

Supplementary material for JCOM 16(05)(2017)A03

Introduction

This SI comprises two parts. The first examines the effect of the experiment conducted by VLFM on political polarization. The second presents a statistical simulation to illustrate the defects of the VLFM structural equation model.

1. Impact of consensus message on political polarization

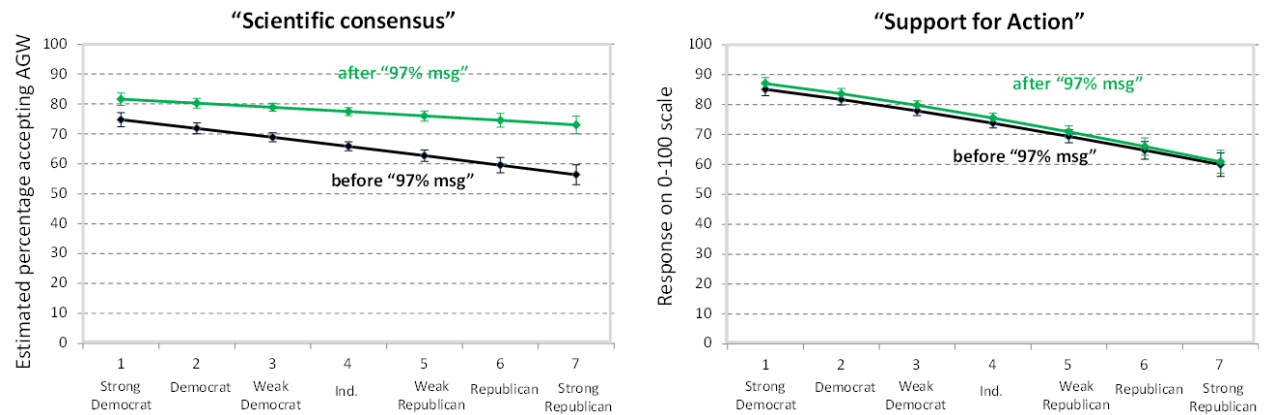
Global warming is a singularly *polarizing* issue in U.S. politics. Accordingly, any proposed intervention to promote more constructive engagement with climate science *must* be evaluated in relation to how it affects individuals of competing cultural or political identities [Bolsen & Druckman 2017; Cook & Lewandowsky 2016].

As explained in the paper, VLFM make a series of general representations relating to how the tested “97% consensus messages” affected individuals of opposing political party affiliations. They state, for example, that “the consensus message had a larger influence on Republican respondents,” and that “consensus-messaging . . . shifts the opinions of both Democrats and Republicans in directions consistent with the conclusions of climate science” [p. 6].

VLFM do not report data that support these claims, much less sufficient data to enable readers to critically assess these conclusions for themselves.

Because the responses of the consensus-message subjects did not differ practically or significantly from the study’s control-group subjects on the study’s key outcome measure, considering how message exposure affected only the former overstates the impact of experimental treatment. But such an analysis still furnishes some relevant information on the strength of the study findings. For this purpose, then, the VLFM experiment is treated as if it were a within-subjects one that compared only the

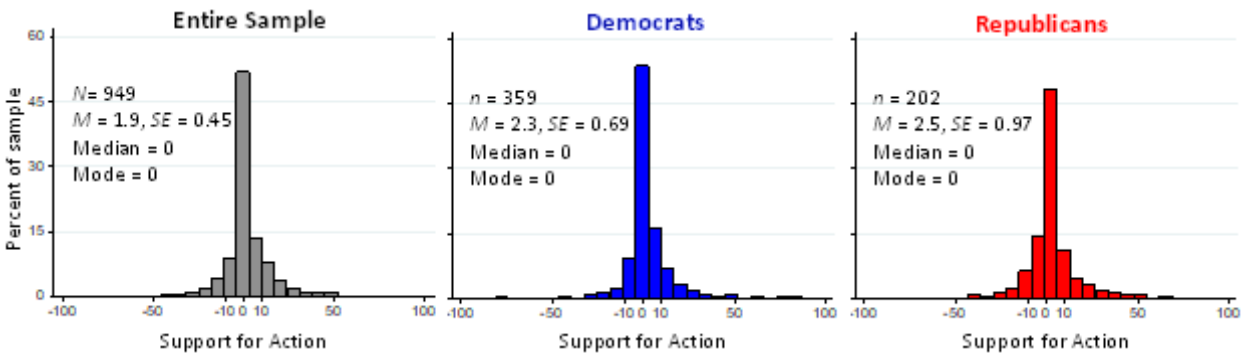
“before” and “after” responses of subjects exposed to a consensus message; any change is assumed to be attributable solely to exposure to *that* message and not to the noise injected into the study by the various “distractor” news stories.



SI Figure 1. Pre- and post-message responses to “scientific Consensus” and “Support for Action” items. *N*’s 944 for Scientific Consensus, “before” and “after”; 936 and 924 for “Support for Action,” “before” and “after,” respectively. Derived via Tobit regression (SI Figure 1). “97% consensus message” subjects only. CIs reflect 0.95 level of confidence.

SI Figure 1 shows how subjects characterized by their self-reported political outlooks revised their answers to the study’s “Scientific Consensus” and “Support for Action” items after viewing a consensus message.¹ Told that “97% of scientists have concluded that human-caused climate change is happening,” subjects who identified as Independents or Republicans (with varying digress of intensity) said on average something closer to “97%” when asked again to estimate the percentage of scientists who subscribe to the consensus position. Accordingly, the gap between the pre-message estimates of Democratic subjects and Republican ones narrowed considerably. But there was no comparable shift in the stances of these subjects on the Support for Action, the study’s key outcome variable.

¹ The Figure uses a Tobit regression model rather than a linear one to account for the censored nature of the 0-100 response scale. The non-significance of the results is unaffected, however, by whether one models the impact of the messages with a Tobit or a standard ordinary-least-squares linear model (SI Table 1).



SI Figure 2. Distribution of differentials for Support for Action among consensus-message group subjects, generally and by party identifications. “Democrats” include subjects who indicated either a “strong,” not strong, or weak identification with the Democratic party on the study’s 7-point partisan identification item. By the same token, “Republicans” include ones who indicated they were either strong, not strong or weak supporters of that party. The mean Support for Action differential for “Independents” was 0.69 ($SE = 0.87$).

As can be seen in (SI Figure 2), the impact of exposure to the experimental manipulation was miniscule. For the sample as a whole, both the modal and median differential on Support for Action was zero. Fully 31% percent of the subjects in the consensus-message group gave the same responses to “Support for Action” both “before” and “after” being told that “97% of scientists have concluded that human-caused climate change is happening.” Indeed, after receiving that information, 60% of the subjects either reiterated their initial response to Support for Action or reduced it.

The story does not change when one examines subjects in relation to their political party affiliations. For both Republicans and Democrats, the modal and median difference between “before” and “after” responses to Support for Action was zero—i.e., no change (SI Figure 2). Among Democrats, 58% of the subjects either stood pat or decreased their response to the Support for Action outcome measure; 57% of Republicans did likewise.

<i>Scientific Agreement</i>								
	Tobit Models				OLS Models			
	Before		After		Before		After	
Partisan ID	-3.32	(-7.37)	-1.77	(-3.96)	-3.17	(-7.37)	-1.63	(-3.77)
constant	79.86	(44.80)	86.89	(49.12)	78.81	(46.34)	85.81	(50.47)
<i>N</i>	823		823		823		823	
<i>R</i> ²	0.06		0.02		0.06		0.02	

<i>Support for Action</i>								
	Tobit Models				OLS Models			
	Before		After		Before		After	
Partisan ID	-5.36	(-9.36)	-5.68	(-10.12)	-4.17	(-9.47)	-4.45	(-10.43)
constant	98.53	(2.31)	101.67	(2.27)	90.07	(51.76)	92.87	(55.21)
<i>N</i>	816		807		816		807	
<i>R</i> ²	0.10		0.11		0.10		0.12	

<i>Belief in Climate Change</i>								
	Tobit Models				OLS Models			
	Before		After		Before		After	
Partisan ID	-7.81	(-11.70)	-7.29	(-11.36)	-6.24	(-9.47)	-5.62	(-11.55)
constant	105.22	(2.70)	107.85	(41.52)	94.56	(51.76)	96.44	(55.21)
<i>N</i>	818		822		818		822	
<i>R</i> ²	0.16		0.14		0.15		0.14	

<i>Counterfactual Cause</i>								
	Tobit Models				OLS Models			
	Before		After		Before		After	
Partisan ID	-4.18	(-8.27)	-4.96	(-9.70)	-4.04	(-8.56)	-4.69	(-9.85)
constant	79.20	(39.60)	86.62	(42.79)	77.88	(41.75)	84.66	(45.07)
<i>N</i>	816		821		816		821	
<i>R</i> ²	0.09		0.11		0.08		0.11	

<i>Worried About Climate Change</i>								
	Tobit Models				OLS Models			
	Before		After		Before		After	
Partisan ID	-6.15	(-10.04)	-6.94	(-10.80)	-5.54	(-10.13)	-5.91	(-10.90)
constant	86.45	(35.56)	95.18	(37.05)	82.42	(38.22)	88.40	(41.28)
<i>N</i>	812		807		812		807	
<i>R</i> ²	0.12		0.13		0.11		0.13	

SI Table 1. Tobit and Ordinary-least-squares regression models for Support for Action and Belief in Climate Change. Consensus-message subjects only. Dependent variables are “before” and “after” differentials. Unstandardized regression coefficients. “Partisan ID” is seven-point measure of party self-identification. Coefficient t- or z-statistics denoted parenthetically. Model *R*²s for Tobit models computed by squaring Pearson correlation of model predicted and observed values. **Bold** denotes that indicated coefficient is significant at *p* < 0.05.

Because partisan subjects were essentially frozen in place, there was no lessening of the distance between them. On the contrary, the correlation between the subjects responses to the “Public Support”

item and their response to the study's 7-point partisan self-identification measure actually increased by a small amount. It did the same for every other study outcome variable other than Belief in Climate Change, where the impact of partisanship was reduced by only a small increment (SI Table 1).

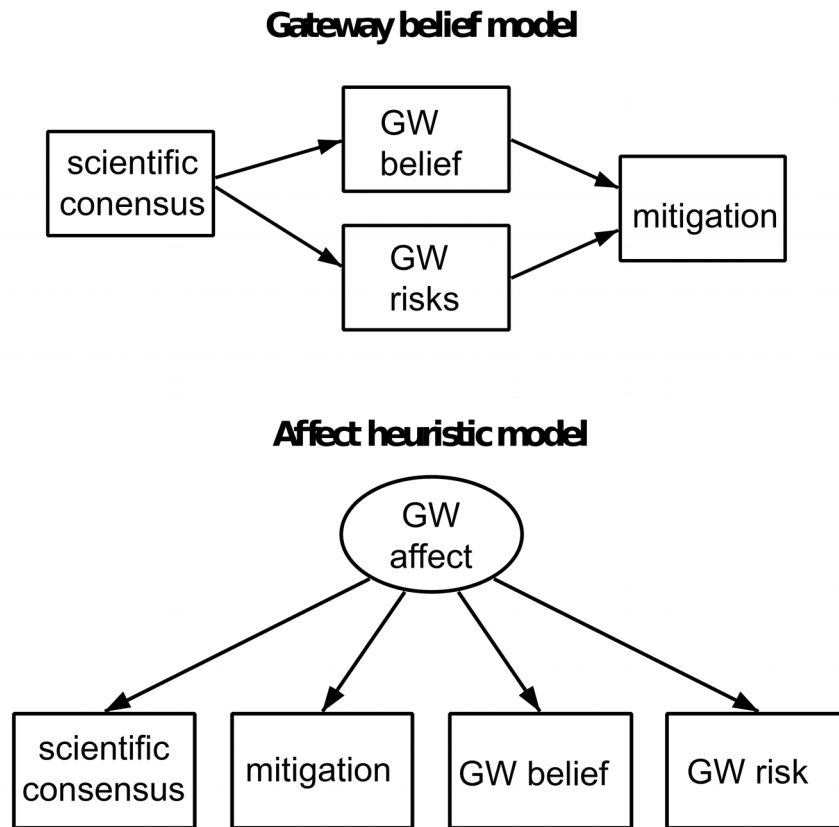
2. Statistical simulation

This section elaborates on the misspecification of the VLFM structural equation model. The model fails to include variables necessary for assessing the impact of the experimental treatment on the study outcome and mediator variables, which will be readily appreciated by those familiar with the use of multivariate regression analysis to assess between-subjects experiment results [Judd 2000]. Other commentaries also suggest ways to analyze between-subjects experiment results with structural equation path models [e.g., Muller, Judd & Yzerbyt 2005; Kraemer, Wilson, & Fairburn 2002, pp. 878-80; Hoyle & Smith 1994, pp. 436-48]. Nevertheless, a statistical simulation can usefully illustrate the consequences of the VLFM misspecification... What the simulation demonstrates is that the path analysis configured in VLFMs study cannot tell the difference between an experiment that confirms VLFM's Gateway Belief hypotheses and an experiment that disconfirms them.

1. Two hypotheses. The Gateway Belief Model can meaningfully be tested only in relation to an alternative account that generates different predictions about how perceptions of scientific consensus relate to other beliefs and attitudes about climate change. One such alternative is the *affect-heuristic model*. Arguably the single most important dynamic identified by the study of public risk perceptions, the affect heuristic, posits that perceptions of risk are *not* a consequence of individuals' assessment of information; instead, their assessment of information is a consequence of their feelings about putative risk sources [Slovic et al. 2004, 2005]. Individuals, on this account, predictably fit their assessments to their affective predisposition, which shapes all manner of belief and attitude about the risk source in question.

The Gateway Belief and affect-heuristic models reflect opposing understandings of how perceptions of scientific consensus relate to climate change beliefs and attitudes. According to the Gateway Belief Model, perceived scientific consensus "either supports or undermines other key beliefs

about climate change, which in turn, influence support for public action” [VLFM, p. 2]. That is, perceived scientific consensus *causes* these beliefs and attitudes.



SI Figure 3. Competing models of relationship between beliefs and attitudes toward climate change. The Gateway Belief Model posits that perceived scientific consensus causes belief in climate change and climate change risk perceptions, which in turn cause support for mitigation. The “affect heuristic model” posits that perceived scientific consensus, support for mitigation, belief in global warming, and global warming risk perceptions are all caused by a latent affective orientation toward climate change.

The affect-heuristic model, in contrast, asserts that such beliefs and attitudes are spuriously correlated with perceptions of scientific consensus. Something else—namely, a general affective orientation toward climate change—causes *all* of them. This orientation necessarily originates in some more remote influence that determines its valence and intensity. One influential account identifies *cultural worldviews* of affective orientations toward risk, a dynamic that explains public controversy over the safety of climate change, nuclear power, and myriad other putative sources [Peters, Burrstone & Mertz 2004; Slovic & Peters 1998; Peters & Slovic 1996].

These two models can be graphically depicted (SI Figure 3). Under the Gateway Belief Model, scientific consensus is posited to cause “key beliefs about climate change,” which “in turn” cause “support for public action” [VLFM, p. 6]. The affect heuristic, in contrast, implies that *all* of these beliefs and attitudes, including perceptions of scientific consensus, are all simply indicators of a general latent orientation, which is conceptualized as causing them.

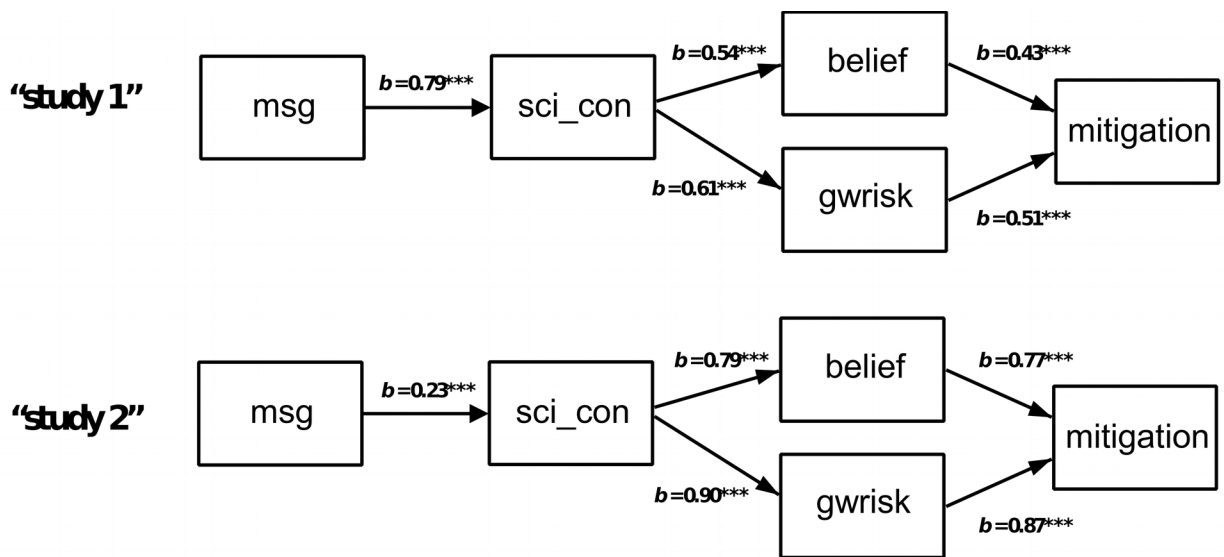
2. An experimental test. An experiment along the lines of the one carried out by VLFM might be viewed as supplying a test of these rival accounts. In the experiment, subjects’ perceptions of scientific consensus are manipulated with a consensus message. The gateway-belief model predicts that the change in perceived consensus will set off a mental “cascade,” changing climate change beliefs and risk perceptions, which in turn will affect support for mitigation policies [VLFM, p. 6]. The affect heuristic, in contrast, predicts that the manipulation of subjects’ perceptions of scientific consensus will have no impact on climate change beliefs, risk perceptions, or policy preferences: since the correlation between perceptions of scientific consensus and the other beliefs and attitudes is spurious, changing the former won’t affect the latter.

3. Two SEMs. Imagine that proponents of these competing hypotheses decide to carry out such an experiment. Indeed, they decide to “run it twice” to minimize the likelihood that they will be misled by either the chance detection of an effect that doesn’t really exist or the chance evasion of detection of an effect that really does.

After the results of the two studies are in, the proponent of the gateway-belief model produces two identically configured SEM models (SI Figure 4). Both reflect a significant parameter estimate for the path between the treatment—exposure to a consensus message (“msg”)—and subjects’ expressed estimates of the extent of scientific consensus (“sci_con”). In addition, the models display positive, statistically significant parameter estimates for paths connecting scientific consensus with both belief in climate change (“belief”) and the perceived global warming risks (“risks”). Finally, both models reflect positive, statistically significant estimates for paths between “belief” and “risks” and “mitigation,” the variables that measure the subjects’ support for “public action to reduce climate change.”

“Well,” says the proponent of the Gateway Belief hypothesis, “I guess that settles that.” “All my stated hypotheses were confirmed: experimentally manipulating perceived scientific consensus with a consensus message caused increased support for mitigation through the impact of perceived consensus on beliefs in climate change and global warming risks.”

But he’s wrong. One experiment produced results that fit that description. The other produced results that reflect the alternative affect heuristic model.



SI Figure 4. Simulated study SEMs. Structural equation models fit to the simulated study results. *** $p < 0.001$.

4. Simulating two studies. This claim can be made with complete confidence because the study results modeled in this way were simulated. In each study, a sample of 1,000 subjects were randomly assigned to either the consensus-message or control-group condition. The simulation algorithms were deliberately constructed to generate opposing experimental outcomes—ones supportive of the affect-heuristic model in one case and the gateway-belief model in the other.²

a. Study 1: affect-heuristic hypothesis confirmed, gateway-belief hypotheses disconfirmed. In “Study 1,” each of the 1,000 subject started with a randomly generated latent “affective orientation” toward climate change, L . L was generated by adding to an integer value (4) a sum drawn randomly from a distribution with a mean of 0 and a standard deviation of 1.

² The simulated data sets can be downloaded at <http://www.culturalcognition.net/browse-papers/the-strongest-evidence-to-date-what-the-van-der-linden-et-al.html>.

The affect heuristic model posits that this latent disposition is the *cause* of *all* the study outcome variables: perceived scientific consensus, belief in climate change, climate change risk perceptions, and support for climate mitigation. Consistent with that premise, subject responses to these measures were randomly generated by multiplying each subject’s latent affective disposition by a specified random variable:

- (1) $sci_con = x1 \times L$;
- (2) $belief = x2 \times L$;
- (3) $gwrisk = x3 \times L$; and
- (4) $mitigation = x4 \times L$.

The simulation assumed, though, that exposure to a “consensus message” did indeed influence subjects’ perceptions of scientific consensus. Accordingly, a randomly generated increment— $x5$ —was added to “*sci_con*” *for the subjects in the consensus message condition only*.

The resulting dataset is one that—by design—reflects results consistent with the affect heuristic model. In the simulation algorithm, the experimental treatment influenced perceived scientific consensus but had no effect on any other outcome variable.

SI Table 2 confirms this “experimental result.” Each study outcome variable is regressed on the experimental treatment, “*msg*.” The only variable for which “*msg*” is statistically significant—indeed, the only one for which it is anything other than trivially different from zero—is the subjects’ perceptions of scientific consensus. This is, of course, exactly what the proponent of the affect-heuristic model predicted.

	<i>sci_con</i>	<i>belief</i>	<i>gwrisk</i>	<i>mitigation</i>
<i>msg</i>	0.78 (11.34)	-0.04 (-0.72)	0.02 (0.29)	0.05 (0.79)
constant	3.57 (73.00)	3.22 (82.53)	3.60 (84.39)	3.57 (83.74)
R^2	0.11	0.00	0.00	0.00

SI Table 2. “Study 1” regression analysis. $N = 1000$. Unstandardized OLS regression coefficients. Parentheticals denote coefficient t-statistic. **Bolded** denotes indicated coefficient is significant at $p < 0.05$.

b. Study 2: Gateway-belief hypotheses corroborated, affect heuristic hypothesis confirmed. In “Study 2,” the study outcome variables were simulated by a process that reflected the premises of the

gateway-belief model. First, “sci_con,” the scientific consensus variable, was determined by adding to an integer (4) a value drawn randomly from a distribution with mean 0 and a standard deviation of 1.

Second, to simulate the impact of the experimental assignment, a random increment— x_1 —was added to the scientific consensus variable, “sci_con.” Next sums equal to the product of “sci_con” and two random variables were assigned to “belief” and “gwrisk,” respectively:

$$(1) \text{ belief} = x_2 \times \text{sci_con}; \text{ and}$$

$$(2) \text{ gwrisk} = x_3 \times \text{sci_con}.$$

Finally, for each subject, values equal to the product of “belief” and a random variable and the product of “gwrisk” and a random variable were summed to create the value for “mitigation”:

$$(3) \text{ mitigation} = x_4 \times \text{belief} + x_5 \times \text{gwrisk}.$$

This algorithm simulates experimental results evincing the “cascade” of beliefs and attitudes posited by the gateway-belief model. Subjects assigned to the consensus message increased their estimates of the extent of scientific consensus. Because they formed higher estimates of scientific consensus, they formed stronger beliefs in climate change and higher perceptions of global warming risks. These perceptions in turn generated greater support for mitigation.

Both the consensus-message and subjects’ resulting perceptions of scientific consensus influenced support for mitigation *indirectly*. The consensus message affected belief in climate change and perceived global warming risks *through* the impact of the message on perceived scientific consensus; and perceived scientific consensus affected support for mitigation *through* the impact of perceived consensus on climate change beliefs and risk perceptions. Perceived scientific consensus, belief in climate change, and global warming risk perceptions were all thus *mediators* of the effect of being exposed to a consensus message.

These effects are all confirmed in SI Table 3. The regression models show that the effects of the experimental treatment and of scientific consensus were both *fully mediated* by their impact on beliefs in climate change and global warming risk perceptions. That is, after taking account of the impact of the latter variables on mitigation, neither exposure to a consensus message nor variance in perceptions of

scientific consensus explained any variance in support for mitigation [Baron & Kenny 1986]. Exactly as the proponent of the gateway-belief model proponent predicted.

	<i>sci_con</i>	<i>Belief</i>	<i>gwrisk</i>	<i>mitigation</i>		
msg	0.24 (3.99)	0.12 (2.11)		0.20 (3.21)		0.27 (2.84) 0.01 (0.28)
sci_con			0.78 (54.94)		0.89 (65.79)	0.05 (1.10)
belief						0.75 (20.57)
gwrisk						0.84 (22.10)
constant	3.99 (92.32)	3.22 (81.62)	0.04 (0.75)	3.60 (83.59)	0.01 (65.79)	5.67 (83.28) 0.03 (0.36)
R^2	0.01	0.00	0.75	0.01	0.81	0.01 0.89

SI Table 3. “Study 2” regression analyses. $N = 1000$. Unstandardized OLS regression coefficients. Parentheticals denote coefficient t-statistic. **Bolded** denotes indicated coefficient is significant at $p < 0.05$.

5. The misspecified gateway SEMs. Yet it is now painfully obvious that the SEM path-analysis proffered by the gateway-model theorist was misspecified. There was nothing about *it* that allowed us to discern that “Study 1” supported the affect-heuristic model and “Study 2” the gateway-belief model. What exactly is wrong with it?

The reason is because it is only structured to measure the impact of the experiment on subjects’ perceptions of scientific consensus. In an SEM path diagram, every exogenous variable is regressed on every other variable that is connect to it by an arrow. “Sci_con” is connected by an arrow to the treatment variable; the parameter estimate associated with it reflects the effect that being exposed to a consensus message had on the subjects’ perceptions of scientific consensus.

But there is no arrow between “msg” and any of the other variables in the SEM. The estimated path parameters are blind to differences in the responses of subjects who were treated with a scientific-consensus message and those who weren’t. There is nothing in the SEM that assesses whether there was “an overall treatment effect on the outcome variable” [Muller, Judd & Yzerbyt 2005, p. 853]. Likewise, there is nothing in it that assesses whether there was a “treatment effect on the mediator[s]” [ibid]. As a result, the gateway model as specified is unable to tell the difference between variables that are casually associated and ones only spuriously correlated.

Except for the path parameter estimate between “msg” and “sci_con,” all the path coefficients in the “Study 1” model are spurious correlations. We know that because we have access to the process that generated these variables: all of them were “caused” by Latent, the unobserved climate-change affect variable. It’s true that values for “sci_con” were higher for subjects assigned to the consensus-message condition. But the *correlations* between “sci_con” and “belief,” on the one hand, and between “sci_con” and “gwrisk,” on the other, were a consequence of the pre-treatment contribution that Latent made to all of these variables; by design, the experimental treatment contributed nothing. The same is true for the correlations between “belief” and “gwrisk”, respectively, and “mitigation.”

In “Study 2,” the parameter estimates for all the represented paths are ones that reflect the causal impact—directly on “sci_con,” indirectly on all the remaining study variables—of the experimental treatment. We know this because we were privy to the process that created these variables.

6. The proper analysis. We also know this through the regression analyses reported in SI Table 1. Those are exactly the analyses that should have been performed by our hypothetical researchers at the outset in order for them to *discover* the results of their experiments.

That, then, is the right way to analyze results from an experiment that reflects the design of the one performed in VLFM.³ Before any sort of path analysis is constructed to test for mediation, the researcher should *first* assess the impact of the experimental assignment on the outcome variables and the posited mediators. Typically this is done, as it was here (SI Table 1), by regressing those variables on the experimental treatment [Muller, Judd & Yzerbyt 2005]. *If* those analyses show that there was an experimental impact on the outcome variable and posited mediators, *then* one can do an SEM to assess the extent to which the experimental impact was direct or indirect, unmediated or instead mediated either “fully” or “partially.” Even, then, however, a model like the one featured in VLFM would *not* be specified appropriately, since it ignores how relationships between the posited mediator and the outcome variable varied conditional on the experimental assignment [Muller, Judd & Yzerbyt 2005; Kraemer,

³ Of course, whether the design is internally valid (footnote 7 of the paper) is another story. If it isn’t, no inferences can be drawn from the regression models either.

Wilson, & Fairburn 2002]. *If*, in contrast, an analysis of the effect of the treatment on the outcome variable and mediators shows that there were no effects, then fitting a path diagram to the data does nothing more than reveal non-causal correlations—as happened when such a model was fit to the simulated “Study 1” data.⁴

7. **VLFM.** The model in VLFM was misspecified in exactly the same way as was the SEM featured in this simulation. Thus, contrary to VLFM’s interpretation of their model, the significant path coefficients did not signify that the consensus message affected “Support for Action,” directly or indirectly. The analyses necessary to determine whether such an effect existed—the regression of the study outcome variables on the experimental treatment—showed that there wasn’t any effect (Table 4 in the paper).

The VLFM experiment, then, didn’t support the Gateway Belief model. It disconfirmed it—and furnished evidence consistent with the rival affect-heuristic model.

4 Some commentators take the position that examination of mediation effects can be investigated even in the absence of a demonstrated effect of a predictor on the outcome variable if one has reason to think the effect was too small to be detected. In that case, though, the SEM simply assumes the causal effect of the predictor and furnishes no independent evidence for it (Judd, Yzerbyt & Muller 2014). Such an assumption here would defeat VLFM’s announced purpose: to remedy the “major short-coming” of previous “correlational” studies by furnishing experimental proof of “the proposed causal relationship between public perceptions of the scientific consensus on climate change and support for public action” (p. 2). In addition, even if the VLFM’s inability to reject the null effect on the *outcome variable* was overlooked, it would still be necessary to determine whether there was an experimental impact on the hypothesized *mediators* (Muller, Judd & Yzerbyt 2005; Kraemer, Wilson, & Fairburn 2002).