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Explaining Perceptions of Climate Change in the US*

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Abstract: A significant proportion of the US population does not believe that climate change is a serious problem and immediate action is necessary. We ask whether individuals' experiences with long-run changes in their local climate can override the power of partisanship that appears to dominate this opinion process. We merge individual-level data on climate change perceptions and the main determinants previously identified by the literature with county-level data on an exogenous measure of local climate change. While we find that local climate change significantly affects perceptions and in the expected direction, partisanship and political ideology maintain the strongest effect. We then field a randomized online experiment to test whether partisanship also drives support for pro-climate policies and the willingness to make environmentally friendly individual choices.

Key Words: Perceptions of Climate Change; Partisanship; Public Opinion; United States.

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1 Introduction

Despite overwhelming scientific evidence, a significant proportion of the US population does not acknowledge that climate change is happening (Howe et al. 2015). Partisanship and, to some extent, political ideology appear to be the primary explanations for these divergent perceptions (Egan and Mullin 2017). The mechanism through which partisanship operates in the complex scientific domain of the climate change issue is two-fold: (1) citizens have little motivation to look for accurate evidence and (2) they perceive low personal stakes in an issue that often seems geographically and temporally distant. Thus, many Americans delegate to partisan elites for information (Egan and Mullin 2012; 2017).

Intuitively, an effective means to form a correct assessment of how the climate is changing would be direct exposure to the reality of climate change. Mounting evidence shows that personal experience with the daily weather is more effective at persuading individuals than statistical information provided by experts because it is more vivid and accessible. Perceived changes in local temperature have been linked causally to changes in global warming beliefs, an effect termed local warming (Zaval et al. 2014).

Yet, climate change differs from weather change as it refers to changing weather patterns over a long period of time. It is not clear whether individuals actually respond to changes in their local climate. Faced with the difficulty of measuring how individuals experience climate change, the literature has taken one of two approaches: (1) measuring changes in the climate with changes in the weather (e.g. Egan and Mullin 2012) or (2) exploiting exposure to extreme weather events (such as excessive heat, droughts, flooding, and hurricanes) that could have a direct impact on climate change perceptions (Konisky et al. 2016). Both approaches have found evidence of a positive relationship between weather changes and expressions of concern about climate change. However, the effects are both modest and short-lived. Overall, the evidence that weather shapes climate change opinions is mixed because of the use of weather changes as a proxy for climate changes, the heterogeneity of the study populations, and weak causal identification strategies (Howe et al. 2019).

Does the direct experience of climate change have a causal impact on climate change perceptions, and can this direct experience mitigate the effect of partisanship on these perceptions? Also, how do partisanship and experience with climate change drive support for environmental policy actions and individual environmental-friendly choices? Moving beyond perceptions and towards actual choices is crucial to define an effective strategy to enact policies to address climate change. Finding that partisanship has a diminished effect on subsequent behavioral choices would open the possibility of promoting important behavioral changes to combat climate change.

As reliable climate data has become available, several papers have discussed improved measures of climate change that use long-term temperature trends (Howe et al. 2019 for a review). One example is the methodology proposed by Kaufmann et al. (2017) to measure local climate change in the US using a county-level index of the number of days per year for which the year of the record high temperature is more recent than the year of the record low temperature over the past several decades. Exploiting this opportunity, we develop a two-stage empirical analysis. First, we merge the county-level index of climate change with detailed individual-level data from the 2014 wave of the Cooperative Congressional Election Study (CCES) panel survey to estimate a model of climate change perceptions where we control for the climate change index in the county of residence and all the relevant determinants of climate change perceptions identified by the previous literature. Second, we field a randomized online experiment to test whether partisanship also drives the willingness to take action to combat climate change and to engage in environmental-friendly choices (such as the installation of

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solar panels or the purchase of hybrid and electric cars). Whatever the role of partisanship in shaping climate change perceptions, finding that policy support and individual actions were less (or not at all) driven by partisanship would provide an important finding to promote active changes to reduce emissions. Taken together, this evidence has the potential to define both the dimensions and the nature of the political challenges needed to combat climate change.

2 Literature Review

Egan and Mullin (2017) review the literature on the attitudinal determinants of climate change and identify the following five groups of determinants, in order of importance: (1) political preferences (partisanship and political ideology), (2) demographics, particularly gender and religiosity, (3) personal experience with climate change, (4) world views on social relationships (e.g. hierarchical versus egalitarian orientation), and (5) media exposure. Overall, several studies show that partisanship and political ideology drive Americans' opinions on climate change more than any other factor, including personal experience with and vulnerability to changes in the weather (Egan and Mullin 2017).

Yet, one significant limitation of the literature is the actual measurement of climate change, most commonly proxied with various measures of local changes in the weather or extreme weather events. Specifically, climate heuristics are calculated by comparing the temperature during a given day (Zaval et al. 2014; Brooks et al. 2014), week (Egan and Mullin 2012), season (Akerlof et al. 2013; Howe and Leiseowitz 2013), or year (Goebbert et al. 2012; Howe et al. 2013) with a long-run average for the corresponding period and by classifying this anomaly as either warmer or cooler than average. However, weather changes and climate change are different: the daily, weekly, seasonal, or annual deviations from the mean do not represent a change in the climate. Climate change is a shift in the long-run weather means. Thus, the use of weather measures to proxy individuals' experiences with climate change could potentially introduce a substantial source of measurement error.

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Recent developments in big data collection and analysis have produced substantially improved measures of individuals' experiences with climate change. Due to increased data availability, several papers have proposed measures of local climate change based on long- term temperature trends (Howe et al. 2019 for a review). One example is the work by Kaufmann et al. (2017) that develops a county-level index of the number of days per year for which the year of the record high temperature is more recent than the year of the record low temperature during a period of the last thirty, forty and fifty years. The index also allows for a differential impact of more recent and extreme changes in temperature to capture two key aspects that influence perceptions of climate change: recency weighting and an emphasis on extreme weather events.

Kaufmann et al. (2017) find a positive correlation between the cross-county variation in the index and aggregate changes in the proportion of the US population that agree that global warming is happening. They also show that recency weighting is key in that recent record temperatures have a particularly strong effect on beliefs and climate skepticism is greater in counties exhibiting recent cooling versus counties that have warmed. However, empirical analyses at an aggregate level -- correlations between geographical variation in climate change and the degree of public awareness across geographical units -- limit our ability to make individual-level inferences. Further, since weather varies geographically, geographic patterns of a particular weather variable may coincide with the geographic distribution of other unmeasured social, cultural, political, or demographic predictors. Consistent with the estimation of potentially spurious correlations rather than causal effects, in a review of the literature that uses aggregate data, Howe et al. (2019) document mixed findings among studies that have investigated the impact of longer-term temperatures or temperature trends on climate change perceptions.

In order to assess the impact of experiencing climate change on peoples' perceptions, it is necessary to perform individual-level analysis. In this paper we do so by estimating an individual-level model of climate change perceptions that includes the climate index developed by Kaufmann et al. (2017) together with the relevant determinants of climate change beliefs identified in the literature (Egan and Mullin 2017). Using individual data is key to our understanding of the challenges to constructing effective political strategies and solutions for combating climate change.

3 Data

We use the final year of the 2010-2014 CCES panel survey, administered online by YouGov. YouGov uses a matched random sample design which involves first selecting a random sample from the target population (American adults) from the Census Bureau's American Community Survey and then identifying the closest matching respondents from their own panel on a range of demographic factors. This creates a representative sample of the target population and post-stratification weights are used to ensure that the resulting sample is representative of American adults on a wide array of demographic and political characteristics. The survey was conducted in two waves, with respondents interviewed in October (before the midterm November 2014 election) and again in November and December (following the election). All variables used in our analyses come from the pre-election wave of the 2014 survey.[1]

The CCES includes detailed information on socio-demographic characteristics, values and attitudes (including partisanship and political ideology), which allows us to control for the main determinants of climate change perceptions previously identified in the literature. Importantly, the

[1] The guide to the CCES panel study provides detailed information on the methodology (Schaffner and Ansolabehere 2015). We use the CCES panel survey rather than the core 2014 CCES because the core 2014 CCES survey does not include the climate change question that is central to our analysis.

CCES also includes a question on climate change perceptions that uses neutral wording and combines the recognition of the problem with the willingness to promote active policy action.[2] The question is as follows:

> "From what you know about global climate change or global warming, which one of the following statements comes closest to your opinion? a. Global climate change has been established as a serious problem, and immediate action is necessary; b. There is enough evidence that climate change is taking place and some action should be taken; c. We don't know enough about global climate change, and more research is necessary before we take any actions; d. Concern about global climate change is exaggerated. No action is necessary; e. Global climate change is not occurring; this is not a real issue."

We reverse coded the question so that increasing values of the dependent variable denote acknowledgement that climate change is happening.[3]

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[2] In order to assess the impact of experiencing climate change on perceptions, we need an individual-level dataset with detailed information on a large set of controls including partisanship and political ideology. Given our research question, we had two main options: the American National Election Studies (ANES) and the CCES. We chose the CCES survey for two main reasons. First, the CCES has a much larger sample size than the ANES, providing more statistical power for our analysis. Second, the CCES dataset has a panel component, which allows us to perform several robustness checks of our empirical results.

[3] The CCES uses climate change and global warming interchangeably, although the former technically refers to all forms of climatic variability introduced by the warming of the Earth's surface and oceans due to the increased accumulation of greenhouse gases in the Earth's atmosphere (see National Research Council. 2001. Climate Change Science. Washington, DC:

Using the information on each individual's county of residence (i.e. FIPS county codes), we merge the 2014 wave of the CCES dataset with the county-level data on the climate indexes constructed by Kaufmann et al. (2017). The climate indexes are constructed using data on the daily high and low temperatures for 18,713 weather stations located in the US. Kaufmann et al. (2017) classify each station according to the number of years for which data are available and the number of observations that are missing, and consider stations with a maximum number of 5, 10 and 15 missing observations. For each station, they construct an index, the $TMax$, which is calculated as the number of days the record high temperature is more recent than the record low temperature over a period of thirty, forty and fifty years. The latest record is 2014, so the sample runs up to 2014 using all data records for the 30, 40 and 50 previous years.[4] This process is repeated for each day of the year, and the values of zero or one are summed over to calculate the index. All portions of US counties are assigned to their nearest weather station. The station-level values of the index are translated to county-level values of the index using a weighted average that is based on the US voting population.

Kaufmann et al. (2017) identify four relevant intervals of the $TMax$ to characterize the long-run time trends in changes in temperature in each county: strong cooling ($TMax \leq 163$), cooling ($163 < TMax \leq 182$), warming ($182 < TMax \leq 201$), and strong warming ($TMax > 201$). Finally, in addition to the $TMax$, they define $High2005$ and $Low2005$, which denote, respectively, recent warming and recent cooling since 2005. In particular, High2005 measures the number of days per year for which the year of the highest temperature is more recent than the year of the lowest temperature and the year of that high temperature is 2005 or later.

National Academy Press.).

[4] To ensure that the index measures long-term changes in the weather, that is a change in the climate, the minimum sample length of temperature data is thirty years.

Reverse, recent cooling, *Low*2005, is computed as the number of days per year for which the year of the lowest temperature is more recent than the year of the highest temperature and the year of that low temperature is 2005 or later.

The additional indexes *High*2005 and *Low*2005 capture recency weighting (*RW*), that is the impact of recent changes in the climate, which could have a stronger impact than less recent changes and thus reinforce the effect of record temperatures (Weber and Stern 2011; Li, Johnson and Zaval 2011). In order to measure recency weighting, Kaufmann et al. (2017) construct four *RW* variables, which are the interactions between recent warming (*High*2005) and recent cooling (*Low*2005) and the climate trends measured by the *TMax*. In particular, *RW*2 (*RW*1) is the interaction between *High*2005 and $163 < TMax \leq 182$ ($TMax \leq 163$) and measures the effect of recent warming in counties that experience sample-wide (strong) cooling. Reverse, *RW*3 (*RW*4) is the interaction between *Low*2005 and $182 < TMax \leq 201$ ($TMax > 201$) and measures recent cooling in counties that experience sample-wide (strong) warming.

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Table 1. Number of observations and counties for different values of the TMax index.

	# CCES Observations	# Counties
Strong cooling	408	313
Cooling	865	685
Warming	2,079	1,681
Strong warming	7,639	6,819

Table 1 presents the number of observations and counties for the four different intervals of the *TMax* index using the 30-year series.[5] Table 1 shows that most US counties have experienced a warming climate: 84% of counties have either warmed or strongly warmed. Tables 2, 3 and 4 present descriptive statistics of the CCES climate change perceptions' question, political ideology and partisanship.[6] Figure 1 presents climate change perceptions by partisanship[7] and clearly shows a strong association between being a Republican and not acknowledging that climate change is happening.[8]

[5] In Table 1, as in the main regressions, we use the *TMax* index constructed using the 30 years' time trends. All results are robust to using the 40- and 50-years series.

[6] The Online Appendix includes descriptive statistics of the rest of the variables that are used in the empirical analysis.

[7] Following the US public opinion literature, we use a self-identification measure of partisanship rather than party registration since we conceive of partisanship as an identity.

[8] While we focus our analysis on the year 2014, Americans' opinions on climate change have not significantly changed since then. The Online Appendix presents a full discussion on how climate attitudes have evolved in the US since 2014.

Table 2: Perceptions of climate change CCES 2014.

	Freq.	Percent	Cum.
Global climate change is not occurring; this is not a real issue.	907	9.57	9.57
Concern about global climate change is exaggerated. No action is necessary.	1,950	20.58	30.15
We don't know enough about global climate change, and more research is necessary before we take any actions.	1,500	15.83	45.97
There is enough evidence that climate change is taking place and some action should be taken.	1,869	19.72	65.70
Global climate change has been established as a serious problem, and immediate action is necessary.	3,251	34.30	100.00
Total	9,477	100.00	

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Table 3: Political ideology of respondents from 2014 CCES

Political Ideology	Freq.	Percent	Cum.
Very liberal	964	10.17	10.17
Liberal	1,748	18.44	28.62
Moderate	2,961	31.24	59.86
Conservative	2,375	25.06	84.92
Very conservative	1,429	15.08	100.00
Total	9,477	100.00	

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Table 4: Partisanship of respondents from 2014 CCES

Party ID	Freq.	Percent	Cum.
Strong Democrat	2,558	26.99	26.99
Not very strong Democrat	887	9.36	36.36
Lean Democrat	878	9.27	45.62
Independent	1,172	12.37	57.99
Lean Republican	1,258	13.28	71.26
Not very strong Republican	888	9.37	80.64
Strong Republican	1,835	19.36	100.00
Total	9,476	100.00	

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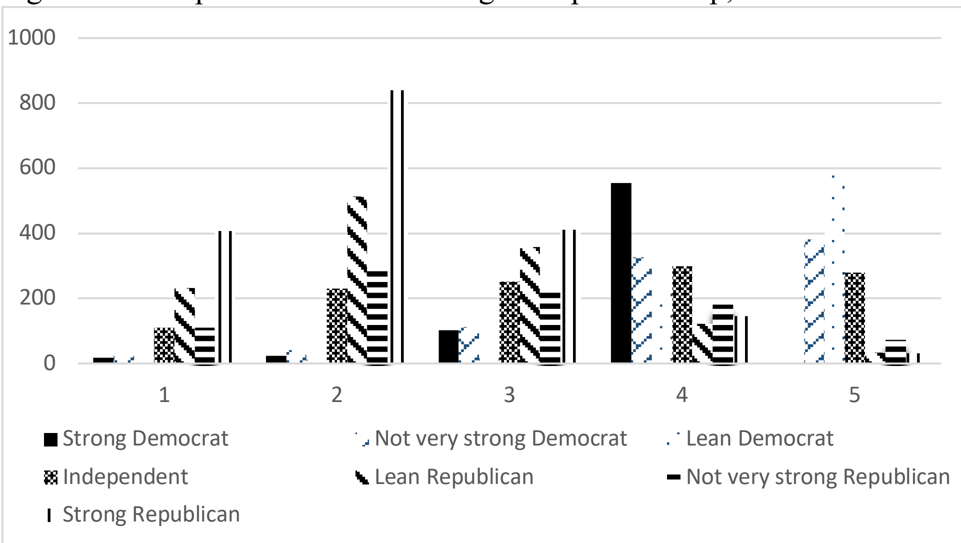
Figure 1: Perceptions of climate change and partisanship, 2014 CCES



Notes: 1: Global climate change is not occurring; this is not a real issue. 2: Concern about global climate change is exaggerated. No action is necessary. 3: We don't know enough about global climate change, and more research is necessary before we take any actions. 4: There is enough evidence that climate change is taking place and some action should be taken. 5: Global climate change has been established as a serious problem, and immediate action is necessary.

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4 Model

We estimate a comprehensive individual-level model of climate change perceptions:

$$y_{ic} = \beta_0 + \beta_1 TMax_c + \beta_2 RW1_c + \beta_3 RW2_c + \beta_4 RW3_c + \beta_5 RW4_c + \quad (1)$$

$$+\beta_6 PID_{ic} + \beta_7 PolId_{ic} + \gamma \mathbf{X}_{ic} + \alpha_c + \varepsilon_{ic}$$

where y_{ic} is the perception of climate change of individual i in US county c. $TMax_c$ and RWj_c, j=1,2,3,4 are, respectively, the $TMax$ index and the four recency weighting effects in county c. PID_{ic} is party identification, $PolId_{ic}$ is political ideology, and $\mathbf{X}_{ic}$ is a vector of individual characteristics (gender, race, age, education, religiosity) of individual i in county c. α_c is the county fixed effect, and ε_{ic} is a normally distributed error term. We cluster the standard errors at the county-level and we estimate the model using ordered probit.

In addition to the standard variables identified by the previous literature (Egan and Mullin 2002), Equation 1 contains the five climate variables that we described in Section 3: the $TMax$ index, which measures local changes in the climate in each county c based on the number of days per year for which the year of the record high temperature is more recent than the year of the record low temperature, and the four recency weighting (RW) variables, which are interaction terms between recent warming and recent cooling temperature trends and the four relevant climate trends measured by the $TMax$.[9]

The model is fully parametric. However, it is useful to understand what helps identify the main effects of the climate variables. The identification of the model exploits cross-county

[9] By construction, *TMax* and the four interaction terms are correlated. However, the correlation coefficient between the *TMax* and each of the four interaction terms is 0.3, thus well below the warning multicollinearity threshold of an absolute correlation coefficient of 0.7 among two or more predictors.

variation. In particular, county dummies control for the impact of permanent regional differences and allow us to identify the effect of the climate indexes on perceptions from the way they change differentially across space. The key identifying assumption is that the climate variables are exogenous to individuals' choices and location given counties' aggregate effects.

By estimating Equation 1, the goal is to test two competing hypotheses: (1) partisanship and political ideology override individuals' experiences with climate change versus (2) climate change experiences moderate the role of partisanship and political ideology in shaping climate change perceptions. Therefore, the key parameters of interest are the coefficients of the climate variables, β_1 to β_5, and the coefficient of party identification, β_6, and political ideology, β_7.

5 Regression Results

Table 5 presents the main estimation results of the climate change perceptions' model: in the first column we only control for the climate variables, in the second column we additionally control for the county fixed effects, and in the third column we fully estimate Equation 1. The results show that the *TMax* index has a positive and statistically significant impact on climate change perceptions, and that the size of its impact increases when we include additional regressors (that is by moving from the model in the first column to the baseline model in the third column of Table 5).

In order to interpret the impact of the *TMax* and the recency effects, we follow Kaufmann et al. (2017) and compute the response in the dependent variable if *TMax* was moved to its sample mean for every county, and, likewise, we quantify the impact of the recency variables by considering their effect on each county if the condition on the *TMax* index is satisfied (*TMax*<163, *TMax*>201, etc.). Table 6 presents the minimum and maximum statistically significant average marginal effect by value of the dependent variable for the *TMax* and the recency effects variables. The effects are sizable and in the expected direction: the individual

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effects of the recency weighting on climate change perceptions range from a minimum of -1.96 percentage point for outcome 1 ("Global climate change is not occurring; this is not a real issue") to a maximum of $+3.19$ percentage points for outcome 5 ("Global climate change has been established as a serious problem, and immediate action is necessary") across all counties; the average marginal effect of the $TMax$ index ranges for a minimum of -0.5 percentage point for outcome 1 to a maximum of 0.82 percentage points for outcome 5. Among the recency effects, strong recent warming in counties that have cooled has the largest positive effect on beliefs that climate change is a serious problem and immediate action is necessary. Figure A3 in the Online Appendix reports the four histograms presenting the full distribution of the $TMax$ and the recency effects variables across all counties for outcome 5, "Global climate change has been established as a serious problem, and immediate action is necessary".[10]

[10] Histograms for each of the other four values of the dependent variable are available from the authors.

Table 5. Baseline model: determinants of climate change perceptions.

	(1)	(2)	(3)
TMax	0.00242**	0.000337*	0.0503***
	(0.000799)	(0.000162)	(0.00421)
Recent warming in counties that have strongly cooled	0.00181	0.0519***	0.250***
	(0.00222)	(0.00131)	(0.0343)
Recent warming in counties that have cooled	-0.000604	0.0292***	0.0499***
	(0.00172)	(0.000296)	(0.00683)
Recent cooling in counties that have warmed	-0.00133	0.0109***	0.0127*
	(0.00148)	(0.000243)	(0.00499)
Recent cooling in counties that have strongly warmed	-0.00168	0.00446***	-0.0170***
	(0.00129)	(0.0000626)	(0.00181)
Very liberal			0.909***
			(0.0776)
Liberal			0.560***
			(0.0470)
Conservative			-0.737***
			(0.0468)
Very conservative			-1.196***
			(0.0611)
Strong Democrat			1.079***
			(0.0580)
Not very strong Democrat			0.568***
			(0.0634)
Lean Democrat			1.096***
			(0.0703)
Lean Republican			-0.681***
			(0.0614)
Not very strong Republican			-0.350***
			(0.0638)
Strong Republican			-0.627***
			(0.0653)
Gender: Male			-0.112***
			(0.0320)
Race/Ethnicity: Black			-0.292***
			(0.0733)
Race/Ethnicity: Hispanic			0.0391
			(0.0786)
Race/Ethnicity: Not White Black or Hispanic			-0.225***
			(0.0618)
Age: 18-24			0.0223
			(0.356)
Age: 25-34			0.177
			(0.0984)
Age: 35-44			0.0558
			(0.0692)

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Age: 55-64			0.0657
			(0.0418)
Age: 65 plus			0.123**
			(0.0416)
Education: High School or less			-0.0568
			(0.0429)
Education: College grad			0.108**
			(0.0382)
Education: Post grad			0.229***
			(0.0473)
Church attendance: Never			0.142*
			(0.0620)
Church attendance: Seldom			0.0267
			(0.0634)
Church attendance: A few times a year			-0.0330
			(0.0644)
Church attendance: Once a week			-0.0900
			(0.0629)
Church attendance: More than once a week			-0.0763
			(0.0692)
Cutoff 1	-0.811***	-0.935***	7.597***
	(0.176)	(0.0568)	(0.973)
Cutoff 2	-0.0238	-0.0253	8.880**
	(0.173)	(0.0437)	(0.975)
Cutoff 3	0.397*	0.462***	9.767***
	(0.173)	(0.0330)	(0.977)
Cutoff 4	0.905***	1.048***	10.87***
	(0.174)	(0.0363)	(0.980)
County dummies	No	Yes	Yes
No. of Obs	9467	9467	9407

Source: CCES 2014. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Notes: Ordered probit. Standard errors clustered at the county-level in parenthesis. Dependent variable: “From what you know about global climate change or global warming, which one of the following statements comes closest to your opinion?

1 Global climate change is not occurring; this is not a real issue.

2 Concern about global climate change is exaggerated. No action is necessary.

3 We don't know enough about global climate change, and more research is necessary before we take any actions.

4 There is enough evidence that climate change is taking place and some action should be taken.

5 Global climate change has been established as a serious problem, and immediate action is necessary.”

TMax: number of days per year for which the year of the record high temperature is more recent than the year of the record low temperature up to 2010. Cooling is 163<TMax<=182; strong cooling is TMax<163; warming is 182<TMax<=201; strong warming is TMax>201. Recent warming (cooling) is defined by the number of the most recent days with record high (low) temperatures since 2005.

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Table 6. Min and max average marginal effect of TMax and recency weighting from baseline model 3 in percentage points.

	Outcome 1		Outcome 2		Outcome 4		Outcome 5	
	Min	Max	Min	Max	Min	Max	Min	Max
TMax	-0.50	0.69	-0.35	0.48	-0.05	0.03	-1.13	0.82
RW 1	-1.96	-0.06	-1.37	-0.04	0.00	0.13	0.10	3.19
RW 2	-0.50	-0.02	-0.35	-0.02	0.00	0.03	0.04	0.82
RW 3	-0.12	0.00	-0.08	0.00	0.00	0.01	0.00	0.19
RW 4	-0.03	0.13	-0.02	0.09	-0.01	0.00	-0.22	0.04

Notes: min and max average marginal effect of TMax and recency weighting from Model 3 Baseline in percentage points. Outcome 1: Global climate change is not occurring; this is not a real issue. Outcome 2: Concern about global climate change is exaggerated. No action is necessary. Outcome 4: There is enough evidence that climate change is taking place and some action should be taken. Outcome 5: Global climate change has been established as a serious problem, and immediate action is necessary.

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While we find evidence that experiencing climate change matters for perceptions, the results in Table 5 show that political ideology and party identification are statistically significant and in the expected direction: being Republican and conservative is associated with a significant reduction in acknowledging the reality of climate change and the urgency to act.

In order to assess the relative importance of experiencing climate change with respect to the impact of partisanship and political ideology, we compute the average marginal effects of each variable included in equation 1 for each value of the dependent variable. The results, which can be found in Figure A4 of the Online Appendix, show that, for each value of the dependent variable, partisanship and political ideology have double the impact of the *TMax* index, as well as all the other variables included in the model. Therefore, experiencing climate change does not override the power of partisanship and political ideology, which remain the main drivers of perceptions of climate change.

Having identified that partisanship prevails over the influence of local experiences with climate change, we augment the model with interaction terms between *TMax* and partisanship and between *TMax* and political ideology to assess whether locally experiencing climate change has heterogeneous effects for Republicans and Democrats. That is, we test whether Republicans and Democrats respond differently to the experience of climate change in their county of residence. The results, provided in Table 7, show that the additional variables leave the main results unchanged and identify only one statistically significant negative interaction between being conservative and experiencing climate change. This significant interaction effect indicates that conservatives experiencing an increasing warming trend demonstrate a reduced propensity to recognize climate change.

The findings are consistent with several possible explanations for the disconnect between lived experience and climate change perceptions of conservatives and Republicans. First, an emerging literature in social psychology has found evidence of American conservatives having a "negativity

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bias" so that the nature of their psychological responses to features of the environment that are negative is stronger than for liberals (Hibbing et Al. 2014). Alternatively, for Republican supporters, the party either provides misleading climate information or demands supporters hold views on climate change that run counter to the scientific consensus (Flynn et al. 2017). Tenacious denial even in the face of personal experience might be partially explained by exposure to elite cues (Brulle et al. 2012; Mildenberger and Leiserowitz 2017), media presentations meant to undermine the climate change consensus (Hart and Nisbet 2012), or the broader role of post-truth factual ambiguities (Lewandowsky et al. 2017; Vosoughi et al. 2018).

6 Robustness Checks

We run several robustness checks of the baseline model's results. First, we perform a series of statistical checks. In particular, we estimate the full model using different maximum of missing values (5 and 15) for the *TMax* index, and different time trends for the temperature series (40 and 50 years). The results are presented in Tables A6 and A7 of the Online Appendix. The main results are unchanged and there is no substantive difference with respect to the baseline model's findings. We also estimated the baseline model using an ordered logit and the results, available from the authors, are unchanged.

Second, we estimate several modified versions of the full model. First, we control for the availability of information on relevant economic outcomes and macroeconomic conditions, which could be an important variable affecting climate change perceptions. In particular, we would expect that the more accurately an individual is able to assess relevant macroeconomic conditions, the more likely the individual correctly perceives reality, thus acknowledging the existence of climate change. The CCES data contain a question on the level and the change of the unemployment rate. Assuming that information on the unemployment rate proxies for information on relevant macroeconomic conditions, we use the deviation of the respondent's

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prediction from the actual value of the unemployment rate to proxy for relevant economic knowledge. In the CCES, individuals report both the unemployment rate in 2014, and its change in the last two years. According to the US Bureau of Labor Statistics, unemployment rate in October 2014 was 5.7%.[11] In October 2012, the unemployment rate was 7.8%, thus between 2012 and 2014 the unemployment rate decreased. While 84% correctly states that unemployment decreased, 75% overestimates the level of unemployment in October 2014 by rating it higher than 6%. We construct a variable capturing the accuracy of a respondents' unemployment rate perceptions which is calculated as the ratio of the absolute difference between the prediction and the actual unemployment rate over the actual unemployment rate. As expected, the percentage inaccuracy in predicting unemployment rate is negative and significant, but it does not affect the sign and significance of the climate variables.

Third, we control for risk aversion, which could also affect perceptions of climate change as a reality that involves a trade-off between the present and the future time. In particular, someone that is risk-seeking may disregard climate change since her utility function more highly discounts the future. We use a series of CCES question on a hypothetical lottery to construct a standard measure of risk aversion. We find that risk aversion is significant and, as expected, positive: the more an individual is risk averse, the higher the propensity to recognize the reality of climate change and the need to take immediate action. However, the inclusion of risk aversion does not change either the sign or the significance of the climate variables.[12]

[11] http://www.ncsl.org/research/labor-and-employment/national-employment-monthly-update.aspx

[12] If we include both risk aversion and the variable on the accuracy of the unemployment rate, we find the same results: both these two variables are statistically significant with

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Fourth, following Egan and Mullin (2012), we recode the dependent variable to a three-category variable. In particular, we construct a new dependent variable that is equal to 1 if $y \leq 2$, it is equal to 2 if $y=3$, and it is equal to 3 if $y \geq 4$. The results, available from the authors, are substantively unchanged.[13]

Finally, we change the estimation sample in three different ways. First, we estimate the model using the 2012 CCES common content dataset. We do so to address an important concern: the sample of respondents in the 2014 CCES wave is affected by attrition since only the sub-sample of those that are willing to participate to the survey again is included. The 2012 CCES wave has 52,632 observations, while the sample size of the 2014 CCES panel wave is less than a fifth of the 2012 sample size. Therefore, it is possible that the 2014 CCES sample might over-represent the more politically interested and motivated. The results, which are

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the expected sign and there is no change in the sign and significance of the climate variables. We also control for interest in government and public affairs using a variable that asks to self-report how much time is spent on following what is going on in government and public affairs. The impact of this additional variable is not statistically significant and leaves the results unchanged.

[13] We also tried to use as a dependent variable a direct question on support for environmental policy. The CCES asks a question on supporting or opposing the American Clean Energy and Security Act that imposes a cap on carbon emissions and allows companies to trade allowances of carbon emissions, and funds research on renewable energy. While in the overall sample, 54% supported the Clean Energy and Security Act, 81% of Republicans oppose it. However, unfortunately, there are only 93 counties for which there is some within county variation on this variable. Therefore, the county dummies saturate the model.

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available from the authors, fully confirm the model's robustness: all explanatory variables have the same sign and statistical significance as in the baseline model.[14]

Estimating the model for 2012 does also help address an additional concern. If people have changed partisanship between 2012 and 2014, there could be some unobserved factors that simultaneously made someone change partisanship and affected their climate change perceptions. Finding no change when we estimate the results for 2012 is consistent with changes in partisanship not affecting the results. We can also measure the stability of party identification and political ideology using the panel data feature of the CCES. Between 2012 and 2014 the within-respondent correlation for party identification is higher than 0.9.

Second, we estimate the model for those who have been living in the same city for at least ten years. For identification we assume that people do not move across counties, thus it is important to assess the robustness of the model to cross-county migration. The 2014 CCES provides information on the number of months each respondent reported living at the current city of residence. We use this information to construct a variable that reports the number of years at the current city of residence, and we re-estimate the model for the sample of those who have been living in the current city of residence for at least ten years. Table A8 in the Online Appendix presents the results. The sample size drops from 9,407 (in the baseline model) to 7,154 observations, and the results are confirmed, with all climate indexes statistically significant and of a similar effect size.

Third, in order to identify the impact of experiencing climate change on individuals'

[14] Since the climate indexes are constructed considering climate trends up to 2014, when we merge them with the 2012 CCES wave, we have to assume that the weather changes between 2012 and 2014 do not strongly affect the 30 years average, so that the index is a relevant explanatory variable for climate change perceptions

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perceptions we would ideally link the survey data with a measure of climate change in the exact location where individuals live. However, the smallest available unit of analysis for which meaningful measures of climate change are constructed is the county, which is a geographical unit that can be of significant geographical size. To address the concern that some counties have a very large land area, we drop counties that are larger than 3,000 square miles and we re-estimate the model. By doing so, we lose 185 counties, but the results (in Table A9 in the Online Appendix) are still robust within this subsample.

7 Experiment

The results in the previous sections show that experiencing climate change at the individual level is associated with climate change perceptions but does not override the power of partisanship and political ideology. We also fail to find evidence of significant interaction effects between experiencing climate change and partisanship so that the ability of acknowledging the existence of climate change seems to be the result of a pure partisanship effect rather than of being more or less able to see climate change as a function of partisanship (for example because one party provides more accurate information than the other). The importance of partisanship confirms the findings from the previous literature (Egan and Mullin 2017).

We now ask the following question: does partisanship drive support for environmental policy actions and individual environmental-friendly choices as much as it drives perceptions? The answer to this question is crucial to define an effective strategy to reduce emissions and enact policies to address climate change. Finding that policy support and individual actions were less or not at all driven by partisanship would provide a potential means through which to promote and advance active changes to reduce emissions. We address this question by fielding an online experiment where we randomly prime information on local climate change and partisanship, and we assess the impact of this priming on individuals' perceptions of

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climate change as well as support for policies to fight climate change and willingness to engage in individual behavior that would address climate change.

Two recent studies are closely related to this work. Guilbeault, Becker, and Centola (2018) assess the impact of partisan priming on the ability to recognize climate change in structured bipartisan networks. They show that belief exchange on climate change in a bipartisan network can significantly improve the ability of both conservatives and liberals to interpret climate data, while social learning can be reduced and polarization maintained when the salience of partisanship is increased, either through exposure to the logos of political parties or through exposure to political identity markers.

Mildenberger, Howe and Miljanich (2019) combine satellite imagery and voter file data to examine the political identities of US households with residential solar installations. They find that while households with solar installations are slightly more likely to be Democratic, households with solar installations exist across the political spectrum, despite extreme ideological polarization around climate change. They also find that solar households are more politically active than adjacent non-solar households, and these differences in political participation are more substantial than cross-group differences in partisanship.

7.1 Experimental Design

We fielded our experiment on a survey of 2,172 American adults from July 31st through August 2nd 2020.[15] Respondents were recruited using the online platform Lucid. Lucid sells samples of individuals who have agreed to take online surveys in exchange for points that can be redeemed for rewards. Coppock and McClellan (2019) show that samples provided by Lucid successfully reproduce experimental effects demonstrated on other platforms such as

[15] This experiment was ruled exempt by the Tufts University Institutional Review Board (STUDY00000381).

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Amazon's Mechanical Turk. Notably, the samples Lucid provides are balanced with regard to various demographics (age, gender, race/ethnicity, income, and education) as well with regard to partisanship. Therefore, we have information on individuals' education, age, gender, race, income, and party identification without having to ask any question. In addition, we also asked a question on religiosity and a question on world views related to social relationships (whether everyone should have equal opportunities), which have been found to be associated with perceptions of climate change (Egan and Mullin 2017). We provide full details on the demographic composition of the sample in Table A1 in the Online Appendix.

The aim of the experiment was to test whether individuals indicated different policy preferences or behavioral intentions related to climate change when they were primed (1) to think about the local effects of climate change or (2) to think about partisanship.

Subjects were randomly assigned to one of four conditions. Subjects in the control condition (N = 614) were not exposed to any prime and after answering demographic questions they simply proceeded directly to the set of questions that make up our dependent variables. In the local information treatment condition ($N = 526$), the priming task involved respondents being presented with a dynamic climate prediction map of the United States. The interactive map that respondents were shown was built to raise public awareness of the implications of climate change (Fitzpatrick and Dunn 2019). The map can be viewed here: https://fitzlab.shinyapps.io/cityapp/.

Subjects were asked to find the city they lived in (or the closest city to where they lived) and then report on which community the map said their climate would most resemble in 60 years given current emissions levels. For example, an individual who chose Washington, DC would see a map that showed that in 60 years their climate would best resemble that of Greenwood, MS and that "the typical summer in Greenwood, Mississippi is 6.4˚F (3.5˚C) warmer and 1.7% drier than summer in Washington." The expectation is that individuals who

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do this task will be primed to think about what climate change will look like in their local community. Following this task, respondents then proceeded to responding to our dependent variables.

In the partisanship priming condition (*N*=584), respondents performed a different task which is modeled after Guilbeault, Becker, and Centola (2018). In this task, respondents were shown the symbols for the Democratic and Republican parties (a donkey and an elephant, respectively) and asked to identify which symbol went with which party. This task was meant to prime partisanship in the subjects' minds just before they answered the questions related to climate policy and actions. Guilbeault, Becker, and Centola (2018) show that party logos are highly effective at priming partisan bias based both on party membership and on political ideology.

Finally, subjects assigned to the fourth condition (N=448) were asked to complete both priming tasks before they encountered the questions about climate policy and actions. The order of these tasks was randomized so that some individuals did the local climate information task first while others did the party labels task first.

Following the experimental treatments, respondents were asked a series of questions with the display order fully randomized. One item is identical to that which we analyze using the CCES data, asking respondents whether they believe in and think action should be taken on climate change. However, we also asked whether subjects supported four specific climate policies:

1. Lower the required fuel efficiency for the average automobile from 35 mpg to 25 mpg (42% support).
2. Require that each state use a minimum amount of renewable fuels (wind, solar, and hydroelectric) in the generation of electricity even if electricity prices increase (69% support).
3. Repeal the Clean Power Plant Rules, which calls for power plants to cut greenhouse gas

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emissions by 32 percent by 2030 (50% support).

4. Withdraw the United States from the Paris Climate Agreement (40% support).

For each item, subjects could indicate whether they supported or opposed the measure.

The percentage supporting each item is indicated above. We used an Item Response Theory (IRT) graded response model to combine all of these policy items into a single scale capturing a subject's overall support for pro-climate policies. An IRT model performs a similar purpose as factor analysis, but the IRT approach is optimal for estimating the latent variable when the manifest items use binary and ordinal response options. IRT models also deal well with missing data, allowing researchers to preserve degrees of freedom. For these reasons, IRT models are increasingly used by political scientists when scaling policy items (see Warshaw 2018 for a review). The IRT model estimates the latent variable – in this case, climate attitudes – on a standard normal scale which we recoded to range from 0 (for subjects providing the most opposition to pro-climate policies) to 1 (the most support for climate- friendly policies). The Online Appendix provides full details on the IRT methodology.

Subjects were also asked about four climate-friendly actions that they could take as individuals – installing solar panels at their home, purchasing a hybrid or electric car, recycling on a daily or weekly basis, and taking steps to increase their home's energy efficiency. For each of these actions, individuals could indicate that they had already taken the action, that they were planning to take the action, or that they did not plan to take the action. We combined the "already taken" and "planning to take" responses and coded those as 1 while coding the "do not plan to take" responses as zero. We then used an IRT two-parameter logistic model to create a personal action scale, with higher values indicating that the in- dividual intended to take more pro-climate actions. Figure 2 shows how respondents are distributed on both of these scales.

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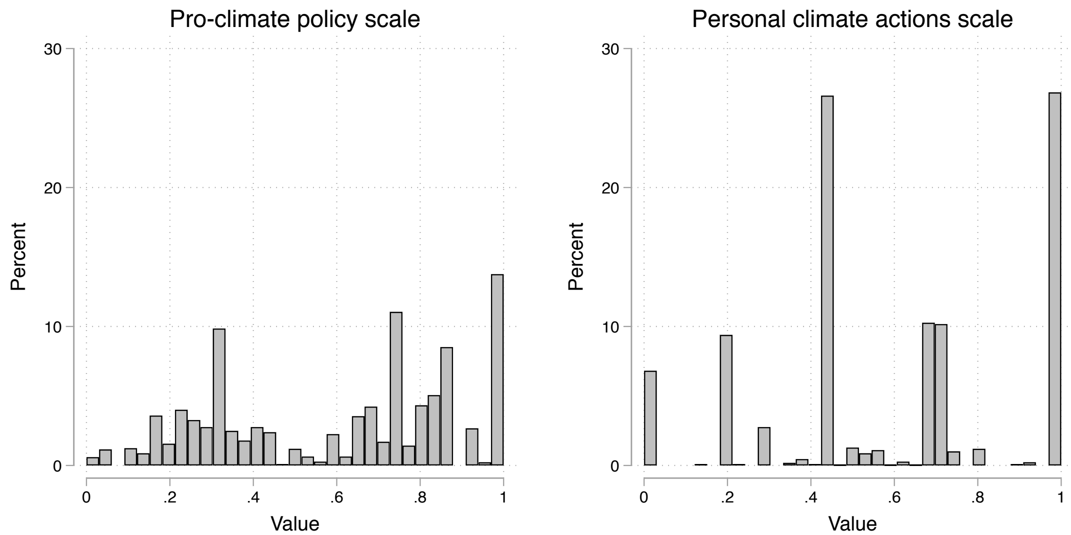
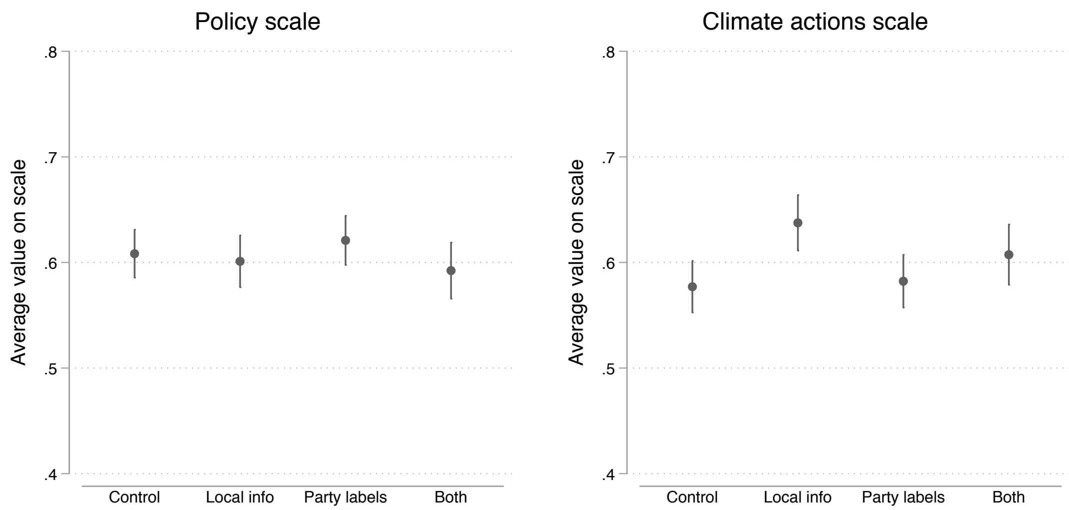
Figure 2: Distribution of subjects on policy and personal actions scales.



7.2 Results of the Experiment

Figure 3 shows the average value on the policy and actions scales for subjects in each of the experimental conditions along with 95% confidence intervals for these estimates. In the first panel of the figure, we can see that policy attitudes are seemingly unaffected by the treatments. The average value on the scale for the control condition is 0.61, while it is 0.60 for those in the local information condition, 0.62 for those in the partisanship condition, and 0.59 in the condition where respondents received both primes. Thus, the differences across these conditions are very small and they are also not statistically significant.

Figure 3: Average values on policy and personal action scales by experimental condition.



Notes: Vertical lines represent 95% confidence intervals.

In the second panel of Figure 3, however, we see larger and statistically significant differences across some conditions. Specifically, individuals assigned to the local information prime condition were significantly more likely than those in the control condition to report that they would take personal actions to combat climate change. Specifically, in the control condition, the average value on the actions scale is 0.58 while the average is 0.64 for those in the local information prime condition; this amounts to a difference of 0.06 (p=0.001). The partisan prime treatment did not produce any notable effects, with those assigned to that condition producing an average value on the actions scale that was nearly identical to that for the control group (0.58). Among those exposed to both primes, there was a small but not statistically significant increase on the scale (0.03, p=0.113). We also estimate the average effect of each treatment by running a regression with all control variables included in the model, that is by controlling for all demographic variables (age, gender, race, level of education, presence of children under the age of 18), church attendance, living in a urban or rural area, egalitarianism, and being a Democrat or

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a Republican.[16] Confirming the mean differences' results, Table A4 in the Online Appendix shows that the only statistically significant (and positive) effect is the one for the local information treatment on individuals' actions.

In addition to calculating a difference of means test between the control group and each of the treatment conditions, we also conducted a Kolmogorov-Smirnov test for equality of the distributions of the scales in the control and treatment groups. One benefit of conducting such a test is to determine whether the difference of means tests are masking heterogeneous treatment effects. This could happen, for example, if one group of subjects shifted more conservative on the climate scale when treated while another group shifted in a liberal direction, thereby canceling each other out when calculating the mean. The Kolmogorov-Smirnov test would be able to detect such a situation since the test in this case is to determine whether the distributions (specifically, the cumulative density functions) are significantly different from each other.

The Kolmogorov-Smirnov tests did not suggest that heterogeneous treatment effects would account for the lack of significant treatment effects with the policy scale analysis. Specifically, the test for the control group versus the local information prime condition yielded a p-value of 0.992 while and for the control group versus the party labels condition the p-value is 0.500. Thus, we cannot reject the null hypothesis that the distribution of values on the scale in the treatment groups is the same as it is for the control group.

For the individual actions scale, the Kolmogorov-Smirnov test did confirm our significant effect from the difference of means test, showing that the distribution of values on the personal actions scale did differ in the local information group compared

[16] Unfortunately, Lucid does not include information on ideological orientation. However, ideology and partisanship are correlated at 0.65 in the 2014 CCES.

to the control group (p = 0.026). But there was no statistically significant difference between the control group and the party label prime condition (p =0.984).

Despite the apparent lack of heterogeneous treatment effects, we still present the mean values for each condition by the subject's partisanship in Figure 4 to examine whether these effects differ based on the subject's partisanship. The three panels in the top row show the policy scale means for each condition separately among those affiliating as Democrats, as Independents or something else, and as Republicans. For Democrats, values on the policy scale are quite consistent across all three conditions. In each case, Democrats have an average value over 0.7, which indicates substantial support for pro-climate policies. For those who do not affiliate with either party, the average policy scale value is actually higher in the control group than it is in either of the treatment conditions. However, these differences are not statistically significant at the 0.05 level. Finally, Republicans register much lower support for pro-climate policies than Democrats, with averages between 0.45 and 0.55. Surprisingly, however, Republicans registered higher levels of pro-climate views when they were exposed to the party labels prime than they did in the control group (p=0.001). But in the other two treatment groups, the average value Republicans registered on the policy scale was quite similar to those in the control group.

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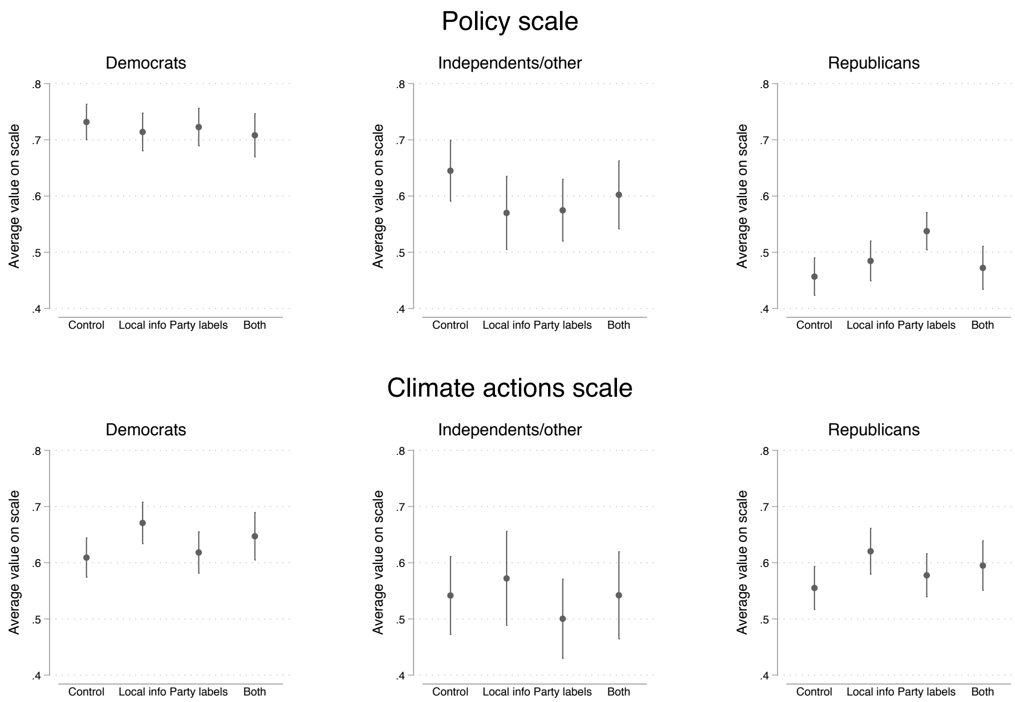
Figure 4: Average values on policy and personal action scales by experimental condition and subject partisanship.



Notes: Vertical lines represent 95% confidence intervals.

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The bottom row of results in Figure 4 breaks out the findings for values on the individual actions' scale. Notably, the patterns are quite similar for Democrats and Republicans. In particular, subjects from both parties appeared to respond to the local information prime by indicating increased intentions to take pro-climate actions. This average increase in intention to take personal action was 6.5 points for Democratic subjects ($p = 0.022$) and 6.2 points for Republicans ($p = 0.017$).

Overall, our experiment finds that increasing the salience of local climate effects appears to increase respondents' intentions to take pro-climate actions in their own lives, but that it does not appear to increase their support for pro-climate policy change. Importantly, however, and consistently with Mildenberger, Howe and Miljanich (2019), the positive effects from the local information prime on intentions to take personal actions occur across party lines.

There are several potential explanations for the finding that pro-climate behaviors for both Democrats and Republicans increase but support for pro-climate policy does not. First, in the US, individual climate-friendly actions like recycling or installing solar panels are not politicized by the parties in the same way that policy proposals are. Additionally, given partisan polarization, people may not believe that politics can make any difference while only individual actions can. Finally, people could be driven by different motivations yet having converging goals. For example, a Democrat may buy a hybrid car for environmental motivations while a Republican may buy the same car for increased fuel efficiency, and thus lower costs. Therefore, while motivations may differ, actual (pro-environmental) behavior may converge.

8 Conclusion

Less than one-third of Americans say that dealing with climate change is a top concern to them personally and less than half say that human activity contributes a great deal to climate change (Tyson et al. 2021). Estimating a comprehensive model of climate change perceptions that controls for an accurate measure of individuals' experiences with local climate change, we find that

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experiencing climate change has important effects on perceptions. Both locally experiencing a warming climate and recent inversions of the long-run weather trend in the county of residence increase the probability of acknowledging the reality of climate change and the urgency to act. Recent warming in counties that have cooled has a particularly positive impact on climate change perceptions. In other words, experiencing a recent warming of the weather's trend in the county of residence increases the probability of agreeing that climate change is happening and immediate action is necessary.

However, experience with climate change is not able to override the powerful tide of partisanship and political ideology that remain the main factors driving perceptions in the US: being Republican and conservative is associated with a significant reduction in acknowledging the reality of climate change and the urgency to act. Overall, in the US, climate change perceptions appear to derive more from parties than from the objective reality of individual experiences with climate change. A number of potential explanations could be driving the disconnect between lived experience and climate change perceptions that conservatives and Republican partisans share: negativity bias, parties either providing misleading information or demanding constituents to hold views on climate change that run counter to the scientific consensus, exposure to media presentations meant to undermine the climate change consensus, and the broader post-truth ambiguities. While we are unable to identify the specific underlying mechanism, all these potential explanations are likely to play a role and interact with each other.

Finally, we conduct an online randomized experiment to test whether partisanship also drives support for pro-climate policies and the willingness to make environmentally friendly individual choices. We find that providing information on local climate effects increases intentions to take pro-climate actions but does not boost support for pro-climate policy change. Importantly, the positive effect of information provision occurs across party lines. In this way,

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the results of the experiment identify one potential avenue for breaking through partisan divisions. Addressing individual actions rather than perceptions may offer a means to align left and right agreements to avoid partisan-driven attitudinal conflicts and thus advance actions and effective policies to address climate change.

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Supplementary Material

Supplementary materials for this article is available with the manuscript on the Political Research Quarterly (PRQ) website. Replication data for this article are available at the following Dataverse site: https://doi.org/10.7910/DVN/BRCDQD

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