# Does Experiencing Natural Disasters Affect Climate Change Beliefs?

**Amrit Hayer**

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Supervised by Dr. Felix Pretis

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Dr. Elisabeth Gugl, Honours Co-Advisor

Dr. Martin Farnham, Honours Co-Advisor

## Abstract

In this paper I empirically examine whether experiencing more extreme weather, as measured by natural disaster occurrences, affects people's climate opinions. I match US county-level natural hazard data from the Spatial Hazard Events and Losses Database for the United States with county-level climate opinion data from the Yale Project on Climate Change Communication. I find that past disaster occurrences do increase the level of personal risk perception associated with global warming, and that disasters associated with cold weather tend to have the opposite effect of disasters associated with warm weather. After using a first-difference model to control for county-level fixed effects, I also find evidence that experiencing natural disasters increases belief that global warming is happening, in addition to increasing personal risk perception associated with global warming.

# 1 Introduction

There is a clear scientific consensus that human activities are the primary driver of global climate change (Linden *et al.*, 2015). Climate change has increased the risk of extreme weather events around the world (Van Aalst, 2006). The US experienced a record year of losses from fires, hurricanes and other weather-related disasters in 2017 (American Meteorological Society, 2018).

In this paper I empirically test whether one's exposure to natural disasters affects one's climate change opinions. I hypothesize that experiential learning influences how the public perceives climate change. If skepticism about climate change is partly determined by personal experience, then after someone experiences a natural disaster they may be more likely to believe in climate change or have higher levels of risk perception associated with climate change.

Though the vast majority of scientists agree that climate change is happening, fewer lay people agree. The proportion of adults who believe in climate change varies across the United States. For example, only 49% of people in Emery County, Utah think that global warming is happening, which is much lower than the 70% of Americans that agree on the national level (Howe *et al.*, 2015). There are many factors that contribute to this spatial variation in beliefs, and one of them may be that the effects of climate change vary across the country. Some regions are more prone to effects of climate change — such as the increased risk of natural disasters — than others.

Climate change can lead to an increase in the frequency and intensity of natural hazards (Field *et al.*, 2014). Natural hazards are unevenly distributed across the US. The Atlantic and gulf coasts are prone to hurricanes, and sea surface temperature increases have been linked to an increase in hurricane frequency, intensity, and duration (Lighthill *et al.*, 1994). In contrast, the western US is prone to wildfires, and an increasing trend in wildfire activity has been detected in recent decades (Westerling, 2016). Since extreme weather events are not experienced equally across the country, this may explain some of the spatial variation in climate opinions.

The effects of climate change include changes in weather patterns and increased frequency and intensity of extreme weather events (Field *et al.*, 2014). There is evidence that Americans think climate change affects the weather. The December 2018 survey results of the Yale Project on Climate Change Communication found that 65% of Americans think global warming is affecting the weather in the United States. Furthermore, about half of Americans think global warming made the 2018 wildfires in the Western U.S. (50%) and/or hurricanes Florence and Michael (49%) worse (Leiserowitz *et al.*, 2018).

If personal experience affects beliefs, then there are important policy implications. Climate opinions have a strong influence on the decision to vote for policies to reduce global warming or prepare for the associated impacts. Some important questions which depend on climate change beliefs include how climate change information should be communicated to the public, whether voters will support additional funding for disaster relief, and how strongly citizens will demand government action to respond to climate change.

I use county-level natural hazard data from the Spatial Hazard Events and Losses Database for the United States (SHELDUS) to measure individual exposure to extreme weather events. I match this to county-level climate belief data from the Yale Program on Climate Change Communication. I use two variables from this dataset: belief that global warming is happening and belief that global warming will harm one personally. I test three hypotheses:

1. People who have experienced more natural hazards are more likely to believe that global warming is happening and that it will affect them personally.

2. The difference in belief that global warming is happening and the belief that it will affect one personally can be explained by natural hazard occurrences.
3. People who experience natural hazards are more likely to believe that global warming is happening and that it will affect them personally, after controlling for unobserved county-level fixed effects.

Previous studies (e.g., Brulle, 2012; Konisky *et al.*, 2016) use a higher level of spatial aggregation of weather data, such as weather in the US as a whole or weather aggregated to the 122 Weather Forecasting Offices in the US. Instead, I use data for the 3142 counties in the US. This more precise level of spatial aggregation increases the probability that an individual has experienced a given weather event. Additionally, I use fifteen hazards in my analysis, not only "warm" hazards (such as heatwaves, drought, or wildfires) which are directly linked to climate change, but also "cold" hazards (such as avalanches or extreme winter weather) which may decrease belief in global warming. Furthermore, the climate opinion dataset I use contains separate variables for belief that global warming is happening and belief that global warming will harm one personally. Previous research has not examined how experiencing extreme weather events affects these two climate opinions differently.

First, I conduct an analysis using the level of natural hazard experience in each county. I find evidence that natural hazard experience causes higher levels of perceived personal harm from climate change. Furthermore, I find that disasters more closely associated with global warming and warm weather have a positive effect on perceived personal harm from climate change, whereas disasters that are associated with cold weather generally have a negative effect. Using this model, I do not find evidence that the level of natural disaster experience in the past affects people's belief that climate change is happening. This result may be due to omitted variable bias, which I address by using a first-difference model.

I conduct a first-difference analysis using the change in beliefs and change in hazards over a two-year period. This analysis controls for unobserved county-level fixed effects. Using this model, I find evidence that experiencing natural disasters affects climate opinions. Specifically, *drought* and *wildfire* events cause an increase in belief in global warming, as well as an increase in predicted personal harm from global warming.

## 2 Literature Review

Climate change is perceived by many as a psychologically distant issue that affects other people or future generations (Liberman and Trope, 2008). Individuals cannot directly observe climate change because it is a slow, cumulative change of average climate conditions (Weber, 2010). In the US, the majority of individuals perceive that climate change has increased the severity of extreme weather events (Leiserowitz *et al*. 2012). Since individuals mainly observe and experience the climate through their own local weather and seasonal events, these could be factors that influence people's formation of beliefs about climate change.

Through experiential learning, individual experience of weather that deviates from the average may affect climate opinions, and information gained from personal experiences may make abstract risks more concrete and may affect personal risk perceptions (Howe *et al*., 2014). Myers *et al.* (2013) find that experiential learning occurs mainly among people who are less engaged in the issue of global warming, which is important given their finding that 75% of Americans currently have low engagement levels.

There are many papers that examine the effect of weather experiences on climate opinions. Akerlof *et al.* (2013) conduct surveys of residents in Alger County, Michigan and find that believing to have personally experienced global warming is a statistically significant predictor of perceptions of local risks associated with global warming. There are several papers which find that higher local temperatures positively influence climate change belief or concern (e.g. Kaufmann *et al.*, 2017; Li *et al.*, 2011; Krosnick *et al.*, 2006). Borick and Rabe (2014) find that variation in snowfall can explain part of the variation in climate change belief in the US between 2008 and 2012. Brody *et al.* (2008) find that vulnerability to sea-level rise and proximity to a coast increase climate change risk perception. Spence *et al.* (2011) use a national survey in the UK to examine the relationship between direct flooding experience and perceptions of climate change. They find that individuals who reported experiencing flooding also reported more concern over climate change.

Other researchers examine similar questions but focus on using extreme weather data to try and explain climate opinions. Brulle (2012) examines whether climate extremes influence concern over climate change, but finds no significant relationship. They use public opinion polls from 2002 to 2010 to create an index and calculate quarterly changes in concern about climate change. They evaluate the effect of various factors on the index using a time series analysis. One of the factors used is extreme weather events, which they model both by using high temperature, precipitation, and drought data, and by using the National Oceanic and Atmospheric Administration's (NOAA) Climate Extremes Index. They find insignificant results with both models. However, since there is spatial variation in climate concern and extreme weather events across the US, using a national climate concern index may not be suitable due to the high level of aggregation. Marquart-Pyatt *et al.* (2014) also use the NOAA Climate Extremes Index to test models using different levels of seasonality and time spans. They use a lower level of spatial aggregation, combining the NOAA's nine climate regions with Gallup Environmental Poll data, however, they also find that public perceptions of climate change are not affected by extreme weather.

Konisky *et al.* (2016) use an even lower level of spatial aggregation to examine the relationship between individual climate opinions and extreme weather events, so that there is more confidence that individuals actually experienced a given event. They use extreme weather data from the NOAA *Storm Events Database*. This data is aggregated using the 122 Weather Forecasting Offices (WFOs) in the US. They only focus on events related to warmer temperatures (more heat waves and drought), increased precipitation, increased tropical storms, and sea-level rise, as these events are predicted to increase in frequency and severity due to climate change. This data is matched to public opinion data from the *Cooperative Congressional Election Study* (CCES) for 2010 to 2012. The survey start time is recorded for each respondent, so the timing of the survey can be matched precisely with the occurrence of weather events, allowing the weather experienced prior to the survey to vary among individuals. The CCES collects individual responses on climate opinion using a 5-point scale, which is used as the dependent variable. The first model uses the sum of extreme weather episodes, while controlling for political and demographic attributes, and WFO-level fixed effects. This model is estimated for the month prior to the individual undertaking the survey, and they find a statistically significant coefficient on extreme weather events, which is small but practically meaningful.

Previous studies use a less precise level of spatial aggregation of data, whereas I use data for the 3142 counties in the US, which increases the probability that an individual actually experienced a given natural hazard. Additionally, I use fifteen hazards in my analysis, not only “warm” hazards (such as heatwaves, drought, or wildfires) which are directly linked to climate change, but also “cold” hazards (such as avalanches or extreme winter weather) which may decrease belief in global warming. Furthermore, the climate opinion dataset I use contains separate variables for belief that global warming is happening and belief that global warming will harm one personally. Other research has not examined how experiencing extreme weather events affects these two climate opinions differently.

# 3 Data

## 3.1 SHELDUS Natural Hazard Data

I use county-level natural hazard data from the Spatial Hazard Events and Losses Database for the United States (SHELDUS) to measure the number of natural hazard events that have taken place. I remove data on *earthquakes*, *tsunamis*, and *volcanos* based on the assumption that individuals do not ascribe these hazards to climate change. Therefore, my analysis uses fifteen hazards, which are listed in Table 1. I use the frequency of natural hazards occurrences in each county as a measure of extreme weather experience.

Scientists have established a close link between some hazards and climate change, while for other hazards the link is more unclear (Van Aalst, 2006). For example, the probability of droughts and heatwaves are very likely to increase due to climate change, but the link between hurricanes and climate change is less certain (Field *et al.*, 2014). Previous research has only included the hazards that are closely linked with climate change, but it is useful to differentiate between “warm” hazards and “cold” hazards to see whether these different hazard types affect people’s beliefs differently. I use “warm” hazards to refer to those that are closely linked to climate change and associated with warm temperatures. In contrast, “cold” hazards are associated with cold weather and winter months. Although there is evidence that climate change can increase the probability of severe winter weather in the US (e.g., Cohen *et al.*, 2018; Kim *et al.*, 2017), I do not expect lay people to interpret the weather they experience in this way. I hypothesize that when an individual experiences "cold" hazards, they may interpret this as evidence that climate change is not occurring, and this would therefore cause a reduction in the climate opinion measures I use. I include each hazard in my analysis as a separate explanatory variable to differentiate the effects of different types of hazards on climate opinions.

### 3.2 Yale Climate Opinion Maps

I match the natural hazard data with county-level data from the Yale Program on Climate Change Communication (YPCCC). This survey-based opinion data contains information on how Americans' climate change beliefs, risk perceptions, and policy positions vary across the country. From the 2014 and 2016 datasets, I use two dependant variables. The first is the estimated percentage of individuals in the county who think that global warming is happening (*%Belief*). The second is individuals' risk perception associated with climate change, measured by the estimated percentage of individuals in the county who think global warming will harm them personally a moderate amount or a great deal (*%Personal*). Appendix 1 contains the survey question wording.

## 4 Methodology

Combining the two datasets, I estimate whether areas that have experienced stronger effects from natural hazards in recent years have higher levels of belief in climate change. I include as right-hand-side variables each of the hazards, along with a control variable for political affiliation in the county which is a proxy for county-level fixed effects.

To conduct the analysis, I sum each type of natural hazard at the county-level over a 10-year period (Table 2 provides summary statistics). I estimate models (1) to (8) using Ordinary

Least Squares (OLS) regression, with robust standard errors to account for spatial clustering of residuals.

### 4.1 Level Model Specification

First, I examine whether higher levels of natural hazard occurrences cause higher levels of belief in climate change or higher levels of perceived personal risk from climate change. The baseline statistical models are:

$$\%Belief_i = \alpha + \beta\%GOP_i + \boldsymbol{Haz_i\delta} + \varepsilon_i \tag{1}$$

and

$$\%Personal_i = \alpha + \beta\%GOP_i + \boldsymbol{Haz_i\delta} + \varepsilon_i \tag{2}$$

where *i* indexes the counties, *%Belief* is the percentage of people in the county in 2016 who believe that global warming is happening, *%Personal* is the percentage of people in the county in 2016 who believe that global warming will affect them personally, *%GOP* is the percentage of people in the county who voted for Trump in the 2016 presidential election, ***Haz*** is a vector of the count of hazards in the previous 10 years for each of the fifteen hazards listed in Table 1, and $\varepsilon$ is an iid error term.

#### 4.1.2 Supplementary Level Models

Climate change may lead to an increase in the frequency of natural hazard occurrences over time. I examine whether trends in natural hazard occurrences over time partly explain climate change opinions. To do so, I estimate the models:

$$\%Belief_i = \alpha + \beta\%GOP_i + \boldsymbol{Haz_i\delta} + \boldsymbol{Trend_i\gamma} + \varepsilon_i \tag{3}$$

and

$$\%Personal_i = \alpha + \beta\%GOP_i + \boldsymbol{Haz_i\delta} + \boldsymbol{Trend_i\gamma} + \varepsilon_i \tag{4}$$

where ***Trend*** is a vector of the trend of each disaster type over the previous 10 years. This is measured by fitting a trendline to the hazard data and only using the trend if it is significant; otherwise I use a zero for the trend. Although using these estimated values may introduce some error, the estimates will be biased towards zero, so I am unlikely to find false positive results. In this model I do not just consider the level of extreme weather experienced in each county, but whether an actual increase or decrease in hazard occurrences in recent years affects climate opinions.

Additionally, I test whether future projected damages from climate change affect county-level climate opinions. I use data from the Climate Impact Lab. It measures projected total damages from climate change as a percent of county income for 2080-2099 under a business-as-usual climate change scenario. It may be the case that expected personal harm from climate change is not caused by previous extreme weather experience, but by the expected economic damages in one's county. I examine whether current perceived risk is more affected by personal experience of disasters or by future projected impacts of climate change. I do not include a specification using *%Belief* because belief in global warming is not likely to be affected by damages that have not yet been incurred, whereas perceived personal risk may be. I estimate the model:

$$\%Personal_i = \alpha + \beta\%GOP_i + \varphi Proj_i + \boldsymbol{Haz_i\delta} + \varepsilon_i \tag{5}$$

Where *Proj* is projected future damages from climate change. Although projected damages are not widely publicized, they may reflect local information that people already have. Therefore, people may respond to these projections even if they do not have precise knowledge about the future monetary damage expected due to climate change in their county.

### 4.2 Difference in Belief vs. Personal Risk Model Specification

In all counties, the belief that global warming is happening is higher than the belief that it will affect one personally. However, the magnitude of this difference varies spatially. I examine whether this difference in opinions can be explained by the natural hazard experience in each county. For example, if a county has a high level of belief in climate change, but a low level of risk perception, this may be explained by an absence of natural disasters in the past. To address the hypothesis that the difference in belief that global warming is happening and the belief that it will affect one personally can be explained by natural hazard occurrences, I estimate the model:

$$\%Belief_i - \%Personal_i = \alpha + \beta\%GOP_i + \boldsymbol{Haz_i\delta} + \varepsilon_i \tag{6}$$

As the number of hazards experienced increases, I expect the difference to become smaller. If this hypothesis holds, we should see negative δ coefficients on the hazard variables in this model.

### 4.3 First-Difference Model Specification

I calculate the change in *%Belief* and *%Personal* from 2014 to 2016. With this data I conduct a cross-sectional analysis to determine whether the change in climate opinions from 2014 to 2016 can be explained by natural hazard occurrences during this time period. This method controls for unobserved county-level fixed effects, while the previous models did not.

Using the base level models (1) and (2), and simplifying by setting *y* as the climate opinion dependent variable, I index all variables for the years t and t-2. I take the first difference of the 2016 and the 2014 base level models:

$$y_{i,t} - y_{i,t-2} = (\alpha - \alpha) + \beta(\%GOP_i - \%GOP_i) + \boldsymbol{\delta}(\boldsymbol{Haz_{i,t}} - \boldsymbol{Haz_{i,t-2}}) + (\varepsilon_{i,t} - \varepsilon_{i,t-2})$$

The time invariant effects ($\alpha$ and *%GOP*$_i$) cancel out, so any time invariant, cross-county variation is controlled for. Substituting *%Belief* and *%Personal* in for *y*, this simplifies to the following models that I estimate:

$$\Delta\%Belief_{i,t} = \Delta \boldsymbol{Haz_{i,t}} \boldsymbol{\delta} + v_{i,t} \tag{7}$$

$$\Delta\%Personal_{i,t} = \Delta \boldsymbol{Haz_{i,t}}\, \boldsymbol{\delta} + \; v_{i,t} \tag{8}$$

where Δ*%Belief* is the change, from 2014 to 2016, in the percentage of people who believe global warming is happening, Δ*%Personal* is the change, from 2014 to 2016, in the percentage of people who believe global warming will affect them personally, and Δ***Haz*** is a vector of the change in natural hazard occurrences over 2014 and 2015. I do not have data on when in 2016 individuals took the climate opinion survey, so I do not include 2016 hazard data in the analysis. From 2014 to 2016, in 95% of counties *%Belief* increased and in 97% of counties *%Personal* increased. I test whether spatial differences in this increase can be explained by spatial differences in hazard occurrences during this period.

There are some data limitations in this analysis. The methodology used in creating the climate opinion datasets has changed over time, which may influence the comparability of data over time. Additionally, my analysis is limited to using two years of data rather than being a true time series, due to data availability. Nonetheless, it is useful to conduct this analysis with the data that is currently available, as this is an interesting and important area for future research.

# 5 Results

## 5.1 Level Analysis

In Table 3 I report the estimates of models (1) and (2). Each column contains estimates using *%Belief* and *%Personal* as the dependent variables. The coefficients on hazards in the *%Belief* specification are generally insignificant or small. Therefore, I do not find evidence that natural hazard occurrences substantially explain variation in belief in global warming under this model specification. Potential explanations for this may be that people don't adjust their belief on whether climate change is occurring based on natural hazard experience, the effect is not strong enough to show up on the aggregate level, or that belief is not strongly affected by natural disasters, but instead by temperature variation or temperature extremes (as found by Kaufmann *et al.*, 2017). Additionally, there may be omitted variable bias which is causing the coefficient estimates to be downward biased. This is addressed in section 5.3 by using a first-difference model which controls for county-level fixed effects.

For the *%Personal* specification, the coefficients on all hazards except *landslide* and *tornado* are statistically significant. I expect "warm" hazards to have positive coefficients and "cold" hazards to have negative coefficients. *Coastal, drought, fog, hail, heat, hurricane/tropical storm*, and *wildfire* have positive and significant coefficient estimates. *Avalanche*, *flooding*, *lightning, severe storm/thunder storm*, *wind,* and *winter weather* have negative and significant coefficient estimates. The estimated coefficients generally (though not always) have the expected signs. I find that coefficients on some hazards related to precipitation have unexpected signs. *Flooding* and *severe storm/thunder storm* have negative coefficients, whereas *fog* and *hail* have positive coefficients. Precipitation events are expected to increase in intensity and frequency due to climate change (Field *et al.*, 2014). Therefore, I generally expect positive coefficients on precipitation related hazards, especially *flooding*. The negative coefficients I find may be explained by precipitation related events being perceived as "cold" hazards by lay people. Alternatively, there may be a mixed interpretation of these types of weather events by lay people, leading to these mixed results.

The coefficient estimates on *hurricane/tropical storm* and *wildfire* are statistically significant and practically meaningful. However, *fog* also has a large coefficient which is unexpected. This may be because the location of *fog* events are mainly in California, which overlaps with areas of *heat* and *drought*, so *fog* may be capturing this effect (Figure 1). I estimate model (2) again, but remove California from the sample, and in this case my results hold, but *fog* is no longer statistically significant (Table 3.1). Also, if *fog* is removed from the sample and model (2) is estimated, the main results still hold (Table 3.1). It is also possible that the large coefficient on *fog* is due to the prior baseline beliefs in counties where *fog* occurs. Most *fog* events occur in California which has historically had high levels of belief and risk perception associated with climate change, so that may be explain this result.

Although models (1) and (2) use the count of hazards over a 10-year window, the results hold if I choose other windows of time. Figure 2.1 and 2.2 show the sensitivity of coefficients when summing the number of hazards over different windows of time. The coefficient estimates remain significant and positive for *hurricane/tropical storm* and *wildfire* over different length time windows, as long as the sample is sufficiently large.

#### 5.1.2 Supplementary Level Analysis

I estimate models (3) and (4) and report the results in Table 4. I find that the effect of the trends of hazards over time are generally insignificant or small, but that my prior results are robust to the inclusion of trends over time.

I estimate model (5) and report the results in Table 5. I find that projected future damages affect personal risk perception associated with climate change. In this specification I find statistically significant and large coefficients on *projected total damages*, *avalanche, fog*, and *wildfire.* Most notably, *hurricane/tropical storm* is no longer significant which may be because projected future damages are concentrated along the southeastern coast of the US (Figure 3). Therefore, I find that perceived personal harm is affected more by how hurricanes may affect an individual in the future than by an individual's past experience of these storms.

### 5.2 Analysis of Difference in Belief vs. Personal Risk

When assessing the results of the specification where I estimate determinants of the difference between *%Belief* and *%Personal*, I expect the $\delta$ coefficients on climate related hazards to be negative, such that counties with more extreme weather have a smaller difference in these opinion measures. I estimate model (6) and find that the hypothesis holds in the data. I report the estimates in Table 6. The results are very similar the prior estimates I find when estimating model (2).

The coefficients on *hurricane/tropical storm, wildfire,* and *fog* are significant and practically meaningful. Additionally, the results generally follow the expected signs for "warm" and "cold" hazards, with positive and significant coefficients on *drought*, *fog, hurricane/tropical storm, severe storm/thunder storm, tornado,* and *wildfire*, and a negative and significant coefficient on *winter weather*.

### 5.3 First-Difference Analysis

I report the estimates for models (7) and (8) in Table 7. These specifications control for county-level fixed effects and account for potential omitted variable bias present in the previous models. For both the *%Belief* and *%Personal* specifications, I find that the estimated coefficients on *drought* and *wildfire* are significant, positive, and large. For the *%Belief* specification I also find negative and significant coefficients on *severe storm/thunder storm* and *winter weather*, and a positive and significant coefficient on *wind.* For the *%Personal* specification I find a negative and significant (but small) coefficient on *flooding*, and a positive and significant coefficient on *wind.*

Unlike the previous models, by using the first-difference model I find that natural hazards have a significant effect on belief that global warming is happening. I also find that *fog* no longer has a significant effect on personal harm associated with global warming once county-level fixed effects are controlled for. This indicates that the previous large coefficients on *fog* I found when estimating the level models (model (2) and (3)) were likely due to the high baseline beliefs in California. Therefore, this suggests that the level models I estimate do not fully capture unobserved county-level fixed effects.

However, I find that these results are not robust to other specifications of the $\Delta$***Haz*** variable. For example, if for the $\Delta$***Haz*** variable I subtract average hazard occurrences in 2012 and 2013 from average hazard occurrences in 2014 and 2015, my results do not hold. As more years of data become available, future research should consider examining whether the results hold over time.

## 6 Discussion

In this paper, I find evidence that natural hazard experience causes higher levels of perceived personal harm from climate change. Furthermore, I find that disasters more closely associated with warm weather have a positive effect on perceived personal harm from climate change, whereas disasters that are associated with cold weather generally have a negative effect. Using my levels models, I do not find evidence that experiencing higher levels of natural disasters leads to higher levels of belief in climate change. An explanation for this is that the levels specification does not completely control for county-level fixed effects, so there may be omitted variable bias that could cause the coefficient estimates to be downward biased.

The first-difference analysis allows me to control for unobserved county-level fixed effects, and under these models, I find evidence that natural hazard experience does affect belief that global warming is happening. Specifically, *drought* and *wildfire* events lead to an increase in belief in global warming, as well as higher levels of predicted personal harm. As more years of climate opinion data becomes available, further research should conduct a time series analysis to further explore the relationship between hazard experience and climate opinions.

Individuals often believe that global warming is a problem for future generations, and that it will not affect them significantly in their lifetime. This leads to less incentive to support policies that mitigate the effects of climate change, because individuals face a cost today but infer that they will receive no benefit. I find evidence that experiencing natural hazards causes an increase in both belief that global warming is happening, and perceived personal risk associated with global warming. Therefore, global warming becomes something that will lead to negative impacts within one's own lifetime. Once people recognize the personal costs that they will face due to climate change, they may be more willing to act on the issue.

This should be taken into consideration when choosing how to communicate climate change information to the public. After a natural disaster, if communication focuses on how natural disasters are linked to climate change, this may help shift people's beliefs. Natural disaster experience presents an opportunity to gain support for policies to mitigate the effects of climate change, decrease carbon emissions, and fund disaster relief.

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## Appendix 1: Survey Question Wording

Survey question used by the YPCCC to estimate the percentage of individuals in the county who think that global warming is happening (*%Belief*):

> "**Global warming is happening**
>
> Recently, you may have noticed that *global warming* has been getting some attention in the news. Global warming refers to the idea that the world's average temperature has been increasing over the past 150 years, may be increasing more in the future, and that the world's climate may change as a result. What do you think: Do you think that global warming is happening?
>
> - Yes
> - No
> - Don't know"

Survey question used by the YPCCC to estimate the percentage of individuals in the county who think global warming will harm them personally a moderate amount or a great deal (*%Personal*):

> "**Global warming will harm me personally**
>
> How much do you think global warming will harm you personally?
>
> - Not at all
> - Only a little
> - A moderate amount
> - A great deal
> - Don't know"

## Appendix 2: Figures

**Figure 1. Count of *fog* events over 10 years**

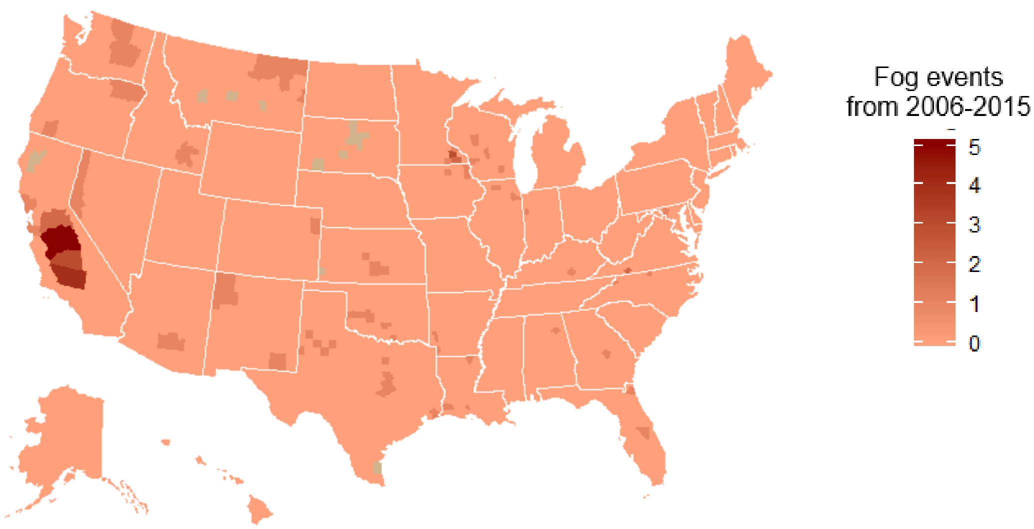


**Figure 2.1. Sensitivity of the coefficient on *hurricane/tropical storm* over different windows of time**

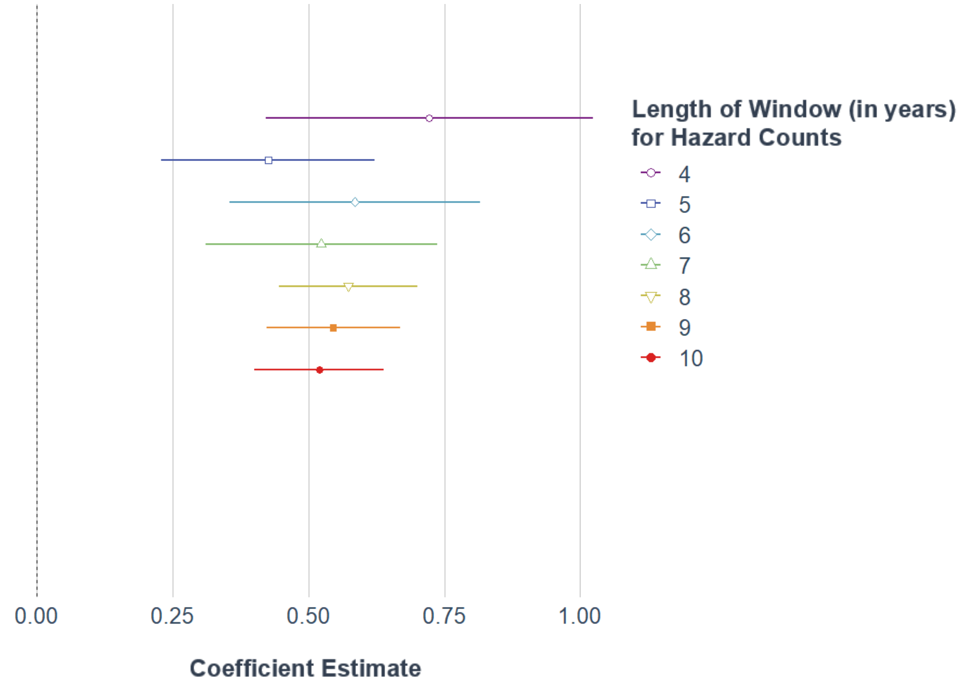



**Figure 2.2: Sensitivity of the coefficient on *wildfire* over different windows of time**

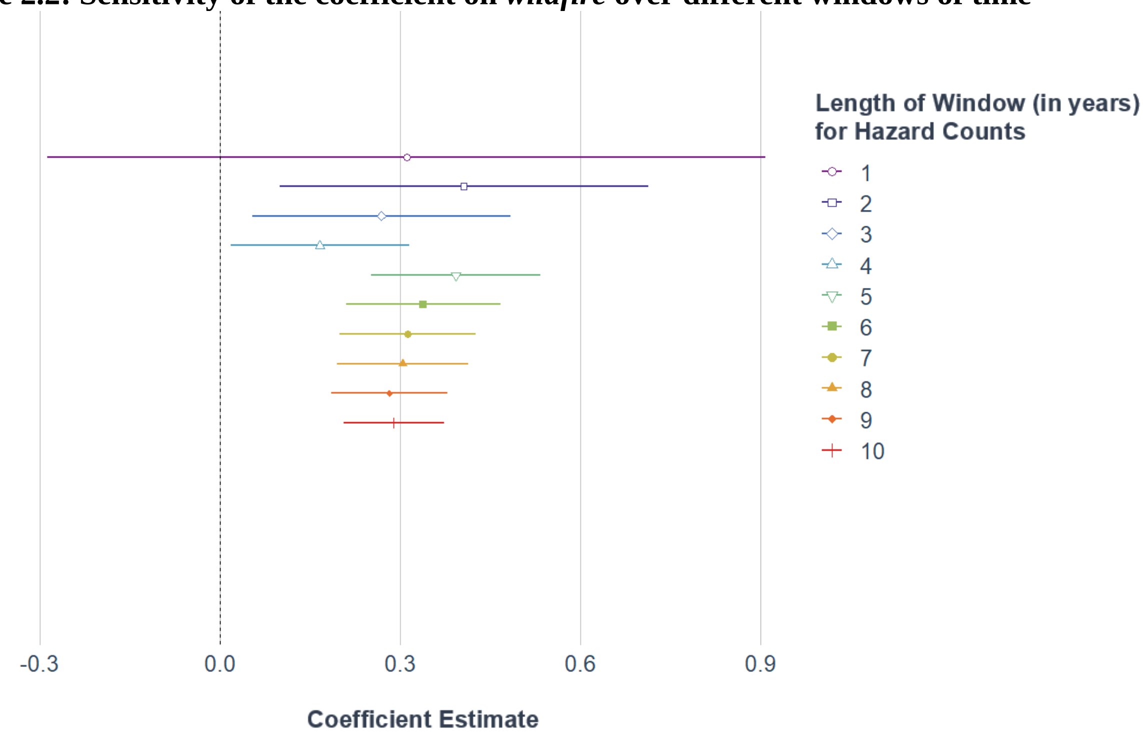
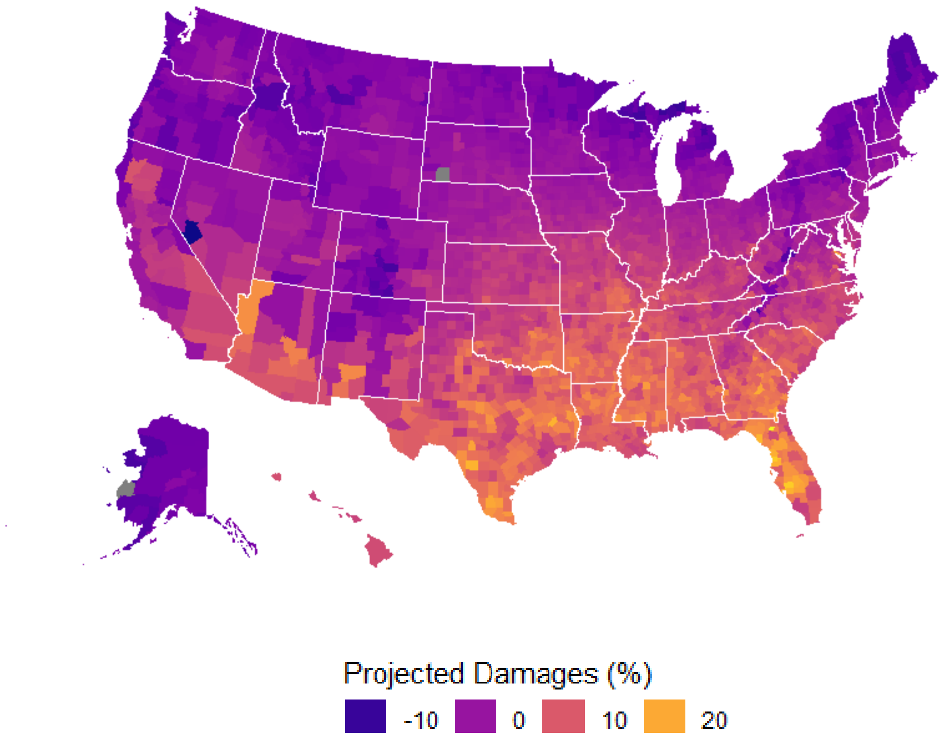


**Figure 3: Projected total damages from climate change as a percent of county income for 2080-2099 under a business-as-usual climate change scenario**



## Appendix 3: Tables

**Table 1. Types of natural hazards**

<table>
<tr><th>Natural Hazards</th><td rowspan="16">Note:<br><br>The original source of this data is the US National Centers for Environmental Information Storm Data and Unusual Weather Phenomena. This data is used for the official National Oceanic and Atmospheric Administration (NOAA) Storm Data publication.<br><br>The Spatial Hazard Events and Losses Database for the United States (SHELDUS) that I use for my analysis compiles data from the NOAA Storm Data publication.<br><br>The official NOAA Storm Data publication includes events that satisfy one or more of the following conditions:<br><br>1. The occurrence of storms and other significant weather phenomena having sufficient intensity to cause loss of life, injuries, significant property damage, and/or disruption to commerce;<br><br>2. Rare, unusual, weather phenomena that generate media attention, such as snow flurries in South Florida or the San Diego coastal area; and<br><br>3. Other significant meteorological events, such as record maximum or minimum temperatures or precipitation that occur in connection with another event.</td></tr>
<tr><td>Avalanche</td></tr>
<tr><td>Coastal</td></tr>
<tr><td>Drought</td></tr>
<tr><td>Flooding</td></tr>
<tr><td>Fog</td></tr>
<tr><td>Hail</td></tr>
<tr><td>Heat</td></tr>
<tr><td>Hurricane/Tropical Storm</td></tr>
<tr><td>Landslide</td></tr>
<tr><td>Lightning</td></tr>
<tr><td>Severe Storm/Thunder Storm</td></tr>
<tr><td>Tornado</td></tr>
<tr><td>Wildfire</td></tr>
<tr><td>Wind</td></tr>
<tr><td>Winter Weather</td></tr>
</table>

**Table 2. Summary statistics (count of hazards at the county-level from 2006-2015; other variables measured in 2016)**

| | Mean | St. Dev. | Min | Pctile(25) | Pctile(75) | Max |
|---|---|---|---|---|---|---|
| ***Avalanche*** | 0.2 | 1.3 | 0 | 0 | 0 | 25 |
| ***Coastal*** | 0.2 | 1.3 | 0 | 0 | 0 | 30 |
| ***Drought*** | 1.2 | 5.6 | 0 | 0 | 0 | 56 |
| ***Flooding*** | 4.7 | 5.0 | 0 | 1 | 7 | 53 |
| ***Fog*** | 0.0 | 0.3 | 0 | 0 | 0 | 5 |
| ***Hail*** | 2.1 | 3.6 | 0 | 0 | 3 | 34 |
| ***Heat*** | 0.4 | 1.2 | 0 | 0 | 0 | 25 |
| ***Hurricane/ Tropical Storm*** | 0.3 | 0.7 | 0 | 0 | 0 | 5 |
| ***Landslide*** | 0.2 | 0.9 | 0 | 0 | 0 | 14 |
| ***Lightning*** | 1.6 | 3.0 | 0 | 0 | 2 | 28 |
| ***Severe Storm/ Thunder Storm*** | 12.7 | 10.6 | 0 | 4 | 20 | 52 |
| ***Tornado*** | 1.8 | 2.0 | 0 | 0 | 3 | 16 |
| ***Wildfire*** | 0.4 | 1.5 | 0 | 0 | 0 | 29 |
| ***Wind*** | 17.0 | 13.2 | 0 | 6 | 25 | 76 |
| ***Winter Weather*** | 2.8 | 4.8 | 0 | 1 | 3 | 48 |
| **%GOP** | 63.5 | 15.6 | 4.1 | 54.6 | 74.9 | 95.3 |
| ***%Belief*** | 64.7 | 5.5 | 48.8 | 60.9 | 67.8 | 84.0 |
| ***%Personal*** | 36.1 | 4.2 | 28.9 | 33.3 | 38.0 | 56.9 |

**Table 3. Level models results using climate opinions as a function of hazard occurrences (Models (1) and (2))**

| | *Dependent variable:* | |
|---|---|---|
| | %Belief | %Personal |
| | (1) | (2) |
| %GOP | -0.304*** | -0.219*** |
| | (0.344) | (0.391) |
| Count Avalanche | -0.078 | -0.159*** |
| | (0.061) | (0.044) |
| Count Coastal | 0.160*** | 0.066* |
| | (0.034) | (0.040) |
| Count Drought | -0.018* | 0.044*** |
| | (0.009) | (0.008) |
| Count Flooding | -0.038*** | -0.054*** |
| | (0.011) | (0.010) |
| Count Fog | 0.197 | 0.871*** |
| | (0.122) | (0.194) |
| Count Hail | 0.063*** | 0.067*** |
| | (0.014) | (0.014) |
| Count Heat | 0.014 | 0.089* |
| | (0.032) | (0.050) |
| Count Hurricane/Tropical Storm | -0.164** | 0.520*** |
| | (0.072) | (0.060) |
| Count Landslide | 0.099 | -0.063 |
| | (0.065) | (0.076) |
| Count Lightning | 0.055*** | -0.086*** |
| | (0.018) | (0.018) |
| Count Severe Storm/Thunder Storm | -0.048*** | -0.015* |
| | (0.009) | (0.009) |
| Count Tornado | -0.107*** | -0.012 |
| | (0.026) | (0.023) |
| Count Wildfire | -0.007 | 0.290*** |
| | (0.033) | (0.042) |
| Count Wind | 0.003 | -0.020*** |
| | (0.007) | (0.007) |
| Count Winter Weather | 0.047*** | -0.046*** |
| | (0.008) | (0.009) |
| Constant | 84.617*** | 50.612*** |
| | (0.240) | (0.293) |
| Observations | 3,128 | 3,128 |
| $R^2$ | 0.795 | 0.652 |

Standard errors in parentheses
$^{*}$p$^{**}$p$^{***}$p<0.01

**Table 3.1. Sensitivity tests related to the *fog* variable**

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | %Belief | | | %Personal | | |
| | Base Model | Sample without California | Sample without fog variable | Base Model | Sample without California | Sample without fog variable |
| %GOP | -0.304$^{***}$ | -0.304$^{***}$ | -0.304$^{***}$ | -0.219$^{***}$ | -0.217$^{***}$ | -0.219$^{***}$ |
| | (0.344) | (0.353) | (0.344) | (0.391) | (0.401) | (0.391) |
| Count Avalanche | -0.078 | -0.083 | -0.080 | -0.159$^{***}$ | -0.120$^{***}$ | -0.171$^{***}$ |
| | (0.061) | (0.063) | (0.060) | (0.044) | (0.041) | (0.046) |
| Count Coastal | 0.160$^{***}$ | 0.185$^{***}$ | 0.161$^{***}$ | 0.066$^{*}$ | 0.053 | 0.072$^{*}$ |
| | (0.034) | (0.038) | (0.034) | (0.040) | (0.043) | (0.039) |
| Count Drought | -0.018$^{*}$ | -0.015 | -0.017$^{*}$ | 0.044$^{***}$ | 0.042$^{***}$ | 0.045$^{***}$ |
| | (0.009) | (0.009) | (0.009) | (0.008) | (0.008) | (0.008) |
| Count Flooding | -0.038$^{***}$ | -0.039$^{***}$ | -0.038$^{***}$ | -0.054$^{***}$ | -0.057$^{***}$ | -0.054$^{***}$ |
| | (0.011) | (0.011) | (0.011) | (0.010) | (0.010) | (0.010) |
| Count Fog | 0.197 | 0.226 | | 0.871$^{***}$ | 0.229 | |
| | (0.122) | (0.261) | | (0.194) | (0.260) | |
| Count Hail | 0.063$^{***}$ | 0.065$^{***}$ | 0.063$^{***}$ | 0.067$^{***}$ | 0.066$^{***}$ | 0.067$^{***}$ |
| | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) |
| Count Heat | 0.014 | 0.009 | 0.016 | 0.089$^{*}$ | 0.082 | 0.095$^{**}$ |
| | (0.032) | (0.033) | (0.032) | (0.050) | (0.050) | (0.048) |
| Count Hurricane/ Tropical Storm | -0.164$^{**}$ | -0.164$^{**}$ | -0.165$^{**}$ | 0.520$^{***}$ | 0.527$^{***}$ | 0.516$^{***}$ |
| | (0.072) | (0.073) | (0.072) | (0.060) | (0.060) | (0.060) |
| Count Landslide | 0.099 | 0.144$^{**}$ | 0.103 | -0.063 | -0.187$^{***}$ | -0.043 |
| | (0.065) | (0.070) | (0.065) | (0.076) | (0.072) | (0.075) |
| Count Lightning | 0.055$^{***}$ | 0.053$^{***}$ | 0.055$^{***}$ | -0.086$^{***}$ | -0.079$^{***}$ | -0.089$^{***}$ |
| | (0.018) | (0.018) | (0.017) | (0.018) | (0.019) | (0.018) |
| Count Severe Storm/ Thunder Storm | -0.048$^{***}$ | -0.047$^{***}$ | -0.050$^{***}$ | -0.015$^{*}$ | -0.011 | -0.020$^{**}$ |
| | (0.009) | (0.009) | (0.009) | (0.009) | (0.009) | (0.009) |
| Count Tornado | -0.107$^{***}$ | -0.107$^{***}$ | -0.107$^{***}$ | -0.012 | -0.014 | -0.013 |
| | (0.026) | (0.026) | (0.026) | (0.023) | (0.023) | (0.023) |
| Count Wildfire | -0.007 | -0.049 | -0.003 | 0.290$^{***}$ | 0.341$^{***}$ | 0.304$^{***}$ |
| | (0.033) | (0.041) | (0.032) | (0.042) | (0.064) | (0.042) |

| | | | | | | |
|---|---|---|---|---|---|---|
| Count Wind | 0.003 | 0.003 | 0.004 | -0.020*** | -0.022*** | -0.015** |
| | (0.007) | (0.008) | (0.007) | (0.007) | (0.007) | (0.008) |
| Count Winter Weather | 0.047*** | 0.047*** | 0.047*** | -0.046*** | -0.043*** | -0.045*** |
| | (0.008) | (0.008) | (0.008) | (0.009) | (0.009) | (0.009) |
| Constant | 84.617*** | 84.578*** | 84.622*** | 50.612*** | 50.468*** | 50.633*** |
| | (0.240) | (0.249) | (0.240) | (0.293) | (0.301) | (0.293) |
| Observations | 3,128 | 3,071 | 3,128 | 3,128 | 3,071 | 3,128 |
| $R^2$ | 0.795 | 0.786 | 0.795 | 0.652 | 0.637 | 0.648 |

Standard errors in parentheses
*p**p***p<0.01

**Table 4. Level models including trend variables (Models (3) and (4))**

| | *Dependent variable:* | |
|---|---|---|
| | %Belief | %Personal |
| | (3) | (4) |
| %GOP | -0.304*** | -0.220*** |
| | (0.347) | (0.393) |
| Count Avalanche | -0.078 | -0.159*** |
| | (0.061) | (0.044) |
| Count Coastal | 0.160*** | 0.066* |
| | (0.034) | (0.040) |
| Count Drought | -0.018* | 0.044*** |
| | (0.009) | (0.008) |
| Count Flooding | -0.038*** | -0.054*** |
| | (0.011) | (0.010) |
| Count Fog | 0.197 | 0.871*** |
| | (0.122) | (0.194) |
| Count Hail | 0.063*** | 0.067*** |
| | (0.014) | (0.014) |
| Count Heat | 0.014 | 0.089* |
| | (0.032) | (0.050) |
| Count Hurricane/Tropical Storm | -0.164** | 0.520*** |
| | (0.072) | (0.060) |
| Count Landslide | 0.099 | -0.063 |
| | (0.065) | (0.076) |
| Count Lightning | 0.055*** | -0.086*** |
| | (0.018) | (0.018) |
| Count Severe Storm/Thunder Storm | -0.048*** | -0.015* |
| | (0.009) | (0.009) |
| Count Tornado | -0.107*** | -0.012 |
| | (0.026) | (0.023) |
| Count Wildfire | -0.007 | 0.290*** |
| | (0.033) | (0.042) |
| Count Wind | 0.003 | -0.020*** |
| | (0.007) | (0.007) |
| Count Winter Weather | 0.047*** | -0.046*** |
| | (0.008) | (0.009) |
| Trend Avalanche | 4.991 | 6.022 |
| | (4.931) | (5.461) |

| | | |
|---|---|---|
| Trend Coastal | -9.942** | 3.773 |
| | (4.182) | (5.675) |
| Trend Drought | 0.464 | 2.706** |
| | (0.662) | (1.137) |
| Trend Flooding | 7.597* | -3.913 |
| | (4.171) | (3.640) |
| Trend Fog | | |
| Trend Hail | 2.028** | 2.500*** |
| | (0.953) | (0.934) |
| Trend Heat | -0.141 | -0.287 |
| | (1.290) | (2.862) |
| Trend Hurricane/Tropical Storm | -3.715 | -8.828 |
| | (16.150) | (13.331) |
| Trend Landslide | 1.197 | 0.381 |
| | (2.867) | (3.665) |
| Trend Lightning | 3.949*** | 1.801 |
| | (1.195) | (1.328) |
| Trend Severe Storm/Thunder Storm | 0.792 | 1.376** |
| | (0.563) | (0.542) |
| Trend Tornado | 0.778 | 2.496 |
| | (2.338) | (1.607) |
| Trend Wildfire | -0.678 | 2.619 |
| | (2.728) | (4.736) |
| Trend Wind | -0.522 | -0.677 |
| | (0.459) | (0.518) |
| Trend Winter Weather | -1.160 | 0.312 |
| | (0.826) | (0.747) |
| Constant | 84.566*** | 50.640*** |
| | (0.243) | (0.297) |
| Observations | 3,097 | 3,097 |
| $R^2$ | 0.797 | 0.658 |

Note: Trend of fog results are unavailable due to small sample size
Standard errors in parentheses
*p **p ***p<0.01

**Table 5: Level model including projected total damages due to climate change (Model (5))**

| | *Dependent variable:* |
|---|---|
| | %Personal |
| | (5) |
| %GOP | -0.226*** |
| | (0.293) |
| Projected Total Damages | 0.195*** |
| | (0.009) |
| Count Avalanche | -0.104*** |
| | (0.036) |
| Count Coastal | 0.071** |
| | (0.035) |
| Count Drought | 0.016* |
| | (0.008) |
| Count Flooding | -0.046*** |
| | (0.010) |
| Count Fog | 0.792*** |
| | (0.150) |
| Count Hail | 0.079*** |
| | (0.014) |
| Count Heat | 0.019 |
| | (0.037) |
| Count Hurricane/Tropical Storm | 0.042 |
| | (0.068) |
| Count Landslide | -0.025 |
| | (0.054) |
| Count Lightning | -0.069*** |
| | (0.017) |
| Count Severe Storm/Thunder Storm | -0.055*** |
| | (0.009) |
| Count Tornado | -0.096*** |
| | (0.025) |
| Count Wildfire | 0.253*** |
| | (0.031) |
| Count Wind | 0.003 |
| | (0.007) |
| Count Winter Weather | -0.020* |
| | (0.011) |
| Constant | 50.469*** |
| | (0.208) |
| Observations | 3,127 |
| $R^2$ | 0.699 |

Standard errors in parentheses
*p**p***p<0.01

**Table 6. Difference in belief vs. personal risk model results (Model (6))**

| | *Dependent variable:* |
|---|---|
| | %Belief - %Personal<br>(6) |
| %GOP | -0.085$^{***}$ |
| | (0.461) |
| Count Avalanche | 0.081 |
| | (0.068) |
| Count Coastal | 0.094$^{**}$ |
| | (0.045) |
| Count Drought | -0.061$^{***}$ |
| | (0.009) |
| Count Flooding | 0.016 |
| | (0.012) |
| Count Fog | -0.673$^{***}$ |
| | (0.230) |
| Count Hail | -0.004 |
| | (0.014) |
| Count Heat | -0.074 |
| | (0.054) |
| Count Hurricane/Tropical Storm | -0.684$^{***}$ |
| | (0.076) |
| Count Landslide | 0.162$^{*}$ |
| | (0.096) |
| Count Lightning | 0.142$^{***}$ |
| | (0.022) |
| Count Severe Storm/Thunder Storm | -0.034$^{***}$ |
| | (0.010) |
| Count Tornado | -0.095$^{***}$ |
| | (0.028) |
| Count Wildfire | -0.296$^{***}$ |
| | (0.041) |
| Count Wind | 0.023$^{***}$ |
| | (0.008) |
| Count Winter Weather | 0.093$^{***}$ |
| | (0.009) |
| Constant | 34.006$^{***}$ |
| | (0.339) |
| Observations | 3,128 |
| $R^2$ | 0.322 |

Standard errors in parentheses
$^{*}$p$^{**}$p$^{***}$p<0.01

**Table 7: First-difference models using the change in climate opinions as a function of change in hazards over time (Models (7) and (8))**

| | *Dependent variable:* | |
|---|---|---|
| | Δ%Belief | Δ%Personal |
| | (7) | (8) |
| ΔAvalanche | -0.093 | 0.186 |
| | (0.263) | (0.198) |
| ΔCoastal | -0.174 | -0.251 |
| | (0.299) | (0.221) |
| ΔDrought | 0.788*** | 0.360*** |
| | (0.150) | (0.089) |
| ΔFlooding | -0.083 | -0.073* |
| | (0.069) | (0.042) |
| ΔFog | 0.483 | 0.655 |
| | (0.648) | (0.593) |
| ΔHail | -0.006 | -0.114 |
| | (0.120) | (0.079) |
| ΔHeat | 0.388 | 0.084 |
| | (0.389) | (0.238) |
| ΔHurricane/Tropical Storm | 0.855 | 0.096 |
| | (1.195) | (1.153) |
| ΔLandslide | -0.111 | -0.197 |
| | (0.167) | (0.122) |
| ΔLightning | -0.167 | -0.050 |
| | (0.117) | (0.079) |
| ΔSevere Storm/Thunder Storm | -0.249* | -0.145 |
| | (0.150) | (0.088) |
| ΔTornado | -0.102 | -0.076 |
| | (0.112) | (0.071) |
| ΔWildfire | 0.616*** | 0.431*** |
| | (0.170) | (0.121) |
| ΔWind | 0.288* | 0.177** |
| | (0.150) | (0.088) |
| ΔWinter Weather | -0.162 | -0.035 |
| | (0.108) | (0.065) |
| Constant | 5.738*** | 4.186*** |
| | (0.084) | (0.051) |
| Observations | 3,141 | 3,141 |
| $R^2$ | 0.014 | 0.012 |

Standard errors in parentheses
*p**p***p<0.01