

# Disaster Experience Mitigates the Partisan Divide on Climate Change: Evidence from Texas<sup>\*</sup>

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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

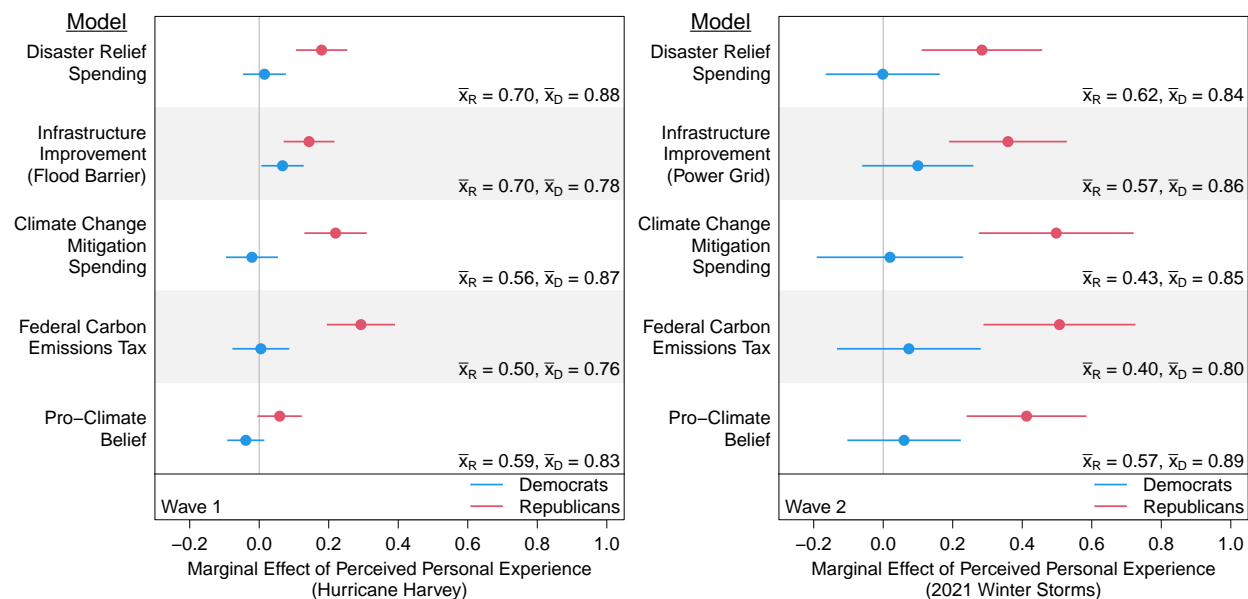
\*Additive scale measures (see Supplementary Information S4)

### 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.)

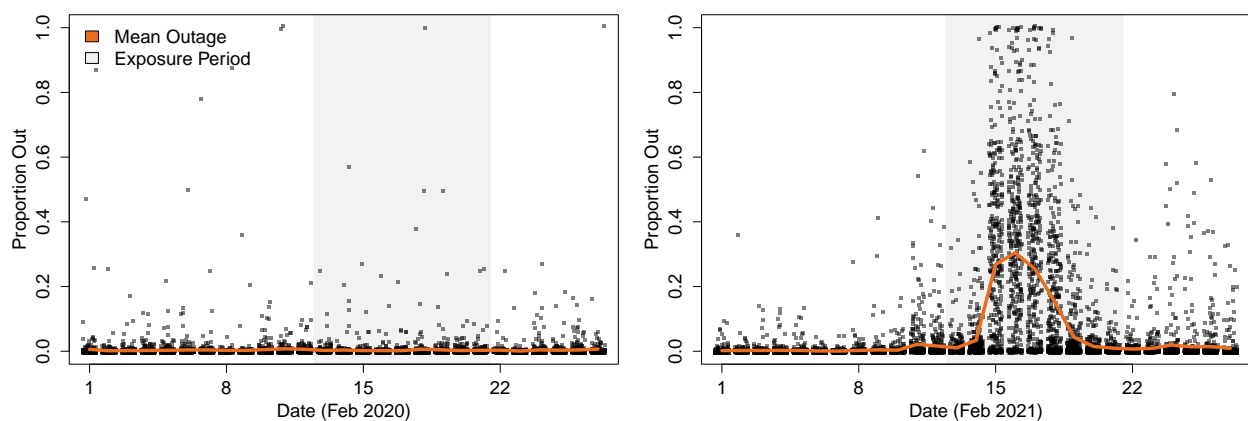
150 In contrast, among Democrats, there is no statistically discernible relationship between  
 151 perceived personal experience and our outcomes. While this discrepancy may appear coun-  
 152 terintuitive, additional tests show that the null finding among Democrats can be attributed  
 153 to a ceiling 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.

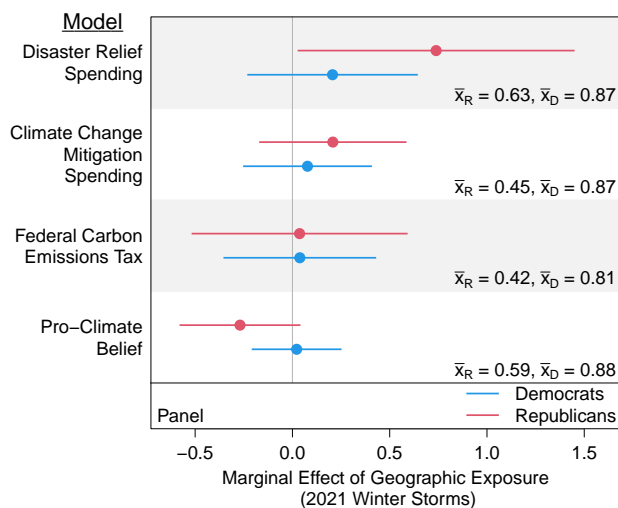


**Figure 2:** Proportion of households experiencing power outage by tracked administrative unit (i.e. counties or cities) in Texas during February 2020 (left) and during the winter storm in February 2021 (right).

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.

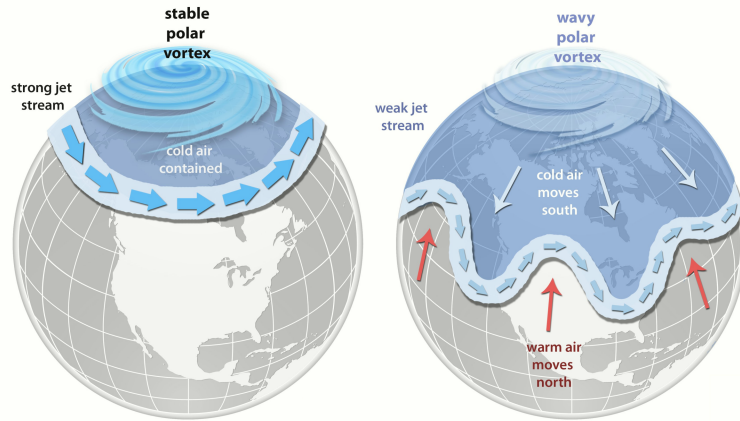
The recent winter storm posed another kind of natural disaster threat to Texas. At least 57 people died in Texas as a result of the recent winter storm, according to the state health agency. The winter storm caused Texas to experience subfreezing temperatures and overwhelmed the state's electricity infrastructure, 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.**



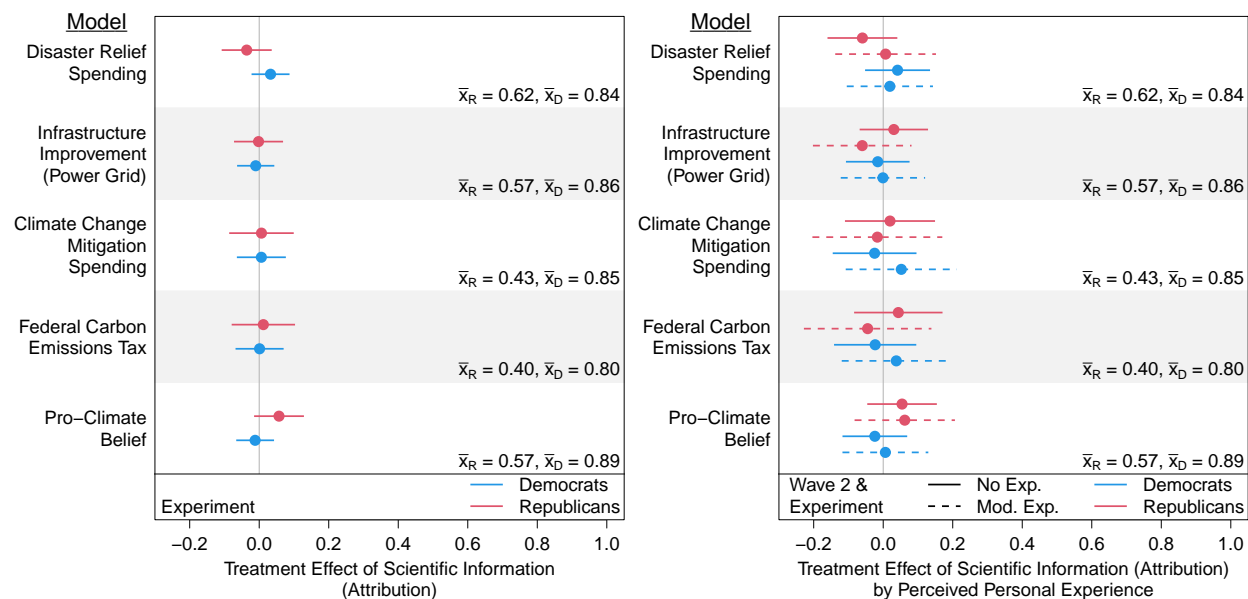
Source: NOAA

**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.

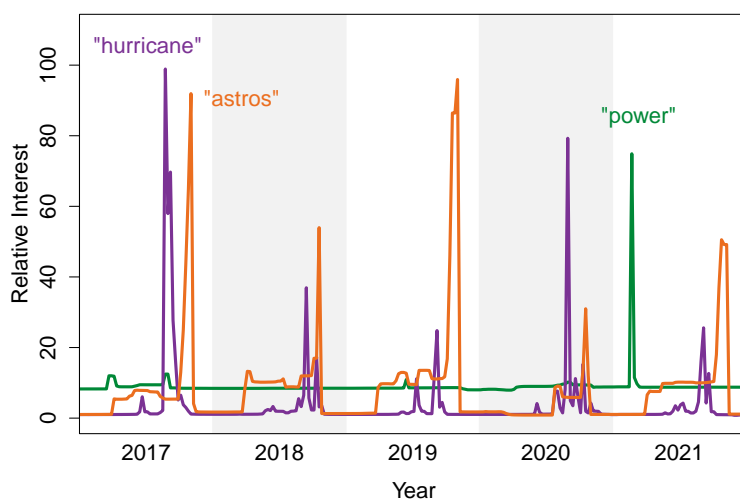
251 As we discussed, a notable shortcoming in the literature is that the experiential stimuli  
252 and informational stimuli have yet to be directly compared to each other. Our research design  
253 allows us to not just compare these two stimuli but also model any potential interaction  
254 between 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.<sup>1</sup> 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
<b>Wave 1</b>				
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
<b>Wave 2</b>				
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

<sup>1</sup>Prior 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.

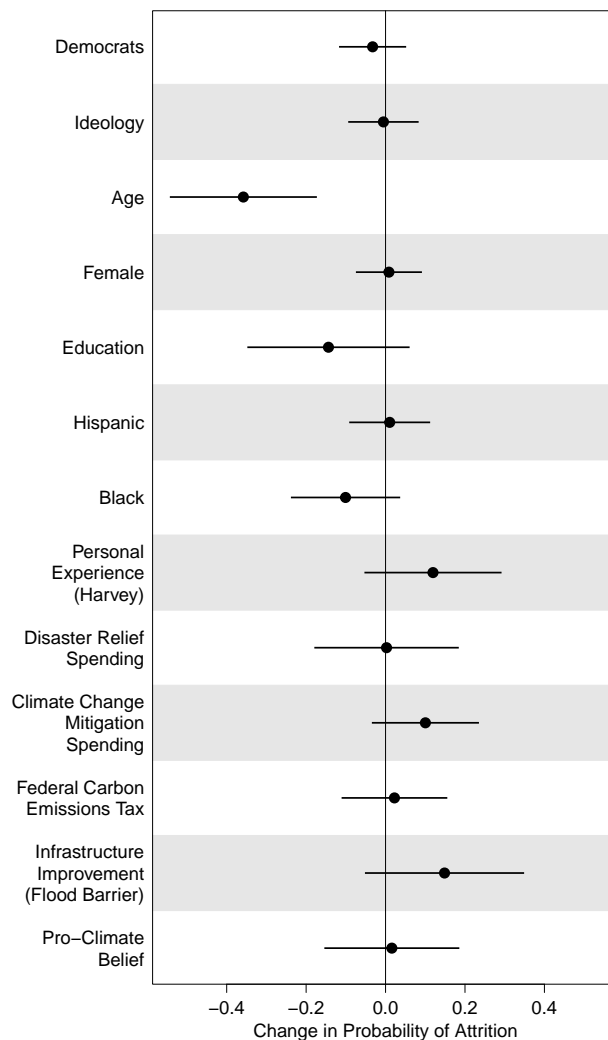
326 These numbers exclude respondents who did not satisfy our sampling criteria (i.e. adults  
 327 residing in Texas and identifying as a Democrat or Republican). In the Prolific and CloudResearch  
 328 samples, we also removed respondents who indicated they had already participated in our  
 329 survey 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

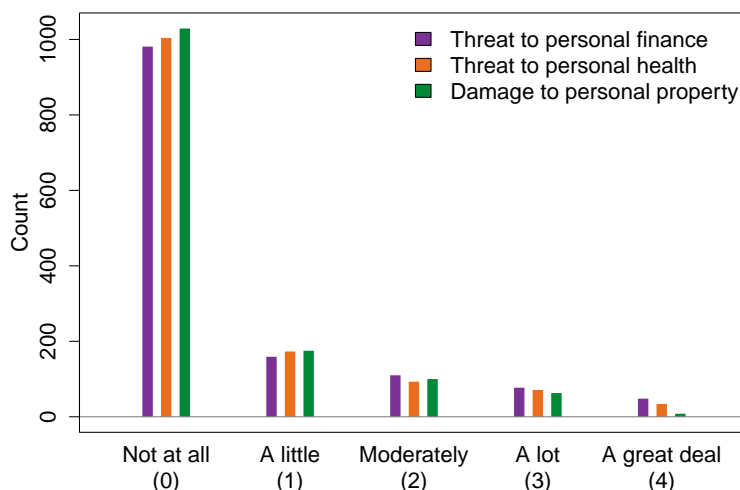
333 We recruited 571 Wave 1 respondents for our Wave 2 survey. Of these, we recaptured 305  
 334 respondents for a 53.4% retention rate. To check if there are discernible differences between  
 335 the retained ( $n = 305$ ) and attritioned ( $n = 266$ ) groups, we tested the bivariate relationships  
 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.

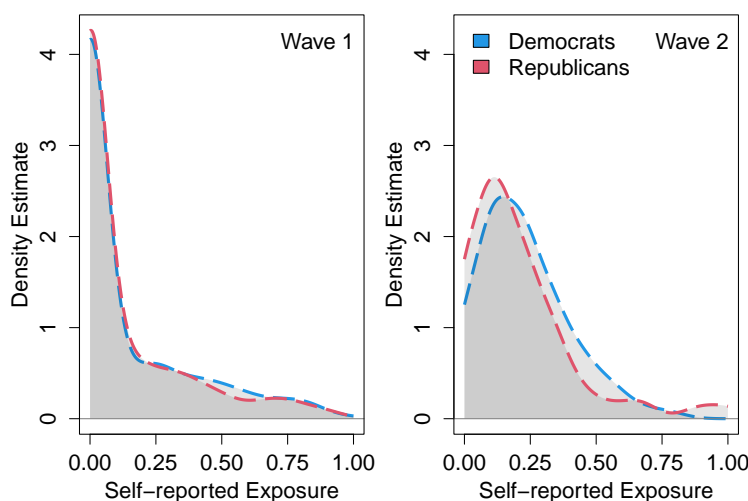
### 4.4 Measuring Geographic Exposure using Power Outage Data

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.<sup>2</sup> 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.

<sup>2</sup>See 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).  $\gamma$  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 ( $\alpha_i$  and  $\tau_t$ ). 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/  
385 floodStorm](https://github.com/tedhchen/floodStorm).

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