Appendix 1: Details on media exposure variable construction

To create a newspaper climate exposure variable, average US monthly coverage of climate change in the month of survey response was multiplied by the following weights based on self-reported weekly newspaper exposure counts: 0 days (weight=0), 1 day (weight=0.2), 2 days (weight=0.4), 3 days (weight=0.6), 4 days (weight=0.8), 5+days (weight=1). The result is a first-order estimate for the quantity of exposure to climate coverage from newspapers at the individual respondent level

A similar scale was developed for exposure to climate coverage from television news broadcasts. Both survey waves asked how often respondents watched or listened to "The national nightly network news on CBS, ABC, or NBC", "The Fox News Cable Channel" and "CNN". We interrogate the Vanderbilt Television News Archive for segments related to either "global warming" or "climate change" in the months of survey response. Consumption habits for each TV source are weighted as follows: Often (1), sometimes (0.5), Hardly ever (0.25) and Never (0). Counts for CBS, ABC, and NBC are averaged to provide an exposure estimate for the "national nightly network news" survey response item. The weighted exposure term is then summed for each respondent for each month into a single TV exposure term. Note however, that TV coverage was very low in both time periods, and this measure thus has very low over-time variation.

Appendix 2 Sensitivity of results to panel attrition

Alternatively, we might also be concerned that the results are an artifact of minor panel attrition among Hispanic and low-education respondents. While reported attrition is mild in absolute terms, it is possible to evaluate whether the paper's core findings hold after an attempt to model this imbalance. Using the full wave 1 dataset (n=2134) as a baseline, propensity to attrit is estimated as a function of gender, age, education, income, ethnicity, martial status, and political affiliation, using a logit model. The survey sample weights were then multiplied by these propensity scores weights to create a new weighting scheme that partially accounts for attrition. The results remain unchanged after re-running our primary

specifications using these new attrition-adjusted weights, as presented in Table A1.

Table A1: Sensitivity of Results to Attrition

	Belief		Priority	
	(1)	(2)	(3)	(4)
zip house value	-0.108 (0.083)	-0.136 (0.094)	-0.356*** (0.083)	-0.377*** (0.094)
income	-0.002 (0.082)	0.013 (0.090)	-0.124 (0.082)	-0.127 (0.090)
state unemployment	-0.032 (0.033)	-0.045 (0.035)	-0.039 (0.033)	-0.042 (0.035)
N	685	672	685	672
Controls?	Y	Y	Y	Y
FE	Y	Y	Y	Y
Weights	survey	attrition	survey	attrition
Robust standard errors in parentheses † significant at p < .10; *p < .05; **p < .01; ***p < .001 Columns 2 and 4 provide attrition-corrected survey weights				

Appendix 3: Question wording for alternative measures of climate policy preferences

For each policy, we code each respondent as a 1 in either panel wave if they answer that they "strongly support" or "support" the policy in question. We code each respondent as a 0 if they answer that they "somewhat oppose" or "strongly oppose" the policy question. The policy statements include: RPS: "Require 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."; gas tax: "Increase taxes on gasoline by 25 cents per gallon and return the revenues to taxpayers by reducing the federal income tax."; research renewables: "Fund more research into renewable energy sources, such as solar and wind power."; efficient car rebate: "Provide tax rebates for people who purchase energy-efficient vehicles or solar panels." climate treaty: "Sign an international treaty that requires the United States to cut its emissions of carbon dioxide 90% by the year 2050."; regulate CO2: "Regulate carbon dioxide (the

primary greenhouse gas) as a pollutant."

Appendix 4: Sensitivity analysis related to the effect of experienced weather on climate beliefs

Table 9 in the main text finds no effect of experienced weather on shifts in climate change opinions. These null results are again robust. First, we change the specification of our proxies for temperature and precipitation deviations. Recent literature has emphasized the importance of correctly specifying the functional relationship between weather and climate change opinion (e.g. Herrnstadt and Muehlegger, 2013). The baseline specification measures deviations from historical monthly average temperature or precipitation in the month of survey response. In doing so, it presumes that opinion response is linearly related to the net value of temperature or precipitation deviation. Recent evidence, however, suggests that individuals respond to weather extremes, not just deviations from historical averages. Further, the response slope could be different below or above these historic means. For instance, climate change beliefs may be more sensitive to heat waves than cold snaps. To account for these possibilities, alternative extreme weather proxies from the PRISM dataset were constructed. First, temperature and precipitation anomaly measures were transformed into measurements of absolute temperature and precipitation deviations. Second, separate measures of positive and negative weather deviations were constructed to allow each type to have a different response slope.

Because individuals may use cumulative experiences with extreme weather as a heuristic rather than just their most recent experiences, indices were developed that tallied the number of months between survey waves in which respondents experienced extreme weather.[1] The possibility that individuals respond to deviations over timescales beyond one month was investigated by constructing a

[1] We tallied the number of months respondents experienced weather in the top 5 percentiles of total experienced deviations across the country. Note that this is not quite the ideal construction, which would tally the number of months in which experienced weather was in the top 5 percentiles of historical deviations in a respondent's local area. However, the PRISM data does not provide historic variance of temperatures on a month-by-month basis.

measure that captures 3-month deviations from historic 3-month means. Finally, because some of the wave 2 respondents were surveyed in early June, before June weather could be experienced, an alternative measure was developed that assigned the temperature and precipitation deviations from May of 2011 to each of these respondents.

For each construction, the base specification was run without controls, including individual and period fixed effects, to predict both levels of climate belief and levels of climate policy preferences (results not provided). Two significant results emerge from this set of tests. First, we found an inverse association between negative monthly temperature anomalies and climate beliefs, i.e. that individuals are more likely to sustain high beliefs in the reality of climate change as cold weather anomalies decrease in frequency. The result holds when economic and political controls are included. Second, some evidence suggests that experiencing large number of temperature anomalies increases prioritization for climate policy, while experiencing large numbers of precipitation anomalies decreases respondents' prioritization of climate policy. While both significant results are consistent with aspects of the weather hypothesis, these results should nevertheless be interpreted with caution, as this analysis did not correct for the large number of specifications we ran using different constructions of similar variables in a single dataset.

This study differs from prior studies in the use of the PRISM climate dataset to model experienced weather trends rather than US weather station data.[2] The PRISM dataset allows this analysis to investigate localized weather trends at a fine resolution; however, this involves a trade-off between spatial and temporal resolution. In particular, PRISM does not model deviations over daily or weekly time periods. A few studies have linked public beliefs about climate change to temperatures on the day of survey response (e.g. Egan and Mullin, 2012), often finding that these effects decay over the course of days to weeks. PRISM estimates of monthly deviations from historic weather normals cannot

[2] It does follow Howe and Leiserowitz (2013) in this use of data, however.

capture this class of weather variation. However, it is unlikely that such daily deviations can explain national shifts in climate opinion over the past half-decade. Recall that the panel's net belief shifts were consistent with a variety of independent surveys on climate beliefs conducted over the past several years. If medium-term weather trends, as modelled here, cannot account for the opinion decline, it is unlikely that daily deviations do. This would require that daily weather deviations across the country were correlated with the timing of different climate opinion surveys, but simultaneously uncorrelated with monthly average weather deviations.

Finally, the current measure has the limitation of assuming that similarly sized anomalies during different times of year have similar effects on individual weather perceptions. Thus, the measure treats a one degree above baseline average temperature in April equally with a one degree deviation in October. However, an individual's expectations about temperature or precipitation normals may be seasonally contingent. In particular, temperature or precipitation extremes during the summer or winter may be more memorable since they involve weather conditions that occur outside of typical annual ranges. Herrnstadt and Muehlegger (2013) find evidence for this type of seasonal effect in their study of Google searches about climate change, finding that summer and winter temperature fluctuations appear to drive larger shifts in the salience of climate change. To investigate this possibility and the role that historic snowstorms in 2010 and 2011 may have played in driving climate opinion declines, an indicator variable for each respondent was constructed that assigns a 1 in the second period if the respondent lived in a state that was effected by historic snowfall in 2010 and 2011, and 0 otherwise.[3] Neither indicator was significantly associated with shifts in climate attitudes.

Appendix 5: Additional analysis related to media coverage and climate belief shifts

[3] For 2010, all the Mid-Atlantic states are coded as experiencing significant snowfall. For 2011, the following states are coded as experiencing unusually significant snowfall: Connecticut, Illinois, Indiana, Iowa, Kansas, Maryland, Michigan, Missouri, New Jersey, New Mexico, New York, Ohio, Oklahoma, Pennsylvania, Texas, and Wisconsin.

Table 9 reports that indices of exposure to climate change coverage in newspapers and television news broadcasts are not associated with shifts in climate change attitudes. This result also holds when media exposure indices summarize three-month rather than one-month averages in climate-related content (results not provided). Although these indices of news exposure were the best proxies available, combining self-reported news consumption patterns with external time- series of climate coverage, they are not ideal. In particular, media exposure indices are subject to an unknown amount of measurement error since individuals may misreport the frequency with which they consume particular media sources, because it is not possible to know whether individuals watched the specific hours of programming that contained climate content, and because the time series data on media content is only partial. For instance, the TV exposure index only draws from climate mentions during nightly news broadcasts, not the full set of news-oriented cable programming. These media coverage proxies are also limited to measuring shifts in the quantity of coverage of climate issues without any reference to quality or nature of that coverage. For all of these reasons, national opinion panels of the sort presented here are ill-equipped to rigorously evaluate the role of shifting media cues in driving changes to individual climate attitudes. Ultimately, this current analysis is constrained in its ability to assess the media coverage hypothesis for climate change attitude declines.

At the same time, more informal tests are possible. Some commentators have suggested that conservative news outlets have played a pivotal role in shaping climate opinion declines. To investigate this possibility, Table A2 presents descriptive statistics on the relationship between media consumption choice and belief shifts. It finds little evidence that respondents who self-report higher consumption of Fox News broadcasts shift their climate beliefs in systematically different ways.

Table A2: Climate Policy Preferences, by Media Choice

	Increase	**Decrease**	**No Change**
How often do you Watch... Fox News?			
Often	8%	35%	56%
Sometimes	12%	41%	47%
Hardly Ever	10%	39%	50%
Never	8%	35%	56%
The Nightly News (CBS, ABC, or NBC)			
Often	11%	44%	44%
Sometimes	10%	38%	51%
Hardly Ever	9%	40%	50%
Never	7%	34%	58%
Note: Cells correspond to distribution by response.			

Appendix Section 6: Robustness of relationship between political cues and climate belief shifts

First, we check that the results are robust to including additional political controls for Democratic party vote share and a Republican take-over of the respondents' congressional seat in the 2010 election, presented as Table A3.

A3: Robustness of Political Effects

	Priority	
	(1)	(2)
zip house price	-0.367***	-0.388***
	(0.088)	(0.094)
income	-0.122*	-0.125**
	(0.048)	(0.048)
county unemployment	-0.032	-0.033
	(0.023)	(0.025)
extremetremp	-0.007	-0.007
	(0.017)	(0.019)
extremeprec	-0.000	-0.000
	(0.000)	(0.000)
newspaper exposure	0.001	0.001
	(0.003)	(0.003)
TV exposure	0.071	0.093

	(0.067)	(0.071)
House LCV scores	0.215** (0.068)	0.314** (0.113)
tea party	0.083 (0.066)	0.068 (0.078)
Dem CV voteshare	0.082 (0.075)	0.072 (0.082)
Republican takeover		-0.069 (0.199)
movedummy		0.153 (0.139)
FE	Y	Y
Survey Weights	Y	Y
N	678	642
Robust standard errors in parentheses. † significant at p < .10; *p < .05; **p < .01; ***p < .001		

Next, we look at the distribution of climate beliefs across survey waves, by demographic attribute. We find little systematic differences in likelihood of shifting belief across gender, education, income, age and race (see Table A4). However, we do see differences by partisanship and ideological orientation.

As show in Table A4, Republicans were nearly 5 times more likely to decrease (34%) than increase (7%) their belief that climate change is happening. Independents were 8 times more likely to decrease (24%) than increase their belief (3%), while Democrats were only slightly more likely to decrease (13%) than increase their belief (9%) that climate change is happening. This pattern repeats when examining the changes by self-reported political ideology: 32% of conservative and very conservative respondent became less convinced that climate change is happening between 2008 and 2011, compared to 22% of moderates, and 5-15% of liberals.

Table A4: Climate Belief Shifts, by Select Attributes of Sample Respondents

	Increase	Decrease	No Change
Gender			
Male	5%	23%	72%

Female	8%	24%	69%
Education			
Less than HS	9%	25%	66%
High School	8%	27%	64%
Some College	8%	25%	67%
Bachelor's	4%	23%	73%
Graduate	4%	13%	84%
Income			
<$25,000	11%	22%	67%
$25,000 to $34,999	7%	25%	68%
$35,000 to $49,999	5%	26%	69%
$50,000 to $74,999	7%	20%	72%
$75,000 to $99,999	4%	24%	72%
>$100,000	5%	25%	70%
Age			
18-29	10%	28%	62%
30-44	5%	20%	74%
45-59	7%	21%	72%
60+	6%	26%	68%
Race			
White, Non-Latino	6%	24%	70%
African American	10%	13%	76%
Latino	4%	20%	76%
Other, Non-Latino	11%	25%	64%
2+ Races, Non-Latino	9%	26%	66%
Partisan Affiliation			
Democrat	9%	13%	79%
Republican	7%	34%	59%
Independent	3%	24%	73%
Not interested in politics	6%	27%	66%
Ideological Orientation			
Very Liberal	5%	5%	90%
Somewhat Liberal	4%	15%	80%
Moderate	7%	22%	70%
Somewhat Conservative	7%	32%	61%
Very Conservative	6%	32%	62%
Note: Cells correspond to distribution by attribute.			