

Disaster Experience Mitigates the Partisan Divide on Climate Change: Evidence from Texas^{*}

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Abstract

Despite the abundance of real world events and scientific information linking the worsening extreme weather to climate change, public attitudes toward climate issues in the United States remain highly divided along partisan lines. We compare the effect of different stimuli linking extreme weather events to climate change – personal experiences and scientific information – in reducing the partisan gap. A two-wave survey corresponding to multiple extreme weather events in Texas, including a natural experiment with power outage data from the 2021 North American Winter Storms, shows that personal experiences with extreme weather reduce the partisan divide in climate beliefs and policies. Scientific information attributing extreme weather events to climate change, however, had no effect in closing the partisan gap. These findings suggest that extreme climate events and disaster experiences force vividly tangible information about the proximity and severity of climate change on exposed individuals, prompting belief-updating and preference-shifting toward pro-climate policies.

Keywords: climate change beliefs, environmental disasters, natural experiment, disaster experiences, pro-environmental policy attitudes

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1 Introduction

Climate change-induced extreme weather events, such as wild fires in the western United States and hurricanes along the Gulf Coast and Eastern Seaboard, occur with increasing frequency, visibility, and consequence [7, 22]. Experience with these extreme climate events and disasters present vividly tangible stimuli about the proximity, severity, and costliness of climate change. Scientific information attributing extreme weather and its consequences to anthropogenic climate change has also become more abundant through both academic research [28] and public science channels [16]. Yet, individual beliefs and policy preferences about climate change in the U.S. remain deeply polarized along partisan lines [19, 9]. This is in spite of the fact that climate-skeptic individuals, who tend to be Republican, are increasingly exposed to ever-growing amounts of experiential and informational stimuli about climate change. This cause of partisan division is of particular importance because it is associated with gridlock on climate policy-making [13].

Can extreme weather experiences and scientific information attributing extreme weather to climate change reduce this partisan gap? Both these *experiential stimuli* (personal experiences with extreme weather) and *informational stimuli* (scientific information attributing these events to climate change) are seen to be key drivers of individuals associating climate change with negative outcomes [27, 29]. However, despite numerous studies investigating how these two stimuli shape climate attitudes, conclusive findings about either factor have yet to be established. Empirical evidence about the experiential stimuli (personal experience [14, 26, 24, 15]) and the informational stimuli (scientific information on attribution [25]) are mixed between exhibiting positive or null effects. Moreover, scientific information even led to backfire effects among specific politically-relevant subgroups (i.e. Republicans [31, 11] and climate skeptics [8, 4]). Recent studies have begun to examine how the relationship between personal experiences and pro-climate attitudes differs across political groups [5, 13, 30, 21]. Notably, Constantino et al. [5] and Zanoocco et al. [30] find evidence that negative personal experience with extreme weather decreased the partisan gap on climate attitudes, as Republicans tended to shift closer to Democrats' positions. Conversely, Hazlett and Mildenberger [13] show that Republican-dominated areas in California were unresponsive to wildfire exposure when voting on climate-policy ballots, which effectively increases the partisan gap.

Critically, existing research does not directly compare the impacts of extreme weather experiences and scientific information, two different types of stimuli prompting individuals to link climate change to negative outcomes, on the same individuals. The lack of within-sample comparisons leaves notable gaps in our understanding of climate attitudes. First, given sample heterogeneity across studies, it is difficult to contextualize findings about different stimuli

56 (i.e. experiential and informational) against one another. Second, personal experiences with
57 extreme weather and scientific information on attribution is likely to conditionally impact or
58 moderate climate attitudes [18], which cannot be examined unless we explicitly model the
59 interaction effect on a sample of individuals.

60 In this paper, we fill these gaps by comparing the effects of personal experiences and
61 scientific information in influencing the climate attitudes of partisan individuals. We achieve
62 this through several research designs that we conducted as part of two-wave survey (2020
63 and 2021) fielded in Texas, U.S., a state that has experienced both major hurricanes and
64 extreme winter storms in recent years. Our surveys draw directly on personal experiences,
65 a preregistered experiment (see Supplementary Information S5), and a natural experiment,
66 each measuring exposure of our survey respondents to the link between climate change and
67 extreme weather. We explored both personal experiences about hardship directly experi-
68 enced from climate disasters and scientific information explicitly highlighting the link. We
69 started with the general expectation that both experiential and informational stimuli will
70 effect pro-climate attitudinal change, then examined how the heterogeneous effects for both
71 stimuli across partisan groups can lead to a reduction in the partisan gap on a set of cli-
72 mate attitudes ranging from belief in anthropogenic climate change to support for various
73 pro-climate policies.

74 As previewed in the introduction of our research design above, results come from three
75 sets of analyses – survey, quasi-experimental, and experimental – that systematically explore
76 how Democrats’ and Republicans’ beliefs about climate change and support for pro-climate
77 policies vary by their personal experiences and exposure to scientific information. We find
78 that Republicans update their beliefs about anthropogenic climate change and climate policy
79 when they personally experience extreme weather events while Democrats generally update
80 their beliefs very little because their existing beliefs are already strongly pro-climate. The
81 observed mechanism that experiences drive pro-climate attitudes, however, also holds for
82 Democrats for outcomes not subject to a ceiling effect (i.e. their willingness to share pro-
83 climate messages on social media). In terms of scientific information, experimentally provided
84 scientific attribution linking climate change and extreme weather events had no measurable
85 impact on climate change attitudes for both partisan groups, even when moderated by ex-
86 isting personal experiences.

87 Beyond being the first study, to our knowledge, that systematically compares the effects
88 of different types of stimuli across a fixed set of individuals from distinct partisan groups, our
89 study makes a number of additional contributions. First, we explicitly study the potential
90 for an interactive effect between the two kinds of stimuli, for which we found none. Second,
91 focusing on Texas afforded a number of benefits (see Methods section 4.1), most notably being

92 able to study individuals' experiences with both expected (i.e. hurricanes) and unexpected
93 (i.e. winter storms) extreme weather events. Here, our findings are highly robust across both
94 contexts. Third, because of the timing of our surveys and the collection of real-world data,
95 we were able to measure personal experience in different ways. Specifically, we measure both
96 perceived personal experience and objective geographic exposure (i.e. being in an afflicted
97 location at the time of an extreme weather event). Perceived personal experience captures
98 important psychological realities [24], but it is hard to identify the causal effect of perception.
99 On the other hand, while geographic exposure – as an externally validated measure of the
100 state of the world – facilitates identified causal estimates, they do not perfectly map onto
101 experience as a construct [24] and are prone to measurement imprecision [1]. Given the
102 shortcomings of any singular measurement approach, we opted to examine both. The results
103 we present about the effects of personal experience are weakly robust to both measurement
104 approaches.

105 Although climate attitudes are widely viewed as inflexible, especially for Republicans,
106 we show that individuals do update their attitudes when experiencing extreme weather
107 events. By directly comparing experiential and informational stimuli about climate change
108 and extreme weather events, we clarify that personal experiences are more effective than
109 information on scientific attribution in effecting pro-climate attitudes.

110 **2 Results**

111 **2.1 Personal Experience with Extreme Weather Events**

112 We conducted a two-wave survey among Texas residents who identified themselves as either
113 Democrat or Republican. (Methods section 4.1 discusses our choice to use Texas as a case.)
114 The first wave took place in fall 2020, three years after Hurricane Harvey ($n = 1375$). The
115 second wave took place in summer–fall 2021, a few months after North American winter
116 storms Uri and Viola, with a subset of the same individuals from Wave 1 ($n = 305$). Table 1
117 summarizes the climate attitudes and policy preferences we examined, which includes, for
118 example, belief in anthropogenic climate change, support for climate-related infrastructure
119 improvement, and willingness to share pro-climate messages on social media. Beyond these
120 main climate attitudes, we also examined additional outcomes in Supplementary Informa-
121 tion S1. (Methods section 4.2 describes our survey methodology and our questionnaire is
122 included in Supplementary Information S4.)

Table 1: Measures of pro-climate attitudes.

Concepts	Survey Measures	Wave
Belief in Anthropogenic Climate Change	Pro-climate Belief*	Both
Support for Climate Change Mitigation	Federal Carbon Emissions Tax	Both
	Climate Change Mitigation Spending	Both
Support for Disaster Resilience Policy	Disaster Relief Spending	Both
	Infrastructure Improvement (Flood Barrier)*	1
	Infrastructure Improvement (Power Grid)*	2
Social Media Activism	Social Media Like	1
	Social Media Retweet	1

*Additive scale measures (see Supplementary Information S4)

2.1.1 Perceived Personal Experiences with Extreme Weather

To measure perceived personal experience with Hurricane Harvey, which caused severe damage in southeast Texas in August 2017, we asked participants in the first wave of our survey whether they were personally harmed by Hurricane Harvey on three dimensions, personal health, financial situation, and property damage. In the second wave, we similarly measured perceived personal experience with the 2021 winter storms with a set of fourteen questions about whether they experienced different negative events during the winter storms, including perceived danger, injury, and property damage (adapted from [12]). For both waves, we summed responses from the different questions then rescaled them to the unit interval to obtain our measure of perceived personal experience. (Methods section 4.3 provides additional information on our perceived personal experience measures.)

To test whether perceived personal experiences with extreme weather promote pro-climate attitudes, we fit linear models that examine how various climate attitudes are associated with our measure. Further, to examine how partisan identity moderates the relationship between perceived personal experience and climate attitudes, we included an interaction term between partisanship and experience in the models. We also included a set of individual-level control variables in all models: ideology, age, gender, education, and indicators for Hispanic and Black identification.

We find a large difference between Republicans and Democrats (Figure 1). In general, among Republicans, perceived personal experience with both Hurricane Harvey (Wave 1) and the 2021 winter storms (Wave 2) are positively and statistically significantly associated with pro-climate attitudes. Specifically, with the single exception of beliefs about anthropogenic

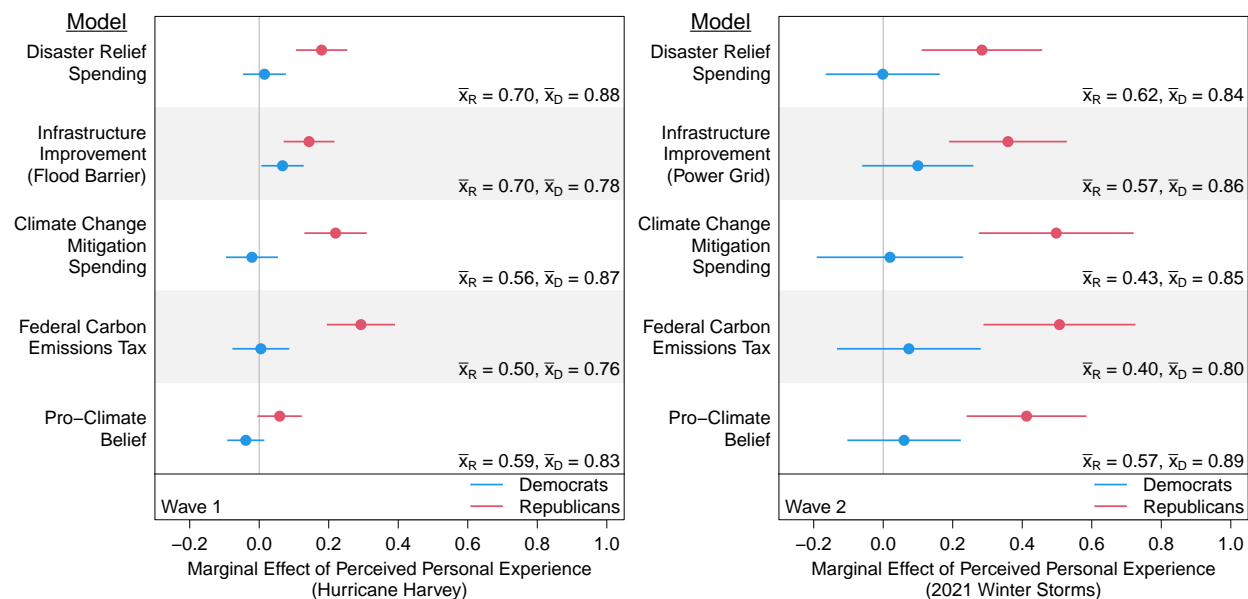


Figure 1: Relationships between perceived personal experience and climate attitudes (point estimates and 95% CIs), for Wave 1 survey respondents (left) and for Wave 2 survey respondents (right). \bar{x}_R and \bar{x}_D refer to, respectively, the sample mean of the outcome variable for the Republican and Democrat groups.

145 climate change in Wave 1, responses indicating more experience with disaster damages is
 146 predictive of greater support for both climate change mitigation and disaster resilience poli-
 147 cies. (We show in Supplementary Information S2 that subsetting the Wave 1 analysis to only
 148 respondents retained in Wave 2 yields similar results. We also discuss evidence that alleviates
 149 concerns about selection bias for Wave 2 results.)

150 In contrast, among Democrats, there is no statistically discernible relationship between
 151 perceived personal experience and our outcomes. While this discrepancy may appear coun-
 152 terintuitive, additional tests show that the null finding among Democrats can be attributed
 153 to a ceiling effect [10, 30], whereby many Democrats already possess high levels of pro-
 154 climate beliefs and therefore cannot increase their support. (See Democrat group means \bar{x}_D
 155 in Figure 1.) In anticipation of this potential ceiling effect, we included in Wave 1 two items
 156 on willingness to share pro-climate information on social media, which tends to have a low
 157 baseline tendency among both partisan groups. We asked respondents how likely they are
 158 to retweet and to ‘like’ on Twitter a pro-climate mitigation report, both of which are costly
 159 public acts of engagement.

160 As expected, because the baseline tendency to engage in social media activism is generally
 161 low, we do not observe the ceiling effect for Democrats. Instead, we find a positive relationship
 162 between perceived personal experiences and social media activism for both partisan groups.
 163 For Republicans, the marginal effect of perceived personal experience on retweeting is 0.39
 164 (95%CI= [0.28, 0.51]) and on ‘liking’ is 0.26 (95%CI = [0.15, 0.37]). For Democrats, the

165 marginal effect on retweeting is 0.21 (95%CI= [0.11, 0.30]) and on ‘liking’ is 0.21 (95%CI
 166 = [0.12, 0.30]). This finding suggests that the mechanism underlying the relationship between
 167 personal experience and pro-climate attitudes is similar across partisan lines.

168 2.1.2 Natural Experiment of Geographic Exposure to the 2021 Win- 169 ter Storms

170 In February 2021, three months after we fielded our first survey, two overlapping winter
 171 storms (Uri and Viola) struck various parts of North America, including Texas. The timing
 172 of this event, occurring right before our Wave 2 survey, allows us to implement a convincing
 173 pretest-posttest design with geographic exposure to the winter storms as the treatment in a
 174 natural experiment.

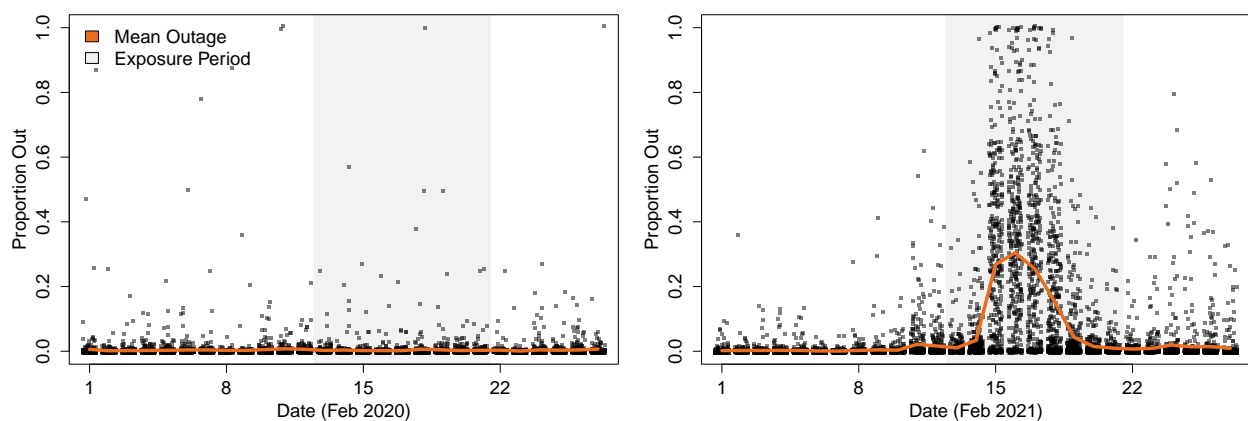


Figure 2: Proportion of households experiencing power outage by tracked administrative unit (i.e. counties or cities) in Texas during February 2020 (left) and during the winter storm in February 2021 (right).

175 For this study, we measured geographic exposure to the winter storms, which is an ex-
 176 ternally validated measure of exposure, as the extent to which individuals experienced power
 177 outages during mid-late February 2021. We estimated this using data from PowerOutage.US,
 178 a data aggregation company that tracks outage reports from utility companies in the U.S.
 179 In Texas, this comprised raw data from 62 utility providers tracking the accounts of 13.4
 180 million customers. We aggregated the outage to the lowest administrative region permitted
 181 by the data (i.e. city or county) as the proportion of customers exposed to outage during the
 182 specified time period. Then, using respondents’ self-reported ZIP codes, we matched them
 183 to the average power outage of an administrative region during the February 13–21 period.
 184 (Methods section 4.4 details our approach.) Figure 2 shows that Texas residents experienced
 185 unusually high levels of outages when the storms hit in February 2021 compared to February
 186 2020.

187 With this treatment variable and outcomes from our surveys, we used a generalized

188 difference-in-differences design to estimate the impact of geographic exposure to extreme
 189 weather events on individuals' climate attitudes. As before, we consider how this effect
 190 varies by partisanship by including an interaction term between the treatment variable and
 191 partisanship. (Methods section 4.5 contains detailed information about our difference-in-
 192 differences approach.)

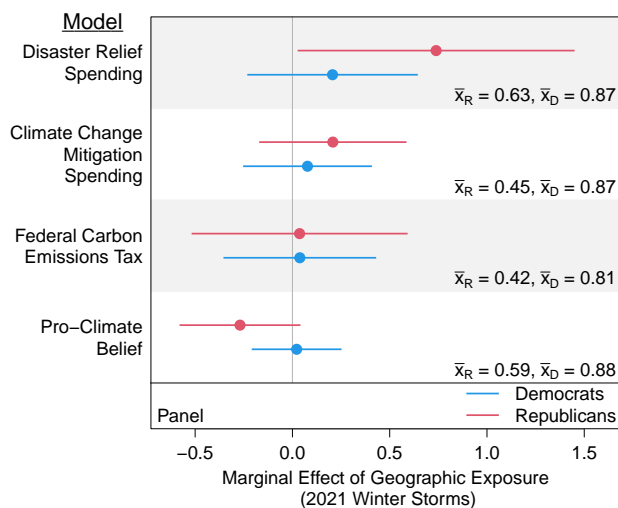


Figure 3: Treatment effects of geographic exposure to the 2021 power outages on climate attitudes (point estimates and 95% CIs), using a panel design for survey respondents who participated in both Wave 1 and Wave 2 surveys.

193 Figure 3 shows the treatment effects of geographic exposure to power outage during
 194 the 9-day period when Texas was hit by the winter storms (February 13–21, 2021). We
 195 find that, on the balance, the effect of geographic exposure to power outages on climate
 196 attitudes is much weaker than the effect we found for perceived personal experience to the
 197 winter storms. Among Republicans, for whom perceived personal experience strongly predicts
 198 greater support for all tested climate mitigation and disaster resilience policies, geographic
 199 exposure to power outages only affects preferences toward disaster relief spending.

200 Additional evidence (Supplementary Information S3) suggests that our null findings are
 201 attributable to the low precision in the operationalized measure of exposure to power outage
 202 – in line with prior work showing that individuals only accurately perceive very localized
 203 extreme weather [1] – and would otherwise be stronger if exposure could be measured with
 204 greater precision at the individual level. Specifically, our ZIP-associated regions are large and
 205 there is likely to be non-negligible variation in power outages within a region, presenting a
 206 type of measurement error that should bias the estimated effect toward zero.

Dangers of natural disasters in Texas: The role of climate change

Hurricanes have exposed Texas to the threat of disaster every year. In recent years, Texas has been affected by major hurricanes, such as Rita in 2015, Harvey in 2017, and Laura in 2020, causing countless deaths and billions of dollars in property damage annually.

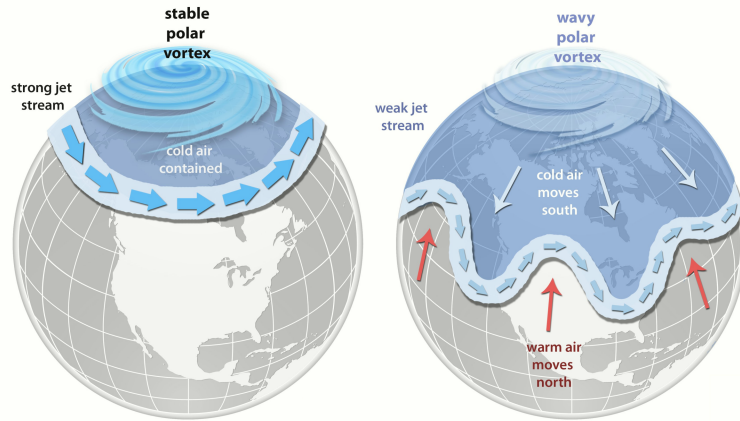
The recent winter storm posed another kind of natural disaster threat to Texas. At least 57 people died in Texas as a result of the recent winter storm, according to the state health agency. The winter storm caused Texas to experience subfreezing temperatures and overwhelmed the state's electricity infrastructure, causing massive power outages. At the height of the crisis, nearly 4.5 million Texas homes and businesses were without power.

Role of Climate Change

In February 2021, the U.S. was gripped by the lowest temperatures it has seen in years. According to NASA, an unusually cold Arctic air mass, called a polar vortex, is responsible for the severe temperatures, which in many areas have plunged well below 0°F (-17.7°C), causing a number of deaths, disruptions to services, and energy outages in the affected areas.

The polar vortex is a large mass of cold air, which normally spins around the North Pole. Usually, a jet stream of winds holds the polar vortex in place (Stable polar vortex).

Increasing temperatures associated with climate change weaken the jet stream (Wavy polar vortex). Paradoxically, this allows extreme cold to move as far south as Texas. Because of the change to the jet stream, **extreme winter storms will become more frequent as the Arctic warms along with the rest of the planet.**



Source: NOAA

Figure 4: Experimental stimuli from the scientific information study. Parts highlighted in green are shown to the treatment group only, while unhighlighted parts are shown to treatment and control groups. (Diagram obtained from the National Oceanic and Atmospheric Administration [20].)

2.2 Scientific Information Experiment with Attribution of Winter Storms to Climate Change

To examine whether scientific information that attribute extreme weather and its costs to climate change reduces the partisan divide on climate attitudes, we embedded an experiment in Wave 2 of our survey that emphasized the link between the winter storms' extreme southward extension and climate change. (Supplementary Information S5 contains our preregistration plan.) Specifically, Wave 2 respondents were randomly assigned with equal probability into treatment and control conditions, where the former were exposed to the highlighted portions of Figure 4 that explain the link between raising temperatures in the arctic and extreme winter storms in Texas. To standardize respondent familiarity with the winter storms, the baseline (unhighlighted) portions outlining the outcome of recent extreme weather events in Texas were shown in both conditions.

We fit linear models where the effect of the treatment variable (i.e. scientific attribution of extreme weather to climate change) on support for pro-climate attitudes varies by respondent partisanship. Figure 5 shows that the scientific information treatment has no discernible effect on pro-climate attitudes. Across all models, the difference between the treatment and control conditions is statistically indistinguishable from zero. To further test whether uptake of scientific information depends on existing personal experiences, we fit additional models that

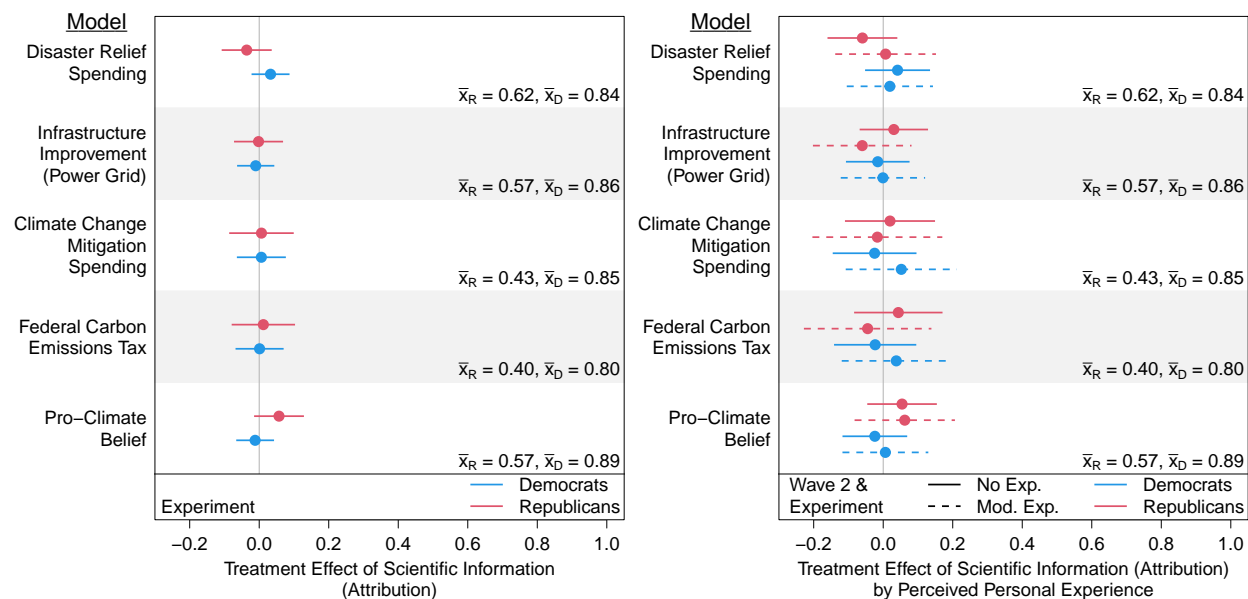


Figure 5: Treatment effect of scientific information attributing extreme weather to climate change (point estimates and 95% CIs), for Wave 2 survey respondents (left), and the same effects moderated by respondents' perceived personal experiences (right). \bar{x}_R and \bar{x}_D refer to, respectively, the sample mean of the outcome variable for the Republican and Democrat groups.

225 let the treatment effect of scientific information vary with the respondent's perceived personal
 226 experience with the 2021 winter storms. As we show in Figure 5, the scientific information
 227 treatment still has no effect when subsetting by respondents' personal experiences. Based
 228 on likelihood ratio tests, the expanded model (i.e. interaction between scientific treatment
 229 and perceived personal experience) and reduced model (i.e. without interaction term) are
 230 statistically indistinguishable from each other for all outcome variables.

231 3 Discussion

232 There is an ever-growing amount of experiential stimuli and informational stimuli that
 233 prompts individuals to link the costs of extreme weather to climate change. Using a two-
 234 wave survey of Texas residents, we examined the effects of personal experiences with extreme
 235 weather and scientific information attributing these events to climate change, two kinds of
 236 stimuli that has been discussed extensively in the literature but never directly compared.
 237 Leveraging Texans' experiences with Hurricane Harvey in 2017 and the North American win-
 238 ter storms in 2021, we conducted the first study to examine these two stimuli simultaneously
 239 for the same sample of individuals. Across a set of survey, quasi-experimental, and exper-
 240 imental results, we show that personal experiences shape people's belief in anthropogenic
 241 climate change and support for pro-climate policies but scientific information on attribution
 242 does not.

243 Measuring personal experience in two ways, we found that self-reported perceived per-
244 sonal experience with hardships was substantially and consistently associated with pro-
245 climate attitudes in various forms, and externally-validated geographic exposure to power
246 outages during the 2021 winter storm exhibited weaker, but causally-identified, effects. Due
247 to what are likely ceiling effects for Democrats, the effect of personal experiences differed by
248 partisan groups, which led to an overall closing of the partisan gap. However, when consid-
249 ering outcomes not subject to the ceiling effect, the positive effect of personal experiences
250 held for Democrats as well.

251 As we discussed, a notable shortcoming in the literature is that the experiential stimuli
252 and informational stimuli have yet to be directly compared to each other. Our research design
253 allows us to not just compare these two stimuli but also model any potential interaction
254 between them. Here, compared to the consistently positive effects for personal experience
255 among Republicans, we find that scientific information attributing the 2021 Texas winter
256 storms to climate change had no discernible effect on climate attitudes for either partisan
257 group, even when accounting for individuals' existing personal experiences. Specifically, with
258 our outcome variables and both independent variables rescaled to the unit interval, the effect
259 of perceived personal experience for Republicans, averaged across all main outcomes, was 0.16
260 for Hurricane Harvey and 0.41 for the 2021 winter storms, and statistically significant for all
261 outcomes but one. On the other hand, the effect of the treatment of scientific information was
262 statistically indistinguishable from zero for all outcomes regardless of whether we included
263 existing personal experiences as a moderator.

264 Overall, our study adds to the nascent body of research indicating that under the right
265 conditions, personal experience with extreme weather or disasters can bridge the partisan
266 gap on climate attitudes [5, 30]. Our findings suggest a number of future research pathways.
267 We identified a context in which Republicans update their beliefs about climate change and
268 climate policy preferences in response to personally-experienced climate threats. However,
269 questions remain as to whether these effects are strong enough to translate to policy-relevant
270 behavior such as voting, and whether the relative strength between experiential and infor-
271 mational stimuli will hold under different contexts. Relatedly, while we found scientific infor-
272 mation to be ineffectual, we focused specifically on scientific attribution regarding unfamiliar
273 extreme weather events. Further work should look to systematically compare different types
274 of scientific attribution and other science-based informational stimuli more broadly.

4 Methods

4.1 Texas as a case study

Texas is an ideal political and environmental context to study change to partisan beliefs about climate change. Politically, though solidly ‘Red’ at the state level, Texas exhibits substantial political and demographic diversity in its major metropolitan areas. Climate change impacts also vary considerably by region in Texas. While Houston is at constant risk of hurricane exposure, the other metro areas are far enough from the coast that they are not directly threatened. In addition to the threat of hurricanes, Texas now faces more winter storm variation because of changes to the polar vortex. Subzero temperatures, once rare along the Gulf Coast region, are becoming more prevalent.

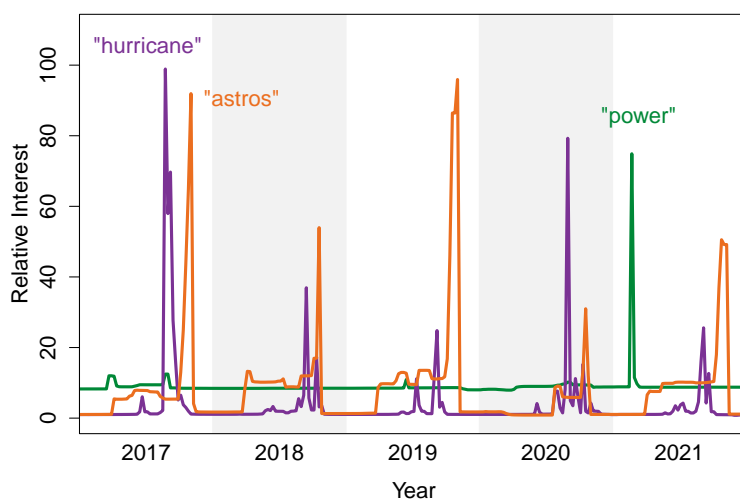


Figure 6: Comparison of relative web search interest from Texas (de-noised Google Trends) for terms associated with Hurricane Harvey, the 2021 North American winter storms, and the Houston Astros.

Further, as we show with Google Trends data (Figure 6), Texas residents have been highly aware of extreme weather events and their consequences, which adds further value to Texas as a case for our examination of how perceived experiences matter to pro-climate attitudes. These trends explicitly capture the relative search interest on given topics within Texas. Our approach is consistent with prior studies that used Google Trends to measure drought awareness in California [17] and global interests in human rights [6]. Major extreme weather events in Texas, such as Hurricane Harvey and the 2021 winter storms, have triggered peaks in disaster awareness. Comparing the relative degree of search interest for specific climate event terms to another popular search term (i.e., ‘astros’ for Houston Astros, a highly competitive Major League baseball team, which won Baseball’s Major League World Series in November 2017 and played in the World Series in 2019), we see the peaks of awareness in Hurricane

296 Harvey, captured by ‘hurricane’, can be found in August–October 2017, and the peaks of
 297 awareness for the winter storms, captured with searches for ‘power’ for power outages, are
 298 found in February 2021.

299 4.2 Survey administration

300 We conducted a two-wave survey of Texas residents with a stated partisan affiliation. The
 301 first wave took place three years after Hurricane Harvey. It was conducted between Oc-
 302 tober 18, 2020 and November 5, 2020, through three survey platforms, Lucid, Prolific, and
 303 CloudResearch.¹ Using prescreening data from each platform, we recruited Democrats and
 304 Republicans who resided in Texas. We originally planned to recruit all participants using
 305 Lucid, but recruitment was slow due to the constrained nature of our target population.
 306 To avoid a large shift in the information environment due to election results reporting on
 307 November 6, we expanded our recruitment to Prolific and CloudResearch. For these subse-
 308 quent samples, we implemented additional quality checks.

309 The second wave took place a few months after North American winter storms Uri and
 310 Viola in 2021. It was conducted between July 7, 2021 and October 14, 2021. For this sample,
 311 we recruited respondents from the first wave from Prolific and CloudResearch, but not Lucid
 312 because it does not support recruitment of past participants.

Table 2: Survey recruitment details by wave.

Field dates	Platform	n_D	n_R	Remuneration
Wave 1				
Oct. 18 – Oct. 23, 2020	Prolific	96	72	\$2
Oct. 24 – Nov. 5, 2020	Lucid	424	380	up to \$4
Oct. 29 – Nov. 5, 2020	Prolific	172	81	\$2
Oct. 30 – Nov. 5, 2020	CloudResearch	87	63	\$2
Wave 2				
Jul. 7 – Aug. 30, 2021	Prolific	116	62	\$2
Aug. 31 – Oct. 14, 2021	Prolific	42	25	\$4
Sep. 24 – Oct. 14, 2021	CloudResearch	36	24	\$2

n_D and n_R respectively indicate sample size of Democrats and Republicans.

313 In both Waves 1 and 2, at the beginning of the study, participants were given a consent
 314 form that described the study instrument (answering questions on demographics and disaster
 315 experiences, reading a news article about disasters), ensured that their responses will be kept

¹Prior to the launch, we conducted a pilot on Lucid with 132 respondents (74 Democrats and 59 Republicans) who are not included in the final data set due to mismatches with our sampling criteria and other data quality concerns (i.e. speeders or spammers). Based on the pilot, we implemented more quality controls for the full launch.

316 anonymous, and that the study involved minimal risks. After the study, participants were
 317 debriefed with the purpose of the study (better understand how citizens are affected by
 318 disasters and evaluate political issues) and were provided with the contact information of
 319 the study team. The Wave 1 survey took approximately 12 minutes to complete and the
 320 Wave 2 survey took approximately 8 minutes to complete.

321 In the first wave, a total of 1375 eligible respondents (779 Democrats and 596 Repub-
 322 licans) were included in the analysis. In the second wave, the sample consisted of 305 re-
 323 spondents (194 Democrats and 111 Republicans) who participated in the first wave. The 305
 324 Wave 2 respondents equate to a 53.4% retention of the subset of Wave 1 respondents we
 325 recruited for our Wave 2 survey.

326 These numbers exclude respondents who did not satisfy our sampling criteria (i.e. adults
 327 residing in Texas and identifying as a Democrat or Republican). In the Prolific and CloudResearch
 328 samples, we also removed respondents who indicated they had already participated in our
 329 survey through other platforms. A full breakdown of the participant pool by survey platform
 330 and partisanship is in Table 2, and Table 3 contains the distribution of basic sociodemo-
 331 graphic variables for our Wave 1 and Wave 2 surveys.

Table 3: 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

332 4.2.1 Wave 2 attrition

333 We recruited 571 Wave 1 respondents for our Wave 2 survey. Of these, we recaptured 305
 334 respondents for a 53.4% retention rate. To check if there are discernible differences between
 335 the retained ($n = 305$) and attritioned ($n = 266$) groups, we tested the bivariate relationships
 336 between attrition and a number of important Wave 1 variables. Our results are presented
 337 in Figure 7. The retained and attritioned group are balanced on sociodemographic charac-
 338 teristics, climate attitudes, and disaster exposure, with the exception of age, where older
 339 individuals were less likely to be attritioned.

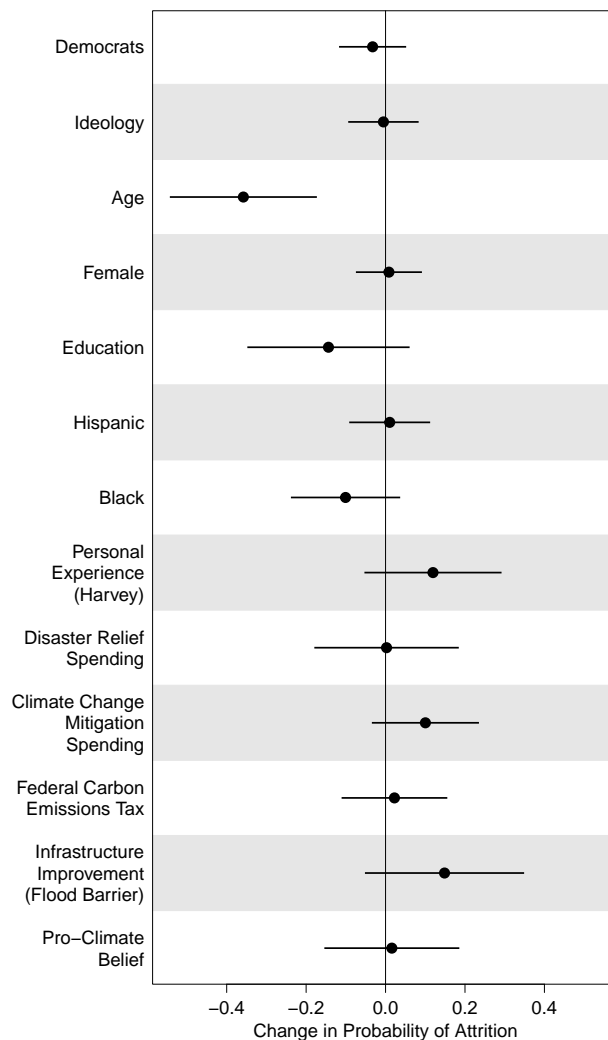


Figure 7: Bivariate relationships between attrition and important Wave 1 variables (point estimates and 95% CIs).

4.3 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 8. 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 [12], shown in Table 4. Both quantities were rescaled to the unit interval using min-max scaling to obtain our measures of perceived personal experience.

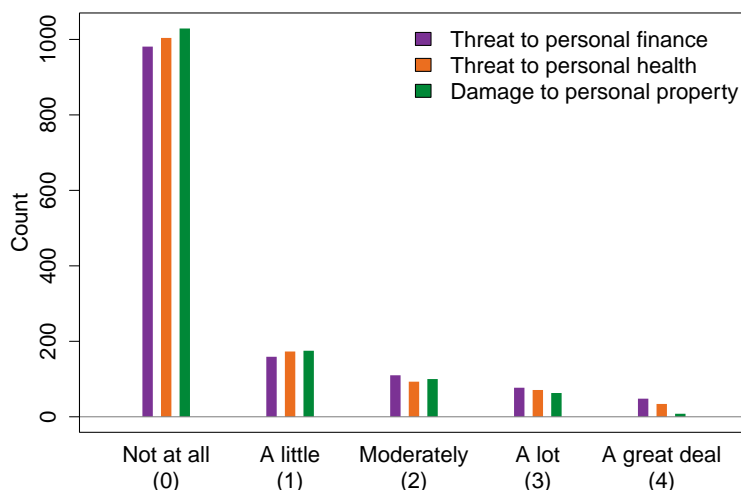


Figure 8: Personal threat and damage experienced during Hurricane Harvey in 2017.

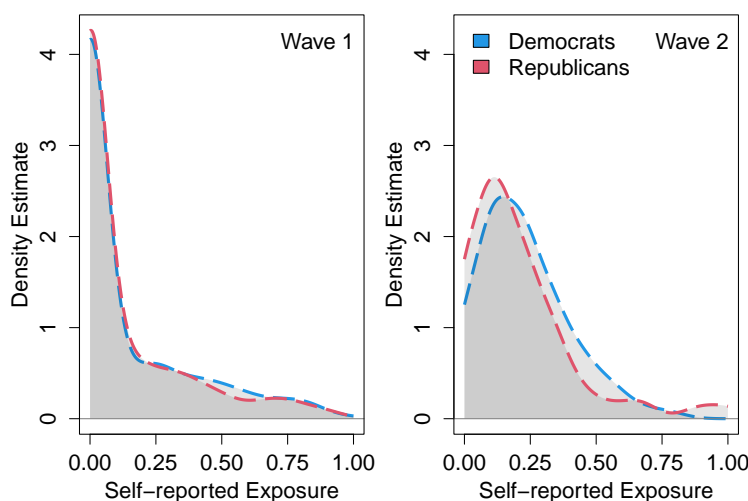
Figure 9 shows the distribution of the self-reported exposure for both waves by partisanship, which illustrate that while our results differed by respondent's partisanship, it is not due to differences in their self-reported experiences.

4.4 Measuring Geographic Exposure using Power Outage Data

To measure personal experience with the winter storms, we estimated the extent to which individuals were exposed to power outages during mid-late February using data from PowerOutage.US, a data aggregation company that tracks outage reports from utility companies

Table 4: 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

**Figure 9:** Distribution of perceived personal experience with Hurricane Harvey (Wave 1) and the 2021 North American winter storms (Wave 2) in Texas, rescaled to the unit interval.

361 in the U.S. Specifically, we have outage data aggregated to the city level or county level
 362 based on raw data from 62 utility providers in Texas tracking the accounts of 13.4 million
 363 customers. We aggregated the raw data (counts of outages and non-outages by geographical
 364 area) to the city level or county level depending on data availability. Specifically, counties
 365 exceeding a certain proportion of tracked-but-not-geolocated households are aggregated to
 366 the county level whereas counties with city-level data exceeding the information threshold
 367 were kept at the more precise city level. We refer to this hybrid-level geographical unit as
 368 the ZIP-associated region.² Then, using respondents' self-reported ZIP codes, we matched
 369 them to the average power outage in their ZIP-associated region during the February 13–21
 370 period which we take as our measure of geographic exposure treatment.

²See Supplementary Information S2 for evidence that our main findings (Figure 3), which was based on a 25% threshold, are robust to thresholds ranging from 5–45%.

371 4.5 Difference-in-differences Analysis

Using our geographic exposure treatment variable and outcomes from our surveys, we used a generalized difference-in-differences design to estimate the impact of geographic exposure to extreme weather events on individuals' climate beliefs and policy preferences. We fit the following linear regression model:

$$Y_{izt} = \alpha_i + \tau_t + \gamma(\text{outage}_z \times \text{storm}_t) + \delta(\text{democrat}_i \times \text{outage}_z \times \text{storm}_t) + \epsilon_{izt}, \quad (1)$$

372 where Y_{izt} is the belief or attitude of individual i at time t , and z indicates the ZIP-associated
373 region individuals reside in. $\text{outage}_z \times \text{storm}_t$ is the treatment of the 2021 winter storms. We
374 are interested in the difference between Republicans and Democrats, so we further interacted
375 the treatment with partisanship (i.e. the *democrat* indicator). γ and $\gamma' \equiv \gamma + \delta$ therefore
376 capture, respectively, the treatment effects for Republicans and Democrats. We additionally
377 included in our model individual and time fixed effects (α_i and τ_t). Because the treatment
378 was assigned to the geographical unit, we conducted the analysis using standard errors that
379 were clustered at the level of the administrative unit.

380 4.6 Analysis and results reproduction

381 All analysis for our study were conducted in R v4.2.2 [23]. Estimation for the difference-
382 in-differences models were done with the `fixest` v0.11.1 package [3]. All marginal effect
383 calculations were done with the `marginalEffects` v0.9.0 package [2]. All reproduction code
384 will be made publicly available under the MIT license at [https://github.com/tedhchen/](https://github.com/tedhchen/floodStorm)
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1 *Supplementary Information:*
2 Disaster Experience Mitigates the Partisan Divide on
3 Climate Change: Evidence from Texas*

4 Ted Hsuan Yun Chen¹ Christopher J. Fariss² Hwayong Shin³ Xu Xu⁴

5 January 5, 2024

6 **Contents**

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16 **S1 Results from additional pro-climate attitudes**

17 To provide further evidence of our findings, we conducted additional analysis on three sets
 18 of attitudes related to climate change from our Wave 2 survey. First, to measure climate-
 19 related policies that are likely to impact the immediate daily lives of respondents, we asked
 20 the subjects additional questions about their views on pro-environmental restrictions such
 21 as banning the use of plastic bags or imposing road fees. Second, we measured trust in
 22 climate science by adapting five items most relevant to our inquiry from the climate science
 23 skepticism scale proposed by Sarathchandra and Haltinner [7]. Finally, we looked at climate
 24 change risk perception. All three measures are additive scales based on the relevant set of
 25 questions summarized in section S4.

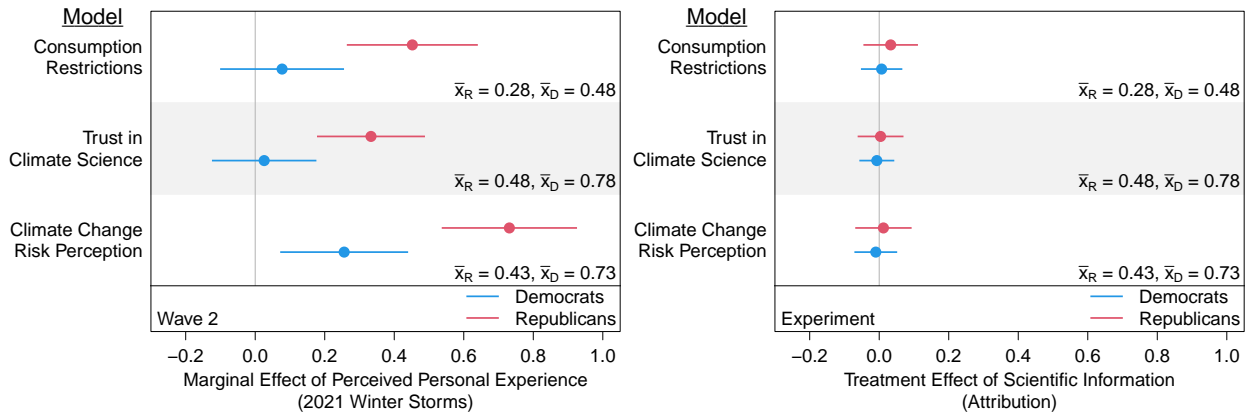


Figure S1.1: Relationships between perceived personal experience and climate attitudes (left) and treatment effects of scientific information attributing extreme weather to climate change on climate attitudes (point estimates and 95% CIs). \bar{x}_R and \bar{x}_D refer to, respectively, the sample mean of the outcome variable for the Republican and Democrat groups.

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

32 As shown in Figure S1.1, the patterns of findings from main analysis are largely retained.
 33 The more severe the perceived experience with the winter storms are, the more likely that
 34 partisans have pro-climate attitudes and behaviors. These patterns are again stronger among
 35 Republicans. As before, scientific information attributing extreme weather events to climate
 36 change exhibits no effect on pro-climate attitudes.

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

37 S2 Robustness checks

38 S2.1 Subsetting Wave 1 analysis to only multi-wave respondents

39 We achieved a 53.4% retention rate for our Wave 2 survey. We showed in the main text that
 40 the attritoned and retained groups are balanced on all relevant demographic and attitudinal
 41 variables but age. To provide additional evidence against attrition bias in our Wave 2 results,
 42 we show in Figure S2.1 that our Wave 1 results are robust to being analyzed on the subset
 43 of respondents we retained for the Wave 2 study. All coefficient estimates have the same sign
 44 and statistical significance with the exception of support for infrastructure improvement.

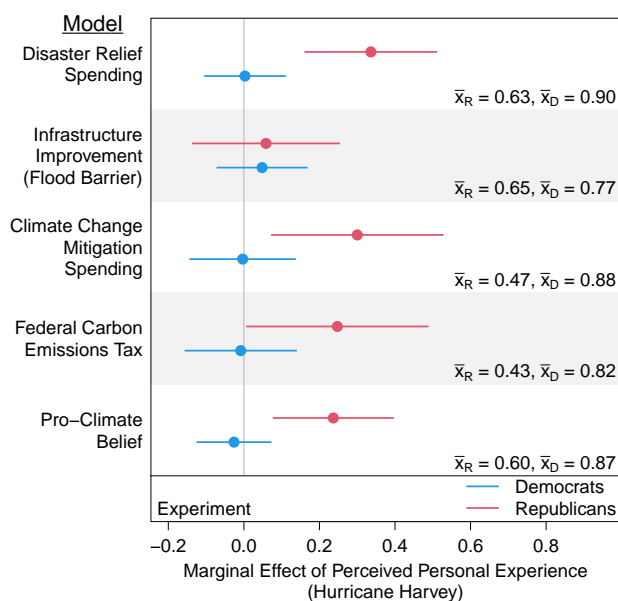


Figure S2.1: Relationships between perceived personal experience and climate attitudes (point estimates and 95% CIs) for subset of Wave 1 survey respondents who we retained for Wave 2.

45 S2.2 Participation selection by remuneration

46 When conducting the Wave 2 survey, we initially set the participation remuneration to
 47 \$2. When recruitment stalled after a month, we raised the participation remuneration for
 48 ongoing Prolific recruits to \$4 for the rest of the recruitment. All CloudResearch participants
 49 were recruited with \$2 remuneration. We show here that our main findings are robust across
 50 the two groups receiving different remuneration. We do so by interacting perceived personal
 51 experience with remuneration group, which we show in Figure S2.2. Based on likelihood ratio
 52 tests, the expanded model (with the remuneration interaction) and the reduced model are
 53 statistically indistinguishable from each other for all outcome variables with the exception
 54 of support for infrastructure improvement.

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

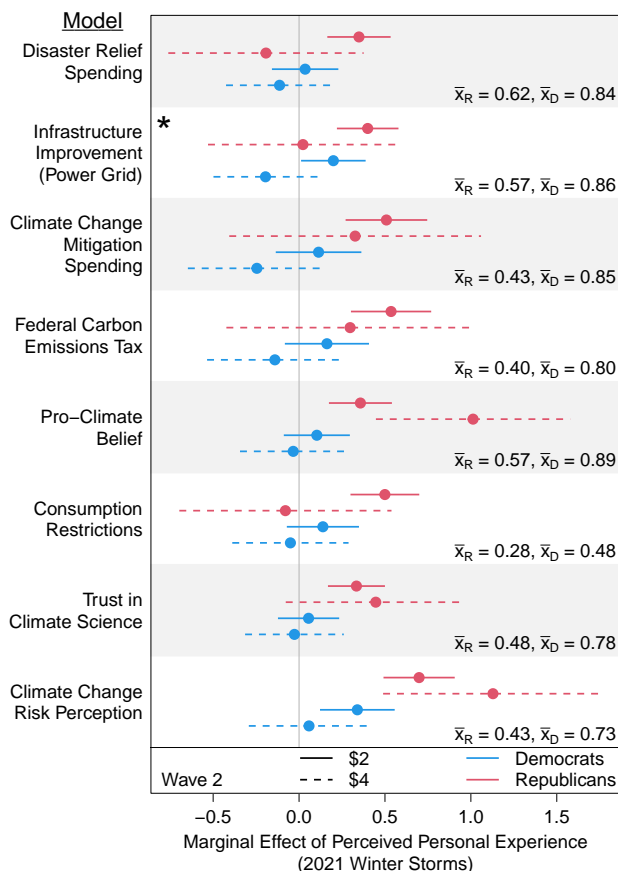


Figure S2.2: Relationships between perceived personal experience and climate attitudes (point estimates and 95% CIs), by remuneration amount. \bar{x}_R and \bar{x}_D refer to, respectively, the sample mean of the outcome variable for the Republican and Democrat groups. Models marked with an asterisk are those statistically significantly different from their reduced forms that do not contain the remuneration interaction.

60 **S2.3 Power outage aggregation**

61 Our raw power outage data is reported at a mixture of county and city levels. Aggregation
 62 to the county level is sometimes required because some counties have a mixture of both
 63 reporting levels. As described in the main text, we estimated geographic exposure to power
 64 outage using a data aggregation algorithm that considers how much uncertainty there is at
 65 lower levels of aggregation. Specifically, for each county, we use city-level aggregation for all
 66 cities within the county until we reach a certain threshold of proportion of households that

67 cannot be placed in a city, at which point we aggregate the entire county to a single unit.

68 In our main text, we reported results using an aggregation threshold of 0.25. Here we
 69 show in Figure S2.3 that our results are robust to a wide range of threshold values.

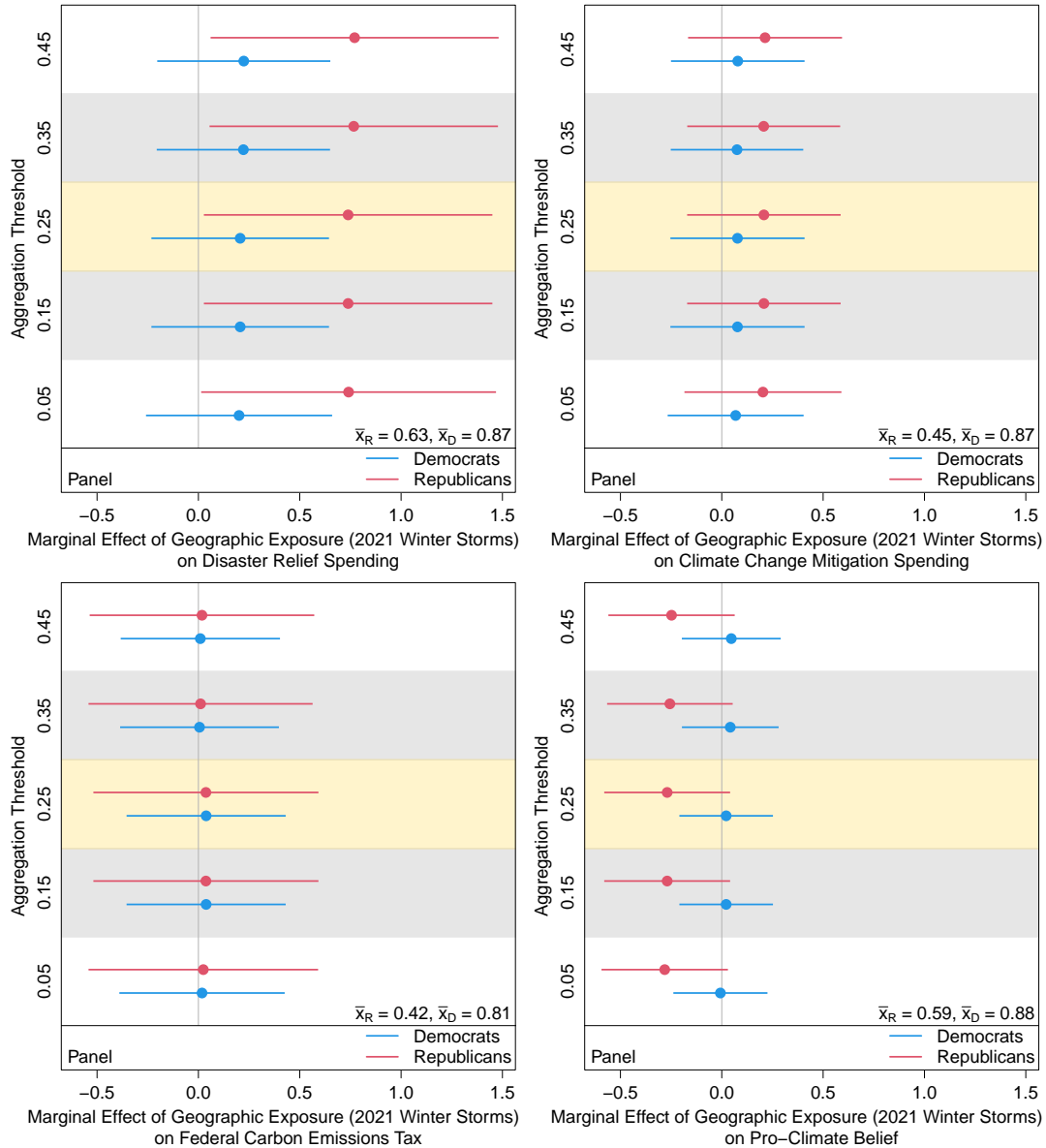


Figure S2.3: Treatment effects of geographic exposure to the 2021 power outages on climate attitudes (point estimates and 95% CIs), by the uncertainty threshold at which city-level outages are aggregated to county-level outages. The models highlighted in yellow, with aggregation thresholds of 0.25, are 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.

S3 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 [1] – 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 S2.3), is summarized as p -values in Figure S3.1.

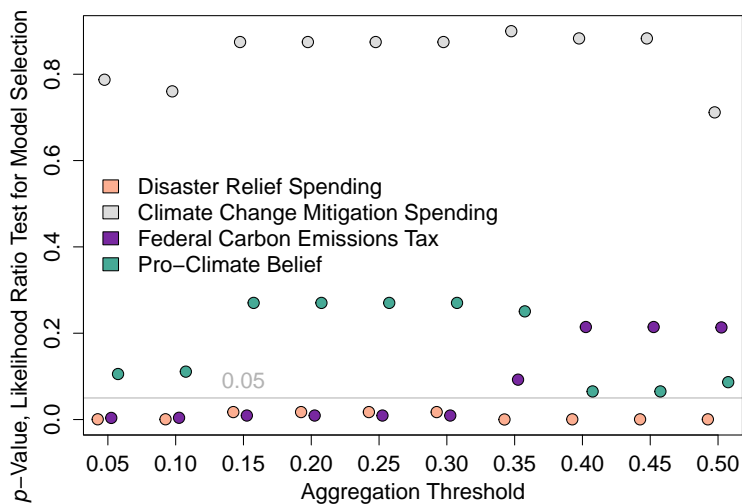


Figure S3.1: p -values from likelihood ratio test for selecting between models that constrain or allow the treatment effect of power outages to vary by whether the individuals’ treatment was aggregated at the city or county level, by the uncertainty threshold at which city-level outages are aggregated 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

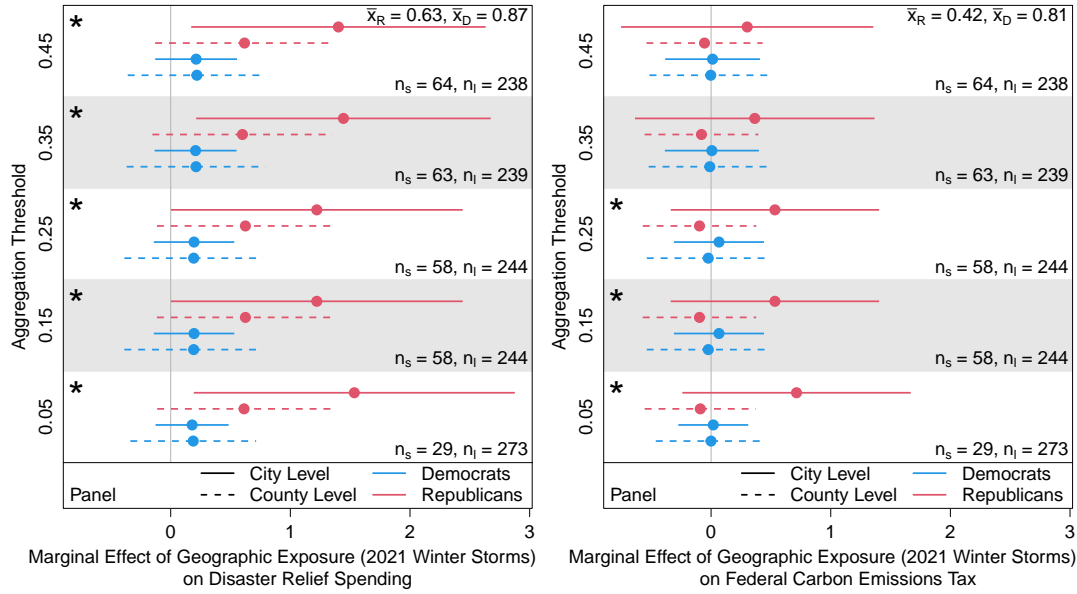


Figure S3.2: Treatment effects of geographic exposure to the 2021 power outages (point estimates and 95% CIs) on disaster relief spending (left) and on federal carbon emissions tax (right), by the threshold at which city-level outages are aggregated to county-level outages. n_s and n_l refer to, respectively, 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.

90 from the inclusion of the interaction term, with the expanded model fitting better across all
 91 or most aggregation thresholds. Focusing on results from these two models, presented in
 92 Figure S3.2, we show that among Republicans for whom we had enough information to
 93 disaggregate their measure of exposure to the city level, power outage has a large effect
 94 on these two climate attitudes. As we are working with relatively small samples – with
 95 between 29–64 respondents for whom we can measure exposure at the more precise city level
 96 – the estimates have wide confidence intervals. However, the magnitude of the effect among
 97 this subgroup compared to the county-aggregation group is striking. The results presented
 98 here provides further evidence that personal experience with extreme weather shapes pro-
 99 climate attitudes, and also that proximity matters, both in terms of practical implications
 100 and research methodology.

101 **S4 Survey questionnaire**

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

Table S4.1: 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 S4.2: 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 S4.3: 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? Q3. poses to other states in the US? Q5. poses right now?

Q2. poses to Texas? Q4. poses to other countries? Q6. will poses 10 years from now?

[none at all / low / moderate / high / extremely high]

104 **S5 Pre-analysis plan: Scientific information experiment**

105 Our pre-analysis plan was deposited to OSF on July 8, 2021.² We reproduce the content of
106 the pre-analysis plan here.

107 **Motivation**

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

116 **Theoretical Background and Hypotheses**

117 The literature on messaging strategies for climate change impact has suggested that a mes-
118 sage can more effectively increase risk perceptions and support for mitigation/adaptation
119 policies when it highlights personally relevant and proximate consequences of climate change
120 [6, 8] and when scientific evidence is presented with visualizations and without politicizing
121 counterarguments [9, 2]. Moreover, personal experiences of extreme weather such as wildfire
122 or hurricanes tend to be associated with climate change beliefs and support for climate mit-
123 igation policies [5, 4]. While higher chance of seasonal snowfall in individuals' local area is
124 negatively associated with their beliefs in climate change [3], we examine the impacts of a
125 message that explains how extreme winter storms can be caused by climate change, specifi-
126 cally due to the rising temperature in the North Pole. Building on these findings, we propose
127 the following hypothesis:

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

132 Does personal experience of natural disasters (e.g., hurricanes, winter storms) amplify
133 or mitigate the effect of the scientific evidence message? We expect the treatment effects of

²It can be accessed at https://osf.io/6bes4?view_only=f8ad46a725fc4d08a6ce6b68871ae83e.

134 the scientific evidence message to be greater for individuals who have experienced disasters,
135 which yields the following testable hypothesis:

136 **Personal Experience Heterogeneous Effect Hypothesis:** The extent to
137 which the science message increases risk perceptions and support for policy mea-
138 sures against climate change will be greater among those who experienced hurri-
139 canes or winter storms, compared to those who did not.

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

142 **RQ1:** Do the treatment effects of the science message differ between Republi-
143 cans and Democrats? Are partisan differences in treatment effects moderated by
144 natural disaster experiences?

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

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

150 **Sampling**

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

159 **Overview of Survey Flow**

160 The study uses experimental designs. To identify the causal impact of the evidence message
161 on risk perceptions and mitigation/adaptation policy preferences, we have two randomized
162 conditions, where each condition presents the scientific evidence message or not. Using the
163 pre-treatment responses on their prior experiences with natural disasters, we will also ex-
164 amine how the treatment effects are moderated by prior experiences with natural disasters.
165 The flowchart of the research design is presented in Figure S5.1.

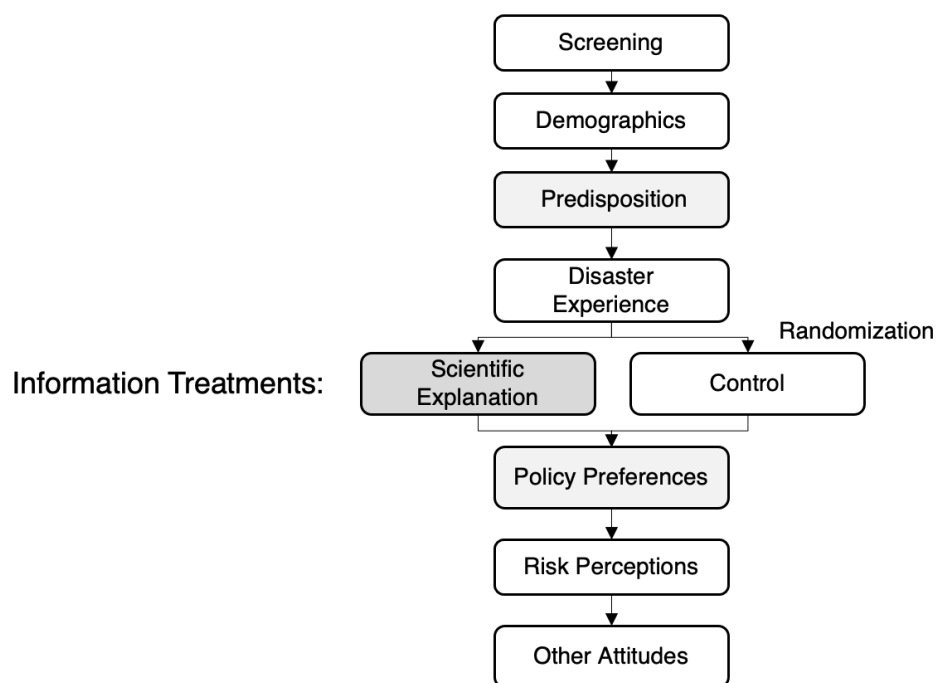


Figure S5.1: Survey flow diagram.

166 **Experimental Conditions**

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

172 **Measurement of Outcome Variables**

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

180 **Analysis**

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

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

S6 References

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