Personal Experience and Self-Interest: Diverging Responses to Global Warming*

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Abstract

How does experiencing climate change affect political beliefs? There is mixed evidence of attitude change, but previous studies have not accounted for how some citizens are more vulnerable to global warming than others. We argue that personal experience is more likely to lead to policy preference change when it is in an individual's self-interest because of one's vulnerability to future climate impacts. We test our argument using economic models of global warming, geospatial data on climate shocks, and rich survey data both across countries and over time with the same individuals. Experiencing climate change heightens risk perceptions and leads to greater support for mitigation only among individuals in locations facing future damages. The effect of experience is strongest among citizens in democratic countries. Incorporating political economy and behavioral theories helps to explain changing policy preferences.

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Leaders have few incentives to fight climate change if citizens do not prioritize the issue. When asked about costly climate policies, publics worldwide express tepid support (Bechtel and Scheve 2013; Dechezleprêtre et al. 2022), which may be one reason why governments have been slow to address global warming. However, a prominent view is that as people experience climate change, the threat will become more concrete, and people will demand their leaders act (Weber 2006; Leiserowitz 2006). How does personal experience with climate change affect the public's concern about the issue and support for government policies to mitigate emissions?

Some scholars find that experience with extreme heat and disasters cause a modest increase in public concern about global warming (Bergquist and Warshaw 2019; Konisky, Hughes, and Kaylor 2016; Egan and Mullin 2012; Arias and Blair 2024), which may also influence voting (Hazlett and Mildenberger 2020; Hoffmann et al. 2022; Baccini and Leemann 2021; Garside and Zhai 2022), trust in institutions (Balcazar and Kennard 2023), and elite behavior (Clark and Zucker 2023). However, others find little relationship between experience and attitudes or voting for green parties (Bechtel and Mannino 2023; Hilbig and Riaz 2023), as summarized in an influential review of 73 papers (Howe et al. 2019).

We argue that one reason for these mixed findings is that previous studies have not accounted for the unequal effects of global warming. Some locations face intense damages in the future, while others are relatively less exposed (Burke, Hsiang, and Miguel 2015; Hsiang et al. 2017; Cruz and Rossi-Hansberg 2023). Building on previous work about vulnerability and policy preferences (Gaikwad, Genovese, and Tingley 2022), we argue that this variation in future climate damages implies that citizens will value mitigation policy differently depending on where they live.

Our focus on the geographically heterogeneous effects of climate change suggests a new hypothesis about the relationship between climate experiences and political attitudes. Rather than a universal effect of experience, we predict a conditional relationship. Citizens in places facing more damage from future climate change should be more likely to respond to personal experience by becoming more concerned and supportive of mitigation, whereas those residing in locations less vulnerable should exhibit limited, if any, attitude change.

We test our argument using high-resolution spatial data on climate change experience, geolocated surveys of individuals, and economic models of how global warming will affect local income around the world. Our first analysis examines whether climate change experience heightens the salience of the issue for people in locations facing future damages. Departing from the predominant focus on the United States, we examine climate attitudes in 124 countries. We deploy existing nationally representative surveys and construct a new crosswalk mapping 135,716 respondents to 2,255 sub-regions. This allows us to pair respondents with data on exposure to long-run changes in temperature variability, a highly comparable measure of climate experience across countries.

A challenge is that factors like income, partisanship, or education might influence exposure to temperature variability and climate attitudes, which could confound our inferences. We approach this problem with covariate balancing propensity scores which weight respondents so their exposure to temperature variability and climate damages is plausibly exogenous (Imai and Ratkovic 2014). We also estimate covariate-adjusted models and doubly robust models with both covariates and weights. Lastly, we conduct sensitivity analyses that suggest extreme levels of confounding would be unlikely to alter our findings (Cinelli and Hazlett 2020).

In general, when asked in an open-ended question, only three percent of people identify global warming as a top risk to their daily life. We find that a standard deviation in long-run temperature variability causes a one percentage point increase in climate risk perceptions. Consistent with our argument, this modest effect only occurs among those who live in a location facing potential climate damage. This relationship is strongest in democracies, which suggests that the freedom of the media may be one mechanism that translates experience into political attitudes (Mutz 1994). Placebo tests indicate that temperature variability only increases concern about climate change but not non-climate issues, which provides evidence consistent with our interpretation of experience providing climate-related information.

Our next analysis focuses on support for government mitigation. We employ a difference-in-differences research design with an existing three-wave panel of American adults in 2010, 2012, and 2014 to explore how policy preferences change over time. We pair survey responses with county-level measures of climate damages and benefits. Here we are able to use comprehensive administrative data on disaster declarations for wildfires, which represent a high-impact climate shock.

Our research design assumes that individuals exposed to wildfires would have exhibited the same average trajectory of climate policy preferences as people in the control group. To enhance the plausibility of this parallel trends assumption, we control for time-varying covariates like partisanship, ideology, and income. We also employ panel matching methods based on covariates that could predict exposure to wildfires (Imai, Kim, and Wang 2023). Placebo tests do not detect evidence of differential pre-trends.

We find that wildfire experience causes a three percentage point increase in climate policy support. This effect lasts for up to two years after the experience, which is longer than previous studies where effects dissipate in as little as 12 days (Egan and Mullin 2012). As hypothesized, people only respond to disaster experience if they live in a county facing future income losses from global warming. Notably, individuals with the strongest prior skepticism about climate change are the least likely to update. In contrast, those undecided about the need for climate action exhibit the most positive updating in response to wildfires.

Our paper brings together political economy and behavioral approaches to better understand how policy attitudes change. In contrast to studies that find a minimal impact of information on behavior (e.g., Achen and Bartels 2016), we show that making such an evaluation requires careful specification of how individuals should respond to experiences that provide information (see also Ashworth, Bueno de Mesquita, and Friedenberg 2018; Balcazar and Kennard 2023). When using an economic model of global warming's effects, people respond in predictable ways based on their self-interest.

We also make empirical and theoretical contributions to climate politics research. Empirically, we test prominent hypotheses about the effect of climate experience using a wealth of subregional and panel data, whereas previous studies have largely focused on the United States or relied on cross-sectional surveys. Theoretically, we reconcile mixed findings about the effects of personal experience on political attitudes. By constructing a benchmark of individuals' preferences if they were fully informed and acting according to self-interest, we can advance and test more precise predictions about how the public will respond to the climate crisis.

Do Climate Experiences Affect Political Attitudes?

We focus on the public's attitudes because they shape the incentives of leaders to pass policies. There is often congruence between citizens' preferences and policies, especially for salient issues (Page and Shapiro 1983; Lax and Phillips 2009). Citizens are less likely to support lawmakers who cast votes that do not align with their preferences (Ansolabehere and Kuriwaki 2022), and out-of-step politicians are more likely to lose reelection (Canes-Wrone, Brady, and Cogan 2002). In the climate context, there is a relationship between public support for mitigation and a country's climate policies (Schaffer, Oehl, and Bernauer 2022; Anderson, Böhmelt, and Ward 2017).

Scholars have sought to understand the factors that shape climate attitudes, paying particular attention to direct experience with climate change (Egan and Mullin 2017). The idea that personal experience could lead to greater concern about climate change has a foundation in psychology. Dual-process theories of reasoning contend that information from experience exerts greater sway compared to analytical information because the former is more vivid and accessible (Evans 2008). Applied to climate change, this theory suggests that people begin with a view of global warming as an abstract, distant phenomenon, but climate experiences render it more concrete and proximate, thereby changing beliefs, preferences, and behavior (Weber 2006, 2010; Marx et al. 2007; van der Linden 2015).

Numerous studies have examined the relationship between personal experience and climate attitudes, but the results are mixed. Recent assessments of this literature are instructive. Two reviews and meta-analyses conclude that there is a small, positive effect of personal experience on belief in climate change (Egan and Mullin 2017; Borick and Rabe 2017; Bergquist et al. 2022; Sugerman, Li, and Johnson 2021; Hornsey et al. 2016). Whereas a recent evaluation of 73 studies on the relationship between climate experiences and public attitudes turned up mixed evidence with comparisons complicated by differences in treatments, outcomes, populations, and research designs (Howe et al. 2019).

One explanation for these conflicting findings is that individuals have strong prior beliefs that make them less likely to change their attitudes in response to climate experiences (Weber 2013; Myers et al. 2013). Even with direct experience, people may interpret the same event using different lenses (Druckman and McGrath 2019). If citizens do not attribute a particular event to climate change, possibly because of their biases about global warming's existence, personal experience would be unlikely to change their level of concern and support for mitigation (Ogunbode et al. 2019; Boudet et al. 2020).

Partisanship is a commonly cited example of motivated reasoning that could inhibit attitude change after climate experiences. Republicans tend to be less likely than Democrats to believe in human-caused global warming, and consequently, Republicans are less likely to attribute disasters to climate change and alter their behavior in response (Hazlett and Mildenberger 2020; Borick and Rabe 2014; Marquart-Pyatt et al. 2014; Bohr 2017). Republican politicians may also hesitate to attribute disasters to climate change, so their constituents do not receive messages that could alter their views (Hai and Perlman 2022).

However, strong prior beliefs are only a partial explanation for why a subset of individuals would not update in response to climate experiences. There should still be a positive effect on average unless the entire population holds strong pre-existing views on climate change. Further, the evidence is not conclusive; some find that Republicans and conservative respondents respond equally and even more strongly to climate experiences (Deryugina 2013; Egan and Mullin 2012; Arias and Blair 2024).

The focus on motivated reasoning is also an artifact of the almost exclusive study of the American public (Howe et al. 2019). Results from high-income Western nations may not generalize to other contexts with less polarization, lower awareness of climate change, or higher levels of climate change vulnerability. Indeed, cross-national surveys suggest that personal experience is a better predictor of climate beliefs in developing countries (Lee et al. 2015). For this reason, our paper examines attitudes across diverse countries.

Integrating Political Economy with Behavioral Theories

We provide a new explanation for mixed findings regarding climate experiences and attitudes. Citizens differ in how intensely they will be materially affected by global warming in the future, so it follows that climate experiences should have differential effects depending on one's future exposure. Previous studies have lacked a model of how people in different locations will be affected by future global warming, so it was not appropriate to infer that climate beliefs would change after experiencing global warming.

It is well-established that global warming has heterogeneous economic effects across space. One model shows that parts of Africa and Latin America face welfare losses as large as 15% compared to a world without climate change, whereas northern regions, including Siberia, Canada, and Alaska, may experience gains as high as 11% (Cruz and Rossi-Hansberg 2023). This inequality vulnerability has created friction at international climate negotiations (Genovese 2020). Within large countries like the US, there is also considerable variation. One model found median losses from climate change exceeded 20% of gross county product in some localities, whereas in others, median gains sometimes exceeded 10% (Hsiang et al. 2017). Much of this variation stems from geographic features such as proximity to coasts, latitude, and elevation. Places that are presently warm will suffer the most from higher temperatures, whereas currently cool locations have more room to adjust (Carleton et al. 2022). While there is heterogeneity in global warming's economic effects across and within countries, for the entire world, the consequences are decisively negative.

There is evidence that people understand how locations differ in their exposure to climate change. People who live closer to coastal regions susceptible to sea level rise are more likely than those in inland regions to be concerned about climate change, believe they will be personally affected, and support climate policy (Reny, Reeves, and Christenson 2022; Hopkins 2018; Brody et al. 2008; Milfont et al. 2014; Gaikwad, Genovese, and Tingley 2022). Looking across countries, people in developing countries vulnerable to climate change are more likely to think that climate change is happening and causing them harm compared to people in less vulnerable countries (Dechezleprêtre et al. 2022; Dabla-Norris et al. 2023; Kim and Wolinsky-Nahmias 2014).

We also conducted a survey in the United States to see if people's perceptions of climate vulnerability correspond with economic predictions about global warming's effects. We find that people living in areas facing future climate damages are more likely to believe their location is vulnerable, even when controlling for predictors of climate attitudes such as partisanship (Appendix A).

Building on these studies and microfoundations, we argue that geographic variation in how an individual's location will be affected by future global warming moderates the effects of personal experience on climate attitudes. Consistent with existing theory, personal experience with climate-related events should lead people to view global warming as more temporally proximate (Weber 2006).

Our innovation is to argue that the consequences of experience vary. For people in places exposed to future climate impacts, learning that global warming is increasingly a present threat should make them more concerned and supportive of actions to solve the problem. For people in places less vulnerable, and possible beneficiaries in the extreme, their updated assessment of global warming's temporal proximity should not elicit the same concern. They may even dismiss their experience with climate change as anomalous because it is unusual for their location.

> **Hypothesis 1**: Individuals in areas with greater vulnerability to future climate change damages should be more likely to respond to climate-related experiences by becoming (a) more concerned about global warming and (b) more supportive of government policies to reduce emissions.

One mechanism behind our hypothesized conditional attitude change is self-interest. In contexts where there are unambiguous costs, self-interest is influential in shaping people's policy preferences (Citrin and Green 1990). Experiments show that citizens, including those with strong prior beliefs, update their attitudes in response to new information when there is money at stake (Hill 2017). For global warming, there are material costs for holding incorrect beliefs in the long run.

Still, prior beliefs will affect how people update in the short run. Belief change should resemble a Bayesian model of learning, where the effect of an experience on one's new beliefs will depend on prior beliefs weighted by the probability of experiencing an event given one's expectations.

> **Hypothesis 2**: Individuals with weaker prior beliefs living in areas with greater vulnerability to future climate change damages should be more likely to respond to climate-related experiences by becoming more concerned about global warming and supportive of government policies to mitigate emissions.

Mobility will also matter for how citizens respond to climate shocks in the long-run. If citizens have the ability to exit a vulnerable location, they may not demand their leaders act on climate change (e.g., Hirschman 1970). Given the costs of migration and the delimited time period of our study, mobility should be less influential and would attenuate the relationship between experience and policy preferences. The analyses also control for factors that influence mobility, such as income, homeownership, and children.

Our argument contrasts with a stream of scholarship that is skeptical of the capacity of citizens to incorporate information from experience.[1] Achen and Bartels (2016) exemplify

1. See Healy and Malhotra (2013) for a review.

this position with their contention that the electorate behaves unpredictably, erroneously blaming incumbents for events outside of their control like shark attacks.[2] This perspective would suggest that the public would blindly punish the incumbent in response to disasters rather than change their policy attitudes in a coherent fashion.

We disagree with this pessimistic assessment of citizens. As Ashworth, Bueno de Mesquita, and Friedenberg (2018) argue, it sometimes can be rational for voters to respond to these events because they provide new information about the incumbent's ability. While we do not study incumbent performance, this point is relevant in shifting the attention to the information encoded in shocks like disasters.

A contribution of our paper is to show that it is rational for voters to respond differently to the same event based on how they are materially affected. It is not sufficient for scholars to study the political consequences of events without having a model of the policy preferences of voters. Political economy models allow us to predict *how* voters respond to new information based on their self-interest, while behavioral theories explain *why* personal experience strongly influences attitude change.

Study 1: Risk Perceptions

We begin by testing the first part of hypothesis 1, the conditional effect of climate experiences on individual risk perceptions. We predict that individuals who are more vulnerable to climate change and have experienced climate-related events should be more likely to see global warming as a threat. By contrast, people who are less vulnerable to global warming in the future should not exhibit heightened risk perceptions when they experience climate events.

Studying this question requires surveys that measure individual risk perceptions with geolocated identifiers to map respondents to climate-related events and measures of their future exposure to global warming. Most surveys examine only a single country, which limits

2. But see Fowler and Hall (2018), who challenge their empirical approach.

one's ability to study the full range of global warming's unequal economic effects. While some countries exhibit substantial subnational heterogeneity in future climate exposure, the distributive consequences are starkest across the globe, with countries in the global South facing the worst impacts.

We leverage unusually large and spatially disaggregated samples of 135,716 people across 124 countries and territories. These data capture both heterogeneity in future exposure to global warming and individual experience with climate-related events. Gallup and Loyd's Register Foundation conducted these surveys as part of the 2019 World Risk Poll.[3] These are probability-based, nationally representative samples of approximately 1,000 respondents in each country.[4] The questions underwent piloting and multiple rounds of review. The questionnaire was translated into the major conversational languages of each country. Teams of trained enumerators administered the survey face-to-face and over the phone.

To better capture personal experience with climate change, we extend these data by constructing a new crosswalk mapping respondents to 2,255 administrative regions within each country at the lowest level of aggregation possible. These subregions are a mix of administrative level 1 boundaries, which are states and prefectures; administrative level 2, which are counties and districts; and cities in some cases. We invested considerable resources to build this crosswalk because the subregion names are not standardized nor readily connected to shapefiles (Appendix B.2).

Figure 1 provides examples of the granularity of these subregions. They represent a remarkable improvement over analyses focused on the country level. The median subregion size is 7,413 km^2, slightly larger than the US state of Delaware. In larger subregions, there will be greater measurement error. Absent individual-level coordinates, subregions are the best approach to capture climate experience.

The primary limitation of these survey data is that they capture a single moment in time. The ideal way to estimate the effects of climate change experience on attitudes would

3. We use surveys from countries for which there is climate damage data.
4. The sample size is higher for China, India, and Russia, and lower for Jamaica.

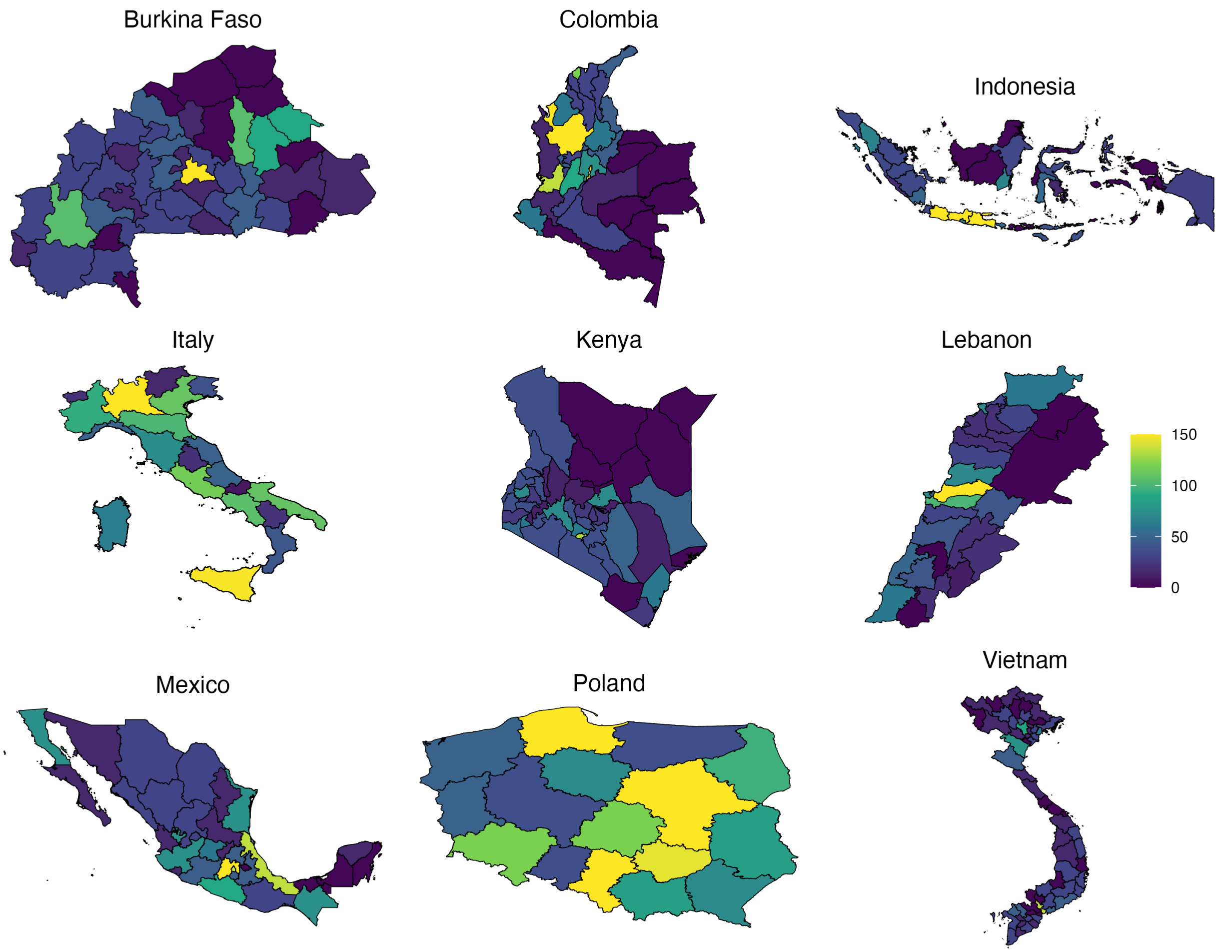

Figure 1: Subregion Examples and Corresponding Sample Size

Notes: To show multiple countries, the geographic area is not equal across plots (e.g., Indonesia is much larger than Poland in reality).

be with panel data with repeated observations of the same person, which we analyze in the second study. Still, this analysis is suggestive of the influence of long-term exposure to climate change on risk perceptions.

Measurement

Climate Risk Perceptions

The outcome is the extent to which individuals believe that global warming presents a danger in their everyday lives. Risk perceptions matter because they motivate individuals to support government policies to address climate change (O'Connor, Bard, and Fisher 1999; Drews and van den Bergh 2016; Bergquist et al. 2022). These perceptions are distinct from the belief that a location is vulnerable to climate change in the future, which might not be enough to make someone worried about global warming, given its long-term nature. The idea of risk perceptions contains within it the belief that global warming is a relevant threat in the here and now.

One challenge in measuring climate risk perceptions is social desirability bias. Questions that ask people for their stated level of concern about global warming often suggest vastly higher levels of worry, which vanishes once respondents consider the costs of climate policy (Bechtel and Scheve 2013).

To avoid this problem, we measure risk perceptions with open-ended questions: "In your own words, what is the greatest source of risk to your safety in your daily life?" After this question, respondents are asked, "Other than what you just mentioned, in your own words, what is another major source of risk to your safety in your daily life?" This question avoids priming and allows for a more accurate assessment of whether individuals perceive climate change as a risk. Indeed, most answers do not mention climate change but instead mention crime, car accidents, and health.

We construct an indicator that takes the value 1 if a respondent identifies climate change as a top or major risk, and 0 if not.[5] For robustness, we also examine results when using an indicator for if the respondent says climate change is only their top risk, which is more restrictive than including major risks.

Future Climate Change Exposure

Our measurement strategy for future climate change exposure focuses on economic damages because they affect people's pocketbooks. There are two challenges to adequately measuring the economic effects of global warming. First, one needs to have a micro-founded model of

5. The World Risk Poll maps these answers to categories including "Climate change, natural disasters or weather-related events (such as floods, drought, wildfires, etc.)."

how the world economy evolves that incorporates endogenous adaptation to climate change. If one were to try to measure future exposure by looking at flood plains, for example, this would not be informative about future economic damage because it does not account for how people can move, or firms reallocate their investment elsewhere. Second, the measure must be spatially resolved and comparable, so we can map the estimates to sub-regions worldwide.

To measure future climate change exposure, we use a spatial integrated economic assessment model of global warming's economic effects (Cruz and Rossi-Hansberg 2023). This model captures how the world economy evolves and incorporates damage functions that account for how local temperature changes impact fundamental productivities and amenities through trade, migration, and innovation. The model builds upon the established spatial growth framework, which has been validated with backcasting exercises and successfully applied to assess sectoral responses to global warming and the effects of sea level rise (Desmet et al. 2021; Conte et al. 2021; Desmet, Nagy, and Rossi-Hansberg 2018). The model accounts for damage from long-run temperature changes, which is a substantial means by which global warming will affect economic growth via heat's effects on mortality, human physiology, violence, productivity, crop yields, energy demand, and population movements (Carleton and Hsiang 2016). The estimates are at the $1° \times 1°$ longitude-latitude resolution, which we aggregate to the sub-region level by averaging across grids.

For the moderator, we construct an indicator of whether a subregion faces potential damages from global warming in the year 2050. The moderator is dichotomous since there is considerable uncertainty about global warming's effects, which reduces the substantive meaning of point estimates. Rather than create a false sense of certainty, an indicator is more realistic by recording whether a sub-region is on the damages or benefits side of the distribution. The results are robust to using a continuous moderator (Appendix B.7.4).

Figure 2 shows the global distribution of damages and losses from higher temperatures. These estimates are overlaid on a map that indicates if countries are in the survey sample (no shading) or not (grey shading). The map shows that by 2050, some subregions face

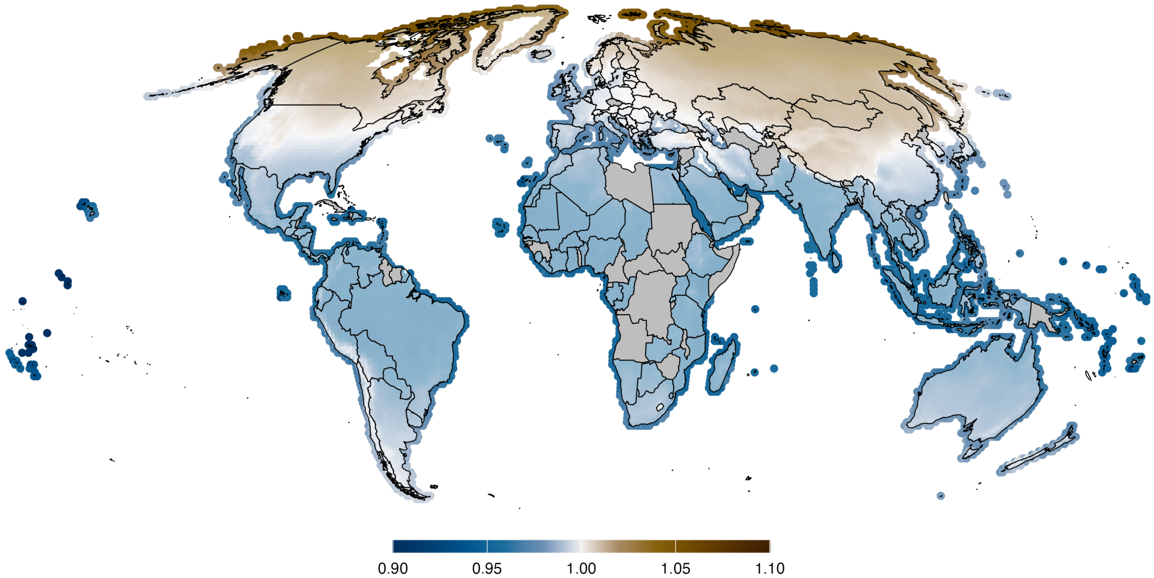

Figure 2: Effect of Global Warming on GDP in Surveyed Countries

Notes: Map depicts the ratio of 2050 GDP in a world of global warming damages to a counterfactual in which temperature has no effect. Values less than 1 denote losses. Our study includes survey data on all countries except those shaded grey. While the analysis uses subregional data, the plot depicts national borders for exposition.

economic losses amounting to about 3% of GDP, while other areas could see benefits of about 2%. If we looked further into the future, these damages would be even larger but strongly correlated because temporally invariant geographic factors largely determine the economic effects of climate change. Overall, the map shows substantial variation across space in future exposure, which is what we are trying to capture.

A limitation is that economic models cannot include all damages, such as cultural losses. Still, we expect economic and non-economic damages to be positively correlated. To the extent that our measure does not incorporate non-economic damages, it would introduce bias against our hypotheses because there would be people in locations (incorrectly) coded as less vulnerable who respond to experiences because they (actually) anticipate losses.

Climate-Related Experience

The coverage of countries and the cross-sectional nature of the data introduce challenges to measuring climate-related experience. The ideal measure needs to be comparable across countries. It also needs to be objective. Self-reported data about experience are biased by people's pre-existing belief in and awareness of global warming (Howe and Leiserowitz 2013).

We measure climate-related experiences in this analysis with temperature data. As discussed above, temperature represents a significant way climate change will affect economic growth (Carleton and Hsiang 2016). There also exist standardized measures across countries that are granular enough to be mapped to the sub-region level. Temperature is also objective, unlike self-reported experience.

A drawback is that temperature in the short-run is potentially a low-quality source of information about climate change (Weber 2010). On any given day, the temperature can fluctuate due to natural variability that might be correlated with a long-run trend but is not dispositive of global warming. Natural disasters which we examine in the subsequent analysis, by contrast, could send a more powerful signal, but these data are not available with regular geo-coordinates around the world.

Instead of short-term variation, we use long-term changes in temperature variability as our treatment. These long-term changes track more closely with actual changes in the climate. This means that our treatment is more likely to capture climate change experience instead of a mechanical relationship between momentary increases in heat on the day of the survey and recall about global warming. In support of this approach, other studies about what events people attribute to climate change show that long-term temperature variability is more influential than short-term variations (Deryugina 2013).

We operationalize our measure by calculating the difference between temperature variability across months in 2018, the year before the survey was fielded, and the average long-run monthly temperature variability.[6] Data come from the Global Historical Climatology Network's Climate Anomaly Monitoring System, which measures monthly global land surface temperature with weather station observations interpolated across space using validated methods (Fan and van den Dool 2008). The data are at the $0.5° \times 0.5°$ resolution, which

6. The benchmark period is 1980-2000 since the median respondent was born around 1980. Results are robust to using an alternative benchmark (Table B7).

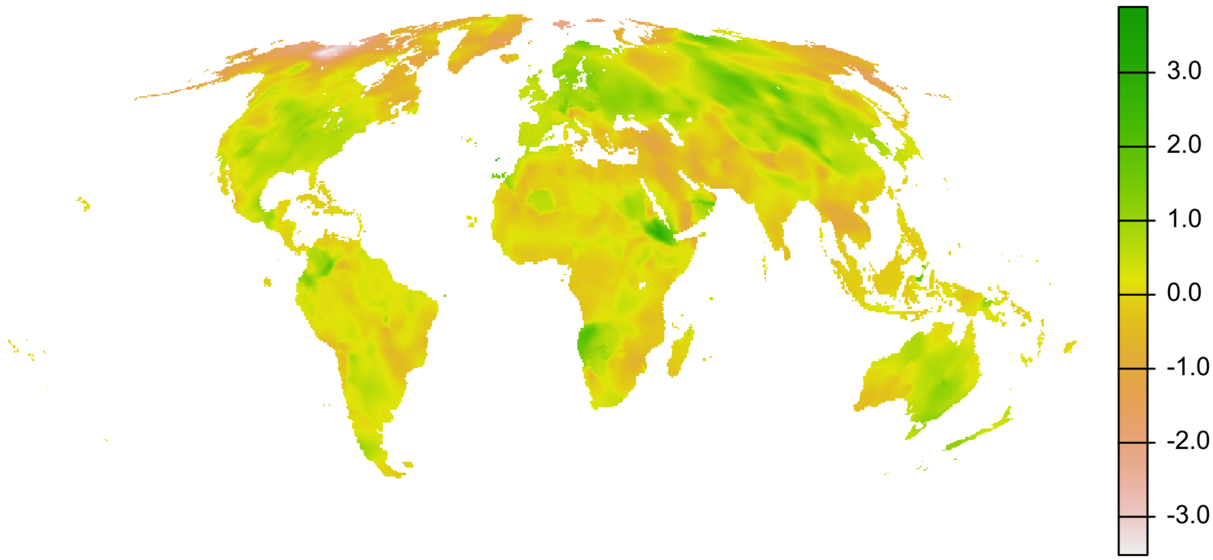

Figure 3: Long-Run Changes in Temperature Variability

Notes: Change in average monthly temperature variability at the $0.5° \times 0.5°$ grid cell level relative to the average level of monthly temperature variability from 1980–2000.

we aggregate by calculating the average of all raster values that are covered by or intersect with a subregion, weighted by the proportion of the intersecting cell area.[7]

Figure 3 plots the spatial distribution of the long-run change in temperature variability. Temperature variability has increased in much of the world, although there are areas where variation has fallen. Since these positive and negative changes fall across regions exposed to future damage and possible benefits from global warming, this provides a more challenging test of the hypothesis. One might expect that increased variability could lead to mistaken inferences in places facing potential net benefits. If this is not the case, the result would be a strong indication that the individuals are updating their preferences in a direction consistent with their narrow self-interest.

7. Less than 1% of subregions have missing temperature values, which we impute using the average of adjacent subregions.

Causal Inference Strategy

Our goal is to estimate the effect of long-run changes in temperature variability on individual global warming risk perceptions, moderated by whether one lives in an area exposed to future climate damages. To do so, we employ the following linear regression model with covariate balancing weights described below:

$$Y_i = \alpha + \beta_1 Temp_i + \beta_2 Damage_i + \delta(Temp_i \times Damage_i) + X\boldsymbol{\beta} + \eta_i + \epsilon_i. \tag{1}$$

The outcome, Y_i, captures whether a respondent identifies climate change as the greatest or a major risk in her everyday life. $Temp$ is the long-run change in temperature variation for a respondent's area. $Damage$ is an indicator of whether a respondent's area faces future damages from climate change. X is a matrix of covariates, which also includes their interactions with the damage moderator. We are interested in δ, which represents the differential effect of climate experience for respondents in areas facing future damages compared to those in less vulnerable subregions. Lastly, η is a fixed effect for large geographic regions such as South Asia.[8]

To interpret these estimates as causal, we assume that after conditioning on covariates, exposure to long-run changes in temperature variation and future climate damages is as good as random. Focusing on temperature variability helps to make this assumption more plausible. While climate change will cause certain regions to see more variability, by including fixed effects for large geographic areas, we are identifying fluctuations within a region that are more plausibly random for a given slice of time.

One might still be concerned that exposure to temperature variability is affected by individual factors, such as socio-economic status, that affect mobility, or geographic factors, such as favorable climates that give rise to urban populations. Such geographic sorting would introduce bias against belief updating because the people most exposed might be

8. We verify that there is sufficient variation in the treatment and moderator after residualizing these fixed effects.

the least concerned. Nonetheless, we control for variables that may predict exposure to temperature variability, future climate damage, and risk perceptions. At the individual level, the covariates include age, gender, number of children, education, income, household size, internet access, and interpretation of risk as a concept.[9,10] Previous studies identify many of these factors as determinants of climate attitudes (Hornsey et al. 2016; Dechezleprêtre et al. 2022; Lee et al. 2015; Bush and Clayton 2023).

At the subregional level, covariates include population, gross domestic product, carbon dioxide emissions, and fossil fuel development potential. Variables like population indirectly capture how more populous urban areas may have unique climates, while GDP relates to an area's ability to adapt to climate change. These validated data sources come from a combination of administrative, survey, satellite, and cell phone data, which we spatially map to the subregions.

At the country level, we account for the country's regime type because democracy influences the availability of information that could translate experiences into political attitudes. We also control for the income level of a country, which could affect the overall level of education and ability to adapt to climate change. Appendix B.1 details the operationalization and data sources of all covariates.

Additionally, we estimate covariate balancing propensity scores (CBPS) to reduce the dimensionality of our covariates (Imai and Ratkovic 2014). The advantage of this methodology is that it can be applied to continuous treatments like ours. We estimate the weights to balance individuals according to both their exposure to long-run temperature variability and whether they face future damages from climate change. Specifically, we interact the treatment with the moderator and balance the covariates relative to that interaction term. This also helps to account for the possibility that temperature variability becomes greater in places that are more vulnerable to climate change.

9. Interpretation of risk controls for whether the respondent thinks of risk as danger or opportunity.

10. The survey did not ask about ideology or partisanship, but it is unlikely that partisanship is associated with temperature variability. Our sensitivity analysis suggests that such an omitted variable would be unlikely to alter the findings.

Lastly, we estimate a doubly robust model that includes both covariates and the CBPS weights. The model is doubly robust in the sense that the the conditional exogeneity holds either via the covariates or the weights.

We take two steps to assess the credibility of our assumption that individual exposure to temperature variation and future climate damages is as good as random after conditioning on covariates or employing weights. First, we estimate how sensitive the results are to omitted variable bias, which the next section reports.

Second, we analyze the covariate balance after reweighting the estimates. Before balancing weights are applied, there are slight imbalances in country-level covariates for democracy and income level (Appendix B.4). After weighting, there is no correlation between the interacted treatment and moderator and the observed covariates. We conduct an equivalence test of the conservative null hypothesis that there is an imbalance. There is evidence of no imbalance after weighting (Hartman and Hidalgo 2018).

Long-Run Temperature Variability and Climate Risk Perceptions

Figure 4 plots the average effect of an increase in long-run temperature variability on climate risk perceptions for people in areas facing future damages or not. A standard deviation increase in long-run temperature variability corresponds with a one percentage point increase in the probability that an individual names climate change as a top risk in her daily life. This positive effect only occurs among people in places facing future climate damages. As hypothesized, there is no effect of experience on climate risk perceptions among individuals in places less vulnerable to future global warming. The results are similar when using the more restrictive outcome that codes only those identifying global warming as the top risk in their daily lives.

The size of these effects is consistent with our theory where people engage in Bayesian updating. Many individuals may have strong prior beliefs, so we would not expect there to be a large shift in beliefs in a given moment of time. Also, since this is a cross-section, it

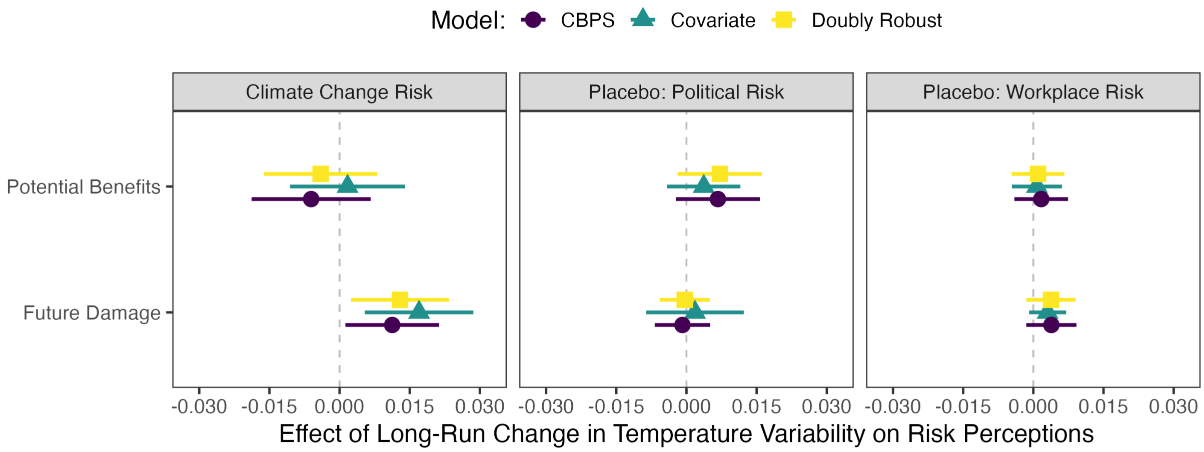

Figure 4: Effect of Long-Run Temperature Variability Change on Risk Perceptions

Notes: Change in long-run temperature variability is scaled so a one-unit shift represents a standard deviation increase. All outcomes are binary indicators for whether a respondent identified a topic as a top or major risk in their daily life. Bars denote 95% confidence intervals with robust standard errors clustered by subregion. Estimates from linear regression models with geographic region fixed effects and either CBPS weights, covariates, or both for doubly robust (Tables B2, B3). 135,611 respondents across 2,255 subregions in 124 countries.

is possible that people had previously shifted their risk perceptions because of experience, which would attenuate the size of the point estimates. Still, this effect is notable compared to the baseline levels of risk perceptions in the sample. Only three percent identify global warming as a top risk to their daily life. Our estimated effect of experience is 30 percent the size of the outcome mean.

We conduct placebo tests to probe the mechanism that temperature variability experience conveys information about global warming. The placebo tests examine the effect of temperature on outcomes theoretically unrelated to climate change. The first placebo, *work*, is whether a respondent says that "work-related accidents; physical injuries" is the greatest risk in her daily life. The second placebo, *politics*, is whether a survey-taker says that "politics/political situation/corruption" is the greatest risk in her daily life. Figure 4 presents the results from placebo tests, which show no effect. These placebo tests suggest that the effect of long-run temperature variability is due to updated beliefs about global warming.

To interpret these estimates as causal, we assume that after conditioning on covariates, exposure to long-run changes in temperature variability and vulnerability to future climate change are as good as random. We conduct a sensitivity analysis to see how extreme an unobserved confounder would have to be to change our conclusions (Cinelli and Hazlett 2020). We use democracy and income as benchmark covariates. The former is one of the strongest predictors of climate risk perceptions, while the latter is one of the best predictors of the interacted moderator and treatment. There would have to be an extreme confounder—orthogonal to the covariates in the model—with more than 30 times the correlation of regime type or income with temperature variability and the outcome to bring the lower bound of the 95% confidence interval to touch 0. Given previous studies on the determinants of climate attitudes, such an extreme confounder is unlikely (Appendix B.7.1).

In addition to the three models presented in the main text, the results are also robust to alternative estimation strategies and treatment operationalizations. First, we employ a multi-level model with random intercepts for each subregion. This accounts for variability between subregions, such as different baseline levels of climate change risk perceptions (Table B5). Second, we re-estimate our models using a different temperature benchmark period. This analysis shows that the results are not dependent on the choice of the period to define long-run changes in temperature variability (Table B7).

Heterogeneity by Regime Type

To further probe the mechanism, we examined whether regime type influenced the effect of experience on climate risk perceptions. In democracies, there is more press freedom, so people may have more knowledge about the global climate debate. Whereas in autocracies, citizens may be less aware of the linkage between the climate and adverse outcomes. So, the strength of the inferential signal may be larger in democracies than in autocracies.

For this analysis, we used the polyarchy measure from V-Dem, which is constructed at the country-year level from the ratings of scholars and experts. Polyarchy is an aggregate index that aims to measure the components of electoral democracy, including free and fair

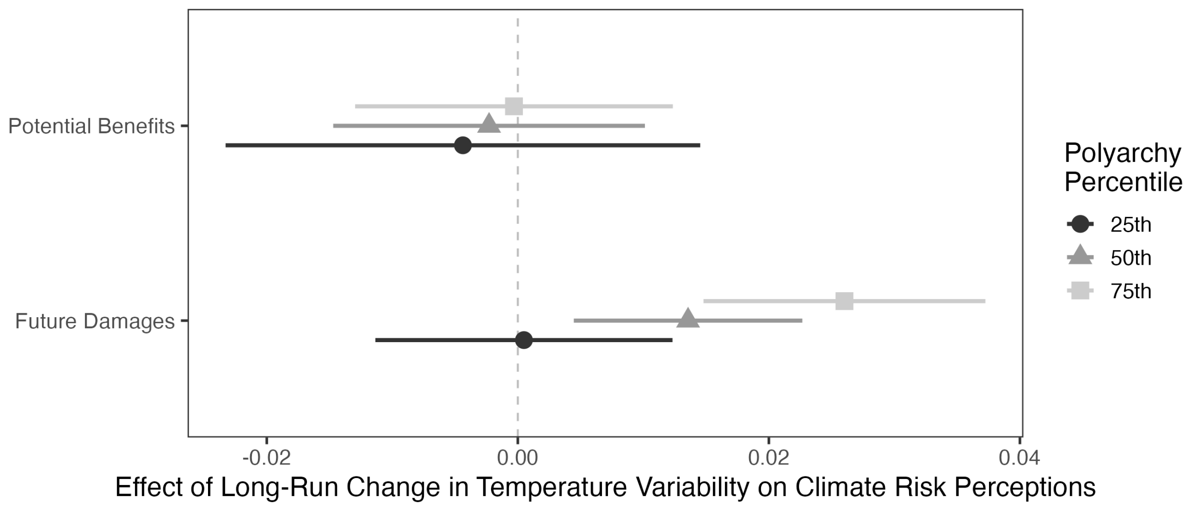

Figure 5: Moderating Effect of Democracy on Climate Experience

Notes: Change in long-run temperature variability is scaled so a one-unit shift represents a standard deviation increase. The outcome is a binary indicator of whether a respondent identified climate change as a top or major risk in her daily life. Bars denote 95% confidence intervals with robust standard errors clustered by subregion. Estimates from the doubly robust estimator with covariates and CBPS weights, geographic region fixed effects, and interactions between polyarchy and all covariates (Table B4). 135,611 respondents across 2,255 subregions in 124 countries.

elections, freedom of expression, associational autonomy, and inclusive citizenship (Coppedge et al. 2019). We construct bins at the 25th, 50th, and 75th quantiles of polyarchy to ensure there is common support when estimating the average marginal effects.

Figure 5 presents the effects of climate experience conditional on risk perceptions, conditional on the national level of democracy. Across all subregions facing potential benefits, there is still no effect of long-run changes in temperature variability on risk perceptions, even at higher levels of democracy. In terms of places facing future damages, the effect of experiencing climate change is stronger for respondents in more democratic countries. However, it is not only the most democratic places where the result holds; there is a strong positive effect of temperature on risk attitudes even at the median level of democracy.

Study 2: Preference Change

Our next analysis examines personal experience and preference change. Here, we employ panel data—repeated surveys of the same individual. Data come from the Cooperative Congressional Election Study's 2010-2014 Panel Study (Ansolabehere and Schaffner 2015), with a sample collected over the Internet by YouGov using the firm's matched random sampling methodology. After accounting for attrition, 9,500 respondents were interviewed in 2010, 2012, and 2014 using a common set of questions across the waves.

Measurement

Climate Beliefs and Policy Preferences

The outcome captures belief in climate change and support for mitigation. Since most respondents exhibit high levels of climate concern, we dichotomize the measure: 1 indicates that the respondent thinks "global climate change has been established as a serious problem, and immediate action is necessary" or that "there is enough evidence that climate change is taking place and some action should be taken." The measure is 0 when the respondent says, "We don't know enough about global climate change, and more research is necessary before we take any actions," "Concern about global climate change is exaggerated. No action is necessary," or that "Global climate change is not occurring, this is not a real issue."

Future Climate Change Exposure

We use county-level estimates of climate change damages from Hsiang et al. (2017). This model has a finer resolution for the US compared to our global estimates. Hsiang et al. (2017) estimate the value of market and non-market damages from higher temperatures in agriculture, crime, coastal storms, energy, human mortality, and labor. Like Cruz and Rossi-Hansberg (2023), they find substantial spatial heterogeneity in the economic effects of higher temperatures. Figure 6 shows how parts of the North and West of the United States may

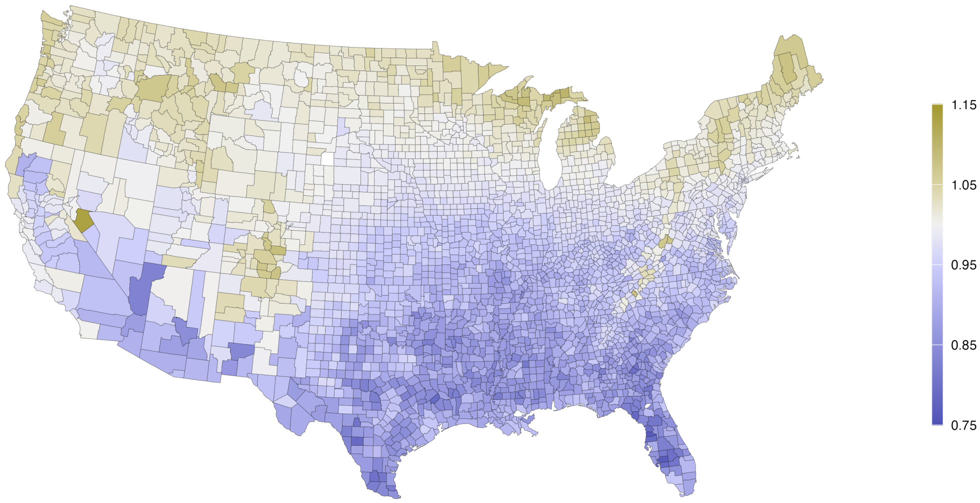

Figure 6: Climate Damage to GDP, County-Level

Notes: Estimates from Hsiang et al. (2017). Blue denotes potential damages, while yellow denotes potential climate benefits.

experience potential gains in terms of GDP, while the South incurs large losses.

We focus on total damage to GDP for comparability across the models. As before, we construct an indicator for if a county faces future climate damage, defined as greater than 0 percent GDP loss from global warming by the late 21st century. We employ a continuous moderator and find consistent results (Appendix C.5).

As mentioned earlier, we also conducted an original survey of the American public to evaluate the relationship between these objective damage estimates and beliefs about future climate change exposure. We find there is a robust correlation that holds even when controlling for predictors of climate attitudes like partisanship (Appendix A). Citizens appear to be aware of how their location is exposed to global warming.

Climate-Related Experience

Wildfires serve as the experiential shock in this analysis. The previous study focused on temperature for greater comparability across global sub-regions. In the American context,

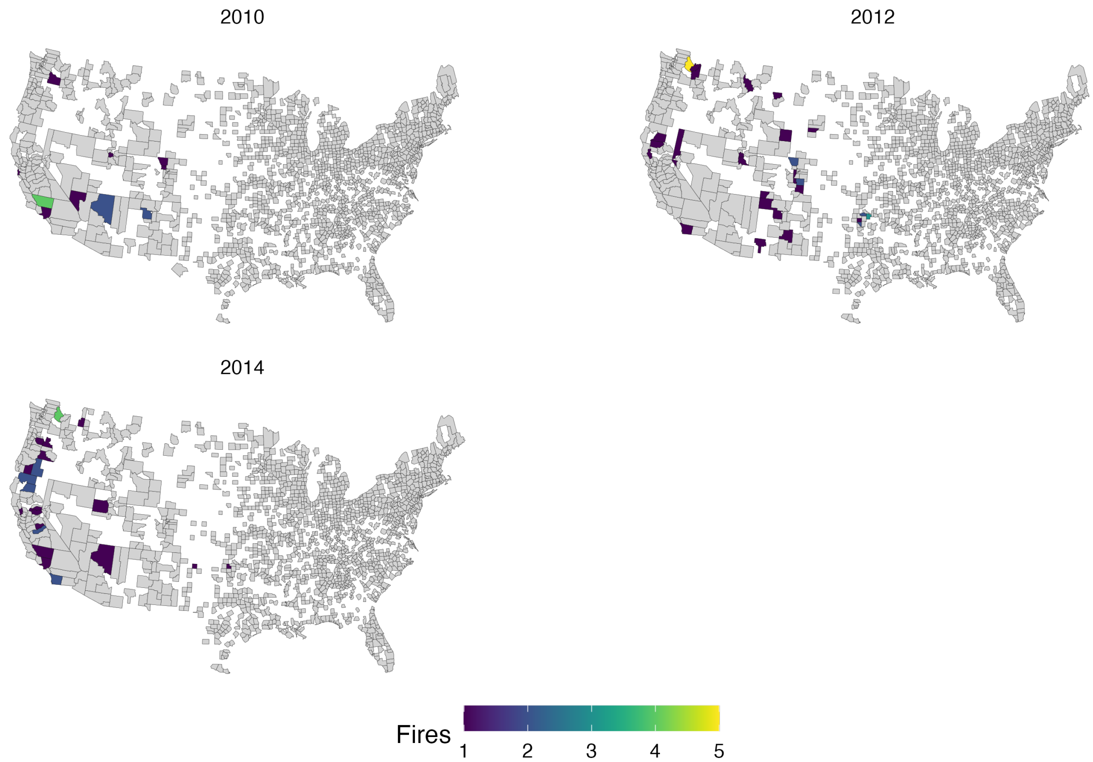

Figure 7: Sampled Counties and Wildfire Disaster Declarations

Notes: Grey areas denote no fire disaster declarations during a panel year but with survey responses. Respondents in Hawaii, Alaska, the District of Columbia, and certain Virginia counties are not shown.

fires are becoming more frequent and longer lasting due to climate change (Westerling et al. 2006), and politicians often rhetorically connect wildfires to global warming. Wildfires can be exceptionally destructive and impressionable, making them a powerful experience that could alter attitudes more so than temperature fluctuations (Egan and Mullin 2017; Koubi et al. 2016).

Previous research has turned up mixed results about the relationship between fires and political attitudes and behavior. Hui et al. (2022) find that proximity to wildfires increased Republican support for adaptation policy, while Hazlett and Mildenberger (2020) find a conditional relationship between fire experience and voting in climate-related referenda. However, researchers have not analyzed wildfires alongside a model of how individuals will be affected by future climate change.

We use data on the annual count of wildfires declared disasters in a county. Data come from the FEMA Disaster Declaration's Summaries. The reports are generated when a locality declares an emergency, which the federal government certifies. There might be wildfires where emergencies were not declared, but these are likely of lesser damage. Local governments also have an incentive to declare a disaster because it unlocks federal funding to assist with the recovery. Figure 7 plots the distribution of wildfires during the panel waves, most of which take place on the West Coast, but there is variation across several states in each panel year.

Causal Inference Strategy

We estimate the effect of wildfire experience on an individual's change in climate policy support with the following model:

$$Y_{it} = \beta_1 Fire_{it} + \beta_2 Damage_i + \delta(Fire_{it} \times Damage_i) + X\boldsymbol{\beta} + \lambda_t + \eta_i + \epsilon_{it}. \quad (2)$$

The outcome, Y_{it}, is the indicator for whether an individual supports climate policy in panel wave t. $Fire_{it}$ is a count of fires in an individual's county during a panel wave. $Damage_i$ indicates whether a respondent's county faces future damages from global warming or not. δ represents the differential effect of wildfire experience for people in counties facing future climate damage versus those with possible net benefits. The matrix X contains time-varying covariates described below.

This model estimates the within-unit change in climate policy support. It does so by including, λ_t, a panel-wave fixed effect, and η_i, an individual fixed effect. The panel wave fixed effect removes any bias that could exert a common effect on individual climate policy attitudes or exposure to wildfires, such as seasonal conditions that make fires more likely or campaign messages discussing global warming. The individual fixed effect removes possible confounding from invariant characteristics of the respondents, such as race.

To treat these estimates as causal, one must assume that had an individual not experienced a wildfire, she would have followed the same average trajectory of climate attitudes as people who did not experience a fire. While we cannot directly test this assumption, we can attempt to falsify it. We conduct several placebo tests using data on future wildfires to examine current climate policy support and find no evidence of differential pre-trends (Figure 8).

A related challenge is that wildfire experience could be non-random. For example, as people become wealthier, they could move away from fire-prone areas while their policy attitudes also change with their increased income. It is also possible that people most worried about climate change choose to live in less vulnerable locations. However, this type of geographic sorting would likely attenuate the size of the effect because the people exposed to fires would have more skeptical prior beliefs that are less susceptible to updating.

We take three approaches to possible non-random exposure to fires. First, we control for individual-level factors that could affect where people live: employment, education, and household income. We also include covariates for partisan identification, ideology, and parenthood, which are predictive of climate attitudes, so they should improve precision (Hornsey et al. 2016; Egan and Mullin 2017; Gazmararian 2024).

Second, as an alternative estimation strategy, we employ the panel matching estimator proposed by Imai, Kim, and Wang (2023). This approach uses CBPS to match individuals exposed to wildfires with a control group of individuals who are otherwise similar in terms of their observed covariates. In addition to the covariates above, we also match on an individual's age, gender, and race.[11] An advantage of the panel matching estimator is that it allows multiple units to switch their treatment status, which is relevant because some individuals may experience a wildfire in one year but not the next. This approach is also more robust to model misspecification than the two-way fixed effects model.

Third, we systematically assess how sensitive our estimates are to an omitted variable that explains wildfire exposure and climate policy support. We benchmark our sensitivity analysis with covariates for Democratic partisanship, education, and parenthood, which are

11. These covariates would be differenced out in the two-way fixed effect model.

strong predictors of climate policy support. We find that it would take an extreme confounder correlated with the treatment, moderator, and outcome that is several orders of magnitude larger than the benchmark covariates to alter our conclusions (Appendix C.4).

Wildfire Experience and Climate Policy Support

Figure 8 plots the average effect of wildfire experience on climate policy support across a variety of estimators and treatment definitions. The left panel shows that wildfire experience causes climate policy support to increase by around 3 to 4 percentage points relative to the control group. This effect only occurs among people in counties facing future climate damages, not those residing in areas less vulnerable that could benefit in terms of GDP.

The magnitude of this coefficient is similar to the 5 to 6 percentage points estimate that Hazlett and Mildenberger (2020) find for the effect of wildfires on support for climate-related ballot measures. Likewise, Egan and Mullin (2012) find that experiencing hot days leads to about a 5 percentage point increase in believing in climate change.

However, our results differ in two ways. First, we show that experience only has an effect for individuals facing future climate damage exposure. This suggests that the material costs of climate change are moderating how people respond to their personal experiences.

Second, our results show more persistence in the effects of personal experience on political attitudes than in past studies. The panel waves are separated by two years, which means the effects we identify last for at least 0-2 years after an individual experiences a wildfire. In contrast, Egan and Mullin (2012) identify an effect that dissipates after only 12 days. Arias and Blair (2024) conducted a follow-up survey six months after Hurricane Ian and found no persistent effects on attitudes. In general, Egan and Mullin (2017) note that the effects of climate experience tend to be ephemeral.

As mentioned, we conduct placebo tests to assess the plausibility of the parallel trends assumption. This assumption would be violated if a time-varying process taking place in counties susceptible to wildfires also led people to change their climate policy attitudes. For

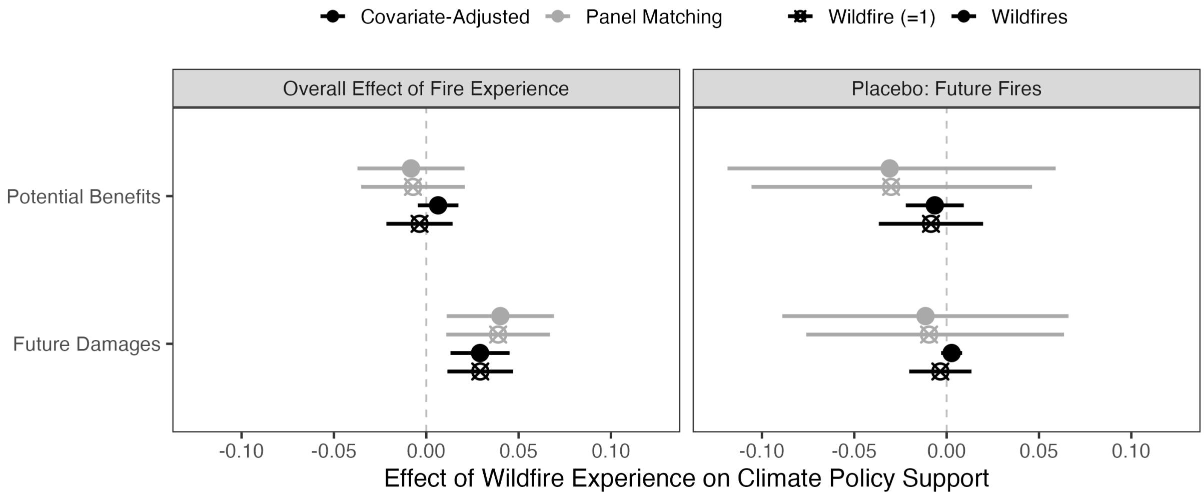

Figure 8: Effect of Wildfire Experience on Climate Policy Support

Notes: The left panel shows the effect of wildfire experience on climate policy support, conditional on whether a respondent's county faces future climate damage or possible net benefits. Estimates come from a covariate-adjusted linear regression model with fixed effects for individuals and panel waves, or a panel-matching estimator, both with robust standard errors that account for serial dependence (Table C2). The outcome is 1 if the respondent supports climate policy and 0 otherwise. The treatment is either a binary indicator for if a county experienced wildfires or a count of wildfires a county experienced in a year. The right panel shows results from placebo tests estimating the effect of future wildfires on current climate policy support. Bars denote 95% confidence intervals. 9,500 respondents $\times$ 3 panel waves in 2010, 2012, and 2014

example, counties at risk of fires might hear more media coverage about climate change, and it is those political messages, as opposed to direct experience, that cause preference change.

The tests use future fires in 2016, 2018, and 2020 as a placebo treatment.[12] These placebo fires would increase climate policy support if there is an unobserved time-varying confounder. However, the right plot in Figure 8 shows there is no effect of future fires on present climate policy attitudes. This suggests that there is not a time-varying feature of places predisposed to fires driving the results. Instead, wildfire experience likely is what is leading policy preference change for those living in counties facing future damages.

12. For the panel matching estimator, which matches on treatment history, the placebo test effectively examines the lagged effect of fires in 2 periods before they happen.

Skeptics, Undecideds, and Believers

Our second hypothesis is that individuals with stronger prior beliefs should be less likely to change their policy attitudes after experiential shocks. We test this claim by subsetting respondents to three groups based on their climate attitudes in the first survey wave. The first group is the *skeptics*, defined as individuals who believed that "Concern about global climate change is exaggerated. No action is necessary," or that "Global climate change is not occurring, this is not a real issue." The second group is the *undecideds*. These individuals believe that "There is enough evidence that climate change is taking place and some action should be taken" or "We don't know enough about global climate change, and more research is necessary before we take any actions." The last group is the believers, those who are convinced that "Global climate change has been established as a serious problem, and immediate action is necessary." Policy support should increase among the undecideds but less so for the skeptics and believers.

We find that wildfire experience corresponds with a 5 percentage point increase in climate policy support among undecideds. This effect only occurs for individuals who face future climate damages. As expected, climate experiences do not affect individuals with stronger prior beliefs. There is no effect for believers, which is unsurprising because there was no room for upward movement. For skeptics, the coefficient on the interaction term is positive but noisily estimated (Appendix C.7).

We are careful in interpreting these results because subsetting the data limits statistical power. Additionally, whether someone is a skeptic, undecided, or believer is not randomly assigned and might be correlated with unobserved factors that confound inference. To the extent that the forces shaping prior beliefs are time-invariant, the individual fixed effects statistically remove this potential source of confounding. However, if the omitted variables are time-varying and not accounted for by our controls, that would undermine a causal interpretation of prior beliefs as a moderator.

While our theory predicts that skeptics will eventually update their beliefs, we find no evidence of this in the available data. Future research should employ panel surveys over an extended period and at frequent intervals to capture how skeptics update their beliefs.

Conclusion

Our paper shows that there is a new type of polarization within and across countries in how citizens respond to global warming. Individuals in locations that face future income losses because of higher temperatures react to extreme heat and wildfires by becoming more supportive of mitigation. Conversely, people living in areas that may experience little damage or even potential benefits do not shift their support for climate policy after experiential shocks.

These differences in climate attitudes matter for the incentives of leaders to fight climate change. If citizens do not prioritize global warming, politicians will face political risks if they enact costly mitigation policies. In parallel work, we connect these changing climate risk perceptions with the policy outputs of nations, where we find a similar relationship that varies by whether a country faces future climate damage or not.

Our findings imply that experience with the effects of global warming is unlikely to mobilize citizens in wealthier, presently cooler climates to pressure their leaders to mitigate emissions. Building a political coalition for climate policy in these locations may depend on emphasizing the co-benefits from mitigation or making normative appeals. In places facing damages, the public should become increasingly concerned about global warming. Experience with climate shocks could turn undecideds into believers, so the pro-climate coalition grows and political leaders in these places are more likely to enact mitigation policies.

Our paper brings together political economy and behavioral theories to better explain how policy attitudes respond to personal experience. The same direct experience has diverging implications for what policies an individual should prefer depending on how one is materially affected by the underlying issue. The effects of personal experience on preference change are not unconditional but can depend on self-interest.

Our theory applies to a broad set of emerging technological, scientific, and economic policy issues. For example, people may be unsure about the consequences of automation, but with the deployment of artificial intelligence chatbots, they come to learn how they are affected through personal experience in the workplace. As we theorize, these experiences could alter their preferences regarding the appropriate public policy response, conditional on one's skill set. Follow-on studies could use our approach to explore how individuals form and change their policy preferences when there is uncertainty about the effects of automation, emerging technologies, or environmental pollution.

There are three limitations of this study that we are addressing in ongoing work. First, more detailed questions would be helpful in pinpointing how climate experiences affect attitudes. For example, it would be useful to know if people believe a disaster was caused by global warming, how much they think it affected their livelihood, and their specific expectations of future damages. Researchers should field surveys that capture a wider set of beliefs related to climate change to better understand the mechanisms linking experience and attitudes.

Second, this paper focuses on climate attitudes, but it would be valuable to examine behaviors such as voting. Belief in climate change and support for climate policy still matter because they are inputs into how leaders make decisions, and they are likely positively correlated with behavior. In parallel work, we are examining outcomes such as voting for politicians who support mitigation or making costly personal adaptation decisions.

Third, studies should build on our framework to incorporate the role of the media, parties, and elites in politicizing personal experience (Mutz 1994). Our results indicate that experience and self-interest go a long way in predicting how attitudes change. These findings invite further research on the role of political communication in activating or depoliticizing personal experience. For example, Hai and Perlman (2022) find that Republican lawmakers have few electoral incentives to attribute disasters to climate change, which could contribute to different responses to personal experiences among partisans, as Hazlett and Mildenberger (2020) find is the case in response to Californian wildfires.

More generally, our paper contrasts with a prominent view that information has little effect on policy attitudes (e.g., Achen and Bartels 2016). Our findings suggest that individuals can sometimes learn the right lesson from personal experience. By using an economic model of individuals' preferences, we can better predict how people react to new information. Previous work on information and voter competence should be revisited using the tools of political economy to provide a benchmark of how attitudes should change in response to direct experience. To the extent that these models fail to generate accurate predictions, it would also be informative by revealing the limits of assuming that an individual's preferences are based partly on economic self-interest.

Lastly, we contribute to the climate politics literature by integrating politics and economic models of global warming. Our approach helps resolve inconsistent results in the fast-advancing body of research on responses to climatic events (Howe et al. 2019). Previous studies have evaluated the effect of experience but without a model of what individuals' preferences would be if they were fully informed and acting according to economic self-interest. Instead, our climate model provides a baseline for what policy preferences should converge to, while our theory supplies a micro-founded causal pathway for how individuals' preferred policies change in response to experiential shocks. In doing so, we help to better understand when and how political mobilization will occur in response to climate change.

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Online Supplementary Information
"Personal Experience and Self-Interest"

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A Objective Vulnerability and Subjective Beliefs

A.1 Measuring Subjective Beliefs

Subjective climate vulnerability: index based on the following variables, all coded so positive values indicate greater perceptions of climate vulnerability:

- *Overall:* respondent's answer to the branched question: "Do you think global warming over the next 50 years will harm, benefit, or have no effect on the place where you currently live?" coded on a -3 to 3 scale, where -3 is "Greatly benefit from global warming," -2 is "Somewhat benefit from global warming," -1 is "Barely benefit from global warming" or don't know respondents who guess their location will benefit, 0 is "Feel no effects of global warming," 1 is "Barely harmed by global warming" or don't know respondents who guess their location will be harmed," 2 is "Somewhat harmed by global warming," and 3 is "Greatly harmed by global warming."

- *Disasters:* respondent's answer to the branched question: "Do you think global warming over the next 50 years will cause the number of natural disasters to increase, decrease, or not change in the place where you currently live?" coded on a -3 to 3 scale, where -3 is "Decrease a great deal," -2 is "Decrease somewhat," -1 is 'Decrease a little" or don't know respondents who guess disasters will decrease, 0 is "Not change," 1 is "Increase a little" or don't know respondents who guess disasters will increase, 2 is "Increase somewhat," and 3 is "Increase a great deal."

- *Income:* respondent's answer to the branched question: "Do you think global warming in 50 years will make people in the place where you currently live richer, poorer, or have no effect?" coded on a -3 to 3 scale, where -3 is "A great deal richer," -2 is "Somewhat richer," -1 is 'A little richer" or don't know respondents who guess their area will become richer, 0 is "Not change," 1 is "A little poorer" or don't know respondents who guess their area will become poorer, 2 is "Somewhat poorer," and 3 is "A great deal poorer."

- *Livability:* respondent's answer to the question: "Do you think global warming in 50 years will make the place where you currently reside a more or less desirable location to live, or will it have no effect?" coded on a -3 to 3 scale, where -3 is "A great deal more desirable," -2 is "Somewhat more desirable," -1 is "A little more desirable" or don't know respondents who guess their area will become more desirable," 0 is "No effect," 1 is "A little less desirable" or don't know respondents who guess their area will become less desirable, 2 is "Somewhat less desirable," and 3 is "A great deal less desirable."

- *Businesses:* respondent's answer to the question: "Do you think global warming will make the place where you currently live more or less desirable for businesses to invest there in 50 years, or will global warming have no effect?" coded on a -3 to 3 scale, where -3 is "A great deal more desirable," -2 is "Somewhat more desirable," -1 is "A little more desirable" or don't know respondents who guess their area will become more desirable for businesses," 0 is "No effect," 1 is "A little less desirable" or don't know respondents who guess their area will become less desirable for businesses, 2 is "Somewhat less desirable," and 3 is "A great deal less desirable."

- *Migration:* respondent's answer to the question: "How likely do you think it is that people in your community will have to move to a safer location in the next 50 years because of global warming?" coded on a -3 to 3 scale, where -3 is "Not at all likely," -2 is "Not too likely," -1 is don't know responses who guess that they are unlikely to have to move, 0 is "Moderately likely," 1 is don't know responses who guess they are likely to have to move, 2 is "Very likely," and 3 is "Extremely likely." The question is repeated with reference to an individual's expectations that she will have to move.

A.2 Sample Description

Table A1: Sample Compared to Population

	Sample	Pop.	N	NA
Age: 18-24	0.08	0.12	619	0
Age: 25-34	0.16	0.18	619	0
Age: 35 to 44	0.20	0.17	619	0
Age: 45 to 64	0.39	0.33	619	0
Age: over 65	0.17	0.21	619	0
Female	0.53	0.51	619	0
White	0.76	0.70	619	0
Black	0.13	0.12	619	0
AAPI	0.05	0.06	619	0
Hispanic	0.11	0.17	619	0
High school or less	0.27	0.38	619	0
Some college	0.39	0.31	619	0
BA or higher	0.34	0.30	619	0
Income Q1	0.19	0.21	619	0
Income Q2	0.19	0.23	619	0
Income Q3	0.18	0.22	619	0
Income Q4	0.13	0.16	619	0
Income Q5	0.31	0.17	619	0
Employed	0.54	0.60	619	0
Student	0.03	NA	619	0
Retired	0.21	NA	619	0
Rural	0.18	0.14	619	0
Northeast	0.21	0.17	619	0
Midwest	0.20	0.21	619	0
South	0.39	0.38	619	0
West	0.19	0.24	619	0
Democrat	0.41	NA	619	0
Republican	0.41	NA	619	0

Notes: National sample collected from Lucid Theorem, January 3-18, 2024. Population data from the 2021 5-Year American Community Survey. Population data for Hispanic from the 2020 Census. Population data on employment come from the December 2023 Bureau of Labor Statistics Employment Situation report. Population data on rural Americans come from USDA's Rural America at a Glance 2021 report.

A.3 Regression Estimates

Table A2: Objective Climate Change Exposure and Vulnerability Beliefs

	DV: Vulnerability Beliefs		
	(1)	(2)	(3)
Objective Damage (=1)	0.35***	0.36***	0.22**
	(0.10)	(0.11)	(0.10)
Above Median Disasters (=1)			0.40***
			(0.08)
Age			−0.08**
			(0.04)
Female (=1)			0.23***
			(0.07)
Some College			0.05
			(0.09)
BA or higher			−0.06
			(0.09)
White (=1)			−0.23**
			(0.10)
Republican			−0.40***
			(0.11)
Independent			−0.38***
			(0.12)
Conservative			−0.27***
			(0.10)
Liberal			0.15
			(0.10)
Unsure of ideology			0.13
			(0.16)
Trust in government (index)			−0.01
			(0.03)
Religiosity (index)			−0.05
			(0.04)
Energy Sector Employment (=1)			−0.13
			(0.11)
Rural (=1)			0.04
			(0.09)
Climate knowledge (=1)			0.32***
			(0.08)
Constant	−0.31***	−0.29**	−0.18
	(0.09)	(0.11)	(0.19)
N	616	616	616
Adjusted R^2	0.01	0.02	0.25
Region Fixed Effects	No	Yes	Yes

Notes: Linear regression of vulnerability beliefs on objective data on vulnerability from Hsiang et al. (2017). Heteroskedasticity-robust standard errors are in parentheses. Data come from our national non-probability sample collected in January 2024. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

B Cross-Sectional Analysis Appendix

B.1 Covariate Data and Measurement

Age: A few observations are right-censored at 100 due to WRP protocol, which we code as 100.
Sex: Coded 1 if a respondent is female, and 0 if not.
Education: Primary, secondary, or tertiary education.
Household income: "Living comfortably on present income," "Getting by on present income," "Finding it difficult on present income," or "Finding it very difficult on present income.
Household Size: Total number of people in a household, which takes the values "1-2 people," "3-4 people," "5-9 people," or "10 or more people."
Children: A binary indicator for if a respondent has any children under 15 in the household.
Internet Access: A binary indicator for if a respondent has used the Internet, including social media, in the past 30 days.
Risk: "When you hear the word RISK, do you think more about opportunity or danger?" with possible answers including, "Danger," "Opportunity," "Both," and "Neither."
Population: Data on 2018 population at the 1-kilometer spatial resolution comes from a Random Forest algorithm and a combination of census, survey, satellite, and cell phone data to generate gridded predictions of population (Tatem 2017). This approach has been validated for its accuracy (Stevens et al. 2015).
GDP: GDP data at the 30 arc-sec resolution come from Kummu, Taka, and Guillaume (2018). This database employs subnational administrative data where available and only scales values where necessary, producing a more accurate measurement of GDP. We use the most recent year of data available (2015).
CO2 emissions: CO2 emissions data from 2018 at the $0.1^\circ \times 0.1^\circ$ resolution come from EDGAR. These data cover all fossil sources of carbon dioxide, such as fossil fuel consumption, cement production, and agricultural use. The measure excludes organic sources of carbon dioxide, such as forest fires and land-use change.
Coal and Oil Development Potential: Coal and oil development potential indices at the 1-kilometer resolution come from Oakleaf et al. (2019), which construct these indices, using data on resource potential and development feasibility, validated by recent leases and claim boundaries for fossil fuels and mining development. Higher index values indicate greater potential for developing fossil fuels.
Polyarchy: We use the polyarchy index from V-Dem (Coppedge et al. 2019).
Income level: Country income level comes from the WRP survey, taking the values "Low income," "Lower middle income," "Upper middle income," and "High middle income."

B.2 Subregion Shapefiles Data Sources

Almost all shapefiles come from the Database of Global Administrative Areas (v4.1). A few shapefiles come from the Humanitarian Data Exchange and other sources. There are a handful of cases where we make assumptions about the regions referenced in the Gallup data. These assumptions and coding decisions are documented in our replication package.

B.3 Summary Statistics

Table B1: Summary Statistics for Cross-National Survey

	Mean	SD	Min	Max	Missing
Outcomes:					
Climate is Top/Major Risk	0.05	0.23	0.00	1.00	0
Climate is Top Risk	0.03	0.17	0.00	1.00	0
Politics is Top Risk (placebo)	0.02	0.13	0.00	1.00	0
Work Accident is Top Risk (placebo)	0.02	0.15	0.00	1.00	0
Treatment:					
Temperature Variability	0.19	0.49	−1.13	3.69	95
Moderator:					
Future Damages	0.80	0.40	0.00	1.00	56
Individual-Level:					
Age	42.88	18.46	15.00	100.00	0
Female	0.54	0.50	0.00	1.00	0
Children	0.51	0.50	0.00	1.00	0
Primary Education	0.31	0.46	0.00	1.00	0
Secondary Education	0.51	0.50	0.00	1.00	0
Tertiary Education	0.17	0.38	0.00	1.00	0
1-2 in Household	0.36	0.48	0.00	1.00	0
3-4 in Household	0.34	0.47	0.00	1.00	0
5-9 in Household	0.26	0.44	0.00	1.00	0
10 or more in Household	0.04	0.19	0.00	1.00	0
Very Difficult Income	0.16	0.36	0.00	1.00	0
Difficult Income	0.22	0.42	0.00	1.00	0
Getting By Income	0.39	0.49	0.00	1.00	0
Comfortable Income	0.21	0.41	0.00	1.00	0
Internet Access	0.58	0.49	0.00	1.00	0
Risk is Danger	0.66	0.48	0.00	1.00	0
Risk is Opportunity	0.20	0.40	0.00	1.00	0
Risk is Opportunity and Danger	0.08	0.26	0.00	1.00	0
Risk is Neither	0.02	0.14	0.00	1.00	0
Subregion-Level:					
GDP (log)	23.35	2.07	11.93	28.40	75
CO2 Emissions	0.00	1.00	−0.29	9.85	46
Population (log)	14.14	1.76	5.93	19.24	46
Coal Development Potential	0.00	1.00	−0.54	3.21	46
Oil Development Potential	0.00	1.00	−0.86	2.30	46
Country-Level:					
Polyarchy	0.54	0.26	0.02	0.92	0
Low Income	0.13	0.34	0.00	1.00	0
Lower Middle Income	0.26	0.44	0.00	1.00	0
Upper Middle Income	0.32	0.46	0.00	1.00	0
High Income	0.30	0.46	0.00	1.00	0

Notes: Data cover 135,716 people in 124 countries and 2,255 regions. Temperature variability is scaled at the subregion level so a one-unit shift represents a standard deviation increase.

B.4 Covariate Balance

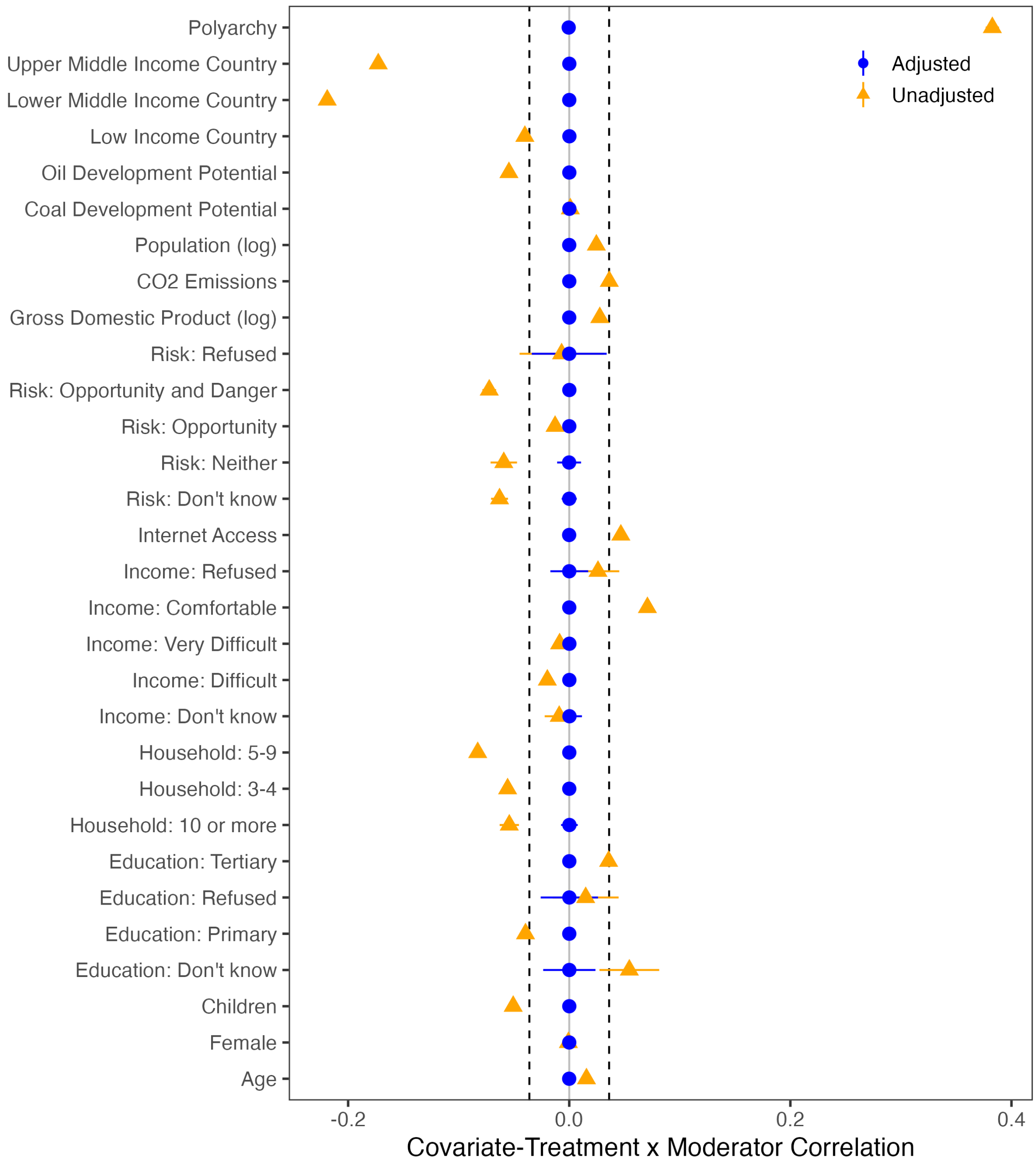

Figure B1: Equivalence Tests of Covariate Balance in Unadjusted and Adjusted Samples

Notes: Adjusted estimates use CBPS weights (Imai and Ratkovic 2014). The treatment is defined as the interaction of the future damages moderator and long-run change in temperature variability. Since the treatment is continuous, the reported balancing statistic is the treatment-covariate Pearson correlation. Dashed black lines denote the equivalence range $[-0.1\sigma_y, 0.1\sigma_y]$ as recommended by Kruschke (2018). Bars around the point estimates are 95% confidence intervals.

B.5 Regression Estimates

Table B2: Conditional Effect of Temperature Variability on Climate Change Risk Perceptions

	Climate Change Risk to Daily Life					
	Top/Major Risk			Top Risk		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.115	0.054***	0.113	0.085	0.036***	0.069
	(0.080)	(0.010)	(0.084)	(0.059)	(0.007)	(0.057)
Temp. Variability	0.002	−0.006	−0.004	−0.001	−0.007	−0.004
	(0.006)	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)
Future Damages	−0.048	−0.004	−0.058	−0.051	−0.006	−0.033
	(0.088)	(0.008)	(0.093)	(0.063)	(0.005)	(0.062)
Temp. Variability × Future Damages	0.015*	0.017**	0.017**	0.012**	0.014***	0.012**
	(0.008)	(0.008)	(0.008)	(0.005)	(0.005)	(0.005)
Age	0.004*		0.003*	0.003*		0.002
	(0.002)		(0.002)	(0.001)		(0.002)
Female	0.004		0.005*	0.002		0.003
	(0.003)		(0.003)	(0.002)		(0.002)
Children	0.003		0.002	0.003		0.003
	(0.004)		(0.004)	(0.003)		(0.003)
Education: Primary	0.000		0.002	0.003		0.005
	(0.006)		(0.006)	(0.005)		(0.005)
Education: Tertiary	0.005		0.005	0.002		0.002
	(0.004)		(0.004)	(0.003)		(0.003)
Education: Don't know	−0.006		−0.010	−0.001		−0.007
	(0.023)		(0.023)	(0.017)		(0.013)
Education: Refused	−0.020		−0.026	−0.014*		−0.017**
	(0.018)		(0.016)	(0.008)		(0.008)
Household: 3-4	−0.003		−0.003	−0.002		−0.002
	(0.004)		(0.005)	(0.003)		(0.003)
Household: 5-9	−0.006		−0.001	−0.005		−0.001
	(0.007)		(0.008)	(0.005)		(0.007)
Household: 10 or more	−0.045***		−0.044***	−0.019		−0.019
	(0.016)		(0.015)	(0.015)		(0.014)
Income: Very Difficult	−0.024***		−0.023***	−0.014***		−0.015***
	(0.006)		(0.006)	(0.005)		(0.005)
Income: Difficult	−0.006		−0.005	−0.004		−0.003
	(0.004)		(0.005)	(0.003)		(0.004)
Income: Comfortable	0.003		0.004	0.001		0.001
	(0.004)		(0.004)	(0.003)		(0.003)
Income: Don't know	−0.002		−0.005	0.003		0.001
	(0.013)		(0.013)	(0.010)		(0.010)
Income: Refused	−0.006		−0.005	0.006		0.006
	(0.011)		(0.011)	(0.009)		(0.009)
Internet Access	−0.001		−0.001	0.002		0.002
	(0.005)		(0.006)	(0.003)		(0.005)
Risk: Opportunity	−0.012***		−0.012***	−0.005*		−0.005
	(0.004)		(0.004)	(0.003)		(0.003)
Risk: Opportunity and Danger	−0.003		−0.004	−0.004		−0.003
	(0.006)		(0.006)	(0.004)		(0.004)
Risk: Neither	−0.016*		−0.017*	−0.003		−0.004
	(0.009)		(0.009)	(0.007)		(0.007)
Risk: Don't know	−0.029***		−0.029***	−0.018***		−0.016***
	(0.007)		(0.007)	(0.005)		(0.005)
Risk: Refused	−0.010		−0.010	0.001		0.002
	(0.031)		(0.030)	(0.025)		(0.025)
Gross Domestic Product (log)	0.001		0.000	−0.001		0.000
	(0.007)		(0.007)	(0.005)		(0.005)
Population (log)	−0.012		−0.010	−0.005		−0.005
	(0.009)		(0.009)	(0.006)		(0.006)
CO2 Emissions	0.008*		0.007*	0.006*		0.006
	(0.004)		(0.004)	(0.003)		(0.003)
Coal Development Potential	0.000		0.002	−0.003*		−0.002
	(0.003)		(0.003)	(0.002)		(0.002)
Oil Development Potential	0.004		0.003	0.004**		0.003*
	(0.003)		(0.003)	(0.002)		(0.002)
Polyarchy	0.050*		0.048	0.009		0.009
	(0.030)		(0.030)	(0.021)		(0.020)
Low Income Country	0.053		0.057	0.029		0.035
	(0.040)		(0.042)	(0.035)		(0.037)
Lower Middle Income Country	0.022		0.024	0.006		0.010
	(0.019)		(0.019)	(0.014)		(0.013)
Upper Middle Income Country	0.032**		0.035**	0.013		0.016
	(0.015)		(0.014)	(0.010)		(0.010)
N	135 611	135 611	135 611	135 611	135 611	135 611
Adjusted R^2	0.012	0.005	0.010	0.013	0.005	0.008
Geographic Region Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Moderator x Covariates	Yes	Yes	Yes	Yes	Yes	Yes
CBPS	No	Yes	Yes	No	Yes	Yes

Notes: Estimates from a linear regression with HC1 standard errors clustered by subregion in parentheses. Temperature variability is scaled so a one-unit shift represents a standard deviation increase. The outcome is a binary indicator for if a respondent says climate change is a top or major risk in her daily life. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table B3: Conditional Effect of Temperature Variability on Non-Climate Placebos

	Placebo					
	Political Risk			Workplace Risk		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.017	0.013***	0.023	0.001	0.023***	−0.014
	(0.046)	(0.004)	(0.045)	(0.039)	(0.008)	(0.042)
Temp. Variability	0.001	0.002	0.001	0.004	0.007	0.007
	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.005)
Future Damages	0.014	−0.002	0.017	0.011	−0.006	0.029
	(0.048)	(0.003)	(0.048)	(0.042)	(0.006)	(0.047)
Temp. Variability × Future Damages	0.002	0.002	0.003	−0.002	−0.008	−0.007
	(0.003)	(0.004)	(0.004)	(0.006)	(0.005)	(0.005)
Age	−0.004***		−0.004***	0.002		0.003
	(0.001)		(0.001)	(0.002)		(0.003)
Female	−0.026***		−0.025***	−0.009***		−0.010***
	(0.002)		(0.002)	(0.002)		(0.002)
Children	0.006**		0.006**	−0.009***		−0.009***
	(0.003)		(0.003)	(0.003)		(0.003)
Education: Primary	−0.005*		−0.005*	−0.011***		−0.012***
	(0.003)		(0.003)	(0.003)		(0.004)
Education: Tertiary	−0.017***		−0.016***	0.012***		0.013***
	(0.003)		(0.003)	(0.002)		(0.002)
Education: Don't know	−0.025***		−0.025***	−0.015		−0.019
	(0.003)		(0.003)	(0.012)		(0.013)
Education: Refused	−0.019***		−0.019***	0.001		−0.002
	(0.004)		(0.004)	(0.014)		(0.013)
Household: 3-4	0.004		0.003	0.002		0.002
	(0.003)		(0.003)	(0.003)		(0.003)
Household: 5-9	−0.001		−0.002	0.007*		0.006
	(0.004)		(0.004)	(0.004)		(0.004)
Household: 10 or more	−0.014		−0.015*	0.002		0.000
	(0.009)		(0.008)	(0.007)		(0.007)
Income: Very Difficult	0.002		0.001	0.005		0.009*
	(0.004)		(0.004)	(0.004)		(0.005)
Income: Difficult	0.000		0.001	0.003		0.005
	(0.003)		(0.003)	(0.002)		(0.003)
Income: Comfortable	−0.002		−0.002	0.003		0.004
	(0.002)		(0.002)	(0.002)		(0.003)
Income: Don't know	−0.016***		−0.015**	−0.007		−0.008
	(0.006)		(0.006)	(0.006)		(0.006)
Income: Refused	0.002		0.001	0.000		−0.001
	(0.007)		(0.007)	(0.007)		(0.007)
Internet Access	0.009***		0.009***	0.005*		0.006*
	(0.003)		(0.003)	(0.003)		(0.003)
Risk: Opportunity	−0.004		−0.003	−0.002		0.000
	(0.002)		(0.002)	(0.002)		(0.002)
Risk: Opportunity and Danger	−0.002		−0.001	0.001		0.002
	(0.003)		(0.003)	(0.003)		(0.003)
Risk: Neither	−0.003		−0.001	−0.003		−0.004
	(0.005)		(0.005)	(0.004)		(0.004)
Risk: Don't know	−0.012***		−0.012***	−0.007***		−0.005
	(0.003)		(0.003)	(0.003)		(0.004)
Risk: Refused	−0.006		−0.005	−0.001		0.006
	(0.017)		(0.017)	(0.018)		(0.027)
Gross Domestic Product (log)	0.004		0.004	−0.008*		−0.011**
	(0.003)		(0.003)	(0.004)		(0.006)
Population (log)	−0.007**		−0.008**	0.013*		0.020**
	(0.003)		(0.004)	(0.007)		(0.008)
CO2 Emissions	−0.001		0.000	−0.004**		−0.006***
	(0.001)		(0.001)	(0.002)		(0.002)
Coal Development Potential	0.004***		0.004***	−0.002		−0.003
	(0.001)		(0.001)	(0.002)		(0.002)
Oil Development Potential	0.001		0.001	−0.004**		−0.004**
	(0.001)		(0.001)	(0.002)		(0.002)
Polyarchy	0.007		0.005	0.028*		0.042**
	(0.011)		(0.011)	(0.016)		(0.017)
Low Income Country	0.028		0.029	−0.014		−0.021
	(0.019)		(0.019)	(0.010)		(0.013)
Lower Middle Income Country	0.011		0.011	−0.010		−0.018
	(0.011)		(0.010)	(0.010)		(0.013)
Upper Middle Income Country	0.003		0.003	0.001		0.000
	(0.006)		(0.006)	(0.006)		(0.007)
N	135 611	135 611	135 611	135 611	135 611	135 611
Adjusted R^2	0.013	0.002	0.013	0.014	0.007	0.016
Geographic Region Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Moderator x Covariates	Yes	Yes	Yes	Yes	Yes	Yes
CBPS	No	Yes	Yes	No	Yes	Yes

Notes: Estimates from a linear regression with HC1 standard errors clustered by subregion in parentheses. Temperature variability is scaled so a one-unit shift represents a standard deviation increase. The outcome is a binary indicator for if a respondent says political or workplace risk is a top risk in her daily life. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

B.6 Heterogeneity by Regime Type

Table B4: Heterogeneous Effects of Temperature Variability by Regime Type

	Climate Change Risk to Daily Life					
	Top/Major Risk			Top Risk		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.384*	0.056***	0.411**	0.223	0.042***	0.195
	(0.199)	(0.016)	(0.204)	(0.151)	(0.013)	(0.150)
Temp. Variability	−0.002	−0.016	−0.008	0.012	−0.003	0.009
	(0.017)	(0.018)	(0.017)	(0.012)	(0.015)	(0.012)
Future Damages	−0.426*	0.000	−0.530**	−0.196	−0.011	−0.203
	(0.218)	(0.016)	(0.230)	(0.162)	(0.012)	(0.163)
Temp. Variability × Future Damages	−0.011	−0.005	−0.012	−0.012	−0.004	−0.015
	(0.021)	(0.021)	(0.020)	(0.014)	(0.016)	(0.014)
Temp. Variability × Future Damages × Polyarchy	0.048*	0.044	0.048*	0.039**	0.030	0.041**
	(0.029)	(0.031)	(0.028)	(0.020)	(0.023)	(0.020)
Polyarchy × Future Damages	0.670**	−0.013	0.809**	0.271	0.005	0.304
	(0.322)	(0.024)	(0.335)	(0.230)	(0.019)	(0.233)
Polyarchy × Temp. Variability	0.007	0.018	0.009	−0.018	−0.004	−0.016
	(0.023)	(0.026)	(0.023)	(0.017)	(0.021)	(0.017)
Age	0.001		0.000	0.002		0.003
	(0.005)		(0.006)	(0.004)		(0.005)
Female	0.000		0.001	0.001		0.001
	(0.007)		(0.006)	(0.005)		(0.005)
Children	−0.009		−0.012	−0.007		−0.006
	(0.013)		(0.012)	(0.010)		(0.009)
Education: Primary	0.021		0.029**	0.028**		0.032***
	(0.015)		(0.015)	(0.012)		(0.011)
Education: Tertiary	−0.005		−0.004	−0.004		−0.006
	(0.012)		(0.012)	(0.008)		(0.009)
Education: Don't know	0.111		0.106	0.028		0.029
	(0.109)		(0.103)	(0.057)		(0.055)
Education: Refused	−0.015		−0.049	−0.074***		−0.082***
	(0.092)		(0.068)	(0.022)		(0.023)
Household: 3-4	0.020*		0.023*	0.017*		0.015
	(0.012)		(0.012)	(0.009)		(0.009)
Household: 5-9	0.026		0.043*	0.026		0.034
	(0.019)		(0.025)	(0.016)		(0.023)
Household: 10 or more	−0.054*		−0.041	−0.036		−0.030
	(0.028)		(0.028)	(0.025)		(0.026)
Income: Very Difficult	−0.040***		−0.046***	−0.031***		−0.039***
	(0.013)		(0.015)	(0.009)		(0.010)
Income: Difficult	0.007		0.013	0.014*		0.020**
	(0.010)		(0.012)	(0.008)		(0.010)
Income: Comfortable	0.004		0.001	0.002		0.001
	(0.009)		(0.009)	(0.006)		(0.006)
Income: Don't know	−0.002		−0.002	0.014		0.015
	(0.030)		(0.030)	(0.027)		(0.029)
Income: Refused	−0.005		0.000	0.019		0.023
	(0.027)		(0.028)	(0.023)		(0.025)
Internet Access	0.009		0.015	0.012		0.017
	(0.012)		(0.016)	(0.010)		(0.015)
Risk: Opportunity	−0.019*		−0.022*	−0.008		−0.009
	(0.010)		(0.012)	(0.008)		(0.009)
Risk: Opportunity and Danger	−0.016		−0.015	−0.012		−0.006
	(0.016)		(0.017)	(0.012)		(0.014)
Risk: Neither	−0.003		−0.009	0.006		0.001
	(0.026)		(0.025)	(0.024)		(0.022)
Risk: Don't know	−0.039***		−0.031**	−0.024**		−0.014
	(0.015)		(0.014)	(0.012)		(0.013)
Risk: Refused	0.004		0.013	0.043		0.048
	(0.078)		(0.081)	(0.076)		(0.080)
Gross Domestic Product (log)	−0.021		−0.024	−0.008		−0.008
	(0.013)		(0.015)	(0.010)		(0.012)
Population (log)	0.007		0.012	−0.004		−0.001
	(0.020)		(0.020)	(0.018)		(0.018)
CO2 Emissions	0.007		0.004	0.008		0.005
	(0.008)		(0.007)	(0.007)		(0.006)
Coal Development Potential	0.006		0.006	0.001		0.001
	(0.006)		(0.006)	(0.004)		(0.004)
Oil Development Potential	0.001		−0.001	0.005		0.004
	(0.008)		(0.007)	(0.005)		(0.005)
Polyarchy	−0.408	0.001	−0.422	−0.217	−0.009	−0.173
	(0.283)	(0.025)	(0.289)	(0.207)	(0.019)	(0.210)
Low Income Country	−0.009		−0.014	0.003		0.003
	(0.055)		(0.057)	(0.048)		(0.050)
Lower Middle Income Country	−0.008		−0.036	0.013		−0.011
	(0.056)		(0.055)	(0.042)		(0.042)
Upper Middle Income Country	0.013		−0.002	−0.001		−0.011
	(0.037)		(0.038)	(0.026)		(0.027)
N	135 611	135 611	135 611	135 611	135 611	135 611
Adjusted R^2	0.016	0.006	0.014	0.016	0.006	0.011
Geographic Region Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Moderators x Covariates	Yes	Yes	Yes	Yes	Yes	Yes
CBPS	No	Yes	Yes	No	Yes	Yes

Notes: Estimates from a linear regression with HC1 standard errors clustered by subregion in parentheses. Temperature variability is scaled so a one-unit shift represents a standard deviation increase. The outcome is a binary indicator for if a respondent says climate change is a top or major risk in her daily life. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

B.7 Robustness Checks

B.7.1 Sensitivity of Estimates to Omitted Variable Bias

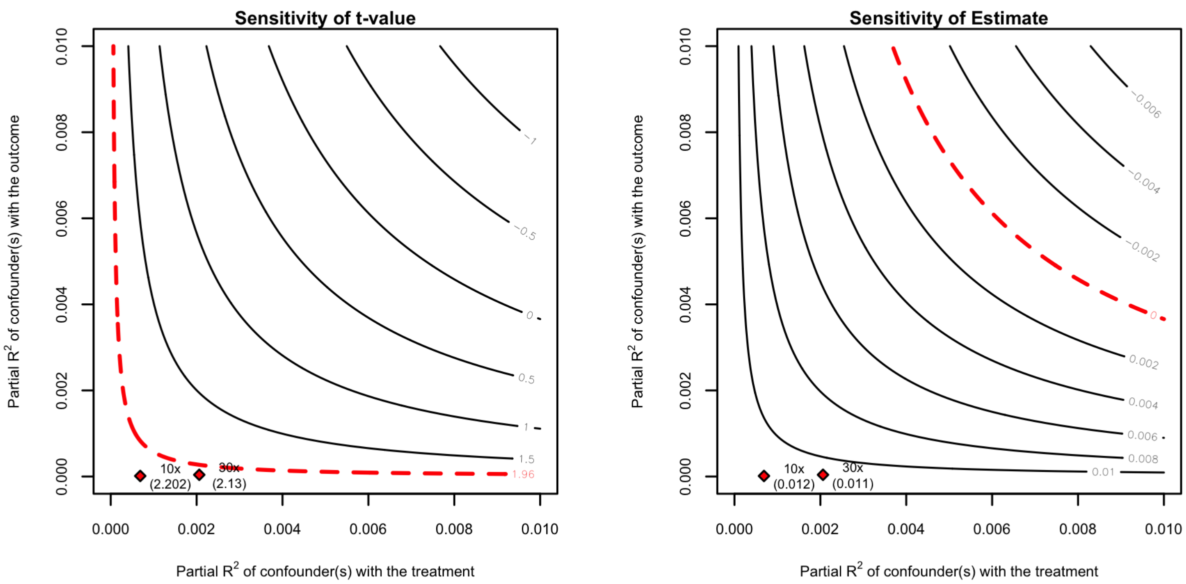

Figure B2: Democracy Benchmark

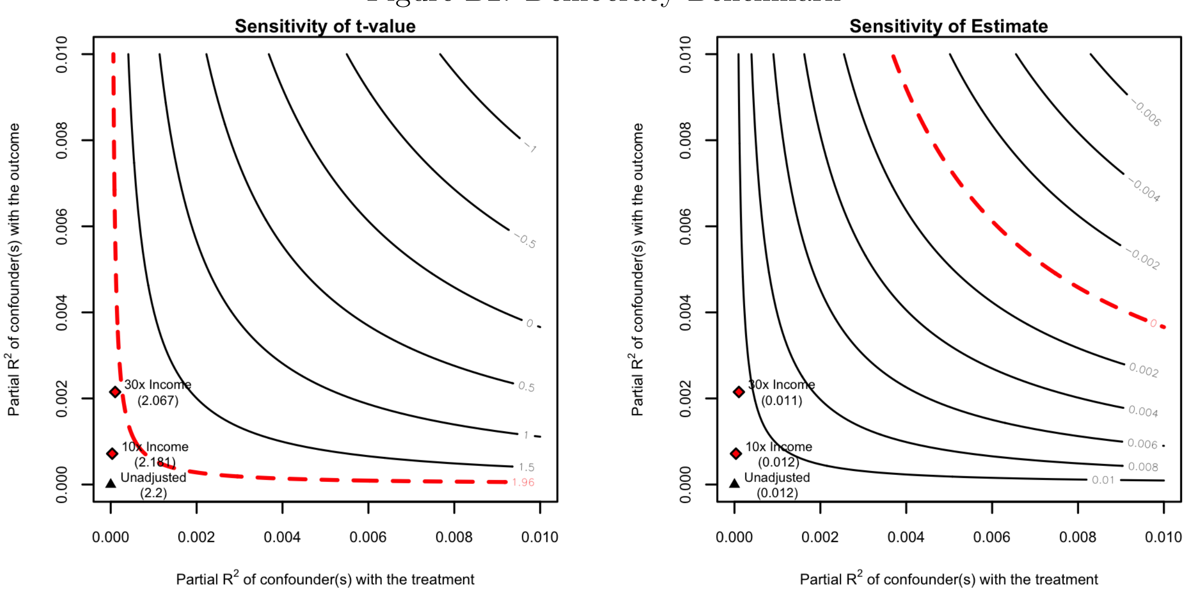

Figure B3: Income Benchmark

Notes: Results from analysis of the sensitivity of the interaction of future damage and temperature variability to omitted variable bias. The bias contour plots on the left indicate that a confounder up to 30 times the size of the observed democracy or income covariates would not bring the lower bound of the confidence below 0 at the 5 percent significance level. The bias contour plots on the right show that a confounder would have to be much larger than 30x the size of the observed democracy or income covariates to bring the estimate to 0. The sensitivity analysis employs linear regression models with the full set of controls and HC1 errors clustered by subregion (Table B2).

B.7.2 Multi-Level Model

Table B5: Multi-Level Model of Temperature Variability Effect on Climate Risk Perceptions

	Climate Change Risk to Daily Life					
	Top/Major Risk			Top Risk		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.065	0.060***	0.076	0.033	0.037***	0.038
	(0.074)	(0.009)	(0.073)	(0.050)	(0.006)	(0.049)
Temp. Variability	−0.007	−0.007	−0.008	−0.005	−0.007*	−0.005
	(0.007)	(0.007)	(0.007)	(0.005)	(0.004)	(0.005)
Future Damages	0.011	−0.013*	0.000	0.007	−0.009**	0.010
	(0.082)	(0.007)	(0.081)	(0.055)	(0.005)	(0.054)
Temp. Variability × Future Damages	0.022**	0.021***	0.022**	0.015**	0.017***	0.015**
	(0.009)	(0.008)	(0.009)	(0.006)	(0.005)	(0.006)
Age	0.004**		0.004**	0.002*		0.002
	(0.002)		(0.002)	(0.001)		(0.001)
Female	0.004		0.005**	0.003		0.003
	(0.003)		(0.003)	(0.002)		(0.002)
Children	0.001		0.000	0.002		0.002
	(0.004)		(0.004)	(0.003)		(0.003)
Education: Primary	−0.005		−0.002	0.001		0.002
	(0.004)		(0.004)	(0.003)		(0.003)
Education: Tertiary	0.006*		0.007**	0.003		0.003
	(0.003)		(0.003)	(0.002)		(0.002)
Education: Don't know	−0.013		−0.018	−0.007		−0.013
	(0.024)		(0.022)	(0.018)		(0.016)
Education: Refused	−0.017		−0.021	−0.014		−0.015
	(0.020)		(0.019)	(0.015)		(0.014)
Household: 3-4	−0.002		−0.002	−0.002		−0.001
	(0.004)		(0.004)	(0.003)		(0.003)
Household: 5-9	0.000		0.003	−0.001		0.001
	(0.006)		(0.005)	(0.004)		(0.004)
Household: 10 or more	−0.037**		−0.037**	−0.013		−0.012
	(0.019)		(0.018)	(0.014)		(0.014)
Income: Very Difficult	−0.022***		−0.021***	−0.013***		−0.014***
	(0.006)		(0.006)	(0.004)		(0.004)
Income: Difficult	−0.007*		−0.005	−0.005*		−0.003
	(0.004)		(0.004)	(0.003)		(0.003)
Income: Comfortable	0.002		0.003	0.000		0.000
	(0.003)		(0.003)	(0.003)		(0.002)
Income: Don't know	0.000		−0.003	0.003		0.002
	(0.013)		(0.012)	(0.009)		(0.009)
Income: Refused	0.000		0.001	0.009		0.009
	(0.012)		(0.011)	(0.009)		(0.009)
Internet Access	0.001		0.002	0.003		0.004
	(0.004)		(0.003)	(0.003)		(0.003)
Risk: Opportunity	−0.010***		−0.011***	−0.004*		−0.004*
	(0.003)		(0.003)	(0.003)		(0.002)
Risk: Opportunity and Danger	−0.004		−0.005	−0.003		−0.002
	(0.005)		(0.004)	(0.003)		(0.003)
Risk: Neither	−0.013		−0.013*	0.000		−0.001
	(0.008)		(0.008)	(0.006)		(0.006)
Risk: Don't know	−0.024***		−0.024***	−0.014***		−0.013***
	(0.006)		(0.006)	(0.004)		(0.004)
Risk: Refused	−0.007		−0.009	0.003		0.002
	(0.030)		(0.029)	(0.022)		(0.022)
Gross Domestic Product (log)	0.001		0.001	0.001		0.001
	(0.007)		(0.006)	(0.004)		(0.004)
Population (log)	−0.010		−0.011	−0.006		−0.006
	(0.008)		(0.008)	(0.005)		(0.005)
CO2 Emissions	0.007		0.007	0.006*		0.006*
	(0.005)		(0.005)	(0.003)		(0.003)
Coal Development Potential	0.002		0.002	−0.002		−0.001
	(0.003)		(0.003)	(0.002)		(0.002)
Oil Development Potential	0.006*		0.006*	0.005**		0.005**
	(0.003)		(0.003)	(0.002)		(0.002)
Polyarchy	0.094***		0.090***	0.042**		0.039**
	(0.026)		(0.026)	(0.018)		(0.018)
Low Income Country	0.161***		0.156***	0.128***		0.124***
	(0.037)		(0.036)	(0.025)		(0.024)
Lower Middle Income Country	0.044***		0.040**	0.022**		0.019*
	(0.016)		(0.016)	(0.011)		(0.011)
Upper Middle Income Country	0.045***		0.043***	0.025***		0.023**
	(0.013)		(0.013)	(0.009)		(0.009)
SD (Subregion Intercept)	0.055	0.056	0.054	0.036	0.036	0.035
SD (Observations)	0.218	0.001	0.001	0.165	0.000	0.000
N	135 611	135 611	135 611	135 611	135 611	135 611
R2 Marg.	0.014	0.100	0.185	0.016	0.154	0.237
Geographic Region Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Covariates x Moderator	Yes	Yes	Yes	Yes	Yes	Yes
CBPS	No	Yes	Yes	No	Yes	Yes

Notes: Estimates from a linear regression with random intercepts for subregions. Temperature variability is scaled so a one-unit shift represents a standard deviation increase. The outcome is a binary indicator for if a respondent says climate change is a top or major risk in her daily life. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table B6: Multi-Level Model of Temperature Variability Effect on Non-Climate Placebos

	Placebos					
	Political Risk			Workplace Risk		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.075**	0.011***	0.075**	−0.012	0.009**	−0.009
	(0.036)	(0.004)	(0.036)	(0.037)	(0.004)	(0.033)
Temp. Variability	0.000	0.000	0.000	0.004	0.006*	0.004
	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)
Future Damages	−0.053	−0.001	−0.050	0.020	0.005	0.016
	(0.040)	(0.003)	(0.040)	(0.041)	(0.003)	(0.037)
Temp. Variability × Future Damages	0.003	0.001	0.003	−0.005	−0.006*	−0.005
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Age	−0.004***		−0.004***	0.002*		0.003***
	(0.001)		(0.001)	(0.001)		(0.001)
Female	−0.026***		−0.026***	−0.008***		−0.008***
	(0.002)		(0.002)	(0.002)		(0.002)
Children	0.006**		0.005*	−0.004*		−0.003
	(0.003)		(0.003)	(0.002)		(0.002)
Education: Primary	−0.006**		−0.006**	−0.009***		−0.010***
	(0.003)		(0.003)	(0.003)		(0.002)
Education: Tertiary	−0.016***		−0.015***	0.010***		0.010***
	(0.002)		(0.002)	(0.002)		(0.002)
Education: Don't know	−0.025		−0.025*	−0.015		−0.020
	(0.016)		(0.015)	(0.014)		(0.013)
Education: Refused	−0.011		−0.011	0.007		0.004
	(0.013)		(0.013)	(0.012)		(0.011)
Household: 3-4	0.004		0.004	−0.002		−0.004*
	(0.003)		(0.002)	(0.002)		(0.002)
Household: 5-9	−0.001		−0.002	0.000		−0.002
	(0.004)		(0.004)	(0.003)		(0.003)
Household: 10 or more	−0.011		−0.012	−0.002		−0.004
	(0.012)		(0.012)	(0.011)		(0.011)
Income: Very Difficult	0.001		0.000	0.004		0.007**
	(0.004)		(0.004)	(0.003)		(0.003)
Income: Difficult	−0.001		0.000	0.003		0.005**
	(0.003)		(0.002)	(0.002)		(0.002)
Income: Comfortable	0.001		0.000	0.004*		0.006***
	(0.002)		(0.002)	(0.002)		(0.002)
Income: Don't know	−0.018**		−0.017**	−0.005		−0.005
	(0.008)		(0.008)	(0.008)		(0.007)
Income: Refused	0.001		0.001	0.001		0.001
	(0.008)		(0.008)	(0.007)		(0.007)
Internet Access	0.008***		0.008***	0.004*		0.005**
	(0.002)		(0.002)	(0.002)		(0.002)
Risk: Opportunity	−0.004		−0.003	−0.002		−0.001
	(0.002)		(0.002)	(0.002)		(0.002)
Risk: Opportunity and Danger	−0.002		−0.001	0.002		0.004
	(0.003)		(0.003)	(0.003)		(0.003)
Risk: Neither	−0.001		0.001	0.000		0.000
	(0.005)		(0.005)	(0.005)		(0.005)
Risk: Don't know	−0.011***		−0.010***	−0.006*		−0.004
	(0.004)		(0.004)	(0.004)		(0.003)
Risk: Refused	−0.006		−0.005	−0.001		0.009
	(0.020)		(0.020)	(0.018)		(0.017)
Gross Domestic Product (log)	0.000		0.000	−0.001		−0.002
	(0.003)		(0.003)	(0.003)		(0.003)
Population (log)	−0.003		−0.003	0.003		0.004
	(0.004)		(0.004)	(0.004)		(0.004)
CO2 Emissions	0.000		0.000	−0.004*		−0.004**
	(0.002)		(0.002)	(0.002)		(0.002)
Coal Development Potential	0.003**		0.003**	−0.001		−0.001
	(0.001)		(0.001)	(0.002)		(0.001)
Oil Development Potential	0.001		0.001	−0.002		−0.003*
	(0.002)		(0.002)	(0.002)		(0.001)
Polyarchy	−0.006		−0.006	0.017		0.018
	(0.013)		(0.013)	(0.013)		(0.012)
Low Income Country	0.006		0.007	−0.007		−0.008
	(0.017)		(0.017)	(0.018)		(0.016)
Lower Middle Income Country	−0.005		−0.005	−0.002		−0.003
	(0.008)		(0.008)	(0.008)		(0.007)
Upper Middle Income Country	−0.007		−0.007	0.001		0.002
	(0.007)		(0.007)	(0.007)		(0.006)
SD (Subregion Intercept)	0.022	0.023	0.022	0.025	0.023	0.022
SD (Observations)	0.147	0.000	0.000	0.131	0.000	0.000
N	135 611	135 611	135 611	135 611	135 611	135 611
R2 Marg.	0.014	0.100	0.376	0.019	0.263	0.383
Geographic Region Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Covariates x Moderator	Yes	Yes	Yes	Yes	Yes	Yes
CBPS	No	Yes	Yes	No	Yes	Yes

Notes: Estimates from a linear regression with random intercepts for subregions. Temperature variability is scaled so a one-unit shift represents a standard deviation increase. The outcome is a binary indicator for if a respondent says political or workplace risk is a top risk in her daily life. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

B.7.3 Alternative Temperature Variability Baseline

Table B7: Effect of Temperature Variability (1980-90 Baseline) on Climate Risk Perceptions

	Climate Change Risk to Daily Life					
	Top/Major Risk			Top Risk		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.115	0.052***	0.113	0.085	0.034***	0.069
	(0.080)	(0.009)	(0.084)	(0.059)	(0.006)	(0.057)
Temp. Variability (1980-1990)	0.001	−0.004	−0.004	0.000	−0.006	−0.003
	(0.006)	(0.007)	(0.006)	(0.004)	(0.005)	(0.004)
Future Damages	−0.049	−0.002	−0.058	−0.052	−0.005	−0.033
	(0.088)	(0.008)	(0.093)	(0.063)	(0.005)	(0.062)
Temp. Variability (1980-1990) × Future Damages	0.016**	0.016*	0.016**	0.012**	0.013**	0.011**
	(0.008)	(0.008)	(0.008)	(0.005)	(0.005)	(0.005)
Age	0.004*		0.003*	0.003*		0.002
	(0.002)		(0.002)	(0.001)		(0.002)
Female	0.004		0.005*	0.002		0.003
	(0.003)		(0.003)	(0.002)		(0.002)
Children	0.003		0.002	0.003		0.003
	(0.005)		(0.004)	(0.003)		(0.003)
Education: Primary	0.000		0.002	0.003		0.005
	(0.006)		(0.006)	(0.005)		(0.005)
Education: Tertiary	0.005		0.005	0.001		0.002
	(0.004)		(0.004)	(0.003)		(0.003)
Education: Don't know	−0.006		−0.010	−0.001		−0.006
	(0.023)		(0.023)	(0.017)		(0.013)
Education: Refused	−0.020		−0.026	−0.014*		−0.017**
	(0.018)		(0.016)	(0.008)		(0.008)
Household: 3-4	−0.003		−0.003	−0.002		−0.001
	(0.004)		(0.005)	(0.003)		(0.003)
Household: 5-9	−0.006		−0.001	−0.005		−0.001
	(0.007)		(0.008)	(0.005)		(0.007)
Household: 10 or more	−0.045***		−0.044***	−0.019		−0.019
	(0.016)		(0.015)	(0.015)		(0.014)
Income: Very Difficult	−0.024***		−0.023***	−0.014***		−0.015***
	(0.006)		(0.006)	(0.005)		(0.005)
Income: Difficult	−0.006		−0.005	−0.004		−0.003
	(0.004)		(0.005)	(0.003)		(0.004)
Income: Comfortable	0.003		0.004	0.001		0.001
	(0.004)		(0.004)	(0.003)		(0.003)
Income: Don't know	−0.002		−0.005	0.003		0.001
	(0.013)		(0.013)	(0.010)		(0.010)
Income: Refused	−0.006		−0.005	0.005		0.006
	(0.011)		(0.011)	(0.009)		(0.009)
Internet Access	−0.001		−0.001	0.002		0.002
	(0.005)		(0.006)	(0.003)		(0.005)
Risk: Opportunity	−0.012***		−0.012***	−0.005*		−0.005
	(0.004)		(0.004)	(0.003)		(0.003)
Risk: Opportunity and Danger	−0.003		−0.004	−0.004		−0.003
	(0.006)		(0.006)	(0.004)		(0.004)
Risk: Neither	−0.016*		−0.017*	−0.003		−0.004
	(0.009)		(0.009)	(0.007)		(0.007)
Risk: Don't know	−0.029***		−0.029***	−0.018***		−0.016***
	(0.007)		(0.007)	(0.005)		(0.005)
Risk: Refused	−0.010		−0.010	0.001		0.002
	(0.031)		(0.030)	(0.025)		(0.025)
Gross Domestic Product (log)	0.001		0.000	−0.001		0.000
	(0.007)		(0.007)	(0.005)		(0.005)
Population (log)	−0.012		−0.010	−0.005		−0.005
	(0.009)		(0.009)	(0.006)		(0.006)
CO2 Emissions	0.008*		0.007*	0.006*		0.006
	(0.004)		(0.004)	(0.003)		(0.003)
Coal Development Potential	0.000		0.002	−0.003*		−0.002
	(0.003)		(0.003)	(0.002)		(0.002)
Oil Development Potential	0.005*		0.003	0.004**		0.003*
	(0.003)		(0.003)	(0.002)		(0.002)
Polyarchy	0.049		0.048	0.009		0.010
	(0.030)		(0.030)	(0.021)		(0.021)
Low Income Country	0.052		0.057	0.029		0.035
	(0.041)		(0.042)	(0.035)		(0.037)
Lower Middle Income Country	0.021		0.024	0.006		0.010
	(0.020)		(0.019)	(0.014)		(0.013)
Upper Middle Income Country	0.032**		0.035**	0.013		0.016*
	(0.015)		(0.014)	(0.010)		(0.010)
N	135 611	135 611	135 611	135 611	135 611	135 611
Adjusted R^2	0.012	0.005	0.010	0.013	0.005	0.008
Geographic Region Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Moderator x Covariates	Yes	Yes	Yes	Yes	Yes	Yes
CBPS	No	Yes	Yes	No	Yes	Yes

Notes: Estimates from a linear regression with HC1 standard errors clustered by subregion in parentheses. Benchmark period for temperature variability is the 1980-1990 average relative to 2018, whereas the main analysis used 1980-2000 average relative to 2018. Temperature variability is scaled so a one-unit shift represents a standard deviation increase. The outcome is a binary indicator for if a respondent says climate change is a top or major risk in her daily life. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table B8: Effect of Temperature Variability (1980-90 Baseline) on Non-Climate Placebos

	Placebo					
	Political Risk			Workplace Risk		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.018	0.012***	0.023	0.003	0.025***	−0.011
	(0.046)	(0.004)	(0.045)	(0.039)	(0.009)	(0.042)
Temp. Variability (1980-1990)	0.002	0.003	0.002	0.004	0.005	0.008*
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)
Future Damages	0.014	−0.001	0.016	0.009	−0.007	0.026
	(0.048)	(0.003)	(0.048)	(0.042)	(0.007)	(0.047)
Temp. Variability (1980-1990) × Future Damages	0.003	0.003	0.004	−0.003	−0.006	−0.009*
	(0.003)	(0.004)	(0.004)	(0.006)	(0.004)	(0.005)
Age	−0.004***		−0.004***	0.002		0.004
	(0.001)		(0.001)	(0.002)		(0.003)
Female	−0.026***		−0.025***	−0.009***		−0.010***
	(0.002)		(0.002)	(0.002)		(0.002)
Children	0.006**		0.006**	−0.009***		−0.009***
	(0.003)		(0.003)	(0.003)		(0.003)
Education: Primary	−0.005*		−0.005*	−0.011***		−0.013***
	(0.003)		(0.003)	(0.003)		(0.004)
Education: Tertiary	−0.017***		−0.016***	0.012***		0.013***
	(0.003)		(0.003)	(0.002)		(0.002)
Education: Don't know	−0.025***		−0.024***	−0.015		−0.019
	(0.003)		(0.003)	(0.012)		(0.013)
Education: Refused	−0.019***		−0.019***	0.001		−0.002
	(0.004)		(0.003)	(0.014)		(0.013)
Household: 3-4	0.004		0.003	0.002		0.002
	(0.003)		(0.003)	(0.003)		(0.003)
Household: 5-9	−0.001		−0.002	0.007*		0.006
	(0.004)		(0.004)	(0.004)		(0.004)
Household: 10 or more	−0.014		−0.015*	0.002		0.000
	(0.009)		(0.008)	(0.007)		(0.007)
Income: Very Difficult	0.002		0.001	0.005		0.008*
	(0.004)		(0.004)	(0.004)		(0.005)
Income: Difficult	0.000		0.001	0.003		0.005
	(0.003)		(0.003)	(0.002)		(0.003)
Income: Comfortable	−0.002		−0.002	0.003		0.005
	(0.002)		(0.002)	(0.002)		(0.003)
Income: Don't know	−0.017***		−0.015**	−0.007		−0.008
	(0.006)		(0.006)	(0.006)		(0.006)
Income: Refused	0.002		0.001	0.000		−0.001
	(0.007)		(0.007)	(0.007)		(0.007)
Internet Access	0.009***		0.009***	0.005*		0.006*
	(0.003)		(0.003)	(0.003)		(0.003)
Risk: Opportunity	−0.004		−0.003	−0.002		0.000
	(0.002)		(0.003)	(0.002)		(0.002)
Risk: Opportunity and Danger	−0.002		−0.001	0.001		0.002
	(0.003)		(0.003)	(0.003)		(0.003)
Risk: Neither	−0.003		−0.002	−0.003		−0.004
	(0.005)		(0.005)	(0.004)		(0.004)
Risk: Don't know	−0.013***		−0.012***	−0.007***		−0.005
	(0.003)		(0.003)	(0.003)		(0.004)
Risk: Refused	−0.006		−0.006	−0.001		0.006
	(0.017)		(0.017)	(0.018)		(0.027)
Gross Domestic Product (log)	0.004		0.004	−0.008*		−0.012**
	(0.003)		(0.003)	(0.004)		(0.006)
Population (log)	−0.007**		−0.008**	0.013**		0.020**
	(0.003)		(0.004)	(0.007)		(0.008)
CO2 Emissions	−0.001		0.000	−0.004**		−0.006***
	(0.001)		(0.001)	(0.002)		(0.002)
Coal Development Potential	0.004***		0.004***	−0.002		−0.004*
	(0.001)		(0.001)	(0.002)		(0.002)
Oil Development Potential	0.001		0.001	−0.004**		−0.004**
	(0.001)		(0.001)	(0.002)		(0.002)
Polyarchy	0.007		0.006	0.028*		0.042**
	(0.011)		(0.011)	(0.016)		(0.017)
Low Income Country	0.028		0.029	−0.014		−0.021
	(0.019)		(0.019)	(0.011)		(0.013)
Lower Middle Income Country	0.011		0.010	−0.011		−0.019
	(0.010)		(0.010)	(0.010)		(0.013)
Upper Middle Income Country	0.003		0.003	0.001		−0.001
	(0.006)		(0.006)	(0.006)		(0.007)
N	135 611	135 611	135 611	135 611	135 611	135 611
Adjusted R^2	0.013	0.002	0.013	0.014	0.007	0.016
Geographic Region Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Moderator x Covariates	Yes	Yes	Yes	Yes	Yes	Yes
CBPS	No	Yes	Yes	No	Yes	Yes

Notes: Estimates from a linear regression with HC1 standard errors clustered by subregion in parentheses. Benchmark period for temperature variability is the 1980-1990 average relative to 2018, whereas the main analysis used 1980-2000 average relative to 2018. Temperature variability is scaled so a one-unit shift represents a standard deviation increase. The outcome is a binary indicator for if a respondent says political or workplace risk is a top risk in her daily life. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

B.7.4 Continuous Moderator

Table B9: Effect of Temperature Variability on Climate Risk Perceptions, Continuous Future Damage Moderator

	Climate Change Risk to Daily Life					
	Top/Major Risk			Top Risk		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.110***	0.061***	0.104***	0.067***	0.036***	0.065***
	(0.036)	(0.007)	(0.036)	(0.024)	(0.005)	(0.023)
Temp. Variability	0.013***	0.006	0.009**	0.008**	0.004	0.005*
	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Future Damages	−0.027	−0.012***	−0.034	−0.023	−0.007**	−0.017
	(0.039)	(0.004)	(0.038)	(0.029)	(0.003)	(0.027)
Temp. Variability × Future Damages	0.006	0.012***	0.007*	0.004	0.008***	0.004
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Age	0.005***		0.005***	0.003***		0.002***
	(0.001)		(0.001)	(0.001)		(0.001)
Female	0.001		0.002	0.000		0.002
	(0.002)		(0.002)	(0.001)		(0.001)
Children	0.004**		0.003	0.006***		0.004**
	(0.002)		(0.002)	(0.001)		(0.002)
Education: Primary	0.002		0.003	0.003**		0.004**
	(0.002)		(0.002)	(0.002)		(0.002)
Education: Tertiary	0.006***		0.005**	0.002		0.002
	(0.002)		(0.002)	(0.001)		(0.002)
Education: Don't know	−0.013		−0.016*	−0.010		−0.011*
	(0.010)		(0.009)	(0.008)		(0.006)
Education: Refused	−0.014		−0.013	−0.011*		−0.007
	(0.010)		(0.011)	(0.006)		(0.008)
Household: 3-4	0.003		0.004**	0.000		0.001
	(0.002)		(0.002)	(0.001)		(0.001)
Household: 5-9	0.000		0.004	−0.003		0.001
	(0.003)		(0.003)	(0.002)		(0.002)
Household: 10 or more	−0.015**		−0.011*	−0.013**		−0.008
	(0.007)		(0.006)	(0.006)		(0.005)
Income: Very Difficult	−0.010***		−0.011***	−0.006***		−0.007***
	(0.002)		(0.003)	(0.002)		(0.002)
Income: Difficult	−0.002		−0.003	−0.002		−0.003
	(0.002)		(0.002)	(0.001)		(0.002)
Income: Comfortable	−0.002		−0.004	−0.001		−0.003*
	(0.002)		(0.002)	(0.001)		(0.002)
Income: Don't know	0.017		0.007	0.026		0.015
	(0.024)		(0.018)	(0.024)		(0.018)
Income: Refused	0.013		−0.001	0.015*		0.004
	(0.010)		(0.008)	(0.008)		(0.006)
Internet Access	0.003		0.001	−0.001		−0.002
	(0.002)		(0.002)	(0.002)		(0.002)
Risk: Opportunity	−0.015***		−0.014***	−0.007***		−0.007***
	(0.002)		(0.002)	(0.001)		(0.001)
Risk: Opportunity and Danger	−0.002		0.002	−0.002		−0.001
	(0.004)		(0.004)	(0.003)		(0.003)
Risk: Neither	−0.021**		−0.020***	−0.012		−0.009
	(0.009)		(0.007)	(0.008)		(0.007)
Risk: Don't know	−0.039***		−0.033***	−0.023***		−0.019***
	(0.003)		(0.003)	(0.003)		(0.003)
Risk: Refused	−0.042***		−0.033***	−0.030***		−0.020**
	(0.013)		(0.011)	(0.010)		(0.009)
Gross Domestic Product (log)	−0.008**		−0.007*	−0.005**		−0.004*
	(0.003)		(0.004)	(0.002)		(0.002)
Population (log)	0.007*		0.005	0.004		0.003
	(0.004)		(0.004)	(0.003)		(0.003)
CO2 Emissions	0.001		0.005*	0.001		0.004
	(0.004)		(0.003)	(0.003)		(0.003)
Coal Development Potential	−0.002		−0.001	−0.002		−0.001
	(0.002)		(0.002)	(0.002)		(0.002)
Oil Development Potential	−0.003		0.000	−0.002*		−0.001
	(0.002)		(0.002)	(0.001)		(0.001)
Polyarchy	0.041***		0.033**	0.026***		0.021**
	(0.014)		(0.014)	(0.009)		(0.009)
Low Income Country	0.062***		0.042**	0.048**		0.032**
	(0.023)		(0.019)	(0.019)		(0.016)
Lower Middle Income Country	0.016*		0.016*	0.008		0.006
	(0.009)		(0.009)	(0.006)		(0.006)
Upper Middle Income Country	0.013**		0.016**	0.006		0.006
	(0.007)		(0.007)	(0.004)		(0.004)
N	135 611	135 611	135 611	135 611	135 611	135 611
Adjusted R^2	0.015	0.006	0.012	0.016	0.006	0.010
Geographic Region Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Moderator x Covariates	Yes	Yes	Yes	Yes	Yes	Yes
CBPS	No	Yes	Yes	No	Yes	Yes

Notes: Estimates from a linear regression with HC1 standard errors clustered by subregion in parentheses. Temperature variability is scaled so a one-unit shift represents a standard deviation increase. The outcome is a binary indicator for if a respondent says climate change is a top or major risk in her daily life. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table B10: Effect of Temperature Variability on Non-Climate Placebos, Continuous Future Damage Moderator

	Placebo					
	Political Risk			Workplace Risk		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.034**	0.015***	0.040***	−0.001	0.022***	0.007
	(0.015)	(0.002)	(0.016)	(0.016)	(0.006)	(0.020)
Temp. Variability	0.002	0.003	0.004	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)	(0.003)
Future Damages	0.006	−0.004**	0.009	−0.023	−0.004*	−0.009
	(0.020)	(0.002)	(0.019)	(0.019)	(0.002)	(0.021)
Temp. Variability × Future Damages	0.000	0.001	0.001	0.000	−0.002	−0.004
	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)	(0.003)
Age	−0.004***		−0.003***	0.002***		0.002***
	(0.001)		(0.001)	(0.000)		(0.001)
Female	−0.027***		−0.027***	−0.007***		−0.008***
	(0.001)		(0.001)	(0.001)		(0.001)
Children	0.005***		0.003**	−0.002*		−0.001
	(0.001)		(0.001)	(0.001)		(0.001)
Education: Primary	−0.002		−0.003**	−0.004***		−0.005***
	(0.001)		(0.001)	(0.001)		(0.001)
Education: Tertiary	−0.009***		−0.010***	0.010***		0.012***
	(0.001)		(0.002)	(0.002)		(0.003)
Education: Don't know	−0.016***		−0.015***	−0.014***		−0.013***
	(0.003)		(0.003)	(0.003)		(0.003)
Education: Refused	−0.014***		−0.015***	0.001		0.000
	(0.004)		(0.003)	(0.006)		(0.005)
Household: 3-4	0.002		0.001	−0.001		−0.001
	(0.001)		(0.002)	(0.001)		(0.002)
Household: 5-9	−0.002		−0.002	0.003**		0.002
	(0.002)		(0.002)	(0.002)		(0.002)
Household: 10 or more	−0.003		−0.004	0.001		0.000
	(0.003)		(0.003)	(0.003)		(0.003)
Income: Very Difficult	−0.002		−0.002	0.004**		0.004**
	(0.002)		(0.002)	(0.002)		(0.002)
Income: Difficult	−0.001		0.000	0.002**		0.001
	(0.001)		(0.001)	(0.001)		(0.001)
Income: Comfortable	−0.001		−0.001	0.000		0.000
	(0.001)		(0.001)	(0.001)		(0.002)
Income: Don't know	−0.008**		−0.009***	0.001		0.001
	(0.003)		(0.003)	(0.003)		(0.003)
Income: Refused	−0.005		−0.005	−0.005		−0.003
	(0.004)		(0.005)	(0.004)		(0.005)
Internet Access	0.001		0.002	0.005***		0.005***
	(0.001)		(0.001)	(0.001)		(0.001)
Risk: Opportunity	−0.003**		−0.003**	−0.001		0.001
	(0.001)		(0.002)	(0.001)		(0.002)
Risk: Opportunity and Danger	0.003		0.006	0.002		0.002
	(0.003)		(0.004)	(0.002)		(0.002)
Risk: Neither	−0.012***		−0.011***	−0.005*		−0.005**
	(0.002)		(0.002)	(0.002)		(0.002)
Risk: Don't know	−0.011***		−0.011***	−0.006***		−0.006***
	(0.001)		(0.001)	(0.001)		(0.001)
Risk: Refused	−0.009		−0.010	−0.001		0.002
	(0.006)		(0.006)	(0.007)		(0.009)
Gross Domestic Product (log)	0.001		0.001	−0.004***		−0.004**
	(0.001)		(0.001)	(0.001)		(0.001)
Population (log)	−0.003**		−0.003*	0.007***		0.005**
	(0.001)		(0.002)	(0.002)		(0.002)
CO2 Emissions	0.001		0.001	−0.009***		−0.008***
	(0.001)		(0.001)	(0.002)		(0.003)
Coal Development Potential	0.002		0.002*	−0.001		−0.001
	(0.001)		(0.001)	(0.001)		(0.001)
Oil Development Potential	0.002*		0.002**	0.000		0.000
	(0.001)		(0.001)	(0.001)		(0.001)
Polyarchy	0.010**		0.012**	0.021***		0.024***
	(0.005)		(0.005)	(0.007)		(0.007)
Low Income Country	0.003		0.007	0.002		0.005
	(0.006)		(0.006)	(0.005)		(0.005)
Lower Middle Income Country	0.004		0.006	0.006		0.005
	(0.004)		(0.004)	(0.005)		(0.005)
Upper Middle Income Country	0.002		0.004	0.010**		0.009**
	(0.003)		(0.003)	(0.004)		(0.004)
N	135 611	135 611	135 611	135 611	135 611	135 611
Adjusted R^2	0.013	0.002	0.014	0.015	0.007	0.016
Geographic Region Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Moderator x Covariates	Yes	Yes	Yes	Yes	Yes	Yes
CBPS	No	Yes	Yes	No	Yes	Yes

Notes: Estimates from a linear regression with HC1 standard errors clustered by subregion in parentheses. Temperature variability is scaled so a one-unit shift represents a standard deviation increase. The outcome is a binary indicator for if a respondent says political or workplace risk is a top risk in her daily life. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

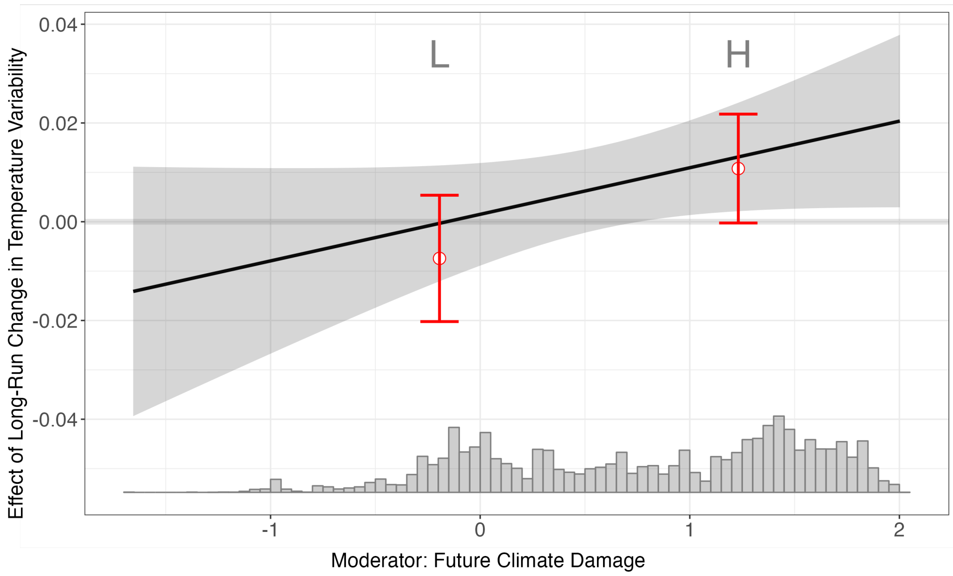

Figure B4: Moderating Effect of Future Climate Damage on the Relationship Between Temperature Variability and Climate Risk Perceptions

Notes: For consistency with the panel analysis, in this plot, we rescale future climate damage so it represents the percentage of county GDP lost because of global warming, so positive values indicate greater damage, whereas negative values indicate possible benefits. Red bars denote 95% confidence intervals around the point estimates from bins of the moderator above and below 1, which differentiates counties into those experiencing future damages and possible net benefits (Hainmueller, Mummolo, and Xu 2019). The model includes covariates or age, gender, parenthood, education, income, Internet access, risk understanding, GDP, population, coal, oil, CO2 emissions, democracy, and country income level. Heteroskedasticity-robust standard errors are clustered by subregion.

C Panel Analysis Appendix

C.1 Questionnaire

1. In what year were you born?
2. Are you male or female?

   Male; Female

3. What is the highest level of education you have completed?

   No HS; High school graduate; Some college; 2-year; 4-year; Post-grad)

4. What racial or ethnic group best describes you?

   White; Black; Hispanic; Asian; Native American; Mixed; Other; Middle Eastern

5. Which of the following best describes your current employment status?

   Full-time; Part-time; Temporarily laid off; Unemployed; Retired; Permanently disabled; Homemaker; Student; Other

6. Generally speaking, do you think of yourself as a ...?

   Democrat; Republican; Independent; Other

7. Would you call yourself a strong [Democrat/Republican] or a not very strong [Democrat/Republican]?

   Strong [Democrat/Republican]; Not very strong [Democrat/Republican]

8. Do you think of yourself as closer to the Democratic or the Republican Party?

   Democratic Party; Republican Party; Neither; Not sure

9. Thinking about politics these days, how would you describe your own political viewpoint?

   Very liberal; Liberal; Moderate; Conservative; Very Conservative; Not sure

10. How important is religion in your life?

    Very important; Somewhat important; Not too important; Not at all important

11. Thinking back over the last year, what was your family's annual income?

    Less than $10,000; $10,000 - $19,999; $20,000 - $29,999; $30,000 - $39,999; $40,000 - $49,999; $50,000 - $59,999; $60,000 - $69,999; $70,000 - $79,999; $80,000 - $99,999; $100,000 - $119,999; $120,000 - $149,999; $150,000 - $199,999; $200,000 - $249,999; $250,000 - $349,999; $350,000 - $499,999; $500,000 or more; $150,000 or more; $250,000 or more

12. Are you the parent or guardian of any children under the age of 18?

    Yes; No

1. From what you know about global climate change or global warming, which one of the following statements comes closest to your opinion?

   Global climate change has been established as a serious problem, and immediate action is necessary;

   There is enough evidence that climate change is taking place and some action should be taken;

   We don't know enough about global climate change, and more research is necessary before we take any actions;

   Concern about global climate change is exaggerated. No action is necessary;

   Global climate change is not occurring, this is not a real issue.

C.2 Summary Statistics

Table C1: Panel Survey Summary Statistics

	Mean	SD	Min	Max	Missing
Climate Policy Support	0.54	0.50	0.00	1.00	73
Wildfires	0.05	0.26	0.00	5.00	2
Wildfire (=1)	0.04	0.20	0.00	1.00	2
Wildfire (Placebo)	0.08	0.42	0.00	5.00	2
Future Damage (=1)	0.80	0.40	0.00	1.00	2
Employed	0.40	0.49	0.00	1.00	0
HS or Less	0.21	0.41	0.00	1.00	0
Some College	0.34	0.47	0.00	1.00	0
BA or Higher	0.45	0.50	0.00	1.00	0
Democrat	0.36	0.48	0.00	1.00	2
Republican	0.30	0.46	0.00	1.00	2
Conservative	0.41	0.49	0.00	1.00	2
Liberal	0.28	0.45	0.00	1.00	2
New Parent	0.01	0.10	0.00	1.00	0
Home Owner	0.80	0.40	0.00	1.00	122
Income Q1	0.07	0.25	0.00	1.00	34
Income Q2	0.34	0.48	0.00	1.00	34
Income Q3	0.26	0.44	0.00	1.00	34
Income Q4	0.14	0.35	0.00	1.00	34
Income Q5	0.07	0.26	0.00	1.00	34
Income Not Say	0.00	0.00	0.00	0.00	34
Religion Very Important	0.40	0.49	0.00	1.00	1
Religion Somewhat Important	0.24	0.43	0.00	1.00	1
Religion Not Too Important	0.15	0.35	0.00	1.00	1
Religion Not At All Important	0.21	0.41	0.00	1.00	1

C.3 Regression Estimates

Table C2: Effect of Wildfire Experience on Climate Policy Support

	Outcome: Climate Policy Support							
	ATT				Placebo Fires (t+2)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Wildfires	0.02***		0.01	0.00	0.00		−0.01	
	(0.00)		(0.01)	(0.01)	(0.00)		(0.01)	
Wildfires (=1)		0.02**				0.00		−0.01
		(0.01)				(0.01)		(0.01)
Future Damage (=1)	−0.02	−0.02	−0.02	−0.02	−0.02	−0.02	−0.02	−0.02
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
Wildfires × Future Damage			0.02**				0.01	
			(0.01)				(0.01)	
Wildfires (=1) × Future Damage				0.03**				0.01
				(0.01)				(0.02)
Employed	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Education: Some College	0.04***	0.04***	0.04***	0.04***	0.04***	0.04***	0.04***	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Education: Bachelor's or Post-Grad	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Household Income: Q2	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Household Income: Q3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Household Income: Q4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Household Income: Not Say	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Homeowner	−0.01	0.00	−0.01	0.00	0.00	0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Democrat	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Republican	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Ideology: Liberal	0.02**	0.02**	0.02**	0.02**	0.02**	0.02**	0.02**	0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Ideology: Moderate	0.02**	0.02**	0.02**	0.02**	0.02**	0.02**	0.02**	0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Ideology: Not Sure	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Religion: Not too important	−0.01*	−0.01*	−0.01*	−0.01*	−0.01*	−0.01*	−0.01*	−0.01*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Religion: Somewhat important	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Religion: Very important	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
New parent	0.03**	0.03**	0.03**	0.03**	0.03**	0.03**	0.03**	0.03**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
N	28500	28500	28500	28500	28500	28500	28500	28500
Adjusted R^2	0.838	0.838	0.838	0.838	0.838	0.838	0.838	0.838
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Estimates from a linear regression model with Newey and West (1986) standard errors in parentheses to account for heteroskedasticity and serial correlation. The outcome is a binary indicator that takes the value 1 if an individual supports climate policy and 0 if not. ATT is the average treatment effect of wildfires. Placebo fires are those that take place two years before a panel year. Missing values imputed using 30 multiple imputations (Blackwell, Honaker, and King 2017). $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

C.4 Sensitivity Analyses

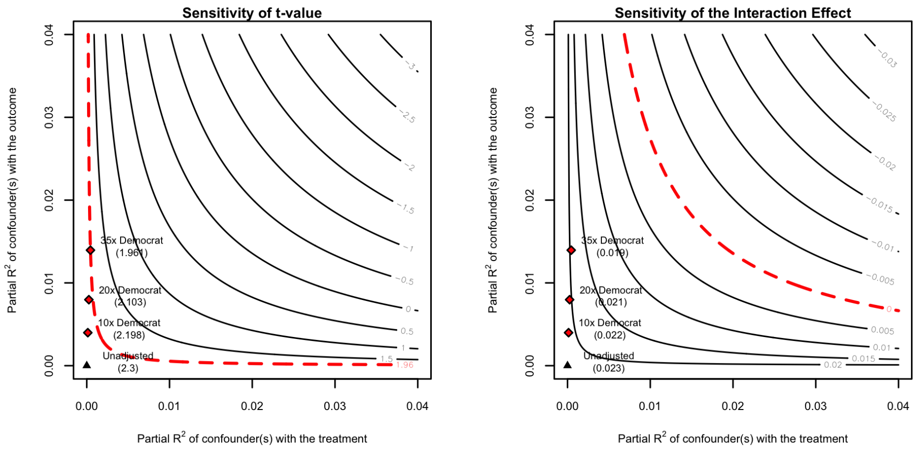

Figure C1: Democrat Benchmark

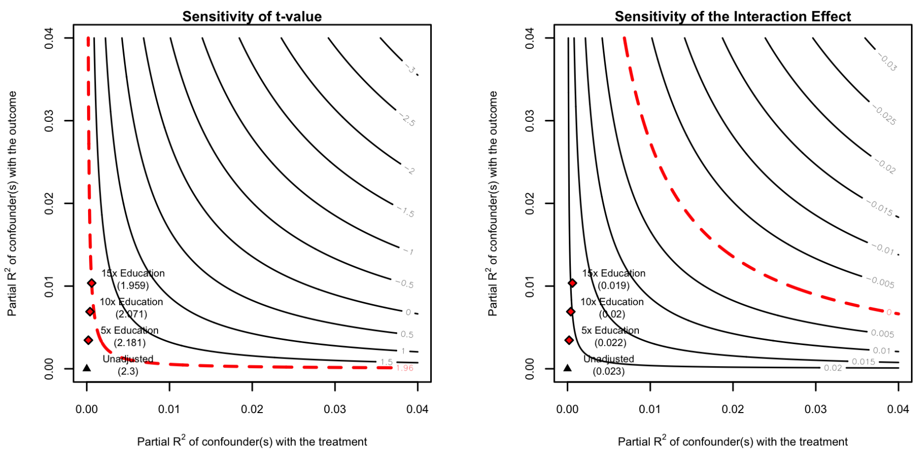

Figure C2: Education Benchmark

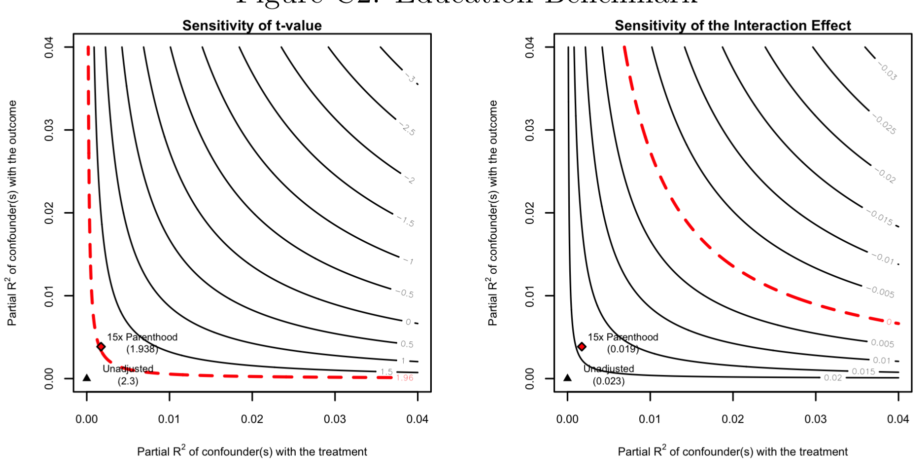

Figure C3: Parenthood Benchmark

Notes: Analysis of the sensitivity of the wildfire and future damages interaction to omitted variable bias. Model 2 in Table C2 employed for analysis.

C.5 Continuous Damages Moderator

Table C3: Effect of Wildfire Experience on Climate Policy Support, Continuous Moderator

	Outcome: Climate Policy Support							
	ATT				Placebo Fires (t+2)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Wildfires	0.02***		0.03***	0.03***	0.00		0.00	
	(0.00)		(0.01)	(0.01)	(0.00)		(0.00)	
Wildfires (=1)		0.02**				0.00		−0.01
		(0.01)				(0.01)		(0.01)
Future Damage (=1)	−0.01*	−0.01*	−0.01*	−0.01*	−0.01*	−0.01*	−0.01*	−0.01*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Wildfires × Future Damage			0.02*				0.00	
			(0.01)				(0.01)	
Wildfires (=1) × Future Damage				0.03*				−0.01
				(0.02)				(0.02)
Employed	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Education: Some College	0.04***	0.04***	0.04***	0.04***	0.04***	0.04***	0.04***	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Education: Bachelor's or Post-Grad	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Household Income: Q2	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Household Income: Q3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Household Income: Q4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Household Income: Not Say	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Homeowner	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Democrat	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Republican	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Ideology: Liberal	0.02**	0.02**	0.02**	0.02**	0.02**	0.02**	0.02**	0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Ideology: Moderate	0.02**	0.02**	0.02**	0.02**	0.02**	0.02**	0.02**	0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Ideology: Not Sure	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Religion: Not too important	−0.01*	−0.01*	−0.01*	−0.01*	−0.01*	−0.01*	−0.01*	−0.01*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Religion: Somewhat important	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Religion: Very important	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
New parent	0.03**	0.03**	0.03**	0.03**	0.03**	0.03**	0.03**	0.03**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
N	28500	28500	28500	28500	28500	28500	28500	28500
Adjusted R^2	0.838	0.838	0.838	0.838	0.838	0.838	0.838	0.838
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Estimates from a linear regression model with Newey and West (1986) standard errors in parentheses to account for heteroskedasticity and serial correlation. The outcome is a binary indicator that takes the value 1 if an individual supports climate policy and 0 if not. Future climate damage moderator is scaled at the county level, so a one-unit shift is a standard deviation increase. ATT is the average treatment effect of wildfires. Placebo fires are those that take place two years before a panel year. Missing values are imputed using 30 multiple imputations (Blackwell, Honaker, and King 2017). $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

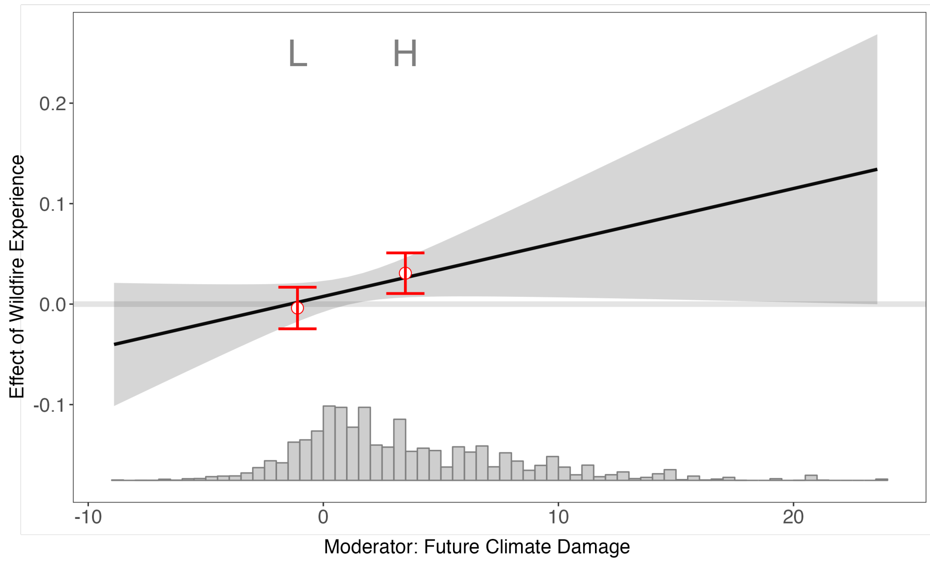

Figure C4: Wildfire Experience and Climate Policy Support Moderated by Future Damage

Notes: Future climate damage represents the percentage of county GDP lost because of global warming, so positive values indicate greater damage, whereas negative values indicate possible benefits. Red bars denote 95% confidence intervals around the point estimates from bins of the moderator above and below 0, which differentiates counties into those experiencing future damages and possible net benefits.

C.6 Covariate Balance

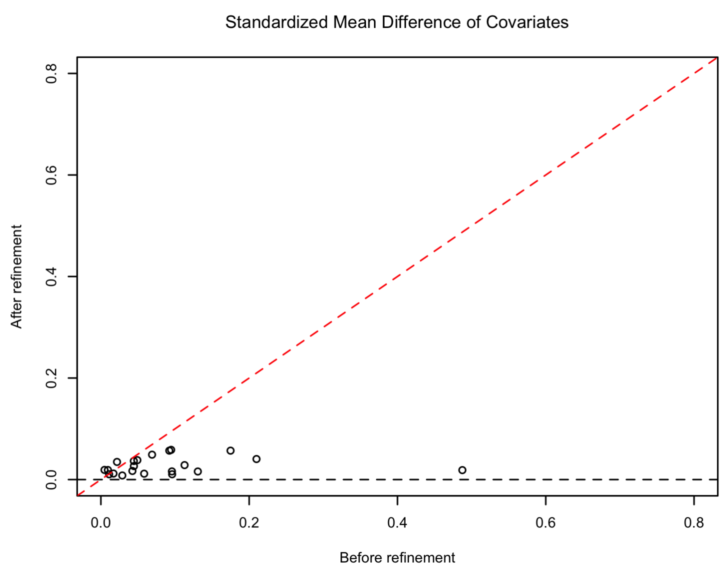

Figure C5: Improvement in Covariate Balance from Panel Matching

Notes: The scatter plot compares the absolute value of standardized mean difference for each covariate before (horizontal axis) and after (vertical axis) the refinement of matched sets. The matching procedure improves balance for most covariates, and the results hold when controlling for covariates with remaining imbalances.

C.7 Skeptics, Undecideds, and Believers Regression Results

Table C4: Effect Wildfire Experience on Climate Policy Support Conditional on Prior Beliefs

	Skeptics	Undecideds	Believers
	(1)	(2)	(3)
Wildfires	0.006	0.008	0.008
	(0.008)	(0.012)	(0.008)
Future Damage (=1)	−0.006	−0.054	−0.002
	(0.012)	(0.036)	(0.009)
Wildfires × Future Damage	0.019	0.041**	−0.005
	(0.017)	(0.020)	(0.010)
Employed	0.007	0.006	0.003
	(0.008)	(0.012)	(0.005)
Education: Some College	0.025*	0.063***	0.020
	(0.014)	(0.022)	(0.015)
Education: Bachelor's or Post-Grad	0.025	0.014	0.007
	(0.018)	(0.029)	(0.018)
Household Income: Q2	−0.020**	0.001	−0.009
	(0.008)	(0.016)	(0.008)
Household Income: Q3	−0.010	0.006	−0.004
	(0.008)	(0.014)	(0.008)
Household Income: Q4	−0.004	0.015	−0.006
	(0.009)	(0.016)	(0.008)
Household Income: Not Say	−0.025*	−0.021	0.024**
	(0.015)	(0.026)	(0.012)
Homeowner	−0.005	−0.022	0.017**
	(0.010)	(0.017)	(0.008)
Democrat	0.008	0.046***	0.007
	(0.033)	(0.017)	(0.005)
Republican	0.000	0.019	0.005
	(0.005)	(0.016)	(0.033)
Ideology: Liberal	0.026	0.028	−0.002
	(0.051)	(0.019)	(0.019)
Ideology: Moderate	0.001	0.031**	−0.012
	(0.011)	(0.014)	(0.018)
Ideology: Not Sure	0.018	0.005	−0.006
	(0.030)	(0.030)	(0.026)
Religion: Not too important	−0.023*	−0.029**	0.000
	(0.013)	(0.015)	(0.006)
Religion: Somewhat important	−0.006	0.006	0.006
	(0.008)	(0.009)	(0.004)
Religion: Very important	0.002	−0.001	0.000
	(0.005)	(0.008)	(0.003)
New parent	0.003	0.086***	0.002
	(0.021)	(0.033)	(0.015)
N	8073	11748	8679
Adjusted R^2	0.222	0.687	0.320
Individual Fixed Effects	Yes	Yes	Yes
Panel Wave Fixed Effects	Yes	Yes	Yes

Notes: Estimates from a linear regression model with Newey and West (1986) standard errors in parentheses to account for heteroskedasticity and serial correlation. The outcome is a binary indicator that takes the value 1 if an individual supports climate policy and 0 if not. Missing values imputed using 30 multiple imputations (Blackwell, Honaker, and King 2017). $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

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