nature human behaviour

LETTERS

https://doi.org/10.1038/s41562-018-0520-3

Extreme opponents of genetically modified foods know the least but think they know the most

Philip M. Fernbach[1]*, Nicholas Light[1], Sydney E. Scott[2], Yoel Inbar[3] and Paul Rozin[4]

There is widespread agreement among scientists that genetically modified foods are safe to consume[1,2] and have the potential to provide substantial benefits to humankind[3]. However, many people still harbour concerns about them or oppose their use[4,5]. In a nationally representative sample of US adults, we find that as extremity of opposition to and concern about genetically modified foods increases, objective knowledge about science and genetics decreases, but perceived understanding of genetically modified foods increases. Extreme opponents know the least, but think they know the most. Moreover, the relationship between self-assessed and objective knowledge shifts from positive to negative at high levels of opposition. Similar results were obtained in a parallel study with representative samples from the United States, France and Germany, and in a study testing attitudes about a medical application of genetic engineering technology (gene therapy). This pattern did not emerge, however, for attitudes and beliefs about climate change.

Genetically modified (GM) foods are judged by the majority of scientists to be as safe for human consumption as conventionally grown foods[1,2], and have the potential to provide substantial benefits to humankind, such as increased nutritional content, higher yield per acre, better shelf life and crop disease resistance[3]—yet there is substantial public opposition to their use around the world[4,5]. In the United States, a poll by the Pew Research Center found that 88% of scientists thought GM foods were safe to eat, while only 37% of laypeople thought so, the largest gap for any of the issues tested[6]. Public opposition to science is often attributed to a lack of knowledge[7–9]. However, findings on the association between knowledge and attitudes about GM foods are mixed, and there is little evidence that educational interventions can meaningfully change public attitudes[10,11]. Sometimes, they even backfire[12,13]. While research on opposition to GM foods has primarily focused on what people actually know, it is also important to consider what they think they know[14,15]. Self-assessed knowledge is a strong predictor of attitudes, and people tend to be poor judges of how much they know[16]. They often suffer from an illusion of knowledge, thinking that they understand everything from common household objects to complex social policies better than they do[17]. This is why people's sense of understanding decreases when they try to generate explanations[18], and why novices are poorer at evaluating their talents than experts[19]. Gaining knowledge in a domain often has the effect of revealing nuance and complexity, hence reducing extremity of belief[20,21]. These results suggest that extreme attitudes sometimes reflect low objective knowledge paired with high self-assessed knowledge[22,23]. We examined the relationships between extremity of opposition to GM foods, objective knowledge about science and genetics and self-assessed knowledge about GM foods. We hypothesize that extremists will display low objective knowledge but high subjective knowledge, and that the gap between the two will grow with extremity.

In Study 1, we surveyed a sample of US adults ($N = 1{,}000$) representative of the population for gender, education, income and ethnicity. Hypotheses and analysis plans were pre-registered on AsPredicted.org before data collection. Participants were either assigned to a study about GM foods ($N = 501$) or climate change ($N = 499$). We first present methods and results for GM foods, then climate change.

In the GM food study (mean age (M_{age}) = 51.1 yr; 56.7% female), participants were first asked two questions to measure attitudes: extremity of opposition to GM foods (1 = no opposition; 7 = extreme opposition) and concern (1 = no concern; 7 = extreme concern). Overall, 90.82% of respondents reported some level of opposition to GM foods and 93.01% reported some level of concern. Responses to these two questions were highly correlated (coefficient of correlation (r) = 0.88; $P < 0.0001$; $N = 501$) and we averaged them to form a measure that we call 'extremity of opposition' for the main analyses. Consistent with previous research, there were no significant differences in extremity of opposition between self-reported liberals, moderates and conservatives[5,24] (see Supplementary Information for complete details of all methods and analyses not reported in the main text).

Next, participants were asked to judge their understanding of GM foods ('self-assessed knowledge'), using instructions and a single-item rating scale adapted from the cognitive science literature[18]. Finally, we measured scientific literacy ('objective knowledge') with 15 true–false questions adapted from the National Science Foundation's Science and Engineering Indicators survey[25], the American Association for the Advancement of Science Benchmarks for Science Literacy[26] and recent work on the public understanding of science[27–29] (for example, "Electrons are smaller than atoms"). We measured responses to the objective knowledge questions on a 7-point scale anchored by 'definitely true' and 'definitely false'. Participants were given −3 to 3 points depending on correctness. For example, when a participant chose definitely true, they received 3 points if the correct answer was 'true', and −3 points if the correct answer was 'false'. We summed points across all questions to measure scientific literacy. For robustness, we replicated all analyses after binarizing the scale and treating scores of 1 to 3 as correct and scores of 0 to −3 as incorrect.

Five of the items in the scientific literacy scale refer to genetics (for example, "All plants and animals have DNA"). We summed responses to these items to create a genetics literacy subscale. For robustness, we also replicated the analyses after removing the genetics questions from the scientific literacy scale.

[1]Leeds School of Business, University of Colorado, Boulder, CO, USA. [2]Olin Business School, Washington University in St. Louis, St. Louis, MO, USA. [3]Department of Psychology, University of Toronto, Toronto, Ontario, Canada. [4]Department of Psychology, University of Pennsylvania, Philadelphia, PA, USA. *e-mail: philip.fernbach@colorado.edu

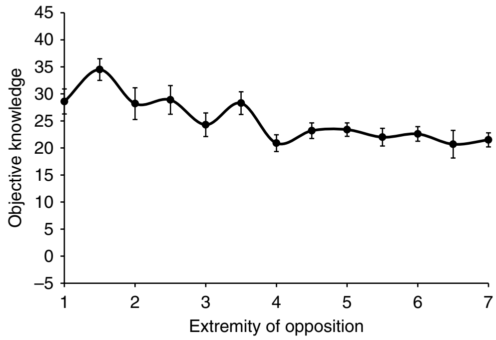

Fig. 1 | Objective and self-assessed knowledge means by extremity of opposition. Error bars represent ±1 s.e.m.

Figure 1 shows average self-assessed knowledge of GM foods and average scientific literacy by extremity of opposition. As extremity of opposition increases, scientific literacy decreases (regression coefficient for extremity ($\beta_{\text{extremity}}$) = −1.35; $t(499) = -4.72$; $P < 0.0001$; 95%confidence interval (CI) (−1.94, −0.78)), while judged understanding of GM foods increases ($\beta_{\text{extremity}} = 26$; $t(499) = 6.81$; $P < 0.0001$; 95% CI (0.17, 0.35)). After z-scoring objective and self-assessed knowledge, we calculated a difference score by subtracting each participant's objective knowledge score from their self-assessed knowledge score. This difference score, which represents gaps between self-assessed and objective knowledge, increases as extremity of opposition increases ($\beta_{\text{extremity}} = 28$; $t(499) = 8.77$; $P < 0.0001$; 95% CI (0.22, 0.35)).

Repeating these analyses using the genetics subscale instead of the overall scientific literacy scale produces nearly identical results. As extremity of opposition increases, objective knowledge of genetics decreases ($\beta_{\text{extremity}} = -0.58$; $t(499) = -4.50$; $P < 0.0001$; 95% CI (−0.81, −0.31)) and the difference score between self-assessed knowledge and objective knowledge of genetics also increases as extremity of opposition increases ($\beta_{\text{extremity}} = 0.28$; $t(499) = 8.35$; $P < 0.0001$; 95% CI (0.21, 0.35)).

Next, we tested whether objective knowledge predicts self-assessed knowledge differentially at different levels of extremity of opposition. We did this by regressing self-assessed knowledge on objective knowledge, extremity of opposition and their interaction. Figure 2 shows the results of this analysis, with lines representing predictions at the tenth, fiftieth and ninetieth percentiles of measured extremity of opposition. The interaction is statistically significant, indicating that the relationship between objective knowledge and self-assessed knowledge differs by extremity of opposition (regression coefficient for interaction ($\beta_{\text{interaction}}$) = −0.014; $t(497) = -4.56$; $P < 0.0001$; 95% CI (−0.02, −0.008)). Objective knowledge is a significant positive predictor of self-assessed knowledge up to an extremity of opposition value of 4.77, but becomes significantly negative at an extremity of opposition value of 7. For extremists, knowing less is associated with thinking one knows more.

Methods and measures in the climate change study were identical to the GM foods study except that the two extremity measures asked respondents to report their concern about, and belief in, human-caused climate change. Both measures were coded such that higher numbers indicated greater divergence from the scientific consensus. The correlation between these two measures was 0.83 ($P < 0.0001$; $N = 499$) and they were averaged to serve as the extremity measure. Unlike beliefs about GM foods, climate change beliefs were highly polarized by political identification, with conservatives much more likely to oppose the scientific consensus than liberals (mean for liberals (M_{liberal}) = 1.92; mean for conservatives ($M_{\text{conservative}}$) = 4.22; $t(496) = 11.90$; $P < 0.0001$; 95% CI (1.92, 2.68)).

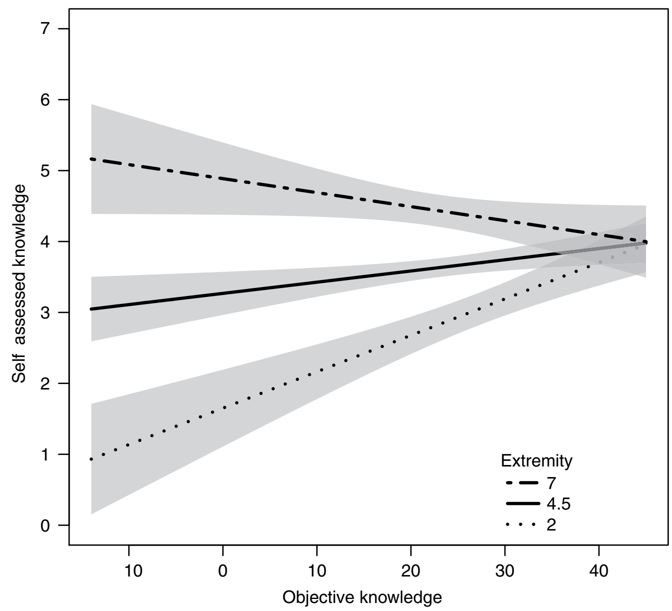

Fig. 2 | Predicted relationship between science literacy and self-assessed knowledge by extremity of opposition. Shading represents the 95% CI.

The pattern of results is directionally the same as for GM foods, but not statistically significant: as extremity of opposition increases, scientific literacy decreases ($\beta_{\text{extremity}} = -0.38$; $t(497) = -1.34$; $P = 0.18$; 95% CI (−0.92, 0.22)) while self-assessed understanding of climate change increases ($\beta_{\text{extremity}} = 0.006$; $t(497) = 0.17$; $P = 0.87$; 95% CI (−0.07, 0.07)). As a result, the gap between z-scored self-assessed and objective knowledge variables widens as extremity grows, but the effect is not statistically significant ($\beta_{\text{extremity}} = 0.04$; $t(497) = 1.15$; $P = 0.25$; 95% CI (−0.03, 0.10)).

As extremity of opposition to GM foods increased, objective knowledge of science and genetics decreased, but self-assessed knowledge increased. For climate change, the direction of the effects was the same, but the results were not statistically significant. The lack of a relationship between scientific literacy and extremity of anti-scientific-consensus climate change beliefs is consistent with previous findings[30,31] and we believe that this is attributable to the polarized nature of the climate change issue. For highly politicized issues, ideological commitments may crowd out effects of individual knowledge on attitudes[32]. We discuss this interpretation in more detail below, along with additional analyses of how the effects of knowledge on attitudes interact with political identification. The remainder of the studies focus exclusively on genetic engineering technology.

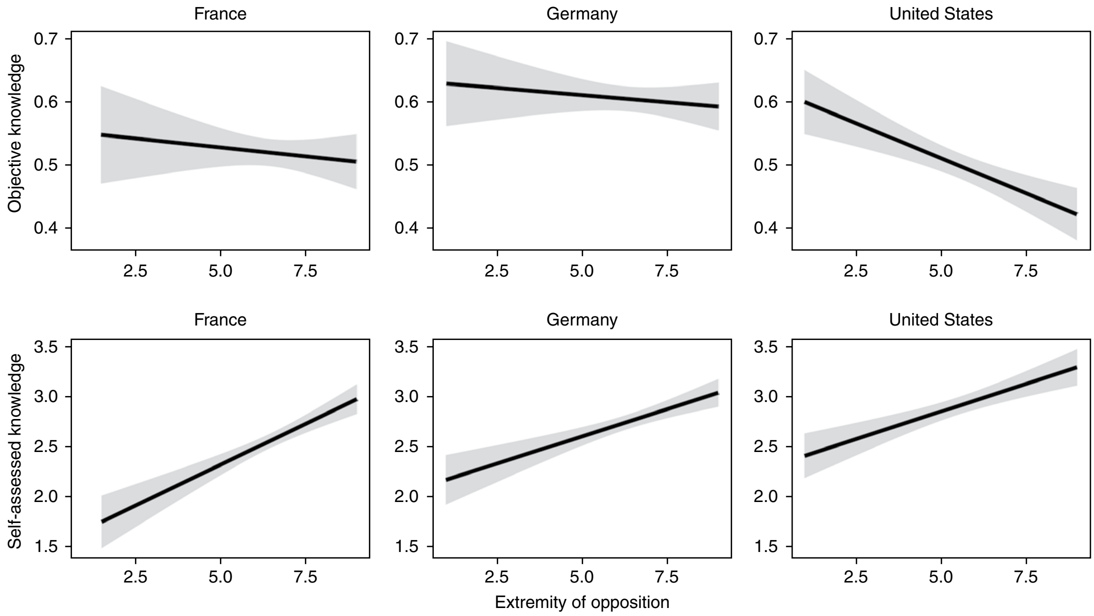

Fig. 3 | Predicted relationships between extremity of opposition and knowledge by country. Shading represents the 95% CI.

In Study 2 measures similar to those used in the GM foods condition of Study 1 were collected as part of a larger survey using samples from the United States ($N = 540$; $M_{age} = 46.4$ yr; 51.3% female), France ($N = 500$; $M_{age} = 47.7$ yr; 52.4% female) and Germany ($N = 519$; $M_{age} = 49.2$ yr; 51.6% female), representative of age, gender and income. The measures were different because this study was planned and executed independently. The use of different measures across studies provides evidence that the results generalize across different operationalizations of the same constructs. Objective genetics knowledge was measured by the percentage of questions correct in a 10-item true–false quiz from the Eurobarometer 64.3[33]. Self-assessed knowledge was measured by asking "How much do you know about genetically modified food?" on a scale from 1 = not at all to 5 = a great deal. Knowledge difference scores were calculated by first z-scoring objective and self-assessed knowledge within each country, and then subtracting each participant's objective knowledge score from their self-assessed knowledge score. Extremity of opposition was measured by averaging across twelve items (Chronbach's $\alpha = 0.89$), three about willingness to buy GM products (reversed scored), five about desire to regulate GM products and four about willingness to actively oppose GM products, for example by participating in a public demonstration.

The results were similar to those from Study 1. Across the whole sample, and controlling for country, objective knowledge decreases as extremity of opposition increases ($\beta_{extremity} = -0.01$; $t(1,555) = -3.47$; $P = 0.001$; 95% CI $(-0.02, -0.005)$) while self-assessed knowledge increases ($\beta_{extremity} = 0.12$; $t(1,555) = 8.06$; $P < 0.001$; 95% CI (0.09, 0.15)) and the difference between z-scored self-assessed and objective knowledge increases as extremity of opposition increases ($\beta_{extremity} = 0.18$; $t(1,555) = 10.96$; $P < 0.001$; 95% CI (0.15, 0.22)).

Next, we examined the relationships within each country by running the same regressions separately for each country. Figure 3 visualizes the results of these analyses and Table 1 provides the statistics. In all three countries, the difference between self-assessed and objective knowledge increases significantly with extremity of opposition. The effect of extremity of opposition on self-assessed knowledge is also significant, positive and similar in magnitude in all three countries. Finally, the effect of extremity of opposition on objective knowledge is negative in all three countries but is weaker in the European countries compared to the United States. This difference is reflected in a significant interaction between country and extremity of opposition (United States versus Germany: $\beta_{interaction} = 0.02$; $t(1,553) = 2.14$; $P = 0.032$; 95% CI (0.001, 0.03)); United States versus France: $\beta_{interaction} = 0.02$; $t(1,553) = 1.73$; $P = 0.084$; 95% CI $(-0.002, 0.03)$).

Finally, we tested for the interaction between extremity of opposition and objective knowledge on the self-assessed knowledge that we found in Study 1. We found a similar pattern, but only for the US sample. Regressing self-assessed knowledge on country, objective knowledge, extremity of opposition, and the interaction between extremity of opposition and objective knowledge reveals that the relationship between objective and self-assessed knowledge differs by extremity of opposition ($\beta_{interaction} = -0.09$; $t(1,553) = -1.80$; $P = 0.072$; 95% CI $(-0.20, 0.01)$), shifting from positive to negative as extremity increases. Running the interaction model separately for each country shows that the effect is driven by a significant interaction effect in the United States, replicating Study 1 ($\beta_{interaction} = -0.32$; $t(536) = -4.13$; $P < 0.001$; 95% CI $(-0.48, -0.17)$). There were no significant interaction effects in France ($\beta_{interaction} = -0.01$; $t(496) = -0.13$; $P = 0.895$; 95% CI $(-0.23, 0.21)$) or Germany ($\beta_{interaction} = 0.13$; $t(515) = 1.30$; $P = 0.194$; 95% CI $(-0.06, 0.32)$).

The results mostly replicated the findings of Study 1, although we did find some differences between the patterns of effects in the United States versus France and Germany. In all countries, self-assessed knowledge increased significantly with extremity and the gap between self-assessed and objective knowledge grew. Objective knowledge decreased significantly with extremity in the United States. However, in the European countries, although the direction of this effect was the same, it was not statistically significant.

To develop a better understanding of the reasons for the difference, we looked at a large, publicly available data set: the Eurobarometer 64.3[33]. This survey assessed objective knowledge (using the same items as Study 2) and extremity of opposition in 25 countries, including France and Germany. There was a highly significant negative effect of extremity on objective knowledge for GM food in France ($r = -0.16$; $P < 0.001$; $N = 499$) and in Germany ($r = -0.18$; $P < 0.001$; $N = 756$). In fact, in 20 out of 25 countries, there was a significant and negative effect of extremity on objective knowledge for GM food (see Supplementary Information for details). In addition, Study 2 included one other measure of

Table 1 | Model output for relationships between extremity of opposition and knowledge by country

	Knowledge difference score			Self-assessed knowledge	Objective knowledge	Self-assessed knowledge	Objective knowledge	Self-assessed knowledge	Objective knowledge
Country	United States	Germany	France	United States	United States	Germany	Germany	France	France
Extremity	0.19***	0.15***	0.21***	0.11***	−0.02***	0.11***	−0.004	0.16***	−0.006
95% CI	(0.14, 0.24)	(0.09, 0.21)	(0.15, 0.27)	(0.06, 0.15)	(−0.03, −0.01)	(0.06, 0.16)	(−0.02, 0.01)	(0.10, 0.22)	(−0.02, 0.01)
N	540	519	500	540	540	519	519	500	500
t value	7.50 (d.f. = 538)	5.10 (d.f. = 517)	6.44 (d.f. = 498)	4.44 (d.f. = 538)	−4.14 (d.f. = 538)	4.70 (d.f. = 517)	−0.69 (d.f. = 517)	5.30 (d.f. = 498)	−0.73 (d.f. = 498)

***$P < 0.01$.

opposition. The first question every participant answered was a simple agree or disagree question as to whether or not they were opposed to GM foods. Opponents in all three countries scored lower on objective knowledge compared with supporters, and this relationship did not vary by country. The difference between opponents' and supporters' objective knowledge was significant in the United States ($P < 0.001$) and Germany ($P = 0.012$) and close to significance in France ($P = 0.15$). Taken together, we believe that the weight of evidence favours the interpretation that in Europe, as in the United States, objective knowledge decreases with extremity of opposition, and the non-significant effects in Study 2 are probably false negatives.

We ran a near replication ($N = 537$; $M_{age} = 36.6$ yr; 57.0% female) of the GM foods condition of Study 1 to resolve two unanswered questions. First, one possible interpretation of the relationship between extremity and self-assessed knowledge that we found in Studies 1 and 2 is that it is an artefact of the order in which we asked the questions. According to this interpretation, respondents may give a high rating of opposition and then feel compelled to justify this rating by giving a high judgement of self-assessed understanding. To test this alternative interpretation, we reversed the order of the opposition and self-assessed knowledge questions.

Second, the scientific consensus surrounding GM foods concerns their safety. It is possible that GM opponents object to GM foods on alternative grounds, such as environmental, social or animal welfare concerns, and view safety as a secondary or even irrelevant issue. If this is true, their lack of scientific and genetics knowledge may not be relevant to their attitudes. To address this possibility, we included an additional question in this study, asking people the primary reason for their opposition, with the following options: food safety/health concerns, moral/religious concerns, animal welfare concerns, environmental concerns, social/political concerns and other.

The results are described in detail in the Supplementary Information and we summarize them here. First, the results were almost identical to those from Study 1, which rules out the interpretation that the effect is an artefact of question ordering. Second, 73% of respondents cited food safety/health concerns as their reason for opposition. Extreme opponents were actually more likely to cite food safety/health concerns than moderates and the main results replicate when we restrict analysis to the subset of participants citing food safety/health concerns. This rules out the possibility that extreme opponents view safety concerns as irrelevant to their attitudes.

People are more accepting of medical applications of genetic engineering than food applications[2,10]. This raises the possibility that GM foods are a special case and that the effects we have documented may have limited generalizability. We therefore ran an additional study to test whether the effects we found in Studies 1–3 generalize to another application of genetic engineering technology: gene therapy. This study used identical methods to Study 1, except that instead of GM foods we asked about gene therapy using language from the Mayo Clinic[34]: "Gene therapy involves altering the genes inside a human body's cells in an effort to treat or stop disease".

As expected, opposition levels were significantly lower than for GM foods (mean for Study 4 = 3.07; mean for Study 1 = 4.54; both 1–7 scales). However, we also found precisely the same pattern of relationships as in Studies 1–3 between extremity of opposition, objective knowledge and self-assessed knowledge. Extreme opponents were less knowledgeable and thought they were more knowledgeable than moderates, and they were also poorer at evaluating their level of knowledge. Complete methods and results are in the Supplementary Information.

Across four studies conducted in three countries, we found that extreme opponents of genetic engineering technology display a lack of insight into how much they know. We next report additional robustness analyses, provide an in-depth discussion of the differences between genetic engineering and climate change and discuss the implications of our results for science communication.

One possible interpretation of the results is that they reflect differences in education rather than science or genetics literacy per se. To test this possibility, we re-ran the main analyses from all studies including education level as a control. All the key findings remain significant.

All analyses in the main text use linear models, but there is some evidence of nonlinearity (see for example the uptick in self-assessed knowledge for those scoring 1 or 2 on extremity of opposition in Fig. 1). We therefore conducted tests of quadratic effects to provide a better understanding of any nonlinearities in the data. For self-assessed knowledge, in all studies there is a significant quadratic effect of extremity of opposition. For most of the range, the effect of opposition on self-assessed knowledge is positive, but the relationship turns negative at low levels of opposition. Thus, the interpretation based on the linear model—that self-assessed knowledge increases with opposition—should be qualified to acknowledge that this is not true at very low levels of opposition. For objective knowledge, we find some weak evidence that the effect decelerates as extremity increases. This effect was marginally significant in Study 1, significant in Study 2 and not significant in Studies 3 and 4.

Contrary to GM foods and gene therapy we found no significant effects of knowledge—objective or self-assessed—on extremity of climate change attitudes. The lack of an effect of objective knowledge is broadly consistent with previous data[30,31]. The null effect has been attributed to 'cultural cognition'[32]. When an issue becomes polarized, people's attitudes reflect affiliation with their ideological group and not individual knowledge. That is, individuals subscribe to whatever their in-group believes, regardless of how much they know about the issue. There is even some evidence that scientific literacy can promote extremity consistent with the community's position, even if the position is counter to the scientific consensus[35]. This may explain our results as well.

A recent analysis of data from the General Social Survey examined the relationship between scientific literacy, political affiliation and extremity of counter-scientific-consensus beliefs across a range of issues such as GM foods, climate change, evolution and the big bang[31]. For most issues, including GM foods, there was an overall negative relationship between scientific literacy and opposition to the consensus, consistent with the idea that knowledge plays a role. However, half of the issues also demonstrated an interaction with political identification; the relationship between knowledge and attitudes was weaker for the political group holding the counter-consensus position, suggesting that ideology can diminish effects of knowledge. This interaction effect was strongest for the climate change issue, where conservatives actually showed an opposite effect: an increase in extremity with scientific literacy. There was no interaction for GM foods or for nanotechnology; respondents from all political groups showed similar decreases in knowledge with greater extremity. These two issues were also the only two that were not politically polarized.

We reanalysed our own data from Study 1, including interactions with political identification, and found similar results. For climate change, liberals and moderates show the common pattern we find for GM foods: the less people know, the more opposed they are to the scientific consensus. Conservatives, however, show no such effect. In fact, the effect is trending in the opposite direction, although not significantly so. Thus, the net effect of scientific literacy on extremity is negative, but weak and non-significant. In contrast, for GM foods there are no interactions at all by political identification, which makes sense because this issue is not polarized along partisan lines the way climate change is. We take these results as evidence that knowledge and ideology both contribute to polarization and impasse around divisive science and policy issues[36]. The relative strength of these forces seems to depend on the specific issue.

A traditional view in the public understanding of scientific literature is that public attitudes that run counter to the scientific consensus reflect a knowledge deficit. Science communicators have made concerted efforts to educate the public with an eye to bringing their attitudes in line with the experts. These initiatives have met with limited success, which has led for calls to abandon this approach altogether[37,38]. Our findings highlight a difficulty that is not generally appreciated. Those with the strongest anti-consensus views are the most in need of education, but also the least likely to be receptive to learning; overconfidence about one's knowledge is associated with decreased openness to new information[39]. This suggests that a prerequisite to changing people's views through education may be getting them to first appreciate the gaps in their knowledge.

Methods

Statistics and data analysis. Unless otherwise stated, all regression coefficients are ordinary least squares estimates and all test statistics are two-sided. For all parametric tests, data were assumed to be normal, but this was not formally tested. However, with the exception of Study 2, all 95% CIs were obtained via bootstrapping with 1,000 iterations, which produces intervals that do not rely on the assumption of normality for valid inference. No statistical methods were used to predetermine sample sizes, but our sample sizes are similar to or larger than those reported in previous publications[4,5,31,40]. Analyses for Studies 1, 3 and 4 were conducted in R using RStudio version 1.1.383 and analyses for Study 2 were conducted using STATA 14. Code for all modelling and analyses can be found in the Supplementary Information and at https://osf.io/t82j3/.

Study 1. The data were obtained in December 2017 by Research Now, an online market research and sampling company. Research Now provided the authors with a nationally representative US sample of 1,000 completes based on age, gender, income, education and ethnicity. Respondents who failed an attention check question or who completed all questions in 150 seconds or less, were eliminated and replaced by Research Now before substantive data analysis began and before the authors saw the data.

There were two versions of the Study 1 survey. Respondents completed either the climate change version or the GM food version. The only differences between the two were with respect to the domain of interest (either climate change or GM foods) in the introduction, in the extremity of opposition questions and in the self-assessed knowledge questions. All other questions were identical. Study 1 items were presented in four blocks (extremity of opposition, self-assessed knowledge, objective knowledge and demographics). Blocks were not presented in randomized order.

Among the 1,000 completes, a Qualtrics quota error resulted in 499 respondents taking the climate change version of the survey and 501 taking the GM food version, as opposed to 500 and 500 respectively. Study 1 was pregistered on AsPredicted.org. The full-text preregistration document can be found at https://aspredicted.org/uy4b8.pdf.

Study 2. Data were obtained in July 2016 by Qualtrics. The authors requested samples of 500 people per country (France, Germany and United States) based on age, gender and income. All Study 2 items were embedded in a larger, 15-minute survey about genetic modification of food. Items were presented in five blocks (self-assessed knowledge, objective knowledge, desire to regulate, willingness to consume and willingness to actively oppose). Blocks were presented in randomized order. Within the extremity of opposition blocks, items were presented in randomized order.

A Qualtrics error resulted in oversampling in the United States and Germany and distributions that were slightly off the representative distributions. Therefore, in all analyses the data were reweighted using the svy function in STATA 14. Reweighting rarely changed any mean or regression weight estimates beyond the hundredth decimal place. The authors also conducted all the same analyses without sampling weights, and without sampling weights and with bootstrapped CIs. Across these analyses, the significance level and direction of the results is always the same, suggesting that the results are robust across different model specifications.

To create German and French translations, we hired four translators—two of whom were fluent in English and German, and two of whom were fluent in English and French. For each translation, one person translated the survey from English to the other language, and then another person backtranslated the survey to English. Any discrepancies were resolved through discussion.

Eurobarometer. We accessed data from the Eurobarometer 64.3. This was a survey conducted in November and December of 2005, and included questions about attitudes to biotechnology. The data is publicly available at http://zacat.gesis.org. We do not use any statistical weighting (population or post-stratification) in the analysis.

All questions were presented in a fixed order (objective knowledge then opposition, with question ordering the same as in the above lists of the measures). Opposition measures were conducted using split ballots, where participants were assigned to complete either questions about gene technology or about GM food.

Study 3. Responses were obtained through an Amazon Mechanical Turk via Qualtrics survey in July 2018; 595 respondents originally took the survey, but 18 didn't fully finish, 22 requested to have their data removed and 18 failed an attention check question. These 58 participants were removed before any data analysis began, resulting in a final sample of 537.

Study 3 was identical to the Study 1 GM food study with three exceptions. First, in Study 1, the GM food concern and opposition questions were asked first, followed by self-assessed and objective knowledge questions. In Study 3, we reversed the order of the opposition and self-assessed knowledge questions such that self-assessed knowledge came first, followed by the extremity of opposition and objective knowledge questions.

Second, Qualtrics display logic showed an added question (that did not appear in Study 1) for those respondents who indicated any response to the GM food concern and opposition questions other than 1 ('not concerned at all' and 'not opposed at all', respectively). This question read, "You indicated at least some concern about or opposition to genetically modified foods. Please select your primary reason for concern/opposition from the options below". Possible responses included food safety/health concerns, moral/religious concerns, animal welfare concerns, environmental concerns, social/political concerns and other (please elaborate). The presentation order of these options was randomized, except the 'other' option always appeared last (from left to right). The third difference between Study 1 and Study 3 was that Study 3 did not use any quota sampling, and thus was not a nationally representative US sample.

Study 4. Study 4 was identical to the GM food condition from Study 1, except that it asked participants about a different genetic engineering topic, gene therapy, and data were obtained from an Amazon Mechanical Turk via Qualtrics survey (without a nationally representative sample) in July 2018. After 19 respondents who failed the attention check question, 10 who asked to have their data removed and 15 who didn't fully finish the survey were removed from the data set before data analysis began, the sample included 505 complete responses.

Code availability. The code used for all models and analyses is available at https://osf.io/t82j3/.

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

Data availability
All data reported in the paper are available at https://osf.io/t82j3/.

Received: 22 May 2018; Accepted: 12 December 2018;
Published online: 14 January 2019

References
1. AAAS. Statement by the AAAS Board of Directors on Labeling of Genetically Modified Foods *AAAS.com* https://www.aaas.org/news/statement-aaas-board-directors-labeling-genetically-modified-foods (2012).
2. Economidis, I., Cichocka, D. & Hoegel, J. *A Decade of EU-funded GMO Research (2001–2010)*. https://doi.org/10.2777/97784 (Publications Office of the European Union, 2010).
3. Sharma, S., Kaur, R. & Singh, A. Recent advances in CRISPR/Cas mediated genome editing for crop improvement. *Plant Biotechnol. Rep.* **11**, 193–207 (2017).
4. Gaskell, G., Bauer, M. W., Durant, J. & Allum, N. C. Worlds apart? The reception of genetically modified foods in Europe and the U.S. *Science* **285**, 384–387 (1999).
5. Scott, S. E., Inbar, Y. & Rozin, P. Evidence for absolute moral opposition to genetically modified food in the United States. *Perspect. Psychol. Sci.* **11**, 315–324 (2016).
6. Funk, C. & Rainie, L. *Public and Scientists' Views on Science and Society* (Pew Research Center, 2015)
7. Bodmer, W. F. The public understanding of science. *R. Soc.* https://royalsociety.org/~/media/Royal_Society_Content/policy/publications/1985/10700.pdf (1985).
8. Gross, A. G. The roles of rhetoric in the public understanding of science. *Public Underst. Sci.* **3**, 3–23 (1994).
9. Ranney, M. A. & Clark, D. Climate change conceptual change: scientific information can transform attitudes. *Top. Cogn. Sci.* **8**, 49–75 (2016).
10. Costa-Font, M., Gil, J. M. & Traill, W. B. Consumer acceptance, valuation of and attitudes towards genetically modified food: review and implications for food policy. *Food Policy* **33**, 99–111 (2008).
11. Allum, N., Sturgis, P., Tabourazi, D. & Brunton-Smith, I. Science knowledge and attitudes across cultures: a meta-analysis. *Public Underst. Sci.* **17**, 35–54 (2008).
12. Frewer, L. J., Howard, C., Hedderley, D. & Shepherd, R. Reactions to information about genetic engineering: impact of source characteristics, perceived personal relevance, and persuasiveness. *Public Underst. Sci.* **8**, 35–50 (1999).
13. Scholderer, J. & Frewer, L. J. The biotechnology communication paradox: experimental evidence and the need for a new strategy. *J. Consum. Policy* **26**, 125–157 (2003).
14. House, L. et al. Objective and subjective knowledge: impacts on consumer demand for genetically modified foods in the United States and the European Union. *AgBioForum* **7**, 113–123 (2004).
15. Knight, A. J. Differential effects of perceived and objective knowledge measures on perceptions of biotechnology. *AgBioForum* **8**, 221–227 (2006).
16. Alba, J. W. & Hutchinson, J. W. Knowledge calibration: what consumers know and what they think they know. *J. Consum. Res.* **27**, 123–156 (2000).
17. Sloman, S. & Fernbach, P. *The Knowledge Illusion: Why We Never Think Alone* (Riverhead Books, New York, 2017).
18. Rozenblit, L. & Keil, F. The misunderstood limits of folk science: an illusion of explanatory depth. *Cogn. Sci.* **26**, 521–562 (2002).
19. Kruger, J. & Dunning, D. Unskilled and unaware of it: how difficulties in recognizing one's own incompetence lead to inflated self-assessments. *J. Pers. Soc. Psychol.* **77**, 1121–1134 (1999).
20. Fernbach, P. M., Rogers, T., Fox, C. R. & Sloman, S. A. Political extremism is supported by an illusion of understanding. *Psychol. Sci.* **24**, 939–946 (2013).
21. Linville, P. W. The complexity−extremity effect and age-based stereotyping. *J. Pers. Soc. Psychol.* **42**, 193–211 (1982).
22. van Prooijen, J.-W. Overclaiming knowledge predicts anti-establishment voting. *SPSP 2018* https://osf.io/v73ap/ (2018).
23. Motta, M., Callaghan, T. & Sylvester, S. Knowing less but presuming more: Dunning-Kruger effects and the endorsement of anti-vaccine policy attitudes. *Soc. Sci. Med.* **211**, 274–281 (2018).
24. Lewandowsky, S., Gignac, G. E. & Oberauer, K. The role of conspiracist ideation and worldviews in predicting rejection of science. *PLoS One* **8**, e75637 (2013).
25. *Science and Engineering Indicators 2016* https://www.nsf.gov/statistics/2016/nsb20161/uploads/1/10/tt07-03.pdf (NSF, 2016).
26. AAAS *Benchmarks for Science Literacy: A Project 2061 Report* (Oxford Univ. Press, 1993).
27. Durant, J. R., Evans, G. A. & Thomas, G. P. The public understanding of science. *Nature* **340**, 11–14 (1989).
28. Mielby, H., Sandøe, P. & Lassen, J. The role of scientific knowledge in shaping public attitudes to GM technologies. *Public Underst. Sci.* **22**, 155–168 (2013).
29. Miller, J. D., Scott, E. C. & Okamoto, S. Public acceptance of evolution. *Science* **313**, 765–766 (2006).
30. Hornsey, M. J., Harris, E. A., Bain, P. G. & Fielding, K. S. Meta-analyses of the determinants and outcomes of belief in climate change. *Nat. Clim. Change* **6**, 622–626 (2016).
31. Drummond, C. & Fischhoff, B. Individuals with greater science literacy and education have more polarized beliefs on controversial science topics. *Proc. Natl Acad. Sci. USA* **114**, 9587–9592 (2017).
32. Kahan, D. M., Jenkins-Smith, H. & Braman, D. Cultural cognition of scientific consensus. *J. Risk Res.* **14**, 147–174 (2011).
33. Gaskell, G. et al. *Europeans and Biotechnology in 2005: Patterns and Trends. Eurobarometer 64.3* (Eurobarometer, 2006).
34. Tests & Procedures: Gene Therapy. *Mayo Clinic* https://www.mayoclinic.org/tests-procedures/gene-therapy/about/pac-20384619 (2018).
35. Kahan, D. et al. The polarizing impact of science literacy and numeracy on perceived climate change risks. *Nat. Clim. Change* **2**, 732–735 (2012).
36. van der Linden, S. et al. Culture versus cognition is a false dilemma. *Nat. Clim. Change* **7**, 457 (2017).
37. Sturgis, P. & Allum, N. Science in society: re-evaluating the deficit model of public attitudes. *Public Underst. Sci.* **13**, 55–74 (2004).
38. Simis, M. J., Madden, H., Cacciatore, M. A. & Yeo, S. K. The lure of rationality: why does the deficit model persist in science communication? *Public Underst. Sci.* **25**, 400–414 (2016).
39. Wood, S. L. & Lynch, J. G. Prior knowledge and complacency in new product learning. *J. Consum. Res.* **29**, 416–426 (2002).
40. Bredahl, L., Grunert, K. G. & Frewer, L. J. Consumer attitudes and decision-making with regard to genetically engineered food products—a review of the literature and a presentation of models for future research. *J. Consum. Policy* **21**, 251–277 (1998).

Acknowledgements
This research was funded by a grant from Humility & Conviction in Public Life, a project of the University of Connecticut sponsored by the John Templeton Foundation to P.M.F., by the Center for Ethics and Social Responsibility at the University of Colorado, by a National Science Foundation DRMS grant (Award Number: 1559371) to S.E.S. and by an SSHRC grant (Award Number: 435-2017-0304) to Y.I. The funders had no role in study design, data collection and analysis, decision to publish or preparation of the manuscript. We thank B. de Langhe, D. Lichtenstein, J. Lynch, G. McClelland, L. Min, J. Pomerance, D. Rothschild, S. Shaw and S. Sloman.

Author contributions
P.M.F. devised the paper's central idea, and independently, as part of a larger study, S.E.S., Y.I. and P.R. considered the same idea. P.M.F. and N.L. developed the predictions and designed Studies 1, 3 and 4. N.L. performed the analyses and P.M.F. supervised the findings. For Study 2, S.E.S., Y.I. and P.R. developed the predictions and design and S.E.S. performed the analysis. P.M.F. and N.L. wrote the original manuscript and all authors contributed to the final manuscript.

Competing interests
The authors declare no competing interests.

Additional information
Supplementary information is available for this paper at https://doi.org/10.1038/s41562-018-0520-3.

Reprints and permissions information is available at www.nature.com/reprints.

Correspondence and requests for materials should be addressed to P.M.F.

Publisher's note: Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

© The Author(s), under exclusive licence to Springer Nature Limited 2019

nature research

Corresponding author(s): Philip M. Fernbach

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.

Statistical parameters

When statistical analyses are reported, confirm that the following items are present in the relevant location (e.g. 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
☐	☒	An indication of 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 statistics 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
☐	☒	Clearly defined error bars *State explicitly what error bars represent (e.g. SD, SE, CI)*

Our web collection on statistics for biologists may be useful.

Software and code

Policy information about availability of computer code

Data collection	Study data were collected in Qualtrics by Research Now, and Study 2 data were collected by Qualtrics. Studues 3 and 4 data were collected on Amazon Mechanical Turk via Turkprime.com
Data analysis	Data analysis was conducted using R with RStudio 1.1.383 and STATA 14.

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 upon request. 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

All data and code referenced in this paper is publicly available and can be found at https://osf.io/t82j3

Field-specific reporting

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

☐ Life sciences ☒ Behavioural & social sciences

For a reference copy of the document with all sections, see nature.com/authors/policies/ReportingSummary-flat.pdf

Behavioural & social sciences

Study design

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

Study description	All study data are quantitative and correlational, collected via online survey.
Research sample	The Study 1 sample was a United States nationally representative sample of 1000 people based on age, gender, income, education, and ethnicity. The Study 2 samples were nationally representative samples of 500 people per country (France, Germany, and USA) based on age, gender, and income. Studies 3 (N = 595 before data removals) and 4 (N = 549 before data removals) were collected via Amazon Mechanical Turk, and did not include quota sampling.
Sampling strategy	Sample sizes of 500 per study, which is similar to or exceed those in previous research, was set before data collection. Plans for Study 1 were preregistered on AsPredicted.org prior to data collection. Studies 3 and 4 were conducted in response to reviewer comments.
Data collection	Study 1 data were obtained in December, 2017 by Research Now, an online market research and sampling company. Research Now provided the authors with a United States nationally representative sample of 1000 completes based on age, gender, income, education, and ethnicity. A Qualtrics error resulted in 501 completes for one condition and 499 for the other. Study 1 data collection, hypotheses, and sample strategy were pre-registered on AsPredicted.org. Study 2 data were obtained in July 2016 by Qualtrics. The authors requested samples of 500 people per country (France, Germany, and USA) based on age, gender, and income. A Qualtrics error resulted in slight oversampling in the USA and Germany. All Study 2 items were embedded in a larger, 15-minute survey about genetic modification of food. Studies 3 and 4 were conducted in response to reviewer comments.
Timing	Study 1 data were obtained continuously in December 2017 until the nationally representative sample was achieved. Study 2 data were obtained in July 2016 in the same manner. Studies 3 and 4 were collected in July 2018 through Amazon Mechanical Turk via TurkPrime.com in response to reviewer comments.
Data exclusions	Study 1 respondents who failed an attention check question, or who completed all questions in 150 seconds or fewer, were eliminated and replaced by Research Now before data analysis began. Study 2 respondents who failed an attention check question were eliminated and replaced by Qualtrics before data analysis began. Respondents to Study 3 who requested to have their data removed (22), who failed an attention check question (18) and who did not fully complete the survey (18) were removed from the data set before analysis. In Study 4, respondents who requested to have their data removed (10), who failed an attention check question (19) and who did not fully complete the survey (15) were removed from the data set before analysis.
Non-participation	Samples and participation were managed solely by Research Now in Study 1, and solely by Qualtrics in Study 2. Participants in Studies 3 and 4 agreed in writing to participate in both studies, and were informed that a) participation was completely voluntary, and b) they could leave the study at any time.
Randomization	Respondents were not allocated into experimental groups.

March 2018