regions in Europe over time. While the level of aggregation allows us to study the relationships for a broad sample of regions and time periods and to compare the role of local conditions in moderating the effects, individual drivers of environmental concerns and voting such as values and attitudes are not captured. Further work, especially at more disaggregated or individual levels is therefore needed to fully grasp the underlying drivers and mechanisms beyond what we can examine in this study.

Second, we rely on Eurobarometer and European Parliamentary election data to construct our main concern and voting outcomes. While these sources provide comparative longitudinal data for Europe over time, they may not capture all relevant aspects and facets of environmental concerns and Green voting decisions. Our concern measure was constructed based on a priority assessment of Eurobarometer respondents. Hence, it does not fully reflect the multi-dimensional nature of the concept of environmental concern, unlike more comprehensive indices, such as the New Ecological Paradigm (NEP) scale by (Dunlap et al., 2000) or the environmental concern scale by (Wesley Schultz, 2001). However, these measures are typically collected in case studies and are not available for comparative longitudinal analyses (Cruz and Manata, 2020).

As for the concern outcome, the regional share of Green voters reflects political support for climate action in a simplified way. In addition, like the results of any election, the outcomes of the European Parliamentary elections can be influenced by voter turnout and selection effects, which were partially accounted for by considering within-regional changes and by controlling for common underlying time trends. Moreover, we are not able to capture all aspects of the supply side and political dynamics of the party system. Some countries might have more credible environmentalist parties; and in other settings longer-term party attachments might prevent environmental concern from turning into Green voting. Again, these influences are captured by the regional fixed effects in our empirical design, and are hence not expected to bias the estimation of climate impacts on voting.

Despite these limitations, this study adds important insights to the scientific literature on the experience, concern and behavior nexus. The use of the harmonized Eurobarometer concern and Europe-wide election measures enables us to achieve comparability across regions and to construct the unique cross-regional trend dataset required for our analysis. Our findings do not only show the role climate extremes play in influencing concerns and voting, but also highlight the importance of regional factors, such as climatic and economic conditions. They can thus help to gain a comprehensive understanding of the underlying drivers of observed changes in concerns and voting patterns across Europe.

## 4. Results

### Experiences influence both concerns and voting

Environmental concerns have been rising across European subnational regions in the past two decades, particularly in Northern and Western Europe (Fig. 1 A). In countries like the Netherlands or Sweden, more than 40% of the population considers environmental issues to be among the most important issues the country is facing. While we also see higher levels of Green voting in these areas, the observed trends over time appear less linear and are characterized by stronger fluctuations, likely reflecting the changing political landscape in the countries. Also, voters can only cast one ballot in a given election, but may have preferences over an inherently multidimensional policy space, explaining the greater volatility in voting outcomes. Parties offer different sets of policies on e.g., taxation, the environment, minority rights, and unemployment, while voters have to choose one bundle, thus trading off their preferences regarding different policy issues.

Table 1 shows the results of panel models, which regress the share of the environmentally concerned population in a region (cols 1–4) and the share of Green voters (cols 5–8) on climate variables capturing temperature anomalies as well as heat and drought episodes in the past 12 months prior to the concern measurement or election date. All models control for regional and temporal fixed effects to account for unobserved heterogeneity and common time trends (Supplementary Figures S3 and S4). The estimates are standardized and corrected for spatial and temporal autocorrelation. They are robust to different sensitivity tests (Supplementary Tables S3-S9), including estimating dynamic models controlling for the lagged depend variable (Supplementary Table S4), models with additional time-varying controls (Supplementary Table S7), and changing the climate variable measurement (Supplementary Tables S8 and S9).

Table 1 - Baseline effects of climate extremes on environmental concerns and Green voting

| | *Dependent variable:* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Environmental concern | | | | Green vote share | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Temperature anomaly | 0.183*** | | | | 0.115** | | | |
| | (0.024) | | | | (0.055) | | | |
| Heat episode (temp.) | | 0.151*** | | | | 0.183*** | | |
| | | (0.026) | | | | (0.055) | | |
| Heat episode (UTCI) | | | 0.120*** | | | | 0.113** | |
| | | | (0.028) | | | | (0.054) | |
| Dry spell | | | | 0.085** | | | | 0.234*** |
| | | | | (0.040) | | | | (0.052) |
| Unit fixed effects | × | × | × | × | × | × | × | × |
| Period fixed effects | × | × | × | × | × | × | × | × |
| Season fixed effects | × | × | × | × | | | | |
| Spatial cutoff (km) | 500 | 500 | 500 | 500 | 500 | 500 | 500 | 500 |
| Temporal cutoff (years) | 1.5 | 1.5 | 1.5 | 1.5 | 5 | 5 | 5 | 5 |
| Observations | 10,263 | 10,263 | 10,263 | 10,263 | 5,682 | 5,682 | 5,682 | 5,682 |
| $R^2$ | 0.478 | 0.473 | 0.468 | 0.464 | 0.768 | 0.772 | 0.768 | 0.777 |

Note: Standardized regression coefficients with standard errors in parentheses. Standard errors were corrected for cross-sectional and serial correlation up to the indicated spatial and temporal cutoffs. All models control for regional and temporal fixed effects to account for unobserved heterogeneity and common time trends. Period fixed effects refer to three-year periods in models 1–4 and election year fixed effects in model 5–8. Coefficients are standardized using the residual variance after applying the fixed effects. Accordingly, the coefficients refer to a marginal effect of a one standard deviation change of the covariates on the outcome within regions and periods. Temperature anomaly is defined as standardized deviation from the long-run monthly temperature mean; heat episode (temp.) is defined as at least three consecutive days with a mean temperature above the local monthly 95 percentile; heat episode (UTCI) is defined as at least three consecutive days with a mean UTCI above the local monthly 95 percentile; dry spells are defined as mean of SPEI below –0.5. All measures are calculated using 1971–2000 as reference period. P-values: * < 0.1, ** < 0.05, *** <0.01.

Experiences with temperature anomalies, heat episodes and drought events are found to significantly increase environmental concerns and the tendency to vote for Green parties. While there are some differences across models, with temperature anomalies and heat waves exerting the strongest effects on concerns and dry spells on voting for Green parties, all climate measures consistently have a positive relationship with the two outcomes. The magnitude of the estimated effects is sizeable. For example, a temperature anomaly of one standard deviation is estimated to increase environmental concerns on average by 0.183 (SE 0.024) and Green voting by 0.115 standard deviations (SE 0.055) within regions, or by 0.9% and 0.3% in absolute terms (Supplementary Table S10). Likewise, an additional heat day per month is estimated to raise green concerns and voting by 0.8% and 0.7% respectively (Supplementary Table S11).

### Positive temperature anomalies have a stronger influence than negative ones

Not only does climate change lead to higher temperatures and more extensive heat and drought episodes, it can also cause more extreme cold weather and temperature fluctuations, including cold snaps. The recent cold episodes in February 2021 in Europe, for example, resulted from the collapse of the polar vortex, a ring of cold winds at the North Pole. The vortex is closely connected to the jet stream, which determines the winter weather in Europe. With increased warming in the Arctic, the jet stream is predicted to weaken which could lead to more dips affecting temperatures in Europe (Woollings and Blackburn, 2012).

While these processes are well understood by climate scientists, negative temperature anomalies and periods of extreme cold have commonly been used by climate sceptics to spread misinformation about global warming (DW, 2021). In additional models (Table 2), we test for the impact of negative temperature anomalies, cold spells and wet episodes on concerns and voting and analyze how their influence differs from the influence of positive temperature anomalies, heat episodes and dry spells. To this end, we split the climate variables used in the baseline models (Table 1, model 1) to create separate measures reflecting both positive and negative temperature anomalies, heat and cold days, and dry and wet spells.

Table 2 - Effects of positive and negative temperature extremes on concerns and voting

| | *Dependent variable:* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Environmental concern | | | | Green vote share | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Temperature anomaly (+) | 0.167*** | | | | 0.203*** | | | |
| | (0.028) | | | | (0.057) | | | |
| Temperature anomaly (–) | -0.036* | | | | 0.077* | | | |
| | (0.019) | | | | (0.046) | | | |
| Heat episode (temp.) | | 0.150*** | | | | 0.188*** | | |
| | | (0.030) | | | | (0.055) | | |
| Cold episode (temp.) | | -0.005 | | | | -0.053 | | |
| | | (0.024) | | | | (0.033) | | |
| Heat episode (UTCI) | | | 0.125*** | | | | 0.115** | |
| | | | (0.030) | | | | (0.053) | |
| Cold episode (UTCI) | | | 0.044 | | | | -0.054 | |
| | | | (0.033) | | | | (0.042) | |
| Dry spell | | | | 0.135*** | | | | 0.244*** |
| | | | | (0.046) | | | | (0.059) |
| Wet spell | | | | 0.098*** | | | | 0.022 |
| | | | | (0.022) | | | | (0.048) |
| Unit fixed effects | × | × | × | × | × | × | × | × |
| Period fixed effects | × | × | × | × | × | × | × | × |
| Season fixed effects | × | × | × | × | | | | |
| Spatial cutoff (km) | 500 | 500 | 500 | 500 | 500 | 500 | 500 | 500 |
| Temporal cutoff (years) | 1.5 | 1.5 | 1.5 | 1.5 | 5 | 5 | 5 | 5 |
| Observations | 10,263 | 10,263 | 10,263 | 10,263 | 5,682 | 5,682 | 5,682 | 5,682 |
| $R^2$ | 0.478 | 0.473 | 0.469 | 0.468 | 0.773 | 0.773 | 0.768 | 0.778 |

Note: Standardized regression coefficients with standard errors in parentheses. Standard errors were corrected for cross-sectional and serial correlation up to the indicated cutoffs. All models control for regional and temporal fixed effects to account for unobserved heterogeneity and common time trends. Period fixed effects refer to three-year periods in models 1–4 and election year fixed effects in model 5–8. Coefficients are standardized using the residual variance after applying the fixed effects. Accordingly, the coefficients refer to a marginal effect of a one standard deviation change of the covariates on the outcome within regions and periods. Temperature anomaly is defined as standardized deviation from the long-run monthly temperature mean; heat episode (temp.) is defined as at least three consecutive days with a mean temperature above the local monthly 95 percentile; heat episode (UTCI) is defined as at least three consecutive days with a mean UTCI above the local monthly 95 percentile; dry spells are defined as mean of SPEI below –0.5. All measures are calculated using 1971–2000 as reference period. P-values: * < 0.1, ** < 0.05, *** <0.01.

While we observe a similar effect of positive temperature anomalies, heat episodes and dry spells as in the baseline models, no consistent influence is found for negative temperature anomalies, cold episodes and wet spells, which are defined as periods with extremely high precipitation and low evaporation due to moderate temperatures. For the latter, a significant positive impact on concerns is also observable (b 0.098, SE 0.022). Overall, the results suggest a stronger relevance of positive temperature extremes and heat-related events for environmental concerns and Green voting. The observed pattern resembles the relationship pattern depicted in Figure 3, Panel c, indicating a positive impact of positive temperature extreme (steep curve), and no consistent impact of negative extremes and related events (flat curve).

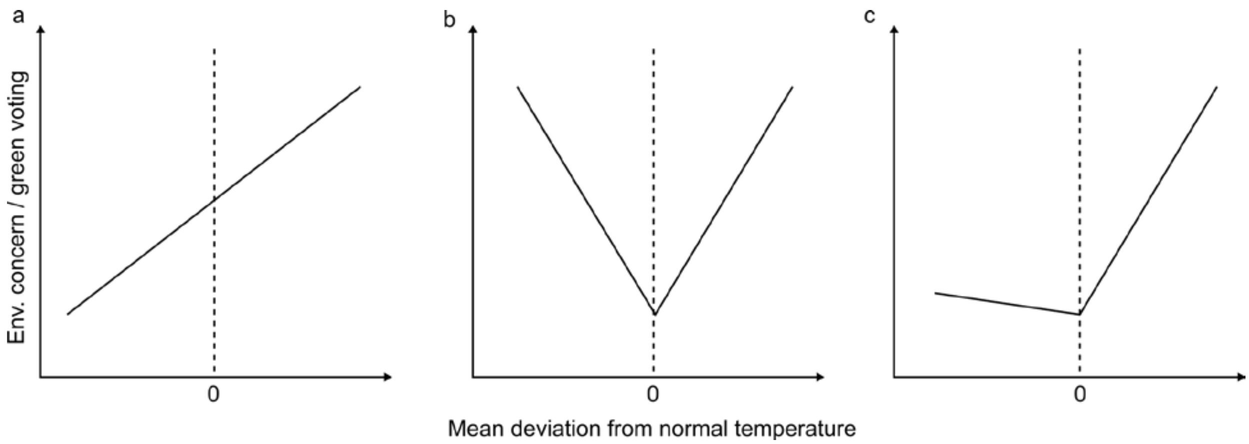


Figure 3 - Hypothetical relationship patterns reflecting different effects of positive and negative temperature extremes on concerns and voting (based on Brooks et al 2014, Figure 1). a) The linear pattern implies a strictly positive effect of positive and a negative effect of negative anomalies, suggesting that cold episodes – unlike heat episodes – reduce concerns and Green vote. b) The inverted v-shaped pattern suggests a positive effect of both positive and negative anomalies. c) The hump-shaped pattern implies a positive effect of positive anomalies, but no effect of negative anomalies or cold episodes. Anomalies are illustrated here as deviations from the long-term mean (vertical dotted line).

In additional models, we tested for the role of time in shaping the influence of climate extremes on concerns and voting outcomes (Supplementary Table S13 – S16). While over greater time horizons, extremes are still found to have an influence, a recency effect is evident. More recent climate events tend to influence concerns and voting more strongly possibly due to a greater salience of the experiences. For example, heat episodes that occurred in the past 12 months (Supplementary Table S14) increase concerns and voting by 0.150 (SE 0.030) and 0.180 (SE 0.055) standard deviations, respectively. For a lag of 24 months, these effect sizes diminish to 0.124 (SE 0.021) and 0.151 (SE 0.050), respectively, and for 48 months to 0.089 (SE 0.021) and 0.079 (SE 0.044), respectively.

### The impacts of climate extremes differ across Europe

Regions across Europe are characterized by different climatic conditions and are affected by different climate extremes and impacts (IPCC, 2014). In additional interaction models (Figure 4), we test for the differential impact of climate extremes on concerns and voting across the main climate zones of Europe (Supplementary Table S17). Based on the Köppen-Geiger typology (Supplementary Figure S5), we distinguish between a hot, arid climate in the Mediterranean, Southern European regions, a temperate climate mainly in Western Europe and colder climate, mainly in Northern and Eastern Europe.

In our additional heterogeneity analyses, we find that the impacts of climate extremes on environmental concern and Green voting are not uniform across climate zones in Europe, but differ from region to region (Figure 4). Temperature anomalies, heat episodes and droughts have a consistently stronger effect on concerns and voting in regions with a temperate and colder climate compared to regions with a warm, arid climate in the Mediterranean regions, for which we find no significant effects. In the temperate and cold climate zones, an increase in heat episodes (temp.) by one standard deviation is estimated to increase concerns by 0.205 (SE 0.027) and 0.185 (SE 0.033) standard deviations, and voting by 0.232 (SE 0.040) and 0.174 (SE 0.047) standard deviations, respectively.

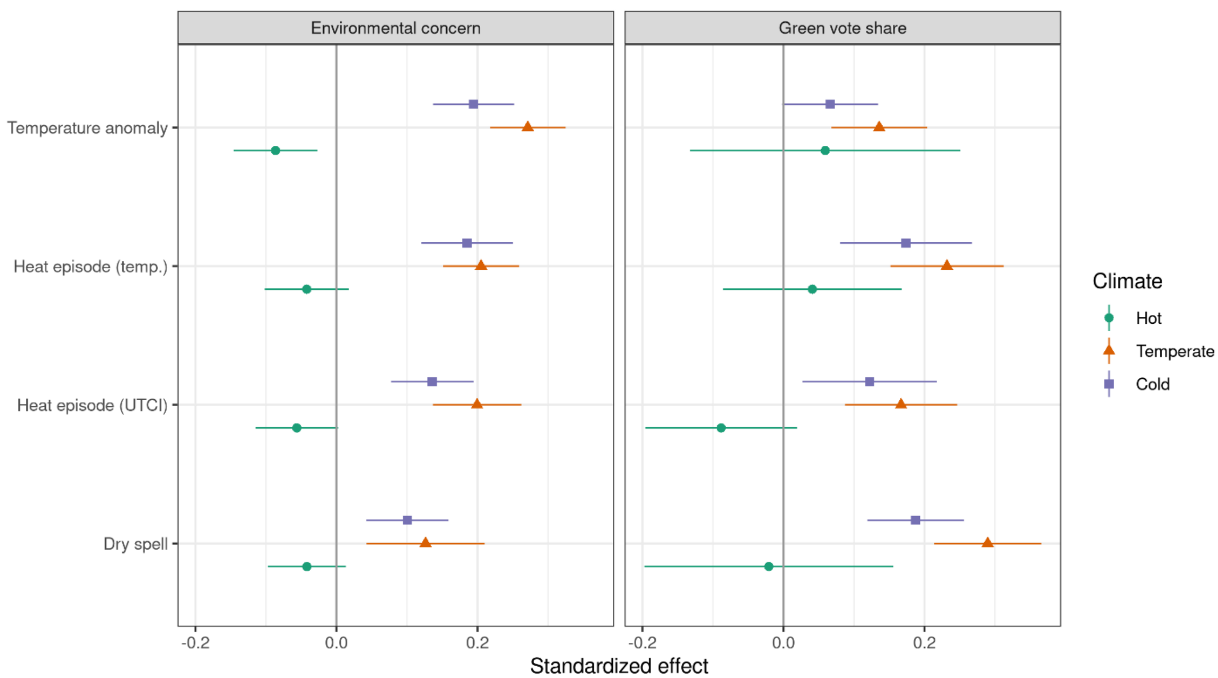


Figure 4 - Effects of climate extremes on environmental concern and Green voting by region. Coefficients are standardized using the observed variance of the variables in the given region after applying the fixed effects (see supplementary Table S16 for the full models). Models include period-region effects to account for region-specific time trends. Lines around the point estimates show the 95% confidence intervals. Regions are classified as "hot" (Bwh, Bwk, Bsh, Bsk, Csa, Csb), "temperate" (Cfa, Cfb, and Cfc), and "cold" (Dsa, Dsb, Dsc, Dfa, Dfb, Dfc, ET, EF) based on the Köppen-Geiger typology (Supplementary Figure S5)

As the Mediterranean climate is already hot and dry in absolute terms, a marginal increase or deviation may have little to no effect on environmental concern and voting. Populations in these regions may have already adapted to the hotter baseline conditions, for instance through air conditioning and well-insulated housing. These findings highlight important differences across Europe in the way how the public responds to extreme climatic conditions and impacts showing the importance of understanding the spatial dimension of environmental concerns and public support for climate actions. Additional models also tested for the differential impact of negative temperature extremes and cold-related events (Supplementary Figure S6). In line with our previous findings, the patterns are less clear here, suggesting that changes in concerns and voting are mainly driven by positive temperature and heat-related extremes, primarily in regions with an Atlantic or Continental climate.

**Economic conditions moderate climate impacts**

Further exploring the underlying regional heterogeneity in the findings, we estimate additional interaction models to test for the influence of economic factors in moderating the relationship between climate change experiences, concerns, and voting. In particular, we are interested in understanding whether the regional differences are also driven by the regions' overall income level, measured as GDP per capita. In the aftermath of the global financial crisis of 2007, for example, a substantial reduction in environmental concerns was observable across all European regions (Fig. 1A), indicating a potential moderating role of economic factors. Previous research has suggested that people's economic interests can lead to a crowding out of concerns for the environment, if there is a perceived trade-off between the two issues (Jakobsson et al., 2018; Scruggs and Benegal, 2012). Hence, in times of economic difficulty, the impact of exposure to climatic extremes on public support for climate action may be reduced. Here, we analyze whether climate impacts on concerns and voting depend on (i) the relatively stable, general economic condition in a region, measured in form of the mean GDP per capita in the period from 1995 to 2019, and (ii) variable changes in the GDP that co-occurred with exposure to climate extremes.

We find consistent evidence that the effects of exposure to climatic extremes on environmental concerns and voting are lower in regions with overall worse economic conditions (Supplementary Table S18). As illustrated in Figure 4 panels a and b, the impact of temperature anomalies on concerns and voting is much steeper in richer regions (GDP per capita at the 75th percentile of income level) as compared to poorer regions (GDP per capita at the 25th percentile of income level). Considering differences in mean GDP levels across regions, we find that the impact of temperature anomalies on environmental concerns is significantly reduced by 0.156 (SE 0.023) standard deviations and on voting by 0.85 (SE 0.029) standard deviations for each one standard deviation decline in mean GDP (Models 1 & 4). These effects also remain robust once further regional characteristics (Models 2 & 5), such as interactions with the urbanization and education level, as well as the regional climate zones (Models 3 & m6) are controlled for. While we find consistent evidence for the importance of average differences in income between regions, changes in GDP over time are not found to moderate the climate effects.

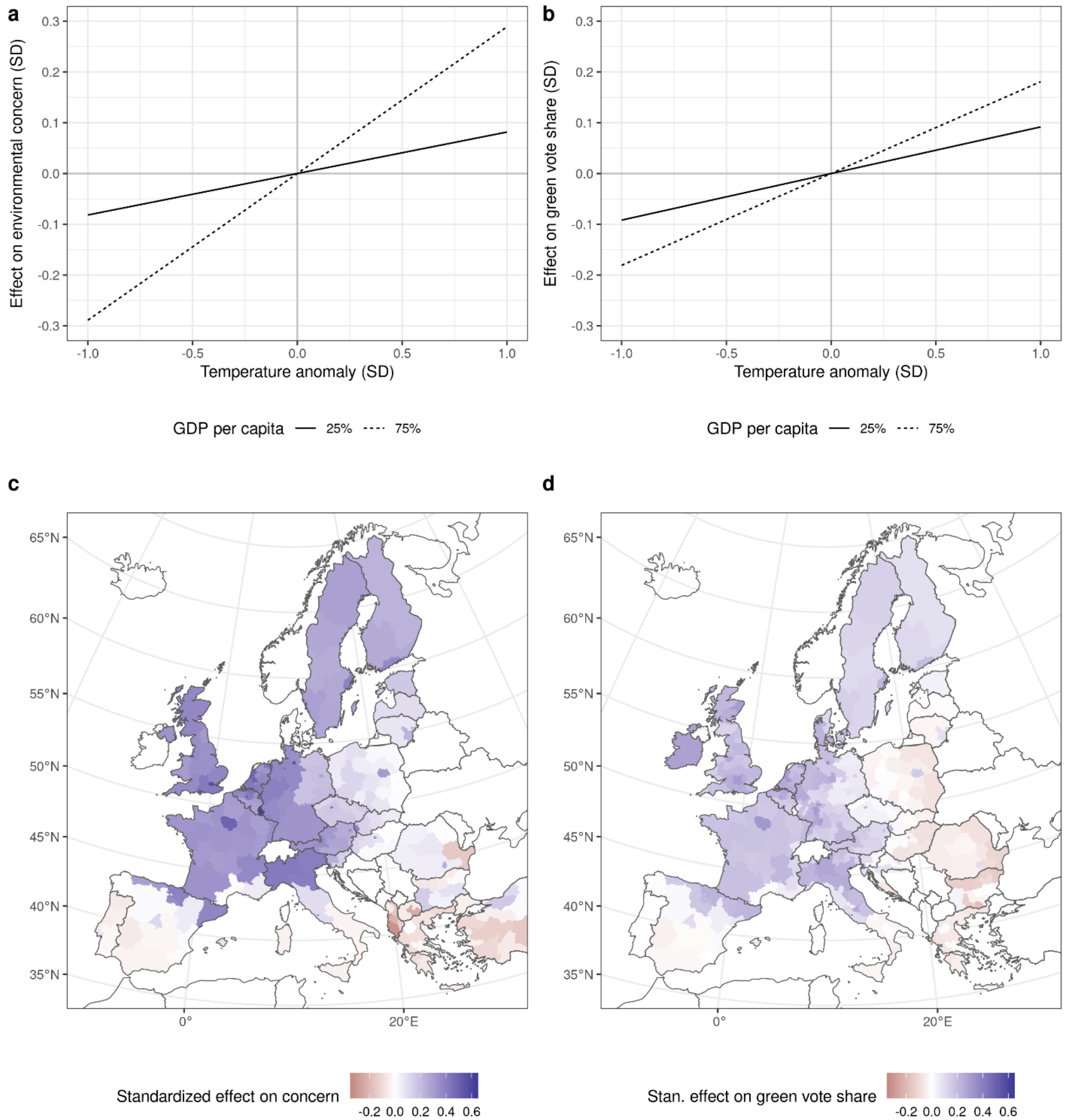


Figure 4 – Estimated marginal effects of temperature anomalies conditional on regional economic conditions. a/b) Marginal effects of temperature anomaly on environmental concerns / Green vote share at the 25th and 75th percentile of income level in terms of log real GDP per capita at purchasing power parity. Estimates are based on interaction models displayed in Supplementary Table S18, m1 & m4. c/d) Marginal effects of a one standard deviation temperature anomaly on environmental concern / Green vote share, given regions' GDP level and climate zone. Estimates are based on interaction models displayed in Supplementary Table S18, m3 & m6.

Figure 4 panels c and d shows the findings from two of the interaction models (Supplementary Table S18, Models 3 & 6) illustrating how climate zones and regional economic differences shape the influence of climate factors on concerns and Green voting leading to substantial regional heterogeneity across Europe. The maps show the marginal effect strength of a one standard deviation temperature anomaly as estimated in our models conditional on the climate zone and mean GDP level of a region. The maps highlight that differences exist not only between countries, but also within countries with wealthier regions responding more strongly to the exposure to climate extremes. Across Europe, urban centers with their relatively wealthier populations, the effects of experiences on concerns and voting outcomes appear to be particularly pronounced.

**Changes in concerns explain climate impacts on voting**

The conceptual model in Figure 2 assumes that experiences of changing climatic conditions activate environmental concerns, which in turn influence Green voting. In this section, we go beyond the reduced form estimation of the impacts of experience on concern and on voting and extend our models to investigate to what extent climate-induced changes in concerns predict voting outcomes (Table 3).

In a first step, we regress the Green vote share in a region on the level of environmental concerns in that region one year (m1) and two years (m2) prior to the election (lag). As a falsification test, we also regress the Green vote share on the level of environmental concerns one year (m3) and two years (m4) after the election (lead). If environmental concerns in a region influence voting outcomes, we expect to see a positive effect in the first two, and no effect in the latter two models.

The results from m1 and m2 suggest a sizeable influence of changes in environmental concerns on voting outcomes. A standard deviation change in average concerns one year prior to an election is estimated to lead to a 0.253 (SE 0.071) standard deviation increase in Green vote (m1) and the average two years prior to an election still to a 0.195 (SE 0.071) increase. In line with our expectation, the lead values of concerns are not found to exert any significant influence on voting outcomes (m3–m4), suggesting that voting is influenced by concerns and not just the realization of an unobserved underlying process.

Models 5–8 use a two-stage instrumental variable approach to estimate the causal impact of changes in concerns on voting. Here the estimation focusses on the variation in concerns that is driven by changes in climatic conditions as an exogenous instrumental variable. This reflects the full causal chain depicted in Figure 2 from the experience of climate extremes to the change in voting behavior. The first stage F-Statistic indicates that the climate variables predict changes in environmental concerns over time and thus are relevant instruments (See Table 1 models 1–4 for first stage estimation).

The instrumental variable estimation suggests a positive impact of concerns on voting of similar size as estimated in the panel models 1 and 2. Model 8, which uses the SPEI as an instrument for changes in environmental concerns, predicts an increase in Green vote shares by 0.257 (SE 0.068) standard deviations with a one standard deviation increase in environmental concerns induced by changes in the climatic conditions.

Table 3 - Effects of environmental concern on Green voting

| | *Dependent variable:* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Environmental concern | | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Env. concern (1 year lagging mean) | 0.253*** | | | | | | | |
| | (0.071) | | | | | | | |
| Env. concern (2 year lagging mean) | | 0.195*** | | | | | | |
| | | (0.071) | | | | | | |
| Env. concern (1 year leading mean) | | | -0.022 | | | | | |
| | | | (0.061) | | | | | |
| Env. concern (2 year leading mean) | | | | -0.060 | | | | |
| | | | | (0.062) | | | | |
| Env. concern (1 year lagging mean) | | | | | 0.127** | 0.241*** | 0.212*** | 0.257*** |
| | | | | | (0.059) | (0.058) | (0.059) | (0.068) |
| Instrument | | | | | Anom-aly | Heat (temp.) | Heat (UTCI) | Dry spell |
| First stage F statistic | | | | | 188.5 | 630.8 | 397.3 | 312.3 |
| Unit fixed effects | × | × | × | × | × | × | × | × |
| Period fixed effects | × | × | × | × | × | × | × | × |
| Spatial cutoff (km) | 500 | 500 | 500 | 500 | 500 | 500 | 500 | 500 |
| Temporal cutoff (years) | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 |
| Observations | 3,847 | 3,850 | 2,913 | 2,943 | 3,847 | 3,847 | 3,847 | 3,847 |
| $R^2$ | 0.821 | 0.816 | 0.852 | 0.852 | 0.805 | 0.795 | 0.788 | 0.764 |

Notes: Standardized regression coefficients with standard errors in parentheses. Standard errors were corrected for cross-sectional and serial correlation up to the indicated cutoffs. All models control for regional and temporal fixed effects to account for unobserved heterogeneity and common time trends. Period fixed effects refer to yearly fixed effects for all models. Coefficients are standardized using the residual variance after applying the fixed effects on both sides. Accordingly, the coefficients refer to a marginal effect of a one standard deviation change of the covariates on the outcome within regions and periods. P-values: * < 0.1, ** < 0.05, *** <0.01.

## 5. Discussion and Conclusion

With the global temperature projected to rise to 1.5 °C above pre-industrial levels between the 2030s and 2050s if the warming trend continues (Tollefson, 2018), delayed climate actions will lead to many irreversible consequences. Accordingly, how to best increase citizens' environmental concerns and support for climate action is of great relevance and has sparked a number of studies in the past years. Using a novel cross-country regional dataset for Europe, we show that exposure to climate anomalies and extremes, in particular related to heat and drought episodes, activate environmental concerns and promote Green voting

With the issue of climate change becoming more concrete and salient, this has activated people's willingness to engage in and support climate action (McDonald et al., 2015), including on the political level in form of voting for pro-environmental parties. The estimated effects of climate experiences on voting behavior are causal and run through increased level of concern about the environment. These changes can contribute to shifts in the political landscape at a larger scale, given the increased share of Green voters across countries in Europe in recent years. Our findings are in line with existing case studies on the role of climate experiences for voting behavior providing comparative evidence on the phenomenon and highlighting its broader implications (Baccini and Leemann, 2020; Hazlett and Mildenberger, 2020).

Obviously, exposure to climate change is not the only way to promote public concern and action. In fact, inducing behavioral and policy change through direct experiences is counterproductive to the goal of minimizing climate impacts. Climate communication and education can help filling the experience gap. Studies have shown that carefully designed messages in climate communications can reduce the psychological distance and promote mitigation behaviors (Jones et al., 2017; Spence et al., 2012). Our findings further highlight the importance of increasing the salience of climate impacts in an inclusive way, particularly for the populations not directly affected by climate impacts. In this regard, it is important to communicate the implications of a future warmer climate and its impacts for local populations in Europe in a clear and accessible manner.

There is also a need to address the substantial geographic differences in concerns and political support for climate action across regions in Europe. We find positive effects of temperature extremes, heat episodes and dry spells on green concern and voting mostly in relatively high-income regions. This finding corresponds with Ronald Inglehart's post-materialist theory which holds that residents of wealthier nations whose basic needs for physical and economic security have been met can afford to pursue other needs which are relevant for improving quality of life such as environmental quality (Inglehart, 1995). This theory also hints that in difficult times such as economic recessions, value orientations towards post-materialist preferences can be given lower priority due to "a renewed prioritization" of material needs (Inglehart, 1983; Kenny, 2018, p. 107).

Furthermore, the differential effects of different climate measures on concern and voting seem to depend on climatic zones in Europe (Beck et al., 2018; Jylhä et al., 2010). Temperature anomalies and extremes increase green concern and voting only in temperate regions, mostly located in Western Europe, and colder regions, mostly located in Northern and Eastern Europe. In contrast, in regions that are characterized by an arid, warm Mediterranean climate, the exposure to relatively higher temperatures does not affect concerns and voting systematically. These heterogeneous effects may reflect differences in exiting infrastructures and adaptation measures, for instance air-conditioning or heating, which are influenced by the baseline climatic conditions.

Our findings are of high relevance for climate policies and the current debates on how to best promote and effectively implement further climate change mitigation measures in line with the Paris Agreement. The EU aims at taking a leading position in the fight against climate change. At the same time, economic challenges, social and political disruptions, and the switching balance of geopolitical and economic power, might hamper the Union's ability to fulfill its role of a policy innovator, pioneering solutions that tackle the pressing challenge of the climate emergency in a sustainable fashion. There is a need for an inclusive and equitable approach to climate protection that comprehensively highlights the potential threats of climate change while taking into account the needs and fears of local populations (Few et al., 2007; Fuso Nerini et al., 2019).

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# Supplementary Materials

# Voting for Tomorrow: Climate Change, Environmental Concern, and Green Voting

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This Supplementary Material contains 4 sections:

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## A. Descriptive statistics

Table S1 and Table S2 show summary statistics of key variables used in our models. The summary statistics are reported separately for the aggregated concern (Table S1) and voting data (Table S2), since the data on environmental concerns were collected in shorter intervals (approximately every 3–4 months). The table reports both the overall standard deviation of each variable across all regions and the within standard deviation after applying the region and period fixed effects. The latter measure reflects the standard deviations from the regional and period means over time and illustrates the extent of within region variability for each measure. In our models, the within standard deviation is used for the standardization of the estimates (Mummolo and Peterson, 2018).

Table S4 - Summary statistics of the concern dataset

| Environmental concern data | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Variable** | **N** | **Min** | **Mean** | **Median** | **Max** | **SD** | **Within SD** |
| Environmental concern | 10263 | 0.000 | 0.048 | 0.027 | 0.671 | 0.066 | 0.049 |
| Temperature anomaly (absolute) | 10263 | -0.637 | 0.649 | 0.614 | 2.107 | 0.407 | 0.351 |
| Temperature anomaly (positive) | 10263 | 0.000 | 0.762 | 0.710 | 2.107 | 0.344 | 0.301 |
| Temperature anomaly (negative) | 10263 | 0.000 | 0.130 | 0.102 | 0.738 | 0.117 | 0.103 |
| Heat episode (temp.) | 10263 | 0.000 | 1.652 | 1.500 | 6.083 | 1.071 | 0.927 |
| Cold episode (temp.) | 10263 | 0.000 | 0.554 | 0.500 | 3.000 | 0.520 | 0.459 |
| Heat episode (UTCI) | 10263 | 0.000 | 1.624 | 1.500 | 6.333 | 0.995 | 0.816 |
| Cold episode (UTCI) | 10263 | 0.000 | 0.346 | 0.250 | 2.417 | 0.346 | 0.318 |
| Dry spell (SPEI3) | 10263 | 0.000 | 0.425 | 0.371 | 1.883 | 0.294 | 0.270 |
| Wet spell (SPEI3) | 10263 | 0.000 | 0.298 | 0.255 | 1.679 | 0.248 | 0.230 |
| Log GDP per capita (within) | 10263 | -0.366 | 0.003 | 0.004 | 0.586 | 0.098 | 0.082 |
| Log GDP per capita (between) | 10263 | 1.834 | 3.100 | 3.169 | 4.336 | 0.445 | |
| Unemployment rate (within) | 9414 | -0.206 | 0.002 | 0.002 | 0.146 | 0.037 | 0.034 |
| Unemployment rate (between) | 9438 | -0.702 | 0.095 | 0.110 | 0.294 | 0.113 | |
| Agricultural share in GVA (between) | 9417 | 0.000 | 0.035 | 0.025 | 0.368 | 0.040 | |
| Population tertiary education (between) | 10155 | 0.074 | 0.266 | 0.262 | 0.535 | 0.090 | |
| Urban population share (between) | 10263 | 0.000 | 0.310 | 0.000 | 1.000 | 0.463 | |

Note: Within refers to measures that change within regions over time. Between refers to measures that stay constant over time and characterize differences between regions. The latter measures are calculated by taking the regional mean of a variable over time. They are used in the interaction models (Table S18) to test for differential climatic impacts. GVA refers to real gross value added. The within standard deviation (SD) refers to the standard deviation after applying the fixed effects. It is used as a basis for the standardization of the estimates of the models.

Table S5 - Summary statistics of the voting dataset

**Green voting data**

| Variable | N | Min | Mean | Median | Max | SD | Within SD |
|---|---|---|---|---|---|---|---|
| Green vote share | 5711 | 0.000 | 0.074 | 0.067 | 0.368 | 0.060 | 0.029 |
| Environmental concern (12m) | 3876 | 0.000 | 0.078 | 0.043 | 0.606 | 0.091 | 0.050 |
| Temperature anomaly (absolute) | 5711 | -0.769 | 0.625 | 0.682 | 1.885 | 0.507 | 0.193 |
| Temperature anomaly (positive) | 5711 | 0.043 | 0.755 | 0.758 | 1.865 | 0.379 | 0.147 |
| Temperature anomaly (negative) | 5711 | 0.000 | 0.145 | 0.105 | 0.919 | 0.160 | 0.082 |
| Heat episode (temp.) | 5711 | 0.000 | 1.473 | 1.250 | 6.167 | 1.177 | 0.712 |
| Cold episode (temp.) | 5711 | 0.000 | 0.514 | 0.333 | 2.583 | 0.513 | 0.290 |
| Heat episode (UTCI) | 5711 | 0.000 | 1.429 | 1.167 | 5.500 | 1.097 | 0.619 |
| Cold episode (UTCI) | 5711 | 0.000 | 0.318 | 0.250 | 2.083 | 0.336 | 0.249 |
| Dry spell (SPEI3) | 5682 | 0.000 | 0.519 | 0.450 | 2.020 | 0.406 | 0.204 |
| Wet spell (SPEI3) | 5682 | 0.000 | 0.315 | 0.200 | 1.395 | 0.314 | 0.212 |
| Log GDP per capita (within) | 4952 | -0.397 | -0.011 | 0.013 | 0.549 | 0.115 | 0.060 |
| Log GDP per capita (between) | 5666 | 2.178 | 3.284 | 3.331 | 5.141 | 0.349 | |
| Unemployment rate (within) | 5574 | -0.285 | 0.001 | 0.002 | 0.668 | 0.042 | 0.034 |
| Unemployment rate (between) | 5666 | -2.032 | 0.087 | 0.095 | 0.387 | 0.126 | |
| Agricultural share in GVA (between) | 5666 | 0.000 | 0.025 | 0.017 | 0.141 | 0.025 | |
| Population tertiary education (between) | 5666 | 0.106 | 0.264 | 0.259 | 0.696 | 0.081 | |
| Urban population share (between) | 5666 | 0.000 | 0.242 | 0.000 | 1.000 | 0.428 | |

Note: Within refers to measures that change within regions over time. Between refers to measures that stay constant over time and characterize differences between regions. The latter measures are calculated by taking the regional mean of a variable over time. They are used in the interaction models (Table S18) to test for differential climatic impacts. GVA refers to real gross value added. The within standard deviation (SD) refers to the standard deviation after applying the fixed effects. It is used as a basis for the standardization of the estimates of the models.

Figure S1 shows trends in the heat-related climate variables considered in our analysis: temperature anomalies, heat episodes (based on temperature and UTCI) and dry spells. Over the past three decades, an upward trend is visible showing a greater exposure to extreme heat across Europe and its different climate zones (cold, hot, and temperate). For the dry spell measure, which is based on the Standardized Precipitation Evapotranspiration Index (SPEI) the long-term pattern is more stable. The measures vary considerably from year to year with some years experiencing stronger anomalies and more extreme conditions compared to the others. Our causal inference is based on the variations in the climatic conditions within regions, which is used to test for the impact of more extreme temperatures and climatic conditions on concerns and voting outcomes. In all models, we control for longer-term trends and patterns to rule out any confounding influences on the results.

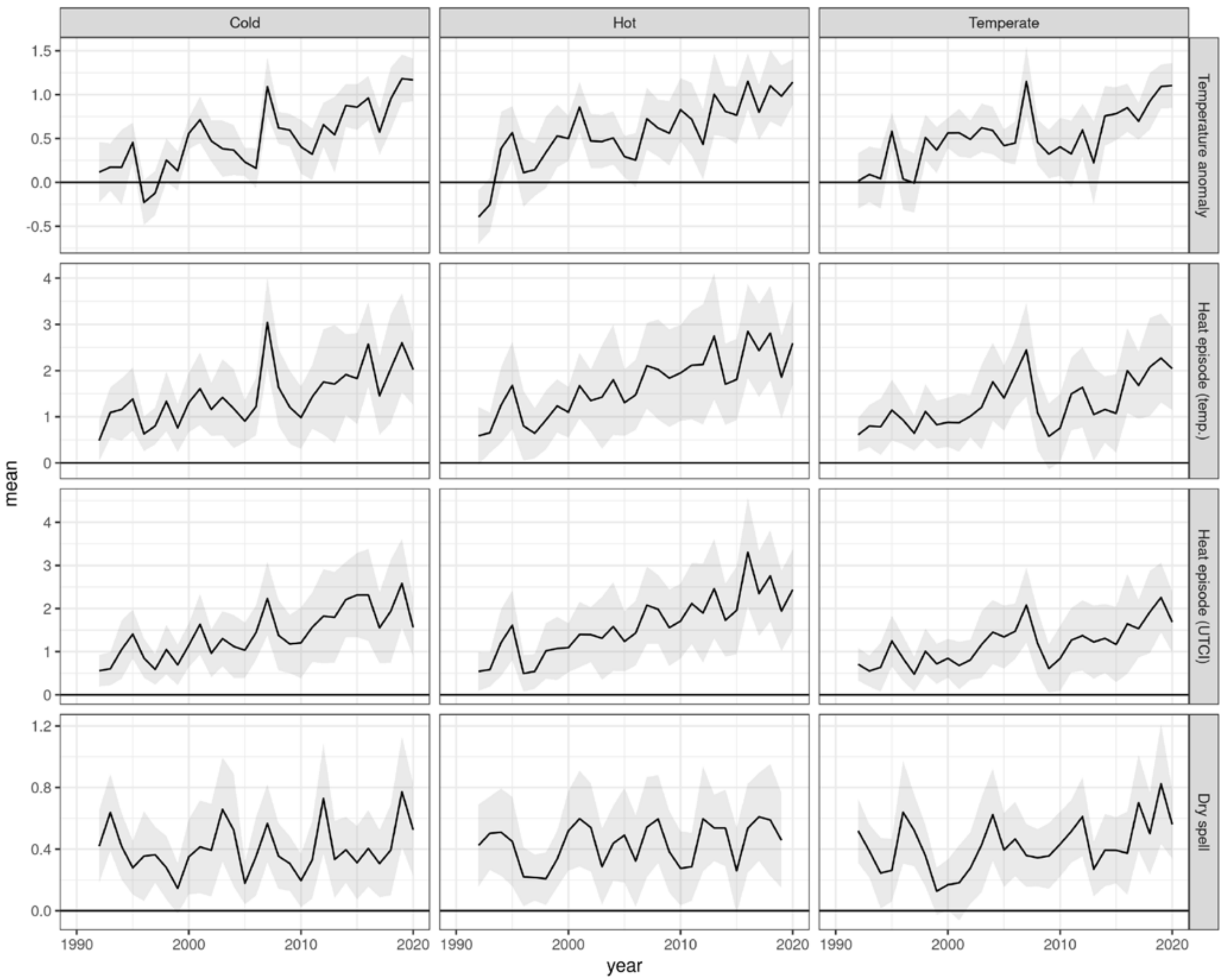


Figure S5 – Climate trends across climate zones (cold, hot, temperate) in Europe from 1994 to 2019. Grey areas show 95% confidence intervals. All displayed measures are standardized. Temperature anomaly is defined as deviations from the long-run monthly temperature mean of the period 1971–2000; heat episode (temp.) is defined as at least three consecutive days with a mean temperature above the local 95 percentile; heat episode (UTCI) is defined as at least three consecutive days with a mean UTCI above the local 95 percentile; and dry spells are defined as months with an SPEI falling 0.5 SD below the average of the reference period 1971–2000.

Figure S2 illustrates the distribution of the four climate measures for the three past decades (1990s, 2000s, and 2010s) in form of boxplots. Also in this graph, the warming trend is visible across climate zones (cold, hot, temperate) for all heat-related measures, except for the SPEI-based dry spell measure, for which the trend is more erratic. Temperature anomalies and heat extremes have become more common in the recent decades, in particular in the period from 2010 to 2019. In addition to the increased average levels of temperature extremes, the boxplots also reveal an increase in the variability over time with more extreme outliers found in more recent years.

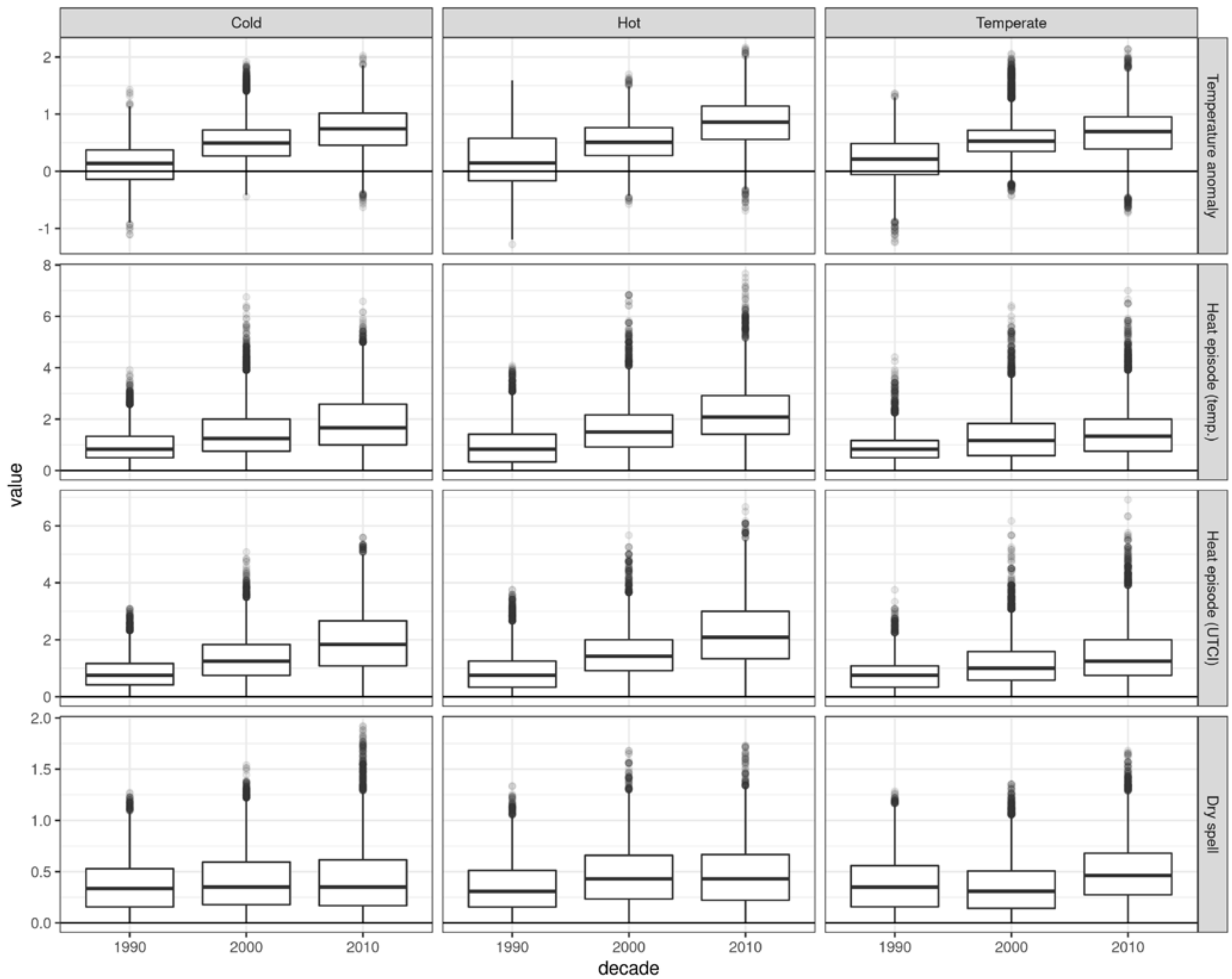


Figure S6 – Distribution of climate variables across climate zones (cold, hot, temperate) in Europe in the last three decades. Boxplots show the median, interquartile ranges (IQR) and related whiskers (most extreme value or 1.5x of the IQR). Points show outliers that are smaller or larger than the 1.5x IQR. All displayed climate measures are standardized. Temperature anomaly is defined as deviations from the long-run monthly temperature mean of the period 1971-2000; heat episode (temp.) is defined as at least three consecutive days with a mean temperature above the local 95 percentile; heat episode (UTCI) is defined as at least three consecutive days with a mean UTCI above the local 95 percentile; and dry spells are defined as months with an SPEI falling 0.5 SD below the average of the reference period 1971–2000.

Figure S3 and Figure S4 show the within distribution of the climate variables considered in the concern (Figure S3) and in the voting data (Figure S4) after controlling for region and period fixed effects. The graphs hence show the deviation from the regional mean over time. In both the concern and the voting data, the measures follow an approximate bell-shaped distribution highlighting that regions have encountered both positive as well as negative temperature anomalies and climate extremes in the observation period compared to the reference period of 1971–2000. Our models build on this variation to estimate climate impacts on concerns and voting. The right tails of the distributions are longer than the left tails indicating that large positive deviations from the unit and period means are more common than large negative deviations.

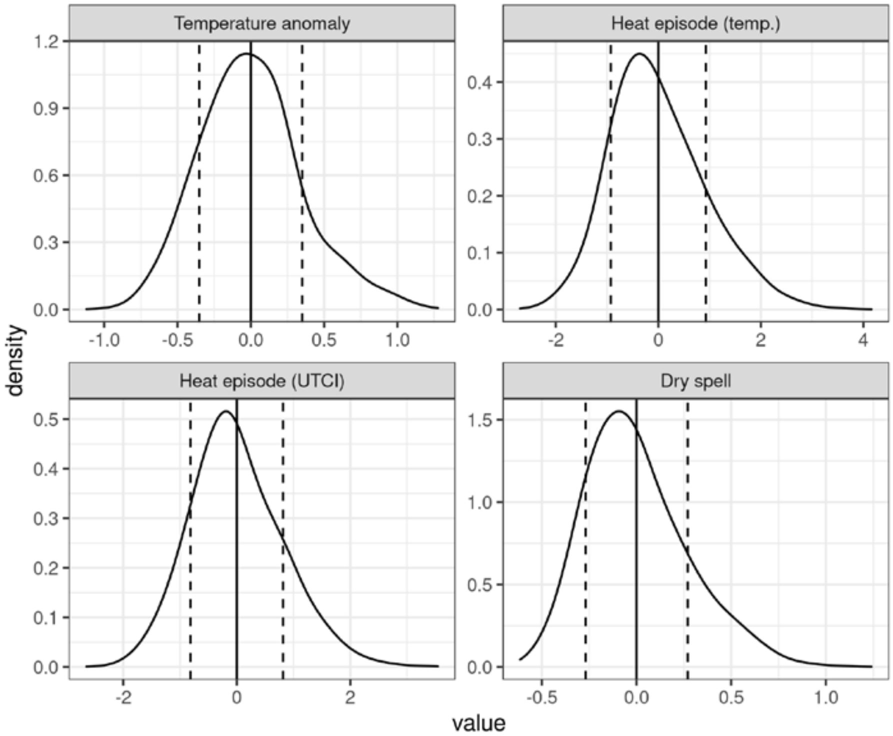


Figure S7 – Within distribution of climate variables in the concern dataset after application of the fixed effects. The solid vertical line indicates the mean, the dashed lines a one standard deviation from the mean.

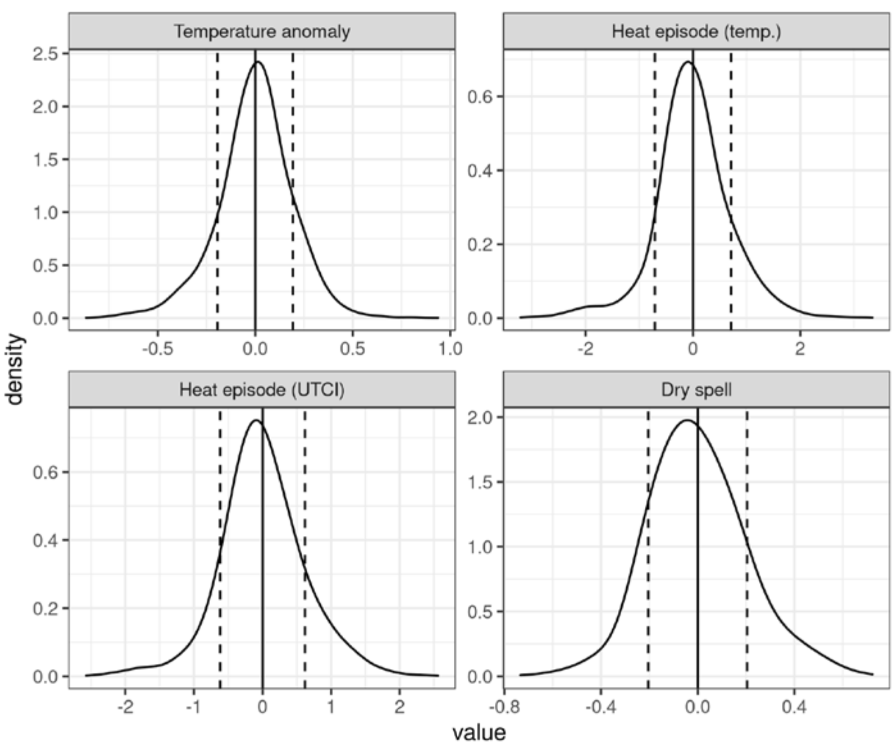


Figure S8 – Within distribution of climate variables in the voting dataset after application of the fixed effects. The solid vertical line indicates the mean, the dashed lines a one standard deviation from the mean.

## B. Sensitivity tests

The following section presents additional results and robustness checks, testing for the sensitivity of the findings presented in the main text. The estimations are based on the baseline models in Table 1. All our results remain robust to changes in the measurement and operationalization of the key variables and the modeling of the relationships.

Table S3 uses a different estimation of the standard errors. While our main models use an approach that explicitly models the autocorrelation from spatial and temporal inter-dependencies, here we use a clustering approach to correct the error statistics. For this, standard errors are clustered at the yearly level and the NUTS 1 (concern outcome) and NUTS 2 level (voting outcome). This alternative error correction method does not alter the main findings of the models, suggesting that our findings are not sensitive to different ways of accounting for autocorrelation in the data.

Table S6 – Robustness test: Baseline models with clustered standard errors

| | *Dependent variable:* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Environmental concern | | | | Green vote share | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Temperature anomaly | 0.183*** | | | | 0.115*** | | | |
| | (0.017) | | | | (0.035) | | | |
| Heat episode (temp.) | | 0.151*** | | | | 0.183*** | | |
| | | (0.018) | | | | (0.036) | | |
| Heat episode (UTCI) | | | 0.120*** | | | | 0.113*** | |
| | | | (0.017) | | | | (0.035) | |
| Dry spell | | | | 0.085*** | | | | 0.234*** |
| | | | | (0.022) | | | | (0.036) |
| Unit fixed effects | × | × | × | × | × | × | × | × |
| Period fixed effects | × | × | × | × | × | × | × | × |
| Season fixed effects | × | × | × | × | | | | |
| Cluster | NUTS1 YEAR | NUTS1 YEAR | NUTS1 YEAR | NUTS1 YEAR | NUTS2 YEAR | NUTS2 YEAR | NUTS2 YEAR | NUTS2 YEAR |
| Observations | 10,263 | 10,263 | 10,263 | 10,263 | 5,682 | 5,682 | 5,682 | 5,682 |
| $R^2$ | 0.478 | 0.473 | 0.468 | 0.464 | 0.768 | 0.772 | 0.768 | 0.777 |

Note: Standardized regression coefficients with clustered standard errors in parentheses. Standard errors were corrected for cross-sectional and serial correlation up to the indicated spatial and temporal cutoffs. All models control for regional and temporal fixed effects to account for unobserved heterogeneity and common time trends. Period fixed effects refer to three-year periods in models 1–4 and election year fixed effects in model 5–8. Coefficients are standardized using the residual variance after applying the fixed effects. Accordingly, the coefficients refer to a marginal effect of a one standard deviation change of the covariates on the outcome within regions and periods. Temperature anomaly is defined as standardized deviation from the long-run monthly temperature mean; heat episode (temp.) is defined as at least three consecutive days with a mean temperature above the local monthly 95 percentile; heat episode (UTCI) is defined as at least three consecutive days with a mean UTCI above the local monthly 95 percentile; dry spells are defined as mean of SPEI below –0.5. All measures are calculated using 1971–2000 as a reference period. P-values: * < 0.1, ** < 0.05, *** <0.01.

Table S4 explicitly models temporal autocorrelation in the data by including the lagged value of the dependent variable (last observation) as an additional independent variable. Also, this form of dynamic autoregressive modeling yields highly similar results to the main models (Table 1). As expected, the lagged concern measure is strongly and positively correlated with the current level of environmental concerns with standardized coefficients ranging from 0.551 (SE 0.049) to 0.565 (SE 0.047), suggesting a high persistence of environmental concerns over time. The lagged voting measure, on the other hand, is negatively related with current voting outcomes with coefficients ranging from -0.138 (SE 0.068) to -0.178 (SE 0.067). This can be a result of the large gap in the measurement of the voting outcome (5 years as electoral cycle) and may also reflect the greater dynamics in the voting process. Parties might be able to increase their vote share in one election, but lose votes again in the subsequent election, contributing to the observed patterns.

Table S7 – Robustness test: Baseline models controlling for lagged dependent variables

| | *Dependent variable:* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Environmental concern | | | | Green vote share | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Temperature anomaly | 0.104*** | | | | 0.124* | | | |
| | (0.015) | | | | (0.063) | | | |
| Heat episode (temp.) | | 0.086*** | | | | 0.192*** | | |
| | | (0.015) | | | | (0.060) | | |
| Heat episode (UTCI) | | | 0.070*** | | | | 0.133** | |
| | | | (0.015) | | | | (0.056) | |
| Dry spell | | | | 0.052** | | | | 0.254*** |
| | | | | (0.021) | | | | (0.057) |
| Concern (lag 1) | 0.551*** | 0.557*** | 0.561*** | 0.565*** | | | | |
| | (0.049) | (0.048) | (0.048) | (0.047) | | | | |
| Green vote (lag 1) | | | | | -0.174*** | -0.163** | -0.172** | -0.138** |
| | | | | | (0.067) | (0.067) | (0.067) | (0.068) |
| Unit fixed effects | × | × | × | × | × | × | × | × |
| Period fixed effects | × | × | × | × | × | × | × | × |
| Season fixed effects | × | × | × | × | | | | |
| Spatial cutoff (km) | 500 | 500 | 500 | 500 | 500 | 500 | 500 | 500 |
| Temporal cutoff (years) | 1.5 | 1.5 | 1.5 | 1.5 | 5 | 5 | 5 | 5 |
| Observations | 10,004 | 10,004 | 10,004 | 10,004 | 4,443 | 4,443 | 4,443 | 4,443 |
| $R^2$ | 0.644 | 0.642 | 0.641 | 0.639 | 0.792 | 0.796 | 0.792 | 0.802 |

Note: Standardized regression coefficients with standard errors in parentheses. Standard errors were corrected for cross-sectional and serial correlation up to the indicated spatial and temporal cutoffs. All models control for regional and temporal fixed effects to account for unobserved heterogeneity and common time trends. Period fixed effects refer to three-year periods in models 1–4 and election year fixed effects in model 5–8. Coefficients are standardized using the residual variance after applying the fixed effects on both sides. Accordingly, the coefficients refer to a marginal effect of a one standard deviation change of the covariates on the outcome within regions and periods. Temperature anomaly is defined as standardized deviation from the long-run monthly temperature mean; heat episode (temp.) is defined as at least three consecutive days with a mean temperature above the local monthly 95 percentile; heat episode (UTCI) is defined as at least three consecutive days with a mean UTCI above the local monthly 95 percentile; dry spells are defined as mean of SPEI below –0.5. All measures are calculated using 1971–2000 as reference period. P-values: * < 0.1, ** < 0.05, *** <0.01.

The measurement of the concern variable in the Eurobarometer surveys has changed twice in the course of our time series. While until 2006 the questionnaires only listed an environment-related answer category i.e. "protecting the environment", the list was extended by adding another category: "energy related issues" from 2007 onwards. From 2011 onwards, the two separate answer categories were merged into a new category called "the environment, climate and energy issues". To account for these changes, Table S5 and Table S6 restrict the model samples to more recent years, 2007–2019 and 2011–2019, respectively, covering different types of concern measurements. Restricting the sample to more recent years allows us to ensure that the concern measurement is harmonious (see Table S19 for an explicit test of differences in response behaviors). We can then test whether our findings remain consistent once the type of concern measurement is held constant. Across all models, the effects remain fully robust to this sampling variation with coefficient sizes increasing slightly for the estimates based on more recent data.

Table S8 – Robustness test: Baseline models restricted to the time period of 2007–2019

| | *Dependent variable:* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Environmental concern | | | | Green vote share | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Temperature anomaly | 0.149*** | | | | 0.312*** | | | |
| | (0.034) | | | | (0.062) | | | |
| Heat episode (temp.) | | 0.157*** | | | | 0.368*** | | |
| | | (0.033) | | | | (0.061) | | |
| Heat episode (UTCI) | | | 0.145*** | | | | 0.343*** | |
| | | | (0.034) | | | | (0.052) | |
| Dry spell | | | | 0.125*** | | | | 0.344*** |
| | | | | (0.048) | | | | (0.070) |
| Unit fixed effects | × | × | × | × | × | × | × | × |
| Period fixed effects | × | × | × | × | × | × | × | × |
| Season fixed effects | × | × | × | × | | | | |
| Spatial cutoff (km) | 500 | 500 | 500 | 500 | 500 | 500 | 500 | 500 |
| Temporal cutoff (years) | 1.5 | 1.5 | 1.5 | 1.5 | 5 | 5 | 5 | 5 |
| Observations | 7,681 | 7,681 | 7,681 | 7,681 | 3,235 | 3,235 | 3,235 | 3,235 |
| $R^2$ | 0.550 | 0.551 | 0.549 | 0.547 | 0.841 | 0.847 | 0.844 | 0.844 |

Note: Standardized regression coefficients with standard errors in parentheses. Standard errors were corrected for cross-sectional and serial correlation up to the indicated spatial and temporal cutoffs. All models control for regional and temporal fixed effects to account for unobserved heterogeneity and common time trends. Period fixed effects refer to three-year periods in models 1–4 and election year fixed effects in model 5–8. Coefficients are standardized using the residual variance after applying the fixed effects on both sides. Accordingly, the coefficients refer to a marginal effect of a one standard deviation change of the covariates on the outcome within regions and periods. Temperature anomaly is defined as standardized deviation from the long-run monthly temperature mean; heat episode (temp.) is defined as at least three consecutive days with a mean temperature above the local monthly 95 percentile; heat episode (UTCI) is defined as at least three consecutive days with a mean UTCI above the local monthly 95 percentile; dry spells are defined as mean of SPEI below –0.5. All measures are calculated using 1971–2000 as reference period. P-values: * < 0.1, ** < 0.05, *** <0.01.

Table S9 – Robustness test: Baseline models restricted to the time period of 2011–2019

| | *Dependent variable:* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Environmental concern | | | | Green vote share | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Temperature anomaly | 0.207*** | | | | 0.487*** | | | |
| | (0.049) | | | | (0.073) | | | |
| Heat episode (temp.) | | 0.181*** | | | | 0.451*** | | |
| | | (0.044) | | | | (0.070) | | |
| Heat episode (UTCI) | | | 0.155*** | | | | 0.416*** | |
| | | | (0.044) | | | | (0.053) | |
| Dry spell | | | | 0.151*** | | | | 0.504*** |
| | | | | (0.058) | | | | (0.067) |
| Unit fixed effects | × | × | × | × | × | × | × | × |
| Period fixed effects | × | × | × | × | × | × | × | × |
| Season fixed effects | × | × | × | × | | | | |
| Spatial cutoff (km) | 500 | 500 | 500 | 500 | 500 | 500 | 500 | 500 |
| Temporal cutoff (years) | 1.5 | 1.5 | 1.5 | 1.5 | 5 | 5 | 5 | 5 |
| Observations | 4,786 | 4,786 | 4,786 | 4,786 | 2,103 | 2,103 | 2,103 | 2,103 |
| $R^2$ | 0.581 | 0.577 | 0.573 | 0.572 | 0.852 | 0.845 | 0.839 | 0.855 |

Note: Standardized regression coefficients with standard errors in parentheses. Standard errors were corrected for cross-sectional and serial correlation up to the indicated spatial and temporal cutoffs. All models control for regional and temporal fixed effects to account for unobserved heterogeneity and common time trends. Period fixed effects refer to three-year periods in models 1–4 and election year fixed effects in model 5–8. Coefficients are standardized using the residual variance after applying the fixed effects on both sides. Accordingly, the coefficients refer to a marginal effect of a one standard deviation change of the covariates on the outcome within regions and periods. Temperature anomaly is defined as standardized deviation from the long-run monthly temperature mean; heat episode (temp.) is defined as at least three consecutive days with a mean temperature above the local monthly 95 percentile; heat episode (UTCI) is defined as at least three consecutive days with a mean UTCI above the local monthly 95 percentile; dry spells are defined as mean of SPEI below –0.5. All measures are calculated using 1971–2000 as reference period. P-values: * < 0.1, ** < 0.05, *** <0.01.

Table S7 extends the baseline models by adding further time-varying controls, which allow to increase the precision of the estimation and to show that our results are not driven by other parallel trends and developments. In particular, we focus here on economic variables, for which reliable data at the subnational level are available: local GDP per capita, unemployment rate and level of agricultural dependence. While concerns and voting are measured at specific days throughout the calendar year depending on the survey and election date, the time-varying economic variables are measured over the whole calendar year. We include these variables with a lag in order to reduce potential reduce confounding influences in the estimation. If the concern or voting outcome was measured in the first half of a calendar year, we take the previous year's value of the contextual economic variable, otherwise the value of the current calendar year.

The estimates show that increases in the real log GDP per capita and decreases in the unemployment rate significantly positively correlate with environmental concern. While GDP has a similarly positive effect on voting, the effect of the unemployment rate changes its direction, suggesting more complex underlying political dynamics. Green parties may for example receive “protest votes” when labor market conditions are unfavorable. An increase in the agricultural dependence is found to have a significantly positive impact on concerns and a non-significant, but positive impact on voting. With the exception of minor deviations in some coefficients, the climate impact estimates remain stable also with the additional economic factors controlled for in the models.

Table S10 – Robustness test: Baseline models with time-varying controls.

| | *Dependent variable:* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Environmental concern | | | | Green vote share | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Temperature anomaly | 0.200*** | | | | 0.135** | | | |
| | (0.027) | | | | (0.059) | | | |
| Heat episode (temp.) | | 0.164*** | | | | 0.223*** | | |
| | | (0.030) | | | | (0.058) | | |
| Heat episode (UTCI) | | | 0.134*** | | | | 0.179*** | |
| | | | (0.032) | | | | (0.055) | |
| Dry spell | | | | 0.091** | | | | 0.258*** |
| | | | | (0.043) | | | | (0.058) |
| GDP per capita | 0.051*** | 0.038* | 0.034* | 0.049*** | 0.093** | 0.097** | 0.107** | 0.063 |
| | (0.019) | (0.020) | (0.020) | (0.019) | (0.042) | (0.039) | (0.042) | (0.040) |
| Unemployment rate | -0.117*** | -0.126*** | -0.130*** | -0.123*** | 0.194*** | 0.199*** | 0.211*** | 0.194*** |
| | (0.018) | (0.019) | (0.019) | (0.018) | (0.049) | (0.049) | (0.050) | (0.049) |
| Agricultural share | 0.071*** | 0.066*** | 0.055*** | 0.048** | 0.020 | 0.032 | 0.025 | 0.033 |
| | (0.021) | (0.021) | (0.021) | (0.021) | (0.036) | (0.036) | (0.035) | (0.035) |
| Unit fixed effects | × | × | × | × | × | × | × | × |
| Period fixed effects | × | × | × | × | × | × | × | × |
| Season fixed effects | × | × | × | × | | | | |
| Spatial cutoff (km) | 500 | 500 | 500 | 500 | 500 | 500 | 500 | 500 |
| Temporal cutoff (years) | 1.5 | 1.5 | 1.5 | 1.5 | 5 | 5 | 5 | 5 |
| Observations | 9,380 | 9,380 | 9,380 | 9,380 | 4,923 | 4,923 | 4,923 | 4,923 |
| $R^2$ | 0.490 | 0.483 | 0.478 | 0.473 | 0.780 | 0.787 | 0.783 | 0.791 |

Note: Standardized regression coefficients with standard errors in parentheses. Standard errors were corrected for cross-sectional and serial correlation up to the indicated spatial and temporal cutoffs. All. All models control for regional and temporal fixed effects to account for unobserved heterogeneity and common time trends. Period fixed effects refer to three-year periods in models 1–4 and election year fixed effects in model 5–8. Coefficients are standardized using the residual variance after applying the fixed effects on both sides. Accordingly, the coefficients refer to a marginal effect of a one standard deviation change of the covariates on the outcome within regions and periods. Temperature anomaly is defined as standardized deviation from the long-run monthly temperature mean; heat episode (temp.) is defined as at least three consecutive days with a mean temperature above the local monthly 95 percentile; heat episode (UTCI) is defined as at least three consecutive days with a mean UTCI above the local monthly 95 percentile; dry spells are defined as mean of SPEI below –0.5. All measures are calculated using 1971–2000 as reference period. P-values: * < 0.1, ** < 0.05, *** <0.01.

Table S8 and Table S9 show results that are based on variations in the definition of climate extremes and anomalies. Table S8 uses a different reference period compared to our main models to calculate long-term monthly means and deviations from them. Instead of the period 1971–2000, we use the period 1961–1990 as baseline reference here. The climate measures considered in Table S9 use different cutoff-values as thresholds for defining what constitutes a heat-related climate extreme. In addition to the 5% cutoff used in the main models, we consider the top and lower 2.5% and 10% of the monthly long-run distribution as thresholds here. The findings remain largely robust to these changes, suggesting that the way we conceptualized and measured the climate variables did not drive our results.

Table S11 – Robustness test: Baseline models using 1961–1990 as climate reference period

| | *Dependent variable:* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Environmental concern | | | | Green vote share | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Temperature anomaly | 0.184*** | | | | 0.131** | | | |
| | (0.026) | | | | (0.055) | | | |
| Temperature anomaly (+) | | 0.168*** | | | | 0.192*** | | |
| | | (0.026) | | | | (0.058) | | |
| Temperature anomaly (–) | | -0.042** | | | | 0.052 | | |
| | | (0.017) | | | | (0.045) | | |
| Heat episode (temp.) | | | 0.156*** | | | | 0.187*** | |
| | | | (0.031) | | | | (0.056) | |
| Cold episode (temp.) | | | 0.020 | | | | -0.067** | |
| | | | (0.026) | | | | (0.031) | |
| Dry spell | | | | 0.129*** | | | | 0.259*** |
| | | | | (0.042) | | | | (0.058) |
| Wet spell | | | | 0.096*** | | | | 0.042 |
| | | | | (0.021) | | | | (0.050) |
| Unit fixed effects | × | × | × | × | × | × | × | × |
| Period fixed effects | × | × | × | × | × | × | × | × |
| Season fixed effects | × | × | × | × | | | | |
| Spatial cutoff (km) | 500 | 500 | 500 | 500 | 500 | 500 | 500 | 500 |
| Temporal cutoff (years) | 1.5 | 1.5 | 1.5 | 1.5 | 5 | 5 | 5 | 5 |
| Observations | 10,263 | 10,263 | 10,263 | 10,259 | 5,682 | 5,682 | 5,682 | 5,674 |
| $R^2$ | 0.478 | 0.479 | 0.473 | 0.468 | 0.769 | 0.772 | 0.773 | 0.778 |

Note: Standardized regression coefficients with standard errors in parentheses. Standard errors were corrected for cross-sectional and serial correlation up to the indicated spatial and temporal cutoffs. All models control for regional and temporal fixed effects to account for unobserved heterogeneity and common time trends. Period fixed effects refer to three-year periods in models 1–4 and election year fixed effects in model 5–8. Coefficients are standardized using the residual variance after applying the fixed effects on both sides. Accordingly, the coefficients refer to a marginal effect of a one standard deviation change of the covariates on the outcome within regions and periods. Temperature anomaly is defined as standardized deviation from the long-run monthly temperature mean; heat episode (temp.) is defined as at least three consecutive days with a mean temperature above the local monthly 95 percentile; heat episode (UTCI) is defined as at least three consecutive days with a mean UTCI above the local monthly 95 percentile; dry spells are defined as mean of SPEI below –0.5. All measures are calculated using 1961–1990 as reference period. P-values: * < 0.1, ** < 0.05, *** <0.01.

Table S12 – Robustness test: Impacts of heat and cold episodes using different thresholds to define climate extremes

| | *Dependent variable:* | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Environmental concern | | | | | | Green vote share | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| Heat episode (2.5% temp.) | 0.147*** | | | | | | 0.177*** | | | | | |
| | (0.032) | | | | | | (0.052) | | | | | |
| Cold episode (2.5% temp.) | -0.019 | | | | | | -0.107*** | | | | | |
| | (0.020) | | | | | | (0.030) | | | | | |
| Heat episode (5% temp.) | | 0.150*** | | | | | | 0.188*** | | | | |
| | | (0.030) | | | | | | (0.055) | | | | |
| Cold episode (5% temp.) | | -0.005 | | | | | | -0.053 | | | | |
| | | (0.024) | | | | | | (0.033) | | | | |
| Heat episode (10% temp.) | | | 0.138*** | | | | | | 0.209*** | | | |
| | | | (0.031) | | | | | | (0.057) | | | |
| Cold episode (10% temp.) | | | -0.021 | | | | | | 0.001 | | | |
| | | | (0.023) | | | | | | (0.036) | | | |
| Heat episode (2.5% UTCI) | | | | 0.139*** | | | | | | 0.066 | | |
| | | | | (0.037) | | | | | | (0.052) | | |
| Cold episode (2.5% UTCI) | | | | 0.045 | | | | | | 0.048 | | |
| | | | | (0.034) | | | | | | (0.031) | | |
| Heat episode (5% UTCI) | | | | | 0.125*** | | | | | | 0.115** | |
| | | | | | (0.030) | | | | | | (0.053) | |
| Cold episode (5% UTCI) | | | | | 0.044 | | | | | | -0.054 | |
| | | | | | (0.033) | | | | | | (0.042) | |
| Heat episode (10% UTCI) | | | | | | 0.117*** | | | | | | 0.181*** |
| | | | | | | (0.030) | | | | | | (0.054) |
| Cold episode (10% UTCI) | | | | | | 0.029 | | | | | | -0.067 |
| | | | | | | (0.031) | | | | | | (0.046) |
| Unit fixed effects | × | × | × | × | × | × | × | × | × | × | × | × |
| Period fixed effects | × | × | × | × | × | × | × | × | × | × | × | × |
| Season fixed effects | × | × | × | × | × | × | | | | | | |
| Spatial cutoff (km) | 500 | 500 | 500 | 500 | 500 | 500 | 500 | 500 | 500 | 500 | 500 | 500 |
| Temporal cutoff (years) | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 5 | 5 | 5 | 5 | 5 | 5 |
| Observations | 10,263 | 10,263 | 10,263 | 10,263 | 10,263 | 10,263 | 5,682 | 5,682 | 5,682 | 5,682 | 5,682 | 5,682 |
| $R^2$ | 0.472 | 0.473 | 0.472 | 0.472 | 0.469 | 0.467 | 0.773 | 0.773 | 0.775 | 0.766 | 0.768 | 0.773 |

Note: Standardized regression coefficients with standard errors in parentheses. Standard errors were corrected for cross-sectional and serial correlation up to the indicated spatial and temporal cutoffs. All models control for regional and temporal fixed effects to account for unobserved heterogeneity and common time trends. Period fixed effects refer to three-year periods in models 1–4 and election year fixed effects in model 5–8. Coefficients are standardized using the residual variance after applying the fixed effects on both sides. Accordingly, the coefficients refer to a marginal effect of a one standard deviation change of the covariates on the outcome within regions and periods. Temperature anomaly is defined as standardized deviation from the long-run monthly temperature mean; heat episode (temp.) is defined as at least three consecutive days with a mean temperature above the local monthly 95 percentile; heat episode (UTCI) is defined as at least three consecutive days with a mean UTCI above the local monthly 95 percentile; dry spells are defined as mean of SPEI below –0.5. All measures are calculated using 1971–2000 as reference period. P-values: * < 0.1, ** < 0.05, *** <0.01.

## C. Extended analyses and further results

This section shows results of extended analyses that build upon our baseline models to explore underlying patterns and relationships in the data. Here, we also display the models used in our heterogeneity analyses to examine the importance of regional climate differences and economic factors in shaping climatic impacts on environmental concerns and green voting.

### Estimations with alternative standardization

Table S11, Table S12 and Table S12 show the results of the baseline models using alternative standardization of the coefficients. Table S12 shows the results of models based on an unstandardized outcome and standardized independent variables. The results show the percentage changes in environmental concerns and Green voting with a one standard deviation change in the climate factor. . Table S11 shows the impact of climatic extremes on concerns and voting without any standardization. The results hence reflect the changes in the share of the local population being concerned about the environment and voting for Green parties with a one-unit change in the climatic measures. While we use the within region standard deviation to standardize the effect sizes in the baseline models, Table S12 uses the full variance of the concern and voting outcomes and the residual variance of the independent variables for the standardization. In terms of the full variance of the outcomes that includes also differences between regions, a one standard deviation increase in anomaly within regions increases concerns by 0.135 (SE 0.018) SDs and 0.056 (SE 0.027) SDs. This may help gauge the importance of the estimated climate impacts in the context of the overall variance of the outcomes between and within regions.

Table S13 – Baseline models with unstandardized outcome and standardized independent variables

| | *Dependent variable:* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Environmental concern | | | | Green vote share | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Temperature anomaly | 0.009*** | | | | 0.003** | | | |
| | (0.001) | | | | (0.002) | | | |
| Heat episode (temp.) | | 0.007*** | | | | 0.005*** | | |
| | | (0.001) | | | | (0.002) | | |
| Heat episode (UTCI) | | | 0.006*** | | | | 0.003** | |
| | | | (0.001) | | | | (0.002) | |
| Dry spell | | | | 0.004** | | | | 0.007*** |
| | | | | (0.002) | | | | (0.002) |
| Unit fixed effects | × | × | × | × | × | × | × | × |
| Period fixed effects | × | × | × | × | × | × | × | × |
| Season fixed effects | × | × | × | × | | | | |
| Spatial cutoff (km) | 500 | 500 | 500 | 500 | 500 | 500 | 500 | 500 |
| Temporal cutoff (years) | 1.5 | 1.5 | 1.5 | 1.5 | 5 | 5 | 5 | 5 |
| Observations | 10,263 | 10,263 | 10,263 | 10,263 | 5,682 | 5,682 | 5,682 | 5,682 |
| $R^2$ | 0.478 | 0.473 | 0.468 | 0.464 | 0.768 | 0.772 | 0.768 | 0.777 |

Note: Standardized regression coefficients with standard errors in parentheses. Standard errors were corrected for cross-sectional and serial correlation up to the indicated spatial and temporal cutoffs. All models control for regional and temporal fixed effects to account for unobserved heterogeneity and common time trends. Period fixed effects refer to three-year periods in models 1–4 and election year fixed effects in model 5–8. Independent variables are standardized, the outcome variables are unstandardized. Accordingly, the coefficients refer to the percentage change of the outcomes with a one standard deviation change of the covariates. Temperature anomaly is defined as standardized deviation from the long-run monthly temperature mean; heat episode (temp.) as at least three consecutive days with a mean temperature above the local monthly 95 percentile; heat episode (UTCI) as at least three consecutive days with a mean UTCI above the local monthly 95 percentile; dry spells as mean of SPEI below –0.5. All measures are calculated using 1971–2000 as reference period. P-values: * < 0.1, ** < 0.05, *** <0.01.

Table S14 – Baseline models without standardization

| | *Dependent variable:* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Environmental concern | | | | Green vote share | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Temperature anomaly | 0.025*** | | | | 0.017** | | | |
| | (0.003) | | | | (0.008) | | | |
| Heat episode (temp.) | | 0.008*** | | | | 0.007*** | | |
| | | (0.001) | | | | (0.002) | | |
| Heat episode (UTCI) | | | 0.007*** | | | | 0.005** | |
| | | | (0.002) | | | | (0.003) | |
| Dry spell | | | | 0.015** | | | | 0.033*** |
| | | | | (0.007) | | | | (0.007) |
| Unit fixed effects | × | × | × | × | × | × | × | × |
| Period fixed effects | × | × | × | × | × | × | × | × |
| Season fixed effects | × | × | × | × | | | | |
| Spatial cutoff (km) | 500 | 500 | 500 | 500 | 500 | 500 | 500 | 500 |
| Temporal cutoff (years) | 1.5 | 1.5 | 1.5 | 1.5 | 5 | 5 | 5 | 5 |
| Observations | 10,263 | 10,263 | 10,263 | 10,263 | 5,682 | 5,682 | 5,682 | 5,682 |
| $R^2$ | 0.478 | 0.473 | 0.468 | 0.464 | 0.768 | 0.772 | 0.768 | 0.777 |

Note: Regression coefficients with standard errors in parentheses. Standard errors were corrected for cross-sectional and serial correlation up to the indicated spatial and temporal cutoffs. All models control for regional and temporal fixed effects to account for unobserved heterogeneity and common time trends. Period fixed effects refer to three-year periods in models 1–4 and election year fixed effects in model 5–8. Coefficients are not standardized. Accordingly, the coefficients refer to a marginal effect of a change of the covariates on the outcome within regions and periods. Temperature anomaly is defined as standardized deviation from the long-run monthly temperature mean; heat episode (temp.) is defined as at least three consecutive days with a mean temperature above the local monthly 95 percentile; heat episode (UTCI) is defined as at least three consecutive days with a mean UTCI above the local monthly 95 percentile; dry spells are defined as mean of SPEI below –0.5. All measures are calculated using 1971–2000 as a reference period. P-values: * < 0.1, ** < 0.05, *** <0.01.

Table S15 – Baseline models standardized using the full variance of the outcomes and the residual variance of the regressors

| | *Dependent variable:* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Environmental concern | | | | Green vote share | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Temperature anomaly | 0.135*** | | | | 0.056** | | | |
| | (0.018) | | | | (0.027) | | | |
| Heat episode (temp.) | | 0.111*** | | | | 0.089*** | | |
| | | (0.019) | | | | (0.027) | | |
| Heat episode (UTCI) | | | 0.088*** | | | | 0.055** | |
| | | | (0.020) | | | | (0.026) | |
| Dry spell | | | | 0.063** | | | | 0.114*** |
| | | | | (0.029) | | | | (0.025) |
| Unit fixed effects | × | × | × | × | × | × | × | × |
| Period fixed effects | × | × | × | × | × | × | × | × |
| Season fixed effects | × | × | × | × | | | | |
| Spatial cutoff (km) | 500 | 500 | 500 | 500 | 500 | 500 | 500 | 500 |
| Temporal cutoff (years) | 1.5 | 1.5 | 1.5 | 1.5 | 5 | 5 | 5 | 5 |
| Observations | 10,263 | 10,263 | 10,263 | 10,263 | 5,682 | 5,682 | 5,682 | 5,682 |
| $R^2$ | 0.478 | 0.473 | 0.468 | 0.464 | 0.768 | 0.772 | 0.768 | 0.777 |

Note: Standardized regression coefficients with standard errors in parentheses. Standard errors were corrected for cross-sectional and serial correlation up to the indicated spatial and temporal cutoffs. All models control for regional and temporal fixed effects to account for unobserved heterogeneity and common time trends. Period fixed effects refer to three-year periods in models 1–4 and election year fixed effects in model 5–8. Coefficients are not standardized. Accordingly, the coefficients refer to a marginal effect of a change of the covariates on the outcome within regions and periods. Temperature anomaly is defined as standardized deviation from the long-run monthly temperature mean; heat episode (temp.) is defined as at least three consecutive days with a mean temperature above the local monthly 95 percentile; heat episode (UTCI) is defined as at least three consecutive days with a mean UTCI above the local monthly 95 percentile; dry spells are defined as mean of SPEI below –0.5. All measures are calculated using 1971–2000 as reference period. P-values: * < 0.1, ** < 0.05, *** <0.01.

## Using different time spans for the measurement of climate variables

Table S13 to Table S16 show the impact of the different climate measures using different time spans for the measurements. For all tables, models 1 and 5 show the impact of the climatic conditions that occurred one month prior to the measurement of the concern outcome or the election date, models 2 and 6 show the impact of conditions in the past 12 months, which we use as benchmark for our baseline models, and models 3 and 7 as well as 4 and 8 show the climatic impact averaging over the past 24 months and 48 months, respectively.

With greater lags in the climate measurement, heat-related extremes are still found to exert a significant influence on concerns and voting. However, a recency effect is observable in the data. More recent climate events tend to influence concerns and voting more strongly possibly due to a greater salience of the experiences. For example, heat periods that occurred in the past 12 months (Table S14) increase concerns and voting by 0.151 (SE 0.026) and 0.183 (SE 0.055) standard deviations, respectively. For a lag of 24 months, these effect sizes diminish to 0.110 (SE 0.019) and 0.150 (SE 0.050), respectively, and for 48 months to 0.070 (SE 0.019) and 0.087 (SE 0.047), respectively. The patterns are less clear for climate extremes that occurred only in the past month. For these, effect sizes are in most cases either weaker than the effect sizes from the 12 months lagged baseline or insignificant. Focusing on a single month in the climate measurement may presumably be a too short time period to evoke actual changes in concerns and voting behaviors.

Table S16 – Effects of temperature anomalies on concerns and voting with different time lags

| | *Dependent variable:* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Environmental concern | | | | Green vote share | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Temperature anomaly (1m, overall) | 0.043* | | | | -0.035 | | | |
| | (0.024) | | | | (0.059) | | | |
| Temperature anomaly (12m, overall) | | 0.183*** | | | | 0.115** | | |
| | | (0.024) | | | | (0.055) | | |
| Temperature anomaly (24m, overall) | | | 0.116*** | | | | 0.121** | |
| | | | (0.023) | | | | (0.054) | |
| Temperature anomaly (48m, overall) | | | | 0.032* | | | | 0.057 |
| | | | | (0.019) | | | | (0.046) |
| Unit fixed effects | × | × | × | × | × | × | × | × |
| Period fixed effects | × | × | × | × | × | × | × | × |
| Season fixed effects | × | × | × | × | | | | |
| Spatial cutoff (km) | 500 | 500 | 500 | 500 | 500 | 500 | 500 | 500 |
| Temporal cutoff (years) | 1.5 | 1.5 | 1.5 | 1.5 | 5 | 5 | 5 | 5 |
| Observations | 10,263 | 10,263 | 10,263 | 10,263 | 5,682 | 5,682 | 5,682 | 4,953 |
| $R^2$ | 0.461 | 0.478 | 0.468 | 0.461 | 0.765 | 0.768 | 0.768 | 0.770 |

Note: Standardized regression coefficients with standard errors in parentheses. Standard errors were corrected for cross-sectional and serial correlation up to the indicated spatial and temporal cutoffs. All models control for regional and temporal fixed effects to account for unobserved heterogeneity and common time trends. Period fixed effects refer to three-year periods in models 1–4 and election year fixed effects in model 5–8. Coefficients are standardized using the residual variance after applying the fixed effects on both sides. Accordingly, the coefficients refer to a marginal effect of a one standard deviation change of the covariates on the outcome within regions and periods. Temperature anomaly is defined as standardized deviation from the long-run monthly temperature mean; heat episode (temp.) is defined as at least three consecutive days with a mean temperature above the local monthly 95 percentile; heat episode (UTCI) is defined as at least three consecutive days with a mean UTCI above the local monthly 95 percentile; dry spells are defined as mean of SPEI below –0.5. All measures are calculated using 1971–2000 as reference period. P-values: * < 0.1, ** < 0.05, *** <0.01.

Table S17 – Effects of heat epsiodes (temperature-based) on concerns and voting with different time lags

| | *Dependent variable:* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Environmental concern | | | | Green vote share | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Heat episode (1m, temp.) | 0.041 | | | | $0.175^{***}$ | | | |
| | (0.025) | | | | (0.049) | | | |
| Heat episode (12m, temp.) | | $0.151^{***}$ | | | | $0.183^{***}$ | | |
| | | (0.026) | | | | (0.055) | | |
| Heat episode (24m, temp.) | | | $0.110^{***}$ | | | | $0.150^{***}$ | |
| | | | (0.019) | | | | (0.050) | |
| Heat episode (48m, temp.) | | | | $0.070^{***}$ | | | | $0.087^{*}$ |
| | | | | (0.019) | | | | (0.047) |
| Unit fixed effects | × | × | × | × | × | × | × | × |
| Period fixed effects | × | × | × | × | × | × | × | × |
| Season fixed effects | × | × | × | × | | | | |
| Spatial cutoff (km) | 500 | 500 | 500 | 500 | 500 | 500 | 500 | 500 |
| Temporal cutoff (years) | 1.5 | 1.5 | 1.5 | 1.5 | 5 | 5 | 5 | 5 |
| Observations | 10,263 | 10,263 | 10,263 | 10,263 | 5,682 | 5,682 | 5,682 | 4,953 |
| $R^2$ | 0.461 | 0.473 | 0.467 | 0.463 | 0.772 | 0.772 | 0.770 | 0.771 |

Note: Standardized regression coefficients with standard errors in parentheses. Standard errors were corrected for cross-sectional and serial correlation up to the indicated spatial and temporal cutoffs. All models control for regional and temporal fixed effects to account for unobserved heterogeneity and common time trends. Period fixed effects refer to three-year periods in models 1–4 and election year fixed effects in model 5–8. Coefficients are standardized using the residual variance after applying the fixed effects on both sides. Accordingly, the coefficients refer to a marginal effect of a one standard deviation change of the covariates on the outcome within regions and periods. Temperature anomaly is defined as standardized deviation from the long-run monthly temperature mean; heat episode (temp.) is defined as at least three consecutive days with a mean temperature above the local monthly 95 percentile; heat episode (UTCI) is defined as at least three consecutive days with a mean UTCI above the local monthly 95 percentile; dry spells are defined as mean of SPEI below –0.5. All measures are calculated using 1971–2000 as reference period. P-values: * < 0.1, ** < 0.05, *** <0.01.

Table S18 – Effects of heat episodes (UTCI-based) on concerns and voting with different time lags

| | *Dependent variable:* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Environmental concern | | | | Green vote share | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Heat episode (1m, UTCI) | 0.088*** | | | | -0.012 | | | |
| | (0.034) | | | | (0.051) | | | |
| Heat episode (12m, UTCI) | | 0.120*** | | | | 0.113** | | |
| | | (0.028) | | | | (0.054) | | |
| Heat episode (24m, UTCI) | | | 0.064*** | | | | 0.107** | |
| | | | (0.019) | | | | (0.049) | |
| Heat episode (48m, UTCI) | | | | 0.006 | | | | 0.028 |
| | | | | (0.019) | | | | (0.058) |
| Unit fixed effects | × | × | × | × | × | × | × | × |
| Period fixed effects | × | × | × | × | × | × | × | × |
| Season fixed effects | × | × | × | × | | | | |
| Spatial cutoff (km) | 500 | 500 | 500 | 500 | 500 | 500 | 500 | 500 |
| Temporal cutoff (years) | 1.5 | 1.5 | 1.5 | 1.5 | 5 | 5 | 5 | 5 |
| Observations | 10,263 | 10,263 | 10,263 | 10,263 | 5,682 | 5,682 | 5,682 | 4,953 |
| $R^2$ | 0.464 | 0.468 | 0.462 | 0.460 | 0.765 | 0.768 | 0.767 | 0.770 |

Note: Standardized regression coefficients with standard errors in parentheses. Standard errors were corrected for cross-sectional and serial correlation up to the indicated spatial and temporal cutoffs. All models control for regional and temporal fixed effects to account for unobserved heterogeneity and common time trends. Period fixed effects refer to three-year periods in models 1–4 and election year fixed effects in model 5–8. Coefficients are standardized using the residual variance after applying the fixed effects on both sides. Accordingly, the coefficients refer to a marginal effect of a one standard deviation change of the covariates on the outcome within regions and periods. Temperature anomaly is defined as standardized deviation from the long-run monthly temperature mean; heat episode (temp.) is defined as at least three consecutive days with a mean temperature above the local monthly 95 percentile; heat episode (UTCI) is defined as at least three consecutive days with a mean UTCI above the local monthly 95 percentile; dry spells are defined as mean of SPEI below –0.5. All measures are calculated using 1971–2000 as reference period. P-values: * < 0.1, ** < 0.05, *** <0.01.

Table S19 – Effects of dry spells on concerns and voting with different time lags

| | *Dependent variable:* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Environmental concern | | | | Green vote share | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Dry spell (1m, SPEI3) | 0.003 | | | | -0.072 | | | |
| | (0.026) | | | | (0.046) | | | |
| Dry spell (12m, SPEI3) | | 0.085** | | | | 0.234*** | | |
| | | (0.040) | | | | (0.052) | | |
| Wet spell (24m, SPEI3) | | | 0.090*** | | | | 0.171*** | |
| | | | (0.034) | | | | (0.049) | |
| Wet spell (48m, SPEI3) | | | | 0.109*** | | | | 0.172*** |
| | | | | (0.038) | | | | (0.061) |
| Unit fixed effects | × | × | × | × | × | × | × | × |
| Period fixed effects | × | × | × | × | × | × | × | × |
| Season fixed effects | × | × | × | × | | | | |
| Spatial cutoff (km) | 500 | 500 | 500 | 500 | 500 | 500 | 500 | 500 |
| Temporal cutoff (years) | 1.5 | 1.5 | 1.5 | 1.5 | 5 | 5 | 5 | 5 |
| Observations | 10,263 | 10,263 | 10,263 | 10,263 | 5,682 | 5,682 | 5,662 | 4,932 |
| $R^2$ | 0.460 | 0.464 | 0.465 | 0.467 | 0.766 | 0.777 | 0.772 | 0.777 |

Note: Standardized regression coefficients with standard errors in parentheses. Standard errors were corrected for cross-sectional and serial correlation up to the indicated spatial and temporal cutoffs. All models control for regional and temporal fixed effects to account for unobserved heterogeneity and common time trends. Period fixed effects refer to three-year periods in models 1–4 and election year fixed effects in model 5–8. Coefficients are standardized using the residual variance after applying the fixed effects on both sides. Accordingly, the coefficients refer to a marginal effect of a one standard deviation change of the covariates on the outcome within regions and periods. Temperature anomaly is defined as standardized deviation from the long-run monthly temperature mean; heat episode (temp.) is defined as at least three consecutive days with a mean temperature above the local monthly 95 percentile; heat episode (UTCI) is defined as at least three consecutive days with a mean UTCI above the local monthly 95 percentile; dry spells are defined as mean of SPEI below –0.5. All measures are calculated using 1971–2000 as reference period. P-values: * < 0.1, ** < 0.05, *** <0.01.**Error! Reference source not found.**

## Heterogeneity of climate impacts by climate zone

In additional models, we study how the impact of the exposure to climate extremes differs across three climate zones in Europe (See section D on Methods and Data for further details). The definition of the climate zones is based on the Köppen-Geiger climate classification (Beck et al., 2018), which distinguishes different classes of climate zones based on their temperature and precipitation (Figure S5 a). Here, we categorize regions with higher temperatures and more arid conditions (Bwh, Bwk, Bsh, Bsk, Csa, Csb) as regions with a "hot climate", regions with moderate temperatures and higher precipitation (Cfa, Cfb, and Cfc) as "temperate climate", and regions with cold temperatures and high precipitation (Dsa, Dsb, Dsc, Dfa, Dfb, Dfc, ET, EF) as "cold climate". While the hot climate zone can be mostly found in the Mediterranean regions of Europe (Figure S5 b), regions with a temperate climate are mostly located in Western Europe, which is influenced by the Atlantic, and regions with a cold climate in the East and Northern Europe, which are characterized by more continental climate conditions.

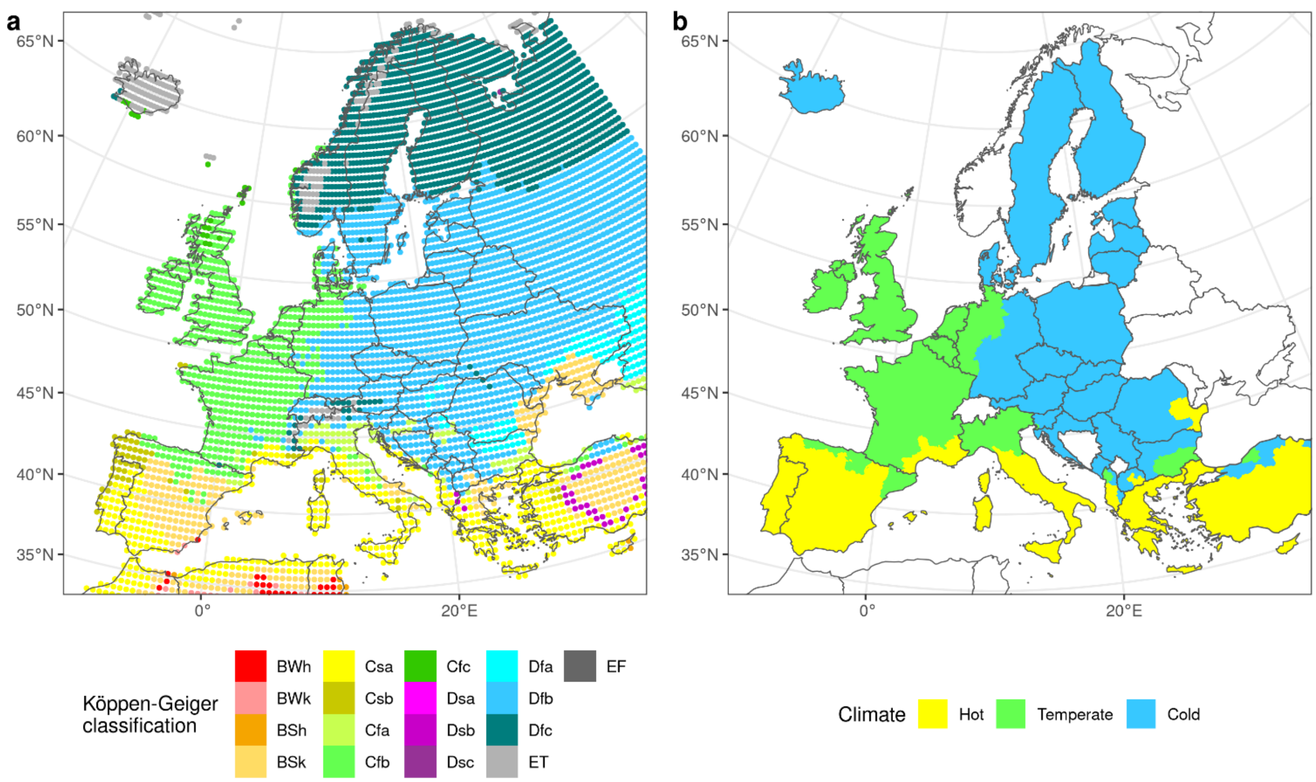


Figure S9 – Classification of regions in Europe in different climate zones based on the Köppen-Geiger classification. Panel a) shows the Köppen-Geiger climate classification plotted at 5° resolution based on Beck et al. (2018). Panel b) shows the classifications of regions in three climate zones with a hot (Bwh, Bwk, Bsh, Bsk, Csa, Csb), temperate (Cfa, Cfb, Cfc), or cold (Dsa, Dsb, Dsc, Dfa, Dfb, Dfc, ET, EF) climate.

Table S17 shows the results of the heterogeneity analyses estimating the impact of the climate variables on concerns and voting for the three climate zones, distinguishing regions with a cold, temperate, and hot climate. The models form the basis for the dot-whisker coefficient plots shown in Figure 3 in the main text. The results show a stronger impact of heat-related extremes in the cold and temperate climatic regions compared to regions with a hot, arid climate, which suggests a greater sensitivity to heat-related extremes in areas with a more temperate or cooler climate. If the long-run distribution is already characterized by a hot and dry climate, a marginal change may have little to no effect, as populations may have better adapted to the warmer baseline conditions, for instance through air conditioning and well-insulated housing.

Further extending Table 2 in the main text, we study differential impacts of both positive temperature extremes and dry spells as well as negative temperature extremes and wet spells across the climate zones. Figure S6 shows dot-whisker coefficient plot for the different climate measures by the climate zones. While the impacts of heat-related events and dry spells are consistent with the heterogeneity described above, the patterns are less clear for cold-related extremes. This is in line with the findings in our main text that changes in concerns and voting are mainly driven by positive temperature extremes and heat-related events.

Table S20 – Climatic impacts on concerns and voting by different climatic zones

| | *Dependent variable:* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Environmental concern | | | | Green vote share | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Temperature anomaly | 0.160*** | | | | 0.072 | | | |
| | (0.025) | | | | (0.056) | | | |
| Temperature anomaly × Hot | -0.103*** | | | | -0.017 | | | |
| | (0.015) | | | | (0.044) | | | |
| Temperature anomaly × Temperate | 0.120*** | | | | 0.111* | | | |
| | (0.045) | | | | (0.061) | | | |
| Heat episode (temp.) | | 0.149*** | | | | 0.157** | | |
| | | (0.027) | | | | (0.063) | | |
| Heat episode (temp.) × Hot | | -0.085*** | | | | -0.060* | | |
| | | (0.017) | | | | (0.035) | | |
| Heat episode (temp.) × Temperate | | 0.085* | | | | 0.118* | | |
| | | (0.045) | | | | (0.062) | | |
| Heat episode (UTCI) | | | 0.113*** | | | | 0.109* | |
| | | | (0.028) | | | | (0.060) | |
| Heat episode (UTCI) × Hot | | | -0.078*** | | | | -0.091** | |
| | | | (0.018) | | | | (0.035) | |
| Heat episode (UTCI) × Temperate | | | 0.093* | | | | 0.085 | |
| | | | (0.052) | | | | (0.063) | |
| Dry spell | | | | 0.082*** | | | | 0.182*** |
| | | | | (0.025) | | | | (0.052) |
| Dry spell × Hot | | | | -0.054*** | | | | -0.081** |
| | | | | (0.016) | | | | (0.036) |
| Dry spell × Temperate | | | | 0.054 | | | | 0.163*** |
| | | | | (0.070) | | | | (0.062) |
| Unit fixed effects | × | × | × | × | × | × | × | × |
| Period fixed effects | × | × | × | × | × | × | × | × |
| Season fixed effects | × | × | × | × | | | | |
| Spatial cutoff (km) | 500 | 500 | 500 | 500 | 500 | 500 | 500 | 500 |
| Temporal cutoff (years) | 1.5 | 1.5 | 1.5 | 1.5 | 5 | 5 | 5 | 5 |
| Observations | 10,263 | 10,263 | 10,263 | 10,263 | 5,682 | 5,682 | 5,682 | 5,682 |
| $R^2$ | 0.492 | 0.480 | 0.476 | 0.467 | 0.770 | 0.777 | 0.772 | 0.785 |

Note: Standardized regression coefficients with standard errors in parentheses. Standard errors were corrected for cross-sectional and serial correlation up to the indicated spatial and temporal cutoffs. All models control for regional and temporal fixed effects to account for unobserved heterogeneity and common time trends. Period fixed effects refer to three-year periods in models 1–4 and election year fixed effects in model 5–8. Coefficients are standardized using the residual variance after applying the fixed effects. Accordingly, the coefficients refer to a marginal effect of a one standard deviation change of the covariates on the outcome within regions and periods. Temperature anomaly is defined as standardized deviation from the long-run monthly temperature mean; heat episode (temp.) as at least three consecutive days with a mean temperature above the local monthly 95 percentile; heat episode (UTCI) as at least three consecutive days with a mean UTCI above the local monthly 95 percentile; dry spells as mean of SPEI below –0.5. All measures are calculated using 1971–2000 as reference period. P-values: * < 0.1, ** < 0.05, *** <0.01.

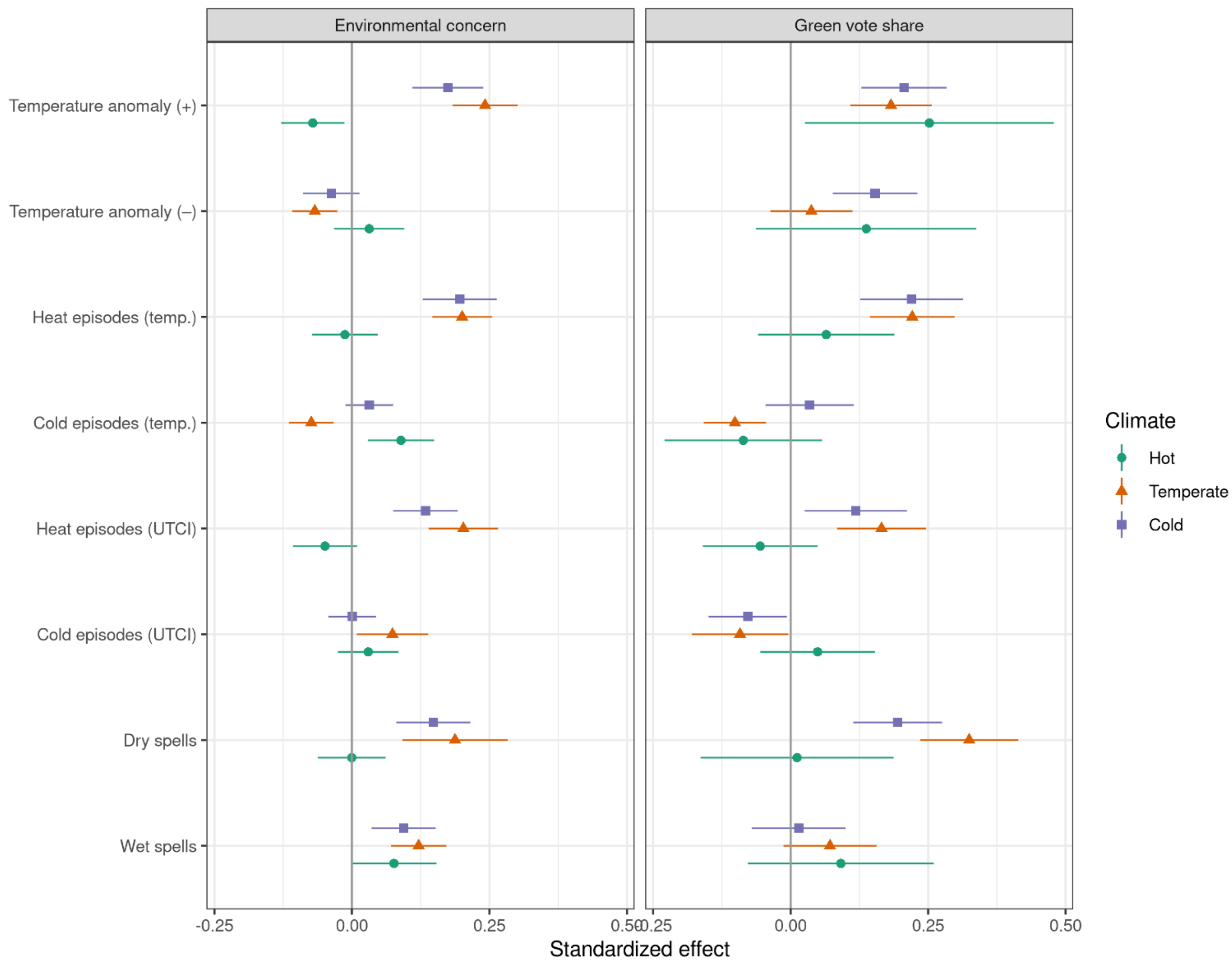


Figure S10 - Effects of heat and cold-related climate extremes on environmental concern and Green voting by climate zones. Coefficients are standardized using the observed variance of the variables in the given region after applying the fixed effects. Models include period-region effects to account for region-specific time trends. Lines around the point estimates show the 95% confidence intervals.

## Heterogeneity of climate impacts by GDP level

Table S18 shows the results of the second main heterogeneity analysis distinguishing climatic impacts by income. Here, we consider both the moderating effect of relatively stable differences in the income level between regions (between differences) and the effect of changes in income that co-occur with changes in the climatic conditions in a region (within changes). To assess the importance of between differences, we calculate the mean level of regional GDP per capita for the period 2000–2019. To capture within difference, we use information on the regional GDP over time (see Table S7). Focusing on the impact of temperature anomalies, we find consistent evidence that the effects of experiencing extremes on environmental concerns and the Green vote share increase in the average income level (m1–m6). These effects also remain consistent once further regional characteristics (m2 & m5) as well as the regional climate zones (m3 & m6) are controlled for. Also within climate zones, economic differences hence explain part of the observed climate effects.

Table S21 – Climatic impacts on concerns and voting by income levels and changes.

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | Environmental concern | | | Green vote share | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Temperature anomaly | 0.185*** | 0.181*** | 0.184*** | 0.133** | 0.138** | 0.095 |
| | (0.023) | (0.023) | (0.025) | (0.065) | (0.063) | (0.064) |
| Log GDP per capita (within) | 0.056*** | 0.060*** | 0.052*** | 0.047 | 0.063 | 0.057 |
| | (0.019) | (0.019) | (0.018) | (0.045) | (0.049) | (0.049) |
| Temp. × GDP (within) | -0.001 | -0.005 | -0.002 | -0.0002 | 0.0004 | -0.001 |
| | (0.011) | (0.011) | (0.011) | (0.018) | (0.017) | (0.018) |
| Temp. × GDP (between) | 0.156*** | 0.171*** | 0.121*** | 0.085*** | 0.124*** | 0.075** |
| | (0.023) | (0.026) | (0.017) | (0.029) | (0.032) | (0.031) |
| Temp. × urban region (between) | | -0.017 | | | 0.003 | |
| | | (0.015) | | | (0.016) | |
| Temp. × tert. edu. share (between) | | 0.004 | | | -0.077** | |
| | | (0.020) | | | (0.038) | |
| Temp. × Hot | | | -0.184*** | | | -0.049 |
| | | | (0.031) | | | (0.083) |
| Temp. × Temperate | | | 0.107 | | | 0.100 |
| | | | (0.071) | | | (0.066) |
| Unit fixed effects | × | × | × | × | × | × |
| Period fixed effects | × | × | × | × | × | × |
| Season fixed effects | × | × | × | | | |
| Spatial cutoff (km) | 500 | 500 | 500 | 500 | 500 | 500 |
| Temporal cutoff (years) | 1.5 | 1.5 | 1.5 | 5 | 5 | 5 |
| Observations | 10,263 | 10,155 | 10,263 | 4,923 | 4,923 | 4,923 |
| $R^2$ | 0.495 | 0.502 | 0.501 | 0.776 | 0.780 | 0.779 |

Note: Standardized regression coefficients with standard errors in parentheses. Standard errors were corrected for cross-sectional and serial correlation up to the indicated spatial and temporal cutoffs. All models control for regional and temporal fixed effects to account for unobserved heterogeneity and common time trends. Period fixed effects refer to three-year periods in models 1–4 and election year fixed effects in model 5–8. Coefficients are standardized using the residual variance after applying the fixed effects on both sides. Accordingly, the coefficients refer to a marginal effect of a one standard deviation change of the covariates on the outcome within regions and periods. agr. GVA share is the agricultural share in the regional gross value added. tert. edu. share is the share of the local population with tertiary education. P-values: * < 0.1, ** < 0.05, *** <0.01.

As indicator for environmental concerns, we use a share of the respondents in each region who consider environmental issues to be among the two most important issues facing their country at the time of survey. The answer categories to this question changed slightly over time. While until 2006 the questionnaires only listed an environment-related answer category i.e. "protecting the environment" (answer type 1), the list was extended by adding another category: "energy related issues" afterwards (answer type 2). From 2011 onwards, the two separate answer categories were merged into a new category called "the environment, climate and energy issues" (answer type 3). As our goal was to create a long, harmonized time-series for environmental concerns in Europe, we counted any responses referring to the environment as relevant irrespective of differences in the set of answer categories provided.

Table S19 tests to what extent measurement effects were relevant and whether the changes in answer categories in the Eurobarometer survey have affected the response behaviors. For this, we compare response behavior immediately before and after the changes in the answer categories to assess whether any discontinuities in response behavior were detectable. In models 1 and 3, we regressed the share of the concerned on a dummy indicating (i) whether respondents participated in the Eurobarometer in Fall 2005 or in Fall 2006 before and after the chang from answer type 1 to type 2 (m1) and (ii) whether they participated in the Eurobarometer in Spring 2010 or in Spring 2011 before and after the change from answer type 2 to type 3 (m3). Holding the season in the comparison constant allows us to implicitly control for seasonality effects. Models 2 and 4 use a wider time span of 2 years before and after the change in answer categories, from 1 to 2 and from 2 to 3, respectively to evaluate answer type effects, while controlling for year fixed effects. Both comparisons (immediately before-after and +/- 2 years) yield very similar results.

We find a minor significant change in response behaviors due to the transition from answer type 1 to answer type 2 (m1 & m2) and no significant change in responses due the transition from answer type 2 to answer type 3 (m3 & m4). According to model 1, the share of respondents concerned about the environment increased by 0.007215 (SE 0.003142) under answer type 2 compared to answer type 1 indicating no substantive change in response behavior, which would have challenged the validity of our results. To ensure that our results are not driven by measurement effects, we reran our main models restricting the analysis to the period during which only answer type 2 or 3 (2007 – 2019, Table S5) were available for which no significant differences in response behavior were documented, and (ii) to the longest period with a uniform concern measurement (2011–2019, Table S6). All our results remain fully robust to these sampling changes providing further support to our findings on the impacts of climate change experiences on concerns over time regardless of the changes in answer categories in the surveys.

Table S22 – Models testing for the impacts of changes in the concern measurement on response behavior

| | Dependent variable: | | | |
|---|---|---|---|---|
| | Environmental concern | | | |
| | At cutoff | +/-2 years | At cutoff | +/-2 years |
| | (1) | (2) | (3) | (4) |
| **Reference: answer type 1 (2002–2006)** | | | | |
| Answer type 2 (2006–2011) | 0.007215*<br>(0.003142) | 0.007583*<br>(0.003806) | | |
| **Reference: answer type 2 (2006–2011)** | | | | |
| Answer type 3 (2011–2019) | | | -0.002832<br>(0.002948) | 0.002666<br>(0.002523) |
| Unit fixed effects | × | × | × | × |
| Year fixed effects | | | × | × |
| Cluster | Unit of obser. | Unit of obser. | Unit of obser. | Unit of obser. |
| Observations | 743 | 2,303 | 505 | 1,970 |
| R2 | 0.50678 | 0.3905 | 0.81395 | 0.60447 |
| Within R2 | 0.00913 | 0.10096 | 0.00367 | 0.00459 |

Note: Regression coefficients with clustered standard errors in parentheses. Standard errors were clustered at the level of the unit of observation (NUTS). All models control for regional and temporal fixed effects to account for unobserved heterogeneity and common time trends. The main independent variables are dummies indicating different answer types used in the Eurobarometer surveys. Models at the cutoff (1 & 3) compare response behavior after the change in the answer categories with response behavior exactly one year prior to keep the season of the measurement constant. Answer type 1 refers to a single answer category "protecting the environment". Answer type 2 adds one additional answer category "energy-related issues". Answer type 3 refers to one combined answer category "the environment, climate and energy issues". Coefficients are non-standardized. P-values: * < 0.1, ** < 0.05, *** <0.01.

# D. Methods and Data

## Correction of standard errors

Standard errors across all models are corrected for serial and cross-sectional dependence which is assumed to decay linearly in time and space until a cutoff value is reached at which it vanishes (Conley, 1999). The choice of cutoffs is informed by tests for serial and cross-sectional correlation of the residuals, which are presented in the following.

Table S20 shows a test for serial correlation of the residuals where dt1 refers to the temporal distance between an observation and its first order lag in each time series, dt2 refers to the temporal distance to the second order lag, and so on. The interaction of the lagged residuals accounts for varying distances between observations in the environmental concern and voting datasets. This dynamic specification allows us to test up to which lag past concern and voting outcomes are related to the current outcomes to determine the temporal inter-dependence in the datasets. For the concern models, the cutoff of the temporal standard error correction is set to 18 months, which corresponds to dt3 in the models below (first non-significant lag). For the vote model, the cutoff is fixed at 5 years or one election cycle, reflecting that only one lag is significantly and sizably related with contemporary voting outcomes, which corresponds to the previous parliamentary election.

Table S23 – Tests for serial correlation of residuals (Columns correspond to Table 1)

| | *Dependent variable:* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Residual | | | | | | | |
| | Environmental concern | | | | Green vote share | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Residual (lag 1) | 0.950*** | 0.972*** | 0.973*** | 0.973*** | -0.323*** | -0.323*** | -0.327*** | -0.290*** |
| | (0.026) | (0.026) | (0.025) | (0.025) | (0.020) | (0.020) | (0.020) | (0.020) |
| Residual (lag 2) | -0.293*** | -0.282*** | -0.271*** | -0.253*** | 0.057*** | 0.060*** | 0.050** | 0.019 |
| | (0.039) | (0.039) | (0.039) | (0.039) | (0.021) | (0.021) | (0.021) | (0.021) |
| Residual (lag 3) | 0.013 | -0.010 | -0.020 | -0.010 | | | | |
| | (0.045) | (0.045) | (0.045) | (0.045) | | | | |
| Residual (lag 4) | -0.015 | -0.013 | -0.044 | -0.048 | | | | |
| | (0.043) | (0.043) | (0.043) | (0.042) | | | | |
| Residual (lag 1) × dt1 | -0.094*** | -0.099*** | -0.099*** | -0.098*** | | | | |
| | (0.005) | (0.005) | (0.005) | (0.005) | | | | |
| Residual (lag 2) × dt2 | 0.043*** | 0.042*** | 0.042*** | 0.038*** | | | | |
| | (0.004) | (0.004) | (0.004) | (0.004) | | | | |
| Residual (lag 3) × dt3 | 0.008** | 0.009*** | 0.010*** | 0.008*** | | | | |
| | (0.003) | (0.003) | (0.003) | (0.003) | | | | |
| Residual (lag 4) × dt4 | 0.002 | 0.001 | 0.003 | 0.003 | | | | |
| | (0.002) | (0.002) | (0.002) | (0.002) | | | | |
| Constant | 0.0004 | 0.0005 | 0.001 | 0.001 | -0.0003 | -0.0003 | -0.0004 | 0.00004 |
| | (0.0004) | (0.0004) | (0.0004) | (0.0004) | (0.001) | (0.001) | (0.001) | (0.001) |
| Observations | 9,227 | 9,227 | 9,227 | 9,227 | 3,208 | 3,208 | 3,208 | 3,208 |
| $R^2$ | 0.329 | 0.329 | 0.333 | 0.328 | 0.083 | 0.084 | 0.083 | 0.065 |

Note: The table shows residuals of the models estimated in Table 1 in the main text regressed on their temporal lags. dt1 refers to the temporal distance between an observation and its first order lag in each time series, dt2 refers to the temporal distance to the second order lag, and so on. The estimates inform the choice of cutoff values for the correction of the standard errors for serial correlation. P-values: * < 0.1, ** < 0.05, *** <0.01.

Table S21 summarizes tests for spatial correlation of the residuals. Moran's I is the correlation coefficient of observations with their spatial lags, given a specified dependence matrix. A positive (negative) test statistic indicates a positive (negative) spatial autocorrelation and a value near 0 no correlation. A Monte Carlo simulation bootstraps the residuals to obtain a sampling distribution based on the randomly assigned attributes. Based on this distribution, a pseudo p-value is computed as $(N_{greater}+1)/(N + 1)$ where N=1000 is number iterations and $N_{greater}$ is the number of simulated statistics greater than the actually observed one. Accordingly, the p-value can be interpreted as the probability of falsely rejecting the null hypothesis of a random spatial distribution.

The test is performed on each of the three cross-sections of environmental concern and green vote share. Not all cross-sections contain all regions since neither panel is balanced. The cross-sections are selected to be spread out over time and contain most regions. The matrices employed for the tests contain the row-normalized inverse distance between region centroids if the distance lies in the specified 500 km band for each test and 0 otherwise. Several bands are checked to determine the distance at which regions can plausibly be assumed to be independent of each other. We choose a cutoff value of 500 km for the correction of standard errors of both concerns and voting since the tests indicate a significant positive autocorrelation within the 0–500 km band. Beyond this value the test statistic is either close to 0 or null hypothesis is not rejected at high significance levels.

Table S24 - Permutation tests for Moran's I statistic of the residuals. The values are taken from Table 1 model 1 for environmental concern and Table1, model 5 for green voting.

| Dep. variable | Min. distance | Max. distance | Statistic | p | # regions | Month |
|---|---|---|---|---|---|---|
| Environmental concern | 0 | 500 | 0.261 | 0.001 | 228 | Oct 2004 |
| Environmental concern | 500 | 1000 | 0.048 | 0.001 | 228 | Oct 2004 |
| Environmental concern | 1000 | 1500 | -0.049 | 0.998 | 228 | Oct 2004 |
| Environmental concern | 0 | 500 | 0.014 | 0.165 | 247 | May 2011 |
| Environmental concern | 500 | 1000 | -0.001 | 0.394 | 247 | May 2011 |
| Environmental concern | 1000 | 1500 | -0.027 | 0.980 | 247 | May 2011 |
| Environmental concern | 0 | 500 | 0.227 | 0.001 | 254 | Mar 2018 |
| Environmental concern | 500 | 1000 | 0.005 | 0.193 | 254 | Mar 2018 |
| Environmental concern | 1000 | 1500 | -0.027 | 0.985 | 254 | Mar 2018 |
| Green vote share | 0 | 500 | 0.192 | 0.001 | 616 | June 2004 |
| Green vote share | 500 | 1000 | -0.038 | 0.999 | 616 | June 2004 |
| Green vote share | 1000 | 1500 | -0.065 | 0.999 | 616 | June 2004 |
| Green vote share | 0 | 500 | 0.474 | 0.001 | 977 | May 2014 |
| Green vote share | 500 | 1000 | -0.002 | 0.705 | 977 | May 2014 |
| Green vote share | 1000 | 1500 | -0.232 | 0.999 | 977 | May 2014 |
| Green vote share | 0 | 500 | 0.386 | 0.001 | 968 | May 2019 |
| Green vote share | 500 | 1000 | 0.006 | 0.002 | 968 | May 2019 |
| Green vote share | 1000 | 1500 | -0.220 | 0.999 | 968 | May 2019 |

## Overview of data availability across countries and over time

Table S22 and Table S23 provide further summary statistics for the aggregated concern and voting datasets. In particular, they contain information about the availability of data across countries in Europe and over time. N shows the number of observations - either region-month (concern) or region-year (voting) - available for each country. The variable NUTS level specifies the extent of disaggregation of the data. Depending on country, the concern and voting data are available at NUTS 1, NUTS 2, or NUTS 3 level. Over time, the NUTS level remains the same or was harmonized by us, to allow for within-regional analyses in our longitudinal analyses.

In the last three columns, the tables provide additional information about the number of NUTS regions for which information is available in the data, the year when the first concern or voting data is available for each country, and the length of the considered time series in terms of different points of data collection over time. For example, for Bulgaria concern data are available since 2004 and was collected in 37 Eurobarometer waves. Voting data for the country is available since 2007 for 4 different elections, which represent the data points over time considered in our analysis.

Table S25 – Data summary for the concern dataset

| Country | N | Region | # NUTS | # cold NUTS | # temperate NUTS | # hot NUTS | NUTS level | Series start | # Eurobarometer |
|---|---|---|---|---|---|---|---|---|---|
| Albania | 108 | East | 12 | 3 | 2 | 7 | 3 | 2014 | 9.0 |
| Bulgaria | 222 | East | 6 | 4 | 2 | 0 | 2 | 2004 | 37.0 |
| Czechia | 319 | East | 8 | 8 | 0 | 0 | 2 | 2004 | 40.0 |
| Estonia | 44 | East | 1 | 1 | 0 | 0 | 2 | 2004 | 44.0 |
| Hungary | 313 | East | 8 | 8 | 0 | 0 | 2 | 2004 | 39.0 |
| Latvia | 245 | East | 6 | 6 | 0 | 0 | 3 | 2004 | 41.0 |
| Lithuania | 386 | East | 10 | 10 | 0 | 0 | 3 | 2004 | 38.0 |
| Montenegro | 16 | East | 1 | 1 | 0 | 0 | 2 | 2011 | 16.0 |
| North Macedonia | 104 | East | 8 | 6 | 0 | 2 | 3 | 2010 | 13.0 |
| Poland | 641 | East | 17 | 17 | 0 | 0 | 2 | 2004 | 37.0 |
| Romania | 234 | East | 8 | 7 | 0 | 1 | 2 | 2002 | 21.0 |
| Slovakia | 152 | East | 4 | 4 | 0 | 0 | 2 | 2004 | 38.0 |
| Slovenia | 477 | East | 12 | 11 | 1 | 0 | 3 | 2004 | 40.0 |
| Turkey | 825 | East | 26 | 7 | 1 | 18 | 2 | 2004 | 31.5 |
| Finland | 206 | North | 4 | 4 | 0 | 0 | 2 | 2002 | 51.5 |
| Sweden | 395 | North | 8 | 8 | 0 | 0 | 2 | 2002 | 51.0 |
| United Kingdom | 582 | North | 12 | 0 | 12 | 0 | 1 | 2002 | 48.0 |
| Cyprus | 43 | South | 1 | 0 | 0 | 1 | 2 | 2004 | 43.0 |
| Greece | 429 | South | 10 | 0 | 0 | 10 | 2 | 2002 | 44.0 |
| Italy | 241 | South | 5 | 0 | 2 | 3 | 1 | 2002 | 48.0 |
| Malta | 21 | South | 1 | 0 | 0 | 1 | 2 | 2010 | 21.0 |
| Portugal | 210 | South | 5 | 0 | 0 | 5 | 2 | 2002 | 43.0 |
| Spain | 703 | South | 16 | 0 | 6 | 10 | 2 | 2002 | 45.5 |
| Austria | 424 | West | 9 | 9 | 0 | 0 | 2 | 2002 | 47.0 |
| Belgium | 537 | West | 11 | 0 | 11 | 0 | 2 | 2002 | 49.0 |
| France | 958 | West | 21 | 0 | 19 | 2 | 2 | 2002 | 46.0 |
| Germany | 771 | West | 16 | 9 | 7 | 0 | 1 | 2002 | 49.0 |
| Luxembourg | 53 | West | 1 | 0 | 1 | 0 | 2 | 2002 | 53.0 |
| Netherlands | 604 | West | 12 | 0 | 12 | 0 | 2 | 2002 | 51.0 |

Table S26 - Data summary for the voting dataset

| Country | N | Region | # NUTS | # cold NUTS | # temperate NUTS | # hot NUTS | NUTS level | Series start | # Elections |
|---|---|---|---|---|---|---|---|---|---|
| Bulgaria | 112 | East | 28 | 19 | 6 | 3 | 3 | 2007 | 4.0 |
| Croatia | 42 | East | 21 | 12 | 5 | 4 | 3 | 2014 | 2.0 |
| Czechia | 56 | East | 14 | 14 | 0 | 0 | 3 | 2004 | 4.0 |
| Estonia | 15 | East | 5 | 5 | 0 | 0 | 3 | 2004 | 3.0 |
| Hungary | 80 | East | 20 | 20 | 0 | 0 | 3 | 2004 | 4.0 |
| Latvia | 17 | East | 6 | 6 | 0 | 0 | 3 | 2009 | 3.0 |
| Lithuania | 40 | East | 10 | 10 | 0 | 0 | 3 | 2004 | 4.0 |
| Poland | 146 | East | 73 | 73 | 0 | 0 | 3 | 2014 | 2.0 |
| Romania | 168 | East | 42 | 36 | 0 | 6 | 3 | 2007 | 4.0 |
| Slovakia | 32 | East | 8 | 8 | 0 | 0 | 3 | 2004 | 4.0 |
| Slovenia | 24 | East | 12 | 11 | 1 | 0 | 3 | 2014 | 2.0 |
| Denmark | 77 | North | 27 | 16 | 11 | 0 | 2 | 1994 | 3.0 |
| Finland | 113 | North | 19 | 19 | 0 | 0 | 3 | 1996 | 6.0 |
| Ireland | 4 | North | 1 | 0 | 1 | 0 | 1 | 1994 | 4.0 |
| Sweden | 105 | North | 21 | 21 | 0 | 0 | 3 | 1999 | 5.0 |
| United Kingdom | 485 | North | 163 | 0 | 163 | 0 | 2 | 2009 | 3.0 |
| Greece | 184 | South | 46 | 2 | 0 | 44 | 2 | 1994 | 4.0 |
| Italy | 540 | South | 90 | 6 | 37 | 47 | 2 | 1994 | 6.0 |
| Spain | 280 | South | 50 | 0 | 13 | 37 | 3 | 1994 | 6.0 |
| Austria | 210 | West | 35 | 35 | 0 | 0 | 3 | 1996 | 6.0 |
| Belgium | 66 | West | 11 | 0 | 11 | 0 | 2 | 1994 | 6.0 |
| France | 565 | West | 96 | 5 | 81 | 10 | 3 | 1994 | 6.0 |
| Germany | 2112 | West | 401 | 220 | 181 | 0 | 3 | 1994 | 6.0 |
| Netherlands | 238 | West | 40 | 0 | 40 | 0 | 3 | 1994 | 6.0 |

## Climate classification

Regions are classified into three climatic zones using the Köppen-Geiger climate typology. The classification defines five climate types, divided into 30 sub-types, on the basis of seasonality of precipitation and temperature and the levels of these two key variables. Data comes from the 0.0083° grid (circa 1 km² cells at the equator) provided by (Beck et al., 2018).

As shown in Figure S5 Panel a, Europe exhibits broadly three climates. Hot, arid regions are located mostly around the Mediterranean Sea which is characterized by high temperatures and dry summers (Bwh, Bwk, Bsh, Bsk, Csa, Csb). Temperate climate is found mostly in Western Europe with moderate temperatures and relatively high precipitation levels (Cfa, Cfb, Cfc). Central Europe, the regions around the Baltic Sea, and the polar regions exhibit a colder climate with relatively low temperatures and mostly no dry season (Dsa, Dsb, Dsc, Dfa, Dfb, Dfc, ET, EF). We calculate the fraction of each region's area that is characterized by each of the 30 sub-types. The sub-types are then grouped in the three broad categories outlined above. The regions are assigned the type that covers the largest fraction.

### Regional background characteristics

The variables that capture regional characteristics are compiled from different sources. The economic measures real gross domestic product (GDP), real gross value added (GVA), sectoral employment, active and total population come from the Annual Regional Database of the European Commission (European Commission 2020). The regional unemployment rate is calculated as 1 – (employed persons / active population). Since the employment is higher than residency in some urban centers the value is negative for a few regions. Since such characteristics are relatively time-invariant and we employ unit fixed effects in all model this, however, does not affect our results. GDP is at 2015 prices and adjusted for differences in purchasing power between countries. The agricultural share in GVA refers to the GVA by NACE code A activities over total GVA.

Measures of education and urbanity are based on Eurostat data. The population share with tertiary education measures the share of population aged 25–64 that has attained an education corresponding to ISCED codes 5-8 (edat_lfs_9918). An urban region is defined based on the Degree of Urbanization methodology of (Eurostat, 2018) which classifies NUTS 3 regions as urban, intermediate, or rural. Regions on lower level than 3 are classified as urban if at least half the population lives in urban level 3 regions.

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