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1 Running head: INFLUENCE AND SEEPAGE

2 Influence and seepage: An evidence-resistant minority can affect public opinion and
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15

Abstract

16 Some well-established scientific findings may be rejected by vocal minorities because the
17 evidence is in conflict with political views or economic interests. For example, the tobacco
18 industry denied the medical consensus on the harms of smoking for decades, and the clear
19 evidence about human-caused climate change is currently being rejected by many
20 politicians and think tanks that oppose regulatory action. We present an agent-based
21 model of the processes by which denial of climate change can occur, how opinions that run
22 counter to the evidence can affect the scientific community, and how denial can alter the
23 public discourse. The model involves an ensemble of Bayesian agents, representing the
24 scientific community, that are presented with the emerging historical evidence of climate
25 change and that also communicate the evidence to each other. Over time, the scientific
26 community comes to agreement that the climate is changing. When a minority of agents
27 is introduced that is resistant to the evidence, but that enter into the scientific discussion,
28 the simulated scientific community still acquires firm knowledge but consensus formation is
29 delayed. When both types of agents are communicating with the general public, the public
30 remains ambivalent about the reality of climate change. The model captures essential
31 aspects of the actual evolution of scientific and public opinion during the last 4 decades.

**Influence and seepage: An evidence-resistant minority can
affect public opinion and scientific belief formation**

More than 150 years ago, John Tyndall demonstrated experimentally that “carbonic acid”, despite being a perfectly colorless and invisible gas, was able to absorb heat radiation. Unlike the atmosphere, carbonic acid was nearly opaque to radiant heat. We now refer to carbonic acid as CO₂, and following on the heels of Tyndall’s discovery, it was recognized more than a century ago that industrial CO₂ emissions may alter the Earth’s climate (Arrhenius, 1896). During the last two decades, the evidence that humans are altering the climate has become unequivocal. There is near unanimity (around 97%) among domain experts that the climate is changing due to emissions of CO₂ and other greenhouse gases, mainly from combustion of fossil fuels (Anderegg, Prall, Harold, & Schneider, 2010; Cook et al., 2013, 2016; Doran & Zimmerman, 2009; Oreskes, 2004). The Intergovernmental Panel on Climate Change (IPCC) periodically summarizes the scientific consensus in Assessment Reports (e.g., most recently AR5; IPCC, 2013).

Notwithstanding this pervasive scientific agreement, the public in some countries continues to be divided on whether or not climate change presents a real risk and is caused by fossil-fuel combustion. For example, Carmichael and Brulle (2017) showed in an analysis of 74 surveys (between 2002–2013) that public concern with climate change in the U.S. peaked in 2008 but then declined until 2011. Although the relevance of those fluctuations in opinion is subject to debate (e.g., Egan & Mullin, 2017), there is no doubt that currently many Americans (around 36%; Egan & Mullin, 2017) are not worried about climate change, and that a similar number or more do not accept its human origins (Hamilton, Hartter, Lemcke-Stampone, Moore, & Safford, 2015). The public also widely underestimates the extent of the scientific consensus. As of 2016, less than 70% of the

57 public recognize that most scientists agree on climate change, although that share has
58 increased from 50% in 2010 (Hamilton, 2016).

59 The reasons for the discrepancy between the scientific agreement and the public's
60 low concern are well understood. Brulle, Carmichael, and Jenkins (2012) showed that
61 public opinion is guided by elite cues and mobilization of advocacy groups, with media
62 coverage being an important conduit of that influence. There is abundant evidence for the
63 existence of a well-organized campaign that seeks to undermine the public's understanding
64 of climate change (e.g., Dunlap & McCright, 2011; Dunlap, 2013; McCright & Dunlap,
65 2003, 2010; Medimorec & Pennycook, 2015; Oreskes & Conway, 2010). Analysis of IRS
66 data puts the income of a network of conservative think tanks at somewhere near \$1
67 billion annually (Brulle, 2013). At least in part, this network is dedicated to questioning
68 the scientific consensus on climate change.

69 The effects of that funding are detectable in a number of ways. The vast majority of
70 books (over 90%) that are critical of mainstream climate science are linked to conservative
71 think tanks (Dunlap & Jacques, 2013; Jacques, Dunlap, & Freeman, 2008). The influence
72 on public discourse of two core funders—ExxonMobil and the Koch family
73 foundations—was identified in a network analysis by Farrell (2015). Organizations that
74 received fundings from those two entities were significantly more central to the network
75 than individuals or organizations without such funding. Moreover, Farrell found that the
76 semantic similarity between the output of this denial network and coverage in the
77 mainstream media increased between 1993 and 2013. A similar increase was observed in
78 the speeches of U.S. presidents, albeit at a lower level of similarity overall. Although the
79 direction of causality cannot be ascertained from those data, one interpretation is that the
80 efforts of conservative think tanks (Brulle, 2013) and Exxon (Supran & Oreskes, 2017)
81 had the intended effect of shaping public discourse with denialist talking points, thereby
82 delaying meaningful mitigation efforts.

83 In particular, the denialist campaign is likely to be behind the public's
84 under-estimation of the consensus among scientists (Hamilton, 2016). This is more than a
85 mere miscalibration, given that appreciation of the consensus has been identified as a
86 "gateway" belief that determines people's policy support (van der Linden, Leiserowitz,
87 Feinberg, & Maibach, 2015). When people are educated about the scientific consensus in
88 experiments, this has been repeatedly shown to increase people's acceptance of the
89 underlying science (Lewandowsky, Gignac, & Vaughan, 2013; S. L. van der Linden,
90 Clarke, & Maibach, 2015; S. van der Linden, Leiserowitz, & Maibach, 2018). Conversely, a
91 single dissenting opinion has been shown to be sufficient to reduce people's beliefs in the
92 adequacy of scientific evidence to guide government policy (Koehler, 2016; see also Bovens
93 & Hartmann, 2004). The creation of a chimerical scientific debate is thus an effective
94 trigger of cognitive mechanisms that are likely to disengage the public and reduce their
95 demands for policy action.

96 In addition to these effects of organized denial on the public and political spheres,
97 there are indications that contrarian activity has also affected the scientific community
98 itself. Freudenburg and Muselli (2010) showed that the IPCC's consensus report (AR4 at
99 the time) had been too conservative rather than too alarmist, as revealed by an analysis of
100 media coverage of subsequent new scientific findings. Further confirmation of the IPCC's
101 conservatism was provided in a textual analysis by Medimorec and Pennycook (2015),
102 which found that the IPCC (AR5) used more cautious and uncertain language than
103 documents produced by a conservative think tank committed to denying the scientific
104 consensus.

105 Other work has identified the "reticence" of scientists to confront the full
106 implications of their findings (Hansen, 2007), their propensity to "err on the side of least
107 drama" (Brysse, Oreskes, O'Reilly, & Oppenheimer, 2013), and their concern of being
108 portrayed as "alarmist" (Risbey, 2008) as factors that might lead the scientific community

109 to paint risks in a less dramatic light. A recent extension of this argument suggested that
 110 denial may have “seeped” into the scientific community itself (Lewandowsky, Oreskes,
 111 Risbey, Newell, & Smithson, 2015). Lewandowsky et al. identified several known
 112 psychological processes, such as stereotype threat or pluralistic ignorance, that might
 113 render scientists’ work vulnerable to contrarian attacks which are often toxic and personal
 114 (Lewandowsky, 2019; Mann, 2012). One avenue of attack involves freedom-of-information
 115 (FOIA) requests, typically for scientists’ personal emails. Depending on jurisdiction, these
 116 requests may result in the release of thousands of emails between researchers, which are
 117 then quote-mined for compromising statements. There is evidence that personal emails
 118 between scientists can be exploited in this manner with a discernible impact on public
 119 opinion (Stoutenborough, Liu, & Vedlitz, 2014). Ley (2018) analyzed the impact of FOIA
 120 requests on scientists through in-depth interviews. He found that all respondents had
 121 altered their means of communication in response to an FOIA requests, with many
 122 scientists engaging in self-censorship and others resorting to phone calls. A minority also
 123 reported a chilling effect on their ability to express research ideas. The self-censorship
 124 that results from FOIA requests may be just one avenue by which pressure from political
 125 operatives could shape scientists’ interpretation of data notwithstanding their
 126 commitment to reject denialist talking points. Lewandowsky, Oreskes, et al. (2015)
 127 illustrated the possibility of such “seepage” within the context of the recent presumed
 128 “pause” or “hiatus” in global warming.

129 The “pause” refers to a period of slower-than-average warming, which is alleged to
 130 have occurred from around 1998 for around a decade, and which climate contrarians
 131 seized on to claim that global warming has “stopped” (e.g., Carter, 2006). Boykoff (2014)
 132 showed how the media and other public actors used the apparent slowdown in warming to
 133 create a frame for discussion around the notion that warming had unexpectedly “stopped”
 134 or “paused.” Statistical evidence for a “pause” or a significant slowdown is scarce or

135 non-existent (Lewandowsky, Risbey, & Oreskes, 2015; Lewandowsky et al., 2018; Risbey et
 136 al., 2018), and the notion of a “pause” has been identified as misleading in a blind expert
 137 test (Lewandowsky, Risbey, & Oreskes, 2016). Nonetheless, the scientific community
 138 responded to the fluctuation in warming rate with, to date, more than 200 peer-reviewed
 139 publications (Risbey et al., 2018). A number of those articles framed the “pause” as a
 140 challenge to the mainstream scientific view of greenhouse-driven global warming (see
 141 Lewandowsky, Risbey, & Oreskes, 2016, Table 2). Lewandowsky, Oreskes, et al. (2015)
 142 argued that the scientific community’s concern with a short-term fluctuation in warming
 143 rate was likely amplified—or even generated—by the rhetoric of contrarian political
 144 operatives and their allies. However, Lewandowsky, Oreskes, et al. could only provide
 145 circumstantial evidence to buttress their argument.

146 This article explores the seepage notion within a quantitative theoretical approach.
 147 We present an agent-based model of the three principal groups of actors: the scientific
 148 community, operatives in the organized denial network, and the public at large. All
 149 actors are represented by rational Bayesian agents that seek information by inspecting
 150 climate data or by communicating with each other. We design our agents to be Bayesian
 151 not only because people’s decisions can conform to Bayesian norms of rationality (e.g.,
 152 Griffiths, Kemp, & Tenenbaum, 2008; Lewandowsky, Griffiths, & Kalish, 2009), but in
 153 particular because even seemingly “irrational” behaviors can emerge from Bayesian
 154 principles. For example, belief polarization (Cook & Lewandowsky, 2016; Jern, Chang, &
 155 Kemp, 2009) can be accommodated within a rational Bayesian framework, and it has been
 156 shown that Bayesian agents can form persistent “echo chambers,” enclosed epistemic
 157 bubbles in which agents share most beliefs (Madsen, Bailey, & Pilditch, 2018). The use of
 158 rational agents also seemed advisable in light of several suggestions that climate denial
 159 can be considered a rational enterprise (Cook & Lewandowsky, 2016; Lewandowsky, Cook,
 160 & Lloyd, 2016), notwithstanding its wholesale dismissal of scientific evidence.

161 We seed the model with the global temperature data from 1950 through 2017,
 162 sampling new observations on an annual basis. During each simulated year, the agents
 163 communicate with each other and update their belief in the hypothesis that the Earth is
 164 warming. The simulations below were designed to answer the following questions: (1) In
 165 the absence of organized denial, how quickly would the scientific community have settled
 166 on the consensus position that greenhouse-driven warming exists? (2) Given the strength
 167 of evidence for warming, how can rational agents remain resistant to the evidence and
 168 continue to deny climate change? (3) What are the effects of denial on the scientific
 169 community? In particular, is there evidence for “seepage”? (4) What are the effects of
 170 denial on the public at large? In particular, can actual public opinion be modeled without
 171 disproportionate representation of denialist messages by the media (e.g., in the name of
 172 balance)?

173 The Model

174 *Climate data input*

175 The model had access to two global temperature datasets: The HadCRUT4 product
 176 curated by the U.K. Met Office (Morice, Kennedy, Rayner, & Jones, 2012) and the
 177 GISTEMP dataset produced by NASA’s Goddard Institute for Space Studies (Hansen,
 178 Ruedy, Sato, & Lo, 2010). Both datasets record global mean surface temperature
 179 (GMST), expressed as anomalies from a climatological baseline. For the purposes of
 180 detecting changes in global climate, individual temperature observations are converted into
 181 deviations from a long-term average temperature (typically across 30 years) for the station
 182 in question. Those deviations, known as anomalies, are then averaged in an area-weighted
 183 manner across all locations around the world to estimate global temperature trends.
 184 Figure 1 shows GMST anomalies for the two datasets. Both datasets show that the Earth
 185 has been warming continuously since around 1970. The “pause” period refers to the

apparent decrease in warming rate during the decade after 1998. The figure also clarifies that this period is now clearly over, given the recent sharp up-tick in temperature.

Although both datasets display very similar long term trends, when the same data are instead represented as trends of varying durations, some differences between datasets emerge. Figure 2 shows trends for HadCRUT4 (panel A) and GISTEMP (panel B). Each panel shows the warming trends that were observable, given the available data at the time, for any vantage point between 1984 and 2016 (horizontal axis). For each vantage point, between 3 and 25 years were included in the trend calculation (vertical axis) by moving backwards in time. Significant trends are indicated by a dot. For example, the entries for the final column in each panel record the trend values that were observable in 2016, considering anywhere between the preceding 3 years (bottom row; 2014–2016) and 25 years (top row; 1992–2016).

Figure 2 clarifies that at any time since 1989, a significant warming trend was detectable if a sufficiently large number of observations was included. However, the figure also shows that if a small number of years is considered, trend values can fluctuate considerably and may in some cases even be negative. Those small-scale fluctuations are of no climatological relevance but offer an opportunity for contrarians to claim that global warming has “stopped” or “paused”. It is also apparent from the figure that the notion of a “pause” during the decade following 1998 was more visible with the HadCRUT dataset (panel A) than GISTEMP (panel B). The reasons for this are well understood: Unlike GISTEMP, HadCRUT does not record observations for much of the Arctic, the region of the globe that is known to warm most rapidly. When those coverage gaps are corrected by interpolation (Cowtan & Way, 2014), the divergence between HadCRUT4 and GISTEMP is largely eliminated (e.g., Lewandowsky, Risbey, & Oreskes, 2015; Risbey et al., 2018).

Our model simulated the gradual acquisition of scientific knowledge about climate change by a population of agents that continually examined the most recent temperature

212 trend available at any given time. The number of years being considered by each agent was
 213 a model parameter, described below. Agents then communicated their perceptions of the
 214 data to each other, updating their prior beliefs with the new evidence and communications
 215 at each round. The top panel in Figure 3 provides a graphical overview of the model.

216 *Classes of agents*

217 The model comprised three classes of agents, representing mainstream scientists,
 218 contrarians, and the general public. One or more of those classes of agents was active in
 219 any given simulation. The proportions of scientists to contrarians, along with their
 220 representation in communicating to the public was manipulated between simulations.

221 *Scientists and contrarians*

222 Scientists and contrarians started with a prior belief in anthropogenic climate change
 223 of 1%, $P(CC) = .01$. Thus, all agents commenced from a position of strong skepticism of
 224 the global-warming hypothesis. The agents then sampled information from the real world
 225 by inspecting the climate data (HadCRUT or GISTEMP), and then updating their belief
 226 in climate change according to either an unbiased (scientists) or biased (contrarian)
 227 interpretation of temperature trends. Data sampling occurred annually. In between data
 228 sampling, scientists and contrarians communicated both among themselves (passing on
 229 trend information) and to the general public (passing on interpretations of the data), such
 230 that recipients of these communications further updated their belief in climate change
 231 (details below). Scientists and contrarians had the same functionality but differed in their
 232 settings of three parameters that defined each class of agents.

233 *Dataset preference.* This parameter, DSP_S and DSP_C , represented the dataset
 234 (GISTEMP or HadCRUT) from which the agent drew data-points. This preference
 235 remained constant across the simulation run.

236 *Memory window.* The memory window parameter (M_S for scientists and M_C for
 237 contrarians, respectively) determined how many historical temperature observations
 238 agents considered as they inspect the data at each iteration to compute a warming trend.
 239 That trend constituted the latest evidence for climate change available to the agent. M
 240 varied between 3 and 30 and differed between scientists and contrarians. For scientists,
 241 M_S was typically set to 15 or 30, representing climatological practice to ignore short-term
 242 fluctuations. For contrarians, M_C was typically set to 3, reflecting the fact that denialist
 243 arguments pervasively rely on “cherry-picking” of short-term trends (Lewandowsky,
 244 Ballard, Oberauer, & Benestad, 2016). If an agent possessed a full memory window, new
 245 data points supplanted the oldest.

246 *Skew.* The skew parameter represented an interpretative bias by determining the
 247 degree to which temperature trends were skewed by the agent during processing. Positive
 248 values of skew bias the agent against climate change, negative values towards climate
 249 change, whereas a value of 0 represented unbiased processing (see Equation 1 below). For
 250 scientists, S_S was set to 0 (unbiased processing) in all simulations. For contrarians, S_C ,
 251 was typically set to positive values, reflecting a bias against detection of climate change.

252 All parameters were set uniformly across all agents within a class for a given
 253 simulation run.

254 *General public*

255 All general-public agents were also skeptical initially, with a prior belief in
 256 anthropogenic climate change of 1%, $P(CC) = .01$. Unlike contrarians and scientists, the
 257 general-public agents do not draw information directly from any datasets. This reflects
 258 the likely fact that members of the public do not read the scientific literature but rely on
 259 interlocutors—represented here by scientific and contrarian voices channeled via the
 260 media—to inform themselves about climate change.

In all simulations, general-public agents were passive listeners whose sole function was to receive interpretations of the data, and update their belief in climate change accordingly (see Equation 2 below). For all simulations including the general public, 1,000 such agents were initialised.

Initialization and evolution over time

All simulations entailed the initialisation of 1000 agents (scientists and/or contrarians), each starting with $P(CC) = .01$. Agents initially drew a sample of three data-points from the chosen dataset into their memory, starting at the specified year of data. For instance, an agent drawing from the GISTEMP dataset with a specified start year of 1950 would draw the data points (GMST anomalies) for 1950, 1951, and 1952 into their initial sample in memory. Those 3 data points enabled the agent to compute the first regression slope (1950-1952). No updates were made based on this initial sample. The initial sample instead set the prior for going forward to all subsequent belief-updating steps.

Data sampling

Data sampling occurred annually (see top panel in Figure 3). Scientists and contrarians sampled a single data-point from their preferred dataset for the current year, adding it to the observations already in their memory window. Thus, for the above example, an agent would add the observation for 1953 to the memory window when an observation for that year became available, and so on. Once data had been sampled, the agents then calculated a standard regression slope, β , from the data points in their memory window (as illustrated in Figure 2). This trend represented the change in temperature up until the present year, going back as far as their memory window allows. Figure 4 illustrates this process for two hypothetical agents with two different sizes of memory window.

A given value of β obtained during data sampling was retained by the agent throughout the 5 communication events, described below, that were presumed to occur during the same year.

Updating beliefs from data

The calculated regression slope, β , was then interpreted as a Likelihood Ratio (LR) that provided evidence for (or against) the climate change hypothesis as follows:

$$LR = 10^{\beta - S}, \quad (1)$$

where the more positive the slope (β), and the lower the skew parameter (S), the larger the LR value. If the $\beta - S$ term is > 0 (and thus the slope is still considered positive, having taken into account a potentially biased interpretation), the LR is > 1 , indicating support for the climate change hypothesis. In the same manner, if the $\beta - S$ term is equal to zero (and no positive trend is perceived, having taken into account a potential bias), the LR value is 1, representing complete ambiguity. Finally, if $\beta - S$ is negative, the LR is < 1 , indicating support against the climate change hypothesis. This process of computing the LR ensured that agents could encounter evidence either for or against the climate-change hypothesis. Unless a bias was introduced by setting S to a non-zero value, our agents were not predestined to inevitably settle either on endorsement or rejection of the hypothesis. Figure 5 illustrates this process.

The LR values are then plugged into the log-odds form of Bayes theorem to update the belief in climate change via Bayesian belief revision, as follows:

$$\frac{P(CC|E)}{P(\neg CC|E)} = \frac{P(CC)}{P(\neg CC)} \times LR. \quad (2)$$

The odds on the right-hand side of the equation represent the agent's beliefs in the climate change hypothesis (CC) and its complement, namely that there is no climate

307 change ($\neg CC$). The odds on the left-hand side of the equation represent the updated
 308 beliefs in the two competing hypotheses, given the evidence (E) just introduced by the
 309 likelihood ratio (LR).

310 *Communication rounds*

311 Each data sampling event was accompanied by 5 communication rounds (see top
 312 panel, Figure 3), during which the agents exchanged information. This mimicked the idea
 313 that although annual data become available once a year, scientists repeatedly exchange
 314 their views about those data throughout the year. Depending on the simulation,
 315 communication could occur just among scientists (S) and contrarians (C) involving all
 316 possible pairings (i.e., $S \rightarrow C$, $S \rightarrow S$, $C \rightarrow C$, and $C \rightarrow S$), or additionally also from
 317 scientists and contrarians to the general public. The manipulation of the communication
 318 regime permitted selective tests of mechanisms within the scientific community (e.g.,
 319 seepage) as well as mechanisms involving the public (e.g., contrarian influence). At each
 320 round, each agent (when present) received exactly one communication according to the
 321 following rules.

322 *Selection of communicators.* For each of the 5 communication rounds, a random
 323 sample of scientists (and contrarians, when present) were selected to be communicators.
 324 Sampling was with replacement, so the same agent might be involved in communicating
 325 on more than one occasion. The selection of a pool of communicators permitted
 326 manipulation of the proportion of scientists and contrarians in the pool independently of
 327 their prevalence in the population (see next section). The number of agents in each pool
 328 was $N = 10$ (Simulation 1), $N = 5$ (Simulation 2), and $N = 100$ (Simulations 3 and 4).

329 *Communication among scientists and contrarians.* When scientists or contrarians
 330 communicate among themselves, a random communicator from the pool passes on their
 331 latest slope estimate obtained during data sampling (β) to a random recipient agent, until

all scientists and contrarians in the simulated population have received exactly one value. Recipients then interpret this slope via Equation 1 (thereby introducing their own bias), before updating their belief in climate change via Equation 2. Communicators are sampled with replacement from the pool so each communicator may be involved in more than one communication.

Communication to the general public. When scientists and contrarians communicate to the general public, a random communicator passes on their latest LR value (Equation 1) to a random member of the public, until all members have received exactly one value. The recipients directly update their belief in climate change using their received LR value via Equation 2.

The public therefore receives the interpretation of the data made by the interlocutors, rather than the original data. This reflects the fact that scientists (and contrarians) do not communicate the exact values of decadal warming trends to the public, but their interpretation of those trends. We additionally model the potential amplifying effects of the media by varying the representation of contrarians in communications independently of their actual number (see next section).

General simulation settings and manipulations

Several further system-wide simulation parameters were manipulated:

StartYear: Time from which the data sampling process starts. Set to 1950 throughout.

ConProp: Proportion of agents that are categorized as contrarians (the remainder being mainstream scientists). In reality, this proportion has been estimated at no more than .03 (3%) of practicing climate scientists across numerous studies (summarized by Cook et al., 2016). Any value greater than 3% thus models the inclusion of other

contrarian operatives, such as bloggers or think tanks, who are known to vocally publicize their own interpretations of the data (Farrell, 2016).

ConRep: The proportion of contrarians represented in the pool of communicators. There is evidence that contrarians tend to receive disproportionately more exposure in the media (Verheggen et al., 2014), presumably because the media seek to “balance” competing voices (Boykoff & Boykoff, 2004). If 3% of the population of agents are contrarian, the communicator pool could either be representative (100 communicators, of which 3 are contrarian), or over-representative (e.g., 6 contrarians—double their prevalence in the population).

All simulations run until the entire historical temperature record (through the end of 2017) has been observed by agents, and the last 5 rounds of communication have been completed. Each simulation experiment involved 100 independent replications within each cell of the experimental design. The dependent variable of greatest interest in all experiments was the belief in climate change, $P(CC)$, over time, split by agent group and averaged across the 100 replications within each experimental cell. The model was programmed in Netlogo (version 6.0.1) and simulations were run using the RNetlogo package in R (Thiele, 2014). The Netlogo source code and output from all simulations is available for download at <https://github.com/StephanLewandowsky/ABM-seepage-and-influence>. The bottom panel in Figure 3 provides an overview of the 4 simulation experiments and indicates their purpose.

Simulation Experiment 1: Scientific consensus formation

The first simulation described how a scientific community builds a consensus belief around climate change by examining and discussing the data over time, and how that consensus is communicated to the public. In this simulation, all agents were unbiased

381 ($S_S = 0$) and the two principal independent variables were the choice of dataset
 382 (GISTEMP vs. HadCRUT) and memory size. Memory size was variously set at 3, 10, 15,
 383 and 30. The largest memory size (30 years) corresponds to the length of climatological
 384 baseline that is taken to exceed the duration of short-term fluctuations and reveals
 385 greenhouse-gas driven warming (Medhaug, Stolpe, Fischer, & Knutti, 2017). The
 386 intermediate trend lengths (10 and 15 years) are diagnostic of short-term fluctuations and
 387 are therefore also often considered in the literature (e.g., Risbey et al., 2018). The shortest
 388 trends (3 years) are scientifically meaningless but are included for comparison, to show the
 389 effects of short-term variability on knowledge accumulation over time.

390 The first run of the experiment (Figure 6) did not include the general public. The
 391 figure traces the scientific community’s emerging confidence in the proposition that the
 392 Earth’s climate is changing. Several observations can be made. First, by around 2000, the
 393 community had settled on the climate-change hypothesis with virtual certainty,
 394 irrespective of the dataset being used and irrespective of the trend duration being
 395 considered. Second, as expected, with the (unrealistically) small memory size ($M_S = 3$),
 396 the collective belief fluctuated more widely, although it also converged on certainty. This
 397 reflects the fact that notwithstanding short-term fluctuations (positive or negative), a
 398 rational Bayesian agent will accumulate knowledge over time, and hence the impact of
 399 short-term fluctuations (represented by the likelihood ratio; LR in Equation 2) will have
 400 decreasing influence as belief in climate change consolidates (odds on the right-hand side
 401 of Equation 2). The ongoing updating of the posterior means that, although the memory
 402 buffer is constantly being updated and earlier memories are forgotten, the new prior
 403 (yesterday’s posterior) is higher (if temperatures go up generally) than, say, 5 years ago.
 404 So at any moment, there is a latent, if not explicit, memory of global warming represented
 405 in the prior for that updating step. Third, GISTEMP supported faster consensus

406 formation than HadCRUT. This was not unexpected given the coverage biases of
 407 HadCRUT that are known to have underestimated warming (Cowtan & Way, 2014).¹

408 It is informative to align the results in Figure 6 with the chronology of the IPCC
 409 consensus statements (vertical dashed lines). The IPCC’s First Assessment Report (FAR)
 410 from 1990 acknowledged that warming appeared to be underway, and stated that “The
 411 size of this warming [0.3° to 0.6°] is broadly consistent with predictions of climate models,
 412 but it is also of the same magnitude as natural climate variability. ... The unequivocal
 413 detection of the enhanced greenhouse effect is not likely for a decade or more.” In fact, it
 414 took less than a decade. The second assessment report (SAR), published in 1996, stated
 415 that “The balance of evidence suggests a discernible human influence on global climate.”
 416 By 2001, the third assessment report (TAR) reported “There is new and stronger evidence
 417 that most of the warming observed over the last 50 years is attributable to human
 418 activities.” The AR4 in 2007 concluded that “Warming of the climate system is
 419 unequivocal” and that “Most of the observed increase in global average temperatures since
 420 the mid-20th century is very likely due to the observed increase in anthropogenic
 421 greenhouse gas concentrations.” Finally, AR5 in 2013 reiterated that “Warming of the
 422 atmosphere and ocean system is unequivocal”, and additionally stated that “It is
 423 extremely likely that human influence has been the dominant cause of observed warming
 424 since 1950, with the level of confidence having increased since the fourth report.” Those
 425 evolving scientific consensus statements map well onto the simulated temporal increment
 426 of belief. While this does not provide a quantitative test of the model, it shows at least
 427 qualitative convergence between the model and the scientific community.

428 The second run of the experiment included 1,000 agents that represented the
 429 general public but was identical to the first run in all other respects (with $M_S = 15$). The
 430 results are shown in Figure 7, indicating that the general public will absorb the
 431 information provided by the scientific community and will converge on the same scientific

consensus, albeit with a delay. The delay reflects the fact that the general public does not have access to the raw data, relying instead on receiving communications from the scientists. The total number of information sources is thus reduced relative to the information available to the scientists themselves.

The results of simulation experiment 1 are straightforward and largely unsurprising: given the evidence available, the scientific community converges onto a consensus position. When the public benefits from the scientific information, they too acquire the consensus position through communication alone. Both runs of simulation experiment 1 only included unbiased agents. The remaining simulation experiments explore the operation and impact of denial in various contexts.

Simulation Experiment 2: Motivated denial

Simulation experiment 2 examined the process of denial. We particularly wanted to identify the conditions that are necessary for a rational Bayesian agent to avoid acquiring a belief in the hypothesis that climate change is real. One known way in which contrarians seek to mislead the public is by focusing on short-term temperature fluctuations (Lewandowsky, Ballard, et al., 2016). For example, the claim that global warming had “stopped” first arose in 2006, based on 8 years of data (Carter, 2006). This experiment therefore manipulated the size of the memory window, with M_C set to 3, 5, and 10. Based on the results of the first experiment, we expected such short-term focus to be insufficient to induce denial in our rational agents. We therefore also manipulated the agents’ bias (see Equation 1) by setting $S_C = .015$ in one condition. This bias effectively prevented an agent from detecting any but the most extreme short term warming trends.

Figure 8 displays the results. Consider first the top row of panels, which represents unbiased agents ($S_C = 0$). It is clear that irrespective of memory size, unbiased agents cannot avoid acquiring belief in climate change. However, this behavior does not capture

the actual nature of denial, which has exhibited persistence across many decades. An analysis of more than 16,000 contrarian documents revealed that organized denial continued unabated during the period 1998 through 2013 (Boussalis & Coan, 2016) . This stability of denial is reflected in the bottom panels of Figure 8. Irrespective of memory size, those agents never accept the hypothesis of climate change, owing to their biased interpretation of the evidence ($S_C = .015$).

The second experiment clarified that persistent denial in Bayesian agents becomes possible only through the introduction of a bias. A focus on short-term trends by itself is insufficient to prevent endorsement of the climate change hypothesis. We next consider what happens when a share of such biased agents are introduced into the scientific community.

Simulation Experiment 3: Seepage of denial?

This simulation experiment examined the effects of denial on the scientific community. Two classes of agents formed the population of 1,000: The mainstream scientists were unbiased ($S_S = 0$) and used a constant memory size of $M_S = 15$. A small proportion of the agents, represented by the parameter *ConProp* that was variously set to 3%, 10%, or 20%, were contrarian. Those agents used a memory size of $M_C = 3$ (to represent extreme focus on short-term fluctuations) and were biased, $S_C = .015$ (to exhibit persistent denial). To accentuate the differences between the two classes of agents, mainstream scientists relied on GISTEMP and contrarians relied on HadCRUT. (In reality, scientists would examine both those datasets and several additional products as well.)

All agents, irrespective of whether they were scientists or contrarians, communicated with each other 5 times after each data-sampling event. During those communication

481 events, the representation of contrarians in the pool of communicators was varied
 482 (specified by *ConRep*) independently of their actual prevalence.

483 The results are shown in Figure 9. Consider first the top-left panel, which most
 484 closely represents the known composition of the scientific community. In this cell, 3% of
 485 the agents are biased contrarians. Like mainstream scientists, they are assumed to publish
 486 in the literature and thus communicate their opinions to the remainder of the community.
 487 This assumption appears realistic in light of the small but measurable number of
 488 contrarian articles that continue to appear in print (Cook et al., 2013).

489 The presence of contrarian voices does not prevent the scientific community from
 490 settling on the consensus position. Indeed, there is little evidence that the small number
 491 of contrarians had any effect on the scientific community, as indicated by the nearly
 492 complete overlap with the denial-free baseline from simulation experiment 1 (dashed gray
 493 line). Note, however, that this reflects extremely conservative assumptions because the
 494 contrarian agents communicate their estimate of the slope (β) *before* applying their bias
 495 (S_C). Their influence is thus limited to the cherry-picking associated with a small memory
 496 window.

497 The remaining 8 panels of Figure 9 explore the effects of increasing the proportion
 498 of contrarians (rows of panels) and their representation in communication (columns). Any
 499 increase in the proportion of contrarians beyond the empirically-established 3% of
 500 scientists involves the assumption that other, non-academic actors such as bloggers and
 501 think tanks contribute to the discussion in the scientific community. Given that blogs
 502 demonstrably contribute to science denial (for a discussion, see Lewandowsky, Oberauer,
 503 & Gignac, 2013; Lewandowsky, Cook, et al., 2015), in particular through harassment of
 504 scientists (e.g., Lewandowsky, Mann, Brown, & Friedman, 2016), this assumption appears
 505 plausible, although the extent of the influence of non-scientific actors on the scientific
 506 community is difficult to quantify. The assumption that contrarians are given

disproportionate access to communication (i.e., the center and right columns of panels) is supported by content analysis of U.S. prestige media. During the period 1988-2002, more than half of that coverage was found to balance scientific and contrarian views (Boykoff & Boykoff, 2004). The share of contrarian discourse in the media peaked around 2009, with more than 3,000 articles in the U.S. media (Boykoff & Olson, 2013). In 2011-2012, contrarians were cited in 17% of media articles on climate change (Brüggemann & Engesser, 2017)

These analyses leave little doubt that contrarian voices are over-represented in public discourse, although the magnitude of that over-representation is uncertain. We therefore take no position on which of the 8 cells is most likely to be “correct.” The next simulation experiment provides more constraints on which of those 8 cells appears most realistic in light of empirical data.

Overall, the pattern in Figure 9 clarifies that contrarian voices, even if amplified beyond their actual numbers, do not prevent the scientific community from settling on a consensus position. This reflects current reality, which has seen the formation of a pervasive scientific consensus notwithstanding intense contrarian activity. In all panels, scientists ultimately converge on complete acceptance of the climate change hypothesis. However, and perhaps most relevant in the present context, we also observed evidence for seepage (Lewandowsky, Oreskes, et al., 2015). Eight out of the 9 panels in Figure 9 exhibit an effect of seepage because the belief formation in the scientific community is delayed relative to the denial-free baseline. The one exception to this pattern is the top-left panel, which effectively assumes that the entire political apparatus that is enveloping the scientific community—from think tanks to bloggers to opinion writers—has no effect on scientific discourse because contrarian voices are limited to 3%. We find this assumption to be overly conservative.

Figure 10 shows the same results, but for 1990 onward only. This close-up on the last three decades is necessary because the alleged “pause” in warming from approximately 1998 onward (Figure 1) was cited as an example of possible seepage by Lewandowsky, Oreskes, et al. (2015). The figure offers limited support for that contention. Clear evidence for seepage arises only when the prevalence of communications between scientists and contrarians is at least 20%. For example, the center panel and bottom-left panel show evidence for seepage when the proportion is 20%, and the right-most column of panels shows strong evidence when the proportion is at 50%. In light of the clear evidence for amplification of contrarian voices, Figure 10 may well point to the presence of seepage, although the evidence is not as clear as for the overall delay of consensus formation in Figure 9.

Figures 9 and 10 also clarify that contrarians are oblivious to the evidence and to communications from mainstream scientists. Note that this outcome was not a foregone conclusion because even though simulation experiment 2 identified the need for a bias ($S_C = .015$) to model the persistence of denial, that was done for a community that exclusively involved biased agents. In the present experiment, by contrast, the 5 communication events associated with each data sampling event involved a population in which the vast majority of agents were unbiased. It follows that the contrarian agents here were exposed to far more information that could have swayed their opinions than in simulation experiment 2. Yet, even after receiving consistent trend information indicative of global warming for decades, the contrarians continued to resist the evidence (compare Figure 8 to the solid orange lines in all panels in Figure 9).

The asymmetry in influence between the two groups of agents is worth noting: On the one hand, scientists, with their unbiased view of the data, can be deleteriously impacted by poor and biased data selection (i.e., short-term trends) from an over-represented minority. Recall that communication among the agents involves

transmission of their estimate of the trend, β , which is then used to update beliefs in the same manner as direct sampling of the data. Contrarians, on the other hand, are protected from the reverse effect because of their bias at the point of interpretation. Thus, whatever estimate of β a contrarian receives, the introduction of a bias (Equation 1) protects them from updating their knowledge in accordance with the evidence.

We next examine the impact of the communication regime introduced in this simulation, involving a majority of mainstream scientists and a small number of contrarians, on the general public.

Simulation Experiment 4: Science, denial, and the public

This simulation included a further 1,000 agents that represented the general public. Except for the addition of communication events with the general public, the experimental design and parameter settings were identical to the preceding simulation experiment.

The results are shown in Figure 11, using the same layout of panels as before. Of greatest interest here is the impact of denial on public opinion. Overall, it is clear that the presence of denial slows the public's convergence onto the scientific consensus position and sometimes prevents that convergence altogether. The details of that effect are informative. First, as shown in the left-most column of panels, increasing the proportion of contrarian voices alone is insufficient to prevent the public's recognition of the scientific consensus. Even with 20% of all interlocutors being contrarian, the public ultimately comes to share the belief of the majority of scientists. Second, for the public to remain unconvinced by the scientific evidence requires an over-representation of contrarian voices in public discourse. Specifically, public opinion in the U.S. at the moment is perhaps best captured by the data shown in the rightmost column of panels. Although it is not straightforward to map survey data into Bayesian probabilities, the finding that around 70% of the American public currently think that global warming is happening (e.g., Leiserowitz,

583 Maibach, Roser-Renouf, Rosenthal, & Cutler, 2017) does not mesh well with values of
 584 $P(CC|E)$ near 1.0 that are observed for the general public in the left column or the top
 585 part of the center column in Figure 11. To capture public opinion, therefore, contrarian
 586 voices must be disproportionately represented, perhaps even to the extent that the
 587 number of mainstream scientific messages received by the public is exactly equal to the
 588 number of contrarian messages that deny climate change (right column).²

589 Are those assumptions warranted? There are several independent lines of evidence
 590 that support the notion that contrarian voices are disproportionately represented in public
 591 discourse. First, contrarian scientists report that they have greater media exposure than
 592 mainstream scientists (Verheggen et al., 2014). Second, the media’s commitment to
 593 “balance” leads to coverage that often favours contrarian talking points (Boykoff &
 594 Boykoff, 2004; Brüggemann & Engesser, 2017). Third, certain media outlets in the U.S.
 595 have taken explicitly contrarian stands, including Fox News, the Washington Times, and
 596 the Wall Street Journal. Others, including Washington Post and New York Times, have
 597 regular columnists who promote contrarian positions. Fourth, contrarian organizations
 598 have regularly placed advertisements in leading newspapers to argue against climate
 599 action or question the science (Supran & Oreskes, 2017). Taken together, those sources of
 600 evidence suggest that the public—unlike the scientific community—may well receive an
 601 equal number of messages that affirm or deny climate change, respectively, from the
 602 interlocutors they are exposed to.

603 Exploration of parameters

604 The simulation experiments relied on two principal parameters: The memory size,
 605 M , and the bias in interpreting the perceived trend, S . It is useful to examine their effects
 606 on the moment-to-moment perception of the data, captured by the likelihood ratio (LR)
 607 in Equation 1. Figure 12 shows the effects of memory size on the LR for a simulation of

the (unbiased) scientific community. The pattern is unsurprising but nonetheless informative. With a small memory buffer, the LR becomes highly variable and frequently dips below 1, implying a temporary reduction in the belief in the climate-change hypothesis. However, even with a small memory buffer, the temperature data contain a sufficiently strong signal for the LR to be, on average, above 1. This explains why a focus on short-term trends, often used by contrarians in public discourse to claim that warming has “stopped” (Carter, 2006), is insufficient to sustain disbelief in global warming without also introducing a bias. With a larger buffer, $M = 15$ and $M = 30$, the LR is consistently above 1 from the mid-1970s onward, in line with the identified onset point of global warming (Cahill, Rahmstorf, & Parnell, 2015).

Figure 13 examines the effect of the bias parameter, S , on the LR. The most notable aspects of those results is that even with a “cooling” bias of .015, the LR does not fall much below 1 during the period of global warming (from mid 1970 onward). The persistence of denial may therefore be best understood as a failure to update an (inappropriately-skeptical) belief in light of evidence.

General Discussion

This paper explored the reasoning components that underpin the potential for disbelieving climate change when faced with the actual observed temperatures. All agents, whether mainstream scientists, contrarians, or the public, revised their beliefs in accordance with Bayesian principles, the gold standard of rational belief formation (see Equations 1 and 2). Our simulations yielded several insights: (a) unbiased agents necessarily acquire belief in the climate-change hypothesis even from an initial position of extreme skepticism; (b) to persist with denial, agents must be biased; (c) the presence of such biased agents can delay, but not prevent, belief formation in the scientific community; (d) the presence of contrarian voices, especially when disproportionately

633 represented, can prevent the public from acquiring the scientific consensus position. We
 634 take up the implications of those results later, after we acknowledge and discuss several
 635 limitations of the present work.

636 *Potential limitations and avenues for future exploration*

637 Our simulations aimed to balance parsimony with realism. We achieved parsimony
 638 by limiting agents to two free parameters, M and S , with the remainder of their
 639 architecture being fixed by Bayesian principles. Those tight constraints on the
 640 architecture limited the realism of our results. For example, although simulation
 641 experiment 4 yielded a realistic estimate of current public opinion with plausible
 642 assumptions about denial (Figure 11), the simulated public acceptance of climate change
 643 lagged far behind the American public, which 20 years ago endorsed the climate-change
 644 hypothesis to a similar extent than is seen now (e.g., Brulle et al., 2012).

645 Several aspects of our model may have contributed to this quantitative mismatch.
 646 For example, the model excluded a number of mechanisms that are known to affect the
 647 public's reasoning about climate change, such as perceived source credibility (Hahn,
 648 Harris, & Corner, 2009; Harris, Hahn, Madsen, & Hsu, 2016), or worldviews and political
 649 attitudes (e.g., Hamilton et al., 2015; Lewandowsky, Gignac, & Oberauer, 2013). The
 650 model also focused on a single scientific updating process, and other regimes might be
 651 worth considering in the future. For example, scientists may consider the long-term record
 652 only, looking for some kind of meaningful change point in the warming trend instead of
 653 recomputing it from observations in the presumed memory window. Moreover, given that
 654 scientists' careers do not extend across the time span simulated here (nearly 70 years),
 655 some inter-generational transmission process must exist that permits junior scientists to
 656 build on existing knowledge in the discipline without monitoring the data for decades.

Inter-generational processes can readily be modeled in an agent-based framework (Holman & Bruner, 2017).

We focused on GMST (Figure 1) as the only source of evidence for climate change. Although GMST is a primary climatic indicator, and arguably the one that is discussed most often in public, it is only one among many. Other indicator variables include sea level rise, cryosphere variables such as the mass balance of glaciers, biological indicators such as species migration, and so on (e.g., Hartmann et al., 2013; Rhein et al., 2013; Vaughan et al., 2013). In reality, scientists consider all of those variables together, and it is their converging support for the same conclusion, known as consilience (Oreskes, 2007), that buttresses the scientific consensus position. Although denialist talking points are known to extend to those other indicator variables (Lewandowsky, Ballard, et al., 2016), it remains to be seen how seepage and influence play out in a multivariate environment.

Implications and potential interventions

Irresistible evidence for global warming

Our simulations showed that unbiased agents necessarily acquire belief in the climate-change hypothesis, even when they start from an initial position of extreme skepticism and even when they rely on unduly short temperature trends. This result meshes well with a previous analysis of the success of hypothetical bettors that placed bets on global temperatures at various points in history. That analysis found that since 1970, any bet against warming—even those involving cherry-picking of short-term cooling trends—would have been unsuccessful (Risbey, Lewandowsky, Hunter, & Monselesan, 2015).

The corollary result, that agents must be biased in order to persist with denial, also meshes well with existing results. For example, the need for biased processing is compatible with the fact that denial is a political operation rather than a scientific

endeavour (Dunlap & McCright, 2011). Biased processing is also revealed when contrarian talking points are subjected to a blind expert test (Lewandowsky, Risbey, & Oreskes, 2016; Lewandowsky, Ballard, et al., 2016). In those studies, climate data and contrarian claims about those data (e.g., “warming has stopped”) were translated into another domain, for example by presenting GMST data as “world agricultural output.” Expert economists and statisticians then judged the contrarian claims to be misleading while endorsing the interpretation advanced by mainstream scientists.

Although we modeled denial by including a bias parameter, it does not follow that resistance to evidence is “irrational.” On the contrary, denial has been identified as a rational political operation of considerable effectiveness (Lewandowsky, Cook, & Lloyd, 2016), and even under a fully Bayesian approach, resistance to evidence can be modeled by inclusion of auxiliary hypotheses (Cook & Lewandowsky, 2016; Gershman, 2018).

Seepage and influence

One purpose of the simulations was to test the idea that denialist talking points may seep into the scientific community, perhaps altering the way in which scientists interpret data (Lewandowsky, Oreskes, et al., 2015). The evidence for this was clear in general, but more mixed in the specific context of the alleged “pause.” On the one hand, consensus formation was delayed by the presence of denial whenever the functional proportion of contrarian voices exceeded their nominal proportion of 3% (Figure 9). As we argued earlier, the known machinery of denial (e.g., blogs, think tanks, opinion pieces) most likely amplifies contrarian voices beyond their actual number, and so it seems warranted to conclude that denial *can* have an effect on the scientific community. On the other hand, an effect of seepage during the period of the presumed “pause” in warming was only observed when liberal assumptions were made about the influence of denial (viz., 20% or more of all voices being heard by scientists are contrarian).

707 It must be noted that our model of the scientific community was highly idealized.
 708 Each agent was fair and unbiased and accurately interpreted the data using a
 709 climatologically reasonable window. Nonetheless, the injection of biased contrarian voices
 710 into this idealized community was sufficient to delay consensus formation. This occurred
 711 without any bad faith, corruption, dishonesty, or bias on the part of scientists, putting to
 712 rest a potential criticism that the seepage notion entails an accusatory or critical stance
 713 against scientists. Other related work has also shown that the pernicious effects of
 714 industry funding of research (e.g., the death toll associated with class-I antiarrhythmic
 715 drugs; Holman, 2017) can arise without corruption of individual scientists, simply from
 716 methodological diversity and a merit-based system (Holman & Bruner, 2017). Similarly,
 717 Weatherall, O'Connor, and Bruner (2018) presented an agent-based model of the tobacco
 718 industry's efforts to undermine the scientific evidence about the harm from smoking. The
 719 model relied on a two-pronged propagandistic effort: first, promoting and sharing of
 720 independent research that conformed to the industry's position, and second, funding of
 721 additional research with selective publication of the results. Both lines of attack have been
 722 well documented by historians (Oreskes & Conway, 2010; Proctor, 2011). Weatherall et al.
 723 (2018) showed that their selective-sharing model could explain how policy makers failed to
 724 recognize the seriousness of the harm from tobacco, and how journalists, by engaging in
 725 “fair” reporting, inadvertently amplified industry's impact on public opinion. The model
 726 showed that there was no need for the tobacco industry to engage in outright fraud or
 727 conduct biased research of their own. Industry could influence public policy by the less
 728 expensive and more furtive strategy of selective sharing and communicating.

729 In summary, there are now multiple demonstrations that distortions of scientific
 730 practice, including but not limited to seepage, can be observed without any corruption or
 731 bias of any individual scientist. One implication of our reliance on an idealized scientific
 732 community is that our simulations likely provided a lower-bound estimate of seepage. Any

733 departure from this ideal, for example by introducing scientists with their own biases,
734 might lead to greater discernible seepage.

735 Turning to the effects of denial on the public, there is no doubt that the presence of
736 contrarian voices can prevent the public from fully acquiring the scientific consensus
737 position (Figure 11). This result is unsurprising, although what is notable is that the
738 public remains misinformed about the scientific consensus only when contrarian voices are
739 amplified beyond their actual proportion. It is only when scientific information and
740 denialist talking points are balanced (or nearly so), that the public will fail to converge on
741 the consensus position. Several analyses have confirmed that contrarian voices are
742 over-represented in media discourse (Boykoff & Boykoff, 2004; Boykoff & Mansfield, 2008;
743 Brüggemann & Engesser, 2017).

744 Our results on seepage and influence fit within the larger context of research on a
745 minority's ability to sway majority opinion (Crano & Seyranian, 2009; Xie et al., 2011,
746 2012). One finding from this research is that a committed minority that is immune to
747 influence can reverse the prevailing majority opinion under certain conditions (for a
748 discussion, see Wiesner et al., 2019). Theoretical work suggests that a minority of 10% is
749 sufficient to flip a majority (Xie et al., 2011), and experimental evidence suggest that
750 around 25% are needed to reverse an initial consensus opinion (Centola, Becker, Brackbill,
751 & Baronchelli, 2018). Although we exposed our scientific community to considerable
752 dissent by a minority that was immune to evidence (some conditions of simulation
753 experiment 4), we did not observe a reversal of the consensus opinion. This resilience,
754 relative to other modeled communities, likely arose from the presence of independent
755 evidence (i.e., the observed temperature trends) which prevented intransigent contrarian
756 opinions from swaying the majority.

757 *Potential interventions*

758 Our model explored specific questions about belief formation in a contested
759 environment. The model also points to a deeper and more general problem: how to model
760 and potentially reduce the dissemination of misinformation in social systems. Humans
761 constantly share their beliefs and information. While this allows for debate, reasoning,
762 and education, such social networks also support the dissemination of sub-standard or
763 downright false information. Our model can point to potential remedial measures: In
764 simulation experiment 4, we found that when contrarian views are communicated to the
765 public in proportion to their actual prevalence, the public will not be thwarted from
766 accepting the scientific consensus position. This result suggests that one effective
767 intervention in public discourse would be to avoid the disproportionate amplification of
768 contrarian voices in media discourse. Fahy (2018) reports several encouraging
769 developments in journalistic practice that may meet this challenge.

770 Further work could build on this foundation by specifying the media-intermediary
771 processes in more detail (e.g., how people select news sources based on political
772 preference, or how people’s perceptions of credibility affect the updating process). Madsen
773 and Pilditch (2018) have successfully deployed a Bayesian source-credibility model to
774 investigate mass-persuasion attempts, pointing to ways in which a more nuanced model of
775 public opinion on climate change might be constructed. Hills (2018) outlined how
776 cognitive heuristics can contribute to polarization and the spread of misinformation.
777 Recommendations to overcome those problems were provided by Hills (2018) and
778 Lewandowsky, Ecker, and Cook (2017).

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1058

Footnotes

1059 ¹ In reality, scientists had access to both products and their judgment in all

1061 likelihood would have rested on an aggregation of information from both datasets.

1062 ² The three panels in the right column are identical. This is no accident because

1063 when the public representations of views are set to be identical (i.e., 50-50 in each panel),

1064 the *actual* proportion of contrarians in the community no longer matters.

Figure Captions

1065

1066 *Figure 1.* Global mean surface temperature (GMST) anomalies from two datasets. GISS
 1067 = NASA GISTEMP (Hansen et al., 2010); HadCRUT4 = UK Met Office (Morice et al.,
 1068 2012). The datasets use slightly different climatological baselines (GISTEMP: 1951–1980;
 1069 HadCRUT: 1961–1990). To align the datasets for display purposes, all anomalies here are
 1070 re-baselined to the period 1981–2010.

1071 *Figure 2.* Observed magnitude of temperature trends as a function of vantage year and
 1072 the number of years included in the computation of the trend. Trends are capped at $\pm 1K$
 1073 for plotting. For each vantage year (columns), trends are computed for all possible
 1074 windows between 3 and 25 years duration (rows), all of which end with the particular
 1075 vantage year. The dots indicate which trends are significant ($p < .05$) in an ordinary least
 1076 squares analysis of annual means, and the horizontal dashed line indicates the number of
 1077 years that must be included for the trend to be significant from all vantage points. **A:**
 1078 Data are HadCRUT4 (Morice et al., 2012). **B:** Data are GISTEMP (Hansen et al., 2010).

1079 *Figure 3. a.* Overview of agent-based model with communication and updating cycles.
 1080 See text for details. **b.** Summary of simulation experiments. See text for details.

1081 *Figure 4.* Illustration of regression slope calculations for a typical scientist agent
 1082 (subscript S) and a contrarian agent (subscript C). The scientist possesses a larger
 1083 memory window ($M_S = 15$) than the contrarian ($M_C = 3$) from t_0 (the current year) back
 1084 through time. This leads to a difference in calculated regression slopes, where β_S reflects
 1085 the long-term warming trend, whereas β_C reflects a short-term cooling trend.

1086 *Figure 5.* Illustration of how perceived regression slopes are converted into likelihood
 1087 ratios (LR) that are then used for belief updating according to Equation 2. The scientist
 1088 agent provides β_S , and because the scientist is unbiased, the positive β_S value is converted

1089 to a positive likelihood ($LR_S > 1$), providing support for the climate change hypothesis.
 1090 By contrast, the positive value of the skew parameter ($S_C = .1$) for the contrarian agent
 1091 accentuates the already negative slope (β_C) as even greater evidence against climate
 1092 change ($LR_C < 1$) For illustrative purposes, the value of S_C is considerably larger here
 1093 than in the simulations.

1094 *Figure 6.* Results of Simulation Experiment 1 involving only a community of scientists.
 1095 All agents are unbiased ($S_S = 0$) and consider data either from GISTEMP (left panel) or
 1096 HadCRUT (right panel). Each plotted line represents a different memory size (M_S); see
 1097 legend. The vertical dashed lines mark release dates of IPCC consensus reports, from the
 1098 First Assessment Report (FAR) through the Fifth Assessment Report (AR5).

1099 *Figure 7.* Results of Simulation Experiment 1 involving a scientific community together
 1100 with a general public. See text for details of how agents communicate with each other. All
 1101 agents are unbiased ($S_S = 0$) and consider data either from GISTEMP (left panel) or
 1102 HadCRUT (right panel). The vertical dashed lines mark release dates of IPCC consensus
 1103 reports, from the First Assessment Report (FAR) through the Fifth Assessment Report
 1104 (AR5).

1105 *Figure 8.* Results of Simulation Experiment 2. Agents are either unbiased ($S_C = 0$; top
 1106 row of panels) or are biased to downplay the observed trend ($S_C = .015$; bottom row of
 1107 panels). Agents consider data either from GISTEMP (left column of panels) or HadCRUT
 1108 (right). Each plotted line represents a different memory size (M_C); see legend. The
 1109 vertical dashed lines mark release dates of IPCC consensus reports, from the First
 1110 Assessment Report (FAR) through the Fifth Assessment Report (AR5).

1111 *Figure 9.* Results of Simulation Experiment 3. Each panel reports a different condition of
 1112 the experiment, with the proportion of contrarians $ConProp$ varying across rows, and the

level of representation of contrarians $ConRep$ varying across columns. In each panel, there are 1,000 agents altogether, some of which are set to be contrarian (i.e., $M_C = 3, S_C = .015$). Acceptance of the climate change hypothesis, $P(CC|E)$, is shown separately for mainstream scientist agents (solid blue line) and contrarian agents (solid orange). The variability across replications is indicated in the thickness of the blue lines. For comparison, the belief acquisition without the presence of contrarians (i.e., from simulation experiment 1) is shown by gray dashed lines. The vertical dashed lines mark release dates of IPCC consensus reports, from the First Assessment Report (FAR) through the Fifth Assessment Report (AR5).

Figure 10. Results of Simulation Experiment 3, shown for 1990 onward. Each panel reports a different condition of the experiment, with the proportion of contrarians $ConProp$ varying across rows, and the level of representation of contrarians $ConRep$ varying across columns. In each panel, there are 1,000 agents altogether, some of which are set to be contrarian (i.e., $M_C = 3, S_C = .015$). Acceptance of the climate change hypothesis, $P(CC|E)$, is shown separately for mainstream scientist agents (solid blue line) and contrarian agents (solid orange). The variability across replications is indicated in the thickness of the blue lines. For comparison, the belief acquisition without the presence of contrarians (i.e., from simulation experiment 1) is shown by gray dashed lines. The vertical dashed lines mark release dates of IPCC consensus reports, from the First Assessment Report (FAR) through the Fifth Assessment Report (AR5).

Figure 11. Results of Simulation Experiment 4. Each panel reports a different condition of the experiment, with the proportion of contrarians $ConProp$ varying across rows, and the level of representation of contrarians $ConRep$ varying across columns. In each panel, there are 1,000 agents that represent mainstream scientists and contrarians, and a further 1,000 agents that represent the general public. Results are shown separately for scientists,

1138 contrarians, and the general public. The variability across replications is indicated by the
 1139 thickness of the lines. The vertical dashed lines mark release dates of IPCC consensus
 1140 reports, from the First Assessment Report (FAR) through the Fifth Assessment Report
 1141 (AR5).

1142 *Figure 12.* Values of LR (Equation 1) observed during simulation experiment 1 for
 1143 different values of M . The horizontal line at 1.0 represents completely ambiguous evidence
 1144 that leaves current belief unchanged during updating (Equation 2). All agents are
 1145 unbiased, $S = 0$, and consider data either from GISTEMP (left panel) or HadCRUT
 1146 (right panel).

1147 *Figure 13.* Values of LR (Equation 1) observed with two different sizes of the memory
 1148 buffer; $M = 3$ in the top row of panels, $M = 15$ in the bottom row. Each panel plots the
 1149 observed LR for different values of the bias parameter, S . The horizontal line at 1.0
 1150 represents completely ambiguous evidence that leaves current belief unchanged during
 1151 updating (Equation 2). All agents consider data either from GISTEMP (left column of
 1152 panels) or HadCRUT (right).

Influence and seepage, Figure 2

A

B

Influence and seepage, Figure 4

Influence and seepage, Figure 5

Influence and seepage, Figure 6

Influence and seepage, Figure 7

Influence and seepage, Figure 8

Influence and seepage, Figure 9

Influence and seepage, Figure 10

Influence and seepage, Figure 11

Influence and seepage, Figure 13