Supplementary Information: Disaster Experience Mitigates the Partisan Divide on Climate Change: Evidence from Texas*

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S1 Descriptive Statistics

S1.1 Survey Sample Characteristics

Table S1.1 contains the distribution of basic sociodemographic variables for our Wave 1 and Wave 2 surveys.

Table S1.1: Distribution of demographic variables (%).

		Wave 1	Wave 2
Age	18-24	16.1	15.4
	25-34	27.1	29.5
	35-44	27.5	25.9
	45-54	14.0	13.4
	55-64	9.7	10.8
	65-	5.5	4.9
Gender	Female	57.5	56.1
	Male	41.8	43.6
	Other	0.7	0.3
Education	No college degree	43.8	43.0
	College degree	56.2	57.0
Partisan Identity	Democrat	56.7	63.6
	Republican	43.3	36.4
Observations		1375	305

S1.2 Measuring Perceived Personal Experience using Self-Reported Survey Items

In both waves of our survey, we asked respondents to recall the extent to which they were affected by disasters. From the first wave, 38.4% of respondents reported being affected by Hurricane Harvey. Those who responded in the positive were asked three follow up questions about the nature and severity of their experiences, in terms of finance, health, and property, which we report in Figure S1.1. We estimate perceived experience with Hurricane Harvey by combining the first stage question and the additive score of the follow up questions. Specifically, individuals who reported not having been affected in the first stage are treated as having experienced zero damage, and the rest received the additive score from the three follow up questions. In the second wave, we estimate experience with the winter storms as the sum of binary responses to a set of disaster experience items, adopted from Harville, Jacobs and Boynton-Jarrett (2015), shown in Table S1.2. Both quantities were rescaled to the unit interval using min-max scaling to obtain our measures of perceived personal experience.

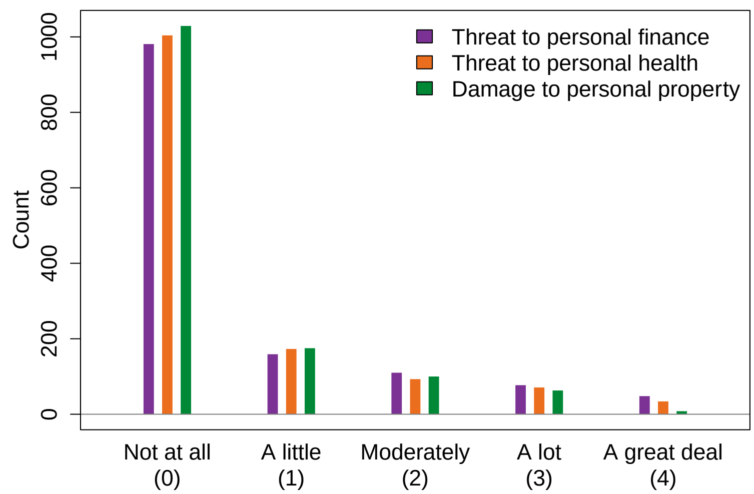

Figure S1.1: Personal threat and damage experienced during Hurricane Harvey in 2017.

Table S1.2: Disaster experiences during the North American winter storms in 2021.

Statement	% yes
Did you lose power in your house during the winter storm?	70.5
Did you ever feel like your life was in danger during the winter storm or in the aftermath?	28.9
Did the water pipes in your house break during the winter storm?	23.6
Were you forced to travel by walking during the winter storm?	15.7
Did the winter storm damage any of your vehicles (e.g., car, truck, or boat)?	11.1
Did any family members not living with you suffer injury or illness because of the winter storm?	9.2
Do you know of any other people, whose pets that died because of the winter storm?	8.5
Did the winter storm cause you to have an illness or injury?	7.5
Did the winter storm cause some other members of your household to have an illness or injury?	7.9
Did you lose anything of sentimental value (e.g., photographs, keepsakes) during the winter storm?	4.9
Did anyone else you know die because of the winter storm?	3.6
Did you have any pets die because of the winter storm?	1.6
Did anyone personally close to you die because of the winter storm?	1.0

S2 Results from additional pro-climate attitudes

To provide further evidence of our findings, we conducted additional analysis on three sets of attitudes related to climate change from our Wave 2 survey. First, to measure climate-related policies that are likely to impact the immediate daily lives of respondents, we asked the subjects additional questions about their views on pro-environmental restrictions such as banning the use of plastic bags or imposing road fees. Second, we measured trust in climate science by adapting five items most relevant to our inquiry from the climate science skepticism scale proposed by Sarathchandra and Haltinner (2021). Finally, we looked at climate change risk perception. All three measures are additive scales based on the relevant set of questions summarized in section S5.

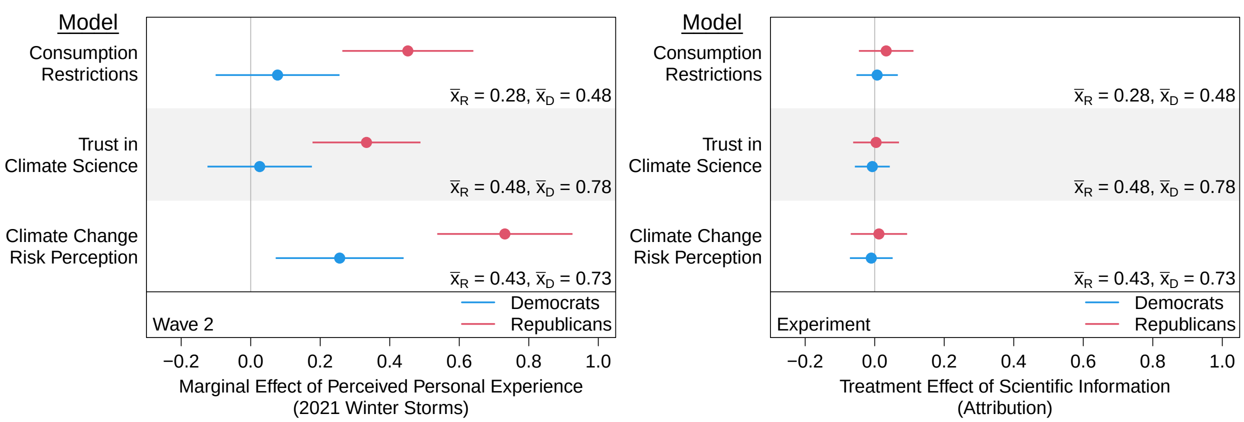

Figure S2.1: Relationships between perceived personal experience and climate attitudes (left) and treatment effects of scientific information attributing extreme weather to climate change on climate attitudes (point estimates and 95% CIs). $\bar{x}_R$ and $\bar{x}_D$ refer to, respectively, the sample mean of the outcome variable for the Republican and Democrat groups.

These three additional analyses, which we conducted for both perceived personal experience to the winter storms and scientific information on attribution, strengthen our body of evidence because they expand our observed relationships to a broader range of applicable attitudinal and perceptual outcome measures, including personally-costly behavioral changes (i.e., support pro-environmental consumption restrictions), trust in climate science,[1] and risk perceptions from climate change.

As shown in Figure S2.1, the patterns of findings from main analysis are largely retained. The more severe the perceived experience with the winter storms are, the more likely that partisans have pro-climate attitudes and behaviors. These patterns are again stronger among Republicans. As before, scientific information attributing extreme weather events to climate change exhibits no effect on pro-climate attitudes.

[1] Trust in science questions were asked before respondents were assigned to the scientific information experimental conditions, so the null result is expected.

S3 Robustness checks

S3.1 Wave 2 attrition

We recruited 571 Wave 1 respondents for our Wave 2 survey. Of these, we recaptured 305 respondents for a 53.4% retention rate. To check if there are discernible differences between the retained ($n = 305$) and attritioned ($n = 266$) groups, we tested the bivariate relationships between attrition and a number of important Wave 1 variables. Our results are presented in Figure S3.1. The retained and attritioned group are balanced on sociodemographic characteristics, climate attitudes, and disaster exposure, with the exception of age, where older individuals were less likely to be attritioned.

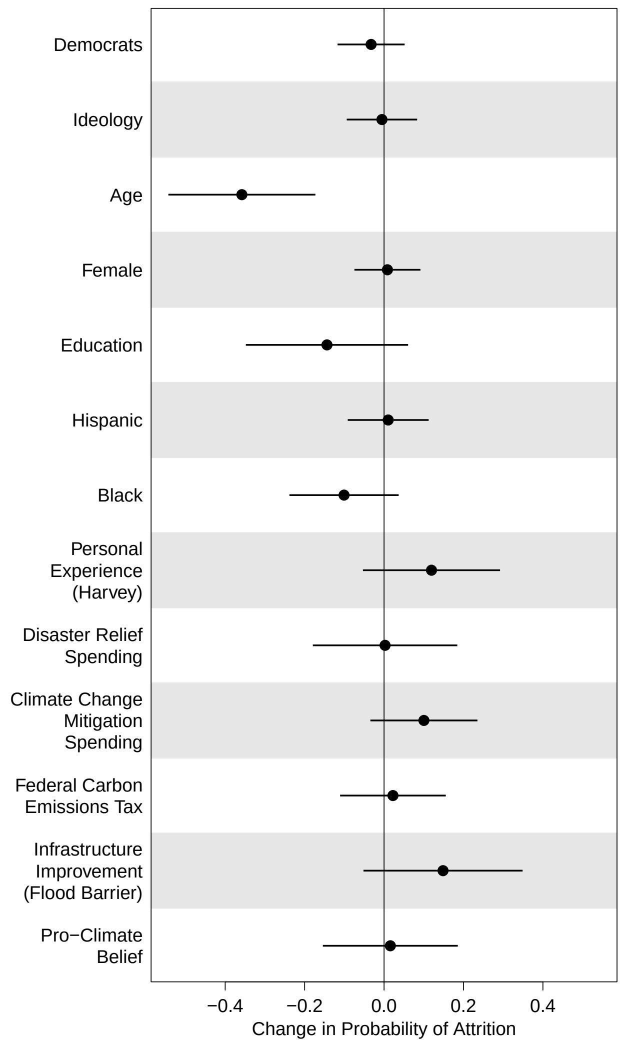

Figure S3.1: Bivariate relationships between attrition and important Wave 1 variables (point estimates and 95% CIs).

S3.2 Subsetting Wave 1 analysis to only multi-wave respondents

To provide additional evidence against attrition bias in our Wave 2 results, we show in Figure S3.2 that our Wave 1 results are robust to being analyzed on the subset of respondents we retained for the Wave 2 study. All coefficient estimates have the same sign and statistical significance with the exception of support for infrastructure improvement.

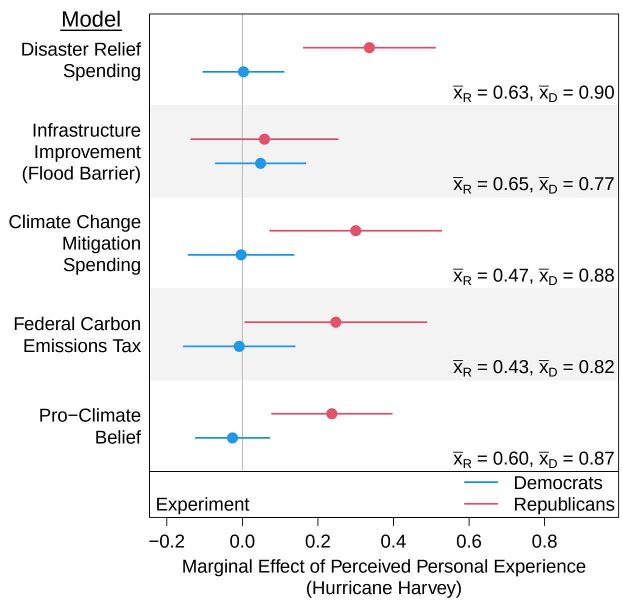

Figure S3.2: Relationships between perceived personal experience and climate attitudes (point estimates and 95% CIs) for subset of Wave 1 survey respondents who we retained for Wave 2.

S3.3 Participation selection by remuneration

When conducting the Wave 2 survey, we initially set the participation remuneration to \$2. When recruitment stalled after a month, we raised the participation remuneration for ongoing Prolific recruits to \$4 for the rest of the recruitment. All CloudResearch participants were recruited with \$2 remuneration. We show here that our main findings are robust across the two groups receiving different remuneration. We do so by interacting perceived personal experience with remuneration group, which we show in Figure S3.3. Based on likelihood ratio tests, the expanded model (with the remuneration interaction) and the reduced model are statistically indistinguishable from each other for all outcome variables with the exception of support for infrastructure improvement.

This finding further reduces concerns about selection bias for Wave 2 results. Whatever the selection mechanism underlying respondents opting into the Wave 2 sample, the fact that there is no difference between those who immediately selected back in and those who required greater financial compensation suggests that the selection mechanism is orthogonal to our explanatory variable.

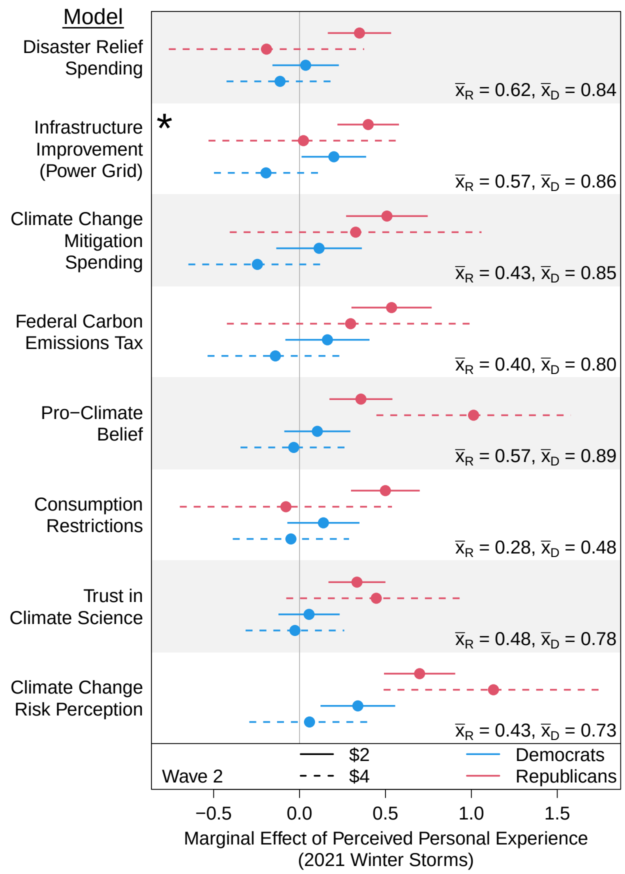

Figure S3.3: Relationships between perceived personal experience and climate attitudes (point estimates and 95% CIs), by remuneration amount. $\bar{x}_R$ and $\bar{x}_D$ refer to, respectively, the sample mean of the outcome variable for the Republican and Democrat groups. Models marked with an asterisk are those statistically significantly different from their reduced forms that do not contain the remuneration interaction.

S3.4 Power outage aggregation

Our raw power outage data is reported at a mixture of county and city levels. Aggregation to the county level is sometimes required because some counties have a mixture of both reporting levels. As described in the main text, we estimated geographic exposure to power outage using a data aggregation algorithm that considers how much uncertainty there is at lower levels of aggregation. Specifically, for each county, we use city-level aggregation for all cities within the county until we reach a certain threshold of proportion of households that cannot be placed in a city, at which point we aggregate the entire county to a single unit.

In our main text, we reported results using an aggregation threshold of 0.25. Here we show in Figure S3.4 that our results are robust to a wide range of threshold values.

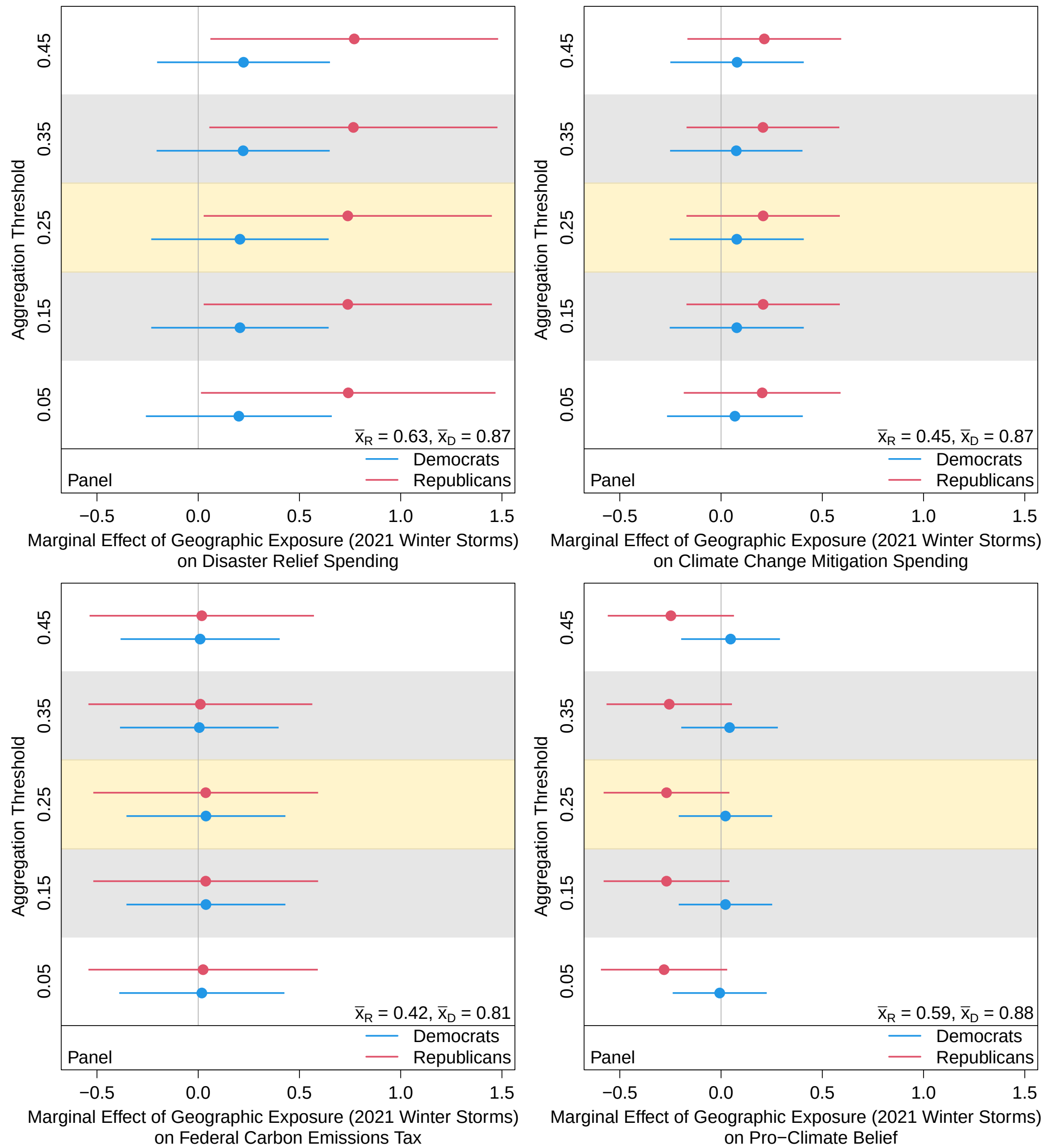

Figure S3.4: Treatment effects of geographic exposure to the 2021 power outages on climate attitudes (point estimates and 95% CIs), by the uncertainty threshold at which city-level outages are aggregated to county-level outages. The models highlighted in yellow, with aggregation thresholds of 0.25, are the results reported in the main text. $\bar{x}_R$ and $\bar{x}_D$ refer to, respectively, the sample mean of the outcome variable for the Republican and Democrat groups.

S4 Geographic Exposure Treatment Precision Analysis

As noted in the main text, measurement imprecision appears to explain some of the null results for our geographic exposure models. The treatment variable for geographic exposure was measured at either the county level or at the city level depending on how much certainty we had about power outages at each respondent's location. Because there is within-region variation associated with aggregated measures, we have a type of measurement error that should bias the estimated effect toward zero – especially with prior work showing that individuals only accurately perceive very localized extreme weather (Akerlof et al. 2013) – which should be greater for respondents with county-level aggregation.

We show this here with tests of whether the treatment effect of power outage exposure varies by being measured at the more precise city level or at the less precise county level. Specifically, we fit the same difference-in-differences model as in the main text, and interacted the geographic exposure variable by whether the respondent's exposure measurement was aggregated at the city level or the county level. For each pro-climate attitude, we compare this expanded model with the reduced model using a likelihood ratio test where rejecting the null means there is a statistically significant difference between city-level and county-level aggregated measures. The results of the likelihood ratio tests, across four outcome variables and aggregation thresholds (discussed in section S3.4), is summarized as p-values in Figure S4.1.

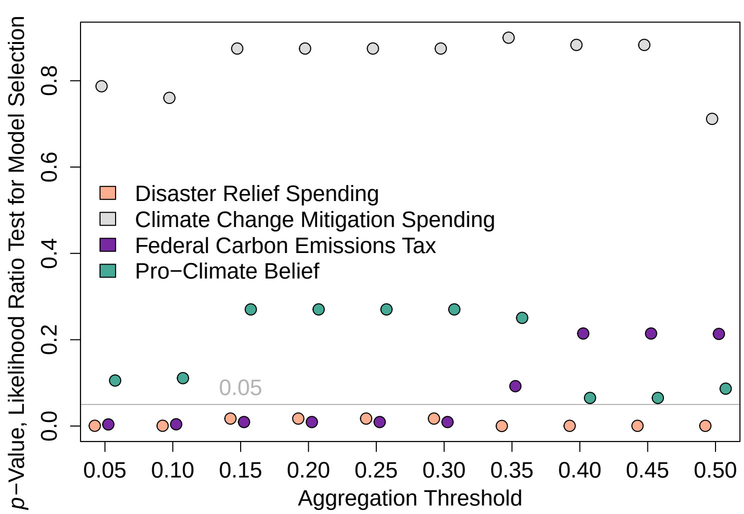

Figure S4.1: p-values from likelihood ratio test for selecting between models that constrain or allow the treatment effect of power outages to vary by whether the individuals' treatment was aggregated at the city or county level, by the uncertainty threshold at which city-level outages are aggregated to county-level outages. p-value below 0.05 indicates a statistically significant improvement in the performance of the expanded model.

We see that models for disaster relief spending and federal carbon emissions tax benefited

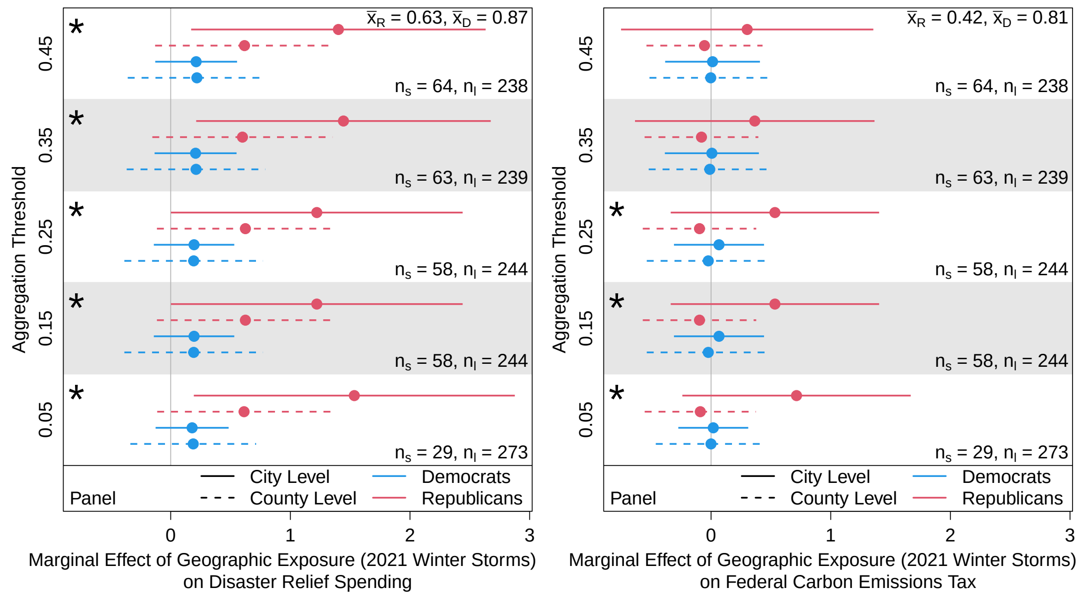

Figure S4.2: Treatment effects of geographic exposure to the 2021 power outages (point estimates and 95% CIs) on disaster relief spending (left) and on federal carbon emissions tax (right), by the threshold at which city-level outages are aggregated to county-level outages. n_s and n_l refer to, respectively, the sample size of respondents whose outage treatment was aggregated at the city and county levels. Models marked with an asterisk are those statistically significantly different from their reduced models that do not contain the aggregation interaction.

from the inclusion of the interaction term, with the expanded model fitting better across all or most aggregation thresholds. Focusing on results from these two models, presented in Figure S4.2, we show that among Republicans for whom we had enough information to disaggregate their measure of exposure to the city level, power outage has a large effect on these two climate attitudes. As we are working with relatively small samples – with between 29–64 respondents for whom we can measure exposure at the more precise city level – the estimates have wide confidence intervals. However, the magnitude of the effect among this subgroup compared to the county-aggregation group is striking. The results presented here provides further evidence that personal experience with extreme weather shapes pro-climate attitudes, and also that proximity matters, both in terms of practical implications and research methodology.

S5 Survey questionnaire

The questionnaire items used to construct outcome or explanatory variables are presented below.

Table S5.1: Questionnaire items for measures of pro-climate attitudes. Each bold heading is a measure, and measures with multiple question items are additive scales. Items marked with (r) are reverse coded.

Question		Wave
Pro-climate belief		Both
To what extent do you disagree or agree with each of the following statements?		
Q1.	(r) The climate is always changing and what we are currently observing is just natural fluctuations.	
Q2.	The burning of fossil fuels over the last 50 years has caused serious damage to the planet's climate.	
Q3.	(r) Humans are too insignificant to have an appreciable impact on global temperature.	
Q4.	Climate change is a process that is already underway.	
Q5.	Human CO_2 emissions cause climate change.	
Q6.	(r) Climate change is not happening.	
	[strongly disagree / somewhat disagree / neither agree nor disagree / somewhat agree / strongly agree]	
Climate Change Mitigation Spending		Both
Q.	How much do you oppose or support increasing government spending for climate change mitigation?	
	[strongly oppose / oppose / slightly oppose / neither oppose nor support / slightly support / support / strongly support]	
Federal Carbon Emissions Tax		Both
Q.	How much do you oppose or support a federal tax on carbon emissions (e.g., coal, oil, gas)?	
	[strongly oppose / oppose / slightly oppose / neither oppose nor support / slightly support / support / strongly support]	
Disaster Relief Spending		Both
Q.	How much do you oppose or support increasing government spending for climate change mitigation?	
	[strongly oppose / oppose / slightly oppose / neither oppose nor support / slightly support / support / strongly support]	
Infrastructure Improvement (Flood Barrier)		1
How much do you oppose or support building a coastal barrier that protects...		
Q1.	the Houston Ship Channel?	
Q2.	the Gulf Coast?	
Q3.	coastlines of the United States?	
	[strongly oppose / oppose / slightly oppose / neither oppose nor support / slightly support / support / strongly support]	
Infrastructure Improvement (Power Grid)		2
How much do you oppose or support each of the following policies and measures?		
Q1.	Regulate the power grid.	
Q2.	Connect the Texas power grid to the national power grid.	
Q3.	Winterize power generation facilities.	
Q4.	Insulate natural gas pipelines.	
Q5.	Electricity bill price cap.	
Q6.	Expand energy storage capacities.	
Q7.	Diversify energy production sources.	
	[strongly oppose / oppose / slightly oppose / neither oppose nor support / slightly support / support / strongly support]	
Social Media Like		1
Q.	How likely would you be to "like" this report on Twitter?	
	[not at all likely / not very likely / somewhat likely / very likely / extremely likely]	
Social Media Retweet		1
Q.	How likely would you be to retweet this report on Twitter?	
	[not at all likely / not very likely / somewhat likely / very likely / extremely likely]	

Table S5.2: Questionnaire items for measures of perceived disaster experience. Each bold heading is a measure. Measure construction is described in the main text.

Question	
Hurricane Harvey (Wave 1)	
We'd like to ask questions about your experiences with Hurricane Harvey in August 2017. The hurricane affected many people's property and health.	
Q0.	Did Hurricane Harvey affect you in any way?
	[yes → continue to Q1–Q3 / no]
Q1.	How much of a threat, if any, was Hurricane Harvey for your personal health?
	[not at all / a little / a moderate amount / a lot / a great deal]
Q2.	How much of a threat, if any, was Hurricane Harvey for your personal financial situation?
	[not at all / a little / a moderate amount / a lot / a great deal]
Q3.	When Hurricane Harvey hit, how much was your property damaged by the storm?
	[not at all / a little / a moderate amount / a lot / totally destroyed]
Winter Storms (Wave 2)	
In February 2021, there was a winter storm in Texas. We'd like to ask you questions about your experience during the winter storm.	
Qs.	See Table 4 in the main text for all binary experience questions.
	[yes / no]

Table S5.3: Questionnaire items for additional outcome measures from the Wave 2 survey. Each bold heading is a measure, and measures with multiple question items are additive scales.

Question	
Pro-environmental Consumption Restrictions	
How much do you oppose or support each of the following policies and measures?	
Q1.	Banning plastic bags at stores
Q2.	Imposing fees for using roads in city centers and during peak times
Q3.	Indoor temperature regulation that limits heating to a maximum of 68°F (winter) and cooling to a minimum of 78°F (summer)
Q4.	Mandatory recycling that imposes fines on residents who recycle improperly
Q5.	Tax on food products with high carbon footprints (e.g., beef, dairy)
	[strongly oppose / oppose / slightly oppose / neither oppose nor support / slightly support / support / strongly support]
Trust in Climate Science	
Q1.	Do you believe climate scientists have enough data to know that human-caused climate change is happening?
	Climate scientists have [no data at all / a little data / a moderate amount of data / a lot of data / complete data]
Q2.	How transparent do you think climate scientists are about their research?
	[not transparent at all / a little transparent / somewhat transparent / very transparent / completely transparent]
Q3.	How much do you think climate science is driven by politics?
	[not at all / a little / somewhat / very/completely]
Q4.	How much do you think climate scientists are influenced by the donors of research funding?
	[not at all / a little / somewhat / very / completely]
Q5.	Which of the following statements do you think most accurately describes the views of expert scientists on climate change?
	[almost all scientists believe that climate change is NOT occurring / most scientists believe that climate change is NOT occurring / scientists are divided in their views on whether climate change is occurring or not / most scientists believe that climate change is occurring / almost all scientists believe that climate change is occurring]
Climate Change Risk Perceptions	
How much risk do you believe climate change...	
Q1.	poses to you personally?
Q2.	poses to Texas?
Q3.	poses to other states in the US?
Q4.	poses to other countries?
Q5.	poses right now?
Q6.	will poses 10 years from now?
	[none at all / low / moderate / high / extremely high]

S6 Pre-analysis plan: Scientific information experiment

Our pre-analysis plan was deposited to OSF on July 8, 2021.[2] We reproduce the content of the pre-analysis plan here.

Motivation

Do personal experiences of natural disasters play a role in reinforcing the impact of a scientific message on climate change? The primary goal of this project is to examine whether personal experiences of hurricanes and winter storms can strengthen the effects of a science-based message about the link between climate change and extreme weather on increasing climate change risk perceptions and policy preferences. We aim to identify the subgroups - categorized by natural disaster experiences and partisan identity - among which the message with scientific evidence more effectively increases risk perceptions and support for policy measures against climate change.

Theoretical Background and Hypotheses

The literature on messaging strategies for climate change impact has suggested that a message can more effectively increase risk perceptions and support for mitigation/adaptation policies when it highlights personally relevant and proximate consequences of climate change (Petrovic, Madrigano and Zaval 2014; Scannell and Gifford 2013) and when scientific evidence is presented with visualizations and without politicizing counterarguments (Van der Linden et al. 2017; Bolsen, Palm and Kingsland 2019). Moreover, personal experiences of extreme weather such as wildfire or hurricanes tend to be associated with climate change beliefs and support for climate mitigation policies (Hazlett and Mildenberger 2020; Egan and Mullin 2017). While higher chance of seasonal snowfall in individuals' local area is negatively associated with their beliefs in climate change (Borick and Rabe 2014), we examine the impacts of a message that explains how extreme winter storms can be caused by climate change, specifically due to the rising temperature in the North Pole. Building on these findings, we propose the following hypothesis:

> **Scientific Evidence Hypothesis:** The message that explains the scientific link between climate change and natural disasters ("science message") will increase risk perceptions and support for policy measures against climate change (e.g., mitigation, adaptation, pro-environmental).

[2] It can be accessed at `https://doi.org/10.17605/OSF.IO/SMQCH`.

Does personal experience of natural disasters (e.g., hurricanes, winter storms) amplify or mitigate the effect of the scientific evidence message? We expect the treatment effects of the scientific evidence message to be greater for individuals who have experienced disasters, which yields the following testable hypothesis:

> **Personal Experience Heterogeneous Effect Hypothesis:** The extent to which the science message increases risk perceptions and support for policy measures against climate change will be greater among those who experienced hurricanes or winter storms, compared to those who did not.

We also expect to find heterogeneous effects across several different variables that we describe in the following research questions.

> **RQ1:** Do the treatment effects of the science message differ between Republicans and Democrats? Are partisan differences in treatment effects moderated by natural disaster experiences?

> **RQ2:** Do the science message affect proximate, short-term, and personal risk perceptions to a different extent compared to distant, long-term, and societal risk perceptions?

> **RQ3:** Do attitudes toward climate science and performance appraisals of political figures moderate the treatment effects of the science message?

Sampling

The subject population will be US adults (over the age of 18) who reside in Texas. The sampling frame will be the online survey platform subject pool (e.g., Prolific, Lucid, CloudResearch). We will conduct a pilot of up to 100 respondents, subject to the restrictions of survey platform, before we fully launch the survey. We will use the platforms' prescreening questions to recruit individuals who reside in Texas and who identify themselves as either a Democrat or a Republican. There will be a fixed payment for the recruitment through survey platforms. The survey will be administered online. Subjects can participate from anywhere they have internet access.

Overview of Survey Flow

The study uses experimental designs. To identify the causal impact of the evidence message on risk perceptions and mitigation/adaptation policy preferences, we have two randomized conditions, where each condition presents the scientific evidence message or not. Using the pre-treatment responses on their prior experiences with natural disasters, we will also examine how the treatment effects are moderated by prior experiences with natural disasters. The flowchart of the research design is presented in Figure S6.1.

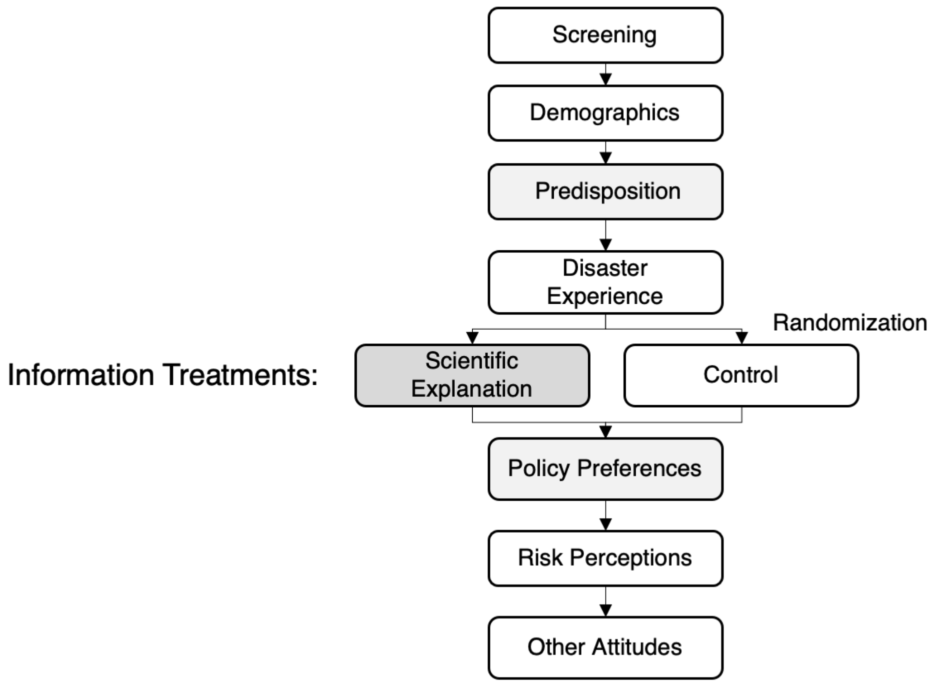

Figure S6.1: Survey flow diagram.

Experimental Conditions

Participants will be randomly assigned to one of two conditions in which they are either given a brief explanation of recent natural disasters in Texas (Condition 1: Baseline) or both the baseline information and scientific explanation on how climate change (i.e., the rising temperature in the North Pole) caused the recent winter storm (Condition 2: Baseline + Scientific evidence).

Measurement of Outcome Variables

Before treatment, participants will indicate their experiences with natural disasters (e.g., number of disasters experienced, severity of damage, injury, or financial loss), partisan identity, vote choice in the 2020 presidential election, and basic demographics. After the treatment, participants will be asked to indicate their opinions on climate change policies (mitigation, adaptation, and pro-environmental), their temporal, spatial, personal, and societal risk perceptions on climate change, and climate change beliefs. We will use latent variable models to assess the dimensionality of the item batteries we use to measure outcomes.

Analysis

We will fit OLS regression models for each outcome variable regressed on the treatment conditions outlined above. We will also use the latent variable values that are estimated from the survey items. We will either construct composite scales of items based on latent variable analysis or use multiple testing corrections in our analysis.

Additionally, we will use training (in-sample)/validation (out-of-sample) methods to look for higher order heterogeneous treatment effects that are not described in our hypotheses above. These methods allow for the discovery of unanticipated patterns in experimental data that, if present, will allow for new theorizing and the generation of novel hypotheses that can be tested using new research.

S7 References

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