Learning About Scientists from Climate Consensus Messaging

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Abstract

Informing people of the overwhelming consensus among climate scientists that human-caused climate change is occurring increases belief in the proposition and the importance of policy action. However, consensus may not be interpreted in the same way; it could emerge from skilled experts converging on the truth, or a biased cabal working for their own gain. We show that the weight that an individual places on the skill and bias of experts affects whether they are persuaded by strong consensus. We demonstrate that beliefs about the skill and bias of pro-consensus scientists (those who express that climate change is occurring) and anti-consensus scientists (those who do not) are central components of a belief system about climate change, determining what individuals learn from climate scientists. However, these characteristics are not fixed as individuals also learn about scientists from consensus. In this way, people learn both *from* and *about* climate scientists given consensus.[1]

Keywords: consensus; belief change; source credibility; causal reasoning; hierarchical inference

Introduction

While nearly all climate scientists agree that human activities play a central role in climate change (Oreskes, 2004; Anderegg, Prall, Harold, & Schneider, 2010; Cook et al., 2013; Cook & Lewandowsky, 2016; Myers et al., 2021), most Americans (76%) underestimate this consensus (Leiserowitz et al., 2021). One of the most prominent ways proposed to convince people of human-caused climate change is to inform them that 97% of climate scientists believe it is happening (Cook, van der Linden, Maibach, & Lewandowsky, 2018; van der Linden, 2021; Rode et al., 2021). Individuals who think the consensus is high tend to believe more in human-caused climate change (Lewandowsky, Gignac, & Vaughan, 2013) and support policies aimed at mitigating it (Ding, Maibach, Zhao, Roser-Renouf, & Leiserowitz, 2011; McCright, Dunlap, & Xiao, 2013).

Despite the prominence of this climate consensus messaging, it remains unclear exactly what meaning people take away from the consensus. Many studies have shown that consensus messaging is, on average, an effective strategy, but for who it will be most or least effective remains an open question (van der Linden, 2021; Rode et al., 2021). The same information can be interpreted in different ways depending upon one's wider beliefs (Cook & Lewandowsky, 2016; Gershman, 2019). Suppose you learn that 97% of climate scientists agree human activities are causing substantial changes to the climate. Is this consensus so strong because climate scientists are knowledgeable and unbiased experts who have converged upon the truth? Or is consensus strong because they form a biased and conspiratorial cabal? The weight someone places on each of these possibilities will clearly influence whether they believe the consensus position. Americans are divided over political party lines in their perceptions of climate scientists: Democrats, more than Republicans, believe that climate scientists understand climate change very well and are mostly influenced by the evidence and concern for the public.[2] To understand how people react to consensus information, we must understand the belief system that surrounds it.

Normative principles of belief updating imply that the way a person responds to data—such as a persuasive message—depends on how they attribute that data to possible underlying causes (Cook & Lewandowsky, 2016; Hahn, Harris, & Corner, 2016; Druckman & McGrath, 2019; Bhui & Gershman, 2020; Gershman, 2019; Perfors, Navarro, & Shafto,

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[2]https://www.pewresearch.org/science/2016/10/04/the-politics-of-climate/

2018). As discussed, whether people respond to scientific consensus should depend on whether they think scientists are knowledgeable and unbiased. More subtly however, beliefs about the underlying causes generating some data or message may themselves be simultaneously shaped by that data in a hierarchical manner (Bovens & Hartmann, 2003; Hahn et al., 2016). For instance, if people are uncertain about how knowledgeable and unbiased climate scientists are in general, the consensus itself can shape their perceptions of these traits: A field in wide disagreement about concrete facts can hardly be uniformly biased, nor can the scientists working in that field all be reliably capable of discerning the truth. This suggests that, when provided with consensus information, people not only learn *from* scientists, they may also learn *about* scientists.

In this project, we study how people interpret information about scientific consensus on human-caused climate change, using a survey experiment. We examine how consensus messaging affects beliefs about *scientists* in addition to beliefs about climate change. Our experiment varies the hypothetical level of consensus (from 50% through 99% agreement), and elicits beliefs about the bias and skill of scientists who agree or disagree with the consensus.

We find evidence that people draw sophisticated inferences *about* scientists, in addition to learning from them. Belief in human-caused climate change is increasing in consensus level across all political orientations. Though there are substantial differences in belief systems across political parties, the degree to which a person attributes consensus to bias versus skill is related to how sensitive they are to the consensus level. Evaluations of scientist skill and bias are contingent on overall consensus and on the scientist's expressed (pro- or anti-consensus) position. While previous work has studied how variables like trust in scientists might modulate sensitivity to scientific consensus (Cook & Lewandowsky, 2016; Chinn, Lane, & Hart, 2018; Kobayashi, 2018), our results reveal how consensus can conversely modulate trust. Our results additionally suggest that consensus acts on climate belief not only through a direct channel but through indirect channels centering on scientist capabilities. Overall, our research helps systematically unpack one of the most influential climate communication strategies by examining the belief system upon which it rests.

Experiment

To explore the relationship between scientific consensus, belief in human-caused climate change, and perceptions of scientist attributes, we recruited 550 participants from a convenience sample of workers on Amazon Mechanical Turk via CloudResearch. 571 participants started the survey and after removing incomplete responses and participants who failed attention checks, we are left with a final sample of 493 subjects. Though this limits the generalizability of some results to the broader US population, the purpose of the experiment is to examine a potential mechanism through which individuals update their beliefs about climate change.

Participants completed a survey composed primarily of questions concerning demographics, their beliefs about climate change, and their beliefs about climate scientists. In the demographics section, we collected data on traditional demographics (age, race, gender, income, and education) plus political demographics (party affiliation, political extremity, and affective polarization). For ethical reasons, income was left as an optional response. The composition of the sample is shown in Table 1 and skews white, educated, and Democratic relative to the country.

Table 1: Demographic Summary Statistics of the Experimental Sample.

Variable	N	Mean	SD
Age	493	41.11	12.53
Female	493	0.52	
White	493	0.83	
College Educated	493	0.61	
Income	345		
... [$0, $40k)	56	0.16	
... [$40k, $80k)	200	0.58	
... [$80k, $150k)	63	0.18	
... $\geq$ 150k	26	0.08	
Party	493		
... Democrat	243	0.49	
... Independent	130	0.26	
... Other (specify)	10	0.20	
... Republican	110	0.22	

Next, we asked participants their belief in human-caused climate-change, their belief in the consensus level among climate scientists, and their confidence in each of these estimates. Additionally, we asked the likelihood that a climate scientist is extremely biased, meaning they will ignore the evidence in their evaluation of whether climate change is happening; and the likelihood that an extremely biased scientist will be biased to say climate change is or is not occurring. The product of these two beliefs gives the prior probability that any given climate scientist is biased in a certain direction. Lastly, we asked participants the likelihood that, conditional on climate change (not) occurring, a climate scientist will correctly identify this.

Finally, we presented participants with the main questions of interest relating to their beliefs about human-caused climate change and pro-consensus scientists (those who express that climate change is occurring) and anti-consensus scientists (those who do not). For each belief—human-caused climate change, the skill of pro-consensus scientists (ProSkill), the skill of anti-consensus scientists (AntiSkill), the bias of pro-consensus scientists (ProBias), the bias of anti-consensus scientists (AntiBias)—we asked participants to hypothetically consider 5 different levels of consensus among climate scientists [50%, 75%, 90%, 97%, 99%] and report their belief at that consensus level. In doing this, we systematically varied the level of consensus among experts allowing us to causally estimate the effect of consensus on each of the beliefs. Additionally, in measuring these related beliefs, we can explore the belief system and updating process that gives rise to patterns in beliefs about climate change.

To provide a measure of the effect of consensus on beliefs, measured between 0% and 100%, we regress the log odds ratio, defined as $\log\left(\frac{y}{100-y}\right)$, of a given belief on consensus for each individual separately.[3] The log odds ratio is an effective way of dealing with ceiling and floor effects (where some individuals reach beliefs close to 0 or 100 and cannot update more). However, the log odds ratio places heavy weight on small (percentage point) updates near the bounds. To deal with this, we set the size of the update from 0% to 1% and 99% to 100% to be the same as the update from 1% to 2% and 98% to 99% in log-odds space. The slope of this curve provides an estimate of an individual's sensitivity to consensus level for each belief.

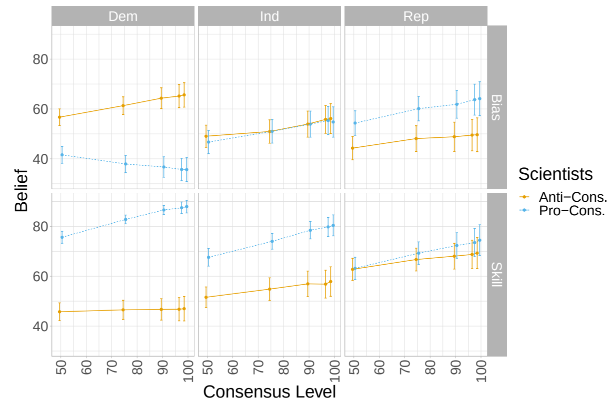

Figure 2: The Responsiveness of Beliefs in About the Attributes of Climate Scientists to Scientific Consensus, Split by Political Party. The mean belief is plotted at 50%, 75%, 90%, 97%, and 99% consensus with 95% confidence intervals.

Results

Using the systematic variation of consensus level, we show that participants both learn *from* and *about* scientists when presented with consensus. First, participants, on average and across political parties, increase their belief in human-caused climate change given expert consensus, as shown in Figure 1. Table 2 demonstrates a robust effect of expert consensus on belief, with the average relationship between consensus and log odds climate belief being strongly positive ($\mu = 0.05$, $t = 16.2$) and 78% of individuals demonstrating a positive relationship.

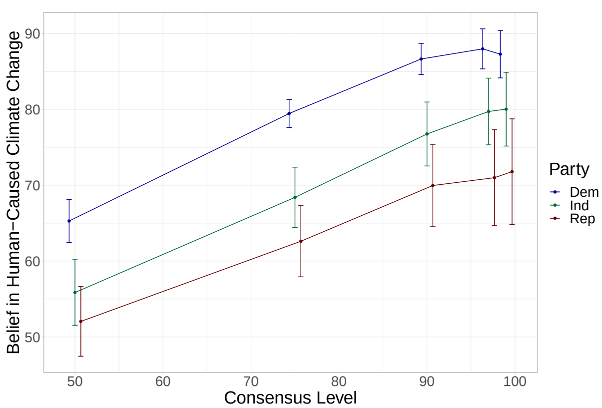

Figure 1: The Responsiveness of Belief in Human-Caused Climate Change to Scientific Consensus, Split by Political Party. The mean belief is plotted at 50%, 75%, 90%, 97%, and 99% consensus with 95% confidence intervals.

In addition to learning about climate change from scientific consensus, participants also use consensus to make inferences about climate scientists themselves. Figure 2 demonstrates that beliefs about the attributes of pro- (blue lines) and anti-consensus (orange lines) climate scientists are influenced by the level of consensus. On average, and for all parties, perceptions of the skill (lower panel) of pro- and anti-consensus scientists increase given consensus level with the mean slope of the relationship being 0.03 ($t = 13.6$) and 0.01 ($t = 2.8$), respectively. Additionally, beliefs about the bias (upper panel) of anti-consensus scientists rise on average ($\mu = 0.01$, $t = 5.8$), indicating that individuals believe that holdouts from consensus are increasingly likely to be biased. However, perhaps surprisingly, the pro-consensus scientists are also viewed as increasingly biased, at least among Independents and Republicans. The average slope is statistically indistinguishable from zero but there is substantial variation by party with the mean relationship being -0.013 ($t = -3.6$), 0.012 ($t = 2.5$), and 0.014 ($t = 3.1$) for Democrats, Independents, and Republicans, respectively.

Table 2: Summary Statistics of the Estimated Relationship between Log-Odds Beliefs and Consensus.

Variable	Mean	SD	Pct > 0	T-stat
Climate Slope	0.045	0.061	0.781	16.183
Pro-Skill Slope	0.0270	0.044	0.688	13.605
Anti-Skill Slope	0.006	0.049	0.544	2.864
Pro-Bias Slope	0.0002	0.057	0.511	0.074
Anti-Bias Slope	0.013	0.051	0.600	5.843

However, the existence of strong positive effects of consensus on each of the scientist attributes alone does not necessarily imply a relationship between the beliefs. To understand the system of beliefs that gives rise to consensus effects, we first examined pairwise correlations of individual-level slope terms, shown in Table 3. The effects of consensus on climate

[3] The equation can be expressed: $\log\left(\frac{y_c}{100-y_c}\right) = \beta_0 + \beta_1 consensus_c$, where y_c is the belief of interest and $consensus_c$ is the consensus level for the c'th consensus level shown.

belief, "Pro-Skill", "Anti-Skill", "Pro-Bias", and "Anti-Bias" are all strongly and positively correlated. This suggests that individuals are making inference in a way that ties together beliefs about the two groups of scientists.

Table 3: Correlation between the Estimated Relationships between Log-Odds Beliefs and Consensus.

	Climate	Pro-Skill	Anti-Skill	Pro-Bias
Climate				
Pro-Skill	0.53****			
Anti-Skill	0.26****	0.45****		
Pro-Bias	0.09*	0.12**	0.29****	
Anti-Bias	0.30****	0.33****	0.01	0.24****

*Signif. Codes: ****: 0.0001, ***: 0.001, **: 0.01, *: 0.05*

A key element of the hierarchical inference process we uncover is that consensus not only has a direct effect on climate beliefs but also indirect effects *through* related beliefs about scientist attributes. Table 4 presents the results from three regressions with two-way clustered standard errors for individuals i and consensus-levels j. The third of these is presented in equation (1):

$$climate_{ij} = \alpha_i + \gamma_j + ProBias_{ij} + AntiBias_{ij} + ProSkill_{ij} + AntiSkill_{ij} + \varepsilon_{ij} \quad (1)$$

where the outcome is individual i's log-odds ratio belief in climate change at consensus-level j. α_i is a vector of dummies for each individual in the sample while γ_j is a vector of dummies for each of the 5 different consensus levels. $ProBias_{ij}$, $AntiBias_{ij}$, $ProSkill_{ij}$, and $AntiSkill_{ij}$ are an individual's belief at a given consensus level in the bias of pro-consensus scientists, the bias of anti-consensus scientists, the skill of pro-consensus scientists, and the skill of anti-consensus scientists, respectively. The models in columns (1) and (2) regress climate belief on the same set of beliefs plus the continuous consensus level. These first two models control for the direct effect of consensus using a linear functional form while the fixed effects model in column (3) does not assume a functional form. In each model, "ProSkill" and "AntiBias" are positive and significant indicating that there is a meaningful indirect channel of consensus working through these beliefs. While a Bayesian inferential process implies joint updating, an intuitive way to understand these indirect channels is that consensus increases belief in "ProSkill" and "AntiBias" which provides additional evidence that the consensus is meaningful for climate change. Results are robust (and nearly identical) across these three specifications.

As a robustness check, we use a multilevel model estimated using the *brms* package in R with a random intercept and slopes for individuals and a random intercept for consensus. Again, "ProSkill" and "AntiBias" are positive with 95% credible intervals excluding 0 while the other related beliefs have a null effect.

As mentioned above, a Bayesian process of hierarchical inference implies joint updating (updating beliefs simultane-

Table 4: Relationship between Beliefs about Scientist Attributes and Belief in Human-Caused Climate Change.

Dependent Variable:		Climate	
Model:	(1)	(2)	(3)
Variables			
Constant	-1.647***		
	(0.2917)		
ProSkill	0.6107***	0.5931***	0.5698***
	(0.0695)	(0.0571)	(0.0635)
AntiSkill	-0.0477	0.0668	0.0697
	(0.0380)	(0.0426)	(0.0430)
ProBias	-0.0534	-0.0119	-0.0089
	(0.0327)	(0.0505)	(0.0500)
AntiBias	0.1190**	0.1944**	0.1918**
	(0.0267)	(0.0517)	(0.0512)
Consensus	0.0270***	0.0258***	
	(0.0030)	(0.0040)	
Fixed-effects			
ID	No	Yes	Yes
Consensus	No	No	Yes
Fit statistics			
Observations	2,465	2,465	2,465
R^2	0.46696	0.77063	0.77337
Within R^2		0.47531	0.25350

Clustered (ID & Consensus) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 5: Bayesian Multilevel Model Estimation Confirming Column (3) of Table 4.

	Climate
Intercept	0.64
	[−0.10; 1.35]
Pro-Bias	−0.03
	[−0.10; 0.04]
Anti-Bias	0.25*
	[0.18; 0.32]
Pro-Skill	0.46*
	[0.38; 0.53]
Anti-Skill	−0.03
	[−0.09; 0.04]

* 0 outside 95% credible interval.

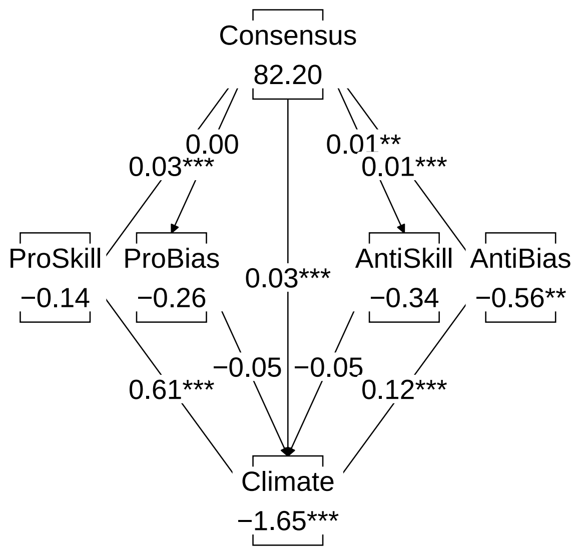

Figure 3: Structural Equation Model Demonstrating Direct and Indirect Pathways between Consensus and Belief in Human-Caused Climate Change. Beliefs are expressed in log-odds space and standard errors are clustered by individual.

ously) rather than sequential updating but the use of structural equation modeling (SEM) can be useful in teasing out the effects of the multiple pathways. Note that this is not the causal schema we believe people hold, merely a way to represent the statistical impact of the relevant beliefs. Figure 3 presents the disagreggated effects from the structural equation model with a direct pathway between consensus and climate belief and indirect pathways through related beliefs about scientist attributes. Standard errors are clustered at the participant-level. The direct effect is positive and significant ($\beta = 0.003, p < 0.01$). Consensus positively shifts all beliefs about scientist attributes other than ProBias. These shifts are then passed through to an increased belief in human-caused climate change for ProSkill ($\beta = 0.61, p < 0.01$) and AntiBias ($\beta = 0.12, p < 0.01$). The SEM validates the results from Table 4 that consensus acts on climate belief both directly and indirectly by providing additional information about the characteristics of climate scientists.

Discussion

We found that climate consensus messaging invokes a process of joint inference whereby beliefs about climate scientists are revised alongside beliefs about climate change itself. These findings point to more sophisticated and nuanced belief updating processes than prior investigations have considered. In line with previous studies, we find evidence that scientific consensus is an important component of belief in climate change with a positive average effect, even over a wide range of consensus levels. However, information about scientific consensus does not just cause updates in the focal belief about human-caused climate change but also an entire system of related beliefs, particularly the attributes of climate scientists. A higher level of scientific consensus increases belief in the bias of anti-consensus scientists and the skill of both pro- and anti-consensus scientists. For Independents and Republicans, perceptions about the bias of pro-consensus scientists also grow, indicating that while it is more likely that consensus is generated from skill, it is also increasingly likely that it is generated from bias. In this way, people learn both *from* and *about* climate scientists when presented with consensus.

The patterns of updating in separate beliefs given varying levels of scientific consensus suggests changes in a system of related beliefs. It appears that individuals are updating their beliefs in a principled manner that can be decomposed into direct and indirect pathways of consensus. The direct pathway, which has been the focus of previous research, is strongly positive, on average. Additionally, the inferences made about the characteristics of climate scientists, given consensus, are associated with either moderation or strengthening of the messaging effect, representing indirect channels through which consensus impacts climate belief. Consensus is positively associated with beliefs about the skill and bias of both pro- and anti-consensus scientists, with the effect on pro-consensus bias being null for Democrats. These attributions are then associated with differences in belief about climate change with pro-consensus skill and anti-consensus bias having strong positive associations with downstream climate belief. Pro-consensus bias and anti-consensus skill have weaker but negative effects.

Taken together, our results suggests that individuals engage in hierarchical inference about climate change when presented with scientific consensus. People systematically update their beliefs about climate change, the characteristics of individual scientists, and the characteristics of the field. When individuals attribute consensus to the skill of scientists, belief in climate change grows. However, when consensus is attributed to bias, consensus messaging can backfire. Given that we use a convenience sample, making generalizations to samples representative of the US or within political parties difficult, future work should explore this proposed belief system with a representative sample.

Additionally, further exploration of the computational underpinnings and structure of this belief network may suggest new methods for approaching climate communications. Already, our results suggest that using interventions to increase belief in either the trustworthiness or credibility of pro-consensus scientists relative to anti-consensus scientists should increase belief in human-caused climate change and, possibly, make consensus messaging more persuasive. Conversely, our findings also suggest that when presented with consensus, individuals will make inferences about the trustworthiness and skill of climate scientists which can impact the persuasiveness of downstream messages (like recommendations made by the scientists to address climate change).

Understanding these dynamics will allow for better targeting of climate messaging and suggest effective combinations of interventions.

Conclusion

Using a survey experiment, we systematically unpack one of the most influential messaging strategies about climate change—consensus messaging. We find consensus to be an important determinant of belief in climate change, consistent with previous research. Moreover, consensus not only provides information about climate change, it also provides information about the scientists who generate that consensus. We show that individuals make inferences about these climate scientists and that these inferences are associated with the persuasiveness of consensus messaging.

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