nature climate change

ARTICLES
https://doi.org/10.1038/s41558-019-0587-5

Acknowledging uncertainty impacts public acceptance of climate scientists' predictions

Lauren C. Howe[1*], Bo MacInnis[2], Jon A. Krosnick[2,3], Ezra M. Markowitz[4] and Robert Socolow[5]

Predictions about the effects of climate change cannot be made with complete certainty, so acknowledging uncertainty may increase trust in scientists and public acceptance of their messages. Here we show that this is true regarding expressions of uncertainty, unless they are also accompanied by acknowledgements of irreducible uncertainty. A representative national sample of Americans read predictions about effects of global warming on sea level that included either a worst-case scenario (high partially bounded uncertainty) or the best and worst cases (fully bounded uncertainty). Compared to a control condition, expressing fully bounded but not high partially bounded uncertainty increased trust in scientists and message acceptance. However, these effects were eliminated when fully bounded uncertainty was accompanied by an acknowledgement that the full effects of sea-level rise cannot be quantified because of unpredictable storm surges. Thus, expressions of fully bounded uncertainty alone may enhance confidence in scientists and their assertions but not when the full extent of inevitable uncertainty is acknowledged.

The study of global warming inherently entails uncertainty, which arises from the incomplete understanding of the climate system and its natural variability, the long timescales involved and the difficulty of anticipating human activities. Climate scientists routinely acknowledge such uncertainty. For example, in 2000, the IPCC Assessment Report expressed uncertainty in various assessments[1]. Acknowledgements of uncertainty are necessary to accurately and honestly depict scientific knowledge. However, uncertainty may have undesirable effects on trust and message acceptance in the general public. Specifically, acknowledging uncertainty may cause people to hesitate before believing findings and thereby undermine the impact of scientific evidence. In fact, much research documents that acknowledging uncertainty can decrease message acceptance. People are more persuaded by eyewitness testimony[2,3] and advice from experts[4–9] when delivered with greater certainty. When scientists describe their uncertainty about risk, this sometimes leads people to conclude that the scientists are incompetent[10,11].

However, evidence suggesting that uncertainty undermines experts' claims may not generalize to situations in which complete certainty is implausible. One definition of being trustworthy is that a person's opinions are honestly based on available information[12], so if a source expresses unwarranted high confidence, this may undermine trust[13,14]. For example, extremely high confidence is hard to justify when predicting the future. When given a deterministic forecast of the weather (for example, a low of 0 °C), more than 95% of people infer uncertainty, anticipating that the real temperature will fall in a range around the prediction[15,16]. The same is true for financial predictions[17]. If a natural scientist were to make a prediction without acknowledging any uncertainty, this might seem implausible to a thoughtful recipient of the message. In contrast, if a scientist were to make a prediction accompanied by an expression of uncertainty, the scientist might gain credibility for acknowledging his or her inability to know exactly what will happen in the future.

Uncertainty can be acknowledged in many ways. The IPCC's Fourth and Fifth Assessment Synthesis Reports (AR4 SYR and AR5 SYR)[18,19] contain various uncertainty expressions (Supplementary Note 1). Many expressions accompany predictions with bounded uncertainty, meaning they specify bounds on the range of possible outcomes, impacts and/or timescales, in a form similar to a confidence interval around a prediction (for example, "Global mean SLR is expected to reach between 14 and 44 cm within this century", p. 180 of AR4) but without specifying the likelihood associated with each of the bounds of the prediction interval.

The research reported here examined the impact of acknowledging uncertainty in two different ways that have been common in science communications about global warming: (1) fully bounded uncertainty (for example, "Global warming will cause sea level to rise about 4 ft but it could be as little as 1 ft or as much as 7 ft"), which conveys best- and worst-case scenarios around a prediction and (2) high partially bounded uncertainty, which describes only a worst-case scenario. Because low partially bounded uncertainty (a most likely future plus a best-case scenario) is relatively uncommon in science communication (Supplementary Note 1), we did not examine the effects of such expressions.

Expressing uncertainty in these ways may have a variety of effects on public reactions to a scientist's message. High partially bounded uncertainty might increase trust and acceptance of scientists' claims compared to no uncertainty because admitting to not knowing the future with complete certainty may seem more credible. Worst-case scenarios might induce concern among message recipients because it acknowledges uncertainty and highlights severe outcomes. Previous research indeed suggests that worst-case scenarios can bias individuals toward more extreme estimates and facilitate action[20,21]. However, predictions including a worst-case scenario might lead to exaggerated, inaccurate estimates, thus misleading the public[20], and/or might be seen as transparently manipulative attempts to whip up public concern, thus undermining trust and persuasion.

[1]Department of Business Administration, University of Zurich, Zurich, Switzerland. [2]Department of Communications, Stanford University, Stanford, CA, USA. [3]Departments of Political Science and Psychology, Stanford University, Stanford, CA, USA. [4]Department of Environmental Conservation, University of Massachusetts, Amherst, Amherst, MA, USA. [5]Department of Mechanical and Aerospace Engineering, Princeton University, Princeton, NJ, USA.
*e-mail: Lauren.howe@business.uzh.ch

Expressing fully bounded uncertainty may also have various possible effects. Past research suggests that presenting this form of uncertainty may cause cognitive overload and confusion[22], particularly among people who are less educated and for whom understanding messages including uncertainty is more challenging[23,24]. This might decrease trust and message acceptance among such individuals. Or perhaps people might choose to focus their thinking on the best-case scenario (as past research suggests[20]) and discount the worst-case scenario to feel less anxious. Alternatively, describing a most likely future plus a best-case scenario and a worst-case scenario might be an especially effective communication strategy. A scientist who uses this approach might be viewed as especially trustworthy and, consequently, might be more persuasive. This prediction resonates with research showing that people viewed scientists who acknowledged study limitations (for example, saying "might" or "could") as more trustworthy and accepted their messages more often[25–27].

The current study took two different approaches to gauging the impact of acknowledging high partially bounded uncertainty or fully bounded uncertainty about global warming-induced future sea-level rise (SLR) on trust in scientists and message acceptance. The first approach involved offering a prediction of the amount of SLR that is likely and placing bounds on that prediction. Such a prediction focuses on the damage to buildings and land use caused by a fixed amount of increase in sea level: leading buildings to be flooded and abandoned or retrofitted, reducing values of coastline property and increasing the cost of insurance.

The second approach involved accompanying predictions of SLR with acknowledgement that the full extent of the consequences of such rise cannot be quantified or bounded, even if the amount of likely SLR can be. This is because the impact of rising sea level along coasts magnifies damage caused by storm surges. That is, storms lead sea water to cause damage further inland than under non-storm conditions. If the frequency and intensity of storms will increase in the future but do so unpredictably, then any bounding of the amount of likely SLR becomes uninformative because the important acknowledged consequences of SLR due to storms cannot be bounded.

Indeed, scientists have routinely noted that global warming is likely to cause an increase in severe storms[28]. For example, in 2017 the United States Environmental Protection Agency's website noted that "[c]limate change is increasing the odds of more extreme weather events taking place"[29]. Such storms have been said to occur unpredictably and to temporarily enhance the damage from SLR, sometimes devastatingly. For example, a publication by the National Oceanic and Atmospheric Administration (NOAA) states "By 2100, storm surges will happen on top of an additional 8 inches to 6.6 feet of global sea-level rise" (https://toolkit.climate.gov/topics/coastal/storm-surge). Thus, an expression of bounded uncertainty was presented not in isolation but in the context of an acknowledgement that the full extent of undesirable consequences of SLR cannot be quantified. Acknowledging uncertainty via this additional contextual information about storm surges may undermine the constructive impact of acknowledging uncertainty about SLR.

The present experiment entailed a 3 (bounded uncertainty) × 2 (irreducible uncertainty versus no irreducible uncertainty) between-subjects design (see Table 1) embedded in a survey of a nationally representative sample of American adults ($n = 1,174$). Respondents were randomly assigned to read a statement offering only a prediction of the most likely amount of future SLR (no uncertainty), a prediction of the most likely amount of SLR plus a worst-case scenario (high partially bounded uncertainty) or a prediction of the most likely amount of SLR plus descriptions of worst-case and best-case scenarios (fully bounded uncertainty). Half of the respondents (randomly assigned) read a second statement acknowledging irreducible uncertainty (that global warming-induced storms will unpredictably exacerbate the impact of gradual SLR). This study design allows assessment of whether bounded uncertainty expressions have less impact when they are accompanied by well-meaning additional context showing that the full extent of damage cannot in fact be quantified. After reading the message, respondents answered questions assessing their acceptance of the scientists' predictions. Trust in scientists was also measured to test the cognitive mechanisms through which expressions of uncertainty affect message acceptance. Specifically, we tested whether the effect of expressions of bounded uncertainty on message acceptance is mediated by trust in scientists (whether changes in message acceptance are the result of changes in trust).

Table 1 | Experimental design

	Irreducible uncertainty	
Bounded uncertainty	**Storm surge not mentioned**	**Storm surge mentioned**
None (single estimate)	No uncertainty ($n = 192$)	No uncertainty and irreducible uncertainty ($n = 194$)
Partial (estimate plus upper bound)	High partially bounded uncertainty ($n = 199$)	High partially bounded uncertainty and irreducible uncertainty ($n = 176$)
Full (estimate plus lower and upper bounds)	Fully bounded uncertainty ($n = 213$)	Fully bounded uncertainty and irreducible uncertainty ($n = 200$)

Bounded uncertainty with/without irreducible uncertainty

Raw mean message acceptance scores and mean trust in scientists are presented in Supplementary Fig. 1 and Supplementary Table 1. Below, we describe the results of analyses that control for demographic variables, political party identification and liberal/conservative ideology (Table 2, Supplementary Table 2 and Supplementary Note 2), to optimize the robustness of results. Supplementary Note 3, Supplementary Tables 3 and 4 and Supplementary Fig. 2 present results of analyses done without these controls, which yielded similar results to those with the controls.

Scientists expressing high partially bounded uncertainty affected respondents similarly regardless of whether or not they read about the unpredictable consequences of SLR due to storms, in terms of message acceptance, $b_{\text{Interaction}} = -0.01$, $t(1,135) = -0.18$, $P = 0.858$, partial $R^2 = 0.00$ and in terms of trust, $b_{\text{Interaction}} = 0.12$, $z(1,135) = 0.55$, $P = 0.585$, Odd's ratio (OR) = 1.13 (Table 2, row 4). However, scientists expressing fully bounded uncertainty affected respondents differently depending on whether or not they also read irreducible uncertainty about the unpredictable consequences of SLR due to storms, in terms of both message acceptance, $b_{\text{Interaction}} = -0.17$, $t(1,139) = -3.63$, $P < 0.001$, partial $R^2 = 0.01$ and trust, $b_{\text{Interaction}} = -0.56$, $z(1,135) = -2.65$, $P = 0.008$, OR = 0.57 (Table 2, row 5).

Therefore, in what follows, we describe how bounded uncertainty affected respondents when they did not read about irreducible uncertainty and, then, we examine how bounded uncertainty affected respondents when they did.

High partially bounded uncertainty

Reading expressions of a worst-case scenario did not alter message acceptance or trust. Message acceptance was the same after reading scientists expressing high partially bounded uncertainty as after reading an expression with no uncertainty, $b = -0.01$, $t(1,135) = -0.20$, $P = 0.844$, $d = -0.02$ (Table 2, row 1, column 1). Likewise, respondents who read high partially bounded uncertainty

Table 2 | Ordinary least squares (OLS) regression coefficients predicting message acceptance and probit regression coefficients predicting trust in scientists

	Regression coefficients	
Predictor	**Dependent variable: message acceptance**	**Dependent variable: trust in scientists**
High partially bounded uncertainty	−0.01 [−0.07, 0.06] (0.03)	0.02 [−0.27, 0.30] (0.15)
Fully bounded uncertainty	0.06⁺ [−0.00, 0.13] (0.03)	0.26⁺ [−0.04, 0.54] (0.15)
Irreducible uncertainty	0.10** [0.04, 0.17] (0.03)	0.25 [−0.05, 0.56] (0.16)
High partially bounded uncertainty × Irreducible uncertainty	−0.01 [−0.10, 0.09] (0.05)	0.12 [−0.31, 0.55] (0.22)
Fully bounded uncertainty × Irreducible uncertainty	−0.17*** [−0.27, −0.08] (0.05)	−0.56** [−0.98, -0.15] (0.21)
Constant	0.45*** [0.36, 0.54] (0.05)	0.46* [0.04, 0.85] (0.21)
n	1,167	1,167
Adjusted R^2	0.15	0.13

Presented are unstandardized OLS regression coefficients (in the first column) and probit regression coefficients (in the second column), with standard errors in parentheses and 95% confidence intervals for the regression coefficients in square brackets. Rows 1 and 2 report the simple effects of high partially bounded and fully bounded uncertainty when irreducible uncertainty was not mentioned. Row 3 reports the simple effect of irreducible uncertainty when no bounded uncertainty was mentioned. Additional predictors in these regressions were dummy variables identifying people who failed to answer each question. Coefficients for those dummy variables are not shown. The omitted substantive categories for the other dummy variable predictors were no bounded uncertainty and no irreducible uncertainty. This table omits coefficients for demographic controls for brevity of presentation; Supplementary Table 2 presents the same information from this table plus the coefficients for demographic controls, and Supplementary Note 2 discusses the control variables. Adjusted R^2 is presented for the model predicting message acceptance and adjusted McFadden pseudo-R^2 is presented for the model predicting trust. See Supplementary Note 4 for question wording and coding of measures in the table. ***$P<0.001$; ** $P<0.01$; * $P<0.05$; ⁺$P<0.10$.

expressed the same trust in scientists as did people who read no expression of uncertainty, $b=0.02$, $z(1{,}135)=0.11$, $P=0.916$, OR = 1.02 (Table 2, row 1, column 2).

Fully bounded uncertainty without irreducible uncertainty

Reading fully bounded uncertainty led to marginally significantly more message acceptance compared to no bounded uncertainty, $b=0.06$, $t(1{,}135)=1.93$, $P=0.054$, $d=0.18$ (Table 2, row 2, column 1). Furthermore, respondents who read fully bounded uncertainty expressed marginally significantly more trust in scientists than did people who read no bounded uncertainty, $b=0.26$, $z(1{,}135)=1.79$, $P=0.074$, OR = 1.30 (Table 2, row 2, column 2). Fully bounded uncertainty also marginally significantly increased trust in scientists and message acceptance when compared to high partially bounded uncertainty (Supplementary Note 5). Because respondents who read no uncertainty and who read high partially bounded uncertainty did not differ significantly from one another, statistical power can be maximized by combining those groups. Doing so causes the increases in message acceptance and trust due to fully bounded uncertainty to become statistically significant, $b_{\text{MessageAcceptance}}=0.07$, $t(1{,}137)=2.43$, $P=0.015$, $d=0.19$, $b_{\text{Trust}}=0.26$, $z(1{,}137)=2.04$, $P=0.041$, OR = 1.29.

The effect of expressing fully bounded uncertainty on message acceptance was mediated[30] by trust in scientists. Acknowledging fully bounded uncertainty caused an increase trust in scientists ($a_1=0.26$, $P=0.041$; see Fig. 1, top panel), which in turn caused an increase in message acceptance ($b_1=0.37$, $P<0.001$).

The direct effect of acknowledging fully bounded uncertainty on message acceptance ($c_1=0.07$, $P=0.015$) was significantly reduced when controlling for the mediator (trust in scientists) ($c_1'=0.04$, $P=0.098$). Confidence intervals for the indirect effect based on bootstrapping with 5,000 simulations indicated that the average causal mediation effect was 0.03, $P=0.04$, with a 95% confidence interval that did not include zero [0.003, 0.06], meaning that the mediational hypothesis was supported. The same mediational pattern was seen when comparing fully bounded uncertainty to high partially bounded uncertainty (Supplementary Note 6 and Supplementary Fig. 3). Sensitivity analyses replicated the same basic results using other plausible analytic approaches, reinforcing confidence in these conclusions (Supplementary Note 7; refs. [31–33]).

High partially bounded uncertainty with irreducible uncertainty

Respondents who read high partially bounded uncertainty with the irreducible uncertainty regarding unpredictable consequences manifested the same level of message acceptance as respondents who read no uncertainty while reading about irreducible uncertainty, $b=-0.02$, standard error (SE) = 0.04, $t(1{,}135)=-0.44$, $P=0.663$, $d=-0.04$ and reported the same level of trust in scientists, $b=0.14$, SE = 0.17, $z(1{,}135)=0.82$, $P=0.411$, OR = 1.15. Thus, regardless of whether or not scientists described irreducible uncertainty regarding unpredictable consequences of global warming via storms and storm surge, including a worst-case scenario again did not affect message acceptance or trust.

Fully bounded uncertainty with irreducible uncertainty

Among people who read about irreducible uncertainty regarding the consequences of SLR via storm surges, respondents who read fully bounded uncertainty manifested significantly less message acceptance than did respondents who read no or high partially bounded uncertainty, $b=-0.10$, SE = 0.03, $t(1{,}137)=-3.44$, $P<0.001$, $d=-0.29$ and reported significantly less trust in scientists, $b=-0.36$, SE = 0.13, $z(1{,}137)=-2.73$, $P=0.006$, OR = 0.70.

Trust in scientists also mediated the negative impact of fully bounded uncertainty on message acceptance in this context. Acknowledging fully bounded uncertainty caused a decreased trust in scientists ($a_1=-0.36$, $P=0.006$; Fig. 1, bottom panel), which in turn caused an increase in message acceptance ($b_1=0.37$, $P<0.001$). The direct effect of acknowledging fully bounded uncertainty on message acceptance ($c_1=-0.10$, $P<0.001$) was significantly reduced when controlling for the mediator (trust in scientists) ($c_1'=-0.06$, $P=0.014$). The average causal mediation effect was −0.04, $P=0.02$ and the 95% confidence interval for the indirect effect did not include zero: [−0.07, −0.01], meaning that the mediational hypothesis was supported. Sensitivity analyses replicated the same basic results (Supplementary Note 5).

Thus, fully bounded uncertainty reduced message acceptance by reducing trust when scientists also acknowledged irreducible uncertainty.

None of the effects described above was significantly moderated by respondents' cognitive skills (measured by respondents' level of formal education) or political party affiliations (Supplementary Notes 8 and 9).

Discussion

This study explored the impact of bounded uncertainty on trust in scientists and acceptance of their predictions and tested mediational pathways of effects, in a nationally representative sample of

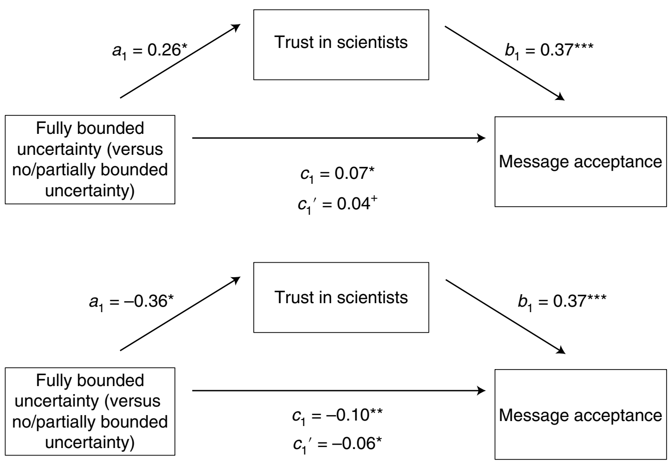

Fig. 1 | Mediation analysis. Trust in scientists as a mediator of the effect of fully bounded uncertainty, compared to no bounded uncertainty and high partially bounded uncertainty, in the without irreducible uncertainty (top panel; average causal mediation effect = 0.03*, total effect mediated = 40.2%) and with irreducible uncertainty (bottom panel; average causal mediation effect = –0.04*, total effect mediated = 36.4%) conditions. See Supplementary Note 4 for question wording and coding of measures in the figure. ***$P < 0.001$; **$P < 0.01$; *$P < 0.05$; $^{+}P < 0.10$.

American adults. In addition, it tested how bounded uncertainty expressions affect the public when they are presented with additional information illustrating that the consequences of predictions cannot be fully quantified and that uncertainty is thus irreducible. The findings suggest that expressions of bounded uncertainty can improve acceptance of climate scientists' findings. In the absence of information about irreducible uncertainty, fully bounded uncertainty increased message acceptance because it increased trust in scientists. These effects appeared equally strongly among people with limited cognitive skills and those with strong cognitive skills (Supplementary Note 9), suggesting that uncertainty messages are easy to process and to use, resonating with other research[34,35]. Moreover, the effects of fully bounded uncertainty appeared to occur regardless of a person's a priori scepticism toward global warming (Supplementary Note 8).

However, expressing fully bounded uncertainty while acknowledging that the full consequences of SLR are unpredictable eliminated the constructive impact of expressing fully bounded uncertainty about the amount of SLR alone. Because scientists often acknowledge the consequences of SLR due to storm surges, this suggests that in most real-world contexts there may be no benefits to be gained by placing bounds on predicted SLR[18] and perhaps some adverse consequences. The irreducible uncertainty respondents read in this experiment emphasized the worst-case scenario (for example, "Scientists believe that global warming will cause these storms to be more intense in the future…") and this may have affected respondents' judgements. Future research could explore other ways of acknowledging irreducible uncertainty and their effects.

Although the effects of the expressions of uncertainty on message acceptance were small-to-medium by standard conventions[36], it is notable that brief exposure to one message could shift global warming attitudes. Repeated exposure to these kinds of messages over time may enhance their impact[37].

Our findings resonate with those of previous studies[24] using convenience samples of students and adults. Surprisingly, however, those studies suggested that a form of fully bounded uncertainty increased trust only among highly educated respondents and did not among less educated respondents. Using a large, representative national sample of American adults, our study did not confirm that finding and thereby suggests that the constructive effects of fully bounded uncertainty expressions are not limited to cognitively sophisticated individuals.

Our findings offer a new interpretation of the finding of a second prior investigation[38] comparing different types of bounded uncertainty expressions that refer to future time or outcome magnitude. Respondents exposed to the former type of uncertainty were subsequently more supportive of government action on global warming than respondents exposed to the latter type of uncertainty. However, without a group of respondents who read predictions made with no uncertainty, it is impossible to disentangle the effects of expressing uncertainty on support (for example, they could have both increased support for government action or both decreased it). The present study suggests that both are likely to have increased support.

Bounding a SLR prediction with only the worst case did not enhance message acceptance or trust. This suggests that attempts to catastrophize by focusing only on how bad things can get may not be effective. We look forward to future research examining the impact of the rarely expressed (Supplementary Note 1) best-case-only type of bounding, which can reveal whether the present finding of no impact of worst-case scenarios generalizes to that type of partial bounding.

The versions of fully bounded uncertainty examined here were accompanied by a best guess (the 4-ft estimate) rather than presenting best-case and worst-case scenarios alone (sea level could rise between 1 and 7 ft). This ensured that all participants received the same information about the best guess and allowed testing the impact of adding best-case and worst-case scenarios to it. However, as ranges of outcomes have often been presented without a best guess in science communication (Supplementary Note 1), these expressions of uncertainty should be compared in future research. In addition, future studies might explore the consequences of quantifying the likelihoods of the bounds of the prediction interval, as is the case with confidence intervals (confidence intervals quantify the level of confidence that a parameter lies in a specified range).

The present research rebuts the often-heard claim that expressing uncertainty undermines persuasion. Lay audiences often operate on the assumption that acknowledging uncertainty acknowledges weakness. Psychologists have found that uncertainty is aversive and that people are motivated to reduce it[39]. Therefore, one might imagine that the public would turn away from experts who make claims while acknowledging their own lack of full understanding. However, people seem to recognize that complete certainty in future predictions is not possible, especially in the context of global warming. Scientists who openly admit the limitations inherent in their predictions may bolster their credibility and as a result may increase the appropriate use of scientific findings by non-experts[40–42]. These gains may be nullified, and even reversed, when scientists acknowledge that no matter how confidently they can make predictions about some future scenarios, the full extent of the consequences of those predictions cannot be quantified. Optimal communication about climate change may involve presenting uncertainty that has predictable bounds without overwhelming the public with the discussion of factors involving irreducible uncertainty.

Online content

Any methods, additional references, Nature Research reporting summaries, source data, statements of code and data availability and associated accession codes are available at https://doi.org/10.1038/s41558-019-0587-5.

Received: 5 March 2018; Accepted: 28 August 2019;
Published online: 14 October 2019

References

1. Moss, R. H., & Schneider, S. H. *Guidance Papers on the Cross Cutting Issues of the Third Assessment Report of the* IPCC (eds Pachuri, R. et al.) 33–51 (World Meterological Organization, 2000).
2. Brewer, N. & Burke, A. Effects of testimonial inconsistencies and eyewitness confidence on mock-juror judgments. *Law. Hum. Behav.* **26**, 353–364 (2002).
3. Penrod, S. & Cutler, B. Witness confidence and witness accuracy: assessing their forensic relation. *Psychol. Public Policy Law* **1**, 817–845 (1995).
4. Bonaccio, S. & Dalal, R. S. Advice taking and decision-making: an integrative literature review, and implications for the organizational sciences. *Organ. Behav. Hum. Decis. Process* **101**, 127–151 (2006).
5. Phillips, J. M. Antecedents of leader utilization of staff input in decision-making teams. *Organ. Behav. Hum. Decis. Process.* **77**, 215–242 (1999).
6. Price, P. C. & Stone, E. R. Intuitive evaluation of likelihood judgment producers: evidence for a confidence heuristic. *J. Behav. Decis. Mak.* **17**, 39–57 (2004).
7. Sniezek, J. A. & Van Swol, L. M. Trust, confidence, and expertise in a judge–advisor system. *Organ. Behav. Hum. Decis. Process* **84**, 288–307 (2001).
8. Van Swol, L. M. & Sniezek, J. A. Factors affecting the acceptance of expert advice. *Br. J. Soc. Psychol.* **44**, 443–461 (2005).
9. Fox, C. R. & Irwin, J. R. The role of context in the communication of uncertain beliefs. *Basic Appl. Soc. Psychol.* **20**, 57–70 (1998).
10. Johnson, B. B. Further notes on public response to uncertainty in risks and science. *Risk Anal.* **23**, 781–789 (2003).
11. Johnson, B. B. & Slovic, P. Presenting uncertainty in health risk assessment: initial studies of its effects on risk perception and trust. *Risk Anal.* **15**, 485–494 (1995).
12. Butler, K. Toward understanding and measuring conditions of trust: evolution of a conditions of trust inventory. *J. Manag.* **17**, 643–663 (1991).
13. Priester, J. R. & Petty, R. E. Source attributions and persuasion: perceived honesty as a determinant of message scrutiny. *Pers. Soc. Psychol. Bull.* **21**, 637–654 (1995).
14. Priester, J. R. & Petty, R. E. The influence of spokesperson trustworthiness on message elaboration, attitude strength, and advertising effectiveness. *J. Cons. Psychol.* **213**, 408–421 (2003).
15. Joslyn, S. & Savelli, S. Communicating forecast uncertainty: public perception of weather forecast uncertainty. *Meteorol. Appl.* **17**, 180–195 (2010).
16. Morss, R. E., Demuth, J. L. & Lazo, J. K. Communicating uncertainty in weather forecasts: a survey of the U.S. public. *Weather Forecast.* **23**, 974–991 (2008).
17. Du, N., McEnroe, J. E. & Stevens, K. The joint effects of management incentive and information precision on perceived reliability in fair value estimates. *Account. Res. J.* **27**, 188–206 (2014).
18. IPCC *Climate Change 2007: Synthesis Report* (eds Core Writing Team, Pachuari, R. K. & Reisinger, A.) (IPCC, 2007).
19. IPCC *Climate Change 2014: Synthesis Report* (eds Core Writing Team, Pachuari, R. K. & Meyer, L. A.) (IPCC, 2014).
20. Joslyn, S., Savelli, S. & Nadav-Greenberg, L. Reducing probabilistic weather forecasts to the worst-case scenario: anchoring effects. *J. Exp. Psychol. Appl.* **17**, 324–353 (2011).
21. Hohle, S. M. & Teigen, K. H. More than 50% of less than 70% chance: pragmatic implications of single-bound probability estimates. *J. Behav. Decis. Mak.* **31**, 138–150 (2018).
22. Eppler, M. J. & Mengis, J. The concept of information overload: a review of literature from organization science, accounting, marketing, MIS, and related disciplines. *Inform. Soc.* **20**, 325–344 (2004).
23. Chae, J., Lee, C. & Jensen, J. D. Correlates of cancer information overload: focusing on individual ability and motivation. *Health Commun.* **31**, 626–634 (2016).
24. Joslyn, S. & LeClerc, J. E. Climate projections and uncertainty communication. *Top. Cogn. Sci.* **8**, 222–241 (2016).
25. Jensen, J. D. Scientific uncertainty in news coverage of cancer research: effects of hedging on scientists' and journalists' credibility. *Hum. Commun. Res.* **34**, 347–369 (2008).
26. Jensen, J. D. et al. Including limitations in news coverage of cancer research: effects of news hedging on fatalism, medical skepticism, patient trust, and backlash. *J. Health Commun.* **16**, 486–503 (2011).
27. Jensen, J. D. et al. Communicating uncertain science to the public: how amount and source of uncertainty impact fatalism, backlash, and overload. *Risk Anal.* **37**, 40–51 (2017).
28. Hansen, J. et al. Efficacy of climate forcings. *J. Geophys. Res.* **110**, D18104 (2005).
29. *Understanding the Link Between Climate Change and Extreme Weather* (US EPA, 2017); https://go.nature.com/2mluCkv
30. MacKinnon, D.P., Fairchild, A.J. & Fritz, M.S. Mediation analysis. *Ann. Rev. Psychol.* **58**, 593-614 (2007).
31. Imai, K., Keele, L. & Tingley, D. A general approach to causal mediation analysis. *Psychol. Methods* **15**, 309–335 (2010).
32. Imai, K., Keele, L. & Yamamoto, T. Identification, inference and sensitivity analysis for causal mediation effects. *Stat. Sci.* **25**, 51–71 (2010).
33. Hicks, R. & Tingley, D. Causal mediation analysis. *Stata J.* **11**, 609–615 (2011).
34. Grounds, M. A., Joslyn, S. & Otsuka, K. Probabilistic interval forecasts: an individual differences approach to understanding forecast communication. *Adv. Meteorol.* **2017**, 1–18 (2017).
35. Harris, A. J. L., Por, H. & Broomell, S. B. Anchoring climate change communications. *Climatic Change* **140**, 387–398 (2017).
36. Cohen, J. *Statistical Power Analyses for the Behavioral Sciences* (Academic, 1969).
37. Prentice, D. A. & Miller, D. T. When small effects are impressive. *Psych. Bull.* **112**, 160–164 (1992).
38. Ballard, T. & Lewandowsky, S. When, not if: the inescapability of an uncertain climate future. *Phil. Trans. R. Soc. A* **373**, 20140464 (2015).
39. Hogg, M. A. Subjective uncertainty reduction through self-categorization: a motivational theory of social identity processes. *Eur. Rev. Soc. Psychol.* **11**, 223–255 (2000).
40. Morton, T. A., Rabinovich, A., Marshall, D. & Bretschneider, P. The future that may (or may not) come: how framing changes responses to uncertainty in climate change communications. *Glob. Environ. Change* **21**, 103–109 (2011).
41. Rabinovich, A. & Morton, T. A. Unquestioned answers or unanswered questions: beliefs about science guide responses to uncertainty in climate change risk communication. *Risk Anal.* **32**, 992–1002 (2012).
42. Joslyn, S. & LeClerc, J. E. Uncertainty forecasts improve weather-related decisions and attenuate the effects of forecast error. *J. Exp. Psychol.* **18**, 126–140 (2012).

Acknowledgements

This study was funded by the Woods Institute for the Environment and the Center for Ocean Solutions at Stanford University. The work was also supported by a National Science Foundation Graduate Research Fellowship grant and the Shaper Family Stanford Interdisciplinary Graduate Fellowship grant to L.C.H. and the Princeton University Institute for International and Regional Studies. J.A.K. is University Fellow at Resources for the Future.

Author contributions

L.C.H., B.M., J.A.K., E.M.M. and R.S. developed the study idea. L.C.H., B.M., J.A.K. and E.M.M. designed the research. L.C.H. and B.M. analysed the data. L.C.H., B.M. and J.A.K. wrote the manuscript and E.M.M. and R.S. provided revisions.

Competing interests

The authors declare no competing interests.

Additional information

Supplementary information is available for this paper at https://doi.org/10.1038/s41558-019-0587-5.

Correspondence and requests for materials should be addressed to L.C.H.

Peer review information *Nature Climate Change* thanks David Budescu, Emily Ho, Susan Joslyn and the other, anonymous, reviewer(s) for their contribution to the peer review of this work.

Methods

Sample. Interviews were conducted with a nationally representative random probability sample of 1,174 American adults via the Internet by GfK Custom Research between 7 and 18 March 2013. The questionnaire was administered in both English and Spanish.

Respondents were drawn randomly from among the members of GfK's KnowledgePanel, American adults who were selected from the population via probability sampling. Some panel members were recruited via random-digit dialling telephone calls and other panel members were recruited via mailed invitations to households selected randomly via address-based sampling. If needed, households were given computers and access to the Internet at no cost, to allow them to answer questionnaires via the Internet. When people joined the panel, GfK collected demographic information such as sex, age, race/ethnicity, education and income. Then, occasional emails inviting panel members to complete questionnaires were sent (for details on the recruitment of GfK's KnowledgePanel, see Supplementary Note 10).

Three days after the initial invitation to complete a survey was sent, automatic email reminders were sent to non-responding panel members and telephone calls were sometimes made to remind people as well. To thank them for their efforts, panel members were entered into raffles or sweepstakes offering cash rewards and other prizes.

The data for the survey were weighted to account for unequal probabilities of selection and to post-stratify in terms of age, sex, race and ethnicity, education, census region, household income, home ownership status, metropolitan area, Spanish language usage and Internet access, using targets from the February 2013 Current Population Survey (CPS) conducted by the US Census Bureau, the 2010 Pew Hispanic Center Survey (which provided the most recent measurements of Spanish language usage) and the October 2010 CPS supplemental survey measuring Internet access. Supplementary Table 5 displays distributions of unweighted and weighted demographics of the survey sample and national benchmarks from the February 2013 CPS. These distributions show that the survey sample was similar to the American population before the weights were applied and was more similar after the data were weighted. Results reported in this paper were computed using weighted data.

Experimental conditions. At the beginning of the survey, all respondents read an introduction:

> During this survey, when we say 'global warming', we will mean the idea that the world's temperature has been increasing over the last 100 years and will increase in the future. Next, you will read some things that scientists who study global warming have said about its effects in the future. Please read the information on the next screen(s). Then, we'll ask whether you remember hearing or reading information like this before today.

Respondents read the following passages in each of the six experimental conditions.

(1) No uncertainty (single estimate for SLR and no irreducible uncertainty; $n=192$).

> Scientists believe that, during the next 100 years, global warming will cause the surface of the oceans around the world to rise about 4 feet. In the United States, sea-level rise will mostly affect towns and cities along the coasts, where millions of people live and work. Sea-level rise will gradually flood these areas, so people living and working along the coasts will have to move their homes and businesses to other places, farther from the ocean.
>
> If sea level rises by 4 feet and nothing is done to prepare for it, about 5 million Americans who currently live and work less than 4 feet above sea level will have to move out of their homes and businesses.

(2) High partially bounded uncertainty (estimate plus worst-case estimate for SLR and no irreducible uncertainty; $n=199$).

> Scientists believe that, during the next 100 years, global warming will cause the surface of the oceans around the world to rise about 4 feet. However, sea level could rise as much as 7 feet. In the United States, sea-level rise will mostly affect towns and cities along the coasts, where millions of people live and work. Sea-level rise will gradually flood these areas, so people living and working along the coasts will have to move their homes and businesses to other places, farther from the ocean.
>
> If sea level rises by 4 feet and nothing is done to prepare for it, about 5 million Americans who currently live and work less than 4 feet above sea level will have to move out of their homes and businesses. If sea level rises by 7 feet and nothing is done to prepare for it, about 8 million Americans who currently live and work less than 7 feet above sea level will have to move out of their homes and businesses.

In the context of SLR, one might consider the worst-case scenario to be more extreme, for example, sudden massive flooding caused by polar ice caps melting. For this study, we are concerned instead with a worst-case scenario that represents the upper bounds of a range in which scientists are reasonably confident that SLR might fall.

(3) Fully bounded uncertainty (estimate plus worst- and best-case estimates for SLR and no irreducible uncertainty; $n=213$).

> Scientists believe that, during the next 100 years, global warming will cause the surface of the oceans around the world to rise about 4 feet. However, sea level could rise as little as 1 foot or it could rise by as much as 7 feet. In the United States, sea-level rise will mostly affect towns and cities along the coasts, where millions of people live and work. Sea-level rise will gradually flood these areas, so people living and working along the coasts will have to move their homes and businesses to other places, farther from the ocean.
>
> If sea level rises by 1 foot and nothing is done to prepare for it, about 1 million Americans who currently live and work less than 1 foot above sea level will have to move out of their homes and businesses. If sea level rises by 4 feet and nothing is done to prepare for it, about 5 million Americans who currently live and work less than 4 feet above sea level will have to move out of their homes and businesses. If sea level rises by 7 feet and nothing is done to prepare for it, about 8 million Americans who currently live and work less than 7 feet above sea level will have to move out of their homes and businesses.

(4) Irreducible uncertainty (single estimate for SLR and storm statement; $n=194$). Respondents read the same passage about SLR as respondents in condition (1) and then read the following additional passage about storms.

> This rise in sea level will make hurricanes, cyclones and other storms worse for people living and working near the coast. Scientists believe that global warming will cause these storms to be more intense in the future. During these storms, oceans will surge as high as 20 feet along hundreds of miles of coastline and will suddenly flood cities with large amounts of water. These floods will be more damaging over the years as sea level rises and floods will be even worse when storms hit during high tide. For example, Hurricane Sandy caused ocean surges as high as 14 feet and flooded tunnels, buildings and other parts of New York and New Jersey.

(5) High partially bounded uncertainty plus irreducible uncertainty (estimate plus worst-case for SLR and storm statement; $n=176$). Respondents read the same passage about SLR as respondents in condition (2) and then read the same passage about storms as respondents in condition (4).

(6) Fully bounded uncertainty plus irreducible uncertainty (estimate plus worst- and best-case estimates for SLR and storm statement; $n=200$). Respondents read the same passage about SLR as respondents in condition (3) and then read the same passage about storms as respondents in condition (4).

Thus, respondents read one of six messages describing scientists' predictions: (1) no uncertainty, describing the most likely amount of future SLR ("global warming will cause the surface of the oceans around the world to rise about 4 feet"), (2) high partially bounded uncertainty, describing a most likely amount plus a worst-case scenario (";…about 4 feet. However, sea level could rise as much as 7 feet"), (3) fully bounded uncertainty, describing a most likely amount, a worst-case scenario and a best-case scenario ("…about 4 feet. However, sea level could rise as little as 1 foot or it could rise by as much as 7 feet"), (4) irreducible uncertainty, describing the most likely amount of future SLR and the potential for storm surges ("floods will be more damaging over the years as sea level rises and floods will be even worse when storms hit during high tide"), (5) high partially bounded uncertainty plus irreducible uncertainty, describing the most likely amount of SLR and a worst-case scenario plus the potential for storm surges and (6) fully bounded uncertainty plus irreducible uncertainty, describing the most likely amount of SLR, worst- and best-case scenarios and the potential for storm surges.

For information on how the estimates of SLR and population displacement were obtained, see Supplementary Note 11.

The research was approved by the Stanford University Institutional Review Board. Informed consent was obtained from all participants.

Measures. Respondents reported whether they remembered previously hearing or reading the presented information and then answered questions assessing their acceptance of the scientists' messages about the consequences of global warming via SLR (see Supplementary Note 4 for all question wordings and their Spanish translations).

Message acceptance. The primary dependent variable was a measure of acceptance of the scientists' messages about the consequences of global warming via SLR (three items, $\alpha=0.86$). A participant's message acceptance score was computed by averaging answers to the following questions coded as follows and therefore ranged from 0 (meaning the least concern) to 1 (meaning the most concern). Analyses predicting each of these items separately yielded patterns consistent with those observed using the combined score.

How serious the effects of global warming via SLR will be: extremely serious = 1.0; very serious = 0.75; moderately serious = 0.5; slightly serious = 0.25; not serious at all = 0.

How bad the effects of global warming via SLR will be: the product of believing global warming will cause SLR (coded 0 for no and 1 for yes) and the index of how bad SLR caused by global warming will be, the latter coded 0 if good or leaning toward good, not leaning; 1 if very bad; 0.67 if somewhat bad; 0.33 leaning toward bad.

How bad the effects of global warming via storms will be: the product of believing global warming will cause storms to be more damaging and the index of how bad the storms caused by global warming will be, the latter coded 0 if good or leaning toward good, not leaning; 1 if very bad; 0.67 if somewhat bad; 0.33 leaning toward bad.

Higher scores indicate more acceptance of SLR global warming consequences. Correlations between these three items are presented in Supplementary Table 6.

Trust in scientists. We examined trust in scientists' statements about the environment, as a potential mediator of the effects of admitting uncertainty on message acceptance. Trust in scientists was measured after the manipulation by the following question: "How much do you trust the things scientists say about the environment—completely, a lot, a moderate amount, a little or not at all?" A dichotomous variable 'trust in scientists' was constructed and set to 1 for respondents who answered "completely", "a lot" or "a moderate amount" and 0 for those who answered "a little" or "not at all".

Demographics, political party identification and political ideology. Respondents reported their sex, age, race, Hispanic ethnicity, education, income and zip code of residence, as well as political party identification and liberal/conservative ideology. Coastal dweller was a dichotomous variable coded 1 for respondents who lived in a county with a coastline bordering the open ocean and 0 for others. Respondents' reports of the zip codes of their residences were linked with a NOAA database to differentiate respondents who lived in a county with a coastline bordering the open ocean from all others. The NOAA database is available at www.census.gov/geo/reference/zctas.html. The list of coastal zip codes was developed using zip code tabulation areas developed by the US Census Bureau for the 402 coastal counties included in the Economics: National Ocean Watch (ENOW) dataset (https://coast.noaa.gov/digitalcoast/data/enow.html) created by the NOAA Coastal Services Center. ENOW's list of counties (https://coast.noaa.gov/digitalcoast/training/enow-counties-list.html) is a modified version of NOAA's list of 'coastal shoreline counties', which includes all counties that have a coastline bordering the open ocean or the Great Lakes or that contain coastal high hazard areas as defined by the Federal Emergency Management Agency.

Missing data. Respondents were allowed to skip questions. Dummy variables identifying people who failed to answer any of the demographic questions were included as predictors in the regressions and such respondents were assigned arbitrary values on demographics. This avoids losing the cases while also preventing distortion of the statistical results. If a participant answered at least one of the message acceptance questions, he or she was included in the analyses, using an average of the substantive answers he or she provided. Ten respondents refused to answer all of the index questions. A value for three of these people was imputed using multiple imputation methods[43], one of the most reliable methods for handling missing data[44]. Ten respondents did not answer the question about trust in scientists. A value for trust in scientists was imputed for seven of these ten respondents using multiple imputation. The seven respondents for whom values on the index could not be imputed failed to answer so many other questions that imputation was not possible on either the index or trust in scientists, so these people were excluded from the analyses, resulting in a total usable sample of 1,167 people.

Analysis method. Ordinary least squares (OLS) linear regression was used to examine the impact of uncertainty on persuasion by predicting concern with the bounded uncertainty variable, the irreducible uncertainty variable and their interaction, controlling for demographics and political party identification and ideology. A probit regression predicting trust in scientists with the same variables as in the linear regression gauged the causal impact of the uncertainty expression conditions tested in the experiment. All statistical tests were two-sided. We considered $P \leq 0.05$ as statistically significant and P between 0.050 and 0.10 as marginally significant. We calculated 95% confidence intervals using the confint() function in R Statistical Software v.3.3.1 (https://www.R-project.org/). For all estimates of probit regression coefficients, we gauged effect sizes with odds ratios, computed using the R function exp(coef()). For all estimates of OLS regression coefficients, we gauged effect sizes with Cohen's *d* computed from the unstandardized regression coefficients, calculated using the R function esc_B from the R package esc[45].

Coding of variables to compare experimental conditions. Examining the interaction between the two variables (the bounded uncertainty variable and the irreducible uncertainty variable) allows us to determine whether participants responded differently to the expressions of bounded uncertainty about SLR depending on whether these expressions were also accompanied with the additional information about irreducible uncertainty regarding the consequences of global warming because of storms and storm surge.

For the bounded uncertainty variable, we created two dummy variables to compare respondents who read no uncertainty to respondents who read (1) high partially bounded uncertainty and (2) fully bounded uncertainty. Specifically, the first dummy variable, 'high partially bounded uncertainty', was set to 1 for respondents assigned to condition (2) whereby they saw high partially bounded uncertainty and did not see irreducible uncertainty and set to 0 for respondents assigned to condition (1) (who read no uncertainty and did not see irreducible uncertainty) or respondents assigned to condition (3) (who read fully bounded uncertainty and did not see irreducible uncertainty). The second dummy variable, 'fully bounded uncertainty', was set to 1 for respondents assigned to condition (3) whereby they saw fully bounded uncertainty and did not see irreducible uncertainty and set to 0 for respondents assigned to condition (1) (who read no uncertainty and did not see irreducible uncertainty) or respondents assigned to condition (2) (who read high partially bounded uncertainty and did not see irreducible uncertainty). Because the models contained an interaction with the irreducible uncertainty variable, the coefficients for these variables presented in Table 2 represent the simple effects of high partially bounded uncertainty and fully bounded uncertainty when no irreducible uncertainty was mentioned.

For the irreducible uncertainty variable, we created one dummy variable to omit respondents who did not read about irreducible uncertainty and compare them to respondents who did read about irreducible uncertainty. This dummy variable was set to 1 for respondents assigned to conditions (4), (5) or (6), whereby respondents read about irreducible uncertainty, and set to 0 for respondents assigned to conditions (1), (2) or (3), whereby respondents did not read about irreducible uncertainty. Because the models contained an interaction with the bounded uncertainty variable, the coefficient for this variable presented in Table 2 represents the simple effect of reading about irreducible uncertainty when no uncertainty was mentioned.

To examine the effects of bounded uncertainty when scientists also mentioned irreducible uncertainty, we re-ran the same analyses as described above (OLS linear regression and probit regression) but dummy coded the irreducible uncertainty variable to omit respondents who read about irreducible uncertainty as the base group. For these analyses, this dummy variable was set to 0 for respondents assigned to conditions (4), (5) or (6), whereby respondents read about irreducible uncertainty, and set to 1 for respondents assigned to conditions (1), (2) or (3), whereby respondents did not read about irreducible uncertainty. This allowed us to then examine the effects of bounded uncertainty among those respondents (by examining simple effects among those respondents).

For the mediational analyses, the R package mediation[46] was used for all calculations.

Reporting Summary. Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability

The data that support the findings of this study are available online at http://osf.io/tgmyh.

References

43. Honaker, J., King, G. & Blackwell, M. Amelia II: a program for missing data. *J. Stat. Softw.* **45**, 1 (2011).
44. McKnight, P. E., McKnight, K. M., Sidani, S. & Figueredo, A. J. *Missing Data: A Gentle Introduction* (Guilford, 2007).
45. Lüdecke, D. esc: Effect size computation for meta-analysis. R version 0.4.0 https://CRAN.R-project.org/package=esc (2019).
46. Tingley, D., Yamamoto, T., Hirose, K., Keele, L. & Imai, K. mediation: R package for causal mediation analysis. *J. Stat. Softw.* **59**, 1–38 (2014).

nature research

Corresponding author(s): Lauren Howe

Last updated by author(s): Aug 20, 2019

Reporting Summary

Nature Research wishes to improve the reproducibility of the work that we publish. This form provides structure for consistency and transparency in reporting. For further information on Nature Research policies, see Authors & Referees and the Editorial Policy Checklist.

Statistics

For all statistical analyses, confirm that the following items are present in the figure legend, table legend, main text, or Methods section.

n/a	Confirmed	
☐	☒	The exact sample size (*n*) for each experimental group/condition, given as a discrete number and unit of measurement
☐	☒	A statement on whether measurements were taken from distinct samples or whether the same sample was measured repeatedly
☐	☒	The statistical test(s) used AND whether they are one- or two-sided *Only common tests should be described solely by name; describe more complex techniques in the Methods section.*
☐	☒	A description of all covariates tested
☐	☒	A description of any assumptions or corrections, such as tests of normality and adjustment for multiple comparisons
☐	☒	A full description of the statistical parameters including central tendency (e.g. means) or other basic estimates (e.g. regression coefficient) AND variation (e.g. standard deviation) or associated estimates of uncertainty (e.g. confidence intervals)
☐	☒	For null hypothesis testing, the test statistic (e.g. F, t, r) with confidence intervals, effect sizes, degrees of freedom and P value noted *Give P values as exact values whenever suitable.*
☒	☐	For Bayesian analysis, information on the choice of priors and Markov chain Monte Carlo settings
☒	☐	For hierarchical and complex designs, identification of the appropriate level for tests and full reporting of outcomes
☐	☒	Estimates of effect sizes (e.g. Cohen's d, Pearson's r), indicating how they were calculated

Our web collection on statistics for biologists contains articles on many of the points above.

Software and code

Policy information about availability of computer code

Data collection	No software was used for data collection
Data analysis	R Statistical Software version 3.3.1 (https://www.R-project.org/) As cited in the manuscript, the following R Statistical Software packages were used in data analysis: Honaker, J., King, G., & Blackwell, M.. Amelia II: A program for missing data. J. Stat. Softw. 45, 1 (2011). Lüdecke, D. Effect size computation for meta-analysis. R package version 0.4.0, https://CRAN.R-project.org/package=esc. Tingley, D., Yamamoto, T., Hirose, K., Keele, L., Imai, K. mediation: R package for causal mediation analysis. J. Stat. Softw. 59, 1-38 (2014).

For manuscripts utilizing custom algorithms or software that are central to the research but not yet described in published literature, software must be made available to editors/reviewers. We strongly encourage code deposition in a community repository (e.g. GitHub). See the Nature Research guidelines for submitting code & software for further information.

Data

Policy information about availability of data

All manuscripts must include a data availability statement. This statement should provide the following information, where applicable:

- Accession codes, unique identifiers, or web links for publicly available datasets
- A list of figures that have associated raw data
- A description of any restrictions on data availability

The data that support the findings of this study are available online at http://osf.io/tgmyh.

Field-specific reporting

Please select the one below that is the best fit for your research. If you are not sure, read the appropriate sections before making your selection.

☐ Life sciences ☒ Behavioural & social sciences ☐ Ecological, evolutionary & environmental sciences

For a reference copy of the document with all sections, see nature.com/documents/nr-reporting-summary-flat.pdf

Behavioural & social sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	Quantitative experimental study
Research sample	Interviews were conducted with a nationally representative random, probability sample of 1,174 American adults via the Internet by GfK Custom Research.
Sampling strategy	Respondents were drawn randomly from among the members of GfK's KnowledgePanel, American adults who were selected from the population via probability sampling. Some panel members were recruited via random-digit dialing (RDD) telephone calls, and other panel members were recruited via mailed invitations to households selected randomly via address-based sampling.
Data collection	Questionnaires were completed over the internet. If needed, households were given computers and access to the Internet at no cost, to allow them to answer questionnaires via the Internet.
Timing	March 7 and 18, 2013
Data exclusions	Respondents were allowed to skip questions. If a participant answered at least one of the message acceptance questions, he or she was included in the analyses, using an average of the substantive answers he or she provided. Ten respondents refused to answer all of the index questions. A value for three of these people was imputed using multiple imputation methods, one of the most reliable methods for handling missing data. Ten respondents did not answer the question about trust in scientists. A value for trust in scientists was imputed for 7 of these 10 respondents using multiple imputation. The seven respondents for whom values on the index could not be imputed failed to answer so many other questions that imputation was not possible on either the index or trust in scientists, so these people were excluded from the analyses, resulting in a total usable sample of 1,167 people.
Non-participation	No participants dropped out other than by refusing to answer the questions.
Randomization	Participants were randomized via survey software to experimental groups.

Reporting for specific materials, systems and methods

We require information from authors about some types of materials, experimental systems and methods used in many studies. Here, indicate whether each material, system or method listed is relevant to your study. If you are not sure if a list item applies to your research, read the appropriate section before selecting a response.

Materials & experimental systems

n/a	Involved in the study	
☒	☐	Antibodies
☒	☐	Eukaryotic cell lines
☒	☐	Palaeontology
☒	☐	Animals and other organisms
☐	☒	Human research participants
☒	☐	Clinical data

Methods

n/a	Involved in the study	
☒	☐	ChIP-seq
☒	☐	Flow cytometry
☒	☐	MRI-based neuroimaging

Human research participants

Policy information about studies involving human research participants

Population characteristics	See above
Recruitment	When people joined the panel run by GfK, GfK collected demographic information such as sex, age, race/ethnicity, education, and income. Then, occasional e-mails inviting panel members to complete questionnaires were sent. Three days after the initial invitation to complete a survey was sent, automatic email reminders were sent to non-responding panel members, and telephone calls were sometimes made to remind people as well. To thank them for their efforts, panel members were entered into raffles or sweepstakes offering cash rewards and other prizes.

Ethics oversight | The protocol was approved by the Stanford University Institutional Review Board.

Note that full information on the approval of the study protocol must also be provided in the manuscript.