Do Disasters Change Risk Perceptions and Policy Preferences about Climate Change?*

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May 4, 2020

Abstract

As the effects of climate change are increasingly realized, concerns about the intensity and frequency of disasters are similarly rising. We study the effect of exposure to natural hazards associated with climate change—such as floods, fires, and hurricanes—on risk perceptions and policy preferences about climate change. We analyze US public opinion data at the county level from 2014 to 2018 using a difference-in-differences strategy, showing that exposure to disasters increases the likelihood of both believing that climate change will harm people and supporting the adoption of measures to address it. Given the time-sensitive nature of climate change and relative climate inaction at the national level, this study helps to better understand how tangible "evidence" of climate impacts may raise concern and lead to growing public support for mitigation efforts.

Keywords: Climate Change, Natural Disasters, Risk Perceptions, Policy Preferences.

*We thank Thomas Birkland, Rosalee Clawson, Logan Strother, Leigh Raymond, Scott Robinson, Wesley Wehde, and seminar participants at APSA, SPSA, Purdue, Universidad Mayor, and Toronto Political Behaviour Workshop for their valuable comments and suggestions. This project was supported by CONICYT/FONDECYT 1191522. All errors are our own.

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1 Introduction

There is substantial evidence that the global climate is changing at present and will continue to transform well into the future. Unmitigated climate change promises myriad environmental and societal effects. Among the most consequential are climate variability and extreme weather that can lead to greater risks of natural disasters with potentially devastating impacts (Van Aalst, 2006; Lippsett, 2012). Natural disasters, including floods, fires, and hurricanes, already threaten human well-being and severe damage across the United States each year. In 2019, for example, homes and thousands of acres of land were engulfed by fires in the West and extreme flooding events inundated towns along the Eastern seaboard. Can exposure to an array of disasters associated with a warming planet affect people's risk perceptions and policy preferences about climate change?[1]

The literature relating natural disasters and the political sphere has grown over the last decade, much of it focusing on the impact of these events on incumbents' vote share (Healy and Malhotra, 2010; Bechtel and Hainmueller, 2011), turnout (Gomez et al., 2007; Chen, 2013), citizens' political attitudes (Carlin et al., 2014; Fair et al., 2017), and the blame attribution process (Maestas et al., 2008; Malhotra and Kuo, 2008). Relatively little is known about the effect of natural hazards on people's concerns and policy opinions about climate change.

There is some mixed evidence suggesting that individuals can perceive a changing climate (Howe et al., 2013; Ripberger et al., 2017; Bergquist and Warshaw, 2019) and that those perceptions may contribute to changing beliefs about global warming (Egan and Mullin, 2012; Myers et al., 2013; Zaval et al., 2014). Nevertheless, believing in climate change may not necessarily translate into thinking that it will directly affect you or that mitigation measures are required.

Understanding people's political attitudes about climate change is particularly important given the time-sensitive nature of climate action and in the context of political debates about changes in global weather patterns, including whether they will cause harm to humans (i.e., risk perceptions) and what actions, if any, should be taken to address them (i.e., policy preferences).

[1] For practical reasons, we use the terms global warming and climate change interchangeably throughout this paper.

Our research provides evidence to better understand how exposure to disasters can affect political attitudes about climate change. To capture the outcomes of interest, we use public opinion data on global warming at the county level from the Yale Project on Climate Change Communication (YPCCC) and the George Mason Center for Climate Change Communication, which was gathered from thousands of respondents and extrapolated via multilevel regression and poststratification (Howe et al., 2015). To identify counties exposed to natural disasters, we rely on the Federal Emergency Management Agency's (FEMA) data for federally declared disasters that could be associated with climate change. These include floods, severe storms, tornadoes, ice storms, mud/landslides, snow storms, fires, hurricanes, and coastal storms (see appendix A).

Identifying the political effects of extreme weather events can be challenging since some areas are more likely to be exposed than others, meaning that exposed and unexposed areas could differ in terms of observed as well as unobserved covariates. To address this concern, we implement a difference-in-differences (DID) design. By assuming that the outcomes move in parallel trends when there is no treatment, we can engage in an analysis even with control and exposed groups that have different characteristics. We also provide a number of robustness checks—constructing a representative matched sample, exploring the existence of spillovers, checking for a dose-response relationship, computing different types of standard errors, and using individual rather than county level data—that support the findings from our main analysis.

We propose three possible explanations for how natural disasters might affect people's opinions on climate change. The first, *no persuasion*, refers to instances when information does not change people's concerns or policy preferences. This might happen because of a biased assimilation process, with victims interpreting events in a way that fits with their previously held beliefs (Lord et al., 1979) or not deeming the new information credible enough (Druckman and McGrath, 2019). The second explanation, *selective persuasion*, describes situations when individuals update their risk perceptions but not their preferences. This may happen because the latter are much "sticker" and harder to modify, generally better explained by slow-moving variables such as partisanship (Campbell et al., 1960). It may also describe situations when only policy preferences are modified, which could be driven by the psychological defense mechanism known as unconscious coping, through which individuals adapt to a threat in their environment without fully internalizing the problem. (Jacobs et al., 1994). *Double persuasion*, finally, refers to scenarios in which exposure to natural disasters shifts both risk perceptions and policy preferences. There is some evidence that suggests that individuals can update their policy preferences after shocks that significantly deteriorate their living conditions, including unemployment (Margalit, 2013) and crime victimization (Visconti, 2019). Each of these explanations offers theoretically plausible accounts for reactions to natural disasters associated with climate change. We therefore use this study to explore which of these explanations best describes public reactions to disaster events that could be associated with climate change.

We find that exposure to natural disasters at the county level in the two years prior to a survey year affects both risk perceptions and certain policy preferences. Notably, the effect in non-Republican counties is larger, and indistinguishable from zero in Republican counties for all the outcomes except one policy preference (limit CO_2). These results provide support for a *double persuasion* explanation for non-Republicans but a *single persuasion* explanation for Republicans counties.

This paper provides multiple contributions to the existing literature on public opinion about climate change, which is according to the United Nations, the most significant political issue of our time.[2] First, given the relatively limited empirical work studying causality between natural disasters associated with climate change and public opinion, we advance this research area by providing evidence from a difference-in-differences design to document this causal link. Second, given the relative paucity of national climate action to date and the rapidly closing window for effective mitigation efforts, we also hope to provide additional insights into the potential for local climate efforts with our attention to county-level public opinion and disaster data. Third, we offer evidence that some counties are more likely than others to update their perceptions and preferences based on negative events, suggesting that certain mitigation measures may be more easily accepted

[2] See: "United Nations: Climate Change."

than others and among different populations. Finally, previous research has shown that individuals' attitudes can play an important role in policy decisions that are ultimately adopted (Brooks and Manza, 2008; Lupu and Pontusson, 2011). Given the time-sensitive nature of effective climate action, such a relationship could be especially consequential. Individuals who are more conscious of the risk associated with global warming and more likely to support policy changes because of exposure to natural disasters might contribute to the adoption of mitigation measures.

2 Theoretical Explanations

Natural disasters are often highly traumatic events that influence exposed individuals in a myriad of complex forms. We therefore present three possible ways in which risk perceptions and policy preferences may shift because of exposure to natural hazards associated with climate change, as illustrated in figure 1, and aim to explore which of these seems to best reflect actual responses to natural disasters. We consider both risk perceptions and policy preferences in broad terms, examining potential changes to different dimensions of these concepts.[3]

The first possibility that we consider is *no persuasion*, which refers to situations where exposed individuals do not update their risk perceptions or policy preferences after being exposed to a disaster. This could occur if exposed individuals interpret "evidence" of climate change in a way that allows them to maintain their beliefs, a process known as biased assimilation. Indeed, there is substantial evidence suggesting that people tend to evaluate empirical evidence in a biased way, especially when they hold strong opinions (Lord et al., 1979; Munro and Ditto, 1997; Dandekar et al., 2013). Given the partisan and controversial nature of climate change at present, it seems reasonable to expect that (certain) disaster victims might interpret such information in a biased manner. For instance, an individual who does not believe that climate change is human driven might interpret a severe flooding event as an "act of God" or a random event not necessarily connected with human

[3] While we recognize that there may be differences based on the type of concern (e.g., personal harm or consequences for others) or policy alternative (e.g., general vs. specific proposals) and we recognize that it could be useful to develop different theoretical expectations for each, we aim to provide foundational insights that could guide future research.

activities. Another possible explanation for a *no persuasion* outcome would be that exposure to a natural disaster might not be as informative as expected (Druckman and McGrath, 2019). The credibility of the information can be explained by different factors such as how it is framed (Wiest et al., 2015; Stokes and Warshaw, 2017) and covered by the media (Atkeson and Maestas, 2012). Some victims may not even connect a disaster to climate change, or for those who do, the impact of a natural hazard might quickly vanish. The *no persuasion* process is illustrated in the first panel of Figure 1, where a disaster may not necessarily change concerns about climate change or result in a greater conviction to act to mitigate its effects.

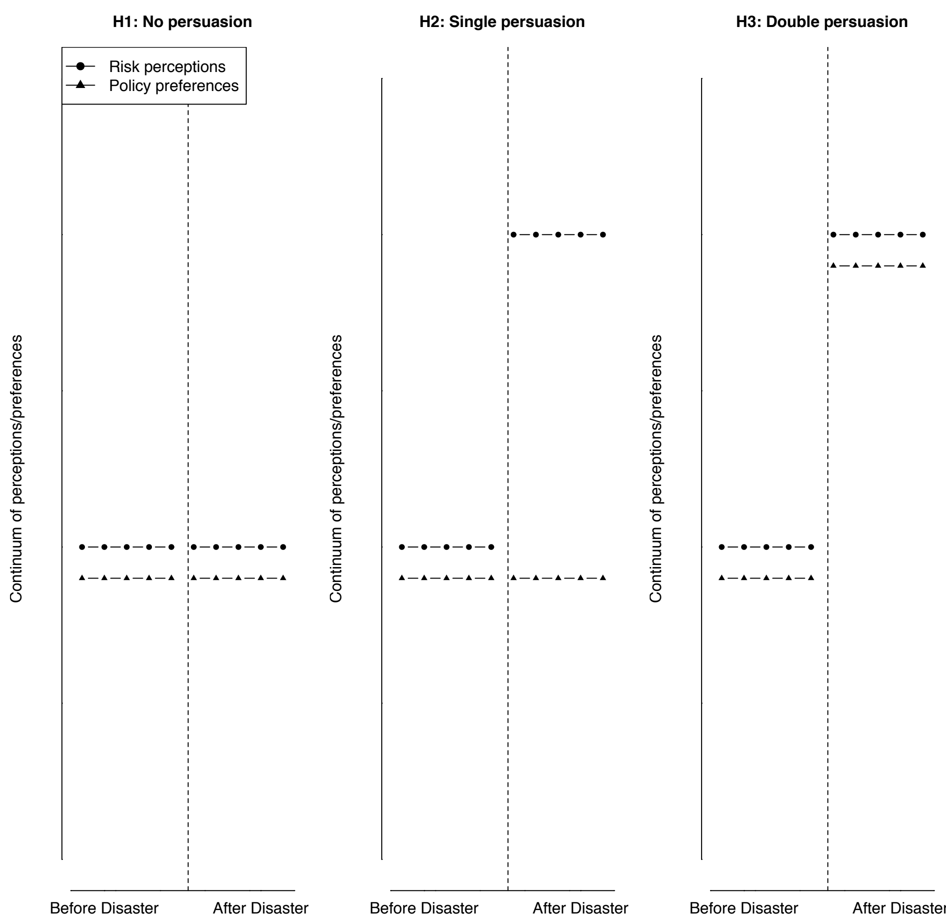

Figure 1: Theoretical explanations

On the other hand, there is evidence that suggests that specific extreme weather events such as floods (Spence et al., 2011) and excessive heat (Konisky et al., 2016) may provoke shifts in concerns about climate change. We therefore propose that exposure to the natural hazards we study may change people's perception of the risk that climate changes poses to them. Given the relatively sticky nature of policy preferences, however, individuals' risk perceptions may change without also shifting their preferences about mitigation measures. This is because policy preferences tend to be explained by long-term variables such as ideology (Jost, 2006) or partisanship (Campbell et al., 1960). For instance, individuals who place themselves on the left side of the ideological continuum are more likely to support wealth redistribution (Alesina and Giuliano, 2009) and welfare policies (Shapiro, 2009) compared with individuals on the right side. Because we would not expect a natural disaster to modify the political identity of citizens, their political preferences regarding climate change may remain unchanged. We refer to such a scenario wherein risk perceptions change but not policy preferences as *single persuasion*, illustrated in the second panel of figure 1. Conversely, this term may also apply to instances when people update their policy preferences but not their risk perceptions. If we understand acknowledging climate change as the potentially harmful process of internalizing a threat or a challenge, and supporting mitigation actions as a process of adapting to a threat or a challenge, changes to only policy preferences could be explained by a defense mechanism known as unconscious coping (Jacobs et al., 1994), through which people adapt to a problem without fully internalizing it. Research has shown this mechanism to be more likely to be used when individuals need to make complex decisions (Horr et al., 2014). For people who are skeptical of man-made global warming, reacting to evidence of a changing climate may be one such complicated choice.

It also seems plausible that exposure to natural disasters could elicit meaningful changes in risk perceptions as well as policy preferences about climate change, which we refer to as *double persuasion.* This may occur because natural disasters are "easily observable variations" that "have been shown to affect political preferences" (Druckman and Lupia, 2016, 15). Further, individuals' risk perceptions and policy preferences might be motivated by self-interest and, as a result, will be updated when their standards of living are affected or if they feel vulnerable to changing circumstances (Erikson and Stoker, 2011). Therefore, the post-disaster context might motivate victims to re-evaluate and update their previous opinions. Even if individuals are myopic (Healy and Malhotra, 2009), they could also be persuaded to update their priors based on the existence of new information such as tangible "evidence" of climate change. We can understand this as a learning process based on the assimilation of new information (Gerber and Green, 1999), following a Bayesian learning approach.

3 Data and Design

Studying the political effects of natural disasters, albeit a topic of interest for many scholars and policymakers alike, is not a simple task. There may be hidden biases when correlating exposure between an extreme weather event and political outcomes, for example, which could confound our analysis and undermine important inferences. To address such concerns about omitted variables, we exploit cross-time and cross-country variation in exposure to natural disasters in the US using a generalized difference-in-differences design (i.e., a two-way fixed effect regression).

Such a design relies on the assumption that unmeasured covariates are either unit-specific but time-invariant or time-specific but unit-invariant. These restrictions imply that the outcomes in each group should: (i) differ by the same amount in every period, and (ii) exhibit a common set of changes across periods (Wing et al., 2018). Therefore, any divergence from these trends can be interpreted as a treatment effect (Angrist and Pischke, 2014). Importantly, this design strengthens our causal claims regarding the relationship between natural disasters and public opinion about climate change, and allows us to provide more credible inferences than designs that control for an array of cross-sectional covariates alone.

Our primary outcomes of interest are risk perceptions and policy preferences about climate change. Such concerns and opinions, however, are not constant across, or even within, states. Rather, because there is considerable variation in public opinion across the United States regarding a changing global climate (Howe et al., 2015), relying on aggregate national- or state-level data could obscure important insights at a local level. For example, although 57 percent of adults across the country believe, on average, that global warming is human caused, that conviction falls to 44 percent in West Virginia; it remains mostly true, however, in Kanawha County (53 percent), home to West Virginia's capital city (Marlon et al., 2018).[4] We draw on a series of nationally representative public opinion surveys conducted for the Yale Project on Climate Change Communication and the George Mason Center for Climate Change Communication (Howe et al., 2015) to account for such variation and explore effects at the county level. This data set is constructed and frequently updated using multilevel regression and poststratification (MRP), which draws on responses from thousands of individuals and "individual-level demographic predictors, state-, district-, and county-level random effects, random effects based on the year of the survey and survey mode, and geographic-level covariates" (Howe et al., 2015, 597).[5] We focus on survey data for 2014, 2016, and 2018. Estimates reflect data for more than 3,000 counties and county equivalents across the US.

To explore risk perceptions about climate change, we use the estimated percentages of respondents that believe global warming will cause a moderate or great deal of harm to them personally (Personal), people in the US (United States), or future generations (Future Generations). While many express concerns about future climate impacts, some are often less concerned about personally experiencing adverse consequences. Analyzing these outcomes allows us to explore different types of risk perceptions that may be affected differently by exposure to a natural disaster.

We also consider an array of policy preferences, including both general mitigation measures and more specific policy proposals, in our study. For example, we explore support for funding renewable energy sources broadly (Fund Renewables), through a policy to "[f]und more research into renewable energy sources, such as solar and wind power." Another area that we assessed was support for management of carbon dioxide (CO_2), known to be a primary contributor to climate change (Regulate CO_2), with a policy to "[r]egulate carbon dioxide (the primary greenhouse gas) as a pollutant." While understanding whether respondents agree, in principle, with the regulation of emissions and use of more renewable energy sources is useful, it is also critical to gauge support

[4] Based on 2018 data.

[5] In 2018, n > 22,000 respondents. See Marlon et al. (2018) and Howe et al. (2015) for more information.

for proposals that would, if implemented, meaningfully facilitate climate mitigation. More specific policy proposals are therefore also considered. These include restrictions on emissions from existing coal-fired power plants (Limit CO_2), through a proposal to "[s]et strict carbon dioxide limits on existing coal-fired power plants to reduce global warming and improve public health." Specifically, "Power plants would have to reduce their emissions and/or invest in renewable energy and energy efficiency. The cost of electricity to consumers and companies would likely increase." We also evaluate support for implementing renewable portfolio standards (Support RPS), via a proposal to "[r]equire electric utilities to produce at least 20% of their electricity from wind, solar, or other renewable energy sources, even if it costs the average household an extra $100 a year." Notably, both of our measures for "stricter" proposals include references to the individual costs that could be incurred, making them clearly distinct from more general statements about reducing emissions.

We provide summary statistics for the outcomes of interest in table 1. Although the majority of respondents (63 percent) believe that global warming will harm future generations and residents of the United States generally (51 percent), only a minority (35 percent) express concern that it will harm them personally. Therefore, while many seem to subscribe to the scientific consensus that climate change is happening and presents a considerable threat to human health and well-being, there is often a disconnect when it comes to perceptions of how a warming planet may present risks for respondents personally. Further, most support all of the aforementioned policy proposals, on average. For example, many indicate support for funding renewables (79 percent) and regulating CO2 emissions generally (72 percent). There is less support, however, for the more fleshed out proposals on "strict" limits on some emitters (61 percent) and implementing renewable portfolio standards (59 percent). While many may agree with taking measures to reduce greenhouse gas emissions, there is relatively less support for policy proposals that have explicit restrictions or requirements that could lead to personal costs.

Regarding exposure to disasters, we provide one main and two alternative approaches to identify affected locations (one alternative in the paper and one in appendix D). In our main approach, we construct a binary indicator of exposure to one or more natural disasters in the two years prior to a survey year (2014, 2016, 2018). For example, a county that experienced a major flooding event in 2012 and/or 2013 would be considered exposed for the 2014 survey year. We use a two-year treatment to avoid overlap between the surveys. This variable was constructed using Federal Emergency Management (FEMA) data for federally declared disasters that could be associated with climate change, which include floods, severe storms, tornadoes, ice storms, mud/landslides, snow storms, fires, hurricanes, and coastal storms, per county in a given year. While individuals in one region of the country may be more likely to experience certain kinds of natural disasters more than others (e.g., hurricanes), each of these disasters could be influenced by climate change and, therefore, are considered together here. Our approach thus diverges from those used in many other studies, which consider only one natural disaster, such as flooding (Whitmarsh, 2008; Spence et al., 2011). In appendix A, we summarize the research connecting these different types of disasters with climate change.

Assessing the relationship between our outcomes of interest and the treatment relies on the assumption that individuals connect a disaster in their county with climate change and update or maintain their opinions accordingly (Druckman and Lupia, 2016). Because we cannot directly observe whether individuals form such an association, our estimand is an intention to treat (ITT). More specifically, we study the effect of being assigned to associate a natural disaster with climate change via the effect of exposure. Although some may have direct experience with the effects of a natural disaster, exposure is defined broadly here to indicate that individuals live in a county with a declared disaster event and, presumably, witnessed its effects. The ITT estimand is commonly used to explore the effectiveness of an intervention, which may include both compliers and non-compliers, and whether it changes outcomes in a "real-world" setting. Non-compliance is less of a concern when this estimand is applied instead of an average treatment effect that assumes all units have received the treatment (Gerber and Green, 2012). This makes it especially useful for this study as an exploration of impact of exposure to a disaster that occurs in a natural (i.e., non-experimental) setting and requires individuals to associate a disaster with climate change to determine whether such events can change public opinion on related topics. As shown in table

1, 41 percent of the units of observation (county-years) were exposed to at least one disaster that could be associated with climate change.

Although we use nine disasters to identify exposed counties, not all of these events are equally likely to occur; 83% of the exposed counties were affected by only three types of disasters: floods (18%), hurricanes (29%), and severe storms (36%). This makes these hazards distinct from more unusual events: none of the other six disasters have a prevalence greater than 10%. In addition to being more prevalent, this subset of disaster events may be easier to associate with climate change than others. Although experiencing a snowstorm can be highly dangerous and costly, it may be hard for some people to blame climate change for an increase in such occurrences as a hurricane during one of the hottest summers in recorded history. Using all disasters would likely make our ITT estimand especially conservative since some exposed counties in our sample may contain individuals who are not complying by associating the disaster they experienced with climate change. Hence, we construct a second binary indicator, as a robustness check, that identifies places affected by this subset of more common natural disasters that can be (more easily) associated with climate change. A zero means that the county was not affected by any disaster. Places that were exposed to less common hazards (e.g., ice or snow storms) are excluded from this particular analysis. We call the first (main) exposure indicator "all disasters," and we refer to the second as "subset of disasters." Results for both exposure indicators are presented in the paper. Disasters may also affect people according to a dose-response relationship, wherein exposure to only one disaster is different than being exposed several disasters. We explore the dose-response relationship in appendix D and report evidence that exposure to multiple events generates an even larger effect on victims' risk perceptions and policy preferences, perhaps because multiple disasters are interpreted as stronger evidence of climate change than one event.

Table 1: Descriptive Statistics

Variables	Mean	SD	Max	Min
Personal	0.35	0.05	0.25	0.59
US	0.52	0.05	0.39	0.73
Future Generations	0.63	0.06	0.47	0.82
Limit CO_2	0.62	0.07	0.32	0.86
Regulate CO_2	0.72	0.04	0.57	0.85
Support RPS	0.59	0.05	0.45	0.76
Fund Renewables	0.79	0.04	0.61	0.91
Natural Disasters	0.41	0.49	0	1

The unit of analysis is a county-year, meaning that each outcome represents the percentage of the public that supports a statement in a given county in a given year (2014, 2016, or 2018). For example, Guadalupe County, New Mexico in 2014 is one unit of observation in our sample. To identify the political effects of natural disasters we use the following OLS regression:

$$Y_{it} = \alpha + \beta T_{it} + \sigma_i + \omega_t + \varepsilon_{it} \tag{1}$$

Y represents the outcome of interest (i.e., risk perceptions or policy preferences) in county i and year t. T corresponds to a binary indicator that identifies whether at least one disaster occurred in that county (all disasters) or whether one of the three most common disasters occurred in that county (subset of disasters). σ represents county fixed effects and ω_t are year fixed effects. β is the coefficient of interest.

It is important to note here that there are two main concerns when estimating uncertainty. First, the assignment of weather events can be highly correlated across space (Cooperman, 2017). Second, having data collected across time can imply serial correlation (Pindyck and Rubinfeld, 1998). Therefore, the standard errors need to account for both spatial and serial correlation. We compute Conley standard errors, which allows for spatial correlations between counties whose centroids are within 100 km of each other and a lag length of 4 years. This nonparametric estimation was developed by Hsiang (2010) and implemented in R by Christensen and Fetzer (2017). In appendix F, as a robustness check, we also compute heteroscedasticity-consistent standard errors that allow us to account for the uncertainty associated with using estimates as outcomes (Lewis and Linzer, 2005), and we follow a more standard approach by clustering standard errors at the level of treatment assignment (i.e., the county). The main findings are not conditional on how we estimate uncertainty.

4 Results

4.1 Difference-in-differences Estimates

Our analysis using a generalized difference-in-differences design demonstrates that exposure to one or more natural disasters increases the perceived threat of climate change. We provide our results by plotting point estimates and 95% confidence intervals (findings are reported in table format in appendix F). Figure 2 illustrates the effects of the two versions of the treatment (all disasters and the subset of disasters) on risk perceptions.[6] The first panel shows the effect of exposure to nine disasters associated to climate change (the control group corresponds to non-exposed counties), and the second panel the effect of exposure to the three most common disasters: i.e., floods, hurricanes, and severe storms (the same control group as before). When using the first indicator of exposure, the results demonstrate that exposure to disasters increases personal concerns about climate change by 0.04 standard deviation units (CI: [0.02-0.05]). Though a 0.02 standard deviation increase is experienced in exposed counties for concerns about the US (CI: [-0.001-0.05]) and about future generations (CI: [-0.004-0.05]), these two results are non-significant. When using the second indicator of exposure, all the outcomes show a significant change. Personal concerns increase by 0.04 (CI: [0.02,0.06]), concerns about the US by 0.03 (CI: [0.001,0.05]), and concerns about future generations by 0.03 (CI: [0.003,0.05]) standard deviation units.

[6] As a reminder, we have fewer observations for the second treatment since we exclude places that were exposed to the less common disasters (e.g., snow and ice storms).

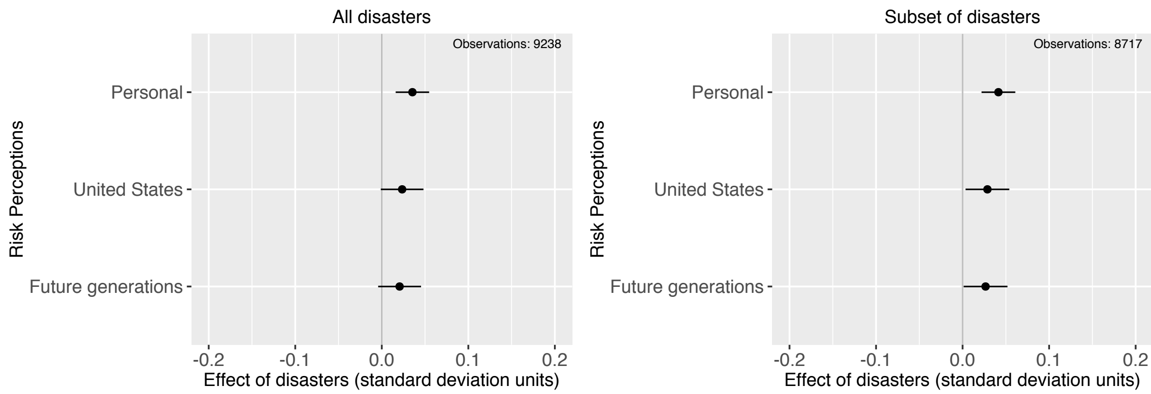

Figure 2: Effects of exposure to "all disasters" and "subset of disasters" on risk perceptions

Figure 3 illustrates the effects of the two treatment indicators on support for some mitigation measures. As in the previous table, the effects of exposure become (slightly) clearer when focusing on the subset of more common disasters. For the more general policy measures, however, there is not clear evidence that exposure to disasters changes policy preferences. This is particularly evident for our measure regarding regulating CO_2 as a pollutant, where exposure increases support for that measure by 0.01 standard deviation units for both all disasters (CI: [-0.01-0.04]) and the subset of disasters (CI: [-0.02-0.04]), both non-significant results. We suggest that this could be a consequence of a ceiling effect, as there is often robust support for such broad measures. When aggregated at the national level in 2018, support for regulating CO_2 (without reference to how or the personal cost) garnered 77 percent approval (Marlon et al., 2018). With another general policy we evaluate, funding for renewable energy, support increases by 0.02 standard deviation units when using all disasters (CI: [-0.0006-0.04] or the subset of disasters (CI: [0.001-0.04]. Interestingly, we find clear evidence that natural disasters increase approval for both of the more specific policy proposals. Support for “strict” limits on existing coal-fired power plants increases by 0.10 (CI: [0.07-0.13]) when using all disasters and by 0.11 (CI: [0.07-0.15]) when using the subset, and support for renewable portfolio standards increases by 0.06 standard deviation units for both all disasters (CI: [0.02-0.10]) and the subset (CI: [0.03-0.10]).

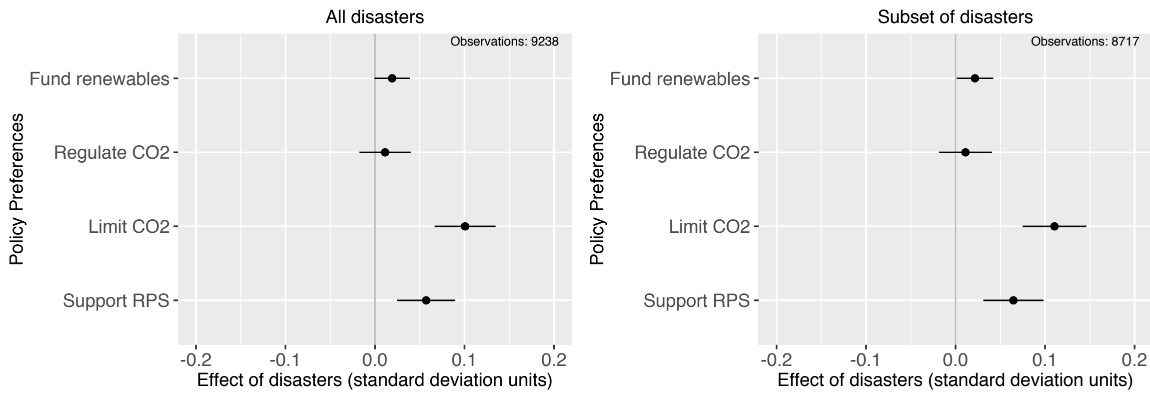

Figure 3: Effects of exposure to "all disasters" and "subset of disasters" on policy preferences

Taken together, these results suggest that exposure to natural hazards that may intensify with climate change increases concerns about the personal threat of climate change as well as support for mitigation measures, particularly more specific ones. Notably, the changes in people's policy preferences occur even though the more detailed mitigation proposals (Limit CO_2 and Support RPS) clearly signal a likely financial cost for many American households. The main results are consistent across the two different exposure indicators.

To provide additional context for these results, an increase in support for limiting CO_2 of 0.1 standard deviation units due to exposure to disasters translates to more than 2 million adults in the US between 2014 and 2018 becoming more likely to support a policy measure that places limits to CO_2 emitters. Therefore, although the effect sizes are not especially large, that nearly half of the counties were exposed to a natural disaster suggests that a non-trivial proportion of US citizens are changing their minds about the risks of climate change and measures to mitigate its effects. As a result, modest effects that apply to a large population could have more meaningful consequences than large effects in a small population. Importantly, these changes extend beyond pro-environmental statements (e.g., regulating CO_2) to include greater approval for proposals with measurable steps toward regulating greenhouse gas emissions and shifting to renewable energy sources in lieu of a dependence on fossil fuels.

In addition, there is reason to believe that the effects are greater than those reported in this section. Given that the natural disasters considered in this paper are anticipated to become more severe and frequent, the results we provide may be relatively conservative and provide useful insights for public opinion regarding climate change as its effects become even more evident in the future. Also, as mentioned earlier, we use an ITT estimand that accounts for potential non-compliance (in this case, not associating a natural disaster with climate change), which is inherently conservative when compared to an average treatment effect (ATE). Further, based on an additional robustness check, we find evidence of spillover effects (see appendix E). The impact of disasters is much larger when using as a control group counties that did not have an adjacent county that was exposed to a disaster. Even if an individual was not directly exposed to a disastrous flooding event in their county, for example, this suggests that they may nonetheless become more concerned about the adverse effects of climate change and willing to incur personal costs to implement mitigation measures to address as they watch their neighbors in the bordering county experience the disaster. We also provide evidence of a dose-response relationship (see appendix D), finding that an accumulation of disaster events in one county can generate an effect three times larger than those that are exposed to only one disaster. Finally, while our estimates are slightly larger when using the "subset of disasters" indicator, the results remain similar to those obtained using the "all disasters" indicator. To simplify, we focus on the "all disasters" indicator throughout the remainder of the article.

4.2 Heterogeneous Treatment Effects

Exploring heterogeneous treatment effects by partisan identification is particularly important since subgroups might update their concerns and preferences in different ways, especially in a highly polarized political climate. If this is the case, there may be nuances to how the trends associated with climate change affect public opinion. To explore these potential differences, we generate a binary indicator for counties where Republicans received more than 50% of votes in the 2008 presidential election.[7] We expand equation 1 to estimate heterogeneous treatment effects by

[7] The 2012 presidential election overlaps with the treatment for the 2014 survey data (disasters that happen two years before the survey).

including a binary indicator for Republican and non-Republican counties, as well as an interaction for Republican counties and being exposed to a disaster.[8]

Figures 4 and 5 illustrate the effects of exposure to a disaster in Republican and non-Republican counties as well as the difference between them. These results suggest that partisanship could be decisive in whether and how natural disasters transform public opinion as they become more frequent and severe. While the results support the *double persuasion* explanation in non-Republican counties, that argument fails to hold for Republican counties that do not update their risk perceptions and only change one policy preference (Limit CO_2) following exposure to one or more natural disasters. We interpret the results for Republican as a *single persuasion* argument since they are not changing their risk perceptions but are updating at least one policy preference. A defense mechanism known as unconscious coping can help illuminate this decision-making process (Jacobs et al., 1994): When people have to make complex choices after a threat, they might adapt without internalizing the challenge. In this case, Republicans might be willing to support certain mitigation strategies without acknowledging that they are at a greater risk of being exposed to a disaster because of climate change.

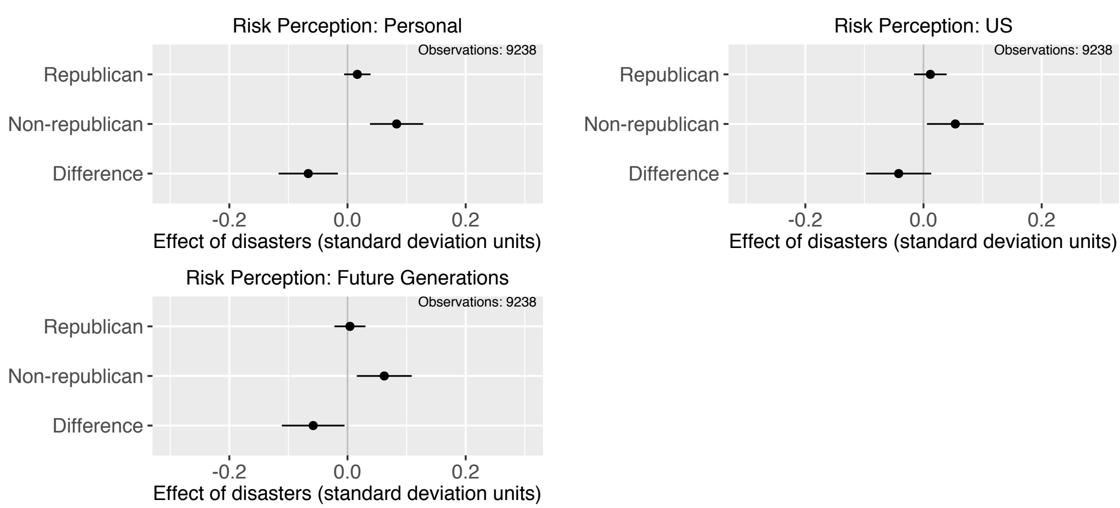

Figure 4: Heterogeneous effects of exposure to "all disasters" on risk perceptions

[8] The code to compute the Conley standard errors does not support the inclusion of the interaction term. As a result, we use cluster standard errors at the county level. In appendix F, we show that the results are consistent across different ways of computing standard errors: Conley, clustered, and robust.

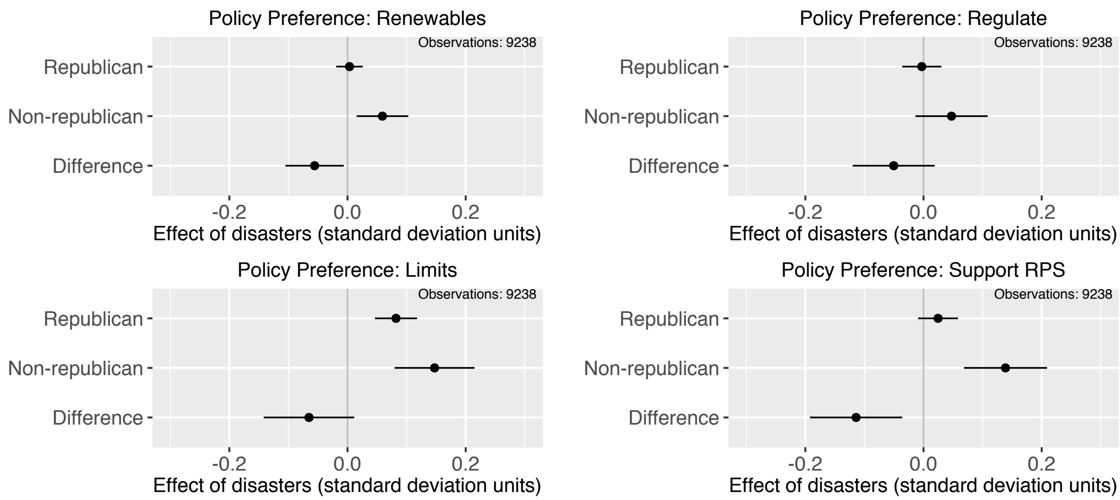

Figure 5: Heterogeneous effects of exposure to "all disasters" on policy preferences

Although it may be relatively unsurprising that majority Republican counties are not as likely to change many of their opinions regarding climate change as their non-Republican counterparts, it is notable that their support for placing limits on existing coal-fired power plants increases, even given information that doing so would likely result in personal financial cost. This suggests that “evidence” of climate change could meaningfully increase support for certain mitigation strategies across party lines, despite significant differences in whether risk perceptions change among Republicans and non-Republicans.

These results are especially interesting when compared to recent findings showing that wildfires in California increased support for pro-climate ballot measures but that the effect was nearly zero in Republican-dominated areas (Hazlett and Mildenberger, 2019). Based on our results, however, it seems that there are some policy issues that are more likely to gain support from Republicans. While focusing on general questions about climate action (e.g., support for renewable energy generally) might lead us to believe that it is not possible to change Republicans’ opinions, including a range of specific mitigation options could reveal greater support across parties. Further research exploring which topics are more or less likely to experience increased support is warranted.

To address common concerns about aggregation issues when using county level data, and especially when making inferences about subgroups within each county, we use survey data at the individual level (see appendix C). We find that both the county and individual data show similar results.

5 Robustness Check

As a robustness check for our main analysis using a difference-in-differences design, we use recent advances in optimal matching and mathematical programming to construct a matched sample that is representative of all US counties and to adjust for approximately 300 covariates (Visconti and Zubizarreta, 2018; Bennett et al., 2019). Although matching is not necessarily an identification strategy alone (Sekhon, 2009; Keele, 2015), it presents strong evidence that the results reported above are consistent across different approaches and identification assumptions.

5.1 Constructing a Representative Matched Sample

We know that random assignment is the best approach for learning about the impact of a particular treatment on outcome(s) of interest (Gerber and Green, 2012; Morgan and Winship, 2014), but it is not a feasible option for studying the causal effect of negative effects such as disasters. One alternative option is to construct an observational study that resembles a simple randomized experiment (Rosenbaum, 2010, 2017). We therefore use matching to construct a group of exposed and unexposed counties that are balanced across hundreds of covariates.

Nevertheless, traditional matching techniques such propensity score matching do not guarantee covariate balance, and can even increase important differences between groups in some instances (King and Nielsen, 2019). Further, such approaches tend to require multiple iterations and substantial guesswork to be able to construct a matched sample (Sekhon, 2009; Hainmueller, 2011).

In contrast, then, we use cardinality matching, which allows us to find the largest matched sample that achieves the researcher-defined covariate balance requirements (Zubizarreta et al., 2014). In this analysis, we define the standardized differences between the matched exposed and control groups to be no greater than 0.1 for all the covariates in our study, a common tolerance used in the literature to illustrate covariate balance (Zubizarreta, 2012; Pimentel et al., 2015). Cardinality matching then finds the sample with the maximum number of observations that meet these mean balance constraints.

Some concerns regarding matching, however, still remain, and are important to address here. Perhaps the most significant of these is the loss of information when pruning units to achieve covariate balance. More specifically, even though the matched sample may be balanced according to researcher-defined requirements, it might be markedly different from the unmatched or original sample. To address this potential problem, we construct a representative matched sample, extending cardinality matching to "anchor the matched samples so that they are not only balanced but also balanced around the distribution of a target population of policy interest" (Visconti and Zubizarreta, 2018, p.224). As a result, our exposed and control groups will be similar across approximately 300 covariates in addition to being similar to the target population: in this case, the original or unmatched sample of counties. We use the mean balance constraint for approximately 300 covariates,[9] specifying that the three groups of interests (i.e., all the counties, matched exposed, and matched control) cannot have imbalances larger than 0.1 standard deviation units for each covariate.[10] The representative matched sample has 4400 units, which amounts to 52 percent of the original sample.

In appendix B, we describe all of the covariates used. To quickly summarize, we constrain by demographics (e.g., total, female, Hispanic, Black, and white population), politics (e.g., turnout, Democratic and Republican vote share since 1980), economics (e.g., income, crime, and poverty), and climate (e.g., temperature and climate zone). Further, we pay close attention to the geographic location of counties when constructing the matched sample, which allows us to compare locations in the same region that have different exposure to disasters. This is a crucial element of

[9] All of these covariates are continuous, ordinal, or binary so the mean balance constraint is a meaningful requirement, which will not be the case if we included nominal covariates.

[10] We use cardinality matching to restrict the standardized differences (i) between the exposed group and all the counties and (ii) between the control group and all the counties to be no larger than 1/20 standard deviation units. As a result, the pooled standard deviation between the matched exposed and control groups cannot be larger than 1/10. We use the `designmatch` package in R to construct the representative matched sample (Zubizarreta and Kilcioglu, 2016).

our robustness check design, as we avoid creating exposed and control groups with very different probabilities of being exposed to a disaster because of their geographic locations. To do this, we generated percentiles for latitude and longitude, and then 100 binary indicators for each to identify the percentile of longitude and latitude for each county. These indicators allow us to adjust for geographic location such that exposure to natural disasters is not correlated with county location.

We present the mean for a small group of selected pretreatment covariates in our original sample (all counties) as well as the matched exposed and matched control groups. We describe and report the results for all the covariates in appendix B. Table 2 shows that the three groups are comparable in terms of their observed characteristics, and thus achieve the primary goal of constructing a representative matched sample.

Table 2: Description of the Representative Matched Sample

Covariate	All counties	Exposed matched	Control matched
Republican 2008	56.80	56.74	56.76
Democratic 2008	41.12	41.28	41.92
Income	55,736	55,713	55,599
Poverty	16.31	16.43	16.17
White	83.36	83.30	83.80
Median age	40.42	40.31	40.43

5.2 Effect Estimates

After obtaining a matched sample, we draw on the inferential approach described in Rosenbaum (2002). This uses a Wilcoxon's signed-rank test statistic to test the sharp null hypothesis of no treatment effect, which is less dependent on distributional assumptions. This test provides both point estimates and confidence intervals. Figure 6 summarizes the findings. Exposed counties have updated both their risk perceptions and policy preferences (for more specific policies). Confidence intervals are larger than those obtained when using a difference-in-differences design, since the unmatched sample is 2.4 times larger than the matched sample.

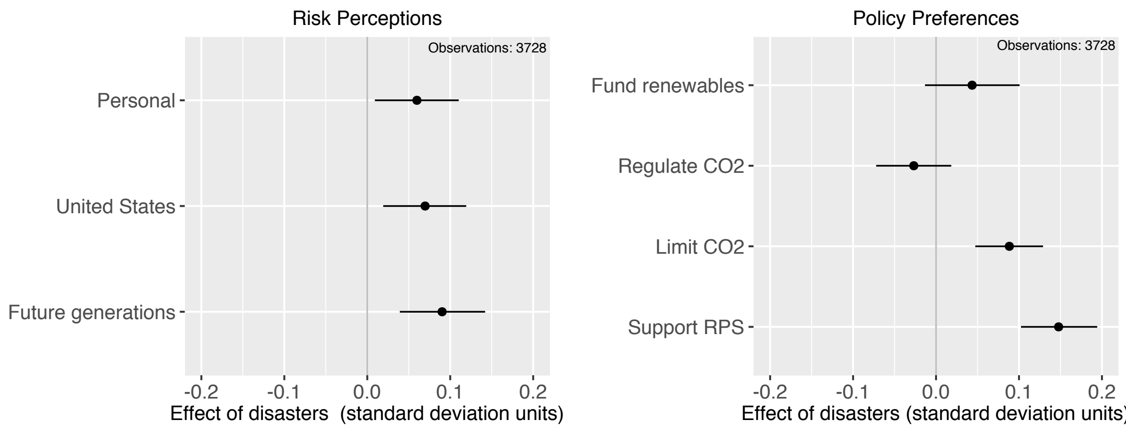

Figure 6: Effect of exposure to "all disasters" on risk perceptions and policy preferences (representative matching)

In sum, the results for both our main analysis and robustness check are congruent overall. This demonstrates the robustness of the main findings and corroborates our conclusion that natural disasters can have meaningful effects on people's opinions about climate change.

6 Conclusions

As the global climate continues to change, some types of natural disasters are expected to become more prevalent and severe. Whether and how these events influence risk perceptions about global warming as well as support for mitigation measures are, therefore, increasingly important questions. We aim to contribute to the literature studying such questions, engaging with several analytical approaches and drawing on 2014 to 2018 county-level public opinion surveys as well as data on federally declared disasters across the United States.

Using a difference-in-differences design, we explore the effect of exposure to one or more natural disasters that could be associated with climate change, finding modest but significant increases across risk perceptions and (certain) policy preferences. These effects are larger when taking spillovers into account and when exploring a dose-response relationship, suggesting that our main estimates are somewhat conservative. We further substantiate the main findings by using a subset of disasters that may be more clearly linked to climate change, constructing a representative matched sample using approximately 300 covariates, computing different types of standard errors, and running the analysis using individual rather than county-level data.

Rather than seeking to confirm one hypothesis for how public opinion may respond to climate change–related natural disasters, we propose several theoretical possibilities and provide empirical evidence to identify which theoretical account(s) offer the most explanatory insight. Exposure to a disaster can increase public concern that climate change poses a serious threat to oneself, to fellow Americans, and to future generations. Such an experience can increase support for certain mitigation measures as well, with the exception of approval for regulating CO_2 generally. We suggest this may be because of a ceiling effect, as broad measures without any clear losers may be more palatable than policies that more definitively prescribe industry or lifestyle changes. Based on our main analysis, a *double persuasion* argument may elucidate how natural disasters that are exacerbated by climate change may shape people's risk perceptions and policy preferences. We believe that this may follow a Bayesian learning approach wherein individuals use new "evidence" for climate change to amend prior beliefs.

Our research finds that this change in policy support occurs most clearly with the most detailed proposals, such as placing strict limits on existing coal-fired power plants, even when financial costs may be incurred as a result. This may indicate that experience with the effects of a changing climate could shift public opinion beyond support for mitigation in principle, to that of more clearly effective policies.

Notably, though, there is strong evidence of heterogeneous treatment effects based on partisan identity. Republican counties do not tend to update their risk perceptions or policy opinions after exposure to disasters, though their support for one policy proposal does increase. In contrast, non-Republican counties update their risk perceptions and policy preferences across most measures. These findings therefore suggest important nuances to whether and how natural disasters influence opinions. While a *double persuasion* argument is useful for understanding how non-Republicans counties react to natural hazards, a *single persuasion* argument may be more helpful for Republican counties. Rather than being entirely explained by a Bayesian learning approach, then, a defense mechanism such as unconscious coping may be required to explain why only policy preferences have changed. Considering the time-sensitive nature of climate change and the complexity suggested by our results, future study is warranted for better understanding what type of mitigation efforts are more likely to be supported.

These findings offer several important contributions. First, unlike previous studies that focus on a single type of natural disaster, we study a range of disasters that can be associated with climate change in the United States. Although it is certainty important to understand how a particular type of natural hazard may affect public opinion, it is also essential to acknowledge that, as climate change continues, associated disasters will likely become more frequent and intense. Whether that means more fires in the West or floods in the East, Americans in most areas will be exposed to events that our results suggest are already changing perspectives about climate change and raising support for certain policy proposals. Importantly, the effects we report are for policies that extend beyond support for climate action in principle; these are policies that respondents backed even knowing their possible personal cost.

Finally, we provide insights into potential policy changes that may occur in the future, particularly at the local level. Previous research has shown that individuals' preferences can affect actual policy outcomes (Hamann and Kelly, 2011). Given evidence that public opinion is already shifting after exposure to natural disasters, it seems plausible that policymakers will respond to increasing support for climate action. However, because disaster events may be more frequent and severe in some areas than others, changes in public opinion may not be uniform across the country. This could mean that climate action motivated by growing public support could occur at a more local level. Therefore, while the ultimate implementation of policies is influenced by a myriad of factors, our analysis indicates that tangible "evidence" of climate change may cause changes in public opinion that could, perhaps, forestall some of the most devastating climate impacts.

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