Preference Updating Under Uncertainty: Evidence from Responses to Global Warming*

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Abstract

How do political preferences emerge and change? Political economy theories typically take preferences as given by material circumstances, whereas behavioral theories view preferences as social in origin. We synthesize these approaches to produce a framework that explains how individuals change their preferences when there is uncertainty about the distributive effects of societal activities. Our theory proposes a process of Bayesian updating where one places greater weight on information from direct experience, which is seen as more credible. We apply our theory in the case of climate change. Using an econometric model of global warming, we derive what individuals' preferences over action to reduce climate damages should be if they were fully informed. Then, we leverage geospatial data on climate disturbances to capture experiential shocks that should cause preference updating. Analyses using cross-sectional survey data in 2,255 regions across 123 countries and panel data in the United States find that experiential climate shocks lead to preference updating in line with how individuals will objectively be affected by global warming. Our theory and findings make broad contributions to the study of political economy, behavior, and climate politics.

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Theories of politics often begin with preferences: individuals have a ranking of choices given their available information and understanding of outcomes. Preferences are the heartbeat of politics because learning who gets what, when, and how requires first knowing who *wants* what, when, and how. Yet the effects of societal activities like production and consumption on the income, assets and wealth of individuals—that is, the distributive consequences—which from the basis of preferences in political economy theorizing, are not always clear. Given this uncertainty, how do individuals form and change their preferences?

Uncertainty about the material effects of societal activities is ubiquitous. How will higher temperatures affect different parts of the globe? How will the geography of supply chains empower or weaken nations? What effect will technological innovation have on who wins and loses from trade? Each example involves actions like the consumption of fossil fuels, production of goods, and investment in innovation, which have distributive effects that in a given moment may be difficult for individuals to understand.

Yet, political economy theories assume that individuals understand the distributive consequences of societal activities, taking these material effects as exogenous and self-evident (e.g., Lake 2009). The advantage of this approach is the ability to deduce precise hypotheses, but as currently constituted, there is little theory about change in preferences. While behavioral theories have rich models of preference formation and change (e.g. Druckman and Lupia 2000), these more psychological microfoundations, absent further specification, do not generate determinant predictions.

In this article, we synthesize behavioral and political economy approaches to explain how individuals change their preferences when there is uncertainty about who gains and loses from societal activities. From social psychology, we apply the insight that *direct experience* provides a credible source of information that can change beliefs (e.g., Nisbett and Ross 1980) and help people process uncertainty (e.g., Marx et al. 2007). From political economy, we propose using models of how societal activities affect material outcomes like the income, assets, and wealth that enable consumption. The economic model provides the foundation for deducing how individuals should adjust their preferences in response to experiential shocks—that is, personal experience with material losses or gains from societal activities. In response to experiential shocks, individuals engage in Bayesian updating, where they incorporate the new information, weighted according to the informativeness of a signal and strength of one's prior beliefs.

We apply our theory to climate change for substantive and theoretical reasons. First, climate change caused by the burning of fossil fuels is a pressing global challenge; extreme weather accelerated and intensified by higher temperatures will cause substantial societal damages (IPCC 2022). Second, the time horizon and scientific nature of global warming injects uncertainty into evaluations of where and how much climate change will impact different parts of the world. As a consequence, public concern about climate change has changed over time (e.g., Egan and Mullin 2012). Overall, the structure of the climate problem lends itself to evaluating theories of preference updating.

Our framework predicts that as individuals have more direct experience with global warming, their preferences for actions to address climate damage should increasingly align with how they will be materially affected by temperature increases. Departing from the vast literature on climate experience and behavior (e.g., Howe et al. 2019; Weber 2010), as in Gazmararian and Milner (2022), we employ a spatial integrated assessment model of how global warming will affect local income (Cruz and Rossi-Hansberg 2021). Although this model is itself the subject of uncertainty, it provides an objective benchmark based on available scientific knowledge of how individuals' preferences should change in response to experiential climate shocks.

We conduct two empirical tests of our hypotheses. Since climate change's differential effects are starkest across countries, we first deploy existing survey data collected in 123 countries in 2019 ($N = 131,380$). To capture subnational variation in climate damages and benefits, we construct a crosswalk that maps each respondent to 2,255 administrative regions within each country at the lowest level of aggregation possible. We pair these regions with geospatial data on long-run changes in temperature variability to measure how direct experience with structural shifts in the distribution of weather—climate change—shape individual preferences. We find that people in regions experiencing long-run climate experience shocks are more likely to identify global warming as the most important risk in their daily life, but only if one lives in a location facing potential climate damages.

The second empirical test uses an existing three-wave panel survey in the United States to explore how preferences change over time. We pair these survey responses with county-level measures of climate damages and benefits. Then, we leverage data on the location of wildfires to capture how individuals update their beliefs and preferences in response to experiential shocks. The results show that experiencing a wildfire leads to greater belief that climate change is a serious threat that warrants a government response, but only if one resides in a location facing future income loss from global warming. Consistent with our economic model, there is no effect of experiential shocks for individuals living in areas not facing climate damages. A placebo test using the incidence of future wildfires provides further evidence of our experiential updating mechanism.

Our paper makes three contributions that we elaborate upon in the conclusion. First, we synthesize political economy and behavioral approaches to generate new predictions about how preferences change when there is uncertainty. While uncertainty has been acknowledged as a source of status quo bias (e.g., Fernandez and Rodrik 1991), we explain how the level of uncertainty can change, even when the objective situation does not. This is especially pertinent for understanding preferences when politics intersects with scientific domains like the environment where uncertainty abounds. Second, in contrast to studies that find a minimal impact of information on preferences or that the public does not respond coherently to new information (e.g., Achen and Bartels 2016), we show that making such an evaluation requires careful specification of what individuals preferences should be. When using an economic model of how places will be impacted by global warming, we find that individuals respond in predictable ways to experiential shocks. Third, we contribute to the climate politics literature by resolving inconsistent results as to the effects of personal experience (e.g., Howe et al. 2019). By constructing an objective benchmark of what political actor's preferences would be if they were fully informed, we are able to provide and test precise predictions about how individuals will respond to one of the most pressing threats of the 21st century: climate change.

Theoretical Silos: Political Economy and Behavior

Research in political economy and behavior take dramatically different approaches to understanding preferences and how they change. Both traditions agree that preferences are orderings of what actors want given the available information, but political economists derive preferences from the material effects of policy, whereas behavioralists start with cognition, personal experience, and values. Both streams of research have generated important insights. Yet, this theoretical and methodological siloing, where insights do not cross-pollinate, has analytical costs. Theories of preference change in political economy lack strong behavioral microfoundations, whereas behavioral theories lack the determinant predictions from political economy. It is our goal to synthesize these approaches.

Certain Preferences in an Uncertain World

Theories in political economy generally assume that individuals understand with certainty the effects of societal activities like trade, air pollution, or innovation on their income, assets, and wealth. Theorizing in this tradition begins by taking a model of economic effects of an action such as a policy or activity like polluting. Based on who wins or losses, the researcher deduces hypotheses regarding the behavior of firms, politicians, and voters. These political actors, by assumption, know with certainty whether they are a winner or a loser, having internalized the lessons from the economic model.

The Open Economy Politics (OEP) paradigm as characterized by Lake (2009) is a prominent example of this mode of analysis. The OEP approach has served as a fruitful foundation for theorizing the politics of trade (e.g., Hiscox 2002; Milner 1988; Rogowski 1987; Scheve and Slaughter 2001b), immigration (e.g., Scheve and Slaughter 2001a; Peters 2015), foreign direct investment (e.g., Scheve and Slaughter 2004), climate (Kennard 2020), and currency (e.g., Broz 1999; Frieden 1991).

Yet in some cases it is unrealistic to assume that political actors know with certainty the effects of societal activities on their incomes and asset holdings. Besides disparities in information gathering and processing capacities, some issues by their very nature involve uncertainty that makes it challenging to understand how one is affected—especially when the political actor is an individual rather than a firm. Climate change, for example, will have differential impacts across both space and time, which makes it difficult to know precisely how and when one might be impacted. In turn, uncertainty makes it hard for individuals to determine the best policy option.

Political economy theories allow for change in preferences when the objective situation changes. However, when preferences evolve as the level of uncertainty changes, it is not the objective situation that transforms, but one's understanding of the world. For example, there is a true mapping between climate change and its material impacts, but this relationship is not known with absolute certainty. If one learns more about how she is impacted by global warming, her preferences may change, but it is not because of the objective situation (e.g., the true mapping from climate change to material impacts) which has remained invariant, but because her understanding of the situation (e.g., level of uncertainty) has evolved. Allowing for uncertainty can make sense of why people's preferences do not reflect their objective material interests in a given moment because they cannot determine their best response, while also explaining change in preferences despite the objective situation remaining the same.

Political economy is not ignorant of uncertainty. Previous work explores how uncertainty affects the strategies of candidates for public office (Ferejohn and Noll 1978; Shepsle 1972), the design of international agreements (Koremenos 2001, 2005; Rosendorff and Milner 2001), the extent of status quo bias (Fernandez and Rodrik 1991), the behavior of interest groups (Stokes 2020), and modes of decision-making (Nelson and Katzenstein 2014). Yet beyond the consequences of uncertainty there remains an unresolved question about how uncertainty may change and affect preferences.

Changing Preferences Without Determinate Predictions

Models of learning that span social sciences provide some traction to begin to understand how preferences change. In international relations, countries may learn about the distribution of power through fighting (e.g., Powell 2004) and leaders can take lessons from history (e.g., Levy 1994; Jervis 1976; Reiter 1996). Learning in this context is with respect to beliefs about the consequences of policies or preferences of other political actors, but less so how individuals come to form policy preferences.

Ideas provide another mechanism of preference change (e.g., Goldstein and Keohane 1993; Rodrik 2014). These studies typically explain the effects of ideas rather than their causes, which would be needed to understand preference change over time. Ideas may emerge in response to new problems (e.g., Allan and Meckling 2021) or from communities of experts (Haas 1989). Although these sources of ideas do not generate concrete and general predictions about when preferences will change, nor are they grounded in behavioral microfoundations about how humans make decisions.

American politics has rich theories, some of which draw on social psychology, to explain how attitudes change. Druckman and Lupia's (2000) review highlights how interaction with one's environment can lead to preference change through the acquisition of new information. As Zaller (1992, 6) puts it, "[e]very opinion is a marriage of information and predisposition." Zaller's (1992) foundational "Receive-Accept-Sample" model of public opinion centers on political communication, where individuals more engaged with an issue have a higher likelihood of receiving a message. New information can lead to opinion updating by altering the considerations that are top of mind. However, this model implies outside of predispositions that influence resistance to new messages, such as partisan attachment (e.g., Campbell et al. 1960; Green, Palmquist, and Schickler 2002) or values (e.g., Lane 1973; Feldman and Zaller 1992), people do not have true preferences. Instead, the public simply reacts to what is salient. This would imply that one could not make determinate predictions about preferences necessary for political economy theorizing.[1]

Encouragingly, there is evidence from decades of surveys that public opinion may be collectively rational and adapts to new information and changing circumstances (Page and Shapiro (1992); but see Achen and Bartels (2016)). Ansolabehere, Rodden, and Snyder (2008) show that when measured correctly, individuals hold stable preferences. Yet what this stability implies for preference change is unclear absent a model of how individuals' preferences ought to respond to new information.

Theory of Preference Updating Under Uncertainty

Our theory synthesizes political economy approaches which generate determinate predictions by using concrete models with behavioral theories that more faithfully explain how individuals process uncertainty by drawing on psychological microfoundations. Although we do not propose a formal model in this paper, our theory provides a heuristic for how the two previously separate understandings of preferences can complement each other to produce novel insights.

Personal experience is the key variable that influences preference formation and evolution. In our theory, the direct experience of being harmed by or benefiting from societal activities alters one's beliefs about the distributive effects of the societal activity in question. By consequence, people's preferences over actions to redress harm or continue benefits from societal activities should more closely reflect what the best available economic model indi-

1. There is a related literature on framing (e.g., Chong and Druckman 2007) and persuasion (e.g., Druckman 2022).

cates their preferences should be if they were fully informed.[2] We assume that individuals employ a Bayesian model of learning, where they use the laws of conditional probability to update her beliefs. Given this learning model, the effect of an experience on one's new beliefs will depend on her prior beliefs weighted by the probability of experiencing an event given one's expectations.

While previous studies have found information to have little effect on beliefs and behavior (e.g., Dunning et al. 2019; Taber and Lodge 2006),[3] there are two reasons why direct experience should be a more impactful source of information.[4] First, direct experience is unmediated, so one does not doubt the bias of the messenger as in the case of other political communications. Second, direct experience helps people process information about risks when there is uncertainty.[5] Although people may have access to analytical information about the effects of social activity like global warming caused by fossil fuel consumption, social psychology research indicates that people rely on an experiential processing system to understand risk. Experience renders abstract analytical evidence more concrete and salient (Marx et al. 2007). The lack of direct experience could contribute to whether people use the analytical tools at their disposal to make sense of situations of uncertainty.

Even with direct experience, people may interpret the same experience using different lenses (e.g., Druckman and McGrath 2019). For instance, Democrats and Republicans exhibited different responses to wildfires in California (Hazlett and Mildenberger 2020), potentially due to differing interpretations as to whether climate change or forest management practices was the primary cause. Although interpretative differences could impede efficient belief updating in the short-run, which is the context of much of the empirical work on motivated

2. Economic models are themselves subject to uncertainty. The standard for what constitutes rational updating will change over time as economic models improve. Economic models should be thought as providing the best benchmark of what preferences should be given present knowledge.

3. Appendix A provides an extended discussion of motivated reasoning.

4. See Gilens (2001) for an exception.

5. Although there are other sources of bias that may increase inefficiencies in belief updating (e.g., Tversky and Kahneman 1974; Achen and Bartels 2016), these biases pertain most directly to contemporaneous decisions and speak less to learning over time. Time allows for learning the consequences of one's past decisions, as well as the collection of additional information. Short-run signals may contain a high level of noise, which makes it hard to learn the right lesson.

reasoning, this is less likely to be the case in the long-run for two reasons. First, interpretive lens themselves rest on higher-order beliefs that can change in response to repeatedly receiving new information via experience. For example, a climate skeptic might dismiss a hurricane as being part of natural variability in weather, but an abnormal series of hurricanes of greater intensity and frequency than one has ever experienced in a lifetime may call into question the interpretation that hurricanes are chance occurrences.

Second, when the costs of holding incorrect beliefs are high, self-interest can lead political actors to question their interpretation of events. While behavioral theories are skeptical of self-interest, material motivations are thought to influence preferences when there are unambiguous costs (Citrin and Green 1990). There is experimental evidence that the public can perform a limited form of Bayesian updating when there are monetary incentives for accuracy (Hill 2017), and are more likely to answer questions correctly (Prior and Lupia 2008; Prior, Sood, and Khanna 2015). For an outcome like global warming, the distributive effects are profound. These costs should create long-run pressures for accuracy. It may be easier to be a motivated reasoner when it comes to other political beliefs where there are not as large of consequences for being wrong.

The second property of direct experience that differs from the standard focus on information provided by political communication is that direct experience is often unmediated. Consider an experience such as a heat wave. One cannot ignore a heatwave, whereas it would be possible to engage in selective viewership of the media—that is, dis-confirmation bias does not apply to direct experience (e.g., Taber and Lodge 2006). People cannot engage in selective exposure to natural disasters, and to the extent that an individual changes her behavior to avoid climate damages, that itself would reveal a belief in the veracity and seriousness of global warming. Distinguishing direct experience from mediated information is an important conceptual contribution that highlights how experiential shocks may be more likely to affect beliefs because individuals cannot opt out of receiving the signal and they do not doubt the bias of the messenger.

The context of receiving new information from direct experience also means that motivated reasoning is less likely to be engaged. The goals that a particular context makes salient can influence motivated reasoning. For example, debate and confrontation motivate people to argue for their side, whereas deliberative context motivate people to seek consensus, which suggest that some motivated reasoning studies may overestimate bias by priming the motivation to counter-argue (Groenendyk and Krupnikov 2021). Experiential shocks take place outside of a context that would prime individuals to counter-argue, making this source of information especially likely to be internalized rather than resisted.

Based on our theory, the first hypothesis is that experiential shocks should lead individuals to update their beliefs. The initial change in beliefs should be the *recognition* that societal activities, such as environmental degradation, are having adverse societal effects.

> **Hypothesis 1**: Greater exposure to experiential should lead to increased recognition that one is harmed by societal activities if they are adversely affected.

Better understanding the material consequences of societal activities also causes the salience of those damages or benefits to intensify, making the issue rise in relative importance with respect to other political matters.

> **Hypothesis 2**: Greater exposure to experiential shocks should increase the likelihood that those adversely affected by societal activities prioritize the problem relative to other political issues.

Then, as understanding and salience of the issue grows, individuals who are negatively impacted should become more willing to support government actions to address the problem. Examples of responses include supporting policies that ameliorate the harm.

> **Hypothesis 3**: Greater recognition of the harm from societal activities should lead to more support for political action to ameliorate the damage among those who are adversely affected.

How political actors revise their beliefs in response to new information will depend on the strength and content of their prior convictions. As a conceptual device, consider three types of people: *skeptics*, *undecideds*, and *believers*. Skeptics have strong prior beliefs that there is no causal connection between industrial activity, for example, and various negative outcomes. Undecideds do not have sufficient knowledge of the mapping, either out of ignorance or uncertainty, and by consequence their preferences exhibit a status quo bias—that is, the activity and its effects lack salience so other issues take precedence when it comes to political mobilization. While believers understand the source and consequences, the way this knowledge translates into preferences will depend on whether the believers gain or lose from societal activities.

> **Hypothesis 4:** Individuals with stronger prior beliefs should be less likely than those with weaker prior beliefs to update their preferences following experiential shocks.

In all, the main implication of our theory is that in the long-run, political actors should update their beliefs in response to experiential shocks. Belief updating should be most efficient—that is, free from bias—when information is acquired through direct experience, and when the costs of holding incorrect beliefs are high. Belief change then leads to preference change when one learns how she is benefited or harmed by the outcomes from societal activity. When there are large costs, the salience of an issue grows, making it more likely to be the basis for political mobilization.

Climate Politics Application

Though our theory is general, we apply it in the context of climate change due to its substantive importance and theoretical applicability. Climate change provides an example where there has been an evolution in individual preferences with respect to climate change action—that is, actions to redress the impacts of higher temperatures which could include mitigation, adaptation, or compensation. Our focus is not on particular policy instruments, but the preference that global warming damages should be combated in contrast to a business as usual pathway.

The primary expectation is that in response to direct experience with climate hazards—experiential shocks—people will better understand how their income, assets, and wealth are affected by global warming. In turn, the preferences over combating global warming damages should increasingly reflect the objective consequences of climate change for a location, which previously was less certain. Individuals in locations facing income losses should become more concerned about global warming and support action to redress damages, whereas individuals expecting no change or potential income gains should become less concerned about higher temperatures and less likely to support climate action.

In this paper we focus on individual-level changes in beliefs and preferences. Elsewhere, we explore the second-order effects of changing preferences on macro-level political outcomes (Gazmararian and Milner 2022).

There has been a proliferation of studies assessing whether experiencing climate change leads people to revise their beliefs. Howe et al. (2019) review this body of scholarship and find mixed evidence of weather shaping climate opinions. There is some support for an effect of local temperature and extreme weather on climate risk perceptions, but heterogeneity of research designs creates difficulty in rendering a synoptic assessment.

Our theory provides a different explanation for these mixed results. Studies of belief updating in response to experiencing climate change have been disconnected from economic models of how individuals will be impacted by future global warming. Previous studies operate from the implicit assumption that all places are equally vulnerable to climate change (e.g., Bergquist and Warshaw 2019; Egan and Mullin 2012; Hazlett and Mildenberger 2020; Hoffmann et al. 2022), so all political actors should become more concerned in response to experiencing climate shocks. However, absent a model of what people's preferences should be if they were fully informed, this claim lacks an empirical foundation.

Using our theoretical approach that synthesizes political economy models with behavioral insights, we are well-positioned to evaluate how individuals update their preferences in response to climate experience. By using an economic model of climate change, we can deduce precise hypotheses about how individuals should respond, given how their location will be impacted by higher temperatures.

Research Design: Global Cross-Sectional Survey

Our empirical analysis first explores cross-national differences in climate change beliefs. Analyzing variation across space is crucial since the distributive effects of climate change as a physical phenomenon are geographic: the Global South will suffer more than the North, for example (Cruz and Rossi-Hansberg 2021). Since some countries are vast and contain areas that may lose or gain from higher temperatures, we conduct our analysis at the subregional-level to capture this heterogeneity.

Our analysis focuses on how long-term structural changes to climatic variability influence preferences. Our theory implies that preferences in a given moment represent a history of past experience shocks, which we capture using long-run trends in climate data. Focusing on long-term changes also mitigates the possibility that reported preferences simply reflect temporary concern made top of mind by a recent event. Although we are limited by cross-sectional data in this analysis from making strong claims about individual-level preference change, we use panel data in subsequent empirical tests to capture this related dynamic. Here, the focus is on macro-level pressures that shape preferences in ways that should manifest differentially across regions.

This analysis focuses on the first and second hypotheses: recognition and high salience of climate change risk. We expect that climate risk salience will be greater for respondents in regions that face potential damages from global warming and have experienced long-term changes in temperature variability. This change in climate should clarify the distribution of climate damages and heighten the salience of the issue.

Data and Measurement

Subregional Survey Data

Our data on climate risk perceptions comes from the World Risk Poll conducted in 2019 by Gallup and Loyd's Register Foundation. The survey was conducted using probability-based and nationally representative samples covering around 150,000 people in 142 countries and territories.[6] In most countries the approximate sample size is $1,000$.[7] The questions underwent intense piloting and multiple rounds of review. The survey instrument was translated into the major conversational languages of each country, and teams of trained enumerators administered the survey using face-to-face interviews and telephone calls.

We build on these data by constructing a new crosswalk that maps respondents to 2,043 administrative regions within each country at the lowest level of aggregation possible. We invested considerable resources in building our crosswalk because while the survey identifies a respondent's subregion, this label is not readily connected to any geospatial shapefiles of administrative borders. Connecting respondents to these geospatial areas is necessary to pair respondents with our climate damage and temperature data described below, which forms the crux of our analysis. Appendix B describes the construction of our crosswalk.

Climate Risk Perceptions

Our main outcome to evaluate hypotheses 1 and 2 is the perception that climate change is a salient risk. Salience here refers to whether a person places greater weight on the importance of a topic. The weight that one associates with a risk is an indication of both belief and importance. To state that climate change is a top risk reflects both one's belief that global warming presents a threat, and the urgency with which the issue must be addressed relative

6. We only use the surveys from the countries for which there are climate damages data.
7. The sample size is higher for China, India, and Russia, and lower in Jamaica.

to other societal matters.

We measure climate risk salience by using responses to two open-ended questions that ask what is the greatest or a major source of risk to one's daily life.

> In your own words, what is the greatest source of risk to your safety in your daily life?
>
> Other than what you just mentioned, in your own words, what is another major source of risk to your safety in your daily life?

Answers to these questions are mapped to categories, one of which is "Climate change, natural disasters or weather-related events (such as floods, drought, wildfires, etc.)". We construct an indicator that takes the value 1 if climate change is a top or major risk to the respondent and 0 if not. A separate indicator records if climate change is only the top risk named (more restrictive than including major risks), and results are equivalent.

We focus on top of mind salience rather than stated concern about climate change (e.g., climate change is important) since stated concern measures suffer from social desirability and hypothetical bias. While many would indicate that global warming is important when asked about the topic, public opinion support for emissions mitigation is sensitive to costs (e.g., Bechtel and Scheve 2013), which suggests that standard measures of climate risk perceptions overstate concern. Our measure avoids this source of bias by using open-ended questions. This open-ended questions is less susceptible to priming and allows for an assessment of whether climate change is truly a concern. As evidence of the importance of focusing on salience, in the World Risk Poll data, there is effectively no correlation between articulating climate change as the greatest source of risk and believing that climate change presents a serious threat in the future ($r = 0.02$).[8] Although many say that climate change is a serious threat, a much small number prioritize it as a top threat. We use this costly measure of climate change risk salience as our main outcome.

8. The stated concern measure asks, "Do you think that climate change is a very serious threat, a somewhat serious threat, or not a threat at all to the people in this country in the next 20 years? If you do not know, please just say so."

Potential Climate Damages as Moderator

As in Gazmararian and Milner (2022), we construct an indicator for if a subregion faces potential damages from global warming in the year 2050. The moderator is dichotomous since there is considerable uncertainty in global warming's effects, which erodes the substantive meaning of point estimates. Rather than create a false sense of certainty, an indicator is realistic by recording whether a subregion is on the damages or benefits curve of the distribution. As evidence of the merit for focusing on the distribution of potential damages and benefits, Gazmararian and Milner (2022) show how perturbing the threshold for dichotomizing this threshold yields no new behavioral results.

The climate damage estimates come from a spatial integrated economic assessment (SIEA) model that accounts for endogenous adaptation to climate change via trade, migration, and innovation (Cruz and Rossi-Hansberg 2021). The SIEA builds upon the established spatial growth framework in Desmet, Nagy, and Rossi-Hansberg (2018), which has been validated with backcasting exercises and successfully applied to assess sectoral responses to global warming (Conte et al. 2021) and the effects of sea level rise (Desmet et al. 2021). The model accounts for damage from long-run temperature changes, which is a substantial means by which global warming will impact economic growth via heat's effects on mortality, human physiology, violence, productivity, crop yields, energy demand, and population movements (Carleton and Hsiang 2016). The damage estimates are recorded at the $1^\circ \times 1^\circ$ longitude-latitude resolution, which we aggregate to the subregion level by taking the average level of damage across the grids.

Temperature Variability as an Experiential Shock

Our analysis captures experience shocks by using data on long-run changes in temperature variability. We focus on changes in variability as these fluctuations should be more visible signals over time, as opposed to changes in the absolute level of temperature. Climate change has been increasing temperature extremes, resulting in greater variability (e.g., Bathiany et al. 2018; Hansen, Sato, and Ruedy 2012; Olonscheck et al. 2021; Schär et al. 2004). Temperature variability is also an important channel through which global warming inflicts economic damage (e.g., Calel et al. 2020; Kotz et al. 2021).

We construct our measure by taking the difference between temperature variability across months in 2018, the year before the survey was fielded, and the average long-run monthly temperature variability.[9] The data come from the Global Historical Climatology Network's Climate Anomaly Monitoring System, which measures monthly global land surface temperature averages at the $0.5° \times 0.5°$ resolution (Fan and van den Dool 2008).[10] The dataset is a combination of two individual collections of weather station observations which are interpolated across space using validated methods. We acquired this data from the National Oceanic and Atmospheric Administration.[11]

Figure 1 plots the spatial distribution of the long-run change in temperature variability. Temperature variability has increased in much of the world, although there are a small number of areas where the level of variation has fallen. Since these positive and negative changes fall across regions experiencing both potential damages and benefits from global warming, this provides a hard test for our information updating theory. 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 the direction consistent with what their underlying interests would be if they were fully informed.

Subregion-Level Covariates

We go to great lengths to include subregion-level covariates that match the administrative areas of where our survey respondents reside. The first subregional control is population.

9. Our benchmark period is from 1980-2000, since the median respondent would have been born around 1980. Results are robust to using an alternative benchmark period (Table C8).

10. We aggregate these data to the climate damage level, since that is the highest level of the gridded data, which we then aggregate to the subregion level.

11. Available online at: https://psl.noaa.gov/data/gridded/data.ghcncams.html

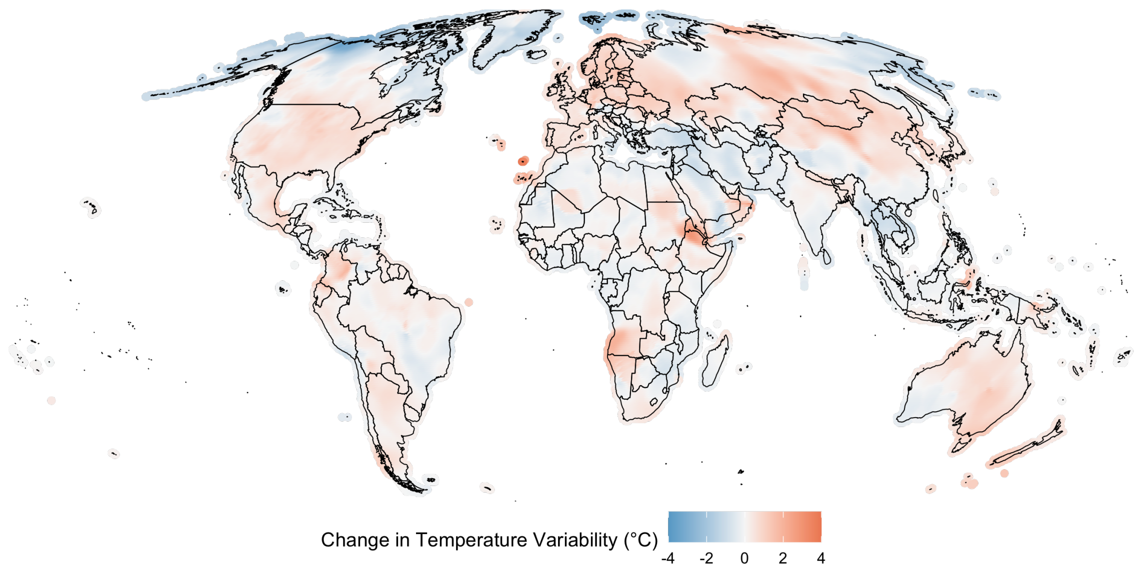

Figure 1: **Spatial distribution of long-run changes in temperature variability.** Data at the $0.5° \times 0.5°$ resolution from Fan and van den Dool (2008).

Regional population may influence climate risk preferences through the multitude of relationships between population and factors like carbon dioxide emissions and economic growth. Population data come from WorldPop (Global 1km Population), which uses 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). We use data from 2018 at the 1 kilometer spatial resolution, which we aggregate to the $1° \times 1°$ level of our climate damage predictions. Once these are aggregated to the region-level, we take the natural logarithm of the population quantity plus one to correct for right-skew.

We also control for gross domestic product (GDP), a standard measure of economic development that influences the level of education in a location as well as the resources to adapt to climate change and implement mitigation policies. High-resolution global spatial data on GDP come from Kummu, Taka, and Guillaume (2018; Data From). Instead of down-scaling national-level data, the authors employ subnational administrative data where available and only scale values where necessary, producing a more accurate measurement of GDP. We use the most recent year of data available (2015) for a measure of total GDP in

2011 international US dollars at the 30 arc-sec resolution, which aggregate up to the level of the damage measure. Once aggregating up again to the region-level we take the logarithm to adjust for right-skew. Since we control for population in our model specifications, we do not convert GDP to a per capita variable.

We also include variables to account for distributive politics theories of climate preferences (e.g., Mildenberger 2020). Distributive politics theories would predict opposition to climate change emerges from consumers with high carbon footprints. We use high-resolution data on CO2 emissions to account for how carbon-intensity could influence preferences. Data come from EDGAR, and cover all fossil sources of carbon dioxide such as fossil fuel consumption, cement production, agricultural use. The measure excludes organic sources of carbon dioxide such as forest fires and land-use change. Data are from 2018 at the $0.1° \times 0.1°$ resolution.

As additional covariates to capture distributive politics theories, we map geospatial indices on coal and oil development potential to the region-level. Oakleaf et al. (2019) construct these indices at the 1-kilometer resolution, 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, which within standard distributive politics theories would imply lower support for climate action. Figures C1 and C2 show the spatial variation in these development potential indices.

Additional Covariates

We control for a set of individual-level covariates in the literature that are predictive of climate beliefs: age, gender, education, and household income quintile. Appendix C.2 describes the construction of these variables. The model includes a variable measuring what the respondent thinks when she hears the word risk, as this mental association might influence answers to our main outcome which is about one's greatest daily risk.[12] The survey did not ask questions about ideology or partisanship. Since these political characteristics are likely

12. Results are robust to dropping this covariate (Table C6).

orthogonal to long-run changes in temperature variability, not including them in the model specification should not confound our results.

Finally, we include a country-level measure of regime type because the level of democracy could influence the availability of information or freedom of news coverage, which could be mechanisms through which experience shocks transmit. Although, we do not have strong expectations about the effect of democracy due to the complex relationship between regime type and environmental performance. Our main regime type measure is the polyarchy index from V-Dem (Coppedge et al. 2019).[13]

Table C1 contains summary statistics.

Methods

We estimate the effect of climate experience shocks on global warming risk perceptions, conditional on whether a region faces potential damages, using the following linear regression model:

$$y_i = Temp_{r(i)} + Damage_{r(i)} + \delta(Temp_{r(i)} \times Damage_{r(i)}) + \beta X_{i,r(i),c(i)} + \eta_{r(i)} + \epsilon_{r(i)} \qquad (1)$$

The subscript i denotes individuals; $r(i)$ and $c(i)$ are functions that map individuals to subregions and countries respectively. y_i is the outcome measure that denotes whether a respondent identifies climate change as the greatest or a major risk. τ is the long-run change in temperature variability for a subregion. $Damage_{r(i)}$ is an indicator for whether a subregion faces potential damages or benefits from global warming. δ is the coefficient from our interaction term of interest. X is a matrix of individual-, subregion-, and country-level covariates. η is a global region fixed effect to account for common regional factors.[14] We employ the HC1 heteroskedasticity-robust covariance estimator with standard errors

13. The results are equivalent when using the Polity2 index (Table C4).

14. There are fifteen regions: Eastern Africa, Central/Western Africa, North Africa, Southern Africa, Latin America and Caribbean, Northern America, Central Asia, East Asia, South-eastern Asia, South Asia, Middle East, Eastern Europe, Northern/Western Europe, Southern Europe, Australia and New Zealand.

clustered by region.

While the battery of individual-, subregional-, and country-level controls address the obvious sources of confounding, we also take additional steps to ameliorate potential omitted variable bias. First, our explanatory variable—long-run changes in temperature variation—is plausibly exogenous to our outcome because these changes are natural phenomena outside of political influence. To confound our results, any omitted variable would have to correlate with both changes in temperature variability and climate risk salience perceptions, and not be accounted for by our battery of controls.

Second, we estimate a separate multi-level regression model that attends to some omitted variable bias. While subregion and country fixed effects are inappropriate because they are either colinear with the treatment or are inefficient, the varying-slopes in our multi-level models capture some confounding because the estimator is a weighted combination of within and between estimators. Specifically, we estimate a model with random-slopes for each subregion. This hierarchical model provides further traction in ameliorating omitted variable bias by partitioning the variance between subregion and individual level covariates.

Our inferential strategy assumes that for the subregion-level measures, all individuals within the administrative borders are equally exposed to climate damages or changes in temperature variability. This claim is plausible for temperature variability which exerts a common effect across a subregion. In terms of climate damages, some individuals may have more resources to adapt to climate change than others, which could attenuate damages. For this reason, we include a control for household income. Even if present, ecological measurement issues would introduce bias against our hypotheses because there are units presumed to be treated but in fact are not.

Results

Table 1 presents the main results from estimating the effect of long-run changes in temperature variability on climate risk perceptions, conditional on whether a respondent resides in a subregion facing potential damages or benefits from global warming. The first column shows that a standard deviation increase in long-run changes in temperature variability increases the probability that climate change is the top or a major concern for people residing in places facing potential damages. There is no effect on recognition or salience of climate change for individuals in places facing potential benefits. Individuals in places facing damages are about 1 percent more likely than those in areas experiencing potential benefits to identify climate change as a salient threat. Although small in absolute terms, this effect size is substantial considering that only 5 percent of the entire sample identify global warming as a top or major risk to their daily life. The result also holds in the second column, where the outcome measure of climate risk salience codes only those identifying global warming as the top risk.

Table 1: **Linear regressions of risk salience on the interaction of long-run change in temperature variability and potential climate damages.** HC1 standard errors clustered by subregion. Temperature variability change is standardized. Respondent-level controls include age, gender, education, income, and understanding of risk. Subregion-level controls include GDP (log), CO2 emissions (log), population (log), coal development potential index, and oil development potential index. Country-level controls include polyarchy. Table C2 contains the complete regression results.

	Climate Risk Salience:		Placebo Tests:	
	Top/Major	Top	Work	Politics
Δ Temp. Variability	−0.004	−0.004	0.001	0.001
	(0.004)	(0.002)	(0.001)	(0.002)
Potential Damages	−0.019**	−0.014**	0.006**	0.002
	(0.009)	(0.006)	(0.002)	(0.003)
Δ Temp. Variability × Potential Damages	0.012***	0.009***	−0.001	0.000
	(0.004)	(0.003)	(0.001)	(0.002)
Individual Controls	Yes	Yes	Yes	Yes
Subregion Controls	Yes	Yes	Yes	Yes
Country Controls	Yes	Yes	Yes	Yes
Global Region Fixed Effects	Yes	Yes	Yes	Yes
N	131 380	131 380	131 380	131 380
F-statistic	37.3	40.0	45.4	41.1

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The next two columns present the results of placebo tests that estimate the effect of changes in temperature variability on the perception that workplace accidents or political strife are the most important risks in one's daily life. These outcomes are theoretically unrelated to temperature variability and should not be affected by climate experience shocks.[15] The coefficient on the interaction term in both cases is almost zero. There is also a null effect for the change in temperature variability constituent term, which represents the effect of climate experience shocks on risk perception among respondents in subregions facing benefits. These two null coefficients suggest that the effect of long-run changes in temperature variability is due to changing beliefs about global warming rather than an erroneous inference by the public.

Figure 2 plots the conditional average treatment effect of long-run changes in temperature variability on respondents in subregions facing potential damages and benefits. The plot helps illustrate the result from Table 1. To be judicious, we only report results for a one standard deviation increase in long-run changes in temperature variability. The moderator is dichotomous—potential damages or not—which ensures that there is common support at all levels of the explanatory variable (e.g., Hainmueller, Mummolo, and Xu 2019).

Other covariates in the model have their expected signs, although we urge caution in interpretation since these are not causal estimates (see Table C2). Having a tertiary education has a positive association with climate risk salience, while greater coal development potential has a negative association. Unlike Bush and Clayton (2022), we do not find detectable differences by gender, although our outcome measure and model specification differ from their design.

These results, which provide support for hypotheses 1 and 2, are robust when employing a multi-level model with random intercepts for subregion (Table C3); using a different benchmark period for long-run changes in temperature variability (Table C8); controlling for the national level of climate policy (Table C7); employing an alternative measure of regime

15. 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.

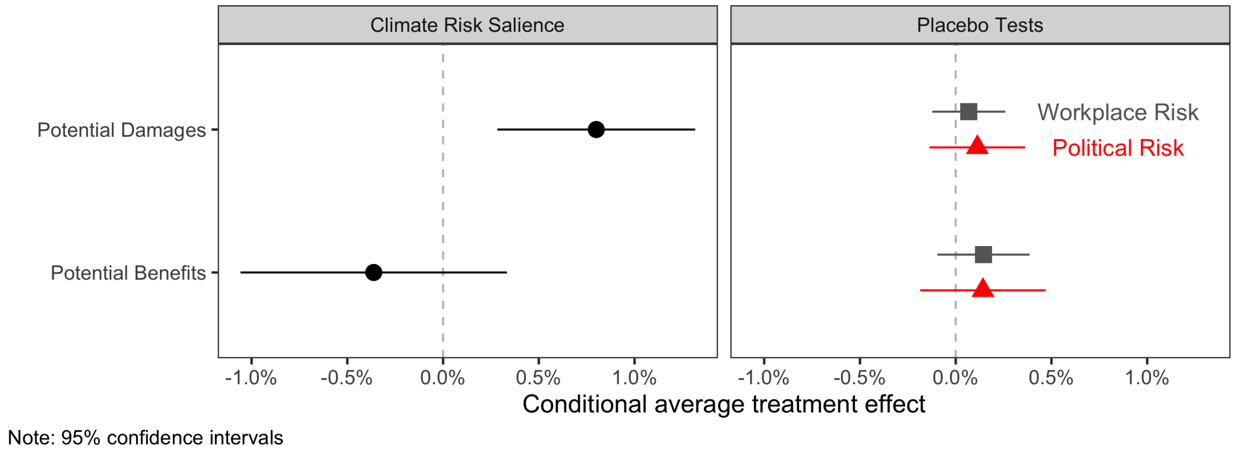

Figure 2: **Conditional average treatment effect of long-run changes in temperature variability (left panel) and placebo tests (right panel) on risk salience for respondents in regions facing potential damages or benefits.** Models include the full set of individual-, subregion-, and country-level controls. HC1 standard errors clustered by region. Table C2 contains the complete regression results.

type (Table C4); and controlling for country-level measures of fossil fuel rents as a share of GDP (Table C5).

Research Design: National Panel Survey

The first empirical analysis demonstrated how long-run changes in temperature variability shape the distribution of climate change risk salience across space. Our next analysis turns to short-term change in preferences. Since our goal is to understand change, we employ panel data—repeated interviews with the same respondent to see how their preferences evolve. To reiterate our expectations, in response to experiencing climate hazards, individuals in places facing damages should become more concerned about global warming and supportive of actions to mitigate the harm from higher temperatures (hypotheses 1 and 3). We also explore how the strength of one's prior beliefs influences updating, anticipating that people with stronger convictions will be less responsive to experiencing climate hazards (hypothesis 4).

Data and Measurement

The panel survey data come from the Cooperative Congressional Election Study's 2010-2014 Panel Study (Ansolabehere and Schaffner 2015). The sample is nationally representative of the United States, and there are approximately $9,500$ respondents who were interviewed in 2010, 2012, and 2014 using a common set of questions across the waves. The total sample size represents all respondents who completed the three waves after accounting for attrition.

Climate Beliefs and Preferences

The outcome measure to capture climate beliefs and preferences comes from the following survey item.

> 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.

This question captures two related constructs. The first construct is the extent to which one believes that global warming is happening and is a serious problem. The second construct is the degree to which one thinks action is needed to address climate change. Together, the item encompasses both belief in the seriousness of the climate problem, and urgency to act, two interrelated concepts that speak to hypotheses 2 and 3. The question is also well-suited for our purposes since our goal is to assess the level of climate action desired, rather than investigate particular policy instruments. Since most respondents exhibit high levels of climate concern, we dichotomize the measure so 1 represents the preference that action should be taken and 0 if not.[16]

16. That action should be taken corresponds with the two highest options on the answer scale.

Potential Climate Damages as Moderator

An advantage of studying the American context is that there are high resolution economic models of climate change that permit even more fine-grained analysis than the Cruz and Rossi-Hansberg (2021) model allows. Using additional models also reduces potential dependence that might result from relying on one approach. We use the county-level estimates of climate change damages from Hsiang et al. (2017). Their model estimates 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 (2021), they find substantial spatial heterogeneity in the economic effects of higher temperatures. As visualized in Figure 3, parts of the north and west of the United States experience potential gains in terms of GDP, while the south incurs large losses.

We focus on the total damage to GDP estimates to maximize comparability across the models. As before, we construct an indicator for if a county faces potential damages defined as experiencing greater than 0 percent GDP loss from climate change by the late 21st century.

Wildfires as Experiential Shocks

In this analysis, wildfires serve as the experiential shock. Wildfires are becoming more frequent and longer lasting in the United States because of climate change (Westerling et al. 2006). Fires can be exceptionally destructive and impressionable events, which should make them a powerful experience that could alter one's preferences and beliefs. Focusing on fires, versus temperature which has been the main focus of previous studies on the climate-attitude nexus (e.g., Bergquist and Warshaw 2019; Egan and Mullin 2012; Hoffmann et al. 2022), should help to avoid false negatives that could result from too weak of a signal being sent to have changed beliefs. While there is work exploring disasters more broadly, and fires in particular, these findings have been mixed (e.g., Hazlett and Mildenberger 2020). Yet, these previous studies have not analyzed wildfires alongside an objective model of what political actors' preferences should be.

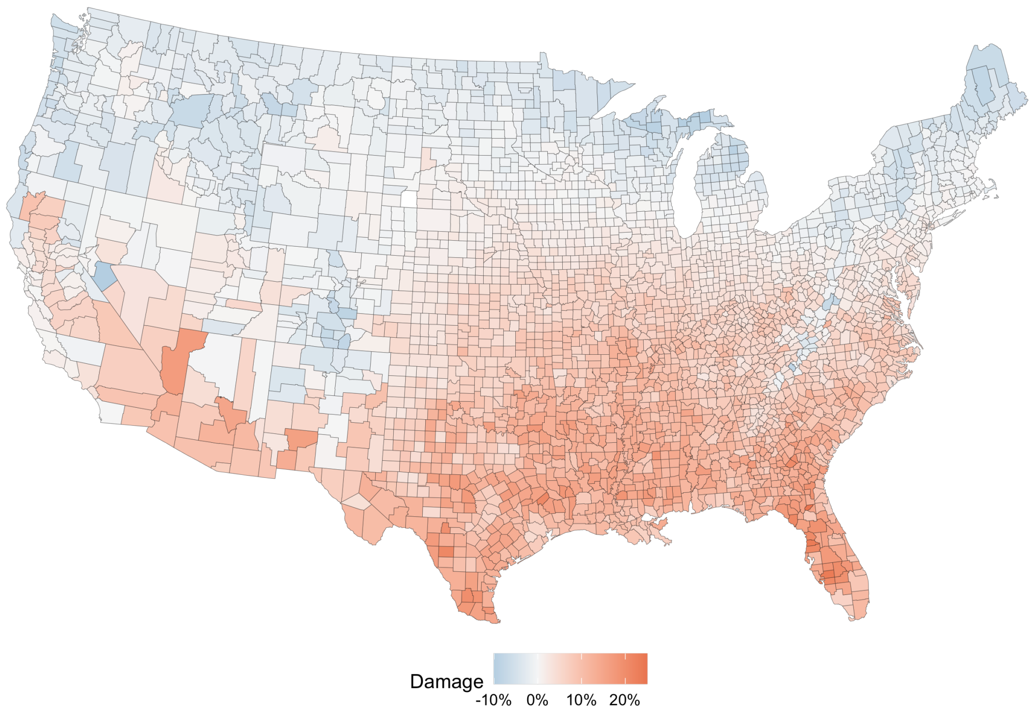

Figure 3: **Spatial distribution of climate damage to GDP in the United States, county-level.** Estimates from Hsiang et al. (2017).

We use data on the count of wildfires declared to be disasters within a county in a given year. Data come from the FEMA Disaster Declaration's Summaries, which lists all official disasters in the United States. The disaster reports are generated when a county (or other level of government) declares an emergency, which is then certified by the federal government. Although there might be wildfires where emergencies were not declared, these are likely of lesser damage. Plus, local governments have an economic incentive to make a disaster declaration because it unlocks federal funding to assist with the recovery. Only around 4 percent of the respondents resided in a county with a wildfire during a panel wave. The reduced statistical power should introduce bias against detecting an effect.

Methods

We estimate the effect of a within-unit change in exposure to wildfires by using the following empirical specification,

$$y_{it} = \alpha + Fire_{c(i)t} + Damage_{c(i)} + \delta(Fire_{c(i)t} \times Damage_{c(i)}) + X_{it}^{\intercal}\beta + \lambda_t + \eta_i + \epsilon_{it} \qquad (2)$$

with standard errors clustered by county to tend to potential auto-correlation.

Here, y_{it} is the climate belief and preference outcome measure. $Fire_{c(i)t}$ is a count of the fires in a county for a panel wave, with $c(i)$ representing a function that maps respondents, i, to counties. $Damage_{c(i)}$ is the indicator for if a county faces potential damages from higher temperatures. δ is the coefficient of interest, representing the differential effect of wildfire exposure in counties facing damages versus those with potential net benefits. The λ_t term is a panel-wave fixed effect, while η_i is an individual fixed effects, which remove all time-invariant omitted variable bias.

The matrix $X_{it}^{\intercal}$ contains time-varying covariates. Since our empirical strategy estimates the effect of *within*-unit changes in covariates, we include only covariates that exhibit within-unit variation and might confound our results.[17] Specifically, we control for individual-level employment, education, partisan identification, ideology, household income, and religious importance.[18]

There are two strategies for drawing causal inferences given this setup. In the first we adopt a difference-in-differences approach, which has the advantage of not requiring exogenous treatment assignment, only parallel trends. The parallel trends assumption is challenging to assess in this context because the treatment is staggered and repeated. Despite these challenges, Appendix D.2 provides some evidence that this assumption is plausible.

17. Age increases by the same rate each year, so it is not necessary to control for. Respondents report having the same gender and racial identity through all waves of the panel, so we do not include these measures either.

18. We impute values for the approximately 10 percent of respondents who do not answer the income question or indicate that they prefer not to answer. The imputation procedure replaces the missing values using the mean household income.

The second approach is to satisfy the strong ignorability assumption—that is, treatment assignment is independent of potential outcomes—by conditioning on a relevant set of covariates. To this end, our individual-level covariates account for time-varying factors that might confound inference, in addition to capturing features that might influence an individual's decision to locate in an area prone to wildfires. To further strengthen the plausibility of conditional exogeneity, in one model we add state fixed effects. The state fixed effects help to account for local forest management policies and environmental characteristics, to the extent that they are time-invariant, which might influence the incidence of forest fires. Lastly, we also estimate a model using a panel matching estimator that includes further county-level characteristics like income and population, which should help increase confidence that treatment assignment is exogenous conditional on the propensity score (Imai, Kim, and Wang 2021). Appendix D.3 reports the results from this separate matching analysis.

Results

Table 2 presents the results of estimating the effect of experiencing a wildfire on belief in the seriousness of global warming and support for action to mitigate climate damages. The first column reports the results with no interaction between wildfires and potential damages, which shows that experiencing a fire causes increases in climate concern and support for action to avoid damages. The next column adds our interaction term, which shows that this positive effect is driven by places that face potential damages—respondents in areas at risk of future climate damages become three percent more likely to view global warming as a significant concern that merits action after experiencing a wildfire. Contrast this effect size with the coefficient for party identification, which is thought to exert a powerful influence over attitudes and preferences (e.g., Campbell et al. 1960). Becoming more identified with the Democratic party increases belief in and preference for climate action by less than one percent. In this model, the effect of direct experience on preference change is larger than the effect of partisan identification.[19]

Turning to the remaining models, the third column adds state fixed effects and the fourth column uses an indicator (instead of count) for wildfires and the coefficient on the interaction term remains equivalent and even increases in magnitude when using the wildfire indicator.

The last column presents the results from a placebo test that uses future fires in 2016, 2018, and 2020, which should have no effect on beliefs and preferences at the time of survey administration. The coefficients on both the constituent term and interaction are precisely estimated at zero. This increases faith that there is not a time-varying feature of places predisposed to fires that drives these results; instead, it is the experience of a wildfire that leads to belief and preference updating, if one resides in a place facing future climate damages. Figure 4 plots the results from the placebo test alongside the true treatment effect.

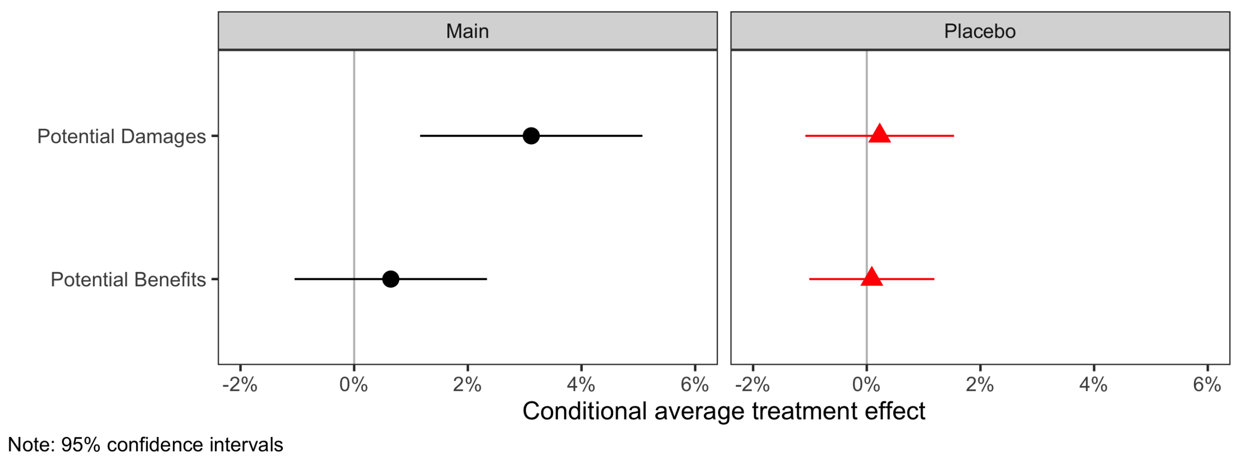

Figure 4: **Marginal effect of wildfires (left panel) and placebo tests (right panel) on climate beliefs and preferences, conditional on potential damages.** Estimates from Table 2. Placebo tests use future fires.

In all, these results provide evidence in support of hypotheses 1 and 3. Experiencing climate change leads individuals to recognize that climate change is a serious problem (hypothesis 1) and become more supportive of taking action to address its impacts (hypothesis 3). However, preference updating only occurs for individuals in places facing income loss

19. One reason might be that partisan change is especially rare (Campbell et al. (1960); but see Gazmararian (2022)).

Table 2: **Multivariate regressions of support for climate mitigation on the interaction of experience shocks and potential climate damage.** Survey data from Ansolabehere and Schaffner (2015). Climate damages data from Hsiang et al. (2017). Fire data from NOAA. Standard errors clustered by county. Education runs from no high school (1) to post-grad (6). Party ID runs from strong Republican (1) to strong Democrat (7). Ideology runs from conservative (1) to liberal (5) Religion runs from not at all important (1) to very important (4).

	(1)	(2)	(3)	(4)	(5)
Fire × Potential Damages		0.025***	0.023***		
		(0.008)	(0.007)		
Fire (=1) × Potential Damages				0.037***	
				(0.010)	
Placebo Fire × Potential Damages					0.001
					(0.004)
Fire	0.017***	0.006	0.007		
	(0.004)	(0.004)	(0.004)		
Fire (=1)				−0.005	
				(0.006)	
Placebo Fire					0.001
					(0.004)
Potential Damages	−0.020	−0.022	−0.020	−0.023	−0.021
	(0.017)	(0.017)	(0.022)	(0.017)	(0.017)
Employed	0.005	0.004	0.005	0.004	0.004
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Education	0.004	0.004	0.004	0.004	0.004
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Party ID	0.007*	0.007*	0.007*	0.007*	0.007*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Ideology	0.004	0.005	0.005	0.005	0.005
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Household Income	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Religion Importance	−0.005	−0.005	−0.005	−0.005	−0.005
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes
Panel Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	No	No	Yes	No	No
N	28 202	28 202	28 202	28 202	28 202
Adjusted R^2	0.841	0.841	0.841	0.841	0.841
F-statistic	16.8	16.8	16.7	16.8	16.8

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

from future climate damages, which suggests that people are changing their preferences and beliefs in a coherent manner.

Skeptics, Undecideds, and Believers

Our fourth hypothesis states that individuals with stronger prior beliefs should be less likely to update their preferences following experiential shocks. We now test this conjecture by subsetting respondents to three groups based on their climate beliefs and preferences in the first survey wave. The first group is the *skeptics*, defined as individuals who believed either 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."[20] The second group is the *undecideds*, individuals who 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." We expect to see preference updating among the undecideds, but less so for the skeptics and believers given the short time-frame of the panel study.[21]

Figure 5 presents the results from estimating the effect of wildfires, conditional on climate damages, on mitigation preferences for skeptics, undecideds, and believers. There is a strong, positive effect of experiencing climate change on beliefs and preferences among undecideds—a 4.7 percent increase in belief in the seriousness of climate change and that the issue merits action. However, among individuals with stronger prior beliefs, there is no effect of experiential shocks. This effect is precisely estimated at zero for believers, which is unsurprising because there was no room for upward movement, but the result validates our expectation that there would not be reversion in beliefs and preferences. For skeptics,

20. See Table D3 for correlations with climate skepticism. Stronger Republicans and more ideologically conservative individuals exhibit greater climate skepticism.

21. Changing the minds of skeptics might take repeated experiences over longer periods of time given the strength of their prior beliefs.

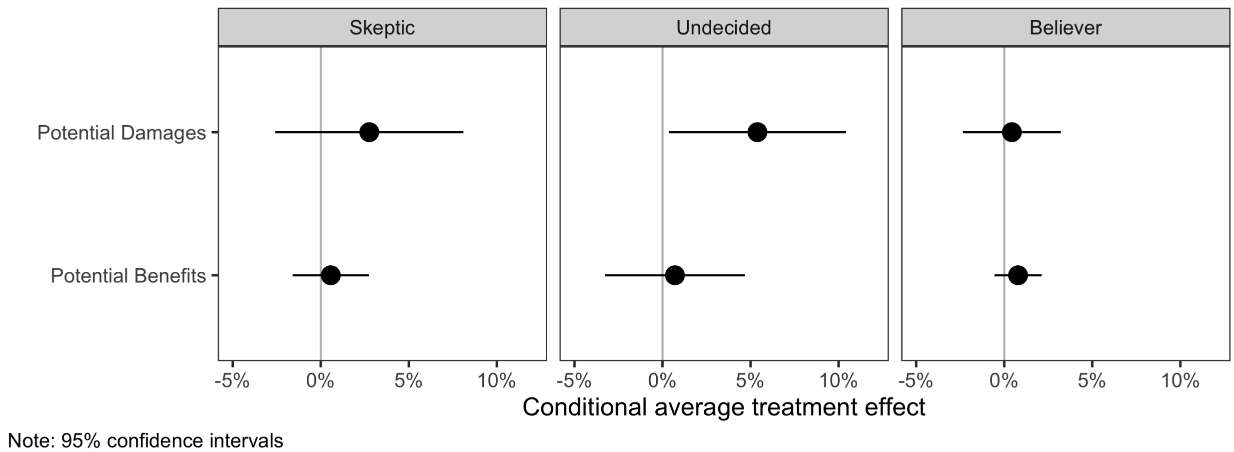

Figure 5: **Marginal effect of wildfires on climate beliefs and preferences, conditional on potential damages for skeptics, undecideds, and believers.** Estimates from Table D2.

the coefficient on the interaction term is positive, but noisily estimated. The research design may have been under-powered to detect what we anticipated to be a small effect here due to the lesser number of skeptics. In all, these results offer support for hypothesis 4.

Discussion and Conclusion

Our paper synthesizes political economy and behavioral theories to explain how preferences change when there is uncertainty about the material effects of societal activities. Direct experience with the consequences of societal activities—what we term experiential shocks—leads to belief and preference updating. In this model, learning is most efficient among individuals with weaker prior beliefs.

We applied our theory to the pressing question of whether experiencing climate change will lead to greater recognition of its existence, salience of the issue, and support for action to mitigate damages. Our results show that individuals learn the right lessons from climate shocks; if they live in areas facing future climate damages, climate recognition, salience, and policy support grows. However, people living in areas that may experience little damage or even potential benefits do not update their beliefs and preferences following experiential shocks.

An important political implication of this finding is that public mobilization to mitigate climate change will not automatically emerge from experiencing disasters. In places expecting damages, the public should become increasingly concerned, which should in the long-run translate into policy outcomes (Gazmararian and Milner 2022). However, in places facing potential benefits, climate disturbances are insufficient to change beliefs and preferences. Building a political coalition for decarbonization in these locations may instead depend on emphasizing the co-benefits from emissions mitigation such as reduced air pollution (e.g., Driscoll et al. 2015).

There are three limitations of this study that we are addressing in future work. First, although the outcome measures capture if beliefs and preferences evolve, more fine-grained measures would be useful to better pinpoint what precisely changed inside one's mind in response to an experiential shock. Additional measures should focus on a wider set of climate beliefs, expectations of future damages, and preferences over policy responses. Second, while our theory predicts that skeptics will eventually update their beliefs, we find no evidence of this in our current study. An appropriate research design would require panel surveys over a longer period of time and at more frequent intervals to capture how skeptics update their beliefs which is likely an incremental process, if at all. Third, our focus here has been on beliefs and stated support for policy action, which may not capture if these attitudes translate into action. In parallel work, we are examining behavioral outcomes like voting for politicians who support addressing climate change.

This paper makes three contributions. First, we demonstrate how political economy theory can incorporate insights from social psychology without sacrificing parsimony. Our synthesis is productive as it generates new predictions. Whereas political economy theories would predict that the material consequences of societal activities must change for preferences to update, our synthesis indicates that personal experience provides credible information that can lead to preference updating even when the material consequences remain the same. This helps move beyond the insight that uncertainty contributes to status quo bias (e.g., Fernandez and Rodrik 1991) to understand how the level of uncertainty can change, and with it, individuals' beliefs and preferences. Our framework is especially relevant for emerging scientific and environmental issues where uncertainty abounds. Future research should explore how individuals change their preferences when their is uncertainty about the effects of automation, emerging technologies, or air pollution.

Second, in contrast to the view that information has little effect on preferences—a vast collection of studies find that people adopt the policies of leaders they like (e.g., Lenz 2012), disregard facts due to the perceptual screen of partisanship (e.g., Campbell et al. 1960), or learn the wrong lessons from events (e.g., Achen and Bartels 2016)—we show how individuals can learn the right lesson from direct experience. Information from direct experience is special because it is unmediated and especially salient, whereas communications from elites may be seen as biased and interventions in survey experiments may lack realism. Also by using an economic model of what individuals' preferences should be, we avoid making ad hoc assumptions about how one should react to new information. Previous work on information and preferences should be revisited using the tools of political economy to provide a more objective benchmark of how attitudes should change in response to direct experience.

Third, we contribute to the climate politics literature by integrating climate assessment models with theories of climate politics (e.g., Gazmararian and Milner 2022). Our approach helps resolve inconsistent results in the fast-advancing body of research on behavioral responses to climatic events (e.g., Howe et al. 2019). Previous studies evaluate the effect of experience shocks, but without an objective model of what a political actor's preferences should be if she were fully informed. Instead, our climate model provides a baseline for what an actor's preferences should converge to, while our theory supplies a microfounded causal pathway for how preferences should change in response to experiential shocks. In doing so, we help to better understand when and how political mobilization will occur in response to global climate change.

References

Achen, Christopher H., and Larry M. Bartels. 2016. *Democracy for Realists.* Princeton University Press.

Allan, Bentley B., and Jonas O. Meckling. 2021. "Creative Learning and Policy Ideas: The Global Rise of Green Growth." *Perspectives on Politics,* 1–19.

Ansolabehere, Stephen, Jonathan Rodden, and James M. Snyder. 2008. "The Strength of Issues: Using Multiple Measures to Gauge Preference Stability, Ideological Constraint, and Issue Voting." *American Political Science Review* 102 (2): 215–232.

Ansolabehere, Stephen, and Brian Schaffner. 2015. *Cooperative Congressional Election Study: 2010-2014 Panel Study.* University of Massachusetts, Amherst.

Bathiany, Sebastian, et al. 2018. "Climate Models Predict Increasing Temperature Variability in Poor Countries." *Science Advances* 4, no. 5 (2018): eaar5809.

Bechtel, Michael M., and Kenneth F. Scheve. 2013. "Mass Support for Global Climate Agreements Depends on Institutional Design." *Proceedings of the National Academy of Sciences* 110 (34): 13763–13768.

Bergquist, Parrish, and Christopher Warshaw. 2019. "Does Global Warming Increase Public Concern about Climate Change?" *Journal of Politics* 81 (2): 686–691.

Broz, J. Lawrence. 1999. "Origins of the Federal Reserve System: International Incentives and the Domestic Free-rider Problem." *International Organization* 53 (1): 39–70.

Bush, Sarah Sunn, and Amanda Clayton. 2022. "Facing Change: Gender and Climate Change Attitudes Worldwide." *American Political Science Review,* 1–18.

Calel, Raphael, et al. 2020. "Temperature Variability Implies Greater Economic Damages from Climate Change." *Nature Communications* 11 (1): 5028.

Campbell, Angus, et al. 1960. *The American Voter.* University of Chicago Press.

Carleton, Tamma, and Solomon Hsiang. 2016. "Social and Economic Impacts of Climate." *Science* 353 (6304).

Chong, Dennis, and James N. Druckman. 2007. "Framing Theory." *Annual Review of Political Science* 10 (1): 103–126.

Citrin, Jack, and Donald P. Green. 1990. "The Self-Interest Motive in American Public Opinion." In *Research in Micropolitics,* edited by S. Long. JAI Press.

Conte, Bruno, et al. 2021. "Local Sectoral Specialization in a Warming World." *Journal of Economic Geography* 21 (4): 493–530.

Coppedge, Michael, et al. 2019. *V-Dem [Country-Year/Country-Date] Dataset V9.* Varieties of Democracy (V-Dem) Project.

Cruz, José-Luis, and Esteban Rossi-Hansberg. 2021. *The Economic Geography of Global Warming.* w28466. NBER.

Desmet, Klaus, Dávid Krisztián Nagy, and Esteban Rossi-Hansberg. 2018. "The Geography of Development." *Journal of Political Economy* 126 (3): 903–983.

Desmet, Klaus, et al. 2021. "Evaluating the Economic Cost of Coastal Flooding." *American Economic Journal: Macroeconomics* 13 (2): 444–486.

Driscoll, Charles T., et al. 2015. "US Power Plant Carbon Standards and Clean Air and Health Co-Benefits." *Nature Climate Change* 5 (6): 535–540.

Druckman, James N. 2022. "A Framework for the Study of Persuasion." *Annual Review of Political Science.*

Druckman, James N., and Arthur Lupia. 2000. "Preference Formation." *Annual Review of Political Science* 3 (1): 1–24.

Druckman, James N., and Mary C. McGrath. 2019. "The Evidence for Motivated Reasoning in Climate Change Preference Formation." *Nature Climate Change* 9 (2): 111–119.

Dunning, Thad, et al., eds. 2019. *Information, Accountability, and Cumulative Learning: Lessons from Metaketa I.* 1st ed. Cambridge University Press, 2019.

Egan, Patrick J., and Megan Mullin. 2012. "Turning Personal Experience into Political Attitudes: The Effect of Local Weather on Americans' Perceptions about Global Warming." *Journal of Politics* 74 (3): 796–809.

Fan, Yun, and Huug van den Dool. 2008. "A Global Monthly Land Surface Air Temperature Analysis for 1948–Present." *Journal of Geophysical Research* 113, no. D1 (2008): D01103.

Feldman, Stanley, and John Zaller. 1992. "The Political Culture of Ambivalence: Ideological Responses to the Welfare State." *American Journal of Political Science* 36 (1): 268.

Ferejohn, John A., and Roger G. Noll. 1978. "Uncertainty and the Formal Theory of Political Campaigns." *American Political Science Review* 72 (2): 492–505.

Fernandez, Raquel, and Dani Rodrik. 1991. "Resistance to Reform: Status Quo Bias in the Presence of Individual- Specific Uncertainty." *American Economic Review* 81 (5): 1146–1155.

Frieden, Jeffry A. 1991. "Invested Interests: The Politics of National Economic Policies in a World of Global Finance." *International Organization* 45 (4): 425–451.

Gazmararian, Alexander F. 2022. "Sources of Partisan Change: Evidence from Unmanaged Energy Transitions in American Coal Country."

Gazmararian, Alexander F., and Helen V. Milner. 2022. "Political Cleavages and Changing Exposure to Global Warming."

Gilens, Martin. 2001. "Political Ignorance and Collective Policy Preferences." *American Political Science Review* 95 (2): 379–396.

Goldstein, Judith L., and Robert O. Keohane. 1993. "Ideas and Foreign Policy: An Analytical Framework." In *Ideas and Foreign Policy: Beliefs, Institutions, and Political Change,* 3–30. Ithaca, NY: Cornell University Press.

Green, Donald, Bradley Palmquist, and Eric Schickler. 2002. *Partisan Hearts and Minds.* Yale University Press.

Groenendyk, Eric, and Yanna Krupnikov. 2021. "What Motivates Reasoning? A Theory of Goal-Dependent Political Evaluation." *American Journal of Political Science* 65 (1): 180–196.

Haas, Peter M. 1989. "Do Regimes Matter? Epistemic Communities and Mediterranean Pollution Control." *International Organization* 43 (3): 377–403.

Hainmueller, Jens, Jonathan Mummolo, and Yiqing Xu. 2019. "How Much Should We Trust Estimates from Multiplicative Interaction Models? Simple Tools to Improve Empirical Practice." *Political Analysis* 27 (2): 163–192.

Hansen, James, Makiko Sato, and Reto Ruedy. 2012. "Perception of Climate Change." *Proceedings of the National Academy of Sciences* 109, no. 37 (2012).

Hazlett, Chad, and Matto Mildenberger. 2020. "Wildfire Exposure Increases Pro-Environment Voting within Democratic but Not Republican Areas." *American Political Science Review* 114 (4): 1359–1365.

Hill, Seth J. 2017. "Learning Together Slowly: Bayesian Learning about Political Facts." *The Journal of Politics* 79 (4): 1403–1418.

Hiscox, Michael J. 2002. "Commerce, Coalitions, and Factor Mobility: Evidence from Congressional Votes on Trade Legislation." *American Political Science Review* 96 (3): 593–608.

Hoffmann, Roman, et al. 2022. "Climate Change Experiences Raise Environmental Concerns and Promote Green Voting." *Nature Climate Change* 12:148–155.

Howe, Peter, et al. 2019. "How Will Climate Change Shape Climate Opinion?" *Environmental Research Letters* 14 (11): 113001.

Hsiang, Solomon, et al. 2017. "Estimating Economic Damage from Climate Change in the United States." *Science* 356 (6345): 1362–1369.

Imai, Kosuke, In Song Kim, and Erik H. Wang. 2021. "Matching Methods for Causal Inference with Time-Series Cross-Sectional Data." *American Journal of Political Science* (2021): ajps.12685.

IPCC. 2022. "Summary for Policymakers." In *Climate Change 2022: Impacts, Adaptation, and Vulnerability,* edited by H.-O. Pörtner et al. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press.

Jervis, Robert. 1976. *Perception and Misperception in International Politics.* Princeton University Press.

Kennard, Amanda. 2020. "The Enemy of My Enemy: When Firms Support Climate Change Regulation." *International Organization* 74 (2): 187–221.

Koremenos, Barbara. 2001. "Loosening the Ties That Bind: A Learning Model of Agreement Flexibility." *International Organization* 55 (2): 289–325.

———. 2005. "Contracting around International Uncertainty." *American Political Science Review* 99 (4): 549–565.

Kotz, Maximilian, et al. 2021. "Day-to-Day Temperature Variability Reduces Economic Growth." *Nature Climate Change,* no. 11, 319–325.

Kummu, Matti, Maija Taka, and Joseph H. A. Guillaume. 2018. "Gridded Global Datasets for Gross Domestic Product and Human Development Index over 1990–2015." *Scientific Data* 5 (1): 180004.

———. 2019. (Data from: Gridded Global Datasets for Gross Domestic Product and Human Development Index over 1990-2015. V. 2).

Lake, David A. 2009. "Open Economy Politics: A Critical Review." *The Review of International Organizations* 4 (3): 219–244.

Lane, Robert E. 1973. "Patterns of Political Belief." In *Handbook of Political Psychology,* edited by Jeanne Knutson. Jossey-Bass.

Lenz, Gabriel S. 2012. *Follow the Leader?* University of Chicago Press.

Levy, Jack S. 1994. "Learning and Foreign Policy: Sweeping a Conceptual Minefield." *International Organization* 48 (2): 279–312.

Marx, Sabine M., et al. 2007. "Communication and Mental Processes: Experiential and Analytic Processing of Uncertain Climate Information." *Global Environmental Change* 17 (1): 47–58.

Mildenberger, Matto. 2020. *Carbon Captured: How Business and Labor Control Climate Politics.* MIT Press.

Milner, Helen V. 1988. *Resisting Protectionism: Global Industries and the Politics of International Trade.* Princeton University Press.

Nelson, Stephen C., and Peter J. Katzenstein. 2014. "Uncertainty, Risk, and the Financial Crisis of 2008." *International Organization* 68 (2): 361–392.

Nisbett, Richard, and Lee Ross. 1980. *Human Inference: Strategies and Shortcomings of Social Judgement.* Prentice-Hall.

Oakleaf, James R., et al. 2019. "Mapping Global Development Potential for Renewable Energy, Fossil Fuels, Mining and Agriculture Sectors." *Scientific Data* 6 (1): 101.

Olonscheck, Dirk, et al. 2021. "Large-Scale Emergence of Regional Changes in Year-to-Year Temperature Variability by the End of the 21st Century." *Nature Communications* 12 (1): 7237.

Page, Benjamin I., and Robert Y. Shapiro. 1992. *The Rational Public.* Chicago University Press.

Peters, Margaret E. 2015. "Open Trade, Closed Borders Immigration in the Era of Globalization." *World Politics* 67 (1): 114–154.

Powell, Robert. 2004. "Bargaining and Learning While Fighting." *American Journal of Political Science* 48 (2): 344–361.

Prior, Markus, and Arthur Lupia. 2008. "Money, Time, and Political Knowledge: Distinguishing Quick Recall and Political Learning Skills." *American Journal of Political Science* 52, no. 1 (2008): 169–183.

Prior, Markus, Gaurav Sood, and Kabir Khanna. 2015. "You Cannot Be Serious: The Impact of Accuracy Incentives on Partisan Bias in Reports of Economic Perceptions." *Quarterly Journal of Political Science* 10 (4): 489–518.

Reiter, Dan. 1996. *Crucible of Beliefs: Learning, Alliances, and World Wars.* Cornell University Press.

Rodrik, Dani. 2014. "When Ideas Trump Interests: Preferences, Worldviews, and Policy Innovations." *Journal of Economic Perspectives* 28 (1): 189–208.

Rogowski, Ronald. 1987. "Political Cleavages and Changing Exposure to Trade." *American Political Science Review* 81 (4): 1121–1137.

Rosendorff, B. Peter, and Helen V. Milner. 2001. "The Optimal Design of International Trade Institutions: Uncertainty and Escape." *International Organization* 55 (4): 829–857.

Schär, Christoph, et al. 2004. "The Role of Increasing Temperature Variability in European Summer Heatwaves." *Nature* 427 (6972): 332–336.

Scheve, Kenneth F., and Matthew J. Slaughter. 2001a. "Labor Market Competition and Individual Preferences over Immigration Policy." *The Review of Economics and Statistics* 83 (1): 133–145.

———. 2001b. "What Determines Individual Trade-Policy Preferences?" *Journal of International Economics* 54, no. 2 (2001): 267–292.

———. 2004. "Economic Insecurity and the Globalization of Production." *American Journal of Political Science* 48 (4): 662–674.

Shepsle, Kenneth A. 1972. "The Strategy of Ambiguity: Uncertainty and Electoral Competition." *American Political Science Review* 66 (2): 555–568.

Stevens, Forrest R., et al. 2015. "Disaggregating Census Data for Population Mapping Using Random Forests with Remotely-Sensed and Ancillary Data." Edited by Luís A. Nunes Amaral. *PLOS ONE* 10, no. 2 (2015): e0107042.

Stokes, Leah. 2020. *Short Circuiting Policy: Interest Groups and the Battle Over Clean Energy and Climate Policy in the American States.* Oxford University Press.

Taber, Charles S., and Milton Lodge. 2006. "Motivated Skepticism in the Evaluation of Political Beliefs." *American Journal of Political Science* 50 (3): 755–769.

Tatem, Andrew J. 2017. "WorldPop, Open Data for Spatial Demography." *Scientific Data* 4 (1): 170004.

Tversky, Amos, and Daniel Kahneman. 1974. “Judgment under Uncertainty: Heuristics and Biases: Biases in Judgments Reveal Some Heuristics of Thinking under Uncertainty.” *Science* 185, no. 4157 (1974): 1124–1131.

Weber, Elke U. 2010. “What Shapes Perceptions of Climate Change?: What Shapes Perceptions of Climate Change?” *Wiley Interdisciplinary Reviews: Climate Change* 1 (3): 332–342.

Westerling, A. L., et al. 2006. “Warming and Earlier Spring Increase Western U.S. Forest Wildfire Activity.” *Science* 313, no. 5789 (2006): 940–943.

WorldPop. 2018. (Global 1km Population).

Zaller, John R. 1992. *The Nature and Origins of Mass Public Opinion.* Cambridge, MA: Cambridge University Press.

Online Appendix
"Preference Updating Under Uncertainty"

A Motivated Reasoning Literature

Motivated reasoning is theorized to occur whenever people have strong prior beliefs. In American politics scholarship, the prominent cause cited for motivated reasoning is partisanship. Campbell et al. (1960) claim that party identification acts as a "perceptual screen" that can distort how partisans respond to new information. Zaller (1992) argue that political awareness leads individuals to filter out information that does not conform to their partisan or ideological predisposition.

The empirical literature on motivated reasoning is vast, and we make no attempt to recount each study. Important findings include Cohen (2003), who suggest that attitudes on social policy depend on the position of one's political party, more so than the objective content of the policy and ideological beliefs. Gerber and Huber (2009) show how economic behavior responds to which party is in power immediately after elections. Bartels (2002) examines opinion on President Bush's performance during the Gulf War and find that although citizens received the same information, they interpreted it according to partisan bias. Jones (2020) finds that partisan differences in retrospective assessments have grown in the United States, and consistent with Zaller (1992), they are largest among the most politically aware. Broockman and Butler (2017) and Lenz (2012) find that people bring their issue attitudes in line with their preferred leaders. Motivated reasoning appears to limit the effectiveness of information provision on controversial issues (Flynn, Nyhan, and Reifler 2017). On issues where attitudes are crystallized due to the strength of predispositions like partisanship, core values, and group identity, new information is unlikely to change policy positions, although it could prime beliefs consistent with the pre-existing crystallized policy opinions (Tesler 2015). While Tesler (2015) argues that priming is more prevalent than opinion change for crystallized attitudes, Lenz (2012) claims that opinion change is possible.

There are related measurement issues that call into question the prevalence of motivated reasoning. An implication of motivated reasoning is that people have misperceptions that are due to aligning their beliefs with their preferences. Studies document how some members of the public hold inaccurate beliefs, such as climate denial or vaccine skepticism. Although, there is a question of whether measurement of misperceptions is valid; respondents who may report absolute certainty in a falsehood may reduce his certainty in the incorrect answer in a subsequent survey (Graham 2022).

The implications of motivated reasoning for preference updating are contested. First, Bayesian models of learning already incorporate motivated reasoning through the weight that one might place on her prior beliefs—although, a key question is whether people interpret new information in the same way.[22] For this reason, Druckman and McGrath (2019) argue that the empirical evidence for motivated reasoning is inconclusive since studies cannot distinguish whether people aim for accurate beliefs but assess the credibility of information in different ways (e.g., Democrats discount information from Fox News). This insight points scholars in the direction of understanding what information is seen as credible.[23]

22. Empirically, there is hopeful evidence of parallel trends in opinion change across different partisan groups (Gerber and Green 1999). Although, see Bartels (2002) for a rejoinder.

23. Gilens (2001), for instance, finds that specific policy knowledge can change people's opinions, even among respondents with high political awareness.

B Sub-Region Data Crosswalk Construction

We construct a crosswalk between the sub-region names in the Gallup data and spatial polygons representing the region. We then map our climate damages and temperature data, which are geocoded to longitude-latitude grids, to the respondent's region as identified by the crosswalk.

Creating the crosswalk is a labor-intensive process. First, we locate shape files for the administrative areas, which are not standardized across countries. Second, we inspect each region name in the Gallup data since spellings are non-uniform. Third, for cases where the Gallup regions do not match official administrative boundaries, we must create our own shape files using the best available information for the country. This appendix describes each of these steps and the data sources we employ.

B.1 Core Shapefile Data

The majority of the shape files come from version 4.0.4 of the Database of Global Administrative Areas (GADM), which delimits 397,119 administrative areas. The administrative areas include lower level subdivisions of countries such as provinces and counties. We downloaded the `world.dbf` attribute table, which contains the smallest administrative level divisions possible.[24]

B.2 Additional Shapefile Data

There are some countries whose sub-regions are unable to be created by what GADM provides. Table B1 contains information about the sources of shapefiles we use for these cases. Some of this data comes from the Humanitarian Data Exchange (HDX), an open platform managed by the United Nations Office for the Coordination of Humanitarian Affairs' Field Information Services Section. Additional sources include the World Bank, national statistical agencies, geographic information system experts, and other standard data repositories. All files were downloaded between June and July 2022.

Country	Shapefile Source	URL
Botswana	HDX	https://bit.ly/3RAPNIq
Kosovo	Justin Meyers	https://bit.ly/3RyHJbb
Montenegro	StackExchange (GIS)	https://bit.ly/3TyPO1o
Morocco	Minnesota Population Center (2020)	https://bit.ly/3RATNsE
Philippines	HDX[25]	https://bit.ly/3TH27Zt
Turkey	`TRmaps` R package[26]	https://bit.ly/3QeH65E
Uganda	World Bank's energydata.info	https://bit.ly/3CWpyZc
United Kingdom	Open Geography PortalX[27]	https://bit.ly/3AJFoDD

Table B1: Data sources for additional shapefiles

B.3 Unavailable Subregion Shapefiles

There are a handful of sub-regions listed in the Gallup data where shape files could not be found. To address this challenge, we identified larger regions that contained the sub-regions. Table B2 lists the country, sub-region ID in the Gallup data, and the name of the larger region containing the subregions.

24. Available online at: https://gadm.org/download_world.html.
25. File downloaded: `phl_adminboundaries_candidate_exclude_adm3.zipSHP`
26. This is an R package for making maps of Turkey.
27. UK Office for National Statistics.

Country	Gallup Subregion ID	Supra-Region Name
Benin	48,53	Athieme and Lokossa
Gambia	41,42,43	Banjul
Gambia	31,33	Upper Baddibu
Gambia	35,36,37	Fulladu East
Gambia	38,39	Wuli
Lebanon	1,3	Beirut
Latvia	1,6	Riga and Pieriga

Table B2: Special cases where sub-region shapefiles were unavailable

B.4 Special Cases

There are a handful of cases where we make assumptions about the regions referenced in the Gallup data. We discuss these cases and the reasons for the coding assumptions below.

B.4.1 Bosnia and Herzegovina

In the Gallup Data Dictionary, Republika Srpska (RS) is divided into RS West, RS East, and RS South. However, RS West/East/South are not official sub-regions of RS. Hence, geographical quadrants were used to define these sub-regions.

B.4.2 Vietnam

In the Data Dictionary, there's a sub-region named Ha Tay (22). However, Ha Tay is a former province as of 2008 and is not a part of Ha Noi.[28] Ha Tay is also not associated with any survey data, so we can trim this region.

B.4.3 Botswana

Four assumptions were made in this country because the sub-region names in the Data Dictionary were difficult to match with the shapefile's attribute table. These assumptions are: (1) When there exists a larger sub-region that matches a Data Dictionary name, assume that the Data Dictionary name refers to this sub-region. (There are often smaller sub-regions of the same name); (2) Bobononj (Shapefile Name) refers to Bobirwa (Data Dictionary) because Google Maps indicates that these regions are in fact the same region; (3) Ngamiland (Shapefile Name) refers to Ngami (Data Dictionary) because there is no other match similar to Ngami; and (4) Okavango (Data Dictionary) is a delta in Ngamiland. Hence, we assume that Okvango refers to Ngamiland Delta (Shapefile Name). There is also no other match similar to Okavango.

B.4.4 Japan

The region Niigata is associated with the Gallup sub-region Hokuriku and Koshinetsu. Since each shape may can only be associated with one Gallup sub-region (so no errors occur when regions are merged to form shapes that correspond to Gallup sub-regions), Niigata is associated with Hokuriku only.

B.4.5 Azerbaijan

The three of the four subregions listed in the Data Dictionary ("Eastern part"," Northern part"," Southern part") are not official sub-regions. Hence, geographical quadrants were used to define these sub-regions.

28. It is possible that Ha Tay refers to Gia Lai. However, Gia Lai is already listed as a sub-region.

B.4.6 Ivory Coast

The four of the five sub-regions listed in the Data Dictionary ("South", "West", "Northeast", "Center") are not official sub-regions. Hence, geographical quadrants were used to define these sub-regions.

B.4.7 Tanzania

The sub-regions Central, Coastal, Islands, Northern, Southern, and Western were roughly determined by using secondary cartographic depictions of the country.

C Cross-Sectional Analysis Appendix

C.1 Summary Statistics

Table C1: **Summary statistics for cross-national survey analysis.** Data cover 123 countries and 2,255 regions. Temperature variability change is standardized. Risk is Danger and Tertiary Education are dichotomized in the summary table for exposition but treated as categorical in analysis to avoid information loss. Income Quintile is numeric in the summary table but treated as categorical in analysis.

	Mean	SD	Min	Max	N	Missing
Outcome Variables:						
Climate is Top/Major Risk	0.05	0.22	0.00	1.00	133683	0
Climate is Top Risk	0.03	0.17	0.00	1.00	133683	0
Politics is Top Risk (placebo)	0.02	0.13	0.00	1.00	133683	0
Work Accident is Top Risk (placebo)	0.02	0.15	0.00	1.00	133683	0
Explanatory Variable:						
Δ Temp. Variability	0.07	0.99	-2.54	7.49	133272	411
Moderator:						
Potential Damages	0.79	0.41	0.00	1.00	133182	501
Individual-Level Controls:						
Age	42.40	18.23	15.00	99.00	133372	311
Female	0.54	0.50	0.00	1.00	133683	0
Risk is Danger	0.66	0.47	0.00	1.00	133683	0
Tertiary Education	0.17	0.38	0.00	1.00	133683	0
Income Quintile	3.20	1.42	1.00	5.00	132603	1080
Subregion-Level Controls:						
GDP (log)	26.68	3.39	0.00	32.28	133182	501
CO2 Emissions (log)	0.00	0.00	0.00	0.01	133182	501
Population (log)	17.73	2.35	0.00	22.41	133182	501
Coal Development Potential Index	0.10	0.21	0.00	0.92	133182	501
Oil Development Potential Index	0.24	0.30	0.00	0.99	133182	501
Country-Level Controls:						
Polyarchy	0.55	0.26	0.02	0.91	133683	0

C.2 Individual-Level Variable Construction

- **Gender**. Gender differences in climate policy preferences manifest in high-income countries (Bush and Clayton 2022). Our empirical model specifications includes a binary indicator for if a respondent identifies as female.

- **Education**. Education supplies information about the scientific mechanisms behind global warming, which is predictive of climate concern (Lee et al. 2015). We control for education using a categorical variable for if a respondent has a primary, secondary, or tertiary education. Since countries have distinct ways of classify education levels, these categories devised by Gallup represent the most consistent way of accounting for the educational attainment of respondents. Primary is the equivalent to completing up to eight years of education; secondary is the equivalent of completing between nine and 15 years of education but not a bachelor's degree or equivalent; and tertiary is 16 years or more, the functional equivalent of a bachelor's degree or more. Since countries have distinct ways of classify education levels, these categories devised by Gallup represent the most consistent way of accounting for the educational attainment of respondents. Primary is the equivalent to completing up to eight years of education; secondary is the equivalent of completing between nine and 15 years of education but not a bachelor's degree or equivalent; and tertiary is 16 years or more, the functional equivalent of a bachelor's degree or more.

- **Household income**. We account for income using a categorical variable for the respondent's monthly household income quintile. This variable is constructed from two questions. The first asks respondents about their monthly household income prior to taxes, which includes all wages, remittances, and other sources. If respondents did not know or refused, they were presented with an income range in the local currency and asked which group they fell into. If the respondent answered neither question, Gallup imputes the missing value using a hot-deck imputation procedure. Then, the income data are annualized and a per capita annual income value is calculated by dividing the household income by the number of people living in the household. This per capita annual income value then serves as the basis for the income quintiles in each country survey.

- **Age**. We use a continuous variable to measure age. A small number of observations are right-censored since the survey firm codes all individuals over the age of 100 as in a single category to protect the respondents identity.

- **Risk**. The item to measure risk interpretation asks, "When you hear the word RISK, do you think more about opportunity or danger?" with possible answers including, "Danger," "Opportunity," "Both," and "Neither."

C.3 Spatial Distribution of Subregion-Level Data

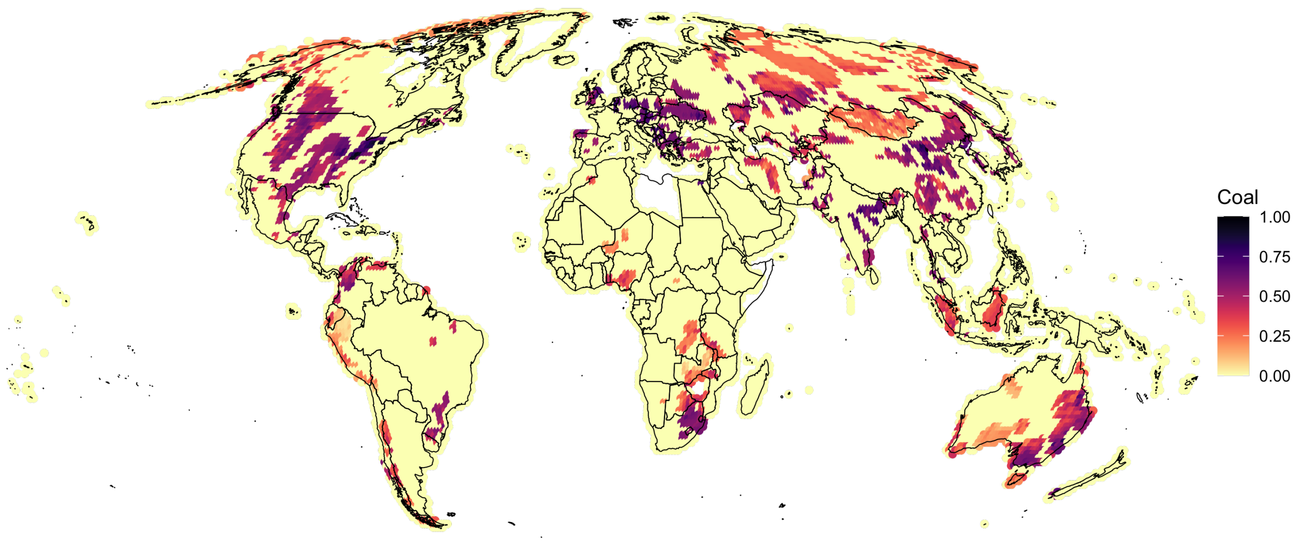

Figure C1: **Spatial distribution of coal development potential.** Data from Oakleaf et al. (2019).

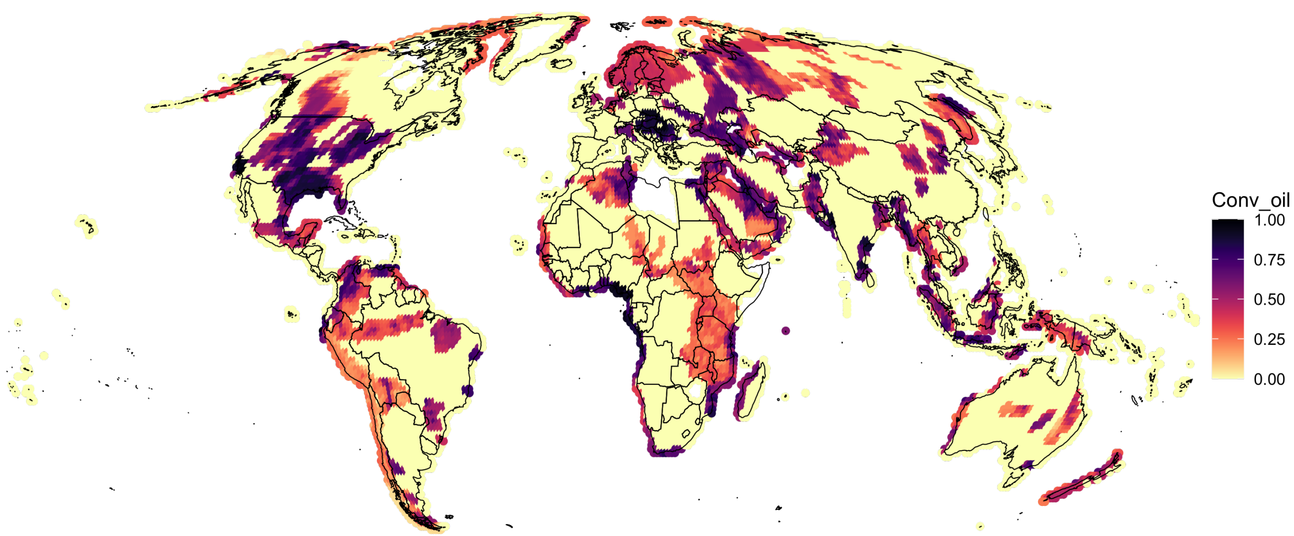

Figure C2: **Spatial distribution of conventional gas development potential.** Data from Oakleaf et al. (2019).

C.4 Complete Multivariate Regression Results

Table C2: **Linear regressions of risk salience on the interaction of long-run change in temperature variability and potential climate damages.** HC1 standard errors clustered by subregion.

	Climate Risk Salience:		Placebo Tests:	
	Top/Major	Top	Work	Politics
Intercept	0.076***	0.056***	0.030***	−0.001
	(0.019)	(0.013)	(0.007)	(0.009)
Individual-Level Controls				
Δ Temp. Variability	−0.004	−0.004	0.001	0.001
	(0.004)	(0.002)	(0.001)	(0.002)
Potential Damages	−0.019**	−0.014**	0.006**	0.002
	(0.009)	(0.006)	(0.002)	(0.003)
Δ Temp. Variability $\times$ Potential Damages	0.012***	0.009***	−0.001	0.000
	(0.004)	(0.003)	(0.001)	(0.002)
Age (standardized)	0.002***	0.002***	−0.005***	0.002***
	(0.001)	(0.001)	(0.001)	(0.000)
Female	0.000	0.001	−0.026***	−0.007***
	(0.002)	(0.001)	(0.001)	(0.001)
Education: Primary	0.003	0.005***	0.000	−0.003***
	(0.002)	(0.002)	(0.001)	(0.001)
Education: Tertiary	0.007***	0.002	−0.011***	0.010***
	(0.002)	(0.001)	(0.001)	(0.002)
Education: Don't know	−0.012	−0.005	−0.013***	−0.013***
	(0.009)	(0.006)	(0.004)	(0.003)
Education: Refused	−0.009	−0.003	−0.015***	−0.003
	(0.011)	(0.007)	(0.004)	(0.006)
Income: Poorest	0.000	0.002	−0.003**	−0.001
	(0.003)	(0.002)	(0.001)	(0.001)
Income: Second	0.001	0.002	0.000	0.000
	(0.002)	(0.002)	(0.001)	(0.001)
Income: Fourth	0.001	0.000	0.003*	0.001
	(0.002)	(0.001)	(0.001)	(0.001)
Income: Richest	0.000	−0.002	0.003**	0.003**
	(0.002)	(0.001)	(0.001)	(0.001)
Risk: Opportunity	−0.016***	−0.008***	−0.002*	−0.002
	(0.002)	(0.001)	(0.001)	(0.001)
Risk: Neither	−0.022***	−0.011	−0.009***	−0.003
	(0.008)	(0.008)	(0.003)	(0.003)
Risk: Opportunity and Danger	−0.002	−0.002	0.004*	0.002
	(0.003)	(0.003)	(0.003)	(0.002)
Risk: Don't know	−0.034***	−0.019***	−0.011***	−0.006***
	(0.003)	(0.002)	(0.001)	(0.001)
Risk: Refused	−0.044***	−0.028***	−0.003	0.003
	(0.012)	(0.010)	(0.008)	(0.009)
Subregion-Level Controls				

Table C2: **Linear regressions of risk salience on the interaction of long-run change in temperature variability and potential climate damages.** HC1 standard errors clustered by subregion. *(continued)*

	Climate Risk Salience:		Placebo Tests:	
	Top/Major	Top	Work	Politics
GDP (log)	0.000	0.000	0.001	−0.001**
	(0.001)	(0.000)	(0.000)	(0.000)
Population (log)	−0.001	−0.001	−0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
Coal development potential index	−0.022***	−0.014**	0.003	−0.006
	(0.008)	(0.006)	(0.003)	(0.004)
Oil development potential index	−0.004	−0.003	0.008***	−0.001
	(0.006)	(0.004)	(0.002)	(0.003)
Country-Level Controls				
Polyarchy	0.021**	0.008	0.017***	0.031***
	(0.011)	(0.008)	(0.004)	(0.009)
Global Region Fixed Effects	Yes	Yes	Yes	Yes
N	131 380	131 380	131 380	131 380
F-statistic	37.3	40.0	45.4	41.1
* p < 0.1, ** p < 0.05, *** p < 0.01				

C.5 Robustness Checks

Table C3: **Multi-level model with random intercepts for subregions.** Regressions of risk salience on the interaction of long-run change in temperature variability and potential climate damages. Models estimated using the `lme4` package in `R`.

	Climate Risk Salience:		Placebo Tests:	
	Top/Major	Top	Work	Politics
Intercept	0.067***	0.050***	0.033***	−0.010
	(0.016)	(0.011)	(0.008)	(0.007)
Individual-Level Controls				
Δ Temp. Variability	−0.003	−0.003	0.002	0.003*
	(0.003)	(0.002)	(0.002)	(0.002)
Potential Damages	−0.019***	−0.012***	0.007**	0.006**
	(0.006)	(0.004)	(0.003)	(0.003)
Δ Temp. Variability × Potential Damages	0.010***	0.008***	−0.002	−0.002
	(0.004)	(0.003)	(0.002)	(0.002)
Age (standardized)	0.004***	0.002***	−0.005***	0.002***
	(0.001)	(0.001)	(0.000)	(0.000)
Female	0.001	0.001	−0.026***	−0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
Education: Primary	0.000	0.003***	0.001	−0.004***
	(0.002)	(0.001)	(0.001)	(0.001)
Education: Tertiary	0.008***	0.003**	−0.010***	0.009***
	(0.002)	(0.001)	(0.001)	(0.001)
Education: Don't know	−0.013	−0.008	−0.013*	−0.011*
	(0.010)	(0.008)	(0.007)	(0.006)
Education: Refused	−0.007	−0.004	−0.012	0.000
	(0.011)	(0.009)	(0.008)	(0.007)
Income: Poorest	0.000	0.001	−0.003**	−0.001
	(0.002)	(0.002)	(0.001)	(0.001)
Income: Second	0.000	0.002	0.000	0.000
	(0.002)	(0.001)	(0.001)	(0.001)
Income: Fourth	0.001	0.000	0.003**	0.001
	(0.002)	(0.001)	(0.001)	(0.001)
Income: Richest	−0.001	−0.002	0.004***	0.003***
	(0.002)	(0.001)	(0.001)	(0.001)
Risk: Opportunity	−0.013***	−0.006***	−0.001	−0.001
	(0.002)	(0.001)	(0.001)	(0.001)
Risk: Neither	−0.016***	−0.007**	−0.008**	−0.002
	(0.005)	(0.003)	(0.003)	(0.003)
Risk: Opportunity and Danger	−0.003	−0.002	0.004**	0.001
	(0.002)	(0.002)	(0.002)	(0.001)
Risk: Don't know	−0.030***	−0.018***	−0.009***	−0.004**
	(0.003)	(0.002)	(0.002)	(0.002)
Risk: Refused	−0.027*	−0.015	−0.005	0.005
	(0.014)	(0.011)	(0.010)	(0.008)
Subregion-Level Controls				

Table C3: **Multi-level model with random intercepts for subregions.** Regressions of risk salience on the interaction of long-run change in temperature variability and potential climate damages. Models estimated using the `lme4` package in R. *(continued)*

	Climate Risk Salience:		Placebo Tests:	
	Top/Major	Top	Work	Politics
GDP (log)	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.000)
Population (log)	0.000	−0.001	−0.002***	0.001**
	(0.001)	(0.001)	(0.001)	(0.001)
Coal development potential index	−0.017**	−0.011**	0.002	−0.007**
	(0.008)	(0.005)	(0.004)	(0.004)
Oil development potential index	−0.004	−0.002	0.008***	0.004
	(0.005)	(0.004)	(0.003)	(0.002)
Country-Level Controls				
Polyarchy	0.033***	0.013**	0.013***	0.031***
	(0.010)	(0.007)	(0.005)	(0.004)
Global Region Fixed Effects	Yes	Yes	Yes	Yes
Num.Obs.	131 380	131 380	131 380	131 380
RMSE	0.21	0.16	0.15	0.13
* p < 0.1, ** p < 0.05, *** p < 0.01				

Table C4: **Polity2 instead of Polyarchy.** Linear regressions of risk salience on the interaction of long-run change in temperature variability and potential climate damages. HC1 standard errors clustered by subregion.

	Climate Risk Salience:		Placebo Tests:	
	Top/Major	Top	Work	Politics
Intercept	0.083***	0.059***	0.035***	0.006
	(0.019)	(0.013)	(0.007)	(0.009)
Individual-Level Controls				
Δ Temp. Variability	−0.004	−0.004	0.002	0.002
	(0.004)	(0.002)	(0.001)	(0.002)
Potential Damages	−0.019**	−0.014**	0.006***	0.003
	(0.009)	(0.006)	(0.002)	(0.003)
Δ Temp. Variability × Potential Damages	0.011***	0.009***	−0.001	−0.001
	(0.004)	(0.003)	(0.001)	(0.002)
Age (standardized)	0.003***	0.002***	−0.005***	0.002***
	(0.001)	(0.001)	(0.001)	(0.000)
Female	0.000	0.001	−0.026***	−0.007***
	(0.002)	(0.001)	(0.001)	(0.001)
Education: Primary	0.003	0.005***	0.000	−0.004***
	(0.002)	(0.002)	(0.001)	(0.001)
Education: Tertiary	0.007***	0.002	−0.010***	0.010***
	(0.002)	(0.001)	(0.001)	(0.002)
Education: Don't know	−0.012	−0.005	−0.013***	−0.013***
	(0.009)	(0.006)	(0.004)	(0.002)
Education: Refused	−0.010	−0.003	−0.016***	−0.004
	(0.011)	(0.007)	(0.004)	(0.006)
Income: Poorest	0.000	0.002	−0.003**	−0.001
	(0.003)	(0.002)	(0.001)	(0.001)
Income: Second	0.001	0.002	0.000	0.000
	(0.002)	(0.002)	(0.001)	(0.001)
Income: Fourth	0.001	0.000	0.003**	0.000
	(0.002)	(0.001)	(0.001)	(0.001)
Income: Richest	0.000	−0.002	0.003**	0.003*
	(0.002)	(0.001)	(0.001)	(0.001)
Risk: Opportunity	−0.016***	−0.008***	−0.002*	−0.002
	(0.002)	(0.001)	(0.001)	(0.001)
Risk: Neither	−0.023***	−0.011	−0.009***	−0.004
	(0.008)	(0.008)	(0.003)	(0.003)
Risk: Opportunity and Danger	−0.003	−0.002	0.004	0.001
	(0.004)	(0.003)	(0.003)	(0.002)
Risk: Don't know	−0.035***	−0.020***	−0.011***	−0.007***
	(0.003)	(0.002)	(0.001)	(0.001)
Risk: Refused	−0.045***	−0.028***	−0.004	0.002
	(0.012)	(0.010)	(0.008)	(0.009)
Subregion-Level Controls				
GDP (log)	0.001	0.000	0.001	−0.001*
	(0.001)	(0.000)	(0.000)	(0.000)

Table C4: **Polity2 instead of Polyarchy.** Linear regressions of risk salience on the interaction of long-run change in temperature variability and potential climate damages. HC1 standard errors clustered by subregion. *(continued)*

	Climate Risk Salience:		Placebo Tests:	
	Top/Major	Top	Work	Politics
Population (log)	−0.001	−0.001	−0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
Coal development potential index	−0.022***	−0.014**	0.004	−0.006
	(0.008)	(0.006)	(0.003)	(0.004)
Oil development potential index	−0.004	−0.003	0.008***	−0.001
	(0.006)	(0.004)	(0.002)	(0.003)
Country-Level Controls				
Polity2	0.000	0.000	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Global Region Fixed Effects	Yes	Yes	Yes	Yes
N	130 381	130 381	130 381	130 381
F-statistic	35.5	39.0	44.7	41.3
* p < 0.1, ** p < 0.05, *** p < 0.01				

Table C5: **Country-level fossil fuel rent controls.** Linear regressions of risk salience on the interaction of long-run change in temperature variability and potential climate damages. HC1 standard errors clustered by subregion.

	Climate Risk Salience:		Placebo Tests:	
	Top/Major	Top	Work	Politics
Intercept	0.075***	0.058***	0.023***	0.000
	(0.020)	(0.014)	(0.007)	(0.010)
Individual-Level Controls				
Δ Temp. Variability	−0.003	−0.003	0.000	0.002
	(0.003)	(0.002)	(0.001)	(0.002)
Potential Damages	−0.020**	−0.015**	0.008***	0.000
	(0.009)	(0.006)	(0.002)	(0.004)
Δ Temp. Variability × Potential Damages	0.012***	0.009***	0.000	−0.001
	(0.004)	(0.003)	(0.001)	(0.002)
Age (standardized)	0.002***	0.002***	−0.005***	0.001***
	(0.001)	(0.001)	(0.000)	(0.000)
Female	0.000	0.001	−0.026***	−0.007***
	(0.002)	(0.001)	(0.001)	(0.001)
Education: Primary	0.004*	0.005***	0.000	−0.003**
	(0.002)	(0.002)	(0.001)	(0.001)
Education: Tertiary	0.007***	0.002	−0.011***	0.010***
	(0.002)	(0.001)	(0.001)	(0.002)
Education: Don't know	−0.011	−0.004	−0.014***	−0.012***
	(0.009)	(0.006)	(0.004)	(0.003)
Education: Refused	−0.009	−0.003	−0.015***	−0.003
	(0.011)	(0.007)	(0.004)	(0.006)
Income: Poorest	0.000	0.002	−0.003**	−0.001
	(0.003)	(0.002)	(0.001)	(0.001)
Income: Second	0.001	0.002	0.000	0.000
	(0.002)	(0.002)	(0.001)	(0.001)
Income: Fourth	0.002	0.000	0.002*	0.001
	(0.002)	(0.001)	(0.001)	(0.001)
Income: Richest	0.000	−0.002	0.003**	0.003**
	(0.002)	(0.001)	(0.001)	(0.001)
Risk: Opportunity	−0.016***	−0.008***	−0.002*	−0.002
	(0.002)	(0.001)	(0.001)	(0.001)
Risk: Neither	−0.022***	−0.011	−0.009***	−0.003
	(0.008)	(0.008)	(0.003)	(0.003)
Risk: Opportunity and Danger	−0.002	−0.002	0.005*	0.001
	(0.003)	(0.003)	(0.003)	(0.002)
Risk: Don't know	−0.034***	−0.020***	−0.010***	−0.006***
	(0.003)	(0.002)	(0.001)	(0.001)
Risk: Refused	−0.044***	−0.028***	−0.004	0.003
	(0.012)	(0.010)	(0.008)	(0.008)
Subregion-Level Controls				
GDP (log)	0.000	0.000	0.001	−0.001**
	(0.001)	(0.000)	(0.000)	(0.000)

Table C5: **Country-level fossil fuel rent controls.** Linear regressions of risk salience on the interaction of long-run change in temperature variability and potential climate damages. HC1 standard errors clustered by subregion. *(continued)*

	Climate Risk Salience:		Placebo Tests:	
	Top/Major	Top	Work	Politics
Population (log)	−0.001	−0.001	−0.002***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Coal development potential index	−0.020**	−0.012**	0.000	−0.003
	(0.008)	(0.006)	(0.003)	(0.004)
Oil development potential index	−0.005	−0.004	0.009***	−0.002
	(0.006)	(0.004)	(0.002)	(0.003)
Country-Level Controls				
Polyarchy	0.026**	0.011	0.014***	0.036***
	(0.011)	(0.008)	(0.004)	(0.009)
Coal rents as % of GDP	−0.002	−0.003	0.006***	−0.004**
	(0.003)	(0.002)	(0.001)	(0.001)
Oil rents as % of GDP	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Global Region Fixed Effects	Yes	Yes	Yes	Yes
N	131 380	131 380	131 380	131 380
F-statistic	36.0	38.7	46.3	41.4
* p < 0.1, ** p < 0.05, *** p < 0.01				

Table C6: **Drop risk understanding controls.** Linear regressions of risk salience on the interaction of long-run change in temperature variability and potential climate damages. HC1 standard errors clustered by subregion.

	Climate Salience:		Placebo Tests:	
	Top/Major Risk	Top Risk	Work	Politics
Intercept	0.067***	0.052***	0.028***	−0.002
	(0.019)	(0.013)	(0.007)	(0.009)
Individial-Level Controls				
Δ Temp. Variability	−0.003	−0.003	0.002	0.001
	(0.004)	(0.002)	(0.001)	(0.002)
Potential Damages	−0.018**	−0.014**	0.006***	0.002
	(0.009)	(0.007)	(0.002)	(0.003)
Δ Temp. Variability × Potential Damages	0.011***	0.009***	−0.001	0.000
	(0.004)	(0.003)	(0.001)	(0.002)
Age (standardized)	0.002**	0.002***	−0.006***	0.002***
	(0.001)	(0.001)	(0.001)	(0.000)
Female	0.001	0.001	−0.026***	−0.007***
	(0.002)	(0.001)	(0.001)	(0.001)
Education: Primary	0.001	0.004**	0.000	−0.003***
	(0.002)	(0.002)	(0.001)	(0.001)
Education: Tertiary	0.007***	0.002	−0.010***	0.010***
	(0.002)	(0.001)	(0.001)	(0.002)
Education: Don't know	−0.015*	−0.007	−0.014***	−0.014***
	(0.009)	(0.006)	(0.004)	(0.003)
Education: Refused	−0.014	−0.006	−0.017***	−0.003
	(0.011)	(0.007)	(0.004)	(0.006)
Income: Poorest	0.000	0.001	−0.003**	−0.001
	(0.003)	(0.002)	(0.001)	(0.001)
Income: Second	0.000	0.002	0.000	0.000
	(0.002)	(0.002)	(0.001)	(0.001)
Income: Fourth	0.002	0.000	0.003**	0.001
	(0.002)	(0.001)	(0.001)	(0.001)
Income: Richest	0.000	−0.002	0.003**	0.003**
Subregion-Level Controls				
	(0.002)	(0.001)	(0.001)	(0.001)
GDP (log)	0.000	0.000	0.001	−0.001**
	(0.001)	(0.000)	(0.000)	(0.000)
Population (log)	−0.001	−0.001	−0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
Coal development potential index	−0.022***	−0.014**	0.003	−0.006
	(0.008)	(0.006)	(0.003)	(0.004)
Oil development potential index	−0.003	−0.003	0.008***	−0.001
	(0.006)	(0.004)	(0.002)	(0.003)
Country-Level Controls				
Polyarchy	0.025**	0.010	0.018***	0.031***
	(0.011)	(0.008)	(0.004)	(0.009)

Table C6: **Drop risk understanding controls.** Linear regressions of risk salience on the interaction of long-run change in temperature variability and potential climate damages. HC1 standard errors clustered by subregion. *(continued)*

	Climate Salience:		Placebo Tests:	
	Top/Major Risk	Top Risk	Work	Politics
Global Region Fixed Effects	Yes	Yes	Yes	Yes
N	131 380	131 380	131 380	131 380
F-statistic	36.1	42.6	50.8	46.7
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$				

Table C7: **Control for the national climate law stock.** Climate law data from (Nachmany et al. 2017). Linear regressions of risk salience on the interaction of long-run change in temperature variability and potential climate damages. HC1 standard errors clustered by subregion.

	Climate Risk Salience:		Placebo Tests:	
	Top/Major	Top	Work	Politics
Intercept	0.074***	0.055***	0.029***	−0.001
	(0.019)	(0.013)	(0.007)	(0.009)
Individual-Level Controls				
Δ Temp. Variability	−0.003	−0.004	0.002	0.001
	(0.004)	(0.002)	(0.001)	(0.002)
Potential Damages	−0.020**	−0.014**	0.006**	0.002
	(0.009)	(0.006)	(0.002)	(0.003)
Δ Temp. Variability $\times$ Potential Damages	0.011**	0.009***	−0.001	0.000
	(0.004)	(0.003)	(0.001)	(0.002)
Age (standardized)	0.002***	0.002***	−0.005***	0.002***
	(0.001)	(0.001)	(0.001)	(0.000)
Female	0.000	0.001	−0.026***	−0.007***
	(0.002)	(0.001)	(0.001)	(0.001)
Education: Primary	0.004	0.005***	0.000	−0.003***
	(0.002)	(0.002)	(0.001)	(0.001)
Education: Tertiary	0.007***	0.002	−0.011***	0.010***
	(0.002)	(0.001)	(0.001)	(0.002)
Education: Don't know	−0.012	−0.005	−0.013***	−0.013***
	(0.009)	(0.006)	(0.004)	(0.003)
Education: Refused	−0.009	−0.003	−0.015***	−0.003
	(0.011)	(0.007)	(0.004)	(0.006)
Income: Poorest	0.000	0.002	−0.003**	−0.001
	(0.003)	(0.002)	(0.001)	(0.001)
Income: Second	0.001	0.002	0.000	0.000
	(0.002)	(0.002)	(0.001)	(0.001)
Income: Fourth	0.001	0.000	0.003*	0.001
	(0.002)	(0.001)	(0.001)	(0.001)
Income: Richest	0.000	−0.002	0.003**	0.003**
	(0.002)	(0.001)	(0.001)	(0.001)
Risk: Opportunity	−0.016***	−0.008***	−0.002*	−0.002
	(0.002)	(0.001)	(0.001)	(0.001)
Risk: Neither	−0.022***	−0.011	−0.009***	−0.003
	(0.008)	(0.008)	(0.003)	(0.003)
Risk: Opportunity and Danger	−0.002	−0.002	0.004*	0.002
	(0.003)	(0.003)	(0.003)	(0.002)
Risk: Don't know	−0.033***	−0.019***	−0.011***	−0.006***
	(0.003)	(0.002)	(0.001)	(0.001)
Risk: Refused	−0.044***	−0.028***	−0.003	0.003
	(0.012)	(0.010)	(0.008)	(0.009)
Subregion-Level Controls				
GDP (log)	0.000	0.000	0.001	−0.001**
	(0.001)	(0.000)	(0.000)	(0.000)

Table C7: **Control for the national climate law stock.** Climate law data from (Nachmany et al. 2017). Linear regressions of risk salience on the interaction of long-run change in temperature variability and potential climate damages. HC1 standard errors clustered by subregion. *(continued)*

	Climate Risk Salience:		Placebo Tests:	
	Top/Major	Top	Work	Politics
Population (log)	−0.001	−0.001	−0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
Coal development potential index	−0.022***	−0.014**	0.003	−0.006
	(0.008)	(0.006)	(0.003)	(0.004)
Oil development potential index	−0.003	−0.003	0.008***	−0.001
	(0.006)	(0.004)	(0.002)	(0.003)
Country-Level Controls				
Polyarchy	0.017	0.006	0.015***	0.031***
	(0.011)	(0.008)	(0.004)	(0.009)
Climate Law Stock	0.000	0.000	0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Global Region Fixed Effects	Yes	Yes	Yes	Yes
N	131 380	131 380	131 380	131 380
F-statistic	36.7	39.1	44.5	40.1
* p < 0.1, ** p < 0.05, *** p < 0.01				

Table C8: **1980-1990 as historical benchmark for temperature variability.** Linear regressions of risk salience on the interaction of long-run change in temperature variability and potential climate damages. HC1 standard errors clustered by subregion.

	Top/Major	Top	Work	Politics
Intercept	0.073***	0.054***	0.030***	−0.001
	(0.019)	(0.013)	(0.007)	(0.009)
Individual-Level Controls				
Δ Temp. Variability	−0.003	−0.003	0.002	0.002
	(0.003)	(0.002)	(0.001)	(0.002)
Potential Damages	−0.018**	−0.013**	0.006**	0.002
	(0.009)	(0.006)	(0.002)	(0.004)
Δ Temp. Variability × Potential Damages	0.011**	0.009***	−0.001	0.000
	(0.004)	(0.003)	(0.002)	(0.002)
Age (standardized)	0.002***	0.002***	−0.005***	0.002***
	(0.001)	(0.001)	(0.001)	(0.000)
Female	0.000	0.001	−0.026***	−0.007***
	(0.002)	(0.001)	(0.001)	(0.001)
Education: Primary	0.004	0.005***	0.000	−0.003***
	(0.002)	(0.002)	(0.001)	(0.001)
Education: Tertiary	0.007***	0.002	−0.011***	0.010***
	(0.002)	(0.001)	(0.001)	(0.002)
Education: Don't know	−0.011	−0.005	−0.013***	−0.013***
	(0.009)	(0.006)	(0.004)	(0.003)
Education: Refused	−0.010	−0.003	−0.015***	−0.003
	(0.011)	(0.007)	(0.004)	(0.006)
Income: Poorest	0.000	0.002	−0.003**	−0.001
	(0.003)	(0.002)	(0.001)	(0.001)
Income: Second	0.001	0.002	0.000	0.000
	(0.002)	(0.002)	(0.001)	(0.001)
Income: Fourth	0.002	0.000	0.003*	0.001
	(0.002)	(0.001)	(0.001)	(0.001)
Income: Richest	0.000	−0.002	0.003**	0.003**
	(0.002)	(0.001)	(0.001)	(0.001)
Risk: Opportunity	−0.016***	−0.008***	−0.002*	−0.002
	(0.002)	(0.001)	(0.001)	(0.001)
Risk: Neither	−0.022***	−0.011	−0.009***	−0.003
	(0.008)	(0.008)	(0.003)	(0.003)
Risk: Opportunity and Danger	−0.002	−0.002	0.004*	0.002
	(0.003)	(0.003)	(0.003)	(0.002)
Risk: Don't know	−0.034***	−0.019***	−0.011***	−0.006***
	(0.003)	(0.002)	(0.001)	(0.001)
Risk: Refused	−0.044***	−0.028***	−0.003	0.003
	(0.012)	(0.010)	(0.008)	(0.009)
Subregion-Level Controls				
GDP (log)	0.000	0.000	0.001	−0.001**
	(0.001)	(0.000)	(0.000)	(0.000)
Population (log)	−0.001	−0.001	−0.002***	0.002***

Table C8: **1980-1990 as historical benchmark for temperature variability.** Linear regressions of risk salience on the interaction of long-run change in temperature variability and potential climate damages. HC1 standard errors clustered by subregion. *(continued)*

	Top/Major	Top	Work	Politics
	(0.001)	(0.001)	(0.001)	(0.001)
Coal development potential index	−0.022***	−0.014**	0.003	−0.006
	(0.008)	(0.006)	(0.003)	(0.004)
Oil development potential index	−0.004	−0.004	0.008***	−0.001
	(0.006)	(0.004)	(0.002)	(0.003)
Country-Level Controls				
Polyarchy	0.022**	0.008	0.017***	0.031***
	(0.011)	(0.008)	(0.004)	(0.008)
Global Region Fixed Effects	Yes	Yes	Yes	Yes
N	131 380	131 380	131 380	131 380
F-statistic	37.2	39.9	45.5	41.1
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$				

Table D1: **Summary statistics for panel survey data analysis.**

	Mean	SD	Min	Max	N	Missing
Climate Belief	0.54	0.50	0.00	1.00	28264	72
Fire	0.05	0.26	0.00	5.00	28336	0
Fire (=1)	0.04	0.20	0.00	1.00	28336	0
Fire (Placebo)	0.19	0.74	0.00	5.00	28336	0
Potential Damage (=1)	0.80	0.40	0.00	1.00	28336	0
Employed	0.40	0.49	0.00	1.00	28336	0
Education	3.91	1.44	1.00	6.00	28336	0
Party ID	4.16	2.28	1.00	7.00	28276	60
Ideology	2.81	1.21	1.00	5.00	28334	2
Household Income	6.89	3.07	1.00	12.00	24953	3383
Household Income (imputed)	6.89	2.88	1.00	12.00	28336	0
Religion Importance	2.83	1.17	1.00	4.00	28336	0

D Panel Analysis Appendix

D.1 Summary Statistics

D.2 Pre-Trends

Since the treatment is staggered, there is not a simple pre-trends plot for all groups. The other challenge is that there are only three survey ways, so any assessment of pre-trends must compare the last wave with the first two. We overcome these limitations by subsetting the data to cases where counties have not experienced a fire until 2014—there is no history of being treated up until 2014. Then, we compare individuals in counties where there was a fire in 2014 and where there was not. While this is a subset of cases which might not generalize to units with different treatment trajectories, it at the very least allows us to probe the plausibility of the parallel trends assumption.

Figure D1 presents the average climate beliefs for groups in counties experiencing a wildfire in 2014 with those that did not. The slopes of the lines from the 2010 to 2012 survey waves are parallel, which suggests that it is plausible to assume that treated units would have changed at the same rate as untreated units had they not been exposed to a wildfire.

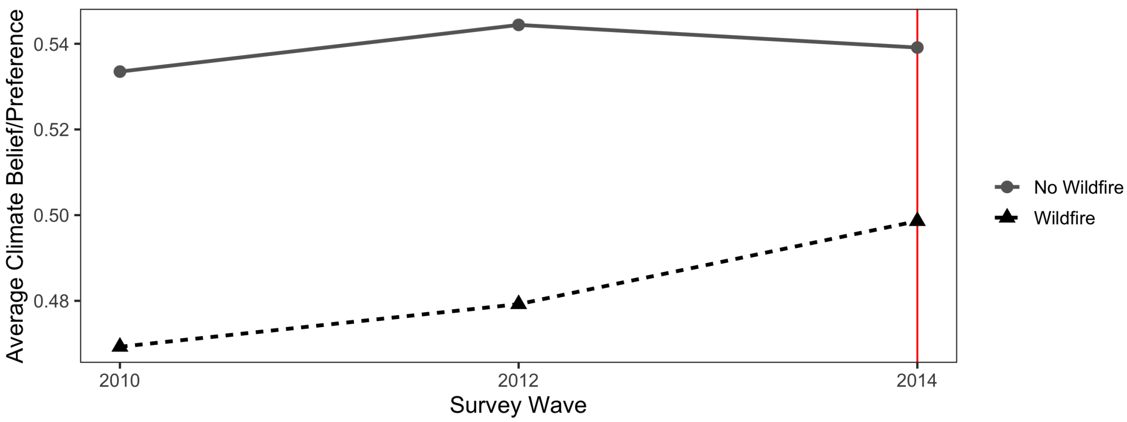

Figure D1: **Average climate belief and preferences by whether an individual was in a county with a wildfire in 2014.** All units are not treated until 2014 for a valid comparison. The slopes of line between the 2010 and 2012 survey waves are parallel, which suggests that units with this pre-treatment history exhibited comparable beliefs and preferences.

D.3 Panel Matching Estimator

We employ the panel matching estimator designed by Imai and Kim (2021). Since we are interested in the effect of wildfires, conditional on whether a location faces potential damages or benefits, we estimate the following models: first, the effect of forest fires on climate beliefs and preferences; second, the effect of forest fires in places facing climate damages on climate beliefs and preferences; and third, the effect of forest fires on climate beliefs in preferences in counties facing potential benefits. The coefficient should be positive for the first two models, and equal to or less than zero for the third.

We employ covariate balance propensity score matching using the following covariates: county population (log) and income (log) in 2012 (Hsiang et al. 2017), a continuous measure of total damage to GDP from global warming (Hsiang et al. 2017). We also match on the following individual-level covariates: employment, education (scale), party identification (7-point scale), ideology (5-point scale), household income, religious importance (4-point scale), birth year, and gender. The technique only allows for continuous covariates, so we could not match using race.

Figure D2 presents the results of estimating the effect of the three defined treatments (wildfire, wildfire $\times$ potential damages, and wildfire $\times$ potential benefits) on climate beliefs and preferences using the panel matching estimator. Consistent with the main results, wildfires lead to increased concern about climate change and support for action, but this effect is most pronounced for respondents in counties facing potential damages. There is no effect of wildfires on climate beliefs and preferences in places facing potential benefits.

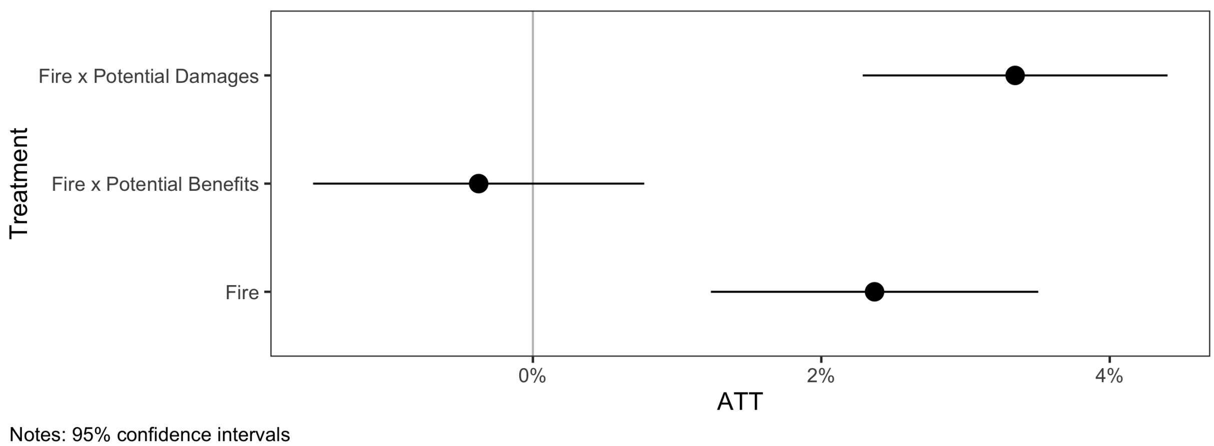

Figure D2: **Average treatment effect on the treated from three models of experience shocks.** Panel matching estimator implemented using the `PanelMatch` package in R (Imai and Kim 2021).

Table D2: **Multivariate regressions of climate mitigation support on the interaction of experience shocks and potential climate damage for skeptics, undecideds, and believers.** Survey data from Ansolabehere and Schaffner (2015). Climate damages data from Hsiang et al. (2017). Fire data from NOAA. Standard errors clustered by county. Education runs from no high school (1) to post-grad (6). Party ID runs from strong Republican (1) to strong Democrat (7). Ideology runs from conservative (1) to liberal (5) Religion runs from not at all important (1) to very important (4).

	Skeptic	Undecided	Believer
Fire × Potential Damages	0.022	0.047**	−0.004
	(0.025)	(0.021)	(0.012)
Fire	0.006	0.007	0.008
	(0.007)	(0.010)	(0.007)
Potential Damages	−0.007	−0.052	−0.001
	(0.014)	(0.042)	(0.009)
Employed	0.006	0.005	0.003
	(0.011)	(0.018)	(0.006)
Education	0.006	0.007	−0.003
	(0.009)	(0.011)	(0.005)
Party ID	0.005	0.009	0.005
	(0.005)	(0.008)	(0.004)
Ideology	−0.006	0.009	0.003
	(0.006)	(0.011)	(0.005)
Household Income	0.003	0.002	−0.002*
	(0.002)	(0.003)	(0.001)
Religion Importance	−0.011	−0.013	0.001
	(0.007)	(0.010)	(0.003)
Individual Fixed Effects	Yes	Yes	Yes
Panel Wave Fixed Effects	Yes	Yes	Yes
N	8012	11 627	8511
Adjusted R^2	0.221	0.690	0.180
F-statistic	1.8	7.6	1.7

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

D.4 Motivated Reasoning Regression Results

Table D3: **Correlation table for climate skeptics, undecideds, and believers.** Damage is an indicator for potential cimate damages. Fire is an indicator for if a county had a wildfire. Edu stands for education.

	Skeptic	Undecided	Believer	Fire	Damage	Employed	Edu	Party ID	Ideology	Income	Religion
Skeptic	1	.	.	.	.	.	.	.	.	.	.
Undecided	−0.53	1	.	.	.	.	.	.	.	.	.
Believer	−0.41	−0.55	1	.	.	.	.	.	.	.	.
Fire	0.00	−0.01	0.02	1	.	.	.	.	.	.	.
Damage	0.02	0.00	−0.01	−0.08	1	.	.	.	.	.	.
Employed	0.01	0.00	0.00	0.00	0.03	1	.	.	.	.	.
Edu	−0.09	−0.07	0.16	0.02	0.03	0.17	1	.	.	.	.
Party ID	−0.54	−0.01	0.54	0.01	−0.01	0.01	0.12	1	.	.	.
Ideology	−0.55	−0.02	0.57	0.02	−0.02	0.02	0.16	0.76	1	.	.
Income	0.02	−0.02	0.00	0.02	0.04	0.30	0.34	−0.05	−0.01	1	.
Religion	0.24	0.06	−0.30	−0.04	0.05	−0.04	−0.10	−0.33	−0.43	−0.08	1

D.5 Correlates of Skeptics, Undecideds, and Believers

References

Ansolabehere, Stephen, and Brian Schaffner. 2015. *Cooperative Congressional Election Study: 2010-2014 Panel Study.* University of Massachusetts, Amherst.

Bartels, Larry M. 2002. "Beyond the Running Tally: Partisan Bias in Political Perceptions." *Political Behavior* 24 (2): 117–150.

Broockman, David E., and Daniel M. Butler. 2017. "The Causal Effects of Elite Position-Taking on Voter Attitudes: Field Experiments with Elite Communication." *American Journal of Political Science* 61 (1): 208–221.

Bush, Sarah Sunn, and Amanda Clayton. 2022. "Facing Change: Gender and Climate Change Attitudes Worldwide." *American Political Science Review,* 1–18.

Campbell, Angus, et al. 1960. *The American Voter.* University of Chicago Press.

Cohen, Geoffrey L. 2003. "Party Over Policy: The Dominating Impact of Group Influence on Political Beliefs." *Journal of Personality and Social Psychology* 85 (5): 808–822.

Druckman, James N., and Mary C. McGrath. 2019. "The Evidence for Motivated Reasoning in Climate Change Preference Formation." *Nature Climate Change* 9 (2): 111–119.

Flynn, D.J., Brendan Nyhan, and Jason Reifler. 2017. "The Nature and Origins of Misperceptions: Understanding False and Unsupported Beliefs About Politics: Nature and Origins of Misperceptions." *Political Psychology* 38:127–150.

Gerber, Alan, and Donald Green. 1999. "Misperceptions about Perceptual Bias." *Annual Review of Political Science* 2:189–210.

Gerber, Alan S., and Gregory A. Huber. 2009. "Partisanship and Economic Behavior: Do Partisan Differences in Economic Forecasts Predict Real Economic Behavior?" *American Political Science Review* 103 (3): 407–426.

Gilens, Martin. 2001. "Political Ignorance and Collective Policy Preferences." *American Political Science Review* 95 (2): 379–396.

Graham, Matthew H. 2022. "Measuring Misperceptions?" *American Political Science Review,* 1–23.

Hsiang, Solomon, et al. 2017. "Estimating Economic Damage from Climate Change in the United States." *Science* 356 (6345): 1362–1369.

Imai, Kosuke, and In Song Kim. 2021. "On the Use of Two-Way Fixed Effects Regression Models for Causal Inference with Panel Data." *Political Analysis* 29 (3): 405–415.

Jones, Philip Edward. 2020. "Partisanship, Political Awareness, and Retrospective Evaluations, 1956–2016." *Political Behavior* 42 (4): 1295–1317.

Lee, Tien Ming, et al. 2015. "Predictors of Public Climate Change Awareness and Risk Perception around the World." *Nature Climate Change* 5 (11): 1014–1020.

Lenz, Gabriel S. 2012. *Follow the Leader?* University of Chicago Press.

Minnesota Population Center. 2020. *Integrated Public Use Microdata Series, International: Version 7.3 [Dataset].*

Nachmany, Michal, et al. 2017. *Global Trends in Climate Change Legislation and Litigation: 2017 Update.* London: Grantham Research Institute. https://bit.ly/3sRWv3l.

Oakleaf, James R., et al. 2019. "Mapping Global Development Potential for Renewable Energy, Fossil Fuels, Mining and Agriculture Sectors." *Scientific Data* 6 (1): 101.

Tesler, Michael. 2015. "Priming Predispositions and Changing Policy Positions: An Account of When Mass Opinion Is Primed or Changed." *American Journal of Political Science* 59 (4): 806–824.

Zaller, John R. 1992. *The Nature and Origins of Mass Public Opinion.* Cambridge, MA: Cambridge University Press.