Online Appendix
Do Disasters Change Risk Perceptions and Policy Preferences about Climate Change?

Giancarlo Visconti* Kayla Young†

May 4, 2020

Contents

*Assistant Professor, Department of Political Science, Purdue University, West Lafayette, IN 47907, email: gviscont@purdue.edu.

†Ph.D. Student, Department of Political Science, Purdue University, West Lafayette, IN 47907, email: young530@purdue.edu.

A Appendix A: Disasters and climate change

There is an emerging scientific consensus that climate change will exacerbate many types of natural disasters, making them more frequent and severe. These effects may vary between regions, however, meaning that some areas could experience more intense wildfire events while others endure extreme snow storms (Field et al., 2012). To account for this, our study includes an array of disasters that can be associated with climate change. We provide evidence that supports our inclusion (or exclusion) of these types of events below.

Floods: While flooding can occur throughout the United States, it most often affects Northeastern and Midwestern communities. Given potential changes in precipitation because of climate change and anticipated sea-level rise, floods may become more severe and more frequent in certain regions (Field et al., 2012; Masson-Delmotte et al., 2018; NASA, 2020). Multiple studies therefore suggest a theoretical rationale for exploring the relationship between exposure to floods and attitudes about climate change (Whitmarsh, 2008; Spence et al., 2011).

Severe storms, coastal storms, and snow: Heavy precipitation, including both rain and snowfall, is believed to have already increased and will likely continue to increase in some regions due to climate change (Masson-Delmotte et al., 2018). There is evidence to suggest that the general public is attuned to these kinds of weather fluctuations (Lang, 2014). Notably, 40 percent of the US population lived in a coastal county in 2016, which are particularly vulnerable to the effects of changing precipitation compounded by sea-level rise (NOAA, 2020; IPCC, 2018).

Tornadoes: Tornadoes are a relatively frequent occurrence in the United States, appearing in the South, Midwest, and Great Plains. Data that supports the correlation between tornadoes and climate change is relatively limited (Field et al., 2012), though some scholars suggest that it may be important to consider these weather events when preparing for the risks of a changing climate (McBean, 2005).

Ice: Although data limitations similarly make understanding the potential connection between climate change and ice storms difficult, they are included in potential weather extremes analyzed by the Intergovernmental Panel on Climate Change (Field et al., 2012). Given the evidence associated with changes in precipitation patterns generally, we include extreme ice events.

Mud/landslides: (Gariano and Guzzetti, 2016, P.228) note that "different phenomena influence the stability of slopes and cause landslides, including e.g., precipitation, snow melting, temperature changes, earthquake shaking, volcanic activity, and various human actions." Therefore, while mud/landslides may not always be a direct cause of climate change, they are often associated with its anticipated alterations of the climate system. Therefore, in areas with higher precipitation, mud/landslides may be more common.

Fire: In the context of a warming planet and changes in precipitation that may lead to intense drought in some areas, fires that devastate entire towns may occur more frequently (NASA, 2020; Marlon et al., 2009). Recognizing this, some scholars have explored whether and how the public thinks about warming, climate change, and fires (Hamilton et al., 2016).

Hurricanes: Fueled in part by warm ocean waters, hurricanes tend to affect the Southern and Eastern coasts of the United States. Major events in the past 20 years include Hurricanes Katrina, Irma, and Michael. There is general consensus that the prevalence and severity of hurricanes is connected with a changing global climate (Mann and Emanuel, 2006; Field et al., 2012; NASA, 2020). Whereas media coverage of previous decades may not have included substantial or any discussion of the potential association between such occurrences and climate change, today there seems to be more media attention to climate change after hurricanes (Cody et al., 2017).

Some disaster types that could be associated with climate change did not occur during the time period of our assessment, namely **typhoon** and **freezing** events (Field et al., 2012).[1] Similarly, **droughts** can also be connected with climate change (Field et al., 2012), but FEMA stopped reporting drought incidents since 1993. There are also federally declared disaster events that do not have clear associations with climate change and were not included in our treatment indicator. These include: earthquakes, tsunamis, terrorist attacks, toxic substance spills, dam/levee collapses, fishing losses, chemical spills, and others (e.g., severe hardship).

Generally, **earthquakes** are not causally connected with climate change; rather, they are caused by tectonic processes not known to be correlated with global warming (Buis, 2019). **Tsunamis** are driven by earthquakes beneath or near the ocean and are not included either. While dam/levee breaks and fishing losses could both be indirectly related to climate change (e.g., Hurricane Katrina as the catalyst for the breaking of a levee in the New Orleans area that caused severe damage), it is much harder to associate these events with global warming. This is also true for disasters that are human caused, such as chemical incidents. These events are therefore not included in our treatment indicator(s).

[1] Guam and Puerto Rico were affected by typhoons but we do not include those territories in our sample.

B Appendix B: Covariate balance

We draw on data from the YPCCC survey, the US Census, and the Inter-university Consortium for Political and Social Research (ICPSR)'s County Characteristics to generate a representative matched sample using approximately 300 relevant covariates. We constrain by demographic, political, economic, climatologic, and geographic considerations. Table A1 provides the mean for the population (i.e., all the units), the exposed group (after matching), and the control group (after matching). As a reminder, we construct a representative matched sample, so the exposed and the control groups are similar to the target population, and as a consequence are similar to each other as well. We report the standardized differences between the matched exposed and control group. The standardized differences between any of these two groups and the target population, by construction, is up to two times smaller than those reported in the table (see Visconti and Zubizarreta (2018) and Bennett et al. (2019) for more details).

Table A1: Covariate balance: Part I

Covariates	Mean Population	Mean Exposed	Mean Control	Standardized Differences
Survey year	2,016	2,016	2,016	0.010
Total population, 2010	98,780.000	112,319.000	92,599.000	0.060
Median age, 2010	40.420	40.310	40.430	0.020
New private housing, 2010	193.400	214.000	185.900	0.050
Crime, 2008	426.200	517.100	388.100	0.060
Vote cast for president 1980	27,616.000	30,669.000	25,797.000	0.050
Vote cast for president 1984	29,546.000	32,979.000	27,555.000	0.060
Vote cast for president 1988	29,240.000	32,675.000	27,421.000	0.060
Vote cast for president 1992	33,342.000	37,177.000	31,453.000	0.060
Vote cast for president 1996	30,768.000	34,268.000	29,079.000	0.060
Vote cast for president 2000	33,683.000	37,535.000	31,762.000	0.060
Vote cast for president 2004	39,052.000	43,609.000	36,815.000	0.060
Vote cast for president 2008	41,881.000	46,896.000	39,527.000	0.060
Vote share democratic candidate 1980	40.520	41.120	39.960	0.090
Vote share democratic candidate 1984	36.640	37.040	36.370	0.060
Vote share democratic candidate 1988	42.900	43.380	42.490	0.080
Vote share democratic candidate 1992	39.440	39.820	39.060	0.070
Vote share democratic candidate 1996	43.640	43.950	43.240	0.060
Vote share democratic candidate 2000	39.510	39.990	39.040	0.080
Vote share democratic candidate 2004	38.400	38.910	37.970	0.070
Vote share democratic candidate 2008	41.120	41.280	40.920	0.030
Vote share republican candidate 1980	53.390	52.850	53.800	0.080
Vote share republican candidate 1984	62.210	61.950	62.300	0.030
Vote share republican candidate 1988	55.690	55.350	55.940	0.060
Vote share republican candidate 1992	39.600	39.300	39.740	0.050
Vote share republican candidate 1996	44.580	44.320	44.800	0.040
Vote share republican candidate 2000	56.830	56.440	57.110	0.050
Vote share republican candidate 2004	60.180	59.780	60.390	0.050
Vote share republican candidate 2008	56.800	56.740	56.760	0.000
Federal government expenditure, 2010	943,104.000	1,051,230.000	877,579.000	0.050
Employment in government, 2007	7,624.000	8,619.000	7,132.000	0.060
All persons under 65 years without health insurance, 2007	17.750	17.620	17.760	0.030
Average household size, 2010	2.480	2.480	2.480	0.010
Total housing units, 2005-2009	40,813.000	45,908.000	38,370.000	0.060
Owner-occupied housing units, 2010	24,363.000	27,409.000	22,875.000	0.070
Mean household income with earnings in the past 12 months, 2005-2009	55,736.000	55,713.000	55,599.000	0.010
People of all ages in poverty, 2009	16.310	16.430	16.170	0.040
Local government finances, 2002	3,826.000	4,352.000	3,626.000	0.050
Land area in square miles, 2010	1,035.000	1,069.000	1,101.000	0.010
Water area in square miles, 2000	67.150	63.050	68.540	0.020
Local government employment, 2007	316,386.000	363,142.000	299,887.000	0.040
Urban population, 2000	70,826.000	81,906.000	65,338.000	0.050
Female population, 2010	50,208.000	56,975.000	47,047.000	0.060
White population, 2010	83.360	83.300	83.800	0.030
Black population, 2010	8.670	8.830	8.130	0.050
Hispanic population, 2010	8.330	7.720	8.940	0.090
Births per 1,000 population, 2007,	13.110	13.130	13.120	0.000
Deaths per 1,000 population, 2007	10.120	10.120	10.060	0.020

Table A2: Covariate balance: Part II

Covariates	Mean Population	Mean Exposed	Mean Control	Standardized Differences
Latitude percentil 1	0.010	0.010	0.010	0.010
Latitude percentil 2	0.010	0.010	0.010	0.040
Latitude percentil 3	0.010	0.010	0.010	0.010
Latitude percentil 4	0.010	0.010	0.010	0.060
Latitude percentil 5	0.010	0.010	0.010	0.060
Latitude percentil 6	0.010	0.010	0.010	0.040
Latitude percentil 7	0.010	0.010	0.010	0.010
Latitude percentil 8	0.010	0.010	0.010	0.030
Latitude percentil 9	0.010	0.010	0.010	0.040
Latitude percentil 10	0.010	0.010	0.010	0.060
Latitude percentil 11	0.010	0.010	0.010	0.070
Latitude percentil 12	0.010	0.010	0.010	0.020
Latitude percentil 13	0.010	0.010	0.010	0.050
Latitude percentil 14	0.010	0.010	0.010	0.040
Latitude percentil 15	0.010	0.010	0.010	0.030
Latitude percentil 16	0.010	0.010	0.010	0.040
Latitude percentil 17	0.010	0.010	0.010	0.040
Latitude percentil 18	0.010	0.010	0.010	0.030
Latitude percentil 19	0.010	0.010	0.010	0.060
Latitude percentil 20	0.010	0.010	0.010	0.010
Latitude percentil 21	0.010	0.010	0.010	0.040
Latitude percentil 22	0.010	0.010	0.010	0.040
Latitude percentil 23	0.010	0.010	0.010	0.020
Latitude percentil 24	0.010	0.010	0.010	0.060
Latitude percentil 25	0.010	0.010	0.010	0.010
Latitude percentil 26	0.010	0.010	0.010	0.010
Latitude percentil 27	0.010	0.010	0.010	0.040
Latitude percentil 28	0.010	0.010	0.010	0.000
Latitude percentil 29	0.010	0.010	0.010	0.030
Latitude percentil 30	0.010	0.010	0.010	0.070
Latitude percentil 31	0.010	0.010	0.010	0.030
Latitude percentil 32	0.010	0.010	0.010	0.030
Latitude percentil 33	0.020	0.020	0.020	0.020
Latitude percentil 34	0.010	0.010	0.010	0.000
Latitude percentil 35	0.010	0.010	0.010	0.050
Latitude percentil 36	0.010	0.010	0.010	0.010
Latitude percentil 37	0.010	0.010	0.010	0.040
Latitude percentil 38	0.010	0.010	0.010	0.050
Latitude percentil 39	0.010	0.010	0.010	0.030
Latitude percentil 40	0.010	0.010	0.010	0.050
Latitude percentil 41	0.010	0.010	0.010	0.030
Latitude percentil 42	0.010	0.010	0.010	0.000
Latitude percentil 43	0.010	0.010	0.010	0.000
Latitude percentil 44	0.010	0.010	0.010	0.050
Latitude percentil 45	0.010	0.010	0.010	0.050
Latitude percentil 46	0.010	0.010	0.010	0.080
Latitude percentil 47	0.010	0.010	0.010	0.040
Latitude percentil 48	0.010	0.010	0.010	0.010
Latitude percentil 49	0.010	0.010	0.010	0.040
Latitude percentil 50	0.010	0.010	0.010	0.020
Latitude percentil 51	0.010	0.010	0.010	0.030
Latitude percentil 52	0.010	0.010	0.010	0.010
Latitude percentil 53	0.010	0.010	0.010	0.050
Latitude percentil 54	0.010	0.010	0.010	0.010
Latitude percentil 55	0.010	0.010	0.010	0.000
Latitude percentil 56	0.010	0.010	0.010	0.030
Latitude percentil 57	0.010	0.010	0.010	0.010
Latitude percentil 58	0.010	0.010	0.010	0.020
Latitude percentil 59	0.010	0.010	0.010	0.020
Latitude percentil 60	0.010	0.010	0.010	0.010
Latitude percentil 61	0.010	0.010	0.010	0.040
Latitude percentil 62	0.010	0.010	0.010	0.050
Latitude percentil 63	0.010	0.010	0.010	0.030
Latitude percentil 64	0.010	0.010	0.010	0.030
Latitude percentil 65	0.010	0.010	0.010	0.090
Latitude percentil 66	0.010	0.010	0.010	0.020
Latitude percentil 67	0.010	0.010	0.010	0.010
Latitude percentil 68	0.010	0.010	0.010	0.010
Latitude percentil 69	0.010	0.010	0.010	0.020
Latitude percentil 70	0.010	0.010	0.010	0.000
Latitude percentil 71	0.010	0.010	0.010	0.040
Latitude percentil 72	0.010	0.010	0.010	0.010
Latitude percentil 73	0.000	0.000	0.000	0.000
Latitude percentil 74	0.010	0.010	0.010	0.050
Latitude percentil 75	0.010	0.010	0.010	0.020
Latitude percentil 76	0.010	0.010	0.010	0.020
Latitude percentil 77	0.010	0.010	0.010	0.030
Latitude percentil 78	0.010	0.010	0.010	0.010
Latitude percentil 79	0.010	0.010	0.010	0.010
Latitude percentil 80	0.010	0.010	0.010	0.010
Latitude percentil 81	0.010	0.010	0.010	0.010
Latitude percentil 82	0.010	0.010	0.010	0.040
Latitude percentil 83	0.010	0.010	0.010	0.030
Latitude percentil 84	0.010	0.010	0.010	0.030
Latitude percentil 85	0.010	0.010	0.010	0.020
Latitude percentil 86	0.010	0.010	0.010	0.020
Latitude percentil 87	0.010	0.010	0.010	0.010
Latitude percentil 88	0.010	0.010	0.010	0.040
Latitude percentil 89	0.010	0.010	0.010	0.020
Latitude percentil 90	0.010	0.010	0.010	0.020
Latitude percentil 91	0.010	0.010	0.010	0.030
Latitude percentil 92	0.010	0.010	0.010	0.100
Latitude percentil 93	0.010	0.010	0.010	0.060
Latitude percentil 94	0.010	0.010	0.010	0.060
Latitude percentil 95	0.010	0.010	0.010	0.080
Latitude percentil 96	0.010	0.010	0.010	0.010
Latitude percentil 97	0.010	0.010	0.010	0.060
Latitude percentil 98	0.010	0.010	0.010	0.010
Latitude percentil 99	0.010	0.010	0.010	0.080
Latitude percentil 100	0.010	0.010	0.010	0.040

Table A3: Covariate balance: Part III

Covariates	Mean Population	Mean Exposed	Mean Control	Standardized Differences
Longitude percentil 1	0.010	0.010	0.010	0.010
Longitude percentil 2	0.010	0.010	0.010	0.020
Longitude percentil 3	0.010	0.010	0.010	0.010
Longitude percentil 4	0.010	0.010	0.010	0.050
Longitude percentil 5	0.010	0.010	0.010	0.010
Longitude percentil 6	0.010	0.010	0.010	0.010
Longitude percentil 7	0.010	0.010	0.010	0.050
Longitude percentil 8	0.010	0.010	0.010	0.040
Longitude percentil 9	0.010	0.010	0.010	0.070
Longitude percentil 10	0.010	0.010	0.010	0.080
Longitude percentil 11	0.010	0.010	0.010	0.050
Longitude percentil 12	0.010	0.010	0.010	0.040
Longitude percentil 13	0.010	0.020	0.010	0.070
Longitude percentil 14	0.010	0.010	0.010	0.050
Longitude percentil 15	0.010	0.010	0.010	0.030
Longitude percentil 16	0.010	0.010	0.010	0.060
Longitude percentil 17	0.010	0.010	0.010	0.030
Longitude percentil 18	0.010	0.010	0.010	0.090
Longitude percentil 19	0.010	0.010	0.010	0.050
Longitude percentil 20	0.010	0.010	0.010	0.030
Longitude percentil 21	0.010	0.010	0.010	0.050
Longitude percentil 22	0.010	0.010	0.010	0.020
Longitude percentil 23	0.010	0.010	0.010	0.050
Longitude percentil 24	0.010	0.010	0.010	0.020
Longitude percentil 25	0.010	0.010	0.010	0.020
Longitude percentil 26	0.010	0.010	0.010	0.000
Longitude percentil 27	0.010	0.010	0.010	0.050
Longitude percentil 28	0.010	0.010	0.010	0.020
Longitude percentil 29	0.010	0.010	0.010	0.030
Longitude percentil 30	0.010	0.010	0.010	0.030
Longitude percentil 31	0.010	0.010	0.010	0.000
Longitude percentil 32	0.010	0.020	0.010	0.060
Longitude percentil 33	0.020	0.020	0.020	0.020
Longitude percentil 34	0.010	0.010	0.010	0.040
Longitude percentil 35	0.010	0.010	0.010	0.030
Longitude percentil 36	0.010	0.010	0.010	0.010
Longitude percentil 37	0.010	0.010	0.010	0.030
Longitude percentil 38	0.010	0.010	0.010	0.010
Longitude percentil 39	0.010	0.010	0.010	0.030
Longitude percentil 40	0.010	0.020	0.010	0.070
Longitude percentil 41	0.010	0.010	0.010	0.040
Longitude percentil 42	0.010	0.010	0.010	0.070
Longitude percentil 43	0.010	0.010	0.010	0.060
Longitude percentil 44	0.010	0.010	0.010	0.030
Longitude percentil 45	0.010	0.010	0.010	0.060
Longitude percentil 46	0.010	0.010	0.010	0.050
Longitude percentil 47	0.010	0.020	0.010	0.090
Longitude percentil 48	0.010	0.010	0.000	0.080
Longitude percentil 49	0.010	0.010	0.010	0.040
Longitude percentil 50	0.010	0.010	0.010	0.020
Longitude percentil 51	0.010	0.010	0.010	0.030
Longitude percentil 52	0.010	0.010	0.010	0.000
Longitude percentil 53	0.010	0.010	0.010	0.020
Longitude percentil 54	0.010	0.010	0.010	0.080
Longitude percentil 55	0.010	0.010	0.010	0.070
Longitude percentil 56	0.010	0.010	0.010	0.060
Longitude percentil 57	0.010	0.010	0.010	0.080
Longitude percentil 58	0.010	0.010	0.010	0.010
Longitude percentil 59	0.010	0.010	0.010	0.040
Longitude percentil 60	0.010	0.010	0.010	0.010
Longitude percentil 61	0.010	0.010	0.010	0.020
Longitude percentil 62	0.010	0.010	0.010	0.030
Longitude percentil 63	0.010	0.010	0.010	0.060
Longitude percentil 64	0.010	0.010	0.010	0.060
Longitude percentil 65	0.010	0.010	0.010	0.070
Longitude percentil 66	0.010	0.010	0.010	0.030
Longitude percentil 67	0.010	0.010	0.010	0.000
Longitude percentil 68	0.010	0.010	0.010	0.030
Longitude percentil 69	0.010	0.010	0.010	0.070
Longitude percentil 70	0.010	0.010	0.010	0.020
Longitude percentil 71	0.010	0.010	0.010	0.050
Longitude percentil 72	0.010	0.010	0.010	0.000
Longitude percentil 73	0.000	0.000	0.000	0.000
Longitude percentil 74	0.010	0.010	0.010	0.010
Longitude percentil 75	0.010	0.010	0.010	0.020
Longitude percentil 76	0.010	0.010	0.010	0.010
Longitude percentil 77	0.010	0.010	0.010	0.000
Longitude percentil 78	0.010	0.010	0.010	0.030
Longitude percentil 79	0.010	0.010	0.010	0.020
Longitude percentil 80	0.010	0.010	0.010	0.050
Longitude percentil 81	0.010	0.010	0.010	0.040
Longitude percentil 82	0.010	0.010	0.010	0.020
Longitude percentil 83	0.010	0.010	0.010	0.040
Longitude percentil 84	0.010	0.010	0.010	0.010
Longitude percentil 85	0.010	0.010	0.010	0.060
Longitude percentil 86	0.010	0.010	0.010	0.070
Longitude percentil 87	0.010	0.010	0.010	0.050
Longitude percentil 88	0.010	0.010	0.010	0.030
Longitude percentil 89	0.010	0.010	0.010	0.010
Longitude percentil 90	0.010	0.010	0.010	0.050
Longitude percentil 91	0.010	0.010	0.010	0.040
Longitude percentil 92	0.010	0.010	0.010	0.040
Longitude percentil 93	0.010	0.010	0.010	0.010
Longitude percentil 94	0.010	0.010	0.010	0.020
Longitude percentil 95	0.010	0.010	0.010	0.030
Longitude percentil 96	0.010	0.010	0.010	0.020
Longitude percentil 97	0.010	0.010	0.010	0.080
Longitude percentil 98	0.010	0.010	0.010	0.010
Longitude percentil 99	0.010	0.010	0.010	0.010
Longitude percentil 100	0.010	0.010	0.010	0.070

Table A4: Covariate balance: Part IV

Covariates	Mean Population	Mean Exposed	Mean Control	Standardized Differences
Binary variable if in New England	0.020	0.020	0.020	0.050
Binary variable if in Mid-Atlantic	0.050	0.050	0.040	0.060
Binary variable if in EN Central	0.140	0.130	0.160	0.100
Binary variable if in WN Central	0.200	0.220	0.190	0.070
Binary variable if in S Atlantic	0.180	0.180	0.160	0.060
Binary variable if in ES Central	0.120	0.110	0.130	0.070
Binary variable if in WS Central	0.150	0.160	0.140	0.050
Binary variable if in Mountain	0.090	0.080	0.100	0.090
Binary variable if in Pacific	0.050	0.060	0.050	0.040
Binary variable if not in a CBSA	0.430	0.420	0.430	0.020
Binary variable if in a metropolitan area	0.340	0.350	0.330	0.050
Binary variable if in a micropolitan area	0.220	0.230	0.240	0.030
Binary variable if farming	0.140	0.130	0.150	0.060
Binary variable if mining	0.040	0.040	0.040	0.010
Binary variable if manufacturing	0.290	0.290	0.290	0.000
Binary variable if government	0.120	0.120	0.130	0.030
Binary variable if services	0.110	0.110	0.100	0.020
Binary variable if nonspecialized	0.300	0.320	0.290	0.060
Standardized temperature for January, 1941-1970 (missingness indicator)	0.010	0.010	0.010	0.010
Standardized temperature for January, 1941-1970 (imputed values)	0.000	0.050	−0.040	0.090
Standardized mean hours of sunlight for January, 1941-1970 (missingness indicator)	0.010	0.010	0.010	0.010
Standardized mean hours of sunlight for January, 1941-1970 (imputed values)	0.000	−0.040	0.020	0.060
Standardized temperature for July, 1941-1970 (missingness indicator)	0.010	0.010	0.010	0.010
Standardized temperature for July, 1941-1970 (imputed values)	0.000	−0.030	0.010	0.050
Standardized mean hours of sunlight for July, 1941-1970 (missingness indicator)	0.010	0.010	0.010	0.010
Standardized mean hours of sunlight for July, 1941-1970 (imputed values)	0.000	-0.030	0.040	0.070
Standardized land surface form typography (missingness indicator)	0.010	0.010	0.010	0.010
Standardized land surface form typography (imputed values)	0.000	0.040	−0.030	0.070
Binary variable if climate zone 1A	0.000	0.000	0.000	0.020
Binary variable if climate zone 2A	0.070	0.080	0.060	0.070
Binary variable if climate zone 2B	0.010	0.000	0.010	0.080
Binary variable if climate zone 3A	0.190	0.200	0.170	0.090
Binary variable if climate zone 3B	0.040	0.030	0.040	0.070
Binary variable if climate zone 3C	0.000	0.000	0.010	0.050
Binary variable if climate zone 4A	0.230	0.230	0.220	0.020
Binary variable if climate zone 4B	0.020	0.010	0.020	0.090
Binary variable if climate zone 4C	0.010	0.020	0.010	0.040
Binary variable if climate zone 5A	0.200	0.210	0.190	0.040
Binary variable if climate zone 5B	0.050	0.050	0.050	0.040
Binary variable if climate zone 6A	0.110	0.100	0.110	0.060
Binary variable if climate zone 6B	0.040	0.030	0.040	0.050
Binary variable if climate zone 7	0.040	0.030	0.040	0.080
Binary variable if climate zone 8	0.000	0.000	0.000	0.020

C Appendix C: Individual level data

Concerns about aggregation problems are common when using county-level data. As a result, we also use survey data at the individual level to study the heterogeneous effects of exposure to disasters. The YPCCC project does not share data at the respondent level; therefore, we use a different survey, The Cooperative Congressional Election Study (CCES), that includes a comparable question that combines both risk perceptions and policy preferences. The CCES survey was implemented in 2014, one of the years of the YPCCC survey data we used for the county-level analysis. Therefore, we can use the same binary indicator for exposure at the county level in 2014 (being exposed to any of the disasters that can be connected to climate change in 2012 and 2013).

The question that captures the outcome of interest asks about what people know about climate change or global warming, with five possible options. We construct a binary indicator where a one corresponds to a response that acknowledges both the existence of climate change and the need for action,[2] and a zero otherwise.[3] Using questions with different framing to construct the outcomes in the county and individual-level analyses functions as an additional robustness check. For partisanship, we generate a binary indicator of answering Republican for the question: "Generally speaking, do you think of yourself as a ... ?" We also include state fixed effects and three placebo covariates (factors that should not be affected by exposure to a natural disaster): education, age, and gender.[4] We interact the binary indicators of exposure and the binary indicator of Republican to explore for heterogeneous treatment effects. Figure A1 summarizes the effect of living in an exposed county on acknowledging climate change and supporting measures to mitigate it. Republicans do not update their opinions after exposure, and changes are driven by non-Republicans.

[2] "Global climate change has been established as a serious problem, and immediate action is necessary," and "There is enough evidence that climate change is taking place and some action should be taken."

[3] "We don't know enough about global climate change, and more research is necessary before we take any actions," "Concern about global climate change is exaggerated. No action is necessary," and "Global climate change is not occurring; this is not a real issue."

[4] There are not enough observations per county to include county fixed effects. Also, we only use data from 2014, so cannot include year fixed effects.

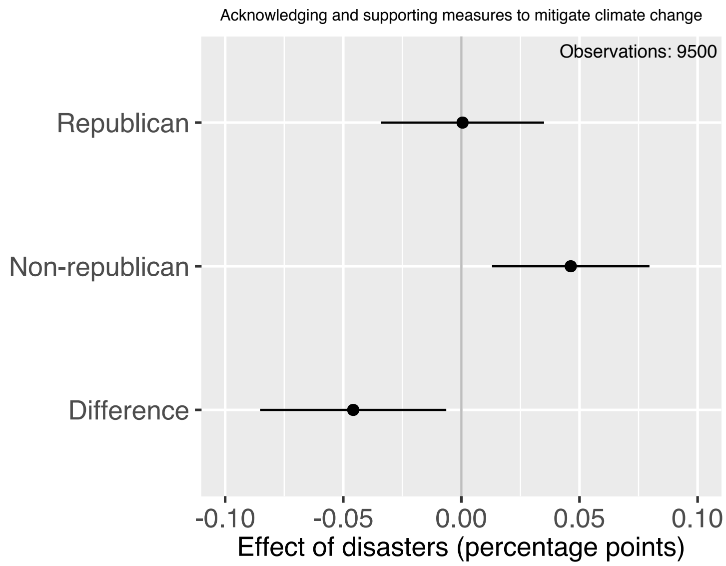

Figure A1: Heterogeneous effects of exposure to natural disasters on climate change opinion (individual-level data)

The results are very similar to those obtained at the county level. Non-Republicans and Republicans have updated their perceptions and preferences in different ways after exposure to a natural hazard. Because the outcome is constructed using a very general question that does not mention specific policy preferences, we do not see Republicans becoming more likely to take action against climate change. However, evidence from the more specific policy outcomes shows that certain topics might be more likely to garner greater support, even for people who have not changed their perceptions about climate change after exposure to a natural disasters, such as Republican voters (see figure 5 in the paper).

D Appendix D: Doses

In the paper we use a binary indicator of exposure to disasters to simplify the analysis and the interpretation. However, being exposed to multiple disasters can be different than being exposed to only one. We acknowledge that exposure might also be represented by a dose-response relationship. As a result, we provide an alternative exposure variable in this section ranging from zero to four: the numbers zero to three represent the exact number of disasters that a county was exposed to in a given year, and a four collapses the cases of exposure to four or more disasters (0: 5485, 1: 2224 , 2: 968, 3: 385, and 4: 176).[5] We use the new exposure variable as a factor, where zero disasters serves as the reference category.

The results show that the effects on personal concerns about climate change are three times larger when a country was affected by four or more disasters than when a county was affected by only one (0.127 vs 0.035 standard deviation units). In the case of risk perceptions about the US and Future Generations, however, there is only an effect for exposure to one but not to multiple disasters.

Table A5: Perceptions of all disasters - doses

	Risk perceptions		
	Personal	US	Future Generations
	(1)	(2)	(3)
1 disaster	0.035***	0.040***	0.033***
	(0.009)	(0.012)	(0.011)
2 disasters	0.015	−0.001	0.006
	(0.016)	(0.021)	(0.021)
3 disasters	0.045**	−0.000	−0.008
	(0.020)	(0.023)	(0.025)
4 disasters or more	0.127***	−0.006	−0.006
	(0.035)	(0.044)	(0.055)
County fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	9238	9238	9238

Note: *p<0.1; **p<0.05; ***p<0.01

In the case of policy preferences, we find similar results as with personal risk perceptions. Exposure to multiple disasters increases support for mitigation measures to address climate change. For at least two of the policy preferences, the effect of exposure to four or more disasters is two times larger than the effect of being exposed to only one.

[5] Only a few cases were exposed to multiples disasters, so it was necessary to generate a single category for them.

Table A6: Preferences regarding all disasters - doses

	Policy preferences			
	Fund renewables	Regulate CO2	Limit CO2	Support RPS
	(1)	(2)	(3)	(4)
1 disaster	0.083***	0.014	0.039**	0.010
	(0.016)	(0.015)	(0.016)	(0.009)
2 disasters	0.115***	−0.003	0.063**	0.024
	(0.028)	(0.023)	(0.027)	(0.016)
3 disasters	0.120***	0.020	0.090**	0.044**
	(0.037)	(0.032)	(0.036)	(0.022)
4 disasters or more	0.195***	0.031	0.180***	0.049
	(0.075)	(0.064)	(0.068)	(0.045)
County fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	9238	9238	9238	542

Note: *p<0.1; **p<0.05; ***p<0.01

E Appendix E: Spillovers

In this section we explore whether spillovers might be affecting our main results. It is possible that counties that were not exposed to a disaster, but are adjacent to a county that was, might also update their risk perceptions and policy concerns as a result of witnessing the consequences of the disaster. As a result, we might interpret the main results as conservative estimates since spillovers should bias the results toward zero.

To understand the possible effects of spillovers, we split the control group into two groups. The first is the spillover group, which corresponds to a group of counties that were not exposed to a disaster but are adjacent to at least one county that was. The second is the pure control group, or counties that were not exposed and are not adjacent to counties that were (exposed counties: 3753, spillover counties: 2641, and pure control counties: 2837).

Figure A2 compares the exposed groups to the spillover group (excluding the pure control). The results show that there is no significant difference between these groups in terms of citizens' risk perceptions and policy preferences. This provides evidence for the claim that non-exposed people living next to exposed places might also update their preferences, and that the results we present in the paper are conservative estimates.

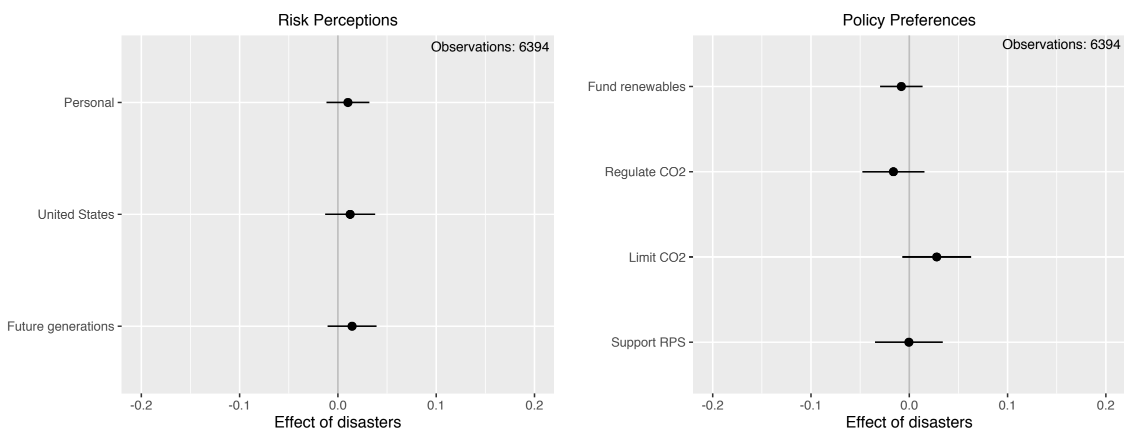

Figure A2: Effects of exposure to natural disasters on risk perceptions (treatment vs. spillover group)

Figure A3 reports the results when comparing the exposed with the pure control group (excluding the spillover group). As expected, the results are much larger than the main findings. For example, in the case of personal risk concerns, the effect of exposure is 2.5 times larger when using the pure control group for the comparison than the control group used in the paper (0.10 vs. 0.04), which is composed of both pure control and spillover counties.

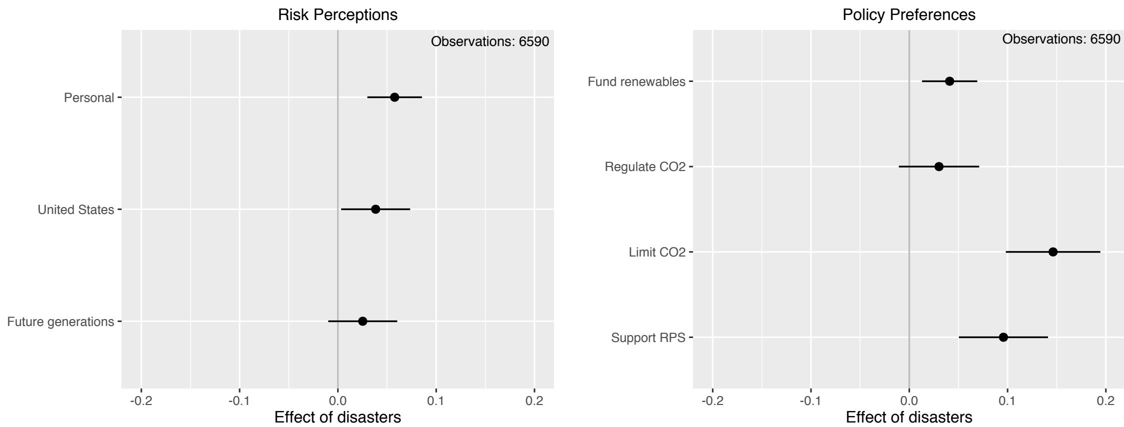

Figure A3: Effects of exposure to natural disasters on risk perceptions (treatment vs. pure control group)

F Appendix F: Alternative standard errors

In this section we provide the main results in table format and two alternative approaches for computing uncertainty when using the "all disasters" indicator for exposure. Tables A7 and A8 show the results when using Conley standard errors to account for spatial and serial correlation (the main approach used in the paper). Tables A9 and A10 provide the results when using a more standard approach by clustering standard errors at the county level, or the level of assignment to exposure to a natural disaster. Tables A11 and A12 illustrate the results when using heteroscedasticity-consistent standard errors that allow us to account for the uncertainty associated with using estimates as outcomes (Lewis and Linzer, 2005). The main findings are not conditional on how we estimate the standard errors.

Table A7: Regression results for perceptions (Conley standard errors)

	Personal	United States	Future Generations
	(1)	(2)	(3)
Natural Disaster (binary)	0.036^{***}	0.024^{*}	0.021
	(0.010)	(0.013)	(0.013)
Year fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
Observations	9238	9238	9238
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A8: Regression results for policy preferences (Conley standard errors)

	Fund renewables	CO2 regulate	C02 limit	Support RPS
	(1)	(2)	(3)	(4)
Natural Disaster (binary)	0.019	0.011	0.101^{***}	0.057^{***}
	(0.017)	(0.015)	(0.017)	(0.010)
Year fixed effects	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes
Observations	9238	9238	9238	9238
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A9: Regression results for perceptions (cluster standard errors)

	Personal	United States	Future Generations
	(1)	(2)	(3)
Natural Disaster (binary)	0.036***	0.024*	0.021*
	(0.010)	(0.012)	(0.012)
Year fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
Observations	9238	9238	9238
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A10: Regression results for policy preferences (cluster standard errors)

	Fund renewables	CO2 regulate	C02 limit	Support RPS
	(1)	(2)	(3)	(4)
Natural Disaster (binary)	0.019*	0.011	0.101***	0.057***
	(0.010)	(0.015)	(0.016)	(0.016)
Year fixed effects	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes
Observations	9238	9238	9238	9238
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A11: Regression results for perceptions (heteroscedasticity-consistent standard errors)

	Personal	United States	Future Generations
	(1)	(2)	(3)
Natural Disaster (binary)	0.036***	0.024**	0.021**
	(0.008)	(0.010)	(0.009)
Year fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
Observations	9238	9238	9238
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A12: Regression results for policy preferences (heteroscedasticity-consistent standard errors)

	Fund renewables	CO2 regulate	C02 limit	Support RPS
	(1)	(2)	(3)	(4)
Natural Disaster (binary)	0.019**	0.011	0.101***	0.057***
	(0.008)	(0.012)	(0.013)	(0.013)
Year fixed effects	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes
Observations	9238	9238	9238	9238

Note: *p<0.1; **p<0.05; ***p<0.01

References

Bennett, M., J. P. Vielma, and J. R. Zubizarreta (2019). Building representative matched samples with multi-valued treatments in large observational studies. *Working paper, Harvard University*.

Buis, A. (2019). Can climate affect earthquakes, or are the connections shaky? https://climate.nasa.gov/news/2926/can-climate-affect-earthquakes-or-are-the-connections-shaky/.

Cody, E. M., J. C. Stephens, J. P. Bagrow, P. S. Dodds, and C. M. Danforth (2017). Transitions in climate and energy discourse between hurricanes katrina and sandy. *Journal of Environmental Studies and Sciences 7*(1), 87–101.

Field, C. B., V. Barros, T. F. Stocker, and Q. Dahe (2012). *Managing the risks of extreme events and disasters to advance climate change adaptation: special report of the intergovernmental panel on climate change*. Cambridge University Press.

Gariano, S. L. and F. Guzzetti (2016). Landslides in a changing climate. *Earth-Science Reviews 162*, 227–252.

Hamilton, L. C., J. Hartter, B. D. Keim, A. E. Boag, M. W. Palace, F. R. Stevens, and M. J. Ducey (2016). Wildfire, climate, and perceptions in northeast oregon. *Regional environmental change 16*(6), 1819–1832.

IPCC (2018). *Summary for Policymakers. In: IPCC Special Report on the Ocean and Cryosphere in a Changing Climate*. IPCC Geneva.

Lang, C. (2014). Do weather fluctuations cause people to seek information about climate change? *Climatic change 125*(3-4), 291–303.

Lewis, J. B. and D. A. Linzer (2005). Estimating regression models in which the dependent variable is based on estimates. *Political analysis 13*(4), 345–364.

Mann, M. E. and K. A. Emanuel (2006). Atlantic hurricane trends linked to climate change. *Eos, Transactions American Geophysical Union 87*(24), 233–241.

Marlon, J. R., P. J. Bartlein, M. K. Walsh, S. P. Harrison, K. J. Brown, M. E. Edwards, P. E. Higuera, M. Power, R. Anderson, C. Briles, et al. (2009). Wildfire responses to abrupt climate change in north america. *Proceedings of the National Academy of Sciences 106*(8), 2519–2524.

Masson-Delmotte, V., P. Zhai, H.-O. Pörtner, D. Roberts, J. Skea, P. R. Shukla, A. Pirani, W. Moufouma-Okia, C. Péan, R. Pidcock, et al. (2018). Global warming of 1.5 c. *An IPCC Special Report on the impacts of global warming of 1*.

McBean, G. (2005). Risk mitigation strategies for tornadoes in the context of climate change and development. In *Mitigation of natural hazards and disasters: International perspectives*, pp. 25–34. Springer.

NASA (2020). https://climate.nasa.gov/effects/.

NOAA (2020). Economics and demographics. https://coast.noaa.gov/states/fast-facts/economics-and-demographics.html.

Spence, A., W. Poortinga, C. Butler, and N. F. Pidgeon (2011). Perceptions of climate change and willingness to save energy related to flood experience. *Nature climate change 1*(1), 46.

Visconti, G. and J. Zubizarreta (2018). Handling limited overlap in observational studies with cardinality matching. *Observational Studies 4*, 217–249.

Whitmarsh, L. (2008). Are flood victims more concerned about climate change than other people? the role of direct experience in risk perception and behavioural response. *Journal of risk research 11*(3), 351–374.