Experimental effects of climate messages vary geographically

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Social science scholars routinely evaluate the efficacy of diverse climate frames using local convenience or nationally representative samples[1–5]. For example, prior research has focused on communicating the scientific consensus on climate change, which has been identified as a "gateway" cognition to other key beliefs about the issue[6–9]. Importantly, although these efforts reveal average public responsiveness to particular climate frames, they do not describe variation in message effectiveness at the spatial and political scales relevant for climate policymaking. Here we use a small-area estimation method to map geographic variation in public responsiveness to information about the scientific consensus as part of a large-scale randomized national experiment ($N = 6301$). Our survey experiment finds that, on average, public perception of the consensus increases by 16 percentage points after message exposure. Yet, substantial spatial variation exists across the United States at state and local scales. Crucially, responsiveness is highest in more conservative parts of the country, leading to national convergence in perceptions of the climate science consensus across diverse political geographies. These findings not only advance a geographical understanding of how the public engages with information about scientific agreement, but will also prove useful for policymakers, practitioners, and scientists engaged in climate change mitigation and adaptation.

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Climate change adaptation and mitigation efforts require behavioral and policy responses across diverse scales, from municipal governments to national policy. As a result, scientists, policy-makers, and practitioners must all communicate climate science to diverse decision makers and publics. Existing literature has analyzed the efficacy of different climate change communication strategies,[1,4] ranging from a focus on public health and national security[3] to increasing the salience of local climate change impacts[5] and comparing the benefits of gain versus loss frames[2]. Our study engages specifically with a growing debate about the value of communicating information about the level of scientific agreement on human-caused climate change.

Although a strong consensus exists among climate scientists that climate change is real, human-caused, and poses substantial economic and social threats to human welfare[10–12], public beliefs about anthropogenic climate change significantly lag this scientific assessment. For example, despite the fact that over 97 percent of climate scientists have concluded that human-caused climate change is happening,[10,13,14] only 11 percent of the American public correctly estimate the scientific consensus on climate change as higher than 90 percent[15]. While it is often assumed that conservatives and liberals have a similar understanding of the issue, selective exposure to ideological content likely contributes to a sharp divergence in awareness, as liberals are about five times more familiar with the scientific consensus than conservatives[15].

Uneven public understanding of the scientific consensus has been linked to systematic disinformation campaigns by carbon-intensive economic actors. While these actors privately accepted the severity of the climate threat as early as the 1980s, they mobilized publicly to undermine public understanding of climate science to stall climate policy reforms[16]. Disinformation efforts were facilitated by 'balancing' media norms that give equal voice to climate skeptics in climate news stories despite their marginal position within scientific debate[17,18]. Public understanding of climate science has also been undermined by a general increase in ideological attacks against science[19,20]. Recent experimental evidence has found that false balance and real-world misinformation about the degree of expert consensus can directly undermine public opinion[21,22].

In fact, previous scholarship has linked misunderstanding of the climate change scientific consensus to reduced levels of belief in climate change[7–9], while experimental studies find that even slight exposure to scientific dissent can reduce public acceptance of environmental risks and undermine support for environmental policy[23]. Because people often rely on consensus cues to form judgments about socio-political issues, recent experimental work has framed beliefs about the scientific consensus as a potential gateway cognition to public acceptance of a range of issues, including climate change[6,22], vaccines[24] and GMOs[25].

In particular, the Gateway Belief Model (GBM)[7] offers a dual-processing account of judgment formation where public opinion on climate change, in both cognitive (belief) and affective (worry) terms is influenced by perceptions of normative agreement among an influential referent group (domain experts). In other words, correcting inaccurate beliefs about the scientific norm on climate change may provide an effective leverage point to enhance public understanding of and concern about anthropogenic climate change. Also, given the degree of political polarization on the issue[26], preemptively warning people about the existence of a scientific consensus has shown to be useful in limiting directional motivated reasoning[22,27].

Critiques of this approach include the potential for belief polarization[28] and the observation that mass communication strategies which attempt to de-bias public perceptions about the scientific consensus do not necessarily engage with the larger socio-political context in which public opinions about contested societal issues are formed[29]. Thus, crucially, this emerging literature has not considered important potential geographic variation in public responsiveness to information about the scientific consensus resulting from varying socio-political contexts.

Accordingly, in this article, we explore treatment effect heterogeneity across diverse political geographies. The development of more efficient approaches to identify treatment effect heterogeneity has become a growing priority for social science scholars, including both parametric and non-parametric forms of response surface modeling[30–33]. However, to date, this research community has focused primarily on estimating effects among demographic (e.g., gender) or ideological (e.g., partisan) subpopulations. By contrast, efforts to model geographically-bounded heterogeneous effects remain rare, despite significant theoretical and substantive relevance to many contemporary social and political debates.

Indeed, much research shows that people in different geographic regions also differ psychologically in important and meaningful ways[34]. For example, the emerging field of "geographical psychology" takes a cross-disciplinary perspective to understanding how important differences in social, economic, political, and climatic factors interact to produce psychological phenomena[35]. In particular, people often choose to live in communities with ideological worldviews similar to their own[36]. Accordingly, investigating spatial variation in public responsiveness to climate change communication frames provides a unique opportunity to advance the social and behavioral science literature on this subject, particularly by exploring how well a given message is likely going to resonate with an audience depending on their unique geographic characteristics.

Prior studies on this topic have almost all been conducted with either convenience samples (for example, student or online panels) or with nationally representative samples. As such, they reveal something about the *average* responsiveness to climate messages. Formally, they identify sample average treatment effects by comparing aggregated treatment and control outcomes across an experimental sample. Yet, substantial variation in climate opinions and preferences exist at subnational and local scales[37–39]. We should expect similar heterogeneity in public responsiveness to climate change consensus messages at the geographic scales relevant to U.S. climate policymaking. However, this policy-relevant heterogeneity remains obscured by existing methods used to analyze climate change communication experiments.

Here we use multilevel regression as an alternative parametric approach for response surface modeling of experimental message effects. Multilevel regression and post-stratification have been widely used for small area estimation, modeling the state and local distribution of public opinion on such diverse topics as gay rights[40], health care[41], and climate change[37–39]. Multilevel regression is used in small area estimation because the method allows one to borrow information from other geographic units in estimating the outcome for any particular unit. As detailed in our Methods section, we use two separate multilevel regressions to model the distribution of the outcome (i.e., change in belief in the scientific consensus) under treatment and control conditions conditional on a set of demographic and geographic predictors. Next, we use these two models to predict the potential outcomes under treatment and control for each stratum, or category of respondent. To obtain each estimate, we post-stratify the predicted differences between treatment and control changes by computing the weighted average treatment effect across the strata in the geographic area. The Methods section provides full details on our experimental design and statistical models.

We perform our analysis using a large national survey experiment conducted in August 2015 (N=6301) to measure the impact of a message about the scientific consensus on human-caused climate change on public opinion. In our experiment, we introduced three sections of questions about popular media topics (of equal length) to mask the real purpose of the study. One of these topics was climate change and included six questions about respondents' climate change attitudes. The most crucial of these six was a measure of subjects' perception of the scientific consensus. Using a slider scale from 0 to 100, respondents answered the following question: "To the best of your knowledge, what percentage of climate scientists have concluded that human-caused global warming is happening?" All respondents also provided demographic characteristics, such as gender, race, education, age, and geographic location.

Next, respondents were randomly assigned to either a treatment or control condition. Respondents in the treatment condition read a statement that said; "97% of climate scientists have concluded that human-caused global warming is happening." In contrast, respondents in the control condition performed a short cognitive exercise unrelated to climate change. After answering several distracting scenarios and questions, respondents were again asked the same set of questions concerning climate change. Because we focus on estimating the effect of the scientific consensus frame, our main outcome of interest is the pre-post change in subjects' belief about the scientific consensus.

Exposing the survey respondents to the message about the scientific consensus increases their perception of the scientific norm by 16.2 percentage points on a 100-point scale. However, our small area estimation suggests this national sample average responsiveness masks substantial heterogeneity at state and local levels. Figure 1 maps this variation at the U.S. state level. At this level, California and the District of Columbia anchor the low end of the range, with effect sizes of 12.2 and 12.4 percentage points, respectively. At the upper range limit, response averages in West Virginia and Wyoming increased by 24.1 and 22.7 percentage points respectively. Figure 2 shows the top ten and bottom ten states' responsiveness levels, with confidence intervals to emphasize the range and uncertainty of state-level responsiveness across the country. In Supplementary Figure 3, we report validation efforts that increase confidence in the accuracy of our treatment effect estimates.

We find the largest messaging effects in states with the lowest pre-treatment belief in the scientific consensus, such as West Virginia, Wyoming, and North Dakota. States with more pro-climate publics (e.g., California, Hawaii) have some of the lowest effect sizes because respondent's initial estimates of the consensus were substantially higher than those in more conservative states, as reported in Figure 3. Our experimental message might have produced a ceiling effect in public perception of the consensus. Post-treatment, state outcomes in the treatment group ranged from 81 to 87 percent, suggesting our treatment led to a national convergence in public perception. This finding is consistent with prior work that has shown that communicating expert consensus can reduce belief and group polarization[6,7,22,27,42,43].

Figure 4 maps responsiveness at the congressional district level. We see similar patterns in variation at the state level, with some of the highest responsiveness levels in the Midwest, Appalachia and the American South. We see particularly strong messaging effects in rural districts. Absent the capacity to measure and estimate local, geographically-specific treatment effects, we could not have comprehensively evaluated whether national findings of the effectiveness of the message were driven by people living in places that are traditionally perceived as more climate-friendly. Instead, we find that the strongest effects of a message about the scientific consensus

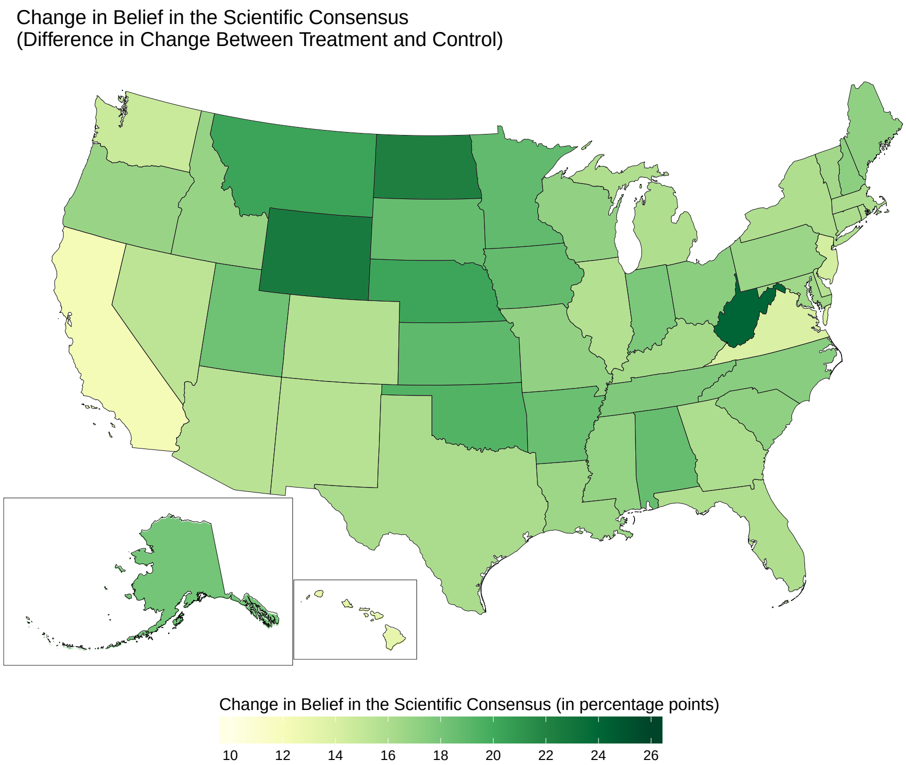

Figure 1: Experimental treatment effect sizes for each US State. Difference in change in belief in the scientific consensus (in percentage points) between the treatment group who were exposed to a message about the consensus on human-caused climate change, and the control group.

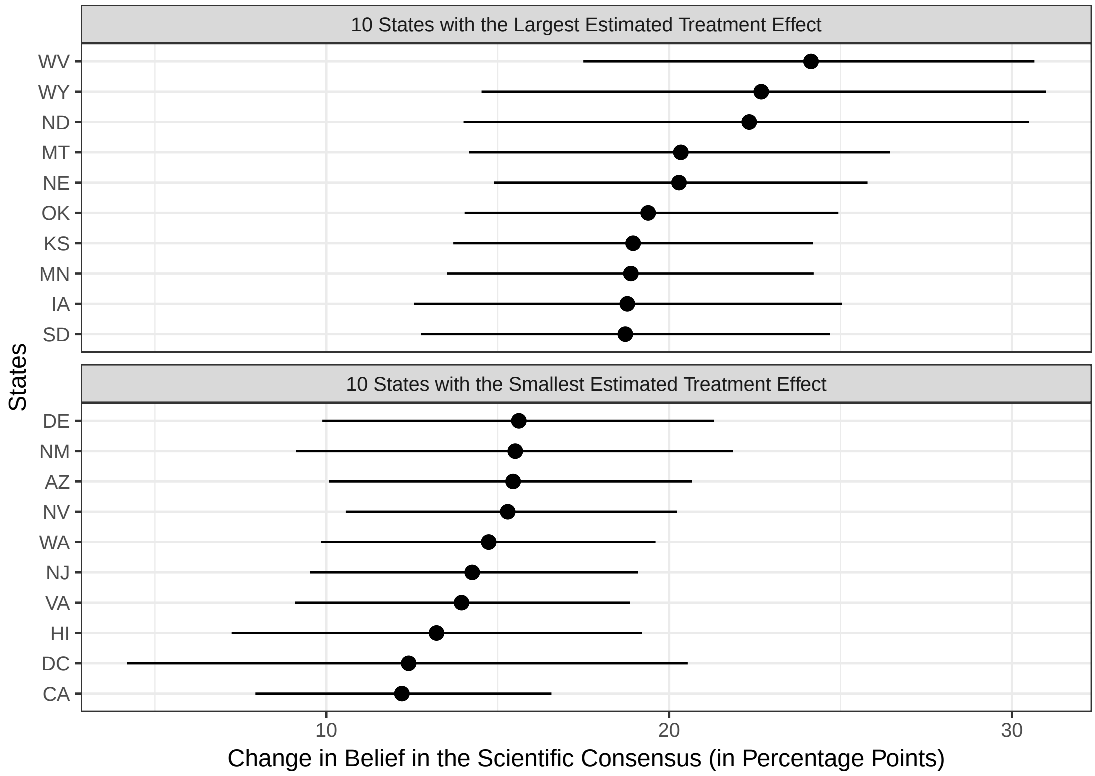

Figure 2: Change in belief in the scientific consensus on climate change for the ten states with the largest estimated treatment effects (top panel) and the ten states with the smallest estimated treatment effects (bottom panel). Error bars display 95 percent prediction intervals.

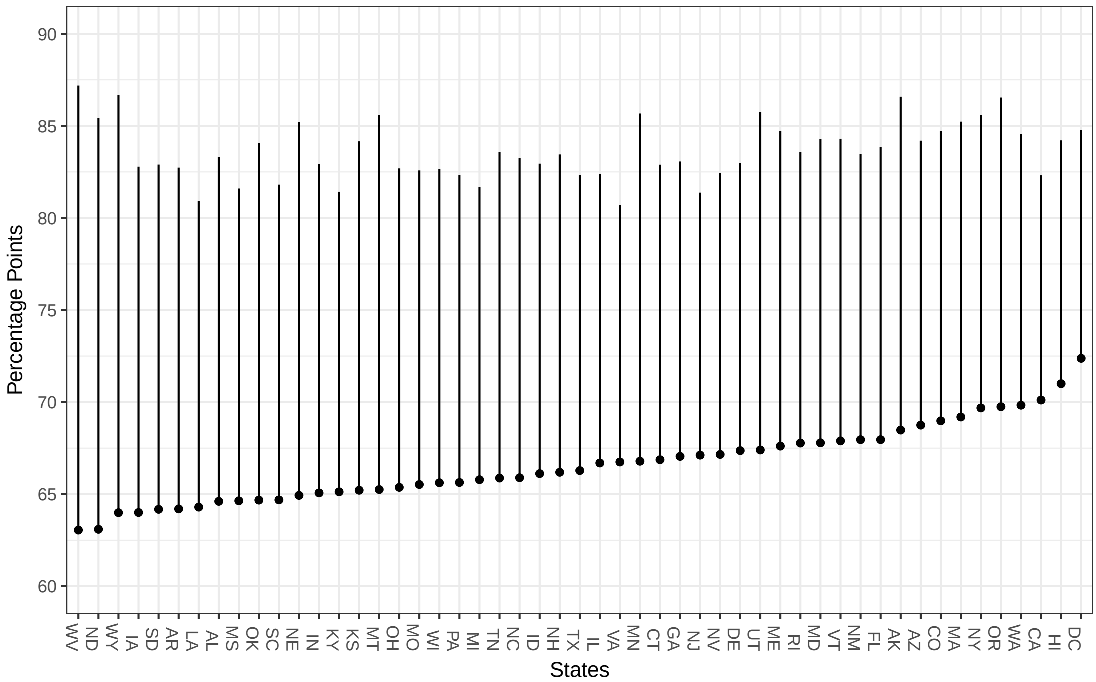

Figure 3: Experimental treatment effect ordered by pre-treatment estimates of beliefs in the scientific consensus. The dots represent the estimates of pre-treatment belief in the scientific consensus. The heights of vertical lines represent the estimated treatment effects.

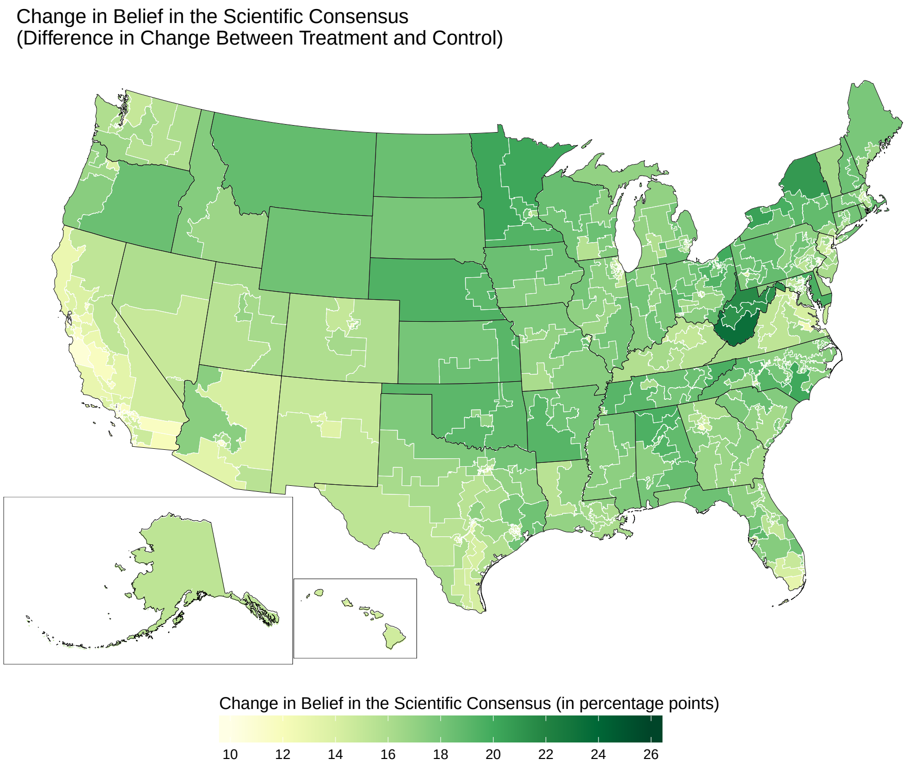

Figure 4: Experimental treatment effect sizes for each US Congressional district. Difference in change in belief in the scientific consensus (in percentage points) between the treatment group who were exposed to a message about the consensus on human-caused climate change, and the control group.

on climate change are possible where the existing understanding of the consensus is low.

The existence of such ceiling effects may prove encouraging for climate change communicators and educators. They suggest that in parts of the United States where smaller proportions of the population are concerned about climate change, larger segments of the population may be responsive to information about the strong scientific consensus on climate change. Importantly, although low initial consensus estimates indicate the potential for attitude change, this in itself does not imply that individuals will also change their attitudes, especially in light of partisan motivated reasoning[28,44]. One potential explanation for the finding that some of the largest effects are observed in more conservative areas of the United States is selective exposure to ideological content[45]. For example, ideologically-segregated geographies can facilitate "filter bubbles"[36] that may inhibit widespread awareness about the scientific consensus. Other research has found that conservatives value conformity to consensus and authority more than liberals[46]. For example, residents in conservative "red states" score disproportionately high on conscientiousness[47], a personality trait associated with respect for conformity and authority[48]. The observed spatial clustering (Figures 1 and 4) is broadly consistent with findings suggesting that residents in the Mountain and West North Central States are particularly high in conscientiousness[34].

However, geographic patterns in public responsiveness do not appear to be solely driven by variation in political orientation. For example, in pairs of state-by-state comparisons, we estimate higher responsiveness in the more liberal-leaning state, such as between Minnesota (higher, more liberal) and Wisconsin (lower, more conservative), or between Oregon (higher, more liberal) and Nevada (lower, more conservative). At the regional level, we also do not find major differences in responsiveness between the Northeastern and Southeastern U.S., two regions that have exhibited sharply different voting patterns in recent elections. These patterns suggest that research should explore additional factors that may drive geographically varying responsiveness to the scientific consensus message, such as differences in education, media exposure, or socio-demographics.

More generally, our results demonstrate the importance of small area estimation of treatment effects for the study of political, risk, and science communication. Our approach can be extended to examine other types of treatment heterogeneity and to any national experiment with sufficient sample size. It offers scholars the option to extend familiar small area estimation methods to experimental research. Our results also add to the emerging body of behavioral science research exploring geographical variation in basic human psychology and communication[35].

Building durable political coalitions for national climate reforms within representative democracies requires coordinated support across diverse electoral geographies. Educators may use this technique to efficiently target education campaigns as they raise awareness of the risks of human-caused climate change. Estimating treatment effects for local geographies allows for a better understanding of the nature and distribution of public beliefs about climate change and provides high-quality data on the mass publics at scales relevant for climate change mitigation and adaptation decision-making.

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Methods

We use multilevel regression and post-stratification (MRP) to estimate treatment effects in small areas. In prior work, scholars have typically used MRP to estimate small-area descriptive statistics, not experimental treatment effects; furthermore, researchers have focused on estimating individual-level heterogeneous treatment effects instead of geographic-level ones. Our method uses multilevel regressions to model the response surface associated with a messaging treatment; combining our modeling with post-stratification allows us to estimate message effects at various geographic levels (e.g., state and congressional districts). Our method has applications to other studies in which researchers conduct large-scale national experiments and seek to estimate treatment effects for smaller sub-national units. The Methods section provides details about our sample, experimental design, and method of analysis. The results of additional analysis are included in the Supplementary Information.

Sample

We conducted a national survey experiment in August 2015 (N=6301) to measure the effect of the consensus message on public perceptions of the scientific consensus on human-caused climate change. The experiment was conducted on a large and diverse national sample obtained from Qualtrics LLC. The sample relied on quotas broadly representative of the U.S. population, including gender, age, region, education, ethnicity, and political party. The treatment and control groups were also each balanced on the same key U.S. socio-demographic and geographic characteristics. We report the demographic characteristics of survey respondents and balance tests in Supplementary Information Tables 1 and 2.

Supplementary Table 1 summarizes the demographic characteristics of the survey respondents. As the table notes, the control group and treatment group are nearly identical on all demographic characteristics. Furthermore, when we regress treatment assignment on all of the available demographic characteristics, we find that none of those variables individually predict treatment assignment nor do they jointly predict treatment assignment (see Supplementary Table 2).

Experimental Design and Procedure

We employed a mixed factorial design measuring pre-post belief change in both the treatment and control groups. In the first part of the survey, respondents were asked to report on various demographic characteristics. Participants were then presented with three randomized sections of questions about popular media topics (of equal length) to mask the true purpose of the study, including six questions about public attitudes toward climate change. The most crucial of these six is a pre-treatment measure of subjects' attitude about the scientific consensus. Using a slider scale from 0 to 100, respondents answered the following question: "To the best of your knowledge, what percentage of climate scientists have concluded that human-caused global warming is happening?" Next, respondents were told that the researchers maintain a large database of media statements and that one media statement would be selected at random for further consideration (the treatment statement was always the same message about climate change). Respondents were randomly assigned to either a treatment or control condition. Respondents in the treatment condition read a statement that said; "97% of climate scientists have concluded that human-caused global warming is happening." In contrast, respondents in the control condition performed a short cognitive exercise unrelated to climate change. After answering several distraction-scenarios and questions (about the latest Star Wars movie), respondents were again asked the six questions concerning climate change. The main outcome of interest is the change in subjects' belief about the scientific consensus (post-treatment minus pre-treatment measure).

Subjects were asked the following question: "To the best of your knowledge, what percentage of climate scientists have concluded that human-caused global warming is happening?" Response options were given on a continuum (slider-scale), ranging from 0 to 100 percent of climate scientists have concluded that human-caused global warming is happening. The research received ethical approval from the Yale University Institutional Review Board and informed consent was obtained from all participants.

Multilevel Regression and Post-Stratification

We estimate the treatment effect of the message for each state and congressional district by adapting multilevel regression with post-stratification (MRP), a common tool for descriptive inferences in small geographic units using national survey data. Although multilevel regression estimators are biased, they increase the accuracy of small-area estimates in terms of mean squared error by reducing the variance of the estimates[49]. In general, multilevel regression shrinks group-level estimates towards the average across all groups, or towards the group-level estimate from a regression model that completely pools data from across groups (i.e., one that does not include group-level random effects). Shrinkage is greater for groups with fewer observations or groups that have smaller standard deviations in the outcome variable.

For each experimental condition, multilevel regression is used first to model the distribution of outcomes conditional on individual and geography-level covariates. Our model includes random effects for 1) race, 2) education, 3) gender, 4) the interaction between race, education, and gender, 5) state, and 6) region; as well as fixed effects for state-level political attitudes, behavior, and per-capita CO2 emissions. This model specification follows the approach detailed in[37] with some modifications to increase model flexibility. For each experimental condition $D = d$, where $d \in \{0, 1\}$, we use the following model specification to model the response for each individual i:

$$y_{i,D=d} \sim N\left(\gamma^0 + \alpha^{\text{race}}_{j[i],D=d} + \alpha^{\text{education}}_{k[i],D=d} + \alpha^{\text{gender}}_{l[i],D=d} + \alpha^{\text{race.education.gender}}_{j[i],k[i],l[i],D=d} + \alpha^{\text{state}}_{s[i],D=d}, \sigma^2_y\right),$$

where

$$\begin{aligned}
\alpha^{\text{race}}_j &\sim N(0, \sigma^2_{\text{race}}) \text{ for } j = 1, ..., 4 \\
\alpha^{\text{education}}_k &\sim N(0, \sigma^2_{\text{education}}) \text{ for } k = 1, ..., 4 \\
\alpha^{\text{gender}}_l &\sim N(0, \sigma^2_{\text{gender}}) \text{ for } l = 1, 2 \\
\alpha^{\text{race.education.gender}}_{j,k,l} &\sim N(0, \sigma^2_{\text{race.education.gender}}) \text{ for } j = 1, ...4;\ k = 1, ...4;\ l = 1, 2 \\
\alpha^{\text{state}}_s &\sim N(\alpha^{\text{region}}_{r[s],D=d} + \gamma^{\text{drivealone}}\text{drivealone}_{s,D=d} + \gamma^{\text{samesex}}\text{samesex}_{s,D=d} + \\
&\quad \gamma^{\text{carbon}}\text{carbon}_{s,D=d} + \gamma^{\text{pres12}}\text{pres12}_{s,D=d}, \sigma^2_{\text{state}}) \text{ for } s = 1, ..., 51 \\
\alpha^{\text{region}}_r &\sim N(0, \sigma^2_{\text{region}}) \text{ for } r = 1, ..., 9
\end{aligned}$$

Each variable is indexed over individual i and over response categories j,k,l, and s for race, education, gender, and state geography variables, respectively. The state variable is further modeled as a function of region and a series of geography-level covariates including the percentage of individuals who drive alone in a given state, the percentage of same-sex households in a given state, the level of point source carbon emissions in a given state, and the 2012 Democratic Presidential vote share in a given state. In models to generate the congressional district effects, the state-level variables are replaced by congressional district-level ones. The models are fitted using the `lmer` function in the R package `lme4`; the `lmer` function fits the model using restricted maximum likelihood.

Regarding the race, gender, education, and interacted race/gender/education variables, we assume exchangeability of the group means across groups in each variable. Regarding the state or congressional district groups, we include geographic-level fixed effects as well as random effects for region. Therefore, for the state or congressional district groups, we assume exchangeability of the group means conditional on the geographic-level fixed effects and the region random effects. These assumptions allow us to "borrow strength" from other groups' data when estimating random effects for a particular group.

Using these two models (of control and treatment response surfaces), we estimate the treatment effect $\widehat{\theta}_q$ for each stratum q used in the post-stratification by subtracting the predicted control outcome from the predicted treatment outcome. (Note that strata are also called cells in some MRP literature.) Each stratum q is defined by gender, race, education, and state (or congressional district) because we use U.S. Census conditional population frequencies (cells in U.S. Census crosstabs) based on these variables for post-stratification. An example of a stratum would be white males with only a high school degree living in Florida. For our state-level estimates, we use 51 (50 states plus the District of Columbia) $\times$ 2 (genders) $\times$ 4 (education levels) $\times$ 4 (racial groups) = 1632 strata. The four levels of education are less than high school, high school, some college, and college. The four racial groups are white (non-Hispanic), black (non-Hispanic), Hispanic, and other.

To estimate the treatment effect for each geographic unit c, we take a weighted mean of the strata treatment effects for the strata in the geographic unit:

$$\widehat{\theta}^{\text{MRP}}_{\text{unit } c} = \frac{\sum_{q \in c} N_q \widehat{\theta}_q}{\sum_{q \in c} N_q},$$

where N_q is the actual population frequency in the stratum q.

To generate the 95 percent prediction intervals for the state-level estimates, we use the `predictInterval` function in the R package `merTools` to generate a sampling distribution for the random effects and fixed effects for each model. Using these sampling distributions, we generate 10000 simulated treatment fitted values and 10000 simulated control fitted values for each stratum. For each simulation, we post-stratify the difference between the treatment group and control group to the state-level. For each state, we derive the 95 percent prediction interval by calculating the 2.5 percentile and 97.5 percentile of the 10000 simulated state treatment effects.

Belief in the Scientific Consensus

Responses to the scientific consensus message converge around the actual percentage of scientists who agree that climate change is real and human-caused (i.e., 97 percent); Supplementary Figures 1 and 2 showcase this trend at the individual and state-level, respectively. (The state-level outcomes are estimated using MRP.) For those not exposed to the consensus message, perceptions of the scientific consensus range widely and is on average much lower than 97 percent. At the individual level, post-treatment, the control group has a mean response of 67.6 (SD = 22.2) while the treatment group has a mean response of 84.4 (SD = 20.5). At the state level, post-treatment, the mean state outcome for the control group is 67.6 (SD = 2.76), and the mean state outcome for the treatment group is 84.3 (SD = 1.62).

Model Validation

We validate our estimated state-level results by comparing them to estimates derived from disaggregation, using a technique developed by Pacheco 2011[50]. Subsamples of varying sizes were randomly selected from states with large sample sizes and used to simulate the samples of less populous states. This procedure operates as follows:

- We draw 99 random samples of size $n = 25$ from the state with the greatest number of respondents (California). In effect, we create 99 smaller simulated Californias. For each draw, we use those "smaller Californias" as the testing set and the rest of the data points as the training set.
- For each testing set, we train the MRP model using the training set and predict the treatment effect using the testing set predictor variables. We compare the estimated treatment effect with the actual treatment effect of Californians. The measure of accurate prediction we use is the mean absolute error between the predicted and actual treatment effects. We also track the mean absolute error using the estimated treatment effect from raw disaggregation.
- We repeat steps 1 and 2 for $n = 50, 10, 200, 400$.
- We repeat steps 1 through 3 for Florida, Texas, and New York.

The results of our validation exercise are reported in Supplementary Figure 3. The figures shows that error increases substantially using disaggregation with smaller simulated sample sizes.

By contrast, error in the MRP estimates is relatively stable and lower than disaggregation across all simulated sample sizes.

Comparing MRP Estimates with Disaggregated Estimates

In Supplementary Table 3, we present the state-level treatment effects estimated using MRP and the disaggregation method (i.e., raw state estimates). The correlation between the MRP estimates and the unweighted disaggregated estimates is 0.58. The correlation between the MRP estimates and the weighted disaggregated estimates is 0.56. For states with sizable numbers of respondents, the MRP estimates and the disaggregated estimates are very similar.

For the unweighted disaggregation method, we estimate the treatment effect for each state using only the survey data for that state. For the weighted disaggregation method, we estimate the treatment effect using the survey data for that state and the researcher-generated survey weights.

We use inverse probability weighting to weight the sample to the March 2016 Current Population Survey (CPS). We combine each sample and the CPS; then we use logistic regression to estimate the probability of being included in the sample. Covariates used in our propensity score model include gender, age, education, race, geographic region, and whether the respondents lived in a metropolitan area. The final weights are the inverse of the estimated probabilities normalized such that the sum of each sample's weights equals the sample size.

Although the disaggregated estimates from states that have very few respondents are unreliable, we can compare MRP estimates with disaggregated estimates from states with a sizable number of respondents. For example, for states with more than 200 respondents, the mean difference between the MRP estimates and the unweighted disaggregated estimates is 0.05 (SD = 0.83); likewise, the mean difference between the MRP estimates and the weighted disaggregated estimates is 0.43 (SD = 1.83).

Random Effects and Fixed Effects Estimates

For transparency, we have also included the random effects and fixed effects estimates from the two multilevel models used to generate our state-level estimates in the Supplementary Information. The point estimates, along with corresponding 95 percent confidence intervals, can be found in Supplementary Figures 4–7.

Data Availability

The data that support the findings of this study are available from the corresponding author, Baobao Zhang, upon request.

Author Contributions

BZ, MM, PDH, and JRM developed and implemented the model. SVL and AL collected the data and designed the national experiment and survey with input from all authors. BZ, SVL, and MM drafted a first version of the manuscript. PDH, JRM, and AL all provided critical input to the writing and results and approved the final version of the manuscript.