The Prevalence and Effects of Scientific Agreement and Disagreement in Media

by

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DEDICATION

This dissertation is dedicated to the memory of my grandma, Pamela Boult.

Thank you for your unending confidence in my every ambition and unconditional love.

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ABSTRACT

Disagreement is inherent to the production of scientific knowledge, but its communication can erode the credibility of science in the eyes of the public. This tension pervades all science communication; however, under conditions of uncertainty it is most vital to act on knowledge about which experts are certain. To better understand how the public responds scientific agreement and disagreement, this dissertation investigates three questions that spring from previous work on the subject. It explores how much scientific disagreement the public is exposed to, how disagreement affects trust in science, and whether motivated perceptions of disagreement can be corrected by scientific agreement messages.

The first study uses multiple computer-assisted content analytic methods to reveal that, in the last thirty years of climate change newspaper coverage, the prevalence of scientific agreement and disagreement have declined but denial messages have increased. The second study examines the effects of civil and uncivil scientific disagreement on a range of science attitudes in an online experiment. Compared to agreement messages, I find that disagreement and incivility not only negatively affect attention to and evaluation of scientific topics, but also trust in science and perceptions about the value of science. The final experiment reveals that agreement messages are insufficient to persuade those motivated by political identities of scientifically supported positions on climate change. It

also highlights that debate about the efficacy of consensus messages in extant research comes in part from the choice by some researchers to pretest climate attitude measures.

In sum, people are frequently exposed to messages about scientific disagreement in news, these messages negatively affect both issue attitudes and broader views about science, and agreement messages are not sufficient to reduce motivated perceptions of scientific disagreement on politicized issues. Understanding the ways in which the public responds to scientific disagreements is important because scientists have an ethical obligation to be honest about uncertainties. Additionally, increasingly competitive political and media systems are likely to amplify scientific disagreements in the public eye. Though trust in science remains high among the US public, this work shows that disagreement messages, amplified by politicization, can have consequences beyond a single issue contexts, with implications for public perceptions about the value of scientific knowledge in social and political life.

CHAPTER I

Why Study Scientific Disagreement?

Disagreement is intrinsic to the scientific process, but its communication is not always well-received by the public. Scientists test competing hypotheses, consider alternative explanations for their results, and subject their work to critique from peers. New methods and evidence challenge the findings of earlier work. Scientific disagreement is therefore a normal condition within the scientific community (Popper, 2005). However, communicating scientific disagreement to the public can erode scientific credibility. The public is more skeptical of information about which scientists disagree (Chinn et al., 2018), believing that the scientists cannot come to agreement because the they are incompetent or motivated by personal interests (Dieckmann et al., 2015; Johnson, 2003; Johnson & Slovic, 1998). Though disagreement is integral to the creation of knowledge through scientific methods, it can also reduce the credibility of science in the public's eyes.

Most scientific issues have areas of certainty, about which scientists agree, and areas of uncertainty, where experts disagree. Yet following expert recommendations on points of certainty is perhaps most important in when our understanding is incomplete. For example, though there is some debate about how severe the impacts of climate change will be (Davenport, 2018), there is widespread scientific agreement that human actions are causing climate change and that actions to address climate change are vital to avert the worst impacts (IPCC, 2018). Similarly, for COVID-19, there is disagreement about how long social distancing will be required (Essley Whyte, 2020) and what benchmarks must be met to lift stay at home orders (Wamsley, 2020). However, there is certainty that social distancing is the best way to reduce the spread of disease, and it is critical that the public follow this guidance to save lives (CDC, 2020; WHO, 2020). Though perspectives from scientific experts are most needed under conditions of uncertainty, the public may be skeptical of experts' views if they are surrounded by disagreement. For these reasons, the study of scientific agreement and disagreement has immediate implications for societal wellbeing in both daily life and in moments of crisis.

In this dissertation, I examine three central puzzles. First, we lack an understanding of how often people are exposed to scientific disagreement in media. Second, we have a limited understanding of how scientific disagreement, and the civility of such disagreement, affects a range of science attitudes including trust in science. Third, there are inconsistent findings on whether a clear scientific consensus message can lead motivated skeptics to hold scientifically supported positions. Following a brief summary of research central to the study of scientific disagreement in media, I will present three studies that respond to these research gaps.

Critical Background

Scientific agreement and disagreement messages affect both attitudes about particular scientific issues and broader perceptions of science as an endeavor. First, agreement and disagreement have immediate effects on attitudes and behaviors relevant to the issue about which one is communicating. These effects may be moderated by the broader social context in which agreement and disagreement cues occur. Politicization of scientific issues can produce and amplify disagreements as well as moderate the effects that these cues have on issue attitudes. Second, exposure to agreement and disagreement information may influence peoples' broader views about science, beyond the context of a particular scientific issue. General views toward science, including trust in or perceived value of science, affect a wide range of outcomes from personal behaviors (e.g., following stay at home orders, wearing masks in public) to support for candidates and policies that are skeptical of expertise (e.g., "Brexit", Donald Trump). The study of scientific disagreement, therefore, is relevant to understanding scientific attitudes around particular issues as well as cultural and societal views about the role of science and expertise in public life. The following section details past work on these areas and the research gaps which remain. This critical background informs the studies that I will present in the subsequent section.

Impacts of Agreement and Disagreement Cues

Scientific agreement and disagreement messages operate as cues that impact peoples' beliefs on the issue about which one is communicating. To start, we know that people notice and understand cues about scientific agreement and disagreement in science messages. Individuals can recognize and comprehend such information presented in many different visual and textual forms (van der Linden et al., 2014), as well as recall that information accurately (Chinn et al., 2018). It is readily apparent that even nonscientists can easily identify and understand scientific agreement and disagreement information.

Beyond understanding these cues, agreement and disagreement information also influences people's attitudes about relevant issues. The public is, reasonably, more skeptical of claims on topics where scientific disagreement is prevalent; people are less likely to hold views in line with scientists' positions after reading the results of poll reflecting scientists' ambivalence (e.g., "65% of scientists agree") (Aklin & Urpelainen, 2014; Chinn et al., 2018). Merely featuring a skeptic's view in a science news article can reduce acceptance of a scientific claim (Feldman et al., 2012; Malka et al., 2009). In sum, the public's acceptance of a given claim is weakened when they are made aware of scientific disagreement about the topic.

Conversely, the public is more accepting and supportive of experts' positions when told that scientists agree. Believing that a large number of scientists agree on a position is associated with believing that position personally (Ding et al., 2011; McCright et al., 2013). As agreement levels increase, individuals are more likely to accept scientists' positions, at least in the absence of motivated skepticism (Aklin & Urpelainen, 2014; Chinn et al., 2018). Thus, the public notices and comprehends cues about scientific agreement and disagreement, which they use to inform their personal beliefs about the issue being discussed.

Scientific Disagreement and Politicization of Science

However, the social context of a scientific issue may also affect the prevalence and effects of agreement and disagreement cues. This is seen quite clearly in cases of politicized science, in which actors emphasize the inherent uncertainty of science to cast doubt on the existence of a consensus (Bolsen & Druckman, 2015). Though scientific disagreement can occur apart from politicization, efforts to amplify or manufacture scientific disagreement for political gain are intended to decrease public support for scientific positions on particular issues and to disrupt the influence that scientific knowledge may have on policy.

This connection between scientific disagreement and politicization is most readily seen in conservatives' climate messaging strategies, in which political actors have historically highlighted and manufactured disagreements to undermine climate policy (Jacques et al., 2008; McCright & Dunlap, 2010). These strategies promoting narratives of disagreement cultivate public doubts about the certainty of scientists' positions (McCright & Dunlap, 2010). By exploiting inherent uncertainties to construct opposing positions on a scientific issue, political elites associate competing stances with political identities and values to build support for their policy aims (Nisbet, 2009). As a result, Republicans have been, in the case of climate change, motivated to hold positions at odds with the scientific consensus (Chinn & Pasek, 2020).

The politicization of science is amplified in media by journalistic norms and economic pressures on news outlets. In an effort to attract audience attention, journalists frame stories with dramatic, personal conflicts, often leaning on political actors as official sources to speak for competing sides (Bennett et al., 2007; Boykoff, 2011). Due to increasing economic pressures on news organizations, newsrooms have fewer resources and incentives to devote to explaining the nuances of scientific positions (Bennett et al., 2007; Boykoff, 2011). For these reasons, news media often amplify the scientific disagreement that is highlighted, and sometimes manufactured by political actors. These tactics produce exciting, sensational content that grabs audience attention in an increasingly fragmented and competitive media environment. In sum, the political and mediated contexts in which scientific issues are communicated affect the structure and effects of agreement and disagreement cues in science messages.

Trust in Science

Finally, scientific disagreement in media may not only affect attitudes toward specific science issues, but also may contribute to mistrust of science more broadly. Those with high trust in science are more willing to listen to expert's recommendations and accept new scientific claims (Druckman & Bolsen, 2011; Lee, 2005; Roberts et al., 2013; Siegrist, 2000). Because most people are unable or unwilling to critically interrogate scientific research (National Science Board, 2016), trust in science is a useful heuristic for making decisions and forming attitudes about scientific topics (Cummings, 2014). Additionally, trust in science is component to anti-intellectual views, which has wide-reaching implications for scientific and political attitudes (Motta, 2018). For these reasons, the ways in which scientific disagreement may affect broader science attitudes like trust are consequential for public acceptance of scientific expertise across a wide range of issue contexts.

Scientific disagreement in media may contribute to polarization of partisans' trust in science. While Democrats' trust has remained high, Republicans' trust in science has declined since the 1980s (Gauchat, 2012). Previous work has found that watching conservative media, which amplifies the disagreement messages spread by conservative elites to a greater extent than non-conservative media, reduces trust in scientists over time (Feldman et al., 2012; Hmielowski et al., 2014). Scientific disagreement in media, amplified by politicization, may negatively affect both issue attitudes and broader science attitudes like trust.

In sum, extant work on scientific disagreement demonstrates that scientific agreement and disagreement cues not only affect issue attitudes but also may affect broader views like trust in science. The public recognizes scientific agreement and disagreement cues in media, which inform issue attitudes. Politicization plays a role in amplifying or manufacturing scientific disagreement in media, as well as shaping partisans' positions on politicized scientific issues. Exposure to scientific disagreement messages may also negatively impact wide-reaching attitudes like trust in science. Mistrust of science is associated with both rejection of scientific positions and support for politicians and political movements that are skeptical of experts (e.g., "Brexit", Donald Trump) (Motta, 2018). Therefore, the role that scientific disagreement plays in shaping the public's science attitudes is likely to have both immediate implications for particular issues and long-term effects on the role of science in public life.

Research Questions

There are three areas in extant work which have seen inconsistent findings or require further research. The following section briefly outlines these research gaps and introduces studies to investigate them.

How Much Scientific Disagreement is in Common Sources of Scientific Information?

News remains the dominant source of scientific information for the U.S. public, whether consumed in print or online (National Science Board, 2016). However, the prevalence of scientific disagreement in science news has yet to be surveyed in a large body of news media or in ways that facilitate comparisons over time. Previous work strongly suggests that disagreement is present in news (Boykoff & Boykoff, 2007; Feldman et al., 2012, 2017; Jacques et al., 2008), but this work has been limited by a focus on narrow slivers of time, often only investigating a few years of coverage from a limited number of sources. While there are concerns that increasing politicization and economic pressures on media companies have led to greater conflict in coverage, we have little evidence to substantiate these claims because very few studies have been able to make comparisons between coverage at different points in time (Boykoff, 2007; Rice et al., 2018). Claims that exposure to disagreement over time have substantially affected science attitudes (Hmielowski et al., 2014) require evidence of trends in scientific disagreement in news over a broader period of time and body of sources than have previously been examined. Put simply, the field would benefit from a more complete understanding of how frequently the public is exposed to scientific agreement and disagreement messages in news, as well as in what forms these messages appear.

The second chapter of this dissertation addresses this gap by using dictionary and machine-learning content analytic methods to quantitatively measure three forms of disagreement in the population of major U.S. climate change newspaper coverage from 1988 and 2018. This chapter measures the prevalence of agreement messages (e.g., “85% of experts agree”); scientific disagreement, which conveys a lack of consensus or competing viewpoints (e.g., “other scientists oppose this conclusion”); and denial of science, which include attempts to undermine the credibility of a competing actor and their position (e.g., “a hoax by junk scientists”). The use of computer-assisted methods allows for the coding of a much wider body of news content, which enables comparisons about the prevalence of scientific disagreement in climate change news coverage at different points over a thirty-year period. In addition to informing survey work looking at over-time changes in Americans’ climate attitudes, this content analysis also provides language for stimuli in the subsequent experimental studies.

How Does Disagreement Affect Trust in Science?

Second, although some survey work suggests that exposure to scientific disagreement reduces trust in science, no experimental work has directly tested this association. Scientific disagreement can depreciate expert credibility in the eyes of the public (Kahan et al., 2011; Vraga et al., 2018), as many attribute disagreements to expert incompetence or self-interest (Dieckmann et al., 2015; Johnson, 2003; Johnson & Slovic, 1998). Survey work suggests that individuals who consume media containing more scientific disagreement cues lose trust in scientists over time (Hmielowski et al., 2014). Yet while disagreement may have negative effects on broader science attitudes like trust in science, we only know about the effects of disagreement on issue-specific attitudes (Aklin & Urpelainen, 2014; Chinn et al., 2018; Malka et al., 2009).

However, the effects of scientific disagreement on trust in science may depend on the tone of that disagreement. Given trends toward increasing incivility in media (Sobieraj & Berry, 2011), this is a growing area of interest for science communication researchers. Strategic political messaging seeking to sow doubt about scientific positions often contains personal attacks on scientists (McCright & Dunlap, 2010). Additionally, the increasing use of social media offers opportunities for scientists to communicate with each other and the public in more informal, and sometimes more uncivil, ways (Simis-Wilkinson et al., 2018; Yuan et al., 2019). However, the effects of uncivil disagreement on trust in science have not been explored. Work from political contexts suggests that civil disagreement does not reduce trust, but that uncivil disagreement does (Mutz & Reeves, 2005). We do not yet know the relative effects of civil and uncivil scientific disagreement on trust in science.

The third chapter, therefore, experimentally tests how scientific agreement, civil disagreement, and uncivil disagreement affect respondents' attention to, evaluation of, and trust in science. It is the first study to explore the effects of scientific disagreement on both issue-specific and broader science attitudes. It further explores whether the tone of disagreement, civil or uncivil, affects people's issue attitudes or trust in science. This is important because disagreement and incivility are increasingly common features of science communication and science media (Sobieraj & Berry, 2011; Yuan et al., 2019). Thus, understanding how the effects of disagreement messages about one scientific topic may "spill over" to attitudes about other scientific and political issues through attitudes like trust in science is a central concern.

Can Agreement Messages Reduce Political Polarization around Science Attitudes?

Third, there is debate concerning whether a clear scientific consensus about a politicized issue can overcome politically motivated perceptions of scientific disagreement and persuade political skeptics to hold expert supported positions. Communicating a scientific consensus may lead skeptics to accept scientists' views (van der Linden et al., 2015), but other work finds that agreement messages not only fail to affect skeptics' beliefs (Bolsen & Druckman, 2018; Dixon, 2016), but may backfire (Cook & Lewandowsky, 2016; Dixon & Hubner, 2018). These inconsistent findings make clear that the conditions in which scientific consensus messages are persuasive are not fully understood.

These inconsistent findings may be an artefact of study design. Work finding that consensus messages reduce attitude polarization typically pretest central attitudes

(Lewandowsky, Gignac, et al., 2012; van der Linden et al., 2015, 2016) while studies that exclude pretests fail to find a similar effect (Cook & Lewandowsky, 2016; Deryugina & Shurchkov, 2016; Dixon, 2016; Dixon et al., 2017; Dixon & Hubner, 2018). The choice to pretest measures of interest may lead to elevated outcomes in posttest responses because respondents are more attentive to related information, resulting in consensus information being more accurate, available, or salient in participants' minds, or because participants have inferred the researchers' intentions (Campbell, 1957; Campbell & Stanley, 1963). This is important to clarify because, despite inconsistent findings, agreement messages are already being deployed around controversial science (@BarackObama, 2013; NASA, 2018; *The Consensus Project*, n.d.).

The final experiment investigates two questions. First, it asks whether a scientific consensus message can attenuate politically motivated perceptions of disagreement to reduce the gap between liberals' and conservatives' climate change attitudes. Second, it investigates whether inconsistent results in previous studies about consensus messages are an artefact of study design by testing whether exposure to a pretest affects participants' responses. By elucidating the conditions in which a scientific consensus about a politicized issue can reduce attitude polarization, this study responds to debate on the relative strength of scientific and political cues (Kahan et al., 2011; van der Linden, 2016).

Broader Impacts and Intellectual Merit

These studies further our understanding of how much scientific disagreement people are exposed to, what effects disagreement has on their science attitudes, and whether agreement information can correct politically motivated perceptions of disagreement. In doing so, this work speaks to many areas of science communication research. First, it investigates the effects of the politicization of science. The second chapter explores to what degree disagreement and denial are highlighted in news coverage of politicized science, while the third chapter sheds light on whether exposure to media that contains scientific disagreement messages is a factor that may contribute to partisan differences that we observe on trust in science (Gauchat, 2012). The fourth chapter also investigates whether, and under what circumstances, agreement messages may be able to reduce politically motivated perceptions of disagreement (Dunlap & McCright, 2008). Thus, the findings of these studies speak to concerns about partisan divisions around science, the role of politicization in amplifying disagreement, and how these factors may affect the ability of science to inform policy (Bolsen & Druckman, 2015; Brossard & Scheufele, 2013).

This work also connects to research on misinformation and disinformation. In the context of climate change, which is explored in the second and fourth chapters, scientific disagreement is a strategic form of disinformation which leads some individuals to hold misperceptions (Chinn & Pasek, 2020). The efficacy of scientific agreement messages as a tool for correcting misperceptions about scientific disagreement is explored in the fourth chapter. But recent work has highlighted that misperceptions are only one consequence of misinformation. Work on political misinformation has highlighted that uncertainty about what to believe, about what is true and what is false, leads to cynicism and mistrust in media, which poses a challenge to democratic deliberations (Chadwick & Vaccari, 2019; Vaccari & Chadwick, 2020). The third chapter extends this line of research by looking at whether uncertainties around scientific positions similarly leads to mistrust in science or erodes perceptions of value of scientific knowledge in policymaking. In doing so, this work contributes to a body of literature looking at how the ways in which our media system amplifies disagreement and conflict can have wide-reaching implications for the democratic processes (Bode & Vraga, 2015; Lewandowsky, Ecker, et al., 2012; Vaccari & Chadwick, 2020; Weeks & Gil de Zúñiga, 2019) and the role of scientific knowledge in democratic deliberations.

However, the questions about scientific disagreement that these studies explore also speak to how individuals engage with science at a more basic level. All scientific information is, to some degree, imbued with the uncertainties of the scientific process (Popper, 2005). Yet we also know that people find making decisions under conditions of uncertainty to be uncomfortable (Kahneman & Tversky, 1979). This tension is inherent to all science communication and is not limited to politicized or controversial issues. Any interaction that individuals have with scientific information—from seatbelts to mammograms—is a context in which one is asked to form an opinion taking some degree of uncertainty into consideration. This work is therefore intimately connected with research on public understanding of science (Chinn & Pasek, 2020.; Sturgis & Allum, 2004), cultural attitudes toward experts (Brossard & Nisbet, 2006), and efforts to communicate transparently about the uncertainties, limitations, and value of scientific research (Lupia, 2013; 2018). Understanding how people respond to scientific disagreement is central to understanding how people understand and value scientific information. By examining the effects that real-world disagreement messages have on both issue attitudes and wider views about science, these studies better our understanding of how people respond to moments of scientific uncertainty (e.g., COVID-19) as well as when and why people question science.

What Follows

What follows are three studies that comprise this dissertation. Chapter two presents the results of the content analysis exploring thirty years of newspaper coverage of a politicized science issue: climate change. It looks at the frequency of scientific agreement, disagreement between scientists, and denial of science. Scientific agreement refers to messages about points of consensus or commonly held views among scientific experts. Disagreement messages, in this study, convey a lack of agreement or consensus among experts, which may be due to inconsistent findings, scientific uncertainties, or debate within the scientific community. Scientific denial refers to the rejection of consensus positions. Denial of science has many rhetorical variants that are dependent on context. The Bush administration characterized an association between abortion and increased cancer risk as scientifically uncertain, in opposition to the consensus that there is no link (Jasen, 2005); those who deny widespread agreement about the efficacy of vaccines argue that they are not anti-vaccination, but rather "pro-safe vaccination" (Kata, 2012). Denial of science can be civil, like when anti-vaccination activists claim to have additional knowledge ("I am an expert on my child"), or may take the form of uncivil personal attacks ("in the pocket of Big Pharma") (Kata, 2012). Because this chapter is on climate change newspaper coverage, I focus on the explicit language of climate denial found in newspaper coverage, which includes name calling ("climate alarmists" "climate deniers"), hoax language ("conspiracy perpetrated by the Chinese"), and attacks on scientific quality ("junk science"), in addition to descriptions of actors "denying," "rejecting," or otherwise "dismissing" climate science. In this study, I capture denial messages both from and about those who reject widely accepted scientific views, and therefore denial messages may include both experts and nonexperts. Common agreement, disagreement, and denial language from this study informs the experimental manipulations in subsequent chapters.

The third chapter is an online experiment which looks at the effects of scientific agreement, civil disagreement, and uncivil disagreement in nonpoliticized contexts. The civil disagreement manipulation in this study parallels the disagreement language in the content analysis. It refers to debate within this scientific community, inconsistent findings, and scientific uncertainties, but maintains a neutral and respectful tone. On the other hand, the uncivil disagreement manipulation conveys a lack of consensus and inconsistent findings by levying personal attacks on individual scientists and their work with aggressive language (e.g., “idiot scientists”). Unlike the denial messages in the previous study, the uncivil disagreement here is not a rejection of a consensus position. However, I draw on some of the uncivil language found in common denial messages (e.g., “junk science”), as well as language from work on aggressive science communication (Yuan et al., 2018; 2019), to inform the uncivil disagreement manipulation. In these ways, this study isolates the effects of civil and uncivil disagreement messages from effects of politicization cues and hoax language. It explores effects of these messages on a number of different outcomes, including attention to and personal beliefs about a scientific topic, as well as broader science attitudes including trust in science.

The fourth chapter presents an online experiment investigating whether scientific agreement messages can lead political skeptics to hold scientifically supported attitudes.

Additionally, it investigates whether inconsistent findings in previous research are the product of different study designs. This study returns to the politicized issue context of climate change and focuses on personal belief outcomes.

Supplemental information for each chapter can be found in Appendices A-C.

Table I.1 Summary of Dissertation Studies

<table>
<tr><th></th><th>Method</th><th>Context</th><th>Forms of (Dis)Agreement</th><th>Outcomes of Interest</th></tr>
<tr><td rowspan="2">Chapter 2</td><td>Content analysis</td><td>Politicized issue</td><td>Scientific agreement
Disagreement
Denial</td><td>Frequency over time</td></tr>
<tr><td colspan="4">How has the frequency of agreement, disagreement, and denial messages varied in the past 30 years of climate change newspaper coverage?</td></tr>
<tr><td rowspan="2">Chapter 3</td><td>Experiment</td><td>Nonpoliticized issues</td><td>Scientific agreement
Civil disagreement
Uncivil disagreement</td><td>Attention to science
Issue attitudes
Trust in science
Broader science attitudes</td></tr>
<tr><td colspan="4">How does scientific disagreement affect peoples' attention to science, personal attitudes, trust in science, and broader science attitudes?

How does the civility or incivility of scientific disagreement affect these outcomes?</td></tr>
<tr><td rowspan="2">Chapter 4</td><td>Experiment</td><td>Politicized issue</td><td>Scientific agreement</td><td>Issue attitudes</td></tr>
<tr><td colspan="4">Can a scientific consensus message about a politicized issue reduce political polarization around that issue?

How have differences in experimental designs affected the findings of consensus message studies?</td></tr>
</table>

CHAPTER II

Scientific Agreement, Disagreement, and Denial in Climate Change News, 1988-2018

There are increasing concerns how the politicization of science might impact public attitudes and the role of science in policymaking. Politicization of science occurs when partisan actors strategically exploit the inherent uncertainty in scientific research to cast doubt on the credibility of that science in pursuit of policy goals (Druckman & Lupia, 2016). In such contexts, the public is more likely to take on the views of their partisan elites (Bolsen et al., 2014; Slothuus & De Vreese, 2010) and is less likely to consider other substantive information (Druckman et al., 2013), raising concerns that politicizing science reduces the value of science in public decision making. With partisan actors attempting to direct scientific research and funding (Prewitt, 2013; Scheufele, 2014) or outright rejecting claims supported by scientific evidence (Druckman & Lupia, 2016; Suhay & Druckman, 2015), important scientific knowledge may go unheeded when science is politicized.

These concerns are realized in the issue of climate change. Though the IPCC has issued warnings of significant impacts, politicization of the issue has inhibited constructive policymaking in the U.S. (Davenport, 2018). U.S. public opinion is increasingly polarized, with significant divisions concerning whether climate change is happening and, if so, whether human activity is to blame (Dunlap et al., 2016). In the case of climate change, politicization of science precludes the broad public support for actions and policies scientists believe are required to avert dramatic consequences.

At the crux of U.S. polarization about climate change is a debate about scientific certainty. Republicans have framed climate change as scientifically debated (Demeritt, 2006; McCright & Dunlap, 2003, 2010) or have outright rejected climate science (e.g., @realDonaldTrump, 2012), while Democrats have reaffirmed their position by emphasizing scientific agreement (e.g., @BarackObama, 2013). Elite debate about climate change is centrally tied to scientific agreement, disagreement, and denial. Thus, understanding how frequently these messages occur in climate change news will inform us about politicization in news and likely effects on public attitudes.

This study aims to offer evidence of these influential features across thirty years of climate change coverage to better inform work on the ways in which media has contributed to public opinion polarization. To do so, this study employs both dictionary methods and supervised machine learning methods in novel ways to quantitatively measure the prevalence of agreement, disagreement, and denial in climate change newspaper coverage. This study develops original dictionaries to measure scientific agreement, disagreement, and denial in climate change coverage, and compares them to findings from Wordscores, a supervised machine learning algorithm. This application of Wordscores is novel both with respect to the substantive content and the volume of text to which it is applied. By using multiple computer-assisted, content analytical methods, this study is the first to quantitatively measure the prevalence of scientific agreement, disagreement, and denial across thirty years of climate change news.

Background

Effects of Scientific Agreement, Disagreement, and Denial

The degree to which scientists agree influences lay people's evaluations of science. Individuals can recognize and comprehend cues about scientific agreement and disagreement presented in different forms, as well as recall that information accurately (van der Linden et al., 2014). Indeed, there is a rich body of experimental work describing the ways in which scientific agreement, disagreement, and denial affect the public's science attitudes.

The public is more skeptical of scientific positions accompanied by scientific disagreement. Scientific disagreement messages describe a lack of consensus within the scientific community, inconsistent findings, or uncertainty around a scientific topic (e.g., "scientists debate whether…"). As individuals perceive greater expert disagreement, they report less acceptance of scientists' claims beliefs (Ding et al., 2011; McCright et al., 2013) and weaker policy support (Gollust et al., 2010; McCright et al., 2013). These effects are consistent across different presentations of scientific disagreement, from ambivalent polls (e.g., Chinn et al., 2018) to merely mentioning that an issue is debated (e.g., Gollust et al., 2010). In sum, the public is more skeptical of scientific claims that are disputed within the scientific community. This of course turns out to be most claims, since scientific progress is catalyzed by skepticism itself.

Denial of science is suggested to have additional negative effects on attitudes. Scientific denial is understood here as rejection of a position on which there is expert consensus as opposed to merely conveying a lack of consensus or competing viewpoints. Though denial rhetoric varies by context (e.g., anti-vaccination activists claim they are "pro-safe vaccination"), in the context of climate change, denial is often characterized by name calling, hoax language, and attacks on scientific research (e.g., "it is a hoax by junk scientists") (Kata, 2012; McCright & Dunlap, 2010). Individuals who consume media featuring more rejection of climate science report greater mistrust of scientists, in addition to less accurate climate beliefs (Feldman et al., 2012; Hmielowski et al., 2014). Exposure to a media message that includes a single climate skeptic is associated with perceiving climate change as less important or serious, in addition to weaker policy support (Malka et al., 2009). Thus, in addition to reducing acceptance of scientific positions and policy support, scientific denial may additionally erode trust in science and perceived importance of issues.

Conversely, the public is more accepting and supportive of positions when told that scientists are in agreement (e.g., "most experts believe…"). A growing body of research has investigated how scientific agreement may lead the public to hold more scientifically supported positions. Such work finds that high levels of scientific agreement are associated with stronger perceptions of scientific certainty, personal agreement, and policy support (Chinn et al., 2018; Ding et al., 2011; Dixon, 2016; Lewandowsky et al., 2012; van der Linden, Leiserowitz, et al., 2015b). Some studies go as far as to argue that communicating scientific agreement can reduce partisan polarization on climate change (Van Der Linden et al., 2018), though other work disputes this (Bolsen & Druckman, 2018; Dixon, 2016). It is apparent that while scientific disagreement and denial negatively affect public attitudes, the public often accepts claims about which scientists agree.

Agreement, Disagreement, and Denial in Climate Change News

Given the ways in which they have been demonstrated to affect science attitudes, the scientific agreement, disagreement, and denial to which the public is exposed is of substantive interest to those investigating how media shapes public opinion on science. However, while previous research has offered abundant evidence for the presence of these features in climate change news coverage, previous work has not been able to offer evidence of how scientific agreement, disagreement, and denial have changed over time. Given increasing polarization of climate attitudes among the U.S. public, it is important to understand trends in these features in news, which remains the dominant source though which Americans learn about science (National Science Board, 2016).

Disagreement is often a part of climate change coverage. Journalists regularly rely on norms and values like personalization, drama, and balance to guide their selection and presentation of news, resulting in coverage that emphasizes personal conflicts or conflicting sources to speak for each side (Bennett et al., 2007). In early coverage, journalists regularly balanced scientific views with those of skeptics (Boykoff & Boykoff, 2004). Though James Hansen had testified that warming was almost certainly caused by a buildup of artificial gasses and not natural processes (Shabecoff, 1988), the IPCC did not make this claim until the Second Assessment Report was published in the mid-1990s (IPCC, 1995). Despite the growing consensus in the 1990s, "balanced" news coverage continued to depict climate science as debated and uncertain until the mid-2000s, when journalists largely began to emphasize the dominant scientific view (Boykoff, 2007). While scientific disagreement disappeared from mainstream coverage, it remained a prominent feature of policy and impacts coverage, where journalists reported on the positions of political elites. To this end, scientific uncertainty and strategy frames remained common in climate change coverage from the late 2000s to mid-2010s, particularly among more conservative news sources (Feldman et al., 2017; Rice et al., 2018). While scientific disagreement is present in climate change news (Boykoff & Boykoff, 2007; Jacques et al., 2008), our understanding of over-time trends remains limited and somewhat conflicted. Given the previous work, it is not clear whether journalists' shifting practices have produced an overall decrease or increase in scientific disagreement in climate change news.

Past work has additionally paid special attention to the role of political and journalistic actors in amplifying denial of climate change. Denial rhetoric has been notably associated with conservative political actors that seek to block climate policies (McCright & Dunlap, 2010). This includes often uncivil attempts to discredit scientists and their research (e.g., accusing mainstream scientific research of being "junk science") and attacks on scientists and their research (McCright & Dunlap, 2003, 2010). These strategies to discredit or threaten mainstream science have been amplified by journalists who write stories about climate change focusing on dramatic, personalized conflicts (Boykoff, 2011). In addition, the perceived need for balanced, objective coverage to give voice to all sides of a debate means that climate denial continues to be featured in news about climate policy debates (Hiles & Hinnant, 2014). Though journalists often attempt to contextualize skeptics as holding a marginal viewpoint, this practice continues to amplify skepticism of scientific views (Brüggemann & Engesser, 2017). While previous work suggests that climate skepticism is not a dominant feature of climate newspaper coverage (Boykoff & Boykoff, 2004; Rice et al., 2018), the noted presence of scientific denial in content analyses from different time periods suggest it remains present in news coverage. However, we still do not know whether scientific denial has increased or decreased in coverage in the thirty-year time span that climate change has been an issue on the public agenda.

Finally, research into the prevalence of scientific agreement in climate change news has been more inconsistent. Early work noted that scientific consensus, along with those disputing it, was a common feature of climate change coverage (Boykoff & Boykoff, 2004). Consensus was widely recognized by journalists who shifted to contextualizing climate skepticism as a marginal view in science news by the early 2000s (Boykoff, 2007). Outside of news sources, activists and experts have also used consensus messages (e.g., “97% of experts agree”) in efforts to persuade the public to adopt positions in line with scientists’ views (@BarackObama, 2013; NASA, 2018; *The Consensus Project*, n.d.). However, we need to know how often scientific agreement messages occurs over time, up to the present. In this way we will understand better how large the societal effects of disagreement coverage might be.

The surveyed literature evidences the presence of scientific agreement, disagreement, and denial in climate change news over the past thirty years. However, at present, describing over-time trends in climate coverage requires piecing together results from studies with different conceptualizations, coding schemes, and sources of data. This study aims to take a step forward in this vital research by moving to populations, rather than samples of data, and documenting trends over a far longer time span than has previously been attempted.

Methods

To survey the prevalence of scientific agreement, disagreement, and denial over a thirty-year time span, we need a different methodological approach than has previously been employed. This study proposes two computer-assisted content analytic approaches: exact-match dictionary keyword searches and a supervised machine learning method. These methods have complementary strengths and weaknesses and are capable of analyzing very large bodies of data in a computationally efficient way.

The dictionary method searches news articles for a list of keywords and phrases, supplied by the researcher, that indicate scientific agreement, disagreement, or denial. Dictionary methods have been used to detect a number of quantities in text corpora, including sentiment (Young & Soroka, 2012) and incivility (Muddiman et al., 2018). This method is computationally efficient, offers substantive results concerning the prevalence of a quantity in a body of text, and is transparent to the researcher (Grimmer & Stewart, 2013). However, there are two reasons that the dictionary method may underestimate the true prevalence these quantities in our data. First, if the quantity of interest, disagreement, is not represented with consistent, unique language, it can be difficult for dictionaries to reliably identify it. This raised a particular concern for the scientific disagreement dictionary. While informal inspection of the data suggested that agreement and denial had consistent languages (e.g., “scientific consensus” or “hoax” language), disagreement was often written in ways that are difficult for a dictionary to reliably capture. For example, journalists often stated a view shared by some scientists and then indicated that “others disagree.” Yet this phrase, “others disagree,” captured a great deal of disagreement unrelated to scientific topics, and thus was not included in the disagreement dictionary. Thus, there was a concern that the disagreement dictionary would not be able to capture some substantive mentions of scientific disagreement in the data.

The second reason that dictionary methods may underestimate the true prevalence of agreement, disagreement, and denial is that they require exactly matches to dictionary keywords or phrases (Grimmer & Stewart, 2013). Though variants of keywords and phrases were included in the dictionaries (e.g., plural and singular forms), the dictionary would not capture agreement, disagreement, or denial if it was expressed in any way that deviated from a pre-defined keyword or phrase (e.g., "some scientists say…but others disagree"). Thus, while dictionary methods are efficient and transparent, they may have difficulty identifying quantities in text which are expressed in ways that are difficult to capture with a parsimonious list of keywords and phrases.

Supervised machine learning methods promise to overcome this limitation of dictionary methods in two ways. First, the machine learning method searches for similar, not exactly matching, language, and thus is not so restricted as the dictionary methods (Laver et al., 2003). Second, with supervised machine learning methods, it is not necessary to define the language that indicates a quantity *a priori*, but only to identify whether scientific agreement, disagreement, or denial is present or absent in a selection of reference texts (Laver et al., 2003; Laver & Benoit, 2002). In addition to using a wider range of language to detect quantities of interest, this helps to address concerns about researcher bias in the dictionary construction. While a central drawback of dictionaries in this application are concerns about underestimation, the greater flexibility afforded to the machine learning algorithm may conversely result in overestimation (Grimmer & Stewart, 2013). Thus, these two methods were selected to be used in combination for their computational efficiency at investigating large bodies of data while complimenting each other's strengths and weaknesses.

What follows is a presentation of the data used in this study, followed by a further discussion of the dictionary and supervised machine learning methods, in which I describe the application of these methods to the present study.

Data

The data for these analyses is the population of environmental news articles that mention climate change from the New York Times, the Washington Post, the Los Angeles Times, the Chicago Tribune, the Houston Chronicle, and USA Today. Data from the four former newspapers begins in 1988, though Lexis Nexis only made data available from USA Today starting in 1989 and data from the Houston Chronicle starting in 1991. In this corpus, there are a total of 46,901 articles or 133,345 paragraphs that mention a climate change keyword (see Table II.1)[1].

The following analyses investigate trends in coverage between 1988 and 2018. The year 1988 is often used as a starting point for work on climate change. In 1988, NASA scientists James Hansen testified to Congress about the human role in global warming and the need for action (Grimmer & Stewart, 2013). Around this time, North America was in the midst of a major heat wave and international attention was being drawn to the threat of global warming, from comments by Prime Minister Margaret Thatcher to the creation of the IPCC (Boykoff & Boykoff, 2004, 2007). For these reasons, 1988 has been the year that previous content analyses of climate change news coverage have typically begun (e.g., Boykoff & Boykoff, 2004, 2007).

[1] Data for this study were drawn from the population of environmental news articles from these newspapers as identified by Lexis-Nexis the subject code "environment." Mentions of climate change refer to the occurrence of one of the three climate change keywords, including, "climate change," "global warming," or "greenhouse gas*".

Table II.1: Data

Newspaper	Date Range	# of Articles	# of Paragraphs
New York Times	1988-2018	13,754	40,782
Washington Post	1988-2018	10,045	29,032
Los Angeles Times	1988-2018	8,909	25,487
Chicago Tribune	1988-2018	6,138	15,317
USA Today	1989-2018	2,684	7,491
Houston Chronicle	1991-2018	5,371	15,236
Total		**46,901**	**133,345**

Dictionaries: Keyword Searches

Dictionary methods search articles for language that exactly matches a list of keywords and phrases supplied by the researcher. When developing a dictionary, therefore, the researcher aims to create a list of language that accurately indicates the quantity of interest without systematically missing relevant mentions. Because language varies across media, time period, and context, it is important to develop dictionaries within the linguistic norms of the media under investigation (Muddiman et al., 2018). For these reasons, the dictionaries for scientific agreement, disagreement, and denial were developed through an iterative process as recommended by past researchers (Muddiman et al., 2018). This involved several rounds running the dictionaries, inspecting a sample of results, modifying the dictionaries, and running them again. This process ensures that dictionaries are not capturing unrelated quantities or missing relevant mentions of the quantities of interest.

The first iterations of the three dictionaries were drawn from existing work, including General Inquirer dictionaries such as "hostile" or "no" (Stone et al., 1966), as well as past research and experimental stimuli on scientific agreement, disagreement, and denial (e.g., Bolsen & Druckman, 2018; Dixon, 2016; van der Linden et al., 2014).

Throughout the process of iterative testing, I read a random draw of approximately 1,000 paragraphs which contained at least one agreement keyword, 1,000 paragraphs containing at least one disagreement keyword, and 1,000 paragraphs containing at least one denial keyword. Inspecting these results allowed me to remove language from the dictionaries that incorrectly identified agreement, disagreement or denial. Additionally, I read a random draw of approximately 1,000 articles that did not contain keywords from any dictionary to ensure that the dictionaries were not systematically missing mentions of agreement, disagreement, or denial. Additional keywords and phrases were added during the iterative process of selecting reference texts for the supervised machine learning, discussed below.

The resultant dictionaries contained both phrases and individual words (e.g., "scientists agree" and "consensus"). In addition to evaluating the validity of the dictionaries, the iterative process allowed me to ensure that the dictionary included changes in language over time. This was particularly important for denial, whose language shifted from accusations of "climate alarmists" to claims of a "hoax" perpetrated by the Chinese. To deal with the issue of negated keywords, I created negation dictionaries for agreement (e.g., "no scientific agreement"), disagreement (e.g., "no scientific debate"), and denial (e.g., "not deny climate science"). Mentions of these negated keywords were subtracted from mentions of words in the original dictionaries to produce the final counts presented here. Finally, some researchers have noted that anti-climate activists have used disagreement or uncertainty rhetoric to undermine climate policy (McCright & Dunlap, 2010). However, these efforts are not captured here as denial. I only included explicit messages by or about those denying climate science in the denial dictionary. Language highlighting uncertainty was included in the scientific disagreement dictionary. Complete dictionaries are listed in Appendix A.

Wordscores: Supervised Machine Learning

The supervised machine learning approach used in this study was Wordscores (Laver et al., 2002). Wordscores compares the relative frequencies of words in coded 'references texts' with word frequencies in uncoded, 'virgin texts' to produce a score indicating how similar the uncoded text is to a reference text on a single dimension. It does this by using the probability, P_{wr}, that one is reading a reference text (r) given the presence of a specific word (w) and the researcher-supplied coding of reference texts, A_{rd}, to produce a score for each word, S_{wd}, for each word along a dimension (d)[2]. The scores for these individual words are then used to estimate a position for each virgin text along the dimension. Wordscores does this by averaging all the scored words in a virgin text, weighted by how frequently the scored words appear relative to the total number of words in the text, F_{wv}. The score that Wordscores assigns virgin texts, S_{vd}, is thus a measure of similarity to the reference texts on a single dimension based on the words that appear in both texts[3].

Identifying Reference Texts

Instead of researcher-defined dictionaries, Wordscores uses a set of reference texts whose values on a dimension of interest are known by some form of independent

[2] In this study, single words (e.g., "overwhelming," "scientific," and "consensus"), bi-grams (e.g., "overwhelming_scientific" and "scientific_consensus"), and tri-grams (e.g., "overwhelming_scientific_consensus") were scored after the removal of stop words (e.g., "the", "a").

[3] Because the virgin texts will contain words that do not appear in the reference texts, the raw scores for virgin texts are on a different scale from the reference texts. Past work has employed a transformation facilitate direct comparison between reference texts and virgin texts (Laver et al., 2002). However, given the artificiality of the reference texts employed in this study, which are designed to contain the complete presence or absence of a given quantity, this study is not interested in directly comparing the virgin texts to the reference texts, and thus does not employ a transformation of the resulting scores.

evaluation (Laver et al., 2002). As with dictionary development, reference texts should be similar in kind to the texts that will be coded. In line with these suggestions, I used my judgment as an expert coder and results from the dictionary-based content analysis to select reference texts. Though Wordscores was offered some of the same language used by the dictionary, it uses this information in a different way. Unlike dictionary methods, Wordscores has the flexibility to identify similar language appearing in different permutations. Using the dictionary results was therefore an efficient means of identifying some reference texts but did not limit Wordscores to only finding the same results that the dictionaries did. Additionally, there was also a concerted effort to select reference texts that clearly included agreement, disagreement, or denial, but that dictionary keywords and phrases could not capture. In the end, approximately half of the reference texts included language identified by the dictionaries.

Reference texts were drawn from over 130,000 paragraphs mentioning climate change in the corpus through an iterative process. To make selections, I inspected three bodies of data: (1) those paragraphs with the highest number of scientific agreement, disagreement, and denial dictionary keywords; (2) random draws of between 300 and 1,000 paragraphs containing at least one keyword for each of the three dictionaries; and (3) a random draw of 400 paragraphs that did not mention any dictionary keyword. To ensure the programming functioned and that the selected reference texts produced valid coding, I ran Wordscores on random draws of 500 paragraphs to evaluate the validity of results and to iteratively select or remove reference texts (see Appendix A for further information on the reference texts).

The final reference texts were comprised of 85 paragraphs whose individual sentences were dummy coded for the presence or absence of agreement, disagreement, and denial. 71 sentences were coded as containing scientific agreement, 89 containing scientific disagreement, and 84 containing denial or rejection of science. An alternative way of thinking about my reference texts is in terms of their length in number of words. After removing stop-words and words referring to climate change so they would not be used in prediction, the body reference texts contained 13,632 words. The agreement reference was 1,927 words long, disagreement was 2,249 words long, and denial was 2,226 words long. For comparison, an average article in my dataset was 795.5 words long.

Analyses

Analyses were run on both full articles and extracted paragraphs surrounding a mention of climate change extracted from those articles. Both show a similar pattern of results. The results presented below are all based on full-length articles, with analyses for paragraphs included in Appendix A. All analyses were run in R using the quanteda package (Benoit, 2018) and are presented with figures depicting mean yearly values with mean standard errors.

Results

Correlations between Dictionaries and Wordscores

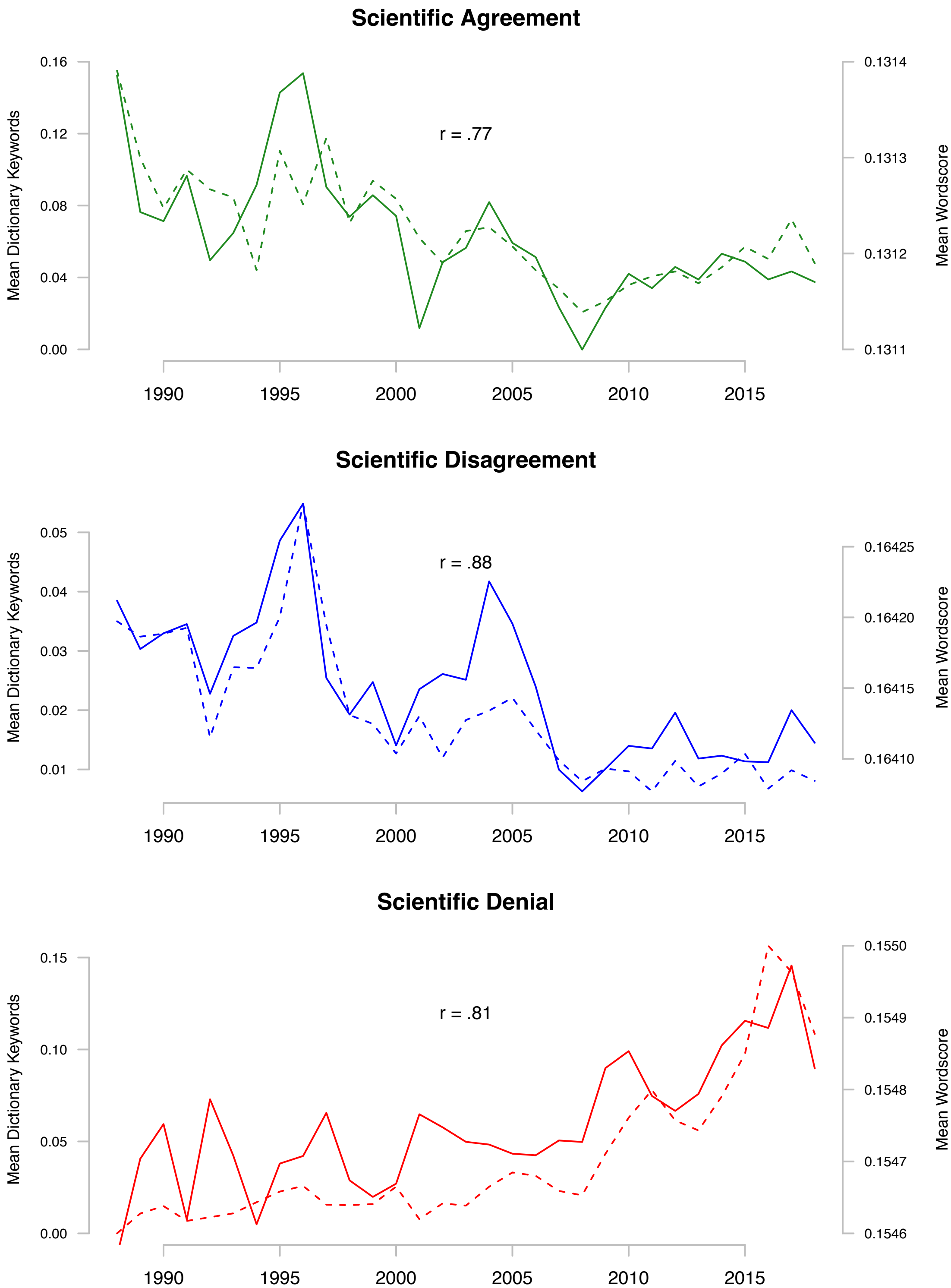
Of particular interest was whether the dictionary and the supervised machine learning methods would detect similar trends in the prevalence of scientific agreement, disagreement, and denial over time, given how the approaches differed. These two methods did indeed produce a similar pattern of results. The agreement dictionary and agreement scoring saw the weakest correlation of 0.77 ($p < .001$), while disagreement

(0.88, $p < .001$) and denial (.81, $p < .001$) saw slightly stronger correlations. The strength of these correlations indicates that the dictionaries and Wordscores methods are measuring similar quantities in the language of news articles. Wordscores appears to be capturing similar language to the dictionaries and the dictionaries are identifying a sufficient range of language indicating the quantities of interest. That these measures are strongly correlated also lends support to the validity of these measures of agreement, disagreement, and denial in climate newspaper coverage.

Trends over Time

Looking at trends over time in real frequencies is necessary to better understand how the public has been exposed to scientific agreement, disagreement, and denial through newspaper coverage of climate change. Figure II.2 offers substantive interpretation to the trends depicted in Figure II.1. The top panel of Figure II.2 shows the results from the dictionary keyword searches, plotting the average number of keywords mentioned in climate change articles annually for each of the dictionaries. Though the dictionaries are likely missing some meaningful mentions of agreement, disagreement, and denial, the mentions they capture are expected to be accurate. The observed trends can therefore be interpreted as a low estimate of the prevalence of scientific agreement, disagreement, and denial in climate change coverage.

Figure II.1: Correlations between Dictionary and Wordscores Results



Note: Dictionary results are represented with the dotted line, wordscores results are represented with a solid line.

The bottom panel of Figure II.2 presents the results from the supervised machine learning method. Wordscores does not provide a definitive answer to whether a quantity of interest is present or absent in the text. Rather, a high score indicates similar language between the reference text, containing the quantity of interest, and a given article. To estimate the substantive prevalence of these messages in news, I make the assumption that the 90th percentile of Wordscores for scientific agreement, disagreement, and denial reliably indicates the presence of that dimension in an article.[4] The bottom panel of Figure II.2 represents the average number of articles that were assigned a score for scientific agreement, disagreement, or denial in the 90th percentile by year. It shows a similar pattern of results to the dictionary findings, though the estimates concerning the prevalence of these quantities, particularly scientific disagreement, are slightly higher.

The dictionary and Wordscores results show that scientific agreement was a more prominent feature of coverage in early years than in the later years of our data. In 1988, these results estimate that between 15.5% and 20.5% of climate change articles contained mentions of scientific agreement. After a dip in intervening years, agreement was similarly prevalent in climate change coverage in the mid-1990s, with agreement mentioned in between 11% and 22.1% of articles in 1995. Since the 1990s, scientific agreement has been covered less frequently in climate change news. In 2018, only between 4.8% and 7.4% of climate change articles mentioned scientific agreement.

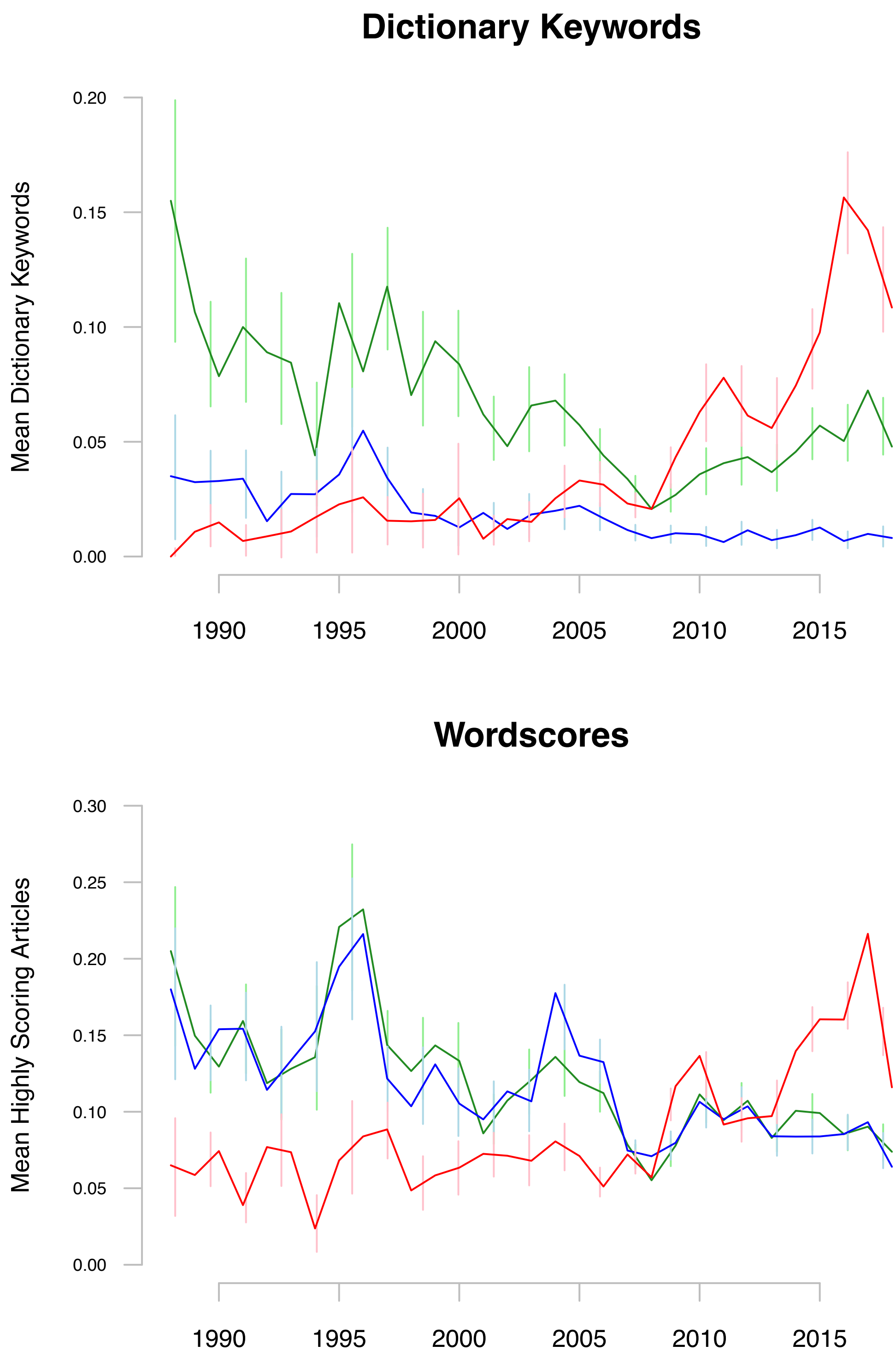
For scientific disagreement, Wordscores results suggest far more disagreement than did the dictionary results, though the over-time trend is similar. In 1988, the results suggest that between 3.5% and 18% of global warming articles mentioned scientific

[4] The 90th percentile is, based off the researcher's inspection, a conservative cutoff, and likely excludes some articles with meaningful mentions of scientific agreement, disagreement, or denial.

disagreement. As with scientific agreement, the mid-1990s also saw significant coverage of scientific disagreement, with 5.5% to 21.6% of articles mentioning disagreement in 1996. However, disagreement has declined in coverage since this time. In the Wordscores results, we see a relative increase in scientific disagreement in the mid-2000s, with Wordscores results suggesting that 17.8% of articles in 2004 likely contained a mention of scientific disagreement (the dictionary results suggest only 2% of articles contained disagreement in 2004). But the downward trend continued, with scientific disagreement being captured in only 0.8% to 6.4% of climate change articles from 2018.

Both Wordscores and dictionary results suggest that there was not very much denial in early climate change coverage. In 1988, the Wordscores analysis suggests that only 6.5% of articles likely contained denial while no article from 1988 matched a keyword in the denial dictionary. In the late 2000s, there begins to be a more substantial increase in the prevalence of scientific denial. In 2010, denial is mentioned in between 6.3% and 13.6% of climate change articles. Denial became a more frequent feature of climate change coverage since then, reaching a high in the mid-2010s when denial was present in 14.2% to 21.6% of articles in 2017. (See Appendix A for yearly estimates by dictionary and Wordscores methods).

Figure II.2: Substantive Levels of Agreement, Disagreement, and Denial in Climate Change Articles



Note: Red lines represent denial, green lines represent agreement, and blue lines represent disagreement

Discussion

In sum, dictionary and supervised machine learning methods of analyzing major newspaper coverage of climate change between 1988 and 2018 produce similar patterns of results, with the dictionary method likely underestimating and the supervised machine learning method possibly overestimating the true prevalence of agreement, disagreement, and denial in news coverage. These results suggest that in the late 1980s, global warming coverage discussed scientific agreement and disagreement more frequently than in later years, while rejection of climate science was nearly absent from coverage. This tracks with contemporary events, such as James Hansen's testimony to Congress and the creation of the IPCC, which brought public attention to scientists' claims that an enhanced greenhouse effect was caused by human activities (Ungar, 1992). Though scientific agreement and disagreement were less frequently part of coverage in the intervening years, in the mid-1990s agreement and disagreement again became more salient features of coverage. This relative increase in scientific agreement occurred around the publication of the IPCC's Second Assessment Report, which claimed that human activities were contributing to an 'enhanced greenhouse effect' (IPCC, 1995), and the negotiation of the Kyoto Protocol to reduce emissions in 1997 (United Nations Framework Convention on Climate Change (UNFCCC), n.d.). Scientific denial continued to be rarely mentioned in coverage of climate change through the 1990s. In the 2000s, we see a decline in both scientific agreement and disagreement, though Wordscores captures a peak in disagreement in the mid-2000s. Beginning in the late 2000s, denial became more prevalent than scientific agreement or disagreement in news coverage, around the time that *An Inconvenient Truth* was released in 2007 and President Obama was elected in 2008. We see a first peak of denial around the 2009 hacking of climate scientists' emails which climate skeptics claimed as proof of conspiracy, an event dubbed "Climategate" and the success of Tea Party candidates in the 2010 U.S. election (Leiserowitz et al., 2012). Since then, denial has become an increasingly common feature of climate change news, reaching a peak between 2016 and 2017. At this point, scientific agreement and disagreement are among their lowest levels in coverage.

These findings are additionally supported by previous content analyses. This work suggests that coverage around from the late 1980s prominently featured scientific experts (Chinn et al., 2020) and that coverage of anthropogenic sources was common until balanced coverage became more dominant in the 1990s (Boykoff & Boykoff, 2004). Though the scientific community was moving toward consensus, in news coverage, balanced reporting created perceptions of uncertainty and disagreement by featuring skeptics' views alongside the dominant scientific position (Boykoff & Boykoff, 2004). That said, articles in which skeptics dominated the story were uncommon at this time (Boykoff & Boykoff, 2004). Though journalists sought to correct falsely balanced coverage in the mid-2000s (Boykoff, 2007), there continued to be political opposition to climate policies, and opponents strategically exploited scientific uncertainty to sow doubt about climate science (McCright & Dunlap, 2010). Recent coverage of climate change has increasingly featured political actors (Chinn et al., 2020) and though science coverage reflects the scientific consensus, policy and impacts coverage continues to feature skeptics prominently (Feldman et al., 2017).

Tracing the prevalence of scientific agreement, disagreement, and denial in climate change news is important because we know that these factors influence public attitudes and that traditional journalism remains the dominant source of scientific information (National Science Board, 2016). Scientific disagreement is associated with weaker acceptance of and policy support for scientific positions (Chinn et al., 2018; Ding et al., 2011; McCright et al., 2013), while denial is additionally suggested to fostering mistrust in scientists (Hmielowski et al., 2014). Conversely, agreement is associated with greater support for and acceptance of scientific positions (Chinn et al., 2018; Van Der Linden et al., 2018). Given the trends of declining scientific agreement and increasing denial in climate change newspaper coverage, it is unsurprising that large segments of the public remain skeptical of climate science (Dunlap et al., 2016).

Contributions and Limitations

Many researchers have noted that, particularly with respect to analyses of large bodies of data, "standard practices of textual data analysis are in flux" (Muddiman et al., 2018, p. 215; Shah et al., 2015). Recent work has sought to develop practices which serve to extract patterns in methodologically rigorous and theoretically informed ways (see, for instance, Muddiman et al., 2018). This study proposes a multi-methodological approach, using both dictionary and supervised machine learning methods in conjunction to overcome the drawbacks of each. With these quantitative measures of scientific agreement, disagreement, and denial, this study is the first to make comparisons concerning the prevalence of these features across thirty years of climate change coverage.

The application of Wordscores in this study is novel for two reasons. The first is the substantive application of the algorithm. Wordscores was developed to estimate the ideological positions of party manifestos and has largely been applied in this context

(Klemmensen et al., 2007; Laver et al., 2002; Laver & Benoit, 2002). However, the algorithm itself is language blind; the interpretation of results is dependent on reference texts provided. Thus, by selecting reference texts that do and do not contain a given quantity, Wordscores can be used to estimate the likely presence or absence of quantities in text. This application is similar to Klüver's (2009) work measuring the influence of interest groups by comparing interest group statements to resulting policy language, in that the presence of language similar to the reference text is interpreted as indicating the presence of the quantity contained in the reference text.

Second, this study applies Wordscores to a greater number of texts than previously examined. While previous work has examined bodies of 7 to 200 texts, Wordscores was efficiently run over 45,000 articles and over 130,000 paragraphs of text for this study. Where previous work has been centrally interested in the positions of individual texts to investigate, for instance, how party platforms have shifted ideologically over time (Laver et al., 2002; Laver & Benoit, 2002), this study focuses instead on aggregated trends in news content over a period of thirty years.

A central reason for presenting results of two methods side by side is to address the limitations of each. Dictionary underestimation was a particular limitation of the disagreement dictionary. Scientific disagreement around climate change was often indicated with language that also described non-scientific disagreements. For this reason, the scientific disagreement dictionary missed a substantial amount of scientific disagreement in the data. Wordscores offered to overcome concerns about dictionary underestimation, but the approach's greater flexibility could lead to overestimation if language similar to the reference texts is also used to indicate something different. For instance, though the reference texts included examples of negation, Wordscores may have over-estimated agreement, disagreement, and denial in cases of negation; this is evidenced by the stronger correlations between dictionary and Wordscores results before removal of negated dictionary keywords.

Finally, the coding of the articles by dictionaries or Wordscores in this study has not been independently validated by human coders. It could be the case these methods were better at identifying one construct over others, or that they were better able to identify a construct at earlier or later points in time. Several choices were made in attempt to account for these concerns. Iterative development of both the dictionaries and reference texts allowed the author to inspect whether the coding appeared to accurately capture the quantities of interest. Dictionary keywords and reference texts were selected to reflect changes in how agreement, disagreement, and denial was expressed over time. The choices to only include dictionary keywords that exclusively identified the quantity and to use the 90^{th} percentile of Wordscores as a cutoff were considered conservative decisions. The similar patterns produced by both methods suggests that they are capturing the similar quantities, which lends support to the argument that the dictionary and Wordscores methods are identifying valid mentions of agreement, disagreement, and denial. The two methodological approaches, used in conjunction, produced a range reflecting how many articles, on average, contained agreement, disagreement, and denial each year, with the dictionary likely underestimating and Wordscores possibly overestimating the prevalence of these constructs in the content. The findings of this study parallel findings of previous work. However, all of this evidence pointing to validity is not a substitute for independent confirmation of the validity of either method by human coding, which would be important to confirming that the comparisons between the amount of agreement, disagreement, and denial are true and not the product of the methods being better or worse at identifying different constructs over time.

Conclusions

The communication of scientific disagreement is an important part of accurately and honestly informing the public of scientific knowledge. Science communicators have an ethical obligation to transparently represent the state of scientific research to the public. However, when political actors strategically exploit inherent uncertainties of scientific research in pursuit of policy support, the resulting politicization has consequences for public attitudes and the role of scientific knowledge in policymaking (Druckman & Lupia, 2016).

This study offers, for the first time, a quantitative comparison of how the prevalence of agreement, disagreement, and denial in news coverage has changed over the past thirty years. As a result, it offers novel insight into the frequency with which the U.S. public has likely been exposed to these cues. Given that these agreement and disagreement cues are known to affect support for scientific positions (Aklin & Urpelainen, 2014; Chinn et al., 2018; Malka et al., 2009), it is vital to recognize their prominence in mainstream news media. Given the prominence of disagreement messages in the 1990s and denial messages in the 2000s and 2010s, it is unsurprising that public opinion has become increasingly polarized around climate change (Dunlap et al., 2016). Despite journalists' general acceptance that climate change is real and human caused (Boykoff, 2007), climate change news coverage has perpetuated discourses of conflict and disagreement with scientific positions. By being the first to document over-time trends in agreement, disagreement, and denial, this study contributes to our understanding of why the U.S. public has become increasingly divided about the importance for climate action while the consensus among the scientific community has only grown stronger.

CHAPTER III

Can't You All Just Get Along?

Effects of Scientific Disagreement and Incivility on Attention to and Trust in Science

Disagreement and incivility are increasingly prevalent in science media content. Economic pressures on news media lead editors prioritize coverage that attracts audience attention with conflict (Bennett et al., 2007; Boykoff & Boykoff, 2007), with coverage of scientific conflicts increasing in news coverage over time (Chinn et al., 2020). In science coverage, conflict may take the form of civil disagreement by reporting on a lack of consensus among scientists or inconsistent findings in a neutral and measured tone. However, this focus on disagreement also parallels a trend toward increasing incivility in media overall (Sobieraj & Berry, 2011). Though this uncivil trend largely concerns non-scientists, there are many examples of scientists using aggressive language to "put down" disbelievers of vaccines or GMOs on the internet (Yuan et al., 2019). This uncivil scientific disagreement highlights expert debate or inconsistent findings with aggressive language and personal attacks. Uncivil scientific disagreement is not necessarily denial of science; an expert may disagree uncivilly with another without rejecting a consensus position, particularly in emergent areas of research. Conversely, scientific denial can be civil, for example, anti-vaccination activists often assert the value of their own expertise (e.g., "I am an expert on my child") rather than directly attacking the credibility of medical professionals (Kata, 2012). Uncivil disagreement, therefore, refers to debate on a scientific claim that is presented with language that violates norms by including personal attacks and aggressive language (Yuan et al., 2018; 2019). Given that scientific disagreement and incivility are becoming increasingly public features of science communication as a result of changing media environments (Dudo, 2015; O'Brien, 2012), it is important to understand how these features affect public attitudes toward science.

There is a growing body of work on how the public views scientific disagreement (Dieckmann et al., 2015; Johnson, 2003) and the negative effects that scientific disagreement has on public support for scientific positions (Aklin & Urpelainen, 2014; Chinn et al., 2018; Ding et al., 2011; Malka et al., 2009; McCright et al., 2013). Previous work has also offered some insight into the effects of uncivil or aggressive communication on science attitudes (Anderson et al., 2014; Thorson et al., 2010; Yuan et al., 2018, 2019), including perceptions of norm violations (Yuan et al., 2019), information quality (Anderson et al., 2018; Yuan et al., 2018), and speaker likeability (Yuan et al., 2018). However, we still know little about the effects that civil and uncivil scientific disagreement have on the public's attention to and trust in science, as has been done in the political domain (e.g., Mutz & Reeves, 2005). Public attention to and trust in science are important for building public support for expert-supported positions, as well as related policies and research funding (Besley et al., 2016). It is therefore necessary to understand what effects news stories that highlights disagreement and incivility are likely to have on public attitudes toward science.

This study seeks to address this gap by investigating how individuals' science attitudes are affected by news stories containing civil and uncivil scientific disagreement, compared to scientific agreement. We explore how civil and uncivil disagreement affect individuals' attention to scientific issues, evaluations of research, trust in science, and broader attitudes about the value of science to society. In doing so, we address gaps in the extant literature concerning the effects of increasingly common features of science coverage – disagreement and incivility – on attitudes known to influence support for evidence-supported policies. We find that even in non-political contexts disagreement and incivility affect a range of outcomes that are known to influence public support for scientific positions, which highlights potential negative impacts of introducing incivility into public scientific disagreements.

The following section reviews previous work informing hypotheses about the effects that civil and uncivil scientific disagreement will have on (a) attention to scientific topics, (b) evaluations of scientific research, (c) trust in science, and (d) broader science attitudes.

Background

Attention

Scientific disagreement may draw the public's attention to scientific topics. Journalists often have a desire to quote all sides of the story in attempt to produce balanced, neutral coverage (Bennett et al., 2007; Boykoff & Boykoff, 2004), so areas of disagreement on an issue are likely to be highlighted by journalists. In addition, journalists often frame stories with dramatic conflict to bringing greater attention and interest to their coverage (Bennett et al., 2007). This conflict may increase anxiety on the part of audiences, which is associated with information seeking (Huddy et al., 2007;

Valentino et al., 2008). For these reasons, we might expect that a message about scientific disagreement may lead to greater attention in the forms of interest and information seeking information seeking than a message about scientific agreement.

Incivility may also trigger attention. Studies examining incivility in politics find that people find incivility more entertaining than civil disagreements (Mutz & Reeves, 2005). In addition, a number of studies find that uncivil disagreement leads to greater political engagement (Borah, 2014; Brooks & Geer, 2007; Masullo Chen & Lu, 2017), even if that engagement is more aggressive or uncivil (Gervais, 2014; Masullo Chen & Lu, 2017). Perhaps because it violates a social norm (Yuan et al., 2019), exposure to uncivil disagreement, compared to civil disagreement, is associated with greater physiological arousal (Mutz, 2007; Mutz & Reeves, 2005). This work suggests that, despite normative concerns about incivility for democratic outcomes, incivility may play a role in motivating engagement and interest.

In the present study I examine the following attention-related outcomes: self-reported interest, likelihood of information seeking, likelihood of engagement, and likelihood of sharing the information one read about. Given that this previous work has found that disagreement and incivility attract audience attention—and that incivility particularly is entertaining, engaging, and motivating—we expect that these features will be positively associated with all outcomes related to respondents' attention. We expect that participants in the uncivil disagreement condition will have higher responses for all attention measures than the civil disagreement condition, and that the civil disagreement condition will have higher responses than the agreement condition. This means that we expect that the agreement condition will be the least interesting to participants and lead to the lowest levels of information seeking, engagement, and sharing. Formally stated:

> **H1**: Participants exposed to scientific agreement will report the least **(H1a) interest in the topic**, **(H1b) information seeking**, **(H1c) engagement**, and **(H1d) intentions to share information**. Participants in the civil disagreement condition will have higher responses on attention measures than those in the agreement condition, but less than the uncivil disagreement condition. Participants in the uncivil disagreement condition will have the greatest interest, information seeking, engagement, and intentions to share.

Evaluation of Scientific Research

Though disagreement and incivility may be expected to increase attention to scientific issues, they may lead to more negative evaluations of the science in question. In general, people are more skeptical of scientific information when it is communicated alongside a disagreement cue, like a skeptic's position or an ambivalent poll (Aklin & Urpelainen, 2014; Chinn et al., 2018; Ding et al., 2011; Malka et al., 2009; McCright et al., 2013). In contrast, the public appears to be more accepting and supportive of positions when they are told or believe that scientists agree (Chinn et al., 2018; Ding et al., 2011; Lewandowsky et al., 2012; van der Linden, Leiserowitz, et al., 2015b). We expect this to be reflected in participants agreement with the study results and evaluation of the research being done on the presented topic.

Incivility has also been shown to affect how individuals evaluate messages. Uncivil messages are seen as less informative and of poorer quality than civil messages (Brooks & Geer, 2007; Yuan et al., 2018). When civil and uncivil messages are presented side-by-side, civil messages are perceived as more credible (Thorson et al., 2010). In addition, uncivil messages are viewed as less fair (Brooks & Geer, 2007) and uncivil comments on a message increase perceptions that the message is biased, particularly among conservatives (Anderson et al., 2018). These evaluations that uncivil messages are less informative, less credible, and less fair than their civil counterparts are important given that, above and beyond mere disagreement, incivility can polarize debates (Anderson et al., 2014) while increasing close-mindedness and attitude certainty (Borah, 2014). Thus, while we previously hypothesized that incivility might draw audience attention to scientific topics, we further expect that it will erode people's acceptance and evaluations of the science being communicated.

We therefore expect to see that individuals are less accepting of a study's findings when scientists disagree, compared to when scientists agree. Further, given research that incivility increases close-mindedness, we hypothesize that uncivil disagreement will lead to less acceptance of the study finding than civil disagreement.

> **H2**: Participants exposed to scientific agreement will report the greatest **acceptance of the study's findings** presented in the news article, followed by those in the civil disagreement condition, while those in the uncivil disagreement condition will report the least acceptance of the study's findings.

Additionally, we expect that participants will perceive scientific research to be of poorer quality when scientists disagree, compared to when they agree. Given prior research concerning incivility and perceptions of information quality, we further expect that when scientists disagree uncivily, participants will perceive the quality of research to be poorer than when scientists disagree civily.

> **H3**: Participants exposed to scientific agreement will report the most positive **perceptions of research quality** being done on the presented topic, followed by those in the civil disagreement condition, while those in the uncivil disagreement condition will report the most negative evaluations of the research.

Trust in Scientists and Scientific Methods

Scientific disagreement not only affects how people evaluate scientific research, but also perceptions of the actors performing that research. While some view the communication of scientific disagreement as an indication of honesty and transparency, others think more negatively of disagreement, believing it indicates that the disagreeing experts are incompetent or self-interested (Dieckmann et al., 2015; Johnson, 2003; Johnson & Slovic, 1998). Other work examining politicized science finds that, in contentious contexts, scientists are viewed as less credible by those who disagree with their position (Kahan et al., 2011; Vraga et al., 2018). These studies point to the possibility that exposure to disagreement could lead individuals to mistrust the scientific actors engaged in the debated research.

The tone of disagreement is also likely to affect perceptions of the scientists who disagree. Previous work has found that scientists who communicate more aggressively are considered less likeable (Yuan et al., 2018), though no work to date has explicitly tested the effects of incivility on trust in scientists. In this absence, we can draw on work about politics to inform expectations, as studies have directly investigated the effects of uncivil disagreement on trust in politics. Mutz and Reeves (2005) find that uncivil disagreement has negative effects on political trust, compared with civil disagreement (Mutz & Reeves, 2005). This may be in part because uncivil politicians are rated more negatively than civil politicians (Mutz, 2007). Together, this work suggests that the uncivil tone of the disagreement may have an additional negative effect on trust in scientists above and beyond the effects of disagreement.

In sum, previous work suggests that when scientific information comes alongside a disagreement cue, individuals may trust the scientists providing that information less than when disagreement information is not present. Additionally, the civility of the disagreement may also affect how trustworthy the scientific sources may appear, with uncivil actors generally receiving less favorable evaluations than civil actors. We therefore expect that participants' trust in both disagreeing parties will be affected by disagreement and incivility. In this experiment, as will be described in further detail below, the stimuli describe the findings of a recent study and the views of a commenting scientist who was not an author on the study, and who may or may not agree with the study's findings. In this context, we expect that:

> **H4**: **The study authors** will be trusted most in the agreement condition, followed by the civil disagreement condition, and will be trusted the least in the uncivil disagreement condition.

> **H5**: **The commenting scientist** will be trusted most in the agreement condition, followed by the civil disagreement condition, and will be trusted the least in the uncivil disagreement condition.

In addition to trust in the scientific actors mentioned in the article, we are additionally interested in how disagreement and incivility affects respondents' *general* trust in science. Trust in science is associated with the acceptance of scientific claims in personal and policy attitudes (Druckman & Bolsen, 2011; Lee, 2005; Roberts et al., 2013; Siegrist, 2000). While disagreement and incivility are likely to affect attitudes toward a specific study, field, or group of scientists, it is of central interest whether these attitudes "spill over" to respondents' trust in science generally. There is a little evidence that there might be spillover; one survey suggests that individuals who consume media containing more dissensus cues lose trust in scientists over time (Hmielowski et al., 2014).

It is also important to note that people can have different levels of trust in scientific actors and scientific methods. Achterberg et al. (2017) found that people may have great trust in scientific methods and principles but mistrust related institutions and actors. We therefore separate the measurement of scientific methods and actors, though we expect the effects of civil and uncivil disagreement on each to be similar. We hypothesize that participants exposed to agreement will report the greatest trust in scientists and scientific methods in general. Those exposed to civil disagreement will report less trust in scientists and scientific methods. Participants exposed to uncivil scientific disagreement are expected to report the least trust in scientists and scientific methods, in general.

> **H6**: Participants exposed to the scientific agreement condition will report the greatest **trust in scientists**, followed by those in the civil disagreement condition, while those in the uncivil disagreement condition will report the least trust in scientists.

> **H7**: Participants exposed to the scientific agreement condition will report the greatest **trust in scientific methods**, followed by those in the civil disagreement condition, while those in the uncivil disagreement condition will report the least trust in scientific methods.

Broader Science Attitudes

The ways in which disagreement and incivility affect perceptions of the value of scientific knowledge is also important to uncover because these views can affect a wide range of scientific and political attitudes. For example, Motta (2018) found that anti-intellectual attitudes were not only associated with rejection of consensus positions, but also were associated with support for political movements and candidates who are skeptical of experts (e.g., “Brexit”, Donald Trump). Perceptions about whether science creates more problems or improves the quality of our lives have been found to more strongly influence public opinion on certain scientific issues than partisan identities (Nisbet & Markowitz, 2014). Given the above literature suggesting that disagreement and incivility may affect attention to scientific topics, evaluations of research, and trust in science, we expect that there may be similar effects concerning people’s broader attitudes about the value of science.

> **H8**: Participants exposed to the scientific agreement condition will report the most positive attitudes about science, including **(a) how science will change things for the next generation**, **(b) whether benefits outweigh harms**, **(c) the utility of science in daily life**, and **(d) the utility in science of policy making**, followed by those in the civil disagreement condition, while those in the uncivil disagreement condition will report the least positive attitudes about science.

Research Questions

It may also be the case that personal differences moderate the effects that disagreement and incivility have on people's science attitudes. We thus propose research questions investigating two possible moderators: Deference to scientific authority and conflict aversion. First, deference to scientific authority is a long-term, stable trait positively associated with many scientific attitudes, including trust in scientists (Brossard & Nisbet, 2006) and scientific institutions (Anderson et al., 2012). Those high in deference believe that scientists are most qualified to make decisions about scientific topics and that scientists know best what is good for the public (Brossard & Nisbet, 2006). Though deference to scientific authority leads individuals to follow the views of scientists, it is not clear how it will affect attitudes when the scientific actors to which one is deferent disagree with one another. We therefore asked whether and how deference to scientific authority moderates the effects of scientific messages containing civil or uncivil disagreement between scientists.

> **RQ1**: Does **deference to scientific authority (DSA)** moderate the effects of scientific agreement, civil disagreement, or uncivil disagreement on attention, evaluation, trust, or broader science attitudes?

Second, individuals' tendency to avoid conflict may affect the impact of messages containing disagreement and incivility. Mutz and Reeves's (2005) study on political incivility and trust found that those who are more conflict averse reported less political trust when exposed to uncivil, compared to civil, disagreement. However, apart from this single finding, we have little direction on expectations regarding whether or how conflict aversion may moderate effects on other outcomes. Given that we are unsure how conflict aversion may moderate effects of experimental conditions, we asked whether the degree discomfort with conflict that people feel would affect the impact of scientific messages containing civil or uncivil disagreement on attention, evaluation, trust, and broader science attitudes.

> **RQ2**: Does **conflict aversion** moderate the effects of scientific agreement, civil disagreement, or uncivil disagreement on attention, evaluation, trust, or broader science attitudes?

Methods

Data

The data for this study was collected via Dynata (formerly Survey Sampling International) between September 23 and September 30, 2019. After removing participants who did not complete the survey because they failed to pass simple attention checks, the sample included 1,995 respondents. In our sample, 47.6% self-identified as male (N = 949) and 52.3% as female (N = 1043), while two respondents (0.1%) identified their gender as "other." 68.3% of respondents identified as White, followed by 15.7% as Black or African American, 7.5% as Hispanic, 5.8% as Asian, and 3.1% as other racial groups. Participants on average identified as "No lean" on a 7-pt scale of political partisanship (M = 2.69, SD = 2.16). Age was measured on an 8-pt scale from "18-24" (1) to "85 or over" (8), with the median age being "45-54" (*Median* = 4, *Mean* = 3.61, SD = 1.65). Education level was measured on a 7-pt scale from "less than high school" (1) to "Master's and/or Doctorate" (7), with the median education of our sample being "some college" (*Median* = 3, *Mean* = 3.80, *SD* =1.77).

Procedure

After providing informed consent and responding to two items measuring *deference to scientific authority*, participants were exposed to a news article created for this study. Each news article described the finding of a recent scientific study followed by quotes from a scientist, who was not an author on the study, commenting on the findings. The study findings that the stimuli presented were based on real scientific discoveries, but the language of agreement or disagreement was created for these stimuli by drawing from common language from the content analysis presented in the second chapter. We utilized stimulus sampling such that participants saw an article about one of three science topics: whether shocking the brain can improve athletic performance (n = 667), whether certain enzymes can convert type A blood to universal donor blood (n = 648), and whether Saturn's rings were caused by a moon collision (n = 680).

The commenting scientist's remarks, as well as the headline, contained the manipulations that defined the three study conditions: scientific agreement (SA, n = 673), civil disagreement (CD, n = 669), and uncivil disagreement (UD, n = 653). In the agreement condition, the commenting scientist agreed with the findings of the study, saying that, "A large majority of scientists share the view," of the study findings, and that, "Most experts agree there is ample evidence to support the findings of the study." This manipulation emphasized agreement and weight of evidence in favor of the findings reported. In the civil disagreement condition, the commenting scientist said, "There has been scientific debate," around such findings and that, "The findings of this study contradict findings from previous research." This condition emphasized that the findings of the study were inconsistent with past research and a subject of debate among scientists. Finally, in the uncivil disagreement condition the commenting scientist talked about the, "lousy research," being done in this area, calling the study findings, "nonsense" and "junk science." This commenting scientist in this condition emphasizes how the findings from this study oppose previous research with language common to some climate denial rhetoric and similar to the language used in Yuan et al.'s (2019; 2018) conceptualization of aggressive communication.

Each article was between 234 and 264 words, and contained no images, graphics, or source attribution. In a pretest the chosen topics had equal levels of self-reported comprehensibility. Full stimuli are in Appendix B.

Measures

Attention

Interest. Interest in the topic of the article was measured with three items, including, "How interested are you in the topic of the article?" (0 = Not at all interested, 4 = Very interested) (Karnowski et al., 2017; Oeldorf-Hirsch & Sundar, 2015); "How much more would you like to learn about this topic, if at all? (0 = "None at all", 4 = "A great deal more") (Oeldorf-Hirsch & Sundar, 2015); and "If you saw another article about this topic, how likely would you be to read it?" (0 = Not at all likely, 4 = Very likely) (Turcotte et al., 2015). These items were averaged to create a measure of *interest* (M = 1.90, SD = 1.27, Cronbach's α = .93).

Information Seeking. Willingness to seek further information was captured with two items. The first was "Will you look for further information on this topic?" (0 = Definitely not, 4 = Definitely yes) (Karnowski et al., 2017). The second told respondents that what they read was the first part of a longer article, and asked "How interested would you be in reading the rest of the article after the survey?" (0 = Not at all interested, 4 = Very interested). These items were averaged into a measure of *information seeking* (M = 1.87, SD = 1.27, r = .82, p < .001).

Engagement. We asked respondents a series of questions concerning their engagement with study authors, engagement with the commenting scientist, and engagement with the topic on social media.

Engagement with study authors. With regards to the study author, participants were asked, "If you had the chance, how likely would you be to ask the scientists who did the study any questions?" Participants responded from on a 5-point scale from 0 = "Not at all likely" to 4 = "Very likely" (*engagement with study authors* M = 1.81, SD = 1.43).

Engagement with commenting scientist. With regards to the commenting scientist, participants were asked, "If you had the chance, how likely would you be to ask Dr. Hammig, who commented on the study, any questions?" *Engagement with commenting scientist* (M = 1.77, SD = 1.43) was coded from 0 = "Not at all likely" to 4 = "Very likely".

Engagement on social media. We also asked more general questions about engagement on this topic with scientists on social media. These questions asked participants, "If you came across a scientist talking about this topic on social media, how likely would you be to read their posts?" and "If you came across a scientist talking about this topic on social media, how likely would you be to engage with their posts? (for example: leaving a comment or asking a question)" (0 = Not at all likely, 4 = Very likely). These two items were averaged into an index of *engagement on social media* (M

= 1.63, *SD* = 1.36, *r* = .8, p < .001).

Sharing. We also asked respondents about the likelihood that they would share the information from this article in their social network. We asked, "How likely would you be to share this article using social media?" (0 = Not at all likely, 4 = Very likely) (Bobkowski, 2015), and "How likely are you to talk about this article with people you know?" (0 = Not at all likely, 4 = Very likely). We averaged the two items into a measure of likelihood of *sharing* (*M* = 1.43, *SD* = 1.35, *r* = .76, p < .001).

Evaluation of Research

Acceptance of study findings. To capture participants acceptance of the study findings they read about, we asked them, "Do you agree or disagree" with the finding of the study in the article (0 = Strongly disagree, 6 = Strongly agree") and "In your opinion, is this study finding […] right or wrong?" (0 = Very wrong, 6 = Very right). These items were averaged to capture respondents' *acceptance of study findings* (*M* = 3.13, *SD* = 1.28, *r* = .74, p < .001).

Perception of research quality. We also captured respondents' attitudes concerning the quality of the scientific research being done on the topic they read about by asking them, "In general, what do you think about the science on" the topic they read about. Respondents reported that the science on that subject was "Trustworthy/Untrustworthy," "Not credible/Credible," "Bad science/Good science," and "Sloppy/Rigorous" on 6-point semantic differential scales (unlabeled). These were averaged to create a measure of *perception of research quality* which was specific to the issue they had read about (*M* = 3.10, *SD* = 1.30, Cronbach's α= .93).

Trust in Science

Trust in the study authors. We measured trust in the study authors, "How much do you trust the scientists who did the study to tell the truth about [TOPIC]?" "How much do you trust the scientists who did the study to do high-quality research on [TOPIC]?" "How much do you trust that the scientists who did the study are unbiased in their research on [TOPIC]?" and "How much do you mistrust the scientists who did the study as a source of information on [TOPIC]? (reverse-coded)." These items were drawn from previous work (Anderson et al., 2012; Cacciatore et al., 2016; Eiser et al., 2009; Hmielowski et al., 2014; Ho et al., 2011) and were measured on a 0 (None at all) to 4 (A great deal) labeled scale. In line with Hasell et al. (2019), all measures included a mention of the study topic to be specific about the context in which respondents trusted the scientific actors. These items were averaged into indices of *trust in the study authors* (M = 2.16, SD = .87, Cronbach's α = .76)

Trust in the commenting scientist. The above items, edited to ask about the commenting scientist, were also used to measure trust in the commenting scientist. They were averaged into indices of *trust in commenting scientist* (M = 2.16, SD = .87, Cronbach's α = .87).

Trust in scientists. We were also interested in how experimental manipulations may affect participants overall trust in scientists and scientific methods. Our measures of general trust in scientists and scientific methods sought to cover the three dimensions of trust: competence, benevolence, and integrity (Hasell et al., 2019). Thus, to capture respondents general trust in scientists, we asked three items on a 0 (Not at all) to 4 (A great deal) scale, including, "How much do you trust that scientists in general are competent at doing scientific research?" "In general, how much do you trust that scientists will use findings from scientific research in ways that benefit the public?" and "How much do you trust scientists in general to do unbiased scientific research?" These items were averaged to create a measure of *trust in scientists* (M = 2.35, SD = .97, Cronbach's α = .89).

Trust in scientific methods. We prefaced questions about trust in scientific methods with the statement, "The following questions are about your opinions on scientific methods, meaning the principles and procedures for the systematic pursuit of knowledge used in scientific research." Concerning scientific methods, we asked, "How much do you trust scientific methods to produce truthful knowledge about the world?" "How much do you trust scientific methods to produce helpful knowledge about the world?" and "How much do you trust scientific methods to produce unbiased knowledge about the world?" on the same 0 (Not at all) to 4 (A great deal) scale. These items were averaged into an index representing participants' *trust in scientific methods* (M = 2.42, SD = 1.01, Cronbach's α = .91).

Broader Science Attitudes

Better or Worse. We asked respondents how they think science will change things for the next generation (0 = Things will be much worse because of science, 4 = Things will be much better because of science; M = 3.06, SD = .95).

Harms v. Benefits. Respondents were asked whether they thought the benefits of science outweigh the harms (0 = Harms are much greater, 4 = Benefits are much greater; M = 2.92, SD = .98).[5]

Daily Life. We asked participants how useful they believe science is for making

[5] Measures *Better or Worse* and *Harms v. Benefits* were drawn from unpublished work by Josh Pasek.

decisions about how we should live (0 = Not at all useful, 4 = Extremely useful; M = 2.33, SD = 1.09).

Policy Making. Finally, we asked about how useful participants think science is for informing laws and policies (0 = Not at all useful, 4 = Extremely useful; M = 2.07, SD = 1.13).

Moderators

Deference to Scientific Authority. At the start of the survey, deference to scientific authority (DSA) was measured by asking participants to, "Please indicate how much you agree or disagree with," two statements on a 0 (Strongly disagree) to 6 (Strongly agree) labeled scale. The statements were, "Scientists know best what is good for the public" and "Scientists should do what they think is best, even if they have to persuade the public that it is right" (Anderson et al., 2012). These items were averaged to create *Deference to Scientific Authority (DSA)* (M = 3.55, SD = 1.38, r = .65, p < .001).

Conflict Aversion. To capture the degree to which individuals avoid or are uncomfortable with conflict, we asked participants to, "Please indicate how much you agree or disagree with," six statements drawn from previous work (Fridkin & Kenney, 2011; Rahim, 1986; Vraga et al., 2015; Wang et al., 2017). All items were presented in random order, and participants reported their agreement on a 0 (Strongly disagree) to 6 (Strongly agree) labeled scale. Example items included, "I try to avoid unpleasant exchanges with others," and "I enjoy challenging the opinions of others [reverse coded]." These items were averaged into an index called *conflict aversion* (M = 3.42, SD = 1.08, Cronbach's α = .77). These items were measured after participants' exposure to the stimuli, immediately before demographic measures, as we were concerned that the items might prime individuals to think about conflict, and thus affect their responses to stimuli that did/did not include conflict. The experimental conditions did not affect conflict aversion $F(2, 1988) = .36$, $p = .700$.

Results

Preliminary Analyses

Random assignment to conditions was successful. Gender, age, race, education, employment status, and partisanship did not significantly vary by condition (all *p*s > .17). As a result, any differences we observe can be attributed to experimental condition. However, we did run all analyses with and without controlling for these demographic variables; the pattern of results was the same with and without demographic controls. The results reported below come from analyses that did not include demographic controls.

Following exposure to the stimuli, respondents were asked to identify the topic of the article from three possible choices (89% correct) and whether the commenting scientist agreed or disagreed with the finding of the study (76.3% correct). All participants were included in the analyses presented here, though analyses run with only those participants who correctly identified the topic as well as agreement or disagreement produce a similar pattern of results. As an additional manipulation check, participants were asked how polite or rude they thought the commenting scientist was on a 0 (Very polite) to 6 (Very rude) scale. The perceived rudeness of the commenting scientists was significantly associated with our experimental conditions $F(2,1991) = 357.40$, $p < .001$. Participants in the uncivil disagreement condition evaluated the commenting scientist as the most rude ($M = 3.77$, $SD = 1.53$) compared to the civil disagreement ($p < .001$) and agreement conditions ($p < .001$). The disagreeing scientists in the civil disagreement condition (M = 2.26, SD = 1.17) was also considered significantly more rude than the commenting scientist in the agreement condition (M = 2.02, SD = 1.13, p = .003) (see Table III.1, row 1).

ANOVA Models

To investigate the hypotheses, we examined the effects of the experimental manipulation on all outcomes by conducting a series of ANOVAs in which the experimental condition and issue topic were entered as the sole predictors. All analyses were also run including an interaction between the experimental condition and article topic. The pattern of results was identical to the results reported here from analyses that did not include an interaction term for all except one outcome (discussed below).

Below, we focus on the effects that the experimental conditions had on outcomes, controlling for the effects of article topic. Given the number of hypotheses this study tests, there was a risk of discovering some false positive results. For this reason, I used post-hoc Tukey tests to look at differences between conditions, as this test includes a correction for multiple tests. Mean differences in outcomes by experimental condition can be found in Table III.1.

In some cases, the topic of the article affected outcomes. When issue topic affected outcomes, it was typically that the topic of shocking the brain to increase neuroplasticity resulted in more negative outcomes than changing blood types or Saturn's rings. Mean differences in outcomes by the topic of the article are reported in Table III.2.

Table III.1: Mean Differences in Outcomes by Experimental Condition

Outcome	**Range**	**Condition**		
		Scientific Agreement	Civil Disagreement	Uncivil Disagreement
Rudeness of Commenting Scientist	0-6	2.02 (1.13)a	2.26 (1.17)b	3.77 (1.53)c
Attention				
Interest	0-4	2.04 (1.27)a	1.87 (1.26)b	1.77 (1.27)b
Information Seeking	0-4	2.01 (1.28)a	1.86 (1.27)ac	1.74 (1.26)bc
Engagement with Study Authors	0-4	1.93 (1.45)a	1.79 (1.42)ac	1.71 (1.40)bc
Engagement with Commenting Scientist	0-4	1.88 (1.43)a	1.78 (1.41)ac	1.65 (1.44)bc
Engagement on Social Media	0-4	1.79 (1.39)a	1.6 (1.35)b	1.48 (1.34)b
Sharing	0-4	1.62 (1.37)a	1.42 (1.37)b	1.25 (1.28)c
Evaluation of Research				
Agreement with Study Findings	0-6	3.51 (1.33)a	3.00 (1.18)b	2.86 (1.23)b
Perception of Research Quality	0-5	3.43 (1.25)a	3.05 (1.25)b	2.81 (1.33)c
Trust in Science				
Trust in Study Authors	0-4	2.39 (.89)a	2.19 (.84)b	1.89 (.82)c
Trust in Commenting Scientist	0-4	2.40 (.88)a	2.22 (.81)b	1.86 (.85)c
General Trust in Scientists	0-4	2.48 (.95)a	2.34 (.97)b	2.23 (.98)b
General Trust in Scientific Methods	0-4	2.54 (.99)a	2.37 (.99)b	2.33 (1.04)b
Broader Science Attitudes				
How will science change things for the next generation?	0-4	3.16 (.88)a	3.05 (.97)ac	2.96 (1.00)bc
Do benefits of science outweigh the harms?	0-4	2.99 (.91)a	2.92 (.99)ac	2.85 (1.02)bc
Science is useful for daily life	0-4	2.36 (1.08)a	2.32 (1.11)a	2.31 (1.09)a
Science is useful for policymaking	0-4	2.10 (1.12)a	2.05 (1.14)a	2.06 (1.13)a

Descriptive condition means were reported with standard deviations in parentheses. Means within the same row with different letters were found significantly different at p<.05 using a Tukey test.

Table III.2: Mean Differences in Outcomes by Article Topic

Outcome	**Range**	**Topic**		
		Convert Blood Type	Shocking the Brain	Saturn's Rings
Attention				
Interest	0-4	1.99 (1.26)a	1.82 (1.29)b	1.87 (1.26)ab
Information Seeking	0-4	1.94 (1.25)a	1.82 (1.30)a	1.86 (1.26)a
Engagement with Study Authors	0-4	1.78 (1.42)a	1.93 (1.43)ab	1.73 (1.42)ac
Engagement with Commenting Scientist	0-4	1.75 (1.42)a	1.87 (1.42)a	1.68 (1.44)a
Engagement on Social Media	0-4	1.63 (1.37)a	1.67 (1.36)a	1.59 (1.36)a
Sharing	0-4	1.53 (1.38)a	1.42 (1.36)ab	1.35 (1.32)b
Evaluation of Research				
Agreement with Study Findings	0-6	3.38 (1.17)a	2.7 (1.39)b	3.31 (1.14)a
Perception of Research Quality	0-5	3.48 (1.22)a	2.57 (1.33)b	3.26 (1.17)c
Trust in Science				
Trust in Study Authors	0-4	2.24 (.85)a	1.91 (.90)b	2.33 (.82)a
Trust in Commenting Scientist	0-4	2.23 (.87)a	2.05 (.87)b	2.21 (.87)a
General Trust in Scientists	0-4	2.43 (.97)a	2.23 (.98)b	2.41 (.96)a
General Trust in Scientific Methods	0-4	2.48 (1.03)a	2.33 (1.02)b	2.44 (.97)ab
Broader Science Attitudes				
How will science change things for the next generation?	0-4	3.14 (.91)a	2.98 (.98)b	3.07 (.96)ab
Do benefits of science outweigh the harms?	0-4	3.01 (.91)a	2.82 (.99)b	2.94 (1.01)a
Science is useful for daily life	0-4	2.38 (1.09)a	2.24 (1.12)a	2.37 (1.07)a
Science is useful for policymaking	0-4	2.10 (1.13)a	1.98 (1.15)ab	2.13 (1.10)ac

Descriptive condition means were reported with standard deviations in parentheses. Means within the same row with different subscripts were found significantly different at p<.05 using a Tukey test.

Attention

We saw very similar patterns of responses to outcomes concerning interest, information seeking, engagement, and likelihood of sharing. As discussed below, contrary to the expectations of H1, respondents were more attentive to the information when exposed to the agreement conditions compared to the disagreement conditions. In general, disagreement and incivility led to less interest, engagement, information seeking, and information sharing, compared to the condition in which scientists agreed. In sum, H1 was not supported.

Interest. Looking first at respondent's interest in the topic, there was a significant main effect of experimental condition $F(2, 1989) = 8.03$, $p < .001$, $\eta_p^2 = .008$. Post-hoc Tukey tests showed that respondents reported greater interest in the agreement condition (*Descriptive Condition Mean (M) = 2.04, Standard Deviation (SD)* = 1.27), compared to the civil disagreement ($M = 1.87$, $SD = 1.26$, $p = .040$) and uncivil disagreement ($M = 1.77$, $SD = 1.27$, $p < .001$) conditions. There was no significant difference between the civil and uncivil disagreement conditions ($p = .268$). These findings were contrary to the expectations of H1a, which was not supported (Table III.1, row 3).

Information Seeking. Concerning respondent's reported likelihood to seek further information, there was a significant effect of experimental condition $F(2, 1990) = 7.40$, $p < .001$, $\eta_p^2 = .007$. However, it followed a pattern opposite to the one hypothesized. Post-hoc Tukey tests revealed that respondents reported greater willingness to seek further information in the agreement condition ($M = 2.01$, $SD = 1.28$), compared to the uncivil disagreement condition ($M = 1.74$, $SD = 1.26$, $p < .001$). The civil disagreement condition ($M = 1.86$, $SD = 1.27$) did not differ significantly from either the agreement (p = .096) or uncivil disagreement (p = .176) condition (Table III.1, row 4). H1b was not supported.

Engagement. We tested effects of experimental condition on three engagement measures: engagement with the study authors, with the commenting scientists, and engagement on social media. Across all these measures, the effects of experimental condition did not follow the pattern hypothesized, so H1c was not supported.

Engagement with study authors. Experimental condition significantly affected engagement with the study authors $F(2, 1989) = 4.40$, $p < .05$, $\eta_p^2 = .004$. Looking at condition differences, those in the agreement condition reported greater likelihood of engagement with the authors (M = 1.93, SD = 1.45) compared to the uncivil disagreement condition (M = 1.71, SD =1.40, p = .010). Respondents in the civil disagreement condition (M = 1.79, SD = 1.42) reported a likelihood of engagement with the study authors between, and not significantly different from, the agreement (p = .146) and uncivil disagreement (p = .540) conditions (Table III.1, row 5).

Engagement with commenting scientist. Experimental condition significantly affected engagement with the commentating scientist $F(2, 1988) = 4.31$, p < .05, η_p^2 = .004. We see that those in the agreement condition (M = 1.88, SD = 1.43) reported greater likelihood of engagement with the commentator compared to the uncivil disagreement condition (M = 1.65, SD = 1.44, p = .010). Respondents in the civil disagreement condition (M = 1.78, SD = 1.41) reported a likelihood of engagement with the commenting scientist between, and not significantly different from, the agreement (p = .395) and uncivil disagreement (p = .232) conditions (Table III.1, row 6).

Engagement on social media. There was a significant effect of the experimental condition $F(2, 1989) = 8.71$, $p < .001$, $\eta_p^2 = .009$ on likelihood to engage on social media. Post-hoc Tukey tests showed that respondents in the agreement condition ($M = 1.79$, $SD = 1.39$) reported a higher likelihood of engagement than respondents in either civil disagreement ($M = 1.60$, $SD = 1.35$, $p = .029$) or uncivil disagreement ($M = 1.48$, $SD = 1.34$, $p < .001$) conditions. There was no significant difference between the civil and uncivil disagreement conditions ($p = .249$, Table III.1, row 7).

Sharing. Finally, evidence condition significantly affected the likelihood that respondents would share this information $F(2, 1990) = 12.96$, $p < .001$, $\eta_p^2 = .013$. Again, however, the effect of experimental condition was contrary to the hypothesized effect. Those in the agreement condition ($M = 1.62$, $SD = 1.37$) were significantly more likely to share than those in the civil disagreement condition ($M = 1.42$, $SD = 1.37$, $p = .017$) and those in the uncivil disagreement condition ($M = 1.25$, $SD = 1.28$, $p < .001$). Participants in the civil disagreement were significantly more likely to share than those in the uncivil disagreement condition ($p = .048$). In sum, those in the agreement condition were most likely to share, followed by those in the civil disagreement condition, while those in the uncivil disagreement condition were the least likely to share (Table III.1, row 8). H1d was not supported.

Evaluation of the Research

Agreement with study findings. Experimental condition affected participants' agreement with the study findings $F(2, 1990) = 53.88$, $p < .001$, $\eta_p^2 = .051$. Participants reported stronger agreement with the findings of the study when there was scientific agreement ($M = 3.51$, $SD = 1.33$) than when there was civil disagreement ($M = 3.00$, $SD = 1.18$, $p < .001$) or uncivil disagreement ($M = 2.86$, $SD = 1.23$, $p < .001$). There were no significant differences between the civil and uncivil disagreement conditions (p = .069). Thus, H2 was partially supported (Table III.1, row 10).

Perception of research quality. Additionally, participants' evaluation of the quality of the research was affected by the experimental condition $F(2, 1977) = 42.65$, p < .001, $\eta_p^2 = .041$. Research was evaluated more positively in the agreement condition (M = 3.43, SD = 1.25) than in the civil disagreement (M = 3.05, SD = 1.25, p < .001) and uncivil disagreement (M = 2.81, SD = 1.33, p < .001) conditions. Further, those in the civil disagreement condition evaluated the research as more positive than those in the uncivil disagreement condition (p = .001) (Table III.1, row 11). These findings supported H3.

Trust in Science

In general, scientists and scientific methods were most trusted when there was scientific agreement. However, there were some differences concerning the role of incivility when looking at general trust in versus trust in the specific actors mentioned.

Trust in study authors. Experimental condition affected trust in the study authors $F(2, 1988) = 60.52$, p < .001, $\eta_p^2 = .057$. Looking at where differences lie, post-hoc Tukey tests show that participants in the agreement condition reported higher levels of trust (M = 2.39, SD = .89) than those in the civil disagreement (M = 2.19, SD = .84, p < .001) and uncivil disagreement (M = 1.89, SD = .82, p < .001) conditions. Additionally, those in the uncivil disagreement condition reported the significantly lower levels of trust than those in the civil disagreement condition (p < .001), supporting H4 (Table III.1, row 13).

Trust in commenting scientist. Experimental condition also affected trust in the commenting scientist $F(2, 1987) = 71.26$, $p < .001$, $\eta_p^2 = .067$. As with trust in the study authors, post-hoc Tukey tests show that participants in the agreement condition reported higher levels of trust ($M = 2.40$, $SD = .88$) than those in the civil disagreement ($M = 2.22$, $SD = .81$, $p < .001$) or uncivil disagreement ($M = 1.86$, $SD = .85$, $p < .001$) conditions. Those in the civil disagreement condition reported significantly more trust than those in the uncivil disagreement condition ($p < .001$), supporting H5 (Table III.1, row 14).

In analyses that included an interaction term between experimental condition and article topic, we observed a significant interactive effect between on trust in the commenting scientist $F(4, 1983) = 5.03$, $p < .001$, $\eta_p^2 = .01$. Visual inspection of this interactive effect showed that respondents reported significantly higher levels of trust in the commenting scientist in the blood and space agreement conditions than in the brain agreement condition. In the civil and uncivil disagreement conditions, participants reported similar levels of trust across all topics (Figure B.1 in Appendix B).

Trust in Scientists. Experimental condition affected respondents' overall trust in scientists $F(2, 1989) = 11.11$, $p < .001$, $\eta_p^2 = .011$. Those in the agreement condition reported higher trust in scientists ($M = 2.48$, $SD = .95$) than did participants in either the civil disagreement ($M = 2.34$, $SD = .97$, $p = .016$) or uncivil disagreement ($M = 2.23$, $SD = .98$, $p < .001$) conditions. However, incivility did not appear to additionally affect trust in scientists or scientific methods, as there was no significant difference between the civil and uncivil disagreement conditions ($p = .125$). This provided partial support for H6 (Table III.1, row 15).

Trust in Scientific Methods. Experimental condition affected respondents' trust in scientific methods $F(2, 1988) = 8.30$, $p < .001$, $\eta_p^2 = .008$. Those in the agreement condition reported higher trust in scientific methods (M = 2.54, SD = .99) than did participants in either the civil disagreement (M = 2.37, SD = .99, p = .006) or uncivil disagreement (M = 2.33, SD = 1.04, $p < .001$) conditions. The civil and uncivil disagreement conditions did not significantly differ (p = .727). H7 was partially supported (Table III.1, row 16).

Broader Science Attitudes

Some, though not all of the broader science attitudes we measured were affected by experimental condition in the ways we hypothesized, providing partial support for H8.

Better or worse. Participants thoughts on whether science will make things better or worse for the next generation was predicted by experimental condition $F(2, 1989)$ = 7.51, p < .001, $\eta_p^2 = .007$. Participants in the agreement condition were significantly more likely to report that science will make things better for the next generation (M = 3.16, SD = .88) than those in the uncivil disagreement condition (M = 2.96, SD = 1.00, $p < .001$). The civil disagreement condition (M = 3.05, SD = .97) did not differ significantly from either the agreement (p = .087) or uncivil disagreement conditions (p = .182), so H8a was partially supported (Table III.1, row 18).

Harms and benefits. Participants' beliefs about whether the benefits of science outweighed possible harms were also predicted by experimental condition $F(2, 1988)$ = 3.36, p < .05, $\eta_p^2 = .003$. Participants in the agreement condition (M = 2.99, SD = .91) were more likely to report that the benefits of science outweighed potential harms compared to those in the uncivil disagreement condition (M = 2.85, SD = 1.02, p = .026). No differences were observed between the civil disagreement condition (M = 2.92, SD = .99) and either the agreement (p = .427) or uncivil disagreement (p = .365) conditions.

Thus, H8b was partially supported (Table III.1, row 19).

Daily life. Experimental condition did not affect respondents' reported beliefs about the utility of science in daily life $F(2, 1988) = .32$, $p = .72$; H8c was unsupported.

Policy making. Experimental condition did not affect respondents' reported beliefs about the utility of science for informing laws and policy $F(2, 1988) = .39$, $p = .68$; H8d was unsupported.

Research Questions

To investigate how different personal characteristics might affect the ways in which participants respond to scientific disagreement and incivility, we conducted a series of post-hoc analyses into the potential moderating effects that participants' deference to scientific authority (RQ1), and aversion to conflict (RQ2) may have on the relationship between experimental condition and outcomes. Significant findings are discussed below, while full descriptions of analyses, results, and figures are included in Appendix B.

Deference to Scientific Authority

Main Effects. In models that do not include interactive effects, deference to scientific authority (DSA) is positively associated with all outcomes (see Tables B.1-B.3 in Appendix B). Those high in DSA report greater attention outcomes, including interest ($\beta = .29$, $p < .001$), information seeking ($\beta = .28$, $p < .001$), engagement with study authors ($\beta = .27$, $p < .001$), engagement with commenting scientist ($\beta = .25$, $p < .001$), engagement on social media ($\beta = .26$, $p < .001$), and sharing ($\beta = .28$, $p < .001$). DSA was also positively associated acceptance of study findings ($\beta = .28$, $p < .001$) and evaluation of research ($\beta = .30$, $p < .001$). Those with greater DSA also reported greater trust in science, including trust in the study authors ($\beta = .25$, $p < .001$), trust in the commenting scientist ($\beta = .20$, $p < .001$), trust in scientists generally ($\beta = .35$, $p < .001$), and trust in scientific methods ($\beta = .35$, $p < .001$). Those with greater DSA also were more likely to report that science would make things better for the next generation ($\beta = .32$, $p < .001$), the benefits of science outweighed the harms ($\beta = .31$, $p < .001$), and that science has greater utility in daily life ($\beta = .39$, $p < .001$) and for policymaking ($\beta = .39$, $p < .001$).

Interactive Effects. We observed two significant interactive effects of DSA and experimental condition (see Tables B.4-B.6 in Appendix B). First, the effect of Uncivil Disagreement v. Agreement on likelihood of engagement with the commenting scientist was significantly moderated by DSA (unstandardized $\beta = .12$, $p < .05$). Those with low deference reported a lower likelihood of engagement with the commenting scientist in the uncivil disagreement condition, compared to the agreement condition, on average. However, among those with high deference, the uncivil disagreement condition did not lead to lower likelihood of engagement with the commenting scientist relative to the agreement condition (see Figure B.2, left panel in Appendix B).

Second, there was a significant interaction between DSA and the Uncivil Disagreement v. Agreement condition on trust in the commenting scientist ($\beta = -.08$, $p < .05$). Uncivil disagreement appeared to slightly attenuate the positive effect that high deference had on trust in the commenting scientist, compared to the agreement condition (see Figure B.2, right panel in Appendix B).

Conflict Aversion

Main Effects. Looking first at main effects, conflict aversion was significantly and negatively associated with all attention-related outcomes, including interest ($\beta = -.13$,

$p < .001$), information seeking ($\beta = -.13$, $p < .001$), engagement with the study authors ($\beta = -.23$, $p < .001$), engagement with the commenting scientist ($\beta = -.25$, $p < .001$), engagement on social media ($\beta = -.15$, $p < .001$), and sharing ($\beta = -.14$, $p < .001$). Conflict aversion was also negatively associated with trust in scientific methods ($\beta = -.05$, $p < .001$) and attitudes about whether the benefits of science outweighed harms ($\beta = -.05$ $p < .05$) (see Tables B.1-B.3 in Appendix B).

Interactive Effects. There were four outcomes for which conflict aversion moderated the effect of Civil Disagreement v. Agreement: information seeking ($\beta = -.12$, $p < .05$), engagement with the study authors ($\beta = -.14$, $p < .05$), engagement with the commenting scientist ($\beta = -.16$, $p < .05$), and sharing ($\beta = -.13$, $p < .05$) (see Tables B.7-B.9 in Appendix B). When visualizing these interactive effects, it appears that those higher in conflict aversion were less likely to seek information, engage with the researchers, or share information in the civil disagreement condition compared to the agreement condition. However, those lower in conflict aversion appeared to seek information, engage with researchers, and share information at similar rates between the civil disagreement and agreement conditions (see Figure B.3 in Appendix B). Interestingly, the effects of the uncivil disagreement condition do not appear to be moderated by conflict aversion, compared to the agreement condition. It should also be noted that interactive effects for the remaining attention-related outcomes followed this same pattern but only reached significance at the $p < .1$ level.

Discussion

Summary of Findings

This study finds that disagreement and incivility in science news, features which may become more prevalent due to changes in the media environment (Bennett et al., 2007; Chinn et al., 2020; Sobieraj & Berry, 2011), affect individuals' attention toward, evaluation of, and trust in science, as well as some general attitudes about the value of science. Some of these findings were expected, but others were contrary to hypotheses. The results shared a similar pattern that scientific agreement had generally more positive effects across the board than disagreement.

Attention

Concerning people's attention to scientific issues, we find that participants reported the most interest, information seeking, engagement, and sharing when scientists agreed about the study finding. This was counter to our expectations concerning what attracts the public's attention, which supposed that individuals would be more drawn to conflict in the forms of disagreement and incivility. This finding highlights possible differences in the public's expectations of scientific versus political actors. That said, studies looking at attention to political incivility have used different measures that were not included in this study, such as physiological arousal (Mutz, 2007) or perceived entertainment (Mutz & Reeves, 2005), to capture attention to uncivil political content. In sum, it appears that both disagreement and incivility may have negative effects on audience attention—in comparison to scientific agreement. Perhaps when scientific information is contested, people perceive it to be less valuable or worth engaging with, and in contrast are more inclined to be attentive to "usable" positions on which scientists agree. However, uncivil disagreement, in most cases, appears to have the most negative effects on attention-related outcomes including information seeking, engagement with scientists, and sharing.

Evaluation of Scientific Research

Consistent with past research (Aklin & Urpelainen, 2014; Chinn et al., 2018; Ding et al., 2011; McCright et al., 2013), we found that participants were less accepting of positions on which scientists disagreed, though there were no differences observed between civil and uncivil disagreement. However, we did see that both disagreement and incivility affected participants' perceptions of research quality. Research quality was perceived to be highest when scientists agreed, followed by the civil disagreement, while the quality of research was evaluated most negatively in the uncivil disagreement condition. In sum, participants' personal attitudes about the scientific claim were driven by scientific agreement, or lack thereof, while their perception of research quality was negatively affected both by disagreement and incivility. This finding suggests that disparaging a piece of opposing research may have the result of negatively affecting perceptions of the field as a whole.

Trust in Science

Trust in the scientists mentioned in the article was affected by both disagreement and incivility. The scientists in the article were most trusted when they agreed, followed by when they disagreed civilly, and were trusted the least when they disagreed uncivilly. This pattern held for *both* trust in the authors of the study and trust in the commenting scientist. Though the study authors were not quoted in the article, they were similarly affected by the commenting scientists' civil or uncivil disagreement. This finding serves as a warning for those who are inclined to attack researchers with whom they disagree; when the commenting scientist was uncivil, he was viewed as negatively as those he was disparaging.

However, participants' general trust in scientists and scientific methods was unaffected by the incivility of an individual scientist, though it was affected by disagreement. Participants reported higher trust in scientists and in scientific methods when scientists agreed compared to either condition in which scientists disagreed. Though scientific disagreement appears to influence trust in scientists and scientific methods, a single incident of incivility did not appear to further erode trust.

Broader Science Attitudes

Finally, incivility affected some broader attitudes about the promise and risks of science, though not its utility in daily life or for policy making. Participants in the uncivil disagreement condition were more likely to report that (a) science will change things for the worse for the next generation and that (b) the harms outweigh the benefits of science than in the agreement condition. No differences were observed between the agreement and civil disagreement conditions or the civil and uncivil disagreement conditions. Thus, it appears that uncivil disagreement may have negative effects on people's general views on science.

Interpreting Interactive Effects

The significant interactions with deference to scientific authority suggest that, for those high in deference, incivility does not reduce the likelihood of engagement with the uncivil, commenting scientist, but that it does reduce the high level of trust in the commenting scientist that a highly deferent individual would have otherwise had. Among those who are low in deference, incivility may slightly reduce engagement with the uncivil, commenting scientist, but it does not affect the level of trust in the commenting scientist that an individual with low deference would have.

Finally, it is interesting to note that, contrary to Mutz and Reeves's (2005) finding, we found that conflict aversion did not moderate trust outcomes, but only moderated attention-related outcomes. This finding suggests that those who are conflict averse may be likely to avoid scientific information that contains disagreement, while those who are less conflict averse are similarly attentive across all conditions. It also appeared that conflict aversion was most influential in the civil disagreement condition; this may represent an intermediate level of conflict which is not as clear cut as the agreement or uncivil disagreement conditions. In the civil disagreement condition, the effect of an individuals' perception and reaction to conflict may be stronger than in the other conditions. This finding raises the point that it is important to be aware of what contexts personal traits are likely to affect attitudes and behaviors.

Strengths and Limitations

A strength of this study includes to the use of a diverse sample for participants and stimulus sampling for the conditions. Stimuli was made as realistic as possible by using common language for disagreement and denial drawn from the content analytic work presented in chapter 1.

It is also important to note several limitations of this study. First, participants considered the commenting scientist to be significantly more rude in the civil disagreement condition ($M = 2.02$) than the scientific agreement condition ($M = 2.26$), though this was not the intention when designing the stimuli. This raises the possibility that some of the differences between the agreement and civil disagreement conditions, attributed to the presence or absence of disagreement, may additionally be driven in part by a perception of greater incivility. However, it is worth noting that the mean difference between the agreement and civil disagreement conditions is quite small (.24 on a 7-point scale) compared to the difference between the civil and uncivil disagreement conditions (1.51).

Second, this study compared differences between news articles that presented scientific agreement, civil disagreement, and uncivil disagreement, but this does not give us a baseline of how people respond to measures (e.g. trust in science) in the absence a message.

Third, our stimuli focused on non-politicized and non-contentious scientific issues. Disagreement and incivility may have different effects in politicized issues among differently motivated partisans. For instance, conservatives have been shown in some cases to have stronger reactions to incivility than liberals (Anderson et al., 2018) and perceptions of incivility may be dependent on whether one feels as though their side is under attack (Anderson et al., 2014; Borah, 2014). Future research should address how disagreement and incivility affect attitudes in contentious contexts, with particular attention to motivated reasoning (Kahan et al., 2011) and the potential for backfire effects (Hart & Nisbet, 2012). In addition, given the frequency with which non-scientist actors comment on scientific topics (Chinn et al., 2020), it is important to investigate whether civil or uncivil disagreement from non-scientists has the same effects as scientists disagreeing.

Finally, this study only looked at effects of a single exposure, but understanding real-world effects requires an understanding of individuals' media diets and the ways in which these effects may decay over time or strengthen with repeated exposure to such messages.

Implications

Changes to our media environment may encourage the prevalence of disagreement and incivility in science communications. Traditional media compete for audience attention by emphasizing conflict (Bennett et al., 2007; Boykoff & Boykoff, 2007) as media generally trend toward greater incivility (Sobieraj & Berry, 2011). These forces may result in traditional science reporting that increasingly emphasizes disagreement and uncivil conflict (Chinn et al., 2020). In addition, internet and social media technologies offer increasingly informal spaces for scientists to communicate. Though spaces like scientist blogs and academic Twitter facilitate a sharing of knowledge, these communications can at times be more uncivil or informal (Anderson et al., 2012). For example, in their study of the content of #overlyhonestmethods on Twitter, Simis-Wilkins et al. (2018) write that some tweets, "show a side of science that is rarely seen in public except after scandals" (p. 16). While science media may be containing greater disagreement and incivility, these features appear to negatively affect many attitudes that are essential for building public support for scientifically supported positions and policies.

This presents a challenge for scientists about how to communicate responsibly and effectively in a media environment that may increasingly emphasize disagreement and incivility. Given that critique, peer review, and debate are necessary to managing the uncertainties and complexities of scientific research, it is important to continue research into how scientific disagreements can be transparently communicated in ways which do not diminish the value of scientific knowledge in the eyes of the public.

CHAPTER IV

Effects of Consensus Messages and Political Ideology on Climate Change Attitudes: Inconsistent Findings and the Effect of a Pretest

Politicization of science is defined as "when an actor emphasizes the inherent uncertainty of science to cast doubt on the existence of scientific consensus (Bolsen & Druckman, 2015, p. 745)." In no context is this more evident than climate change. In the U.S., conservative political actors have sought to sow doubt about climate science by amplifying and manufacturing scientific disagreement for the purpose of making the public believe that scientific opinion is unsettled or not to be trusted (Jacques et al., 2008; McCright & Dunlap, 2010). The effects of this can be seen in polling data showing that conservatives, more so than liberals, express doubt about whether climate change is happening and what is causing it (McCright & Dunlap, 2011). In the meantime, scientific consensus about climate change and its human causation has grown (Cook et al., 2013). Given that scientific agreement is associated with public acceptance of scientific positions (Ding et al., 2011; Lewandowsky et al., 2012), there has recently been a proliferation of research on whether communicating scientific agreement information, in the form of a consensus message, can reduce partisan perceptions of disagreement and build support for climate change.

However, there have been inconsistent findings concerning whether consensus messages are capable of persuading skeptics. Some research shows that partisans are either similarly affected by consensus message or that conservatives are more positively affected than liberals (Goldberg, van der Linden, Ballew, Rosenthal, Gustafson, et al., 2019; Goldberg, van der Linden, Ballew, Rosenthal, & Leiserowitz, 2019; van der Linden et al., 2016; van der Linden, Leiserowitz, et al., 2015b, 2019). However, other work fails to replicate such findings, instead showing that partisan skeptics are less affected by consensus messages, or that these messages may backfire (Bolsen & Druckman, 2018; Cook & Lewandowsky, 2016; Dixon, 2016; Dixon et al., 2017; Dixon & Hubner, 2018; Ma et al., 2019). The proposed study investigates a factor which may shed light on the inconsistent findings: the decision whether or not to ask participants about their attitudes on climate change before a consensus message is provided. The inclusion of such a pretest appears to be a confound in previous work, such that a pretest is employed in studies finding a reduction in partisan polarization of climate attitudes (Lewandowsky et al., 2012; van der Linden, Leiserowitz, et al., 2015b, 2019) whereas this pretest is not included in studies that fail to find a similar effect (Bolsen & Druckman, 2018; Cook & Lewandowsky, 2016; Dixon et al., 2017). To date, no previous work has directly compared the impact that this pretest may have—by investigating this factor, this study responds to ongoing debate about the efficacy of consensus messages in politicized settings and provides important feedback on methodologies used for future research.

Background

Agreement Estimates as a Gateway Belief

Initial survey work suggested that individuals who believed that there was a high level of scientific agreement on climate change were more likely to believe that climate change was happening and to support public action (Ding et al., 2011; McCright et al., 2013). Building on this, researchers investigated whether scientific consensus messages could cultivate belief in scientific agreement and support for experts' positions (van der Linden, Clarke, et al., 2015a; van der Linden, Leiserowitz, et al., 2015b). Scientific consensus messages (e.g., "97% of climate scientists agree") have repeatedly been shown to affect people's estimates of the level of scientific agreement (e.g., Chinn et al., 2018; van der Linden, Leiserowitz, et al., 2019). In turn, these agreement estimates are positively associated with holding personal beliefs and policy attitudes in line with scientific positions (e.g., Chinn et al., 2018; Ding et al., 2011; van der Linden, Leiserowitz, et al., 2019). For these reasons, van der Linden et al. (2015a) have argued that scientific agreement estimates act as a "gateway belief" for holding scientifically supported positions. Through agreement estimates, consensus messages have positive, indirect effects on personal beliefs, worry about climate change, and support for public action (van der Linden, Leiserowitz, et al., 2015b, 2019).

Inconsistent Findings Concerning Political Skeptics

However, there remains debate about the efficacy of consensus messages at persuading political skeptics. Proponents argue that consensus messages can overcome political polarization on climate change, even claiming that they may be more impactful among conservatives than liberals. A good deal of work has found that consensus messages affect liberals and conservatives similarly; liberals and conservatives shift their agreement estimates by similar amounts in reaction to a consensus message (Deryugina & Shurchkov, 2016; Goldberg, van der Linden, Ballew, Rosenthal, & Leiserowitz, 2019;

Goldberg, van der Linden, Ballew, Rosenthal, Gustafson, et al., 2019; van der Linden, Clarke, et al., 2015b; van der Linden et al., 2016). A few studies found that consensus messages about climate change were more impactful on the agreement estimates of conservatives' (van der Linden, Leiserowitz, et al., 2015b) or those with strong free market beliefs (in Australia) (Lewandowsky et al., 2012). Initial research was therefore optimistic that consensus messages could be an effective tool for reducing political polarization around climate change in the United States because they led partisans across the political spectrum to acknowledge scientific agreement on climate change, and thus update their personal attitudes.

However, other work encourages caution. A substantial body work has failed to find a that consensus messages can overcome politically motivated skepticism. Motivated reasoning is a central challenge to persuading the public to adopt scientists' views; individuals may resist accepting scientists' claims if doing so requires going against the positions of one's social group or updating one's prior beliefs (Bolsen & Druckman, 2018; Kahan et al., 2011). A number of studies have found that consensus messages only influence those who are predisposed to believe scientists (Bolsen & Druckman, 2018; Dixon, 2016; Dixon et al., 2017). Even studies that find consensus messages moderate negative effects of free market beliefs on climate attitudes in other parts of the world do not find such an effect among a U.S. sample (Cook & Lewandowsky, 2016). Additionally, there are concerns that consensus messages may not only fail to persuade skeptics, but they may backfire (Bolsen & Druckman, 2018; Cook & Lewandowsky, 2016) or cause reactance, as conservatives may consider such messages to be manipulative (Dixon et al., 2019; Dixon & Hubner, 2018; Ma et al., 2019; van der

Linden, Maibach, et al., 2019). In sum, there are reasons to be skeptical about the efficacy of consensus messages at persuading political skeptics to hold expert supported positions on politically divisive issues.

Moderation Inconsistencies

Compounding the confusion from these inconsistent findings, there has not been a clear theoretical argument concerning what associations between consensus messages, agreement estimates, and attitudinal outcomes we would expect political ideology to moderate. Work that asserts the efficacy of agreement estimates as a gateway belief has generally focused on how ideology moderates the effect of consensus messages on agreement estimates, assuming that downstream effects of agreement estimates on outcomes will be unmoderated by ideology (van der Linden, Leiserowitz, et al., 2015b, 2019). In contrast, work that casts doubt on the efficacy of consensus messaging has sought to demonstrate that even if skeptics acknowledge similar levels of scientific agreement they may not be similarly swayed to hold expert supported positions—that is, that factors like ideology could moderate the association between agreement estimates and outcomes (Dixon, 2016). Without clear theoretical direction of where to expect moderation, some studies have tested whether ideology moderates the effect of consensus messages on agreement estimates (Goldberg, van der Linden, Ballew, Rosenthal, Gustafson, et al., 2019; Goldberg, van der Linden, Ballew, Rosenthal, & Leiserowitz, 2019; Myers et al., 2015; van der Linden, Leiserowitz, et al., 2015b). Others have tested effects of moderators on the association between agreement estimates and personal attitudes (Dixon, 2016). A small number of studies have looked at how political attitudes moderate both of these associations (Cook & Lewandowsky, 2016), and yet others have looked at how the direct effects of consensus messages on personal attitudes are moderated by political attitudes (Lewandowsky et al., 2012; van der Linden, Clarke, et al., 2015b). In sum, previous studies have tested moderation of some or all hypothesized associations, often yielding inconsistent results.

Previous Explanations for Inconsistent Findings

To date, work has largely focused on how differences in stimuli may explain previous results. Studies exploring effects of numerical stimuli have produced inconsistent results concerning skeptics (Cook et al., 2017; Cook & Lewandowsky, 2016; Deryugina & Shurchkov, 2016; Dixon, 2016; Dixon et al., 2017; Lewandowsky et al., 2012; van der Linden, Leiserowitz, et al., 2015b; van der Linden et al., 2016). However, those investigating qualitative stimuli (e.g., "most scientists believe," (Dixon & Hubner, 2018) or mere mentions of consensus (Bolsen & Druckman, 2018) suggest that partisans are not influenced by consensus messages. Additionally, we have not seen differences between visual and textual stimuli (van der Linden, Leiserowitz, et al., 2015b).

However, other work has raised the point that analytical decisions may be in part to blame for apparently inconsistent findings. Kahan's (2017) reanalysis of van der Linden et al.'s (2015a) study shows that despite the authors' claims that their findings supported the efficacy of consensus messages, they failed to report that there were no significant mean differences in climate attitudes between control and treatment conditions. Kahan (2017) argued that the lack of treatment differences, "was obscured by the authors' use of a misspecified structural equation model" (p. 17). The respective authors have also debated the appropriate sample size to observe small effects while maintaining responsible research practices (Kahan, 2017; van der Linden, Leiserowitz, et al., 2017).

The Decision to Pretest

There is another methodological factor that may be affecting consensus messaging research: the decision to pretest climate attitude measures. Studies claiming that consensus messages reduce attitude polarization regularly pretest central outcomes (van der Linden, Leiserowitz, et al., 2015b, 2019), while studies that fail to find a similar effect typically do not employ a pretest (Cook & Lewandowsky, 2016; Dixon, 2016; Dixon et al., 2017). Work by Myers et al. (2015) suggests that asking respondents to estimate agreement before revealing the consensus level is more effective at shifting climate attitudes than merely exposing participants to a consensus message. Though they found that effects in neither the pre-/post-test condition nor the post-test only condition were moderated by political ideology, they did find that estimates were elevated in the pre-/post-test control condition. That is, participants who estimated agreement on climate change twice reported higher estimates the second time, even when they had not seen a consensus message. Van der Linden et al. (2015a) find similar differences between respondents pre- and post-test responses, even in control conditions.

Work by van der Linden et al. (van der Linden, Leiserowitz, et al., 2015b, 2019) among others, claim that using pre-/post-test designs increases the statistical power of their studies by leveraging a within- and between-subjects design. These studies often use pre-/post-test differences as outcomes their analyses. One study where the authors found similar effects among conservatives and liberals using a post-test only design is van der Linden, Leiserowitz, et al. (2015a) on vaccination, rather than climate change. Studies using this pre-/post-test design are responsible for the bulk of the evidence arguing that consensus messages equally or more positively affect the attitudes of skeptics, compared to non-skeptics (see Table IV.1).

However, studies that do not pretest central outcomes rarely find evidence that consensus messages have similar effects among skeptics and non-skeptics. Studies that use post-test only designs often find that skeptics are more weakly affected by the consensus message than non-skeptics (Dixon, 2016; Dixon et al., 2017) or that they backfire among skeptics (Bolsen & Druckman, 2018; Cook & Lewandowsky, 2016; Dixon & Hubner, 2018). That said, Ma et al. (2019) do find that consensus messages cause reactance even when using a pre-/post-test design. In sum, the majority of studies that provide evidence that consensus messages may not be effective among skeptics use a post-test only design (See Table IV.1). This is important to consider because the post-test only design more closely approximates real-world strategic messaging flows, meaning findings from such studies may be more generalizable.

Table IV.1: Study Design and Findings of Prior Experimental Research Examining Moderating Influence on the Effects of Consensus Messages with U.S. Samples.

	Pre-/Post-Test Experimental Design	**Post-Test Only** Experimental Design
Consensus message effect **IS** moderated, such that the consensus message <u>positively affects skeptics' attitudes more than non-skeptics'</u> attitudes.	Lewandowsky et al. (2012) *climate change, free market beliefs (Australian sample)* Van der Linden et al. (2015) *climate change, prior beliefs* Van der Linden et al. (2019) *climate change, political ideology*	
Consensus message effect **IS NOT** moderated. The consensus message affects <u>all individuals similarly</u>.	Lewandowsky et al. (2012) *climate change, free market beliefs (U.S. sample)* Van der Linden et al. (2015) *climate change, political ideology* Van der Linden et al. (2016) *climate change, political ideology* Deryugina & Shurchov (2016) *climate change, political ideology* Goldberg et al. (2019a) *climate change, political ideology* Goldberg et al. (2019b) *climate change, political ideology*	Van der Linden et al. (2015) *vaccines, political ideology*
Consensus message effect **IS** moderated, such that the consensus message <u>does not affect skeptics' attitudes as strongly as non-skeptics'</u> attitudes OR causes <u>backfire effects</u> among skeptical individuals.	Ma et al. (2019) *Climate change, reactance*	Dixon (2016) *GMOs, prior beliefs* Cook & Lewandowsky (2016) *climate change, free market beliefs (U.S. sample)* Dixon et al. (2017) *climate change, political ideology* Bolsen & Druckman (2018) *climate change, partisanship & knowledge* Dixon & Hubner (2018) *climate change & nuclear power, political ideology*

Note: Below each study in italics are the substantive topics the studies engaged with, followed by the moderator interacted with exposure to a consensus message.

Mechanisms Driving Pretest Effects

If the decision to pretest or not affects outcomes, it behooves us to understand why. Despite the presence of distractor tasks in some (van der Linden, Leiserowitz, et al., 2015b, 2019) but not all (Goldberg, van der Linden, Ballew, Rosenthal, Gustafson, et al., 2019; Goldberg, van der Linden, Ballew, Rosenthal, & Leiserowitz, 2019) work that uses a pre-/post-test design, the inclusion of a pretest measuring consensus estimates could affect reported attitudes in ways that appear to attenuate skepticism by several mechanisms. For one or more of the following reasons, differences in the findings of pre-/post-test and post-test only studies could be driven by artefacts of study design. First, an interaction between exposure to a pretest and the manipulation could sensitize participants to be more attentive to consensus information in the stimuli, which could result in more accurate recall (Campbell, 1957; Campbell & Stanley, 1963; Nosanchuk et al., 1972) and elevated outcomes (Willson & Putnam, 1982).

The second mechanism concerns availability or salience. Consensus may come to mind quickly when responding to post-exposure outcomes because consensus was highlighted repeatedly in the survey. Additionally, having seen the items earlier in the survey, participants' attitudes concerning climate change may be more top of mind. A pretest may make the consensus information more salient when reporting attitudes where it may not have been as important a consideration to respondents in the absence of the pretest (Brossard, 2010; Chong & Druckman, 2007; Schwarz, 1999; Tourangeau et al., 2000). This could affect the respondents' response speed in the post-test (Tourangeau et al., 2000). If this were the case, we may expect the time that respondents take to respond to outcomes to differ based on study design. Additionally, if we ask respondents about what informs their beliefs on climate change, we may expect that those in pre-/post-test conditions will more often report that scientists or scientific agreement informs their attitudes than those in post-test only conditions.

Finally, a pre-/post-test design risks exposing the aim of the study to the participant by signaling outcomes of interest (Hauser et al., 2018; Parrot & Hertel, 1999) and providing contextual information for respondents to infer what a "good" participant will look like (Nosanchuk et al., 1972), causing respondents to modify their responses in later measures. To test this possibility, we expect that individuals in pre-/post-test conditions will more frequently report that the survey is about climate change, despite the inclusion of other distractor tasks, than those in post-test only designs.

Hypotheses and Research Questions

Based on the findings of the previous research discussed above, we have the following expectations:

> **H1**: Exposure to a consensus message (97% of climate scientists agree) will result in a higher estimate of scientific agreement on climate change.
>
> **H2**: Exposure to a consensus message (97% of climate scientists agree) will result in greater **(a)** belief in global warming, **(b)** belief in human causation, **(c)** worry and concern about climate change, **(d)** support for public action, and **(e)** support for government action.
>
> **H3**: Higher agreement estimates will be positively associated with **(a)** belief in global warming, **(b)** belief in human causation, **(c)** worry and concern about climate change, **(d)** support for public action, and **(e)** support for government action.
>
> **H4**: Effects of consensus messages on **(a)** belief in global warming, **(b)** belief in human causation, **(c)** worry and concern about climate change, **(d)** support for public action, and **(e)** support for government action will be mediated through agreement estimates.

Concerning the effects of including a pretest, we test the following hypotheses concerning the effects of study design drawn from the research discussed above:

> **H5**: Among those participants who see a consensus message, those in the pre-/post-test condition will report a higher estimate of scientific agreement on climate change than those in the post-test only condition.
>
> **H6**: Among those participants who see a consensus message, those in the pre-/post-test condition will report greater **(a)** belief in global warming, **(b)** belief in human causation, **(c)** worry and concern about climate change, **(d)** support for public action, and **(e)** support for government action than those in the post-test only condition.
>
> **H7**: Conservatives' agreement estimates and climate attitudes will be more positively affected by a consensus message in the pre-/post-test condition than in the post-test only condition.
>
> **H8**: Those in pre-/post-test conditions will respond to the post-exposure mediator and outcome measures at a faster rate than those in post-test only conditions.
>
> **H9**: Those in pre-/post-test conditions will more frequently identify scientific agreement as informing their climate change attitudes, compared to those in post-test only conditions.
>
> **H10**: Those in pre-/post-test conditions will more frequently identify climate change as the topic of the survey, compared to those in post-test only conditions.

Given the inconsistent findings and lack of theoretical guidance as to how we might expect political ideology to moderate associations, we propose the following three research questions:

> **RQ1**: How does political ideology moderate the effect of exposure to a consensus message on estimates of scientific agreement?
>
> **RQ2**: How does political ideology moderate the effect of exposure to a consensus message on **(a)** belief in global warming, **(b)** belief in human causation, **(c)** worry and concern about climate change, **(d)** support for public action, and **(e)** support for government action?
>
> **RQ3**: How does political ideology moderate the effect of agreement estimates on **(a)** belief in global warming, **(b)** belief in human causation, **(c)** worry and concern about climate change, **(d)** support for public action, and **(e)** support for government action?

The Present Study

This study investigates how consensus messages affect the agreement estimates and climate attitudes of liberals and conservatives. In answering this, it improves our understanding of whether consensus messages are effective at building support for expert supported positions in politically divisive issue contexts. Second, it tests whether inconsistent findings about the efficacy of consensus message are an artefact the choice to pretest outcomes and, if so, why including a pretest may lead to more positive effects. Particularly because consensus messaging strategies are already being employed concerning politically divisive science (@BarackObama, 2013; NASA, 2018; *The Consensus Project*, n.d.), it is vital to understand when these messages are effective and whether they have the potential to backfire. In doing so, this study responds to ongoing debate concerning the relative strength of scientific information and partisan cues (Kahan & Carpenter, 2017; van der Linden, Maibach, et al., 2017) by elucidating the conditions under which a scientific consensus on a politicized issue may or may not reduce polarization.

Methods

Data

The data for this study were collected from Lucid Theorem, a diverse national online panel, between March 27 and March 30, 2020. After removing participants who did not complete the survey because they failed to pass simple attention checks, the sample included 1,999 respondents. In our sample, 48.2% self-identified as men (N = 964) and 51.7% as women (N = 1034). Five participants who reported their gender as "other" were removed from the sample because the size of this group was too small to allow for meaningful comparison to other groups.[6] 71.3% of respondents identified as White, followed by 12.1% as Black or African American, 8.2% as Hispanic, 5.1% as Asian, and 3.4% as other racial groups. Age was measured on an 8-point scale from "18-24" to "85 or older," with the median response being "35-44" (*Mean (M)* = 3.55, *Standard Deviation (SD)* = 1.67). Education was also measured on an 8-point scale from "Less than high school diploma" to "Doctorate (e.g. PhD)," with the median response being "Some college, no degree" (*M* = 3.73, *SD* = 1.52). Finally, yearly household income was measured on a 7-point scale from "Less than $20,000" to "over $150,000," with the median response being "$35,000 to $49,999" (*M* = 3.38, *SD* = 1.76).

Design

This online experiment is a two by two design, crossing the treatment (exposure to a consensus message or not) and the study design (pre-/post-test or post-test only). This results in four conditions: a pre-/post-test treatment condition (TPP, *n* = 485), in which participants responded to a battery of climate attitude measures before and after reading a consensus message; a pre-/post-test control condition (CPP, *n* = 497), in which participants responded to climate attitude measures twice but do not see a consensus message; a post-test only treatment condition (TPO, *n* = 551), in which participants only responded to climate attitude measures after reading a consensus message; and finally, a post-test only control condition (CPO, *n* = 465), in which respondents do not see a consensus message and only responded to climate attitude measures once. The remainder

[6] Our intention was not to exclude individuals who selected "other" for their gender from our study but rather to ensure that any comparisons between gender identity groups had enough statistical power to be meaningfully interpreted. Results from analyses run with and without these respondents did not differ.

of this chapter refers to experimental conditions by these acronyms; the “T” or “C” indicates whether it is a “treatment” or “control” condition—that is, whether or not participants in these conditions saw a consensus message—while the “PP” refers to pre-/post-test conditions and “PO” refers to post-test only conditions.

Procedure

After consenting to participate, participants were told that they were taking a public opinion survey about popular topics and would see questions about several different topics. The first set of measures asked participants about (a) social media use; (b) travel; and, for those in the pre-/post-test conditions (TPP and CPP), (c) the climate change pretest measures. The climate change pretest consisted of the consensus estimate and climate attitude measures (described below). These question blocks were presented in random order. As in previous studies including a pretest (van der Linden, Leiserowitz, et al., 2019), presenting the pretest with other question blocks about popular topics was intended to obscure the purpose of the study and to create space between the identical pretest and posttest questions. Respondents in post-test only conditions (TPO and CPO) only responded to the social media use and travel questions, presented in random order, to ensure that participants in different conditions had similar levels of fatigue and to control for any inadvertent effects the distractor questions may have had.

Second, participants in the treatment conditions (TPO and TPP) were exposed to the consensus message. Participants in treatment conditions (TPO and TPP) were told that the researchers keep a large database of media messages and that they would be randomly shown one of these messages. This prompt has been widely used in past work on consensus messages (Goldberg, van der Linden, Ballew, Rosenthal, Gustafson, et al., 2019; Goldberg, van der Linden, Ballew, Rosenthal, & Leiserowitz, 2019; van der Linden, Leiserowitz, et al., 2015b, 2019). All participants in the treatment conditions saw a short message which read: “Did you know? 97% of climate scientists have concluded that human-caused climate change is happening” (Dixon et al., 2017). We then asked participants in the treatment conditions to identify whether they had seen a message about the environment, crime, or movies, as a manipulation check.

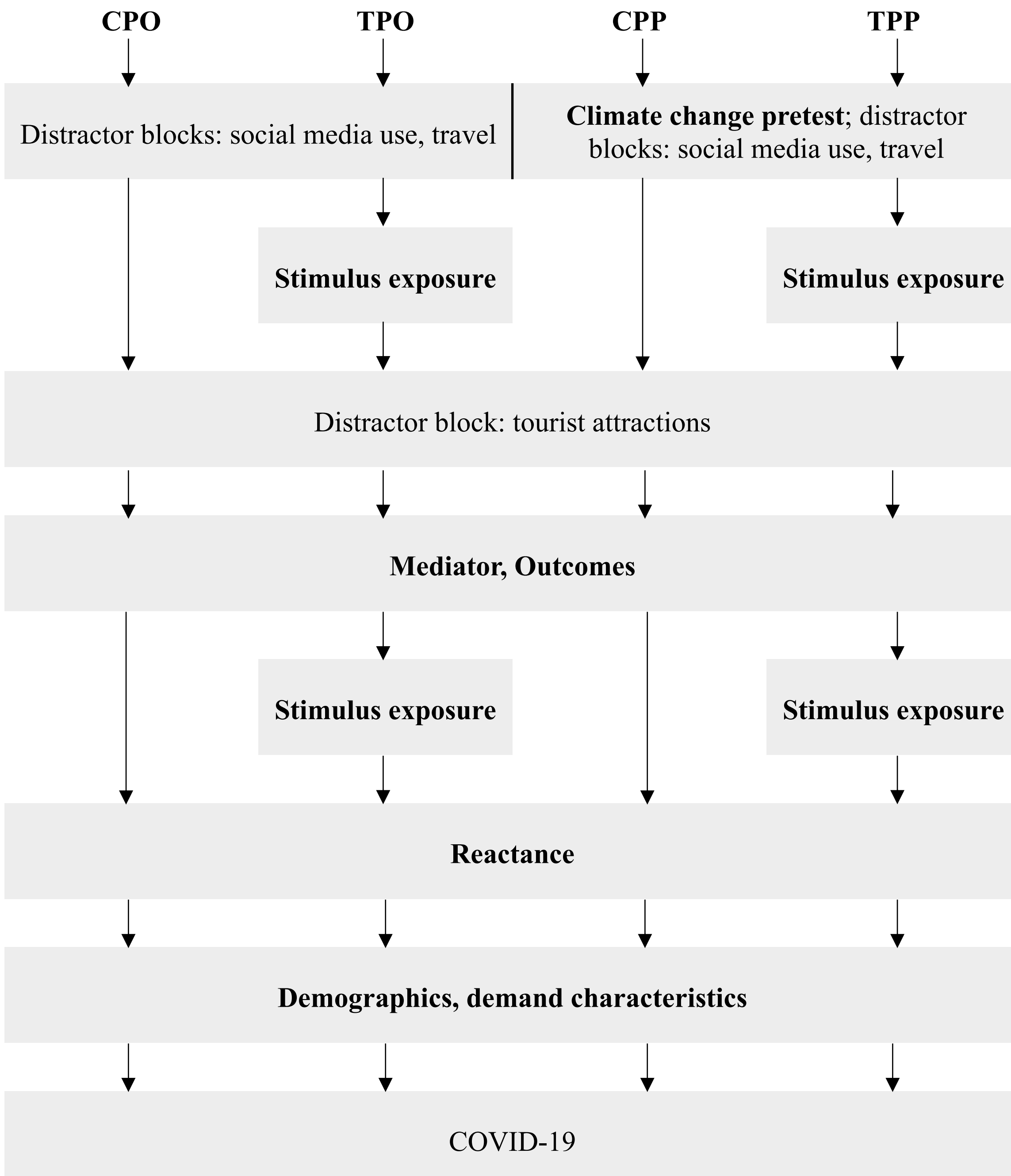
Third, all participants completed a distractor block in which they identified what images of different cities most made them want to visit those cities. As in past studies (van der Linden, Leiserowitz, et al., 2015b, 2019), this was designed to create space between the stimulus and outcome measures.

Fourth, all participants estimated the level of scientific consensus on climate change (mediator) and responded to climate attitude measures (outcomes).

Finally, all participants responded to an open text question about what informed their views on climate change, demographics, and an open-text question asking what they thought the study was about. Given that data was collected in March of 2020, we also asked all participants two questions about their concern about COVID-19.[7] Figure IV.1 visually depicts the procedure, showing the order of question blocks seen by respondents in each condition.

[7] Though not a part of the analyses presented here, all participants also responded to measures about reactance after responding to questions about their climate attitudes and what informs their beliefs on climate change, but before responding to the question asking the what the survey was about. During the reactance measures, those in the treatment conditions saw the consensus message for a second time.

Figure IV.1: Study Procedure



Measures

Moderator

Political ideology was measured on a 7-point scale from "Very liberal" (1) to "Very conservative" (7) (*Mean (M)* = 3.95, *Standard Deviation (SD)* = 1.70).

Mediator

Agreement estimate was measured by asking participants, "To the best of your knowledge, what percent (%) of climate scientists say that human activity is causing climate change? (0 - 100)" (*M* = 77.12, *SD* = 25.62) (Goldberg, van der Linden, Ballew, Rosenthal, Gustafson, et al., 2019; Goldberg, van der Linden, Ballew, Rosenthal, & Leiserowitz, 2019; van der Linden et al., 2016; van der Linden, Leiserowitz, et al., 2015b, 2019).

Outcomes

Belief in climate change was measured by asking respondents, "How strongly do you believe that climate change is or is not happening?" (van der Linden et al., 2016; van der Linden, Leiserowitz, et al., 2015b, 2019). Respondents reported their beliefs on a 5-point scale from "I strongly believe that climate change IS NOT happening" (1) to "I strongly believe that climate change IS happening" (5). The scale mid-point was, "I do not know whether climate change is or is not happening" (3) (*M* = 4.14, *SD* = 1.12).

Belief in human causation was measured by asking respondents, "Assuming climate change IS happening, to what extent do you think climate change is human-induced as opposed to a result of Earth's natural changes?" (van der Linden et al., 2016; van der Linden, Leiserowitz, et al., 2015b, 2019). Participants reported their beliefs on a 5-point scale from "Climate change is completely caused by natural changes" (1) to

"Climate change is completely caused by human activity" (5). The scale mid-point was, "Climate change is equally caused by human activity and natural changes" (3) ($M = 3.42$, $SD = 1.12$).

Worry was measured by asking participants, "How worried are you about climate change?" (van der Linden et al., 2016; van der Linden, Leiserowitz, et al., 2015b, 2019). Responses were captured on a 5-point scale from "Not at all worried" (1) to "Extremely worried" (5). We also asked, "How concerned are you about climate change?" Responses were captured on a 5-point scale from "Not at all concerned" (1) to "Extremely concerned" (5). These measures of worry and concern about climate change were averaged to create a measure of *worry and concern* ($M = 3.35$, $SD = 1.33$, $r = .92$, $p < .001$).

Support for public action was measured with the question, "What do you think of peoples' efforts to address climate change? Do you think that people should be putting more, less, or about the same amount of effort toward addressing climate change?" (van der Linden et al., 2016; van der Linden, Leiserowitz, et al., 2015b, 2019). Participants responded on a 5-point scale from "People should put MUCH LESS effort toward addressing climate change" (1) to "People should put MUCH MORE effort toward addressing climate change" (5). The scale mid-point was, "People should do what they have been doing to address climate change" (3) ($M = 4.08$, $SD = 1.16$).

Finally, we asked participants about their *support for government action* with the question, "How strongly do you support or oppose government action to address climate change?" Responses were recorded on a 7-point scale from "Strongly support" (1) to "Strongly oppose (7). The scale mid-point was, "Neither support nor oppose" (4) ($M =$

5.26, $SD = 1.74$).

Mechanisms

The time participants take to respond to post-exposure outcomes (*response time*) was captured non-invasively. *Response time* captured how long respondents took to respond to the mediator and outcome variables listed above, in seconds ($M = 76.99$, $SD = 99.25$, min = 11.24, max = 2,311.47 (38.52 minutes)).

Additionally, participants were asked to write about what they think informs or influences their attitudes on climate change in an open-text box, as well as what participants thought was the topic of the study. Concerning *salience*, we were interested in how often respondents reported that scientists, experts, or scientific consensus influenced their attitudes on climate change (*salience,* $M = .09$, $SD = .28$). For demand characteristics, we were interested in whether respondents were aware that the survey was about climate change (*demand characteristics,* $M = .52$, $SD = .50$). These open-text responses were dummy coded as containing or not containing the language of interest with simple dictionaries. Because survey respondents, who may have been on mobile devices or moving quickly through the survey, often misspelled words, I used fuzzy matching, which counted keyword mentions in responses even when these words were did not exactly match the spelling of a dictionary keyword. In a sample of 200 responses from each question, the dictionaries were highly correlated with my own human coding ($r_{\text{salience}} = .92$, $p < .001$; $r_{\text{demand characteristics}} = .92$, $p < .001$). Further discussion of how I coded the open-text responses is in Appendix C.

COVID-19

These data were collected while many U.S. states were under stay at home orders due to COVID-19. To control for differences in risk perceptions that COVID-19 may be causing, we asked participants two questions about their COVID-19 concern, including "How worried are you about the coronavirus (COVID-19)?" and "Overall, how much of a threat is posed by the coronavirus (COVID-19)?" Responses to both questions were coded on a 5-point scale, with low responses indicating no worry or threat (1) and high responses indicating extreme worry and threat (5). These measures were averaged into a scale of *COVID-19 concern* ($M = 3.91$, $SD = 1.02$, $r = .73$, $p < .001$).

Results

Random Assignment

While conditions did not differ with respect to income ($p = .33$), conditions did differ with respect to gender (chi-squared = 9.22, $p = .03$) and age $F(3, 1993) = 2.65$, $p = .048$. Differences between conditions with respect to education were also marginally significant $F(3, 1994) = 2.33$, $p = .072$. Therefore, despite random assignment to experimental conditions, the analyses presented below control for gender, age, and education, as well as concern about COVID-19.[8] Analyses run without these controls follow a very similar pattern of results.

Direct Effects

I first turn to the effects of experimental conditions on the mediator and outcome variables. I ran a series of OLS regressions with experimental condition and political ideology as predictors, as well as gender, age, education, and concern about COVID-19. For these OLS regressions, the CPO condition (control, post-test only) is used as the comparison group. This condition is less likely than the CPP (control, pre-/post-test) to

[8] Though concern about COVID-19 did not differ by condition ($p = .790$), I was curious about the associations between concern about COVID-19 and climate attitudes, and so included it as a control in these models. Results from analyses run with and without concern for COVID-19 as a control do not differ.

influence participants' responses in any way, and thus it is used as a baseline in these analyses. However, I also looked at pairwise comparisons between all experimental conditions with post-hoc Tukey tests. I therefore note explicitly in the results that follow which control condition is being used as the comparison group and when we are making comparisons between the two treatment conditions. Results from OLS regressions can be found in Tables IV.3 and IV.4, while descriptive means for each outcome by condition and significant differences between conditions can be found in Table IV.2.

Table IV.2: Outcomes by Experimental Condition

	CPO	**CPP**	**TPO**	**TPP**
Consensus Estimate (0-100)	67.28 (25.17)a	67.66 (25.91)a	84.03 (22.80)b	88.57 (20.25)c
Belief in Global Warming (1-5)	4.14 (1.10)a	4.03 (1.20)ab	4.19 (1.11)ac	4.21 (1.08)ac
Belief in Human Causation (1-5)	3.36 (1.10)a	3.32 (1.12)a	3.44 (1.12)ac	3.57 (1.13)bc
Worry and Concern (1-5)	3.28 (1.31)a	3.34 (1.35)a	3.33 (1.30)a	3.45 (1.33)a
Support for Public Action (1-5)	4.03 (1.15)a	4.04 (1.19)a	4.1 (1.17)a	4.15 (1.13)a
Support for Government Action (1-7)	5.12 (1.73)a	5.3 (1.72)a	5.29 (1.75)a	5.36 (1.76)a
Response Time, to above measures (in seconds)	95.64 (115.58)a	54.29 (43.31)b	93.36 (129.80)a	63.78 (73.66)b

Note: Descriptive condition means reported with standard deviations in parentheses. Means within the same row with different subscripts were found significantly different at p<.05 using a Tukey test.

Mediator

Agreement estimates were significantly affected by exposure to a consensus message, evidenced by significant effects in the OLS regression on agreement estimates for both the TPO (v. CPO) (unstandardized $\beta = 16.67$, $p < .001$) and TPP (v. CPO) ($\beta = 21.03$, $p < .001$) conditions. When looking at all condition differences with post-hoc Tukey tests (Table IV.2), we observe that consensus estimates were higher in the TPP condition (descriptive condition mean (*M)* = 88.57, standard deviation (*SD)* = 20.25) than all other conditions (all *ps* < .011). Consensus estimates were higher in the TPO condition (*M* = 84.03, *SD* = 22.80) than the CPP (*M* = 67.66, *SD* = 25.17) or CPO conditions (*M* = 67.28, *SD* = 25.17) (all *ps* < .001). However, consensus estimates did not significantly differ between the CPP and CPO conditions (*p* = .993). Thus, we find support for both H1, that exposure to consensus messages elevates agreement estimates, and for H5, that among participants who saw the consensus message, estimates are higher in the pre-/post-test condition than in the post-test only condition.

Consensus estimates were also significantly and negatively associated with political ideology (unstandardized β = -2.05, *p* < .001), such that conservatives were more likely to estimate agreement at lower levels than liberals.

Outcomes

Belief in global warming. Belief in global warming appeared to not be affected by exposure to a consensus message. In results of the OLS regression, the only significant association we see is between the CPP (v. CPO) condition and belief in global warming (B = -.14, *p* < .05), such that the CPP condition appears to be associated with less accurate beliefs about whether global warming is happening compared to the CPO condition. However, looking at the results of the post-hoc Tukey tests, which includes a correction for multiple tests, a slightly different pattern emerges. We see significant differences between the CPP (*M* = 4.03, *SD* = 1.20) and TPP conditions (*M* = 4.21, *SD* = 1.08, *p* = .016), as well as the CPP and TPO conditions (*M* = 4.19, *SD* = 1.11, *p* = .048). However, we do not see any differences between the two treatment conditions (TPP and TPO, *p* = .967) or between the CPO condition (*M* = 4.14, *SD* = 1.10) and any other condition, including the CPP condition (all *ps* > .243). Thus, H2a is partially supported, and H6a is unsupported.

In addition, belief in global warming was significantly and negatively associated with political ideology (β = -.18, $p < .001$), such that conservatives were more likely to report that global warming was not happening than liberals.

Belief in human causation. Using OLS regression we observed one significant association between experimental condition and belief in human causation in the TPP (v. CPO) condition (β = .20, $p < .001$). When we look at all condition differences with post-hoc Tukey tests (Table IV.2), we see that the TPP condition ($M = 3.57$, $SD = 1.13$) is significantly different from the CPP ($M = 3.32$, $SD = 1.12$, $p < .001$) as well as the CPO ($M = 3.36$, $SD = 1.10$, $p = .008$) conditions. There are no differences between the two control conditions (CPP and CPO, $p = .934$), between the two treatment conditions (TPP and TPO, $p = .115$), or between the TPO condition ($M = 3.33$, $SD = 1.30$) and either control condition (*ps* > .319). H2b is partially supported, and H6b is unsupported.

Belief in human causation was also significantly and negatively associated with political ideology (β = -.17, $p < .001$), such that conservatives were more likely to say that global warming was not caused by human activity than liberals.

Worry and concern. In the OLS regression, we observed one significant effect of experimental condition and worry and concern about climate change in the TPP (v. CPO) condition (β = .14, $p < .05$). However, in the post-hoc Tukey tests, this difference between the TPP and CPO conditions is not significant at the p < .05 level. In fact, the Tukey tests reveal no significant differences in worry and concern by experimental condition. Thus, H2c and H6c are unsupported.

Worry and concern was, however, associated with political ideology ($\beta = -.23$, $p < .001$), such that conservatives reported being less worried and concerned about climate change than liberals.

Support for public action. Support for public action on climate change was not significantly affected by experimental condition in either the results of the OLS regression or post-hoc Tukey tests (H2d and H6d are unsupported). However, political ideology was significantly and negatively associated with support for public action ($\beta = -.20$, $p < .001$), such that conservatives were less supportive of public action on climate change than liberals.

Support for government action. In the OLS regression, I observed one significant effect of experimental condition and support for government action: the TPP (v. CPO) condition was positively associated support for government action ($\beta = .22$, $p < .05$). However, the results of the post-hoc Tukey tests do not find this association to be significant at the $p < .05$ level. The results of the Tukey tests suggest that there are no significant differences between experimental conditions on support for government action (H2e and H6e are unsupported).

However, political ideology was significantly and negatively associated with support for government action ($\beta = -.26$, $p < .001$), such that conservatives were less supportive of government action than liberals.

Table IV.3: Main and Interactive Effects of Experimental Condition and Political Ideology on Mediator, Outcomes (1/2)

	Consensus Estimate				Belief in Climate Change				Belief in Human Causation			
CPP (v. CPO)	.10	(1.51)	-5.60	(3.82)	-.14 **	(.07)	-.32 *	(.16)	-.05	(.07)	-.16	(.17)
TPO (v. CPO)	16.67 ***	(1.47)	3.80	(3.72)	.03	(.06)	-.11	(.16)	.06	(.07)	-.08	(.16)
TPP (v. CPO)	21.03 ***	(1.51)	2.95	(3.84)	.04	(.07)	-.06	(.17)	.20 ***	(.07)	.13	(.17)
Political Ideology	-2.05 ***	(.32)	-4.46 ***	(.65)	-.18 ***	(.01)	-2.12 ***	(.03)	-.17 ***	(.01)	-.19 ***	(.03)
Gender	.44	(1.06)	.32	(1.06)	.02	(.05)	.02	(.05)	.06	(.05)	.06	(.05)
Age	.26	(3.18)	.26	(.32)	.01	(.01)	.01	(.01)	-.04 ***	(.01)	-.04 ***	(.01)
Education	.94 ***	(.35)	.80 **	(.35)	.01	(.02)	.01	(.02)	.01	(.02)	.01	(.02)
COVID-19 Concern	2.79 ***	(.53)	2.90 ***	(.53)	.34 ***	(.02)	.34 ***	(.02)	.26 ***	(.02)	.27 ***	(.02)
Interactions												
CPP (v. CPO) x Political Ideology			1.47 *	(.89)			.05	(.04)			.03	(.04)
TPO (v. CPO) x Political Ideology			3.28 ***	(.87)			.04	(.04)			.03	(.04)
TPP (v. CPO) x Political Ideology			4.62 ***	(.90)			.03	(.04)			.02	(.04)
Constant	59.47 ***	(3.49)	69.20 ***	(4.11)	3.43 ***	(.15)	3.53 ***	(.18)	3.02 ***	(.15)	3.10 ***	(.18)
Observations	1,998		1,988		1,995		1,995		1,995		1,995	
Adjusted R^2	.18		.19		.21		.21		.17		.17	
Residual Standard Error	23.234 (df = 1979)		23.073 (df = 1976)		0.997 (df = 1986)		0.997 (df = 1983)		1.022 (df = 1986)		1.022 (df = 1983)	
F Statistic	54.764*** (df = 8; 1979)		43.189*** (df = 11; 1976)		68.784*** (df = 8; 1986)		50.128*** (df = 11; 1983)		50.484*** (df = 8; 1986)		36.756*** (df = 11; 1983)	

Note: *p<0.1; **p<0.05; ***p<0.01

Table IV.4: Main and Interactive Effects of Experimental Condition and Political Ideology on Mediator, Outcomes (2/2)

	Worry and Concern				Support for Public Action				Support for Government Action			
CPP (v. CPO)	.03	(.07)	-.08	(.17)	.00	(.07)	.00	(.17)	.16	(.10)	.20	(.26)
TPO (v. CPO)	.02	(.07)	-.22	(.17)	.06	(.07)	.02	(.17)	.17	(.10)	.39	(.26)
TPP (v. CPO)	.14 **	(.07)	-.01	(.18)	.11	(.07)	-.06	(.17)	.22 **	(.10)	.28	(.27)
Political Ideology	-.23 ***	(.01)	-.26 ***	(.03)	-.20 ***	(.01)	-.21 ***	(.03)	-.26 ***	(.02)	-.24 ***	(.05)
Gender	.07	(.05)	.07	(.05)	.12 ***	(.05)	-.12 **	(.05)	-.02	(.07)	-.03	(.07)
Age	-.05 ***	(.02)	-.05 ***	(.01)	-.04 **	(.01)	-.04 **	(.01)	-.02	(.02)	-.02	(.02)
Education	.04 ***	(.02)	.04 ***	(.02)	-.03	(.02)	-.03 *	(.02)	.01	(.02)	.01	(.02)
COVID-19 Concern	.59 ***	(.02)	.59 ***	(.02)	.33 ***	(.02)	.33 ***	(.02)	.43 ***	(.04)	.43 ***	(.04)
Interactions												
CPP (v. CPO) x Political Ideology			.03	(.04)			.00	(.04)			-.01	(.06)
TPO (v. CPO) x Political Ideology			.06	(.04)			.01	(.04)			-.06	(.06)
TPP (v. CPO) x Political Ideology			.04	(.04)			.04	(.04)			-.02	(.06)
Constant	1.83 ***	(.16)	1.95 ***	(.19)	3.56 ***	(.15)	3.17 ***	(.18)	4.53 ***	(.24)	4.45 ***	(.29)
Observations	1995		1,995		1994		1,994		1,994		1,994	
Adjusted R^2	0.369		.37		0.218		.22		.16		.16	
Residual Standard Error	1.052 (df = 1986)		1.052 (df = 1983)		1.027 (df = 1985)		1.027 (df = 1982)		1.600 (df = 1985)		1.601 (df = 1982)	
F Statistic	146.985*** (df = 8; 1986)		107.068*** (df = 11; 1983)		70.561*** (df = 8; 1985)		51.421*** (df = 11; 1982)		47.412*** (df = 8; 1985)		34.547*** (df = 11; 1982)	

Note: *p<0.1; **p<0.05; ***p<0.01

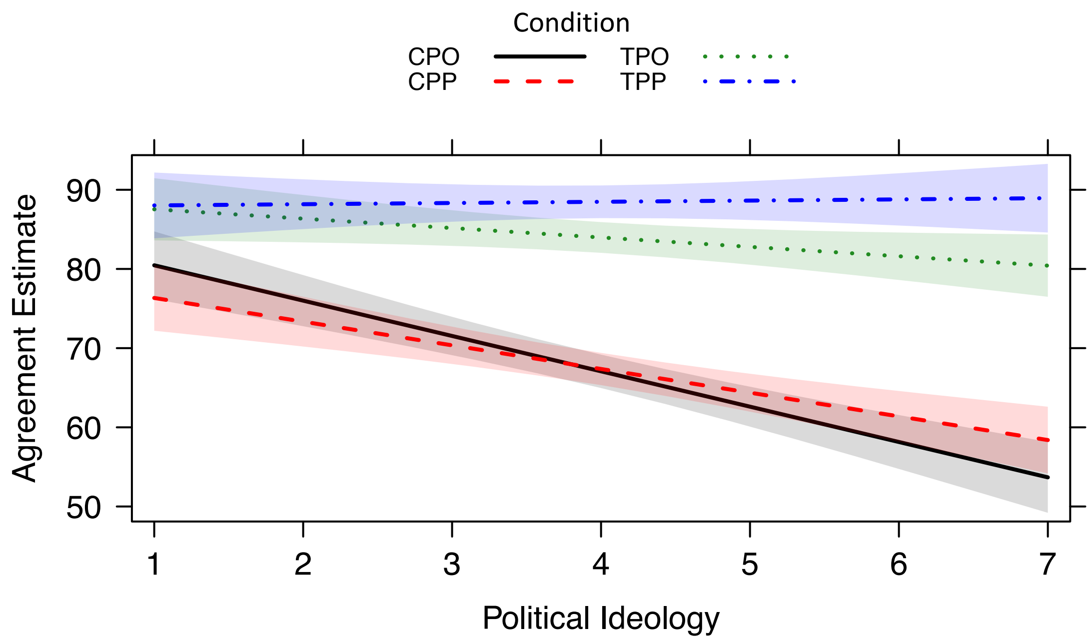
Interactive Effects of Condition and Political Ideology

We were interested in whether liberals and conservatives responded similarly or differently to exposure to a consensus message. We therefore ran a series of regressions looking at the interactive effect of experimental condition and political ideology on our mediator (RQ1) and outcome variables (RQ2), controlling for gender, age, education, and COVID-19 concern. The CPO condition was selected as the comparison group. Full results can be found in Tables IV.3 and IV.4.

We only observed significant interactions between experimental condition and political ideology on agreement estimates (the proposed mediator). There were significant interactive effects between TPO (v. CPO) and political ideology (unstandardized $\beta = 3.28$, $p < .001$) and between TPP (v. CPO) and political ideology ($\beta = 4.62$, $p < .001$). Visual inspection of these interactions reveals that conservatives' consensus estimates were more strongly impacted by the treatment conditions, versus the CPO condition, than liberals' consensus estimates. This was largely due to the fact that conservatives' agreement estimates in the absence of a consensus message were lower than those of liberals. After exposure to the consensus message, liberals and conservatives reported similar agreement estimates (see Figure IV.2).

This also reveals that we observe a similar interaction occurring in both the pre-/post-test and post-test only treatment conditions. In both treatment conditions, for agreement estimates, the difference between conservatives who do and do not see the consensus message are greater than the difference between liberals. However, we do not see interactive effects of condition and political ideology on any other outcome (H7 is partially supported).

Figure IV.2: Interactive Effects of Condition and Political Ideology on Agreement Estimates



Effects of Agreement Estimates

We hypothesized that agreement estimates would be positively associated with our outcomes. To test this, we ran a series of OLS regressions looking at the effect of agreement estimate, as well as political ideology, on our outcome variables, controlling for experimental condition, gender, age, education, and COVID-19 concern. The CPO condition was selected as the comparison group. Full results can be found in as the first step of regressions in Tables IV.5 and IV.6.

Agreement estimates were positively associated with all outcomes, supporting H3a-e. When people reported higher agreement estimates, they were also more likely to report greater belief in global warming (unstandardized $\beta = .01$, $p < .001$), belief in human causation ($\beta = .01$, $p < .001$), worry and concern about climate change ($\beta = .01$, p

$< .001$), support for public action ($\beta = .01$, $p < .001$), and support for government action ($\beta = .02$, $p < .001$).

However, it should also be noted that all outcomes were also negatively associated with political ideology, such that conservatives, on average, reported less belief in global warming ($\beta = -.16$, $p < .001$), belief in human causation ($\beta = -.15$, $p < .001$), worry and concern about climate change ($\beta = -.21$, $p < .001$), support for public action ($\beta = -.18$, $p < .001$), and support for government action ($\beta = -.24$, $p < .001$).

Table IV.5: Main and Interactive Effects of Agreement Estimate and Political Ideology on Outcomes (1/2)

	Belief in Global Warming		Belief in Human Causation		Worry and Concern	
Consensus Estimate	.01 *** (.00)	.02 *** (.00)	.01 *** (.00)	.02 *** (.00)	.01 *** (.00)	.02 *** (.00)
Political Ideology	-.16 *** (.01)	-.11 *** (.04)	-.15 *** (.01)	-.08 ** (.04)	-.21 *** (.01)	-.08 * (.05)
CPP (v. CPO)	-.14 ** (.06)	-.14 ** (.06)	-.05 (.06)	-.05 (.06)	.03 (.07)	.03 (.07)
TPO (v. CPO)	-.17 *** (.06)	-.16 *** (.06)	-.15 ** (.06)	-.15 ** (.06)	-.13 *** (.07)	-.13 * (.07)
TPP (v. CPO)	-.21 *** (.07)	-.21 *** (.07)	-.06 (.07)	-.06 (.07)	-.04 (.07)	-.04 (.07)
Gender	.01 (.04)	.01 (.04)	.04 (.05)	.04 (.05)	.06 (.05)	.06 (.05)
Age	.01 (.01)	.01 (.01)	-.04 *** (.01)	-.05 (.01)	-.06 *** (.01)	-.06 *** (.01)
Education	.00 (.02)	.00 (.02)	.00 (.02)	.00 (.02)	.03 ** (.02)	.03 ** (.02)
COVID-19 Concern	.30 *** (.02)	.30 *** (.02)	.23 *** (.02)	.23 *** (.02)	.56 *** (.02)	.56 *** (.02)
Interactions						
Consensus Estimate x Political Ideology		.00 (.00)		.00 (.00)		.00 *** (.00)
Constant	2.73 *** (.15)	2.51 *** (.23)	2.32 *** (.16)	2.04 *** (.23)	1.30 *** (.17)	.75 *** (.25)
Observations	1,988	1,988	1,988	1,988	1,988	1,988
Adjusted R^2	.28	.28	.24	.24	.39	.40
Residual Standard Error	0.954 (df = 1978)	0.954 (df = 1977)	0.976 (df = 1978)	0.976 (df = 1977)	1.033 (df = 1978)	1.031 (df = 1977)
F Statistic	86.376*** (df = 9; 1978)	77.935*** (df = 10; 1977)	68.826*** (df = 9; 1978)	62.236*** (df = 10; 1977)	143.995*** (df = 9; 1978)	131.012*** (df = 10; 1977)

Note: *p<0.1; **p<0.05; ***p<0.01

Table IV.6: Main and Interactive Effects of Agreement Estimate and Political Ideology on Outcomes (2/2)

	Support for Public Action						Support for Government Action					
Consensus Estimate	.01	***	(.00)	.01	***	(.00)	.02	***	(.00)	.01	**	(.00)
Political Ideology	-.18	***	(.01)	-.17	***	(.04)	-.24	***	(.02)	-.27	***	(.07)
CPP (v. CPO)	.03		(.07)	.00		(.07)	.17		(.10)	.16		(.10)
TPO (v. CPO)	-.10		(.07)	-.10		(.07)	.01		(.10)	.01		(.10)
TPP (v. CPO)	-.11		(.07)	-.10		(.07)	.02		(.11)	.02		(.11)
Gender	.12	**	(.05)	.12	**	(.05)	-.03		(.07)	-.03		(.07)
Age	-.04	***	(.01)	-.04	***	(.01)	-.02		(.02)	-.02		(.02)
Education	-.04	**	(.02)	-.03	**	(.02)	.00		(.02)	.00		(.02)
COVID-19 Concern	.31	***	(.02)	.31	***	(.02)	.40	***	(.04)	.40	***	(.04)
Interactions												
Consensus Estimate x Political Ideology				.00		(.00)				.00		(.00)
Constant	2.95	***	(.16)	2.91	***	(.24)	3.97	***	(.26)	4.11	***	(.38)
Observations	1,987			1,987			1,987			1,987		
Adjusted R^2	.26			.26			.17			.17		
Residual Standard Error	0.999 (df = 1977)			1.000 (df = 1976)			1.586 (df = 1977)			1.587 (df = 1976)		
F Statistic	77.776*** (df = 9; 1977)			69.969*** (df = 10; 1976)			46.934*** (df = 9; 1977)			42.246*** (df = 10; 1976)		

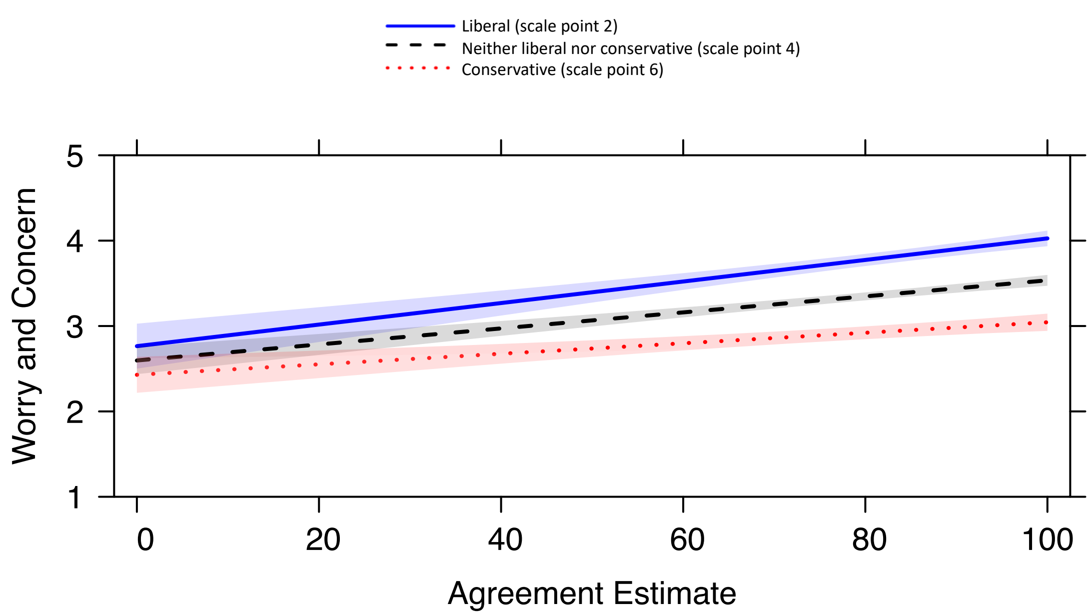
Note: *p<0.1; **p<0.05; ***p<0.01

Interactive Effects of Agreement Estimate and Political Ideology

We were additionally in whether one's political ideology would moderate the effect that consensus estimate may have on different climate change attitudes (RQ3). We therefore ran a series of regressions looking interactive effect of consensus estimate and political ideology on our outcome variables, controlling for experimental condition, gender, age, education, and COVID-19 concern. Full results can be found as the second step of regressions in Tables IV.5 and IV.6.

We only observed one significant interaction between consensus estimate and political ideology, which was on worry and concern ($\beta = -.002$, $p < .001$). Visual inspection of this interactions reveals that worry and concern about climate change increased with higher consensus estimates among liberals more so than among conservatives (see Figure IV.3).

Figure IV.3: Interactive Effects of Agreement Estimate and Political Ideology on Worry and Concern about Climate Change



Indirect Effects

To examine indirect and total effects, we used the package *mediation* in R, which computes indirect effects with bootstrapped 95% confidence intervals (Tingley et al., 2014). The constituent parts of the mediation analyses were identical to the regressions presented above. The first step of the model predicting agreement estimates included experimental condition and political ideology, as well as an interaction between the two, as predictors. For all outcomes except worry and concern, the second step of the model included condition, agreement estimate, and political ideology as predictors, but no interaction between the agreement estimate and ideology. Given that we found a significant interactive effect of agreement estimate and political ideology on worry and concern, the interactive term was included in the second step of the model for that outcome. All models included gender, age, education, and COVID-19 concern as controls. When looking at indirect effects, we looked at differences between the two treatment conditions (TPP v. TPO), between the two pre-/post-test conditions (TPP v. CPP), and between the two post-test conditions (TPO v. CPO).

Belief in Global Warming

We find significant indirect effects on belief in global warming for TPP v. TPO (point estimate (PE) = .05, 95% CI (.02, .09)), TPP v. CPP (PE = .26, 95% CI (.21, .31)), and TPO v. CPO (PE = .20, 95% CI (.16, .26)). H4a is supported. However, of these comparisons, we only see significant total effects for the TPP v. CPP comparison (PE = .18, 95% CI (.06, .31)). These results suggest that only those in the TPP condition see effects of exposure to a consensus message on belief in global warming, while those in the TPO condition do not.

Belief in Human Causation

We find significant indirect effects on belief in human causation for TPP v. TPO (PE = .05, 95% CI (.02, .09)), TPP v. CPP (PE = .26, 95% CI (.21, .32)), and TPO v. CPO (PE = .21, 95% CI (.16, .26)). H4b is supported. However, we only see significant total effects for TPP v. TPO (PE = .14, 95% CI (.03, .27)) and TPP v. CPP (PE = .24, 95% CI (.11, .37)). Again, it appears that only those in the TPP condition see effects of exposure to a consensus message on belief in human causation, while those in the TPO condition do not.

Worry and Concern

We see significant indirect effects on worry and concern about climate change for TPP v. TPO (PE = .03, 95% CI (.01, .06)), TPP v. CPP (PE = .18, 95% CI (.14, .23)), and TPO v. CPO (PE = .14, 95% CI (.10, .19)). H4c is supported. However, we saw no significant total effects in any of these comparisons.

Support for Public Action

We did observe significant indirect effects on support for public action for TPP v. TPO (PE = .04, 95% CI (.02, .08)), TPP v. CPP (PE = .21, 95% CI (.16, .27)), and TPO v. CPO (PE = .17, 95% CI (.13, .21)). H4d is supported. However, for none of these comparisons did we see significant total effects.

Support for Government Action

Finally, we find significant indirect effects on support for government action for TPP v. TPO (PE = .04, 95% CI (.02, .07)), TPP v. CPP (PE = .20, 95% CI (.14, .27)), and TPO v. CPO (PE = .16, 95% CI (.10, .22)). H4e is supported. However, in none of these comparisons did we see significant total effects.

Effects of a Pretest

Finally, we turn to questions of why the decision to pretest may affect responses to climate change measures. We expected that exposure to a pretest would be associated higher, more accurate consensus estimates (H5) and elevated outcomes (H6). We found support for the former, but not for the later.

Response time was significantly associated with experimental condition $F(3, 1986) = 22.95$, $p < .001$, $\eta_p^2 = .034$, and post-hoc Tukey tests (see Table IV.2) reveal that those in the pre-/post-test conditions completed the questions significantly faster than those in the post-test only conditions (*ps* < .001). Thus, H8 is supported.

We also sought to measure salience or availability of consensus information, as well as demand characteristics, with open-text question that were coded as containing (1) or not containing (0) the quantity of interest. To look at how experimental condition affected these outcomes, we ran two logistic regressions with experimental condition and political ideology as predictors, while also controlling for gender, age, education, and COVID-19 concern. The CPO condition was selected as the comparison group.

We observed that participants in the TPP condition were more likely to list scientists, experts, or consensus as influencing their climate change attitudes than participants in the CPO condition ($\beta = .60$, $p < .001$). However, we observed no differences between other conditions relative to the CPO condition (see the first column of Table IV.7). Therefore, H9 is supported. We also observed that individuals who were more conservative were less likely to say that scientists or consensus influenced their climate attitudes than those who were more liberal ($\beta = -.15$, $p < .001$).

Concerning demand characteristics, individuals in the CPP condition ($\beta = .61$, $p <$

.001), the TPO condition (β = .63, $p < .001$), and the TPP condition (β = .87, $p < .001$), were all more likely to say they thought the study was about climate change than those in the CPO condition (see the second column of Table IV.7). We had expected that the pre-/post-test conditions would more frequently identify climate change as the topic of the survey, compared to those in post-test only conditions. However, those in the TPO condition identified the topic of the survey at similar rates as those in the CPP condition. Therefore, H10 is partially supported.

Table IV.7: Logistic Regressions Predicting Salience and Demand Characteristics

	Salience			Demand Characteristics		
CPP (v. CPO)	-.10		(.25)	.62	***	(.13)
TPO (v. CPO)	.26		(.23)	.63	***	(.13)
TPP (v. CPO)	.59	***	(.23)	.87	***	(.13)
Political Ideology	-.15	***	(.05)	-.02		(.03)
Gender	-.21		(.16)	.18	**	(.09)
Age	.14	***	(.05)	.08	***	(.03)
Education	.11	**	(.05)	.05		(.03)
COVID-19 Concern	.11		(.09)	-.05		(.05)
Constant	-3.04	***	(.55)	-.97	***	(.31)
Observations	1,995			1,995		
Log Likelihood	-583.30			-1348.29		
Akaike Inf. Crit.	1184.60			2714.58		

Note: *p<0.1; **p<0.05; ***p<0.01

Discussion

This study is primarily focused on two overarching questions: does consensus messaging have positive effects on climate attitudes and is such an effect moderated by pretesting for consensus estimates?

Exposure to a consensus message did consistently, across different analyses and robustness checks, increase respondents' agreement estimates. In fact, consensus messages appeared to be more influential among conservatives, who in the absence of a consensus message reported lower agreement estimates than liberals, on average. After exposure to a consensus message, liberals and conservatives reported similar agreement estimates.

Concerning other outcomes, the effect is less clear. It appears that consensus messages had positive effects on belief in climate change and human causation, but this effect appears largely driven by the TPP condition; we do not see a similar effect in the TPO condition. Though we see some significant effects of the consensus messages on other outcomes from the OLS regression results, analyses that include corrections for multiple tests (post-hoc Tukey tests) reveal no significant differences between conditions for worry and concern, support for public action, or support for government action. The tenuous nature of these findings is also reflected in the indirect and total effects. Though we see that agreement estimates do have positive impacts on all outcomes, and that they significantly mediate the effects of consensus messages, the total effect on outcomes is often not significant. We do observe significant total effects on belief in global warming and in human causation, but only for comparisons with the TPP condition. These findings are in large part consistent with Kahan et al.'s (2017) re-analyses of van der Linden et al.'s (2015a) study.

In addition, our response to the question of whether consensus messages "work" for skeptics is mixed. Given inconsistencies in previous literature about how political ideology might moderate associations, we tested whether ideology moderated the direct effects of consensus messages on outcomes, as well as each leg of the mediated effects. I observe that consensus messages mostly affect partisans similarly. That said, consensus information appeared to boost conservatives' agreement estimates more than liberals, though higher agreement estimates produced more concern about climate change among liberals than conservatives. That said, political ideology remained a strong predictor of climate attitudes despite consensus information. Thus, while we see positive, indirect effects of consensus messages on some climate attitudes, the indirect effect is often too small to contribute to a significant total effect—often because the average direct effect was negative due to political ideology—in this application of consensus messaging. In debates about the efficacy of consensus messages, the moderate associations we observe and sometimes absence of total effects should be considered. While there may be valid theoretical reasons to expect indirect associations between variables, that we observe them does not immediately imply that consensus messaging is a silver bullet for reducing political polarization around climate attitudes. This is particularly important to consider given that effects are demonstrated with longitudinal data to decay over time, even among those who are inclined to believe scientists (Deryugina & Shurchkov, 2016; Kerr & Wilson, 2018).

This study also presents strong evidence that the choice of whether to include a pretest of consensus estimates is likely to influence results. We observed that the post-test only treatment condition led to lower agreement estimates than the pre-/post-test treatment condition. As a result, only the TPP condition saw cases of both significant indirect effects and significant total effects on belief in global warming and human causation.

In addition to higher, more accurate agreement estimates, participants in the TPP condition were also faster to respond to mediator and outcome measures than those in the TPO condition, suggesting this information was more available or top-of-mind. They were also more likely to say that scientists or consensus informed their beliefs on climate change compared to those in the CPO condition, while we saw no such difference between the TPO and CPO conditions. Thus, it is suggested by these findings that for participants in the pre-/post-test treatment condition, consensus information may be more accurate, salient, and available than those in the post-test only treatment condition.

These findings highlight that we should be aware of how study design may impact our respondents and inferences we make with their data. Though van der Linden et al. (2015a, 2019) and others using the pre-/post-test study design claim that the between- and within-subjects design gives their studies greater statistical power, it also has the potential to affect responses in ways which may bias these studies in the direction of finding results. Additionally, it is important to utilize study designs that are most relevant to the study of real-world effects. For researchers interested in the effects of consensus messages in mass media environments (e.g., news broadcasts, online advertisements), post-test only designs better parallel such contexts. Alternatively, the findings of studies using pre-/post-test designs may be more applicable to interactive or educational settings where "conceal and reveal" techniques may be employed (Myers et al., 2015).

Strengths and Limitations

This study was well powered with nearly 500 respondents in each condition from a diverse online panel. With this sample, we offer the first investigation that we are aware of into how the decision to pretest on science consensus estimates may affect the impact of consensus messages.

Though this study tested a series of associations and the mediated effects of consensus message on outcomes through agreement estimates, this study did not test the full serial mediation model proposed by van der Linden et al. (2015a). Where this model differs from our tests is with respect to support for public action, the effect of consensus message on which van der Linden et al. (2015a) claim is serially mediated through both agreements estimates and personal beliefs. We did not test this indirect pathway. It may be that consensus messages affect conservatives' agreement estimates which affect personal beliefs which, finally, affect conservatives' support for public action. However, this overall impact of such a serial indirect effect is captured within our testing of total effects – that is, in instances where a total effect is not observed we can infer that such an indirect effect would have been counteracted by other influences on the variable of interest.

Additionally, our measures designed to investigate why a pretest may have affected respondents' outcomes are limited. Our measure of participants' response times to questions in the online survey may be less accurate than measures of response times captured in-person. Additionally, that the dictionaries used to code open-text responses were only tested against my own human coding limits assumptions we can make about their validity. Finally, it is important to note that while a national diverse sample is used, it is not a representative sample, and appropriate caution for top-line results should be taken.

Conclusions

The debate around consensus messaging research concerns how effective this communicative strategy may be for reducing political polarization around the issue of climate change in the United States. While many studies, including this one, find evidence for indirect effects of consensus messages on climate attitudes through agreement estimates, this does not mean that consensus messages are a silver bullet for changing minds on climate change. The findings of this study do find evidence that conservatives' agreement estimates are more impacted by consensus messages and that agreement estimates are positively associated with climate attitudes. But we also fail to observe substantive effects of consensus messages on people's emotional responses and policy attitudes. These findings reflect concerns raised by Kahan (2017) who argues that significant correlations between climate attitude measures does not imply that consensus messages cause changes in attitudes that are not observed in mean differences. Researchers promoting consensus messaging often cite articles whose authors conclude against the efficacy of consensus messaging (e.g., Deryugina & Shurchkov, 2016) as part of "the vast majority of research in this field" that supports the use of consensus messaging strategies (Cook, 2019). We therefore want to be explicit on this point: the results of the present study do not find that consensus messaging is likely to lead to greater public engagement or policy support on the issue of climate change.

Further, this study reveals that effects of consensus messaging may be strongest in the most artificial contexts, and that in the absence of pretesting climate attitudes, consensus messages may not have similar effects. This highlights the importance of designing studies that mimic real-world messaging conditions to produce the best understanding of real-world effects. Pre-/post-test designs may be applied to the study of consensus messaging in classrooms or other interactive settings (e.g., interactive Instagram stories). Post-test only designs, on the other hand, can better speak to messaging contexts like online advertisements or news coverage. A focus on real-world messaging contexts also highlights the need to look at how consensus messages fare in competitive information environments. Consensus messages on social media appear in a feed of other content; news articles often use consensus messages to contextualize the marginal positions of contrarians (Boykoff & Boykoff, 2004; Brüggemann & Engesser, 2017). As Americans are increasingly getting their scientific information from online sources (National Science Board, 2016), we need to consider what effects that comments, shares, and different source attributions have on the efficacy of consensus messages (Messing & Westwood, 2012). However, to date, researchers have not looked at the effects of consensus messages embedded in realistic, competitive information environments. More realistic studies on consensus messages will better enable us to answer questions about whether consensus messages are capable of reducing political divisions on climate change in the United States.

CHAPTER V

Conclusions

This dissertation explored questions of how much scientific disagreement people are exposed to, what effects that disagreement has on issue attitudes and more general views about science, and whether consensus messages can reduce perceptions of scientific disagreement that are intertwined with political identities. This work is part of a larger body of work aimed at understanding when and why people question scientific knowledge. It speaks to questions about how politicization, misinformation, and information asymmetries may affect people's willingness to follow expert recommendations in conditions of uncertainty and the ability of science to inform policy in democratic societies.

Summary of Findings

The second chapter examined the prevalence of scientific agreement, disagreement, and denial messages in thirty years of climate change newspaper coverage. Throughout this time period, scientific knowledge on climate change has grown from an emergent phenomenon to well-established scientific fact with a broad consensus that global warming is happening and caused by human activity (Cook et al., 2013, 2016). However, in newspaper coverage we see that discussion of scientific agreement and disagreement were more common before 2000 than after, while scientific denial has become increasingly prominent in later years of coverage. We therefore observe a disconnect between conversations about climate change in the scientific community and those which take place in newspaper coverage.

This study was methodologically innovative in several ways that contribute to the field's use of computer-assisted methods to investigate large text corpora. Though the availability of "big data" and computational tools to parse textual data have expanded, the field does not yet have firmly established norms or standard practices for large-scale, computer-assisted textual data analysis (Muddiman et al., 2018, p. 215; Shah et al., 2015). This study demonstrates the advantages and efficiency of using a multimethodological approach to analyze large bodies of textual data. The use of multiple tools enables researchers to overcome the limitations of one or another; because dictionaries are likely to underestimate the prevalence of a construct in text and machine learning may conversely overestimate the true prevalence, using these methods in conjunction provides a range in which the true prevalence of agreement, disagreement, and denial in news coverage likely fall.

To employ this multimethodological approach, this study applied the supervised machine learning tool Wordscores in a novel way. Application of tools like Wordscores and Wordfish have increasingly shown utility beyond the scope of their initial intention, which was to identify political positions from texts (Klemmensen et al., 2007; Laver et al., 2002; Laver & Benoit, 2002). For example, Klüver (2009) measured the influence of interest groups on policy by using Wordscores to identify similarities in language between interest group statements and resulting policy. Chinn, Hart, and Soroka (2020) utilized Wordfish (Slapin & Proksch, 2008), an unsupervised word scaling method, to quantitatively measure the extent of politicization in climate change newspaper coverage over time, using the same data as in the second chapter. The work presented here demonstrated that Wordscores could be effectively used to measure constructs like agreement, disagreement, and denial in textual data, and, in doing so, could be applied to over 45,000 articles and over 130,000 paragraphs in a computationally efficient way.

With a novel data set and methodological approach, the second chapter offered, for the first time, a quantitative comparison of how the prevalence of agreement, disagreement, and denial has changed in news coverage of politicized science over the past thirty years. It offers evidence that debate around climate change in the form of disagreement and denial have been common features of coverage over time, despite journalists' efforts to communicate the scientific consensus on climate change and to contextualize contrarians as holding a marginal position (Boykoff, 2007; Brüggemann & Engesser, 2017). As a result, we reveal that the U.S. public has been repeatedly exposed to both agreement and disagreement messages, but since the 2000s has been increasingly exposed to denial messages, in elite, mainstream newspaper coverage of climate change.

The third chapter investigated what effects scientific disagreement messages have, both on personal beliefs about issues and broader attitudes toward science. Previous work has demonstrated that issue attitudes are affected by scientific disagreement (Aklin & Urpelainen, 2014; Chinn et al., 2018; Malka et al., 2009), but I was particularly interested the effects that exposure to disagreement may have on general trust in science, which is both a heuristic for forming attitudes on novel scientific information (Druckman & Bolsen, 2011; Lee, 2005; Roberts et al., 2013; Siegrist, 2000) and support for politicians and political movements that are skeptical of experts (Motta, 2018). However, there was mixed evidence about whether skepticism of specific science issues may “spill over” to other scientific attitudes (Chinn & Pasek, 2020; Roberts et al., 2013). This study extended previous survey work (Hmielowski et al., 2014) by experimentally testing the effects that disagreement messages had on respondents’ trust in science. In doing so, it is the first study I am aware of to empirically demonstrate that general trust in scientists and scientific methods is negatively affected by scientific disagreement, relative to agreement messages. In doing so, it supports claims made by survey work that exposure to media containing more or less disagreement messages may contribute in part to partisan differences in trust in science (Gauchat, 2012; Hmielowski et al., 2014).

This study also contributes to an emerging area of research exploring the effects of incivility in science communications (Anderson et al., 2014, 2018; Yuan et al., 2018; Yuan, Besley, et al., 2019; Yuan & Besley, 2018; Yuan & Lu, 2020). Increasing politicization (McCright & Dunlap, 2010) and use of digital communication technologies (Simis-Wilkinson et al., 2018; Yuan, Ma, et al., 2019) open opportunities for science communication to become more uncivil. This study contributes a novel understanding of how this incivility may affect attention to science issues, personal beliefs, trust in science, and broader science attitudes. Though we expected that disagreement and incivility would make people more interested and engaged in the science presented, they had the opposite effects. In most cases, uncivil disagreement had the most negative effects on attention-related outcomes including information seeking, engagement, and sharing. This finding highlights possible differences in the public’s expectations of scientific versus political domains, where uncivil messages are evaluated as more entertaining (Mutz & Reeves, 2005). Our finding that perceptions of research quality were negatively impacted by incivility suggests that disparaging a piece of opposing research may have the result of negatively affecting perceptions of the field as a whole. And though we found that a single uncivil scientist did not lead individuals to generally mistrust scientists or scientific methods, incivility did lead participants to think that science would change things for the worse for the next generation and that the harms outweigh the benefits of science. These novel findings reveal several potential negative impacts of introducing incivility into public scientific disagreements.

Finally, the finding that disagreement and incivility not only affected people's attitudes toward a single issue, but also had the potential to affect their broader attitudes, is a novel one. While prior research has well-demonstrated effects on specific issues (e.g., Chinn et al., 2018; Yuan et al., 2018), few studies have looked at the ways in which disagreement and incivility are associated more general attitudes toward science. That said, it is not clear from this study if the effects of a single exposure on general science attitudes are persistent over time, though there is some suggestion that repeated exposure to disagreement reduces trust in science over time (Feldman et al., 2012; Hmielowski et al., 2014). Also, though we know from past work that attitudes like trust in science do affect a wide range of political and scientific beliefs (Motta, 2018), we did not demonstrate such effects in this study. This study raises a central challenge of communicating scientific knowledge, which is always uncertain to some degree. Though disagreement is inherent and normal to the production of scientific knowledge, its mere presence, even when respectfully communicated, reduces attention, perceptions of research quality, and trust in science, even in the absence of politicization.

The fourth chapter investigated whether consensus messaging was capable of reducing partisan polarization around climate attitudes and whether inconsistent results on this point were the product of different study designs. In this study, we returned to the politicized issue of climate change, in which there is a clear scientific consensus but politically motivated rejection and perceptions of scientific disagreement (Chinn & Pasek, 2020), which have likely been informed, in part, by exposure to disagreement and denial messages like those we saw in the second chapter.

We find support for the claim that consensus messages affect agreement estimates, which in turn act as a "gateway belief" for holding more scientifically supported climate attitudes. We also find consensus messages to be more influential on conservatives' agreement estimates than liberals'; conservatives' estimates in the absence of a message were lower than those of liberals, and after exposure to a consensus message liberals and conservatives reported estimates at similar levels. These agreement estimates are indeed positively associated with climate attitudes, and we see significant indirect effects of consensus messages on climate attitudes through agreement estimates. These findings are in line with work by researchers who advocate for consensus messaging as a tool to reduce partisan polarization around climate attitudes (Cook, 2019; van der Linden et al., 2019).

However, we also reveal that consensus messaging is not a silver bullet for reducing political polarization around climate attitudes. Political ideology continues to have a strong influence on all climate attitudes. Though we see significant indirect effects of consensus messages, there is a noticeable lack of total effects, suggesting the effects of consensus messages on climate attitudes through agreement estimates are too small to overcome other influences on climate attitudes. While there are some cases in which a consensus message does appear to help people hold more correct beliefs about climate change, consensus messages do not produce greater concern about climate change or support for climate action in our study. These findings make clear that though consensus messages are operating as theoretically expected, their effects may be too small to change minds on climate change, a point that others have raised in critique of consensus messaging strategies (Bolsen & Druckman, 2018; Deryugina & Shurchkov, 2016; Dixon et al., 2017; Kahan, 2017; Kerr & Wilson, 2018).

With respect to study design, the decision to pretest does, in fact, make a difference. Participants report higher consensus estimates when they are in a pre-/post-test treatment condition, as opposed to a post-test only treatment condition. This difference may be the reason that we only observe significant total effects when making comparisons with the pre-/post-test treatment condition, and not the post-test only treatment condition. It may be that consensus messaging strategies are more effective in interactive contexts than large-scale advertising campaigns. This finding additionally complicates evidence for the efficacy of consensus messages, which are largely drawn from studies using pre-/post-test designs. Though consensus messages may have some positive effects on climate attitudes, it is clear that alone their impact in mass messaging environments will be limited. Thus, while scientific agreement is one tool that can be used to persuade audiences of scientific positions, it is necessary to more fully address the reasons for perceptions of scientific disagreement as they relate to identities, values, and affective responses to uncertainties.

Taken together, the studies investigated in this dissertation find the following: (1) there is a good amount of scientific disagreement in mainstream news coverage of scientific issues, which is a main source of scientific information for the U.S. public (National Science Board, 2016); (2) this disagreement has negative effects on specific issue attitudes as well as trust in science generally; and (3) though agreement does have positive effects on science attitudes, consensus messaging strategies are not enough to overcome political polarization on scientific issues whose disagreement and uncertainties have been strategically exploited by political actors.

Implications

Understanding effects of scientific disagreement is important because political and media systems are evolving in ways that are likely to amplify disagreement messages (Allgaier, 2019; Bennett et al., 2007; Sobieraj & Berry, 2011). Science and politics often intersect in cases from environmental regulation to COVID-19 response. An increasingly polarized and competitive political environment leads to greater politicization of science as candidates try to champion (Newman, 2019) or deny (McCright & Dunlap, 2010) science to distinguish themselves from their political rivals. As scientific uncertainties are exploited by political actors (Bolsen & Druckman, 2015), traditional reporting and digital communication technologies are likely to amplify scientific disagreements. Economic pressures on traditional news organizations have resulted in increasing efforts to attract audience attention with sensational coverage while cutting the number of science beat journalists (Bennett et al., 2007; Boykoff & Boykoff, 2007). Digital and social media technologies enables the broader spread of scientific information to audiences who may not have had access to it in the past, but also enables nonscientists to create and amplify disagreement and denial with scientific positions (Kata, 2012). Even scientists' communication on social media may make scientific disagreements more public, whether due to the more informal nature of social media or frank discussions on private-but-public spaces like #academictwitter and #overlyhonestmethods (Simis-Wilkinson et al., 2018; Yuan & Lu, 2020). In sum, there are a multitude of ways in which political competition and media structures may contribute to increasing public exposure to scientific disagreement messages.

We learned from these studies that people are, in general, not comfortable with scientific disagreement. Not only does it impact people's issue attitudes, scientific disagreement may cast doubt on the credibility and value of scientific knowledge more generally. This highlights challenges in communicating the limitations and uncertainties of scientific knowledge. Though transparency has been advocated as a trust-building tool for scientists (Lupia, 2018), it can also have negative impacts on science attitudes. This tension between the ethical obligation to communicate about disagreement and uncertainty openly and the ways in which that may reduce public trust in science is one that should be further explored.

We also learned that telling people that scientists do, in fact, agree, does not immediately correct scientific attitudes. We did see some evidence that consensus messages led to people holding more correct beliefs concerning the level of scientific agreement, that climate change was happening, and that humans were causing it. However, consensus messages did not appear to impact concern or support for action. Thus, it appears that the effects of perceiving scientific disagreement are not remedied by a concise consensus message. This could be the case for several reasons. First and foremost, people's beliefs about scientific disagreement may be motivated by identities which are not mollified by a consensus message (Kahan et al., 2011). But these studies also highlight other reasons why an agreement message may not correct perceptions of disagreement. Because people are made uncomfortable by uncertainty (Kahneman & Tversky, 1979), they may be more attentive to negative, disagreement information (Soroka & McAdams, 2015). The negative effects of disagreement information on issue attitudes and broader trust in science may, for this reason, be persistent even in the face of an agreement message. Additionally, work from the field of misinformation notes that these kinds of misperceptions and the attitudes they influence are difficult to correct because they require retrieving the incorrect information in one's mind (Lewandowsky et al., 2012). Thus, while scientific agreement messages appear to lead to more positive science attitudes in general, their utility as a strategy for correcting misperceptions of scientific disagreement may be limited.

Perhaps one of the most important findings across these studies is that disagreement, even when respectful and measured, can have negative effects on trust in science. Though there will always be areas of uncertainty on scientific issues, it is still critical to take action on aspects of an issue on which there is agreement. This is perhaps most crucial for novel technologies, emergent phenomena, or moments of crisis; for example, though there is disagreement among experts about when to lift stay at home orders (Essley Whyte, 2020; Wamsley, 2020), it is vital that the public follows expert recommendations on social distancing to reduce the spread of disease in the absence of a treatment (CDC, 2020; WHO, 2020). However, uncertainties and disagreements around expert recommendations have led to frustration and rejection on the part of some Americans (Gabbatt, 2020). The finding that even civil disagreement affects trust in science helps us to understand people's behaviors in moments of crisis, as well as explain more everyday behaviors and attitudes, such as why people may turn to alternative experts for medical treatment.

This finding also raises the concern that repeated exposure to scientific disagreement may result in widespread cynicism or rejection of scientific knowledge. However, trust in scientists is very high in the United States, particularly when compared to politicians and the media (Pew Research Center, 2019). Despite the uncertainties and debates, public health experts remain the most trusted sources of information about COVID-19 by liberals and conservatives (Montanaro, 2020). Thus, any claims about disagreement eroding trust in science should also point out the context of high trust and support for scientists. Yet this finding connects to work by Vaccari and Chadwick (2020) which has raised the point that uncertainty not only impacts whether or not the public knows correct facts, but also whether the public knows who to trust as a source of information. While the high degree of trust in science suggests that the amplification of uncertainties and competing claims may be a greater problem for political actors than for scientific ones, the higher levels of scientific disagreement observed in conservative news sources (Feldman et al., 2012, 2017) and growing political polarization around trust in science (Gauchat, 2012) may give some cause for concern. Together, these findings offer insights into how people respond to and make sense of scientific agreement and disagreement messages, both in times of crisis and normalcy.

Future Directions

The goal of future research is to better understand when and why people question science. I am particularly interested in how scientific uncertainty is communicated, understood, and exploited. Uncertainty is inherent to all scientific knowledge; critique, peer review, and debate are necessary to managing the uncertainties and complexities of scientific research. For this reason, Karl Popper (2005) described science as that science as less a "body of knowledge," and more "a system of guesses or anticipations" (p. 318). But uncertainty is uncomfortable and something that, in general, people try to avoid (Kahneman & Tversky, 1979). This ambivalence around scientific uncertainty is central to understanding how people understand and engage with science. But research into the communication and effects of scientific uncertainties also speak to concerns about how politicization, misinformation, and information asymmetries affect people's willingness to listen to experts and the extent to which science can inform policy.

This work presented in this dissertation expands our understanding of the prevalence, effects, and limitations of scientific agreement and disagreement messages, but it also reveals remaining gaps in the study of scientific disagreement. In these final sections, I detail how this work provides theoretical foundations and methodological tools to further investigate into (a) how scientific information varies across different media, (b) what effects different types of disagreement and uncertainty messages have on attitudes, (c) how social and informational vulnerabilities lead individuals to hold counter-scientific positions, and (d) what strategic interventions can build trust in and support for scientists' positions.

Exposure

The first direction for future research extends the work of the second chapter to better understand where and in what forms people encounter scientific disagreements in media. The second chapter found evidence of significant scientific disagreement in mainstream news; however, we know that elite newspapers are not the public's only source of science information. Partisan news and digital media are not only common sources of information (National Science Board, 2016), they are also sources which are likely to have an even greater prevalence of scientific disagreement messages (Feldman et al., 2012; Simis-Wilkinson et al., 2018; Yuan & Lu, 2020). The methodological work in the second chapter, as well as that of others (Muddiman et al., 2018), demonstrates that computational methods can effectively measure these quantities in textual data. The content analytic work in the second chapter therefore provides a foundation for future investigations of scientific disagreement, denial, and incivility in partisan and online sources of science information to better understand how people with different media diets may be exposed to substantively different science information.

We know that partisan news sources differ in their coverage of science news. Studies of cable news coverage of climate change has found that Fox News contains more scientific disagreement and denial than MSNBC or CNN (Feldman et al., 2012). Other work has found that the Fox News discusses experts with a more negative tone than other networks (Stecula & Motta, 2019). However, such work typically offers only a snapshot of how scientific disagreement is portrayed on cable news outlets at a specific moment in time. The tools developed for the study of climate change newspaper coverage can easily be translated to the study of cable news coverage to uncover how the presentation of disagreement, denial, and agreement have changed over time on different news outlets. Documenting these over time trends will better inform survey work on how partisans' attitudes toward issues like climate change have changed over time (McCright & Dunlap, 2011) and the influence that partisan media may have on such attitudes (Hmielowski et al., 2014). In addition to the issue of climate change, these tools can additionally be applied to news coverage (newspaper and TV) of different scientific issues to determine whether science coverage is in general has become more conflictual over time or whether disagreement messages are common to only a small number of politically-salient issues.

> *How prevalent are scientific agreement, disagreement, and denial messages in coverage of climate change on different cable news stations (Fox News, MSNBC, CNN)? How have the prevalence of these features in coverage changed over time?*
>
> *How prevalent are scientific agreement, disagreement, and denial messages in mainstream newspaper and cable news coverage of other scientific issues? Is there increasing disagreement or denial in coverage scientific issues, or is disagreement and denial in coverage limited to a small number of scientific issues?*

The methods and tools to look at these quantities in news coverage can also be applied to online sources of scientific information. We know that people are increasingly getting science information from online sources (National Science Board, 2016). The internet offers the ability to spread scientific knowledge and empower non-scientific actors to voice traditionally undervalued expertise in local knowledge and community preferences (Wynne, 1992). However, there are also a number of ways in which digital communication technologies disrupt scientific communication, particularly with respect to scientific highlighting uncertainties and disagreements (Simis-Wilkinson et al., 2018; Yuan, Ma, et al., 2019). For instance, the technological features and affordances of different online platforms alter the structure of science information shared on that platform (Hiaeshutter-Rice, 2019) and algorithms driven by engagement can lead individuals toward content that rejects scientific positions (Allgaier, 2019). Individuals' personal curation of information online and that of their social networks will affect what information they are exposed to (Thorson & Wells, 2016). Additionally, the ability to create content and network communities can empower marginalized actors to increase public circulation of empirically false claims (e.g., Holocaust denial, vaccine-autism link) (Kata, 2012). Though there is some work describing specifically located science information online (Simis-Wilkinson et al., 2018; Yeo et al., 2017), there is little work comparing the content of science information across different platforms, networked communities, and content creators. The methods used in the second chapter offer tools for looking at how content differs in online scientific information, such as:

> *How do social media platforms alter the structure of scientific content posted by well- and ill-intentioned actors?*
>
> *In what digital media are people more or less likely to encounter scientific questioning or denial?*
>
> *What patterns of media use are more or less associated with incidental exposure to scientific questioning or denial, or other information asymmetries?*

Effects

The experimental work presented in here can be immediately expanded in several directions. For example, the third chapter looked at effects of agreement, civil disagreement, and uncivil disagreement messages in isolation, but the process of selecting reference texts and inspecting results from the content analyses in chapter two made clear that these messages often co-occurred. Scientific agreement messages have often been used to contextualize disagreement, or to explain how a denier held a marginal position (Brüggemann & Engesser, 2017). The effects of these mixed messages remain unexplored. Perhaps agreement mitigates some negative effects of scientific disagreement messages, or, conversely, the disagreeing exemplar may be more influential on attitudes (Zillmann, 1999).

How does a consensus message accompanied by an exemplar who disagrees with *or denies the consensus position affect individuals' beliefs and attitudes?*

The third chapter also restricted its focus to disagreement between scientists. While competing scientific claims may be common, conflict between scientists and non-scientists in media may be just as, if not far more, common (Chinn et al., 2020). This is immediately seen in recent conflicts between President Trump and the WHO (Wamsley, 2020) or lead members of the White House Coronavirus Task Force (Alonso-Zaldivar, 2020; CNN, 2020). Given that scientific uncertainties are associated with politicization of science (Bolsen & Druckman, 2015), it is important to extend the study of scientific disagreements to look at disagreements between scientists and politicians. On the one hand, the public trusts scientists far more than politicians (Pew Research Center, 2019), and thus may be more likely to take their side. That said, partisan motivated reasoning has been well established as a motivation to reject scientists' positions on issues like climate change (McCright & Dunlap, 2011). Competition between scientific and political cues is a common feature of science media, and one which ought to be explored in contexts beyond the most politically divisive issues.

Additionally, as people increasingly turn to digital sources of information, there are more opportunities for lay people to disagree with scientists and assert their own claims about scientific topics. Non-scientists often leverage different forms of expertise (e.g., spirituality, motherhood, personal experience), which may appeal to people who hold similar values or shared experiences (Cvetkovich & Winter, 2003; Kata, 2012). In addition, scientific information in digital spaces may be forwarded by members of one's social network or come with other cues, such as large numbers of likes and shares, which appear to give the non-scientist's claim weight (Messing & Westwood, 2012; Thorson &

Wells, 2016). Understanding how individuals evaluate competing claims of scientists and non-scientists will better our understanding of (a) the effects that exposure to disagreement about science in digital spaces has on science attitudes and (b) how misinformation and disinformation spreads online.

> *Who do people trust as sources of information about scientific topics? How are evaluations of these sources affected by social identities and social networks?*
>
> *How does disagreement from non-scientific sources affect perceptions of scientific issues and scientific actors?*

Understanding

When exploring public disagreement with science, it is important to take seriously the social contexts, emotions, and structural vulnerabilities that can lead one to question science. In general, the quantitative study of public understanding of science has been largely focused on political partisanship or ideology as a motivation for rejection of scientific positions, as was explored in chapter four. However, there are increasingly public disagreements with science that do not fall cleanly along party lines—vaccination and GMOs, for example (Pew Research Center, 2015).

Mistrust or rejection of science may be a reasonable response to a set of circumstances. During the 2019 measles outbreak in the pacific northwest, journalists and researchers explicated the links between vaccine skepticism among immigrants from the former Soviet Union and a mistrust of healthcare institutions, which grew out of Soviet misinformation, propaganda and oppression (Belluz, 2019). Public health experts have sought to quell rumors in African American communities that COVID-19 is a hoax or that black people are immune to COVID-19; in this case, mistrust of experts is directly tied to a long history of involuntary medical experimentation (Breslow, 2020). Public attention to or experience of abuse of women during labor, from ignoring consent for medical procedures to physical violence (the GVtM-US Steering Council et al., 2019), may make choices like homebirth and freebirth more appealing to women (Zadrozny, 2020). Anecdotally, online communities that question or reject science emphasize narratives of empowerment, encouraging people to "do their own research" or that they are the expert on what is best for their body, rather than spreading ominous, conspiratorial narratives. Though a great deal of research on disagreement with scientific positions has focused on political motivations, a great deal of rejection may be driven by social, historical, and informational vulnerabilities. Though research from science and technology studies (STS) has long engaged with these motivations for mistrust and skepticism, this only recently becoming a focus of public understanding of science and political science literatures (Oliver & Wood, 2018).

What leads people to online communities that mistrust or reject expert recommendations, beyond political identities?

How are digital and social media associated with narratives of empowerment and scientific rejection?

Additionally, work on political misinformation has raised the point that uncertainty—competing claims, false news, disagreement with experts—is not only consequential in terms of not knowing facts, but also breeds a culture of indeterminism and cynicism (Chadwick & Vaccari, 2019; Vaccari & Chadwick, 2020). Vaccari and Chadwick's (2020) work advocates taking more seriously what it means when people respond "don't know" to our measures, arguing that whether or not people know a fact is less consequential than whether or not people know who to trust as a source of information. A culture of indeterminism—in which people cannot tell what information is true and what is false—is likely to erode the perceived value of scientific information for informing personal beliefs, behaviors, and policies. Though scientists have an ethical obligation to be transparent about uncertainties, which some argue plays a role in bolstering scientific credibility (Lupia, 2018), uncertainties are also exploited and amplified by political and lay actors to press false claims (Bolsen & Druckman, 2015; Kata, 2012). Therefore, the ways in which scientific uncertainties are communicated in media could negatively affect the quality of public deliberation on scientific topics and the value of science in the policymaking process (Scheufele & Krause, 2019; Vaccari & Chadwick, 2020). Investigating conditions under which the interplay of politicization, public questioning of science, and new media technologies may cultivate a culture of indeterminism, mistrust, and cynicism is therefore a concern for science as well as politics.

> *Under what conditions does the communication of scientific uncertainties and disagreement lead to cynicism about the value of scientific knowledge, and when might they bolster perceptions of scientific credibility?*

Intervention

This work will inform a body of normatively motivated research into how to build trust in science and support for expert-supported positions while transparently and accurately communicating uncertainties. As previously discussed at length, people tend to be skeptical of information that is uncertain, but science communicators have an ethical obligation to transparently represent the state of scientific research to the public. The central challenge is therefore to communicate transparently about uncertainties while maintaining or building trust in experts. We can readily see the importance of simultaneously building support for expert recommendations while communicating about uncertainties during this COVID-19 outbreak.

Drawing from work presented in the fourth chapter, this line of research will examine the effects of various messaging strategies. We found that agreement messages alone may be insufficient to overcome partisan divisions, however, work from the third chapter indicated that such messages do have positive effects on attitudes, particularly in nonpolitical contexts. It may therefore be worth exploring whether emphasizing points of agreement when reporting scientific disagreement is an effective way of being transparent about uncertainties without losing trust in experts. Alternatively, it is not clear whether reminding people that uncertainty and disagreement are normal in the production of scientific knowledge leads to further mistrust of science or greater tolerance for uncertainty. Finally, though we have a good deal of research showing ineffective strategies for engaging with skeptics online (e.g., Yuan, Ma, et al., 2019), I plan to pursue research that looks into how scientists should engage with skeptical communities to build trust in science, for instance by emphasizing shared values (Dixon et al., 2017) or building rapport over time.

> *What messaging strategies effectively communicate scientific uncertainties while building confidence in experts' positions and recommendations?*
>
> *How should scientists engage with skeptical communities in online to build trust and acceptance of scientific positions?*

Conclusion

This body of work will contribute novel information to help us better understand when and why the public questions science. This dissertation exploring the prevalence and effects of scientific disagreement is a first step in this broader research agenda. Future work about scientific uncertainties and disagreements with a wider range of actors and media environments will broaden the field's understanding of how people respond to scientific information and why people may come to mistrust science. It also will supply an understanding of how media diet may contribute to information asymmetries. This research agenda connects to work about political misinformation, perceptions of expertise, social identities, emotion, and cognitive biases. Collectively, this work will help to determine what kinds of interventions can best shift science attitudes in different social and mediated conditions, as well as different issue contexts. By better understanding how the public engages with scientific disagreement, and how to effectively communicate uncertainties while maintaining credibility, this work will help science communicators to promote public safety and wellbeing in an increasingly divisive and competitive information environment.

APPENDICES

APPENDIX A

Coding Reference Texts

The selected reference texts include 85 paragraphs drawn from the more than 130,000 paragraphs mentioning climate change in the dataset. Scientific agreement, disagreement, and denial often co-occurred within paragraphs. For this reason, references paragraphs were broken into complete sentences and dummy coded for the presence ("1") or absence ("0") of scientific agreement, disagreement, and denial on the sentence level. When coding, each sentence was evaluated independently of the context of the paragraph. For an example, Table A.1 shows how a paragraph was coded.

Sentences were not coded as containing multiple concepts. In cases in which a sentence contained more than one concept, the sentence was broken apart and coded as two sentences. This was the case for sentences like, "But underlying the uncertainty is a broad scientific consensus on the fundamentals of the warming forecast," and, "More broadly, there's significant skepticism, especially among Republicans, about the scientific consensus inside and outside of NASA that the burning of fossil fuels and other human activity is warming the atmosphere," which contain both scientific agreement and disagreement.[9]

[9] In rare cases in which two concepts appearing in a sentence could not be disentangled by splitting the sentence, the sentence was removed from the body of reference texts. This occurred in a single case, for the sentence, "But there's another scientific consensus that the Environmental Protection Agency bucked Tuesday when it announced it is unraveling the Obama administration's effort to reduce carbon dioxide emissions from the nation's electricity sector, known as the Clean Power Plan.

There were a few ways in which the choice to code a sentence as containing scientific disagreement or denial was not clear. The first concerned the ways in which scientific uncertainty and debate has been used as a rhetorical strategy by political actors who aim to block climate legislation. This strategy is well-documented by researchers (McCright & Dunlap, 2010), and can be seen in the sentence, "The Bush administration's mantra on climate change is this: The science is not yet in to prove a link between man's gas-and-coal guzzling habits and rising global temperatures that are causing glaciers to shrink, polar ice caps to melt and seas to rise." The paragraph proceeded to describe how the science is, indeed, settled, but how claiming scientific uncertainty supported Bush's legislative goals. For two reasons, sentences like these were coded as scientific disagreement rather than rejection of science. First, the decision to more precisely identify concepts at the sentence level means that each sentence should be coded without considering the context of the surrounding paragraph, since that is how Wordscores will evaluate the reference texts. Second, I am substantively interested in capturing scientific disagreement, both real and manufactured, in news, in part to explore when and how oppositional rhetoric may have changed from disagreement to denial. For similar reasons, discussion of "skeptics" was coded as indicating denial, as this is a common term for those who reject climate change along with "denier" or "contrarian." However, when the sentence described "skepticism" about science or "skeptical" actors, the sentence was coded as indicating scientific disagreement.

As can be seen in the example paragraph above, some sentences were not coded as containing any concept of interest. These sentences remained in the body of reference texts. This gave the algorithm examples of cases in which the language communicating agreement, disagreement, and denial did and did not occur. Offering Wordscores the text surrounding the concept of interest as examples of when the concept does not occur, rather than a random draw of sentences that do not contain the concepts of interest, was intended help the algorithm differentiate between language describing the subject of agreement, disagreement, and denial and language describing the agreement, disagreement, and denial itself. There were a few paragraphs added as reference texts specifically for this reason. For instance, a few of the disagreement reference texts were discussing the subject of hurricanes. I therefore added paragraphs in which hurricanes are discussed in other contexts so that the word "hurricane" would not be scored as being highly indicative of scientific disagreement. A few paragraphs mentioning "scientists" and "percent" often, but not in the context of scientific agreement, were added for similar reasons. Sentences with negated mentions of agreement, disagreement, or denial were coded as "0" for not containing these quantities.

Table A.1: Coding Reference Texts

Sentence	Coding
[cut off] …we will talk about global warming . . . and we will act."	*Removed, incomplete sentence*
But Bush has assumed a cautious stance in office, bowing to advisers who view global warming as a scientific fad and see proposals to curb greenhouse gases, created by the burning of coal and oil, as potentially ruinous to the U.S. industrial base.	*Denial*
Although he supports a United Nations-sponsored panel considering an international convention on global warming, Bush has backed away from plans by some European nations to freeze or cut emissions of carbon dioxide - - the primary greenhouse gas - - by early next century.	*none*
Instead, he publicly questions the scientific certainty of global warming, even avoiding use of the popular term in favor of the more innocuous " climate change. "	*Scientific disagreement*
Few scientists doubt that steady increases in carbon dioxide emissions will raise world temperatures as they have since industrialization.	*Scientific agreement*
The question is how much, with most estimates ranging from 3 to 8 degrees by the middle of next century.	*none*
A scientific team assigned by the U.N. panel to sort out the uncertainties issued a draft report last month affirming… [cut off]	*Removed, incomplete sentence*

Table A.2: Reference Texts by Newspaper

	NYT	WPO	LAT	CTR	USA	HCR
Agreement	22	23	16	7	5	11
Disagreement	15	19	21	22	3	9
Denial	15	25	13	10	3	5

Paragraph-Level Results

In addition to full articles, we also extracted a corpus containing every paragraph that mentions climate change. These paragraphs captured the 100 words coming before and after a mention of a climate change keyword. In cases where the mention of climate change appeared within the first or last 100 words of an article, the paragraph started or ended with the beginning or end of the article, respectively. This resulted in a database of

133,345 paragraphs. In cases where a climate change keyword appeared twice in the space of 100 words, the paragraphs overlapped somewhat.

Figure A.1: Paragraph-level Dictionary Results

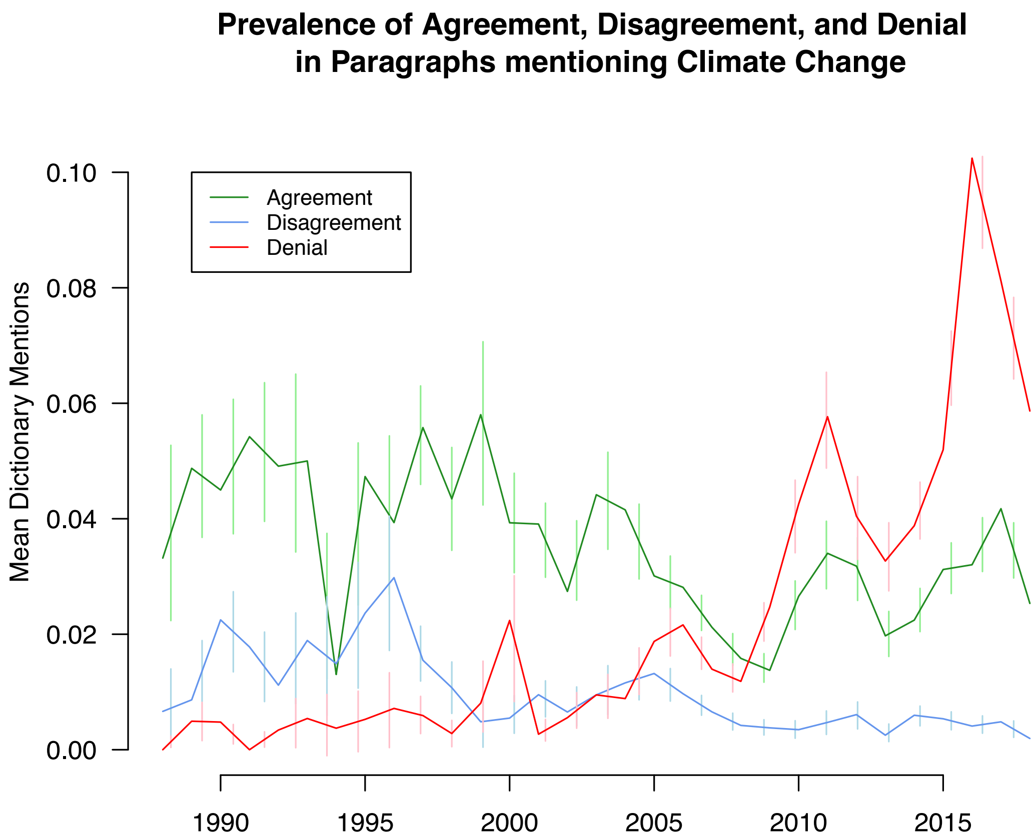
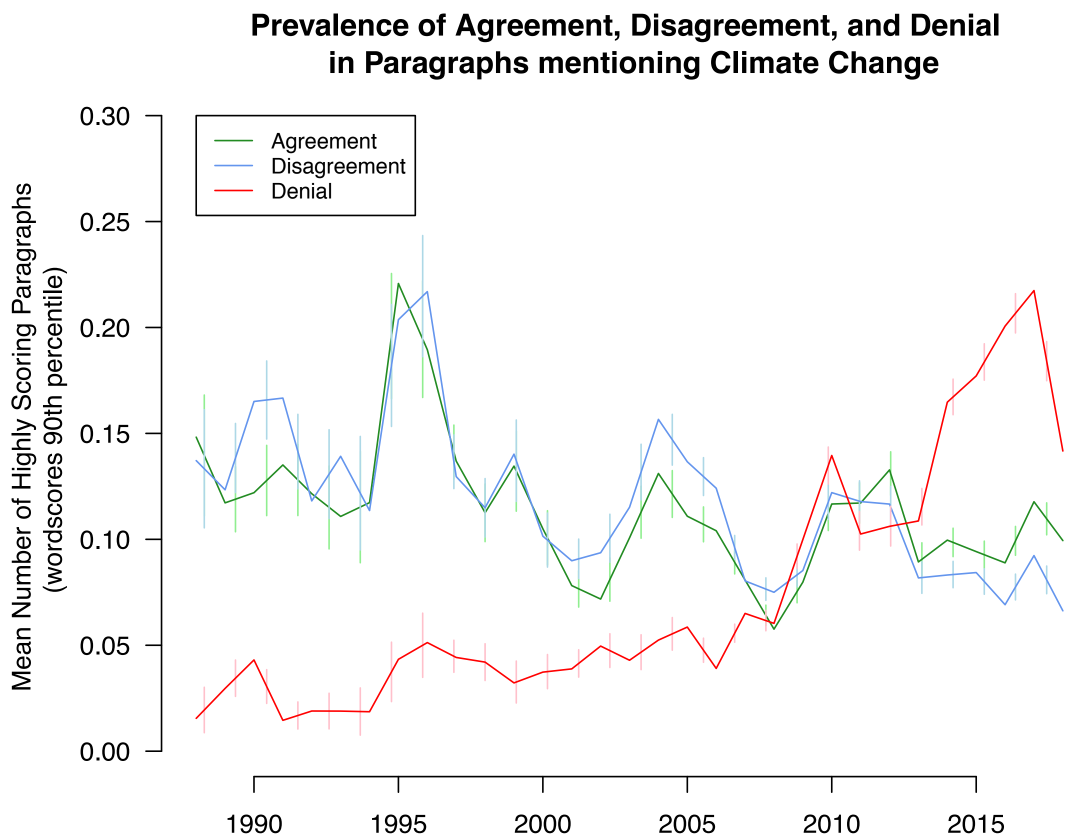


Figure A.2: Paragraph-level Wordscores Results



Wordscores results from the extracted paragraphs may be slightly less reliable than Wordscores results from the full articles. The Wordscores algorithm estimates the score of a text with the frequency of words from the reference texts relative to the length of the text. Given that paragraphs are shorter than full articles, there is the possibility that words which occur more frequently in a paragraph will be, in a sense, over-weighted. This is a particular concern in the estimation of scientific agreement, as some of the most discerning words (e.g., “scientists” and “percent”) can occur densely in paragraphs that do not in fact reference scientific agreement, but instead study findings or poll results. Because full articles contain more words than paragraphs, the results from the full articles are less likely to be over-estimated, though there is the increased chance that the scientific agreement, disagreement, or denial detected in the article is more tangentially related to the issue of climate change.

Estimates of the Prevalence of Agreement, Disagreement, and Denial in Articles

Table A.3: Percent of Climate Change Articles Containing Mentions, by Year

	Agreement		Disagreement		Denial	
Year	Dictionary	Wordscores	Dictionary	Wordscores	Dictionary	Wordscores
1988	15.5%	20.5%	3.5%	18.0%	0.0%	6.5%
1989	10.6%	15.0%	3.2%	12.8%	1.1%	5.9%
1990	7.9%	13.0%	3.3%	15.4%	1.5%	7.4%
1991	10.0%	15.9%	3.4%	15.4%	0.7%	3.9%
1992	8.9%	11.9%	1.5%	11.4%	0.9%	7.7%
1993	8.4%	12.8%	2.7%	13.4%	1.1%	7.4%
1994	4.4%	13.6%	2.7%	15.3%	1.7%	2.4%
1995	11.0%	22.1%	3.6%	19.5%	2.3%	6.8%
1996	8.1%	23.2%	5.5%	21.6%	2.6%	8.4%
1997	11.8%	14.4%	3.4%	12.2%	1.6%	8.8%
1998	7.0%	12.7%	1.9%	10.4%	1.5%	4.9%
1999	9.4%	14.3%	1.8%	13.1%	1.6%	5.8%
2000	8.4%	13.3%	1.3%	10.5%	2.5%	6.3%
2001	6.2%	8.6%	1.9%	9.5%	0.8%	7.2%
2002	4.8%	10.7%	1.2%	11.3%	1.6%	7.1%
2003	6.6%	12.1%	1.8%	10.7%	1.5%	6.8%
2004	6.8%	13.6%	2.0%	17.8%	2.5%	8.1%
2005	5.7%	11.9%	2.2%	13.7%	3.3%	7.1%
2006	4.4%	11.2%	1.7%	13.2%	3.1%	5.1%
2007	3.4%	7.8%	1.2%	7.5%	2.3%	7.2%
2008	2.1%	5.5%	0.8%	7.1%	2.1%	5.7%
2009	2.7%	7.8%	1.0%	8.0%	4.3%	11.7%
2010	3.6%	11.1%	1.0%	10.6%	6.3%	13.6%
2011	4.1%	9.5%	0.6%	9.5%	7.8%	9.2%
2012	4.3%	10.7%	1.1%	10.4%	6.1%	9.6%
2013	3.7%	8.3%	0.7%	8.4%	5.6%	9.7%
2014	4.6%	10.1%	0.9%	8.4%	7.4%	14.0%
2015	5.7%	9.9%	1.3%	8.4%	9.8%	16.0%
2016	5.0%	8.5%	0.7%	8.5%	15.6%	16.0%
2017	7.2%	9.0%	1.0%	9.3%	14.2%	21.6%
2018	4.8%	7.4%	0.8%	6.4%	10.8%	11.6%

Note: For dictionaries, percentages indicate the mean frequency of dictionary keywords in articles, by year. For Wordscores, percentages indicate the percent of articles in a year which scored in the 90th percentile for agreement, disagreement, or denial.

Agreement Dictionary

Below are the keywords included in the agreement dictionary. Mentions of negated variants of keywords, not listed here (e.g., "*not* all experts agree"), were subtracted from the initial dictionary count to produce the final dictionary counts presented in Chapter 2.

experts agree, scientists agree, researchers agree, scientific community agrees, agreement among experts, agreement among scientists, agreement among researchers, agreement among climate experts, agreement among climate scientists, agreement among climate researchers, agreement in the scientific community, agreement among the scientific community, scientific agreement, expert agreement, scientists are in agreement, experts are in agreement, researchers are in agreement, scientific community is in agreement, scientific consensus, consensus among scientists, consensus among experts, consensus among researchers, consensus among climate scientists, consensus among climate experts, consensus among climate researchers, consensus among the scientific community, consensus in the scientific community, consensus science, expert consensus, consensus on the science, many scientists believe, many scientists agree, many experts believe, many experts agree, many researchers believe, many researchers agree, many climate scientists believe, many climate scientists agree, many climate experts believe, many climate experts agree, many climate researchers believe, many climate researchers agree, most scientists believe, most scientists agree, most experts believe, most experts agree, most researchers believe, most researchers agree, most climate scientists believe, most climate scientists agree, most climate experts believe, most climate experts agree, most climate researchers believe, most climate researchers agree, majority of scientists believe, majority of scientists agree, majority of experts believe, majority of experts agree, majority of researchers believe, majority of researchers agree, majority of climate scientists believe, majority of climate scientists agree, majority of climate experts believe, majority of climate experts agree, majority of climate researchers believe, majority of climate researchers agree, all scientists believe, all scientists agree, all experts believe, all experts agree, all researchers believe, all researchers agree, all climate scientists believe, all climate scientists agree, all climate experts believe, all climate experts agree, all climate researchers believe, all climate researchers agree, percent of scientists, percent of researchers, percent of climate scientists, percent of climate researchers, percent of experts, percent of climate experts, percent of the scientific community, percent of the literature, percent of the scientific literature, percent of climate literature, percent of published papers, percent of all scientists, percent of all researchers, percent of all climate scientists, percent of all climate researchers, percent of all experts, percent of all climate experts, percent of the thousands of scientists, percent of the thousands of researchers, percent of the thousands of climate scientists, percent of the thousands of climate researchers, percent of the thousands of experts, percent of the thousands of climate experts, percent of published scientists, percent of published researchers, percent of published climate scientists, percent of published climate researchers, percent of published experts, percent of published climate experts, percent of published authors, percent of most published scientists, percent of most published researchers, percent of most published climate scientists, percent of most published climate researchers, percent of most published experts, percent of most published climate experts, percent of most published authors, percent of actively-publishing scientists, percent of actively-publishing researchers, percent of actively-publishing climate scientists, percent of actively-publishing climate researchers, percent of actively-publishing experts, percent of actively-publishing climate experts, percent of the most published authors, percent of the most published scientists, percent of the most published researchers, percent of the most published climate scientists, percent of the most published climate researchers, percent of the most published experts, percent of the most published climate experts, percent of the most published authors, percent of working scientists, percent of working researchers, percent of working climate scientists, percent of working climate researchers, percent of working experts, percent of working climate experts, percent of those scientists, percent of those researchers, percent of those climate scientists, percent of those climate researchers, percent of those experts, percent of those climate experts, percent of surveyed scientists, percent of surveyed researchers, percent of surveyed climate scientists, percent of surveyed climate researchers, percent of surveyed experts, percent of surveyed climate experts, percent of the world's scientists, percent of the world's researchers, percent of the world's climate scientists, percent of the world's climate researchers, percent of the world's experts, percent of the world's climate experts, percent of the scientists, percent of the researchers, percent of the climate scientists, percent of the climate researchers, percent of the experts, percent of the climate experts, percent of the most actively publishing scientists, percent of the most actively publishing researchers, percent of the most actively publishing climate scientists, percent of the most actively publishing climate researchers, percent of the most actively publishing experts, percent of the most actively publishing climate experts

Disagreement Dictionary

Below are the keywords included in the disagreement dictionary. Mentions of negated variants of keywords, not listed here (e.g., "*not* all experts agree"), were subtracted from the initial dictionary count to produce the final dictionary counts presented in Chapter 2.

scientists disagree, experts disagree, researchers disagree, scientists differ, experts differ, researchers differ, scientists diverge, experts diverge, researchers diverge, scientists question, experts question, researchers question, scientists doubt, experts doubt, researchers doubt, scientists debate, experts debate, researchers debate, scientists dispute, experts dispute, researchers dispute, scientists are uncertain, experts are uncertain, researchers are uncertain, scientists are skeptical, experts are skeptical, researchers are skeptical, scientists are unsure, experts are unsure, researchers are unsure, scientists are of two minds, experts are of two minds, researchers are of two minds, scientists are not sure, experts are not sure, researchers are not sure, science is unsettled, science is inconsistent, science is far from settled, science is not sure, science is not definitive, science is not conclusive, science is inconclusive, science is disputed, science is open to debate, science is uncertain, science casts doubt, research is unsettled, research is inconsistent, research is far from settled, research is not sure, research is not definitive, research is not conclusive, research is inconclusive, research is disputed, research is open to debate, research is uncertain, research casts doubt, findings are inconsistent, findings are open to debate, findings are uncertain, findings are not conclusive, findings are inconclusive, findings are debated, findings are disputed, findings are contradictory, findings are at odds with, findings are in conflict with, findings oppose, findings cast doubt, competing findings, conflicting findings, contending findings, contradictory findings, debated findings, disputed findings, inconsistent findings, differing findings, divergent findings, uncertain findings, scientific dispute, scientific skepticism, scientific debate, scientific disagreement, scientific uncertainty, uncertainty among scientists, disagreement among scientists, doubt among scientists, debate among scientists, skepticism among scientists, uncertainty among researchers, disagreement among researchers, doubt among researchers, debate among researchers, skepticism among researchers, uncertainty among experts, disagreement among experts, doubt among experts, debate among experts, skepticism among experts, uncertainty among climate scientists, disagreement among climate scientists, doubt among climate scientists, debate among climate scientists, skepticism among climate scientists, uncertainty among climate researchers, disagreement among climate researchers, doubt among climate researchers, debate among climate researchers, skepticism among climate researchers, uncertainty among climate experts, disagreement among climate experts, doubt among climate experts, debate among climate experts, skepticism, among climate experts, scientific opinion diverges, scientific opinion differs, scientific opinion is divided, expert opinion diverges, expert opinion differs, expert, opinion is divided, multiple scientific views

Denial Dictionary

Below are the keywords included in the denial dictionary. Keywords that include an asterisk capture all variants of that keyword which include that stem (e.g., “reject scien*” captures mentions of “reject science” and “reject scientific”). Mentions of negated variants of keywords, not listed here (e.g., “*not* all experts agree”), were subtracted from the initial dictionary count to produce the final dictionary counts presented in Chapter 2.

reject scien*, rejected scien*, rejecting scien*, rejects scien*, reject research*, rejected research*, rejecting research*, rejects research*, reject expert*, rejected expert*, rejecting expert*, rejects expert*, reject finding*, rejected finding*, rejecting finding*, rejects finding*, reject a finding, rejected a finding, rejecting a finding, rejects a finding, reject a report, rejected a report, rejecting a report, rejects a report, reject climate scien*, rejected climate scien*, rejecting climate scien*, rejects climate scien*, reject climate research*, rejected climate research*, rejecting climate research*, rejects climate research*, reject climate expert*, rejected climate expert*, rejecting climate expert*, rejects climate expert*, reject a climate report, rejected a climate report, rejecting a climate report, rejects a climate report, reject climate report*, rejected climate report*, rejecting climate report*, rejects climate report*, reject the fact*, rejected the fact*, rejecting the fact*, rejects the fact*, dismiss scien*, dismissed scien*, dismissing scien*, dismisses scien*, dismiss research*, dismissed research*, dismissing research*, dismisses research*, dismiss expert*, dismissed expert*, dismissing expert*, dismisses expert*, dismiss finding*, dismissed finding*, dismissing finding*, dismisses finding*, dismiss a finding, dismissed a finding, dismissing a finding, dismisses a finding, dismiss a report, dismissed a report, dismissing a report, dismisses a report, dismiss climate scien*, dismissed climate scien*, dismissing climate scien*, dismisses climate scien*, dismiss climate research*, dismissed climate research*, dismissing climate research*, dismisses climate research*, dismiss climate expert*, dismissed climate expert*, dismissing climate expert*, dismisses climate expert*, dismiss a climate report, dismissed a climate report, dismissing a climate report, dismisses a climate report, dismiss climate report*, dismissed climate report*, dismissing climate report*, dismisses climate report*, dismiss the fact*, dismissed the fact*, dismissing the fact*, dismisses the fact*, undercut scien*, undercutting scien*, undercuts scien*, undercut research*, undercutting research*, undercuts research*, undercut expert*, undercutting expert*, undercuts expert*, undercut finding*, undercutting finding*, undercuts finding*, undercut a finding, undercutting a finding, undercuts a finding, undercut a report, undercutting a report, undercuts a report, undercut climate scien*, undercutting climate scien*, undercuts climate scien*, undercut, climate research*, undercutting climate research*, undercuts climate research*, undercut climate expert*, undercutting climate expert*, undercuts climate expert*, undercut climate report*, undercutting climate report*, undercuts climate report*, undercut a climate report, undercutting a climate report, undercuts a climate report, undercut the fact*, undercutting the fact*, undercuts the fact*, distort scien*, distorted scien*, distorting scien*, distorts scien*, distort research*, distorted research*, distorting research*, distorts research*, distort expert*, distorted expert*, distorting expert*, distorts expert*, distort finding*, distorted finding*, distorting finding*, distorts finding*, distort a finding, distorted a finding, distorting a finding, distorts a finding, distort a report, distorted a report, distorting a report, distorts a report, distort climate scien*, distorted climate scien*, distorting climate scien*, distorts climate scien*, distort climate research*, distorted climate research*, distorting climate research*, distorts climate research*, distort climate expert*, distorted climate expert*, distorting climate expert*, distorts climate expert*, distort a climate report, distorted a climate report, distorting a climate report, distorts a climate report, distort climate report*, distorted climate report*, distorting climate report*, distorts climate report*, distort the fact*, distorted the fact*,distorting the fact*,distorts the fact*, deny scien*, denied scien*, denying scien*, denies scien*, deny research*, denied research*, denying research*, denies research*, deny expert*, denied expert*, denying expert*, denies expert*, deny finding*, denied finding*, denying finding*, denies finding*, deny a finding, denied a finding, denying a finding, denies a finding, deny a report, denied a report, denying a report, denies a report, deny climate scien*, denied climate scien*, denying climate scien*, denies climate scien*, deny climate research*, denied climate research*, denying climate research*, denies climate research*, deny climate expert*, denied climate expert*, denying climate expert*, denies climate expert*, deny a climate report, denied a climate report, denying a climate report, denies a climate report, deny climate report*, denied climate report*, denying climate report*, denies climate report*, deny the fact*, denied the fact*, denying the fact*, denies the fact*, suppress scien*, suppressed scien*, suppressing scien*, suppresses scien*, suppress research*, suppressed research*, suppressing research*, suppresses research*, suppress expert*, suppressed expert*, suppressing expert*, suppresses expert*, suppress finding*, suppressed finding*, suppressing finding*, suppresses finding*, suppress a finding, suppressed a finding, suppressing a finding, suppresses a finding, suppress a report, suppressed a report, suppressing a report, suppresses a report, suppress climate scien*, suppressed climate scien*, suppressing climate scien*, suppresses climate scien*, suppress climate research*, suppressed climate research*, suppressing climate research*, suppresses climate research*, suppress climate expert*, suppressed climate expert*, suppressing climate expert*, suppresses climate expert*, suppress a climate report, suppressed a climate report, suppressing a climate report, suppresses a climate report, suppress climate report*, suppressed climate report*, suppressing climate report*, suppresses climate report*, suppress the fact*, suppressed the fact*, suppressing the fact*, suppresses the fact*, debunk scien*, debunked scien*, debunking scien*, debunks scien*, debunk research*, debunked research*, debunking research*, debunks research*, debunk expert*, debunked expert*, debunking expert*, debunks expert*, debunk finding*, debunked finding*, debunking finding*, debunks finding*, debunk a finding, debunked a finding, debunking a finding, debunks a finding, debunk a report, debunked a report, debunking a report, debunks a report, debunk climate scien*, debunked climate scien*, debunking climate scien*, debunks climate scien*, debunk climate research*, debunked climate research*, debunking climate research*, debunks climate research*, debunk climate expert*, debunked climate expert*, debunking climate expert*, debunks climate expert*, debunk a climate report, debunked a climate report, debunking a climate report, debunks a climate report, debunk climate report*, debunked climate report*, debunking climate report*, debunks climate report*, debunk the fact*, debunked the fact*, debunking the fact*, debunks the fact*, undermine scien*, undermined scien*, undermining scien*, undermines scien*, undermine research*, undermined research*, undermining research*, undermines research*, undermine expert*, undermined expert*, undermining expert*, undermines expert*, undermine finding*, undermined finding*, undermining finding*, undermines finding*, undermine a finding, undermined a finding, undermining a finding, undermines a finding, undermine a report, undermined a report, undermining a report, undermines a report, undermine climate scien*, undermined climate scien*, undermining climate scien*, undermines climate scien*, undermine climate research*, undermined climate research*, undermining climate research*, undermines climate research*, undermine climate expert*, undermined climate expert*, undermining climate expert*, undermines climate expert*, undermine a climate report, undermined a climate report, undermining a climate report, undermines a climate report, undermine climate report*, undermined climate report*, undermining climate report*, undermines climate report*, undermine the fact*, undermined the fact*, undermining the fact*, undermines the fact*, discredit scien*, discredited scien*, discrediting scien*, discredits scien*, discredit research*, discredited research*, discrediting research*, discredits research*, discredit expert*, discredited expert*, discrediting expert*, discredits expert*, discredit finding*, discredited finding*, discrediting finding*, discredits finding*, discredit a finding, discredited a finding, discrediting a finding, discredits a finding, discredit a report, discredited a report, discrediting a report, discredits a report, discredit climate scien*, discredited climate scien*, discrediting climate scien*, discredits climate scien*, discredit climate research*, discredited climate research*, discrediting climate research*, discredits climate research*, discredit climate expert*, discredited climate expert*, discrediting climate expert*, discredits climate expert*, discredit a climate report, discredited a climate report, discrediting a climate report, discredits a climate report, discredit climate report*, discredited climate report*, discrediting climate report*, discredits climate report*, discredit the fact*, discredited the fact*, discrediting the fact*, discredits the fact*, misleading information, misleading finding*, misleading conclusion*, inaccurate information, inaccurate finding*, inaccurate conclusion*, misinformation, disinformation, hoax*, contrarian*, junk scien*, denialism, denier*, denial of the scien*, denial of scien*, denial of climate, anti-science, antiscience, anti science, disregard for scien*, climate exaggerator*, bias against scien*, bias against climate , bias against expert*, biased against scien*, biased against climate , biased against expert*, sow doubt, sowed doubt, sowing doubt, sows doubt

APPENDIX B

Stimuli

Topic: Blood, Condition: Agreement

Scientists Agree with New Study's Claim that Enzymes Convert Type A Blood to Universal Donor

by Trevor Bailey

Until recently, researchers have been struggling to create universal donor blood from other blood types. However, a new study published this week claims to have identified enzymes that can convert type A blood into the universal donor type.

Universal donor blood, O-negative, can be given to anyone because it lacks sugar molecules on red blood cells that immune systems attack, so researchers set about looking into whether enzymes that eat sugar could convert other types of blood into universal donor blood.

They found that two bacterial enzymes taken from the human gut can convert type A into type O-negative blood. Converting other types of blood into a form that is more universally accepted could increase the supply of blood in emergency rooms and ease shortages.

Other scientists agree with the study's findings.

"A large majority of researchers share the view that bacterial enzymes that process sugar can convert blood to more accepted types," said Dr. Jonathan Hammig, who also researches hematology and blood transfusions.

“The findings of this study are in line with findings from previous research. Other studies have also found that these enzymes remove sugar molecules from red blood cells. Most experts agree that there is ample evidence to support the findings of this study.”

Hammig emphasizes that this study’s suggestions are consistent with past research. “The available data strongly indicate that bacterial enzymes can strip offending sugars from red blood cells, so the results really come as no surprise.”

Topic: Blood, Condition: Civil Disagreement

Scientists Disagree over New Study’s Claim that Enzymes Convert Type A Blood to Universal Donor

by Trevor Bailey

Until recently, researchers have been struggling to create universal donor blood from other blood types. However, a new study published this week claims to have identified enzymes that can convert type A blood into the universal donor type.

Universal donor blood, O-negative, can be given to anyone because it lacks sugar molecules on red blood cells that immune systems attack, so researchers set about looking into whether enzymes that eat sugar could convert other types of blood into universal donor blood.

They found that two bacterial enzymes taken from the human gut can convert type A into type O-negative blood. Converting other types of blood into a form that is more universally accepted could increase the supply of blood in emergency rooms and ease shortages.

Other scientists are skeptical of the study’s findings.

“There has been scientific debate in recent years on whether bacterial enzymes that process sugar can convert blood to more accepted types,” said Dr. Jonathan Hammig, who also researches hematology and blood transfusions.

“The findings of this study contradict findings from previous research. Other studies have not found that these enzymes remove sugar molecules from red blood cells. There is still considerable disagreement on this topic within the scientific community."

Hammig emphasizes that this study's results are inconsistent with past research. "This study challenges previous data we have suggesting that bacterial enzymes cannot strip offending sugars from red blood cells, so the results will really stir debate among scientists."

Topic: Blood, Condition: Uncivil Disagreement

Scientists Attack New Study's Claim that Enzymes Convert Type A Blood to Universal Donor

by Trevor Bailey

Until recently, researchers have been struggling to create universal donor blood from other blood types. However, a new study published this week claims to have identified enzymes that can convert type A blood into the universal donor type.

Universal donor blood, O-negative, can be given to anyone because it lacks sugar molecules on red blood cells that immune systems attack, so researchers set about looking into whether enzymes that eat sugar could convert other types of blood into universal donor blood.

They found that two bacterial enzymes taken from the human gut can convert type A into type O-negative blood. Converting other types of blood into a form that is more universally accepted could increase the supply of blood in emergency rooms and ease shortages.

Other scientists reject the study's findings.

"There has been a lot of lousy research in recent years on whether bacterial enzymes that process sugar can convert blood to more accepted types," said Dr. Jonathan Hammig, who also researches hematology and blood transfusions.

"The findings of this garbage study go against findings from previous research. Other studies have not found that these enzymes remove sugar molecules from red blood cells. The idiot authors of this study are clearly just writing nonsense."

Hammig emphasizes that this study's results completely oppose other research. "This study is so far off base from previous data we have suggesting that bacterial enzymes cannot strip offending sugars from red blood cells, so this study is really just junk science."

Topic: Brain, Condition: Agreement

Scientists Agree with New Study's Claim that Shocking Brain Can Improve Athletic Performance

by Trevor Bailey

A recent trend in fitness is neuropriming: sending electrical currents into your brain to stimulate better performance. A new study published this week claims to provide evidence that these brain boosting headsets are effective at improving athletic performance.

Brain-boosting headsets aim to improve muscle memory by stimulating the brain, so researchers set about looking into whether exposing the brain to these electrical currents before physical activity had any effect on performance.

They found that these electrical currents increased physical performance. People who used the headsets were able to make new neural pathways more quickly, which led to improved performance on physical tasks, such as the how high someone could jump.

Other scientists agree with the study's findings.

"A large majority of researchers share the view that priming your brain

with electrical currents can help you to learn faster," said Dr. Jonathan Hammig, who also researches neurophysiology and neuroscience.

"The findings of this study are in line with findings from previous research. Other studies have also found evidence of improved performance. Most experts agree that there is ample evidence to support the findings of this study."

Hammig emphasizes that this study's results are consistent with past research.

"The available data strongly indicate that this technology can improve the speed at which people learn new movements, so the results really come as no surprise."

Topic: Brain, Condition: Civil Disagreement

Scientists Disagree over New Study's Claim that Shocking Brain Can Improve Athletic Performance

by Trevor Bailey

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Brain-boosting headsets aim to improve muscle memory by stimulating the brain, so researchers set about looking into whether exposing the brain to these electrical currents before physical activity had any effect on performance.

They found that these electrical currents increased physical performance. People who used the headsets were able to make new neural pathways more quickly, which led to improved performance on physical tasks, such as the how high someone could jump.

Other scientists are skeptical of the study's findings.

"There has been scientific debate in recent years on whether priming your brain with electrical currents can help you to learn faster," said Dr. Jonathan Hammig, who also researches neurophysiology and neuroscience.

"The findings of this study contradict findings from previous research. Other studies have found no evidence of improved performance. There is still considerable disagreement on this topic within the scientific community."

Hammig emphasized that this study's results are inconsistent with past research. "This study challenges previous data we have suggesting that this technology does not improve the speed at which people learn new movements, so the results will really stir debate among scientists."

Topic: Brain, Condition: Uncivil Disagreement

Scientists Attack New Study's Claim that Shocking Brain Can Improve Athletic Performance

by Trevor Bailey

https://ww

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Hammig emphasizes that this study's results completely oppose other research. "This study is so far off base from previous data we have suggesting this technology does not improve the speed at which people learn new movements, the results are really just junk science."

Topic: Space, Condition: Agreement

Scientists Agree with New Study’s Claim that Saturn’s Rings Caused by Moon Collision

by Trevor Bailey

Until recently, researchers have been struggling to understand how Saturn’s rings formed and how old they are. However, a new study published this week claims that two of Saturn’s moons collided, creating the rings relatively recently.

Knowing that Saturn’s rings were affected by planetary dynamics, researchers set about looking into whether simulations of gravitational interactions in the past could reveal the origin of Saturn’s rings.

They found that the orbits of Saturn’s moons were disrupted about 100 million years ago. They suggest the Sun’s gravitational influence nudged one of Saturn’s moons into a collision with another, the debris from which formed Saturn’s rings.

Other scientists agree with the study’s findings.

“A large majority of researchers share the view that Saturn’s rings were formed by some kind of moon collision,” said Dr. Jonathan Hammig, who also researches astronomy and planetary science.

“The findings of this study are in line with findings from previous research. Other studies have also found that the orbits of Saturn’s moons are different from what they used to be. Most experts agree that there is ample evidence to support the findings of this study.”

Hammig emphasizes that this study’s suggestions are consistent with past research. “The available data strongly indicate that a moon collision created Saturn’s rings, so the results really come as no surprise.”

Topic: Space, Condition: Civil Disagreement

Scientists Attack New Study’s Claim that Saturn’s Rings Caused by Moon Collision

by Trevor Bailey

https://ww

Until recently, researchers have been struggling to understand how Saturn’s rings formed and how old they are. However, a new study published this week claims that two of Saturn’s moons collided, creating the rings relatively recently.

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Topic: Space, Condition: Uncivil Disagreement

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Until recently, researchers have been struggling to understand how Saturn's rings formed and how old they are. However, a new study published this week claims that two of Saturn's moons collided, creating the rings relatively recently.

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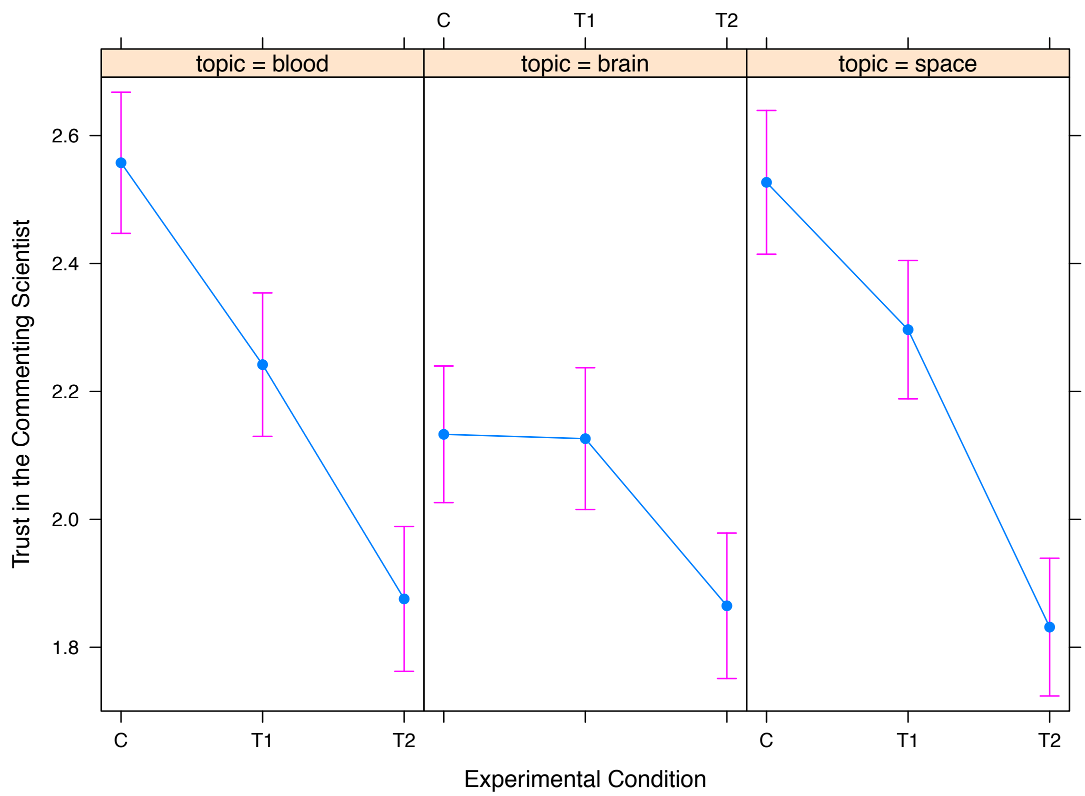
Interactive Effect of Experimental Condition and Topic on Trust in the Commenting Scientist

Figure B.1: Interactive Effect of Condition and Topic on Trust in Commenting Scientist



Note: C = Agreement, T1 = Civil Disagreement, T2 = Uncivil Disagreement

Interaction Analyses and Results

There is no significant correlation between deference to scientific authority and conflict aversion (*r* = -0.03, p = .26).

We used stepwise OLS regressions to look at the main and moderating effects of partisanship, deference to scientific authority, and conflict aversion. The first step, OLS regressions including experimental condition, topic, partisanship, deference to scientific authority, and conflict aversion can be found in Tables B.1-B.3. The second step included interactive effects of experimental condition and the moderator under investigation. The moderating effects of deference to scientific authority can be found in Tables B.4-B.6. The moderating effects of conflict aversion can be found in Tables B.7-B.9. Visualization of significant interaction effects can be found in Figures B.2 and B.3.

Table B.1: Main Effects of Deference to Scientific Authority and Conflict Aversion on Outcomes (1/3)

	Interest			Information Seeking			Engagement with Study Authors			Engagement with Commenting Scientist			Engagement on Social Media		
Civil Disagreement (v. Agreement)	-.15	**	(.07)	-.13	*	(.07)	-.12	*	(.07)	-.08		(.07)	-.17	**	(.07)
Uncivil Disagreement (v. Agreement)	-.25	***	(.07)	-.24	***	(.07)	-.19	**	(.07)	-.19	**	(.07)	-.28	***	(.07)
Brain (v. Blood)	-.20	***	(.07)	-.14	**	(.07)	.14	*	(.08)	.10		(.08)	.02		(.07)
Space (v. Blood)	-.13	**	(.07)	-.08		(.07)	-.05		(.07)	-.07		(.07)	-.04		(.07)
Independents (v. Democrats)	-.18	***	(.06)	-.13	*	(.06)	-.13	*	(.07)	-.18	**	(.07)	-.19	***	(.07)
Republicans (v. Democrats)	.05		(.07)	.07		(.07)	.04		(.08)	.06		(.08)	.05		(.08)
Deference to Scientific Authority	.29	***	(.02)	.28	***	(.02)	.27	***	(.02)	.25	***	(.02)	.26	***	(.02)
Conflict Aversion	-.13	***	(.03)	-.13	***	(.03)	-.23	***	(.03)	-.25	***	(.03)	-.15	***	(.03)
Constant	1.62	***	(.14)	1.55	***	(.14)	1.73	***	(.15)	1.84	***	(.15)	1.42	***	(.15)
Observations	1,987			1,988			1,987			1,986			1,987		
Adjusted R^2	.13			.12			.11			.11			.10		
Residual Standard Error	1.192 (df = 1978)			1.198 (df = 1979)			1.348 (df = 1978)			1.351 (df = 1977)			1.298 (df = 1978)		
F Statistic	36.351*** (df = 8; 1978)			33.371*** (df = 8; 1979)			31.010*** (df = 8; 1978)			30.355*** (df = 8; 1977)			27.284*** (df = 8; 1978)		

Note: *p<0.1; **p<0.05; ***p<0.01

Table B.2: Main Effects of Deference to Scientific Authority and Conflict Aversion on Outcomes (2/3)

	Sharing			Acceptance of Study Findings			Evaluation of Research			Trust in Study Authors			Trust in Commenting Scientist		
Civil Disagreement (v. Agreement)	-.18	***	(.07)	-.51	***	(.06)	-.37	***	(.06)	-.20	***	(.04)	-.17	***	(.04)
Uncivil Disagreement (v. Agreement)	-.34	***	(.07)	-.65	***	(.06)	-.61	***	(.06)	-.49	***	(.04)	-.53	***	(.04)
Brain (v. Blood)	-.13	*	(.07)	-.71	***	(.06)	-.95	***	(.06)	-.36	***	(.04)	-.21	***	(.04)
Space (v. Blood)	-.19	***	(.07)	-.08		(.06)	-.24	***	(.06)	.08	*	(.04)	-.03		(.04)
Independents (v. Democrats)	-.18	***	(.07)	-.01		(.06)	-.14	**	(.06)	-.09	**	(.04)	-.04		(.04)
Republicans (v. Democrats)	.09		(.07)	.16	**	(.07)	-.02		(.07)	-.06		(.04)	.00		(.05)
Deference to Scientific Authority	.28	***	(.02)	.28	***	(.02)	.30	***	(.02)	.25	***	(.01)	.20	***	(.01)
Conflict Aversion	-.14	***	(.03)	-.03		(.02)	-.02		(.02)	-.02		(.02)	-.01		(.02)
Constant	1.24	***	(.15)	2.82	***	(.13)	2.88	***	(.13)	1.73	***	(.09)	1.79	***	(.09)
Observations	1,988			1,988			1,975			1,986			1,985		
Adjusted R^2	.11			.20			.23			.26			.18		
Residual Standard Error	1.274 (df = 1979)			1.145 (df = 1979)			1.142 (df = 1966)			0.754 (df = 1977)			0.794 (df = 1976)		
F Statistic	32.938*** (df = 8; 1979)			62.384*** (df = 8; 1979)			76.153*** (df = 8; 1966)			87.323*** (df = 8; 1977)			54.314*** (df = 8; 1976)		

Note: *p<0.1; **p<0.05; ***p<0.01

Table B.3: Main Effects of Deference to Scientific Authority and Conflict Aversion on Outcomes (3/3)

	Trust in Scientists	Trust in Scientific Methods	Better or Worse	Harms v. Benefits	Utility for Daily Life	Utility for Policy Making
Civil Disagreement (v. Agreement)	-.13 *** (.05)	-.16 *** (.05)	-.10 ** (.05)	-.05 (.05)	-.02 (.05)	-.04 (.05)
Uncivil Disagreement (v. Agreement)	-.22 *** (.05)	-.18 *** (.05)	-.18 *** (.05)	-.11 ** (.05)	-.01 (.05)	-.01 (.05)
Brain (v. Blood)	-.23 *** (.05)	-.18 *** (.05)	-.20 *** (.05)	-.21 *** (.05)	-.17 *** (.05)	-.15 *** (.05)
Space (v. Blood)	-.04 (.05)	-.06 (.05)	-.10 ** (.05)	-.10 ** (.05)	-.04 (.05)	-.01 (.05)
Independents (v. Democrats)	-.16 *** (.04)	-.17 *** (.05)	-.16 *** (.05)	-.11 ** (.05)	-.14 *** (.05)	-.21 *** (.05)
Republicans (v. Democrats)	-.14 *** (.05)	-.13 ** (.05)	-.10 ** (.05)	-.01 (.05)	-.23 *** (.05)	-.27 *** (.06)
Deference to Scientific Authority	.35 *** (.01)	.35 *** (.02)	.32 *** (.01)	.31 *** (.02)	.39 *** (.02)	.39 *** (.02)
Conflict Aversion	-.02 (.02)	-.05 *** (.02)	-.02 (.02)	-.05 ** (.02)	-.01 (.02)	-.02 (.02)
Constant	1.50 *** (.09)	1.65 *** (.10)	2.27 *** (.10)	2.17 *** (.10)	1.18 *** (.11)	.96 *** (.11)
Observations	1,987	1,987	1,988	1,987	1,987	1,987
Adjusted R^2	.28	.26	.24	.21	.26	.26
Residual Standard Error	0.822 (df = 1978)	0.868 (df = 1978)	0.834 (df = 1979)	0.867 (df = 1978)	0.941 (df = 1978)	0.973 (df = 1978)
F Statistic	99.314*** (df = 8; 1978)	86.672*** (df = 8; 1978)	78.747*** (df = 8; 1979)	65.646*** (df = 8; 1978)	88.344*** (df = 8; 1978)	88.088*** (df = 8; 1978)

Note: *p<0.1; **p<0.05; ***p<0.01

Table B.4: Interactive Effects of Manipulation and Deference to Scientific Authority on Outcomes (1/3)

	Interest			Information Seeking			Eng. w/ Study Authors			Eng. w/ Commenting Scientist			Eng. on Social Media		
Civil Disagreement (v. Agreement)	-.21		(.18)	-.28		(.19)	-.24		(.21)	-.19		(.21)	-.31		(.20)
Uncivil Disagreement (v. Agreement)	-.33	*	(.18)	-.32	*	(.18)	-.47	**	(.21)	-.61	***	(.21)	-.47	**	(.20)
Brain (v. Blood)	-.20	***	(.07)	-.14	**	(.07)	.14	*	(.08)	.10		(.08)	.02		(.07)
Space (v. Blood)	-.13	**	(.07)	-.08		(.07)	-.05		(.07)	-.08		(.07)	-.05		(.07)
Independents (v. Democrats)	-.18	***	(.06)	-.12	*	(.06)	-.12	*	(.07)	-.17	**	(.07)	-.18	***	(.07)
Republicans (v. Democrats)	.06		(.07)	.07		(.07)	.04		(.08)	.06		(.08)	.05		(.08)
Deference to Scientific Authority	.27	***	(.04)	.26	***	(.04)	.23	***	(.04)	.20	***	(.04)	.23	***	(.04)
Conflict Aversion	-.13	***	(.03)	-.13	***	(.03)	-.23	***	(.03)	-.25	***	(.03)	-.15	***	(.03)
Interactions															
Civil Disagreement (v. Agreement) * DSA	.02		(.05)	.04		(.05)	.03		(.05)	.03		(.05)	.04		(.05)
Uncivil Disagreement (v. Agreement) * DSA	.02		(.05)	.02		(.05)	.08		(.05)	.12	**	(.06)	.06		(.05)
Constant	1.68	***	(.17)	1.63	***	(.17)	1.88	***	(.19)	2.03	***	(.19)	1.54	***	(.19)
Observations	1,987			1,988			1,987			1,986			1,987		
Adjusted R^2	.12			.12			.11			.11			.10		
Residual Standard Error	1.192 (df = 1976)			1.199 (df = 1977)			1.348 (df = 1976)			1.350 (df = 1975)			1.299 (df = 1976)		
F Statistic	29.081*** (df = 10; 1976)			26.756*** (df = 10; 1977)			25.032*** (df = 10; 1976)			24.839*** (df = 10; 1975)			21.932*** (df = 10; 1976)		

Note: *p<0.1; **p<0.05; ***p<0.01

Table B.5: Interactive Effects of Manipulation and Deference to Scientific Authority on Outcomes (2/3)

	Sharing			Acceptance of Study Findings			Evaluation of Research			Trust in Study Authors			Trust in Commenting Scientist		
Civil Disagreement (v. Agreement)	-.34	*	(.20)	-.44	**	(.18)	-.35	**	(.18)	-.30	**	(.12)	-.22	*	(.12)
Uncivil Disagreement (v. Agreement)	-.43	**	(.20)	-.38	**	(.18)	-.46	***	(.18)	-.38	***	(.12)	-.25	**	(.12)
Brain (v. Blood)	-.13	*	(.07)	-.71	***	(.06)	-.95	***	(.06)	-.36	***	(.04)	-.21	***	(.04)
Space (v. Blood)	-.19	***	(.07)	-.08		(.06)	-.24	***	(.06)	.08	*	(.04)	-.03		(.04)
Independents (v. Democrats)	-.18	***	(.07)	-.02		(.06)	-.15	**	(.06)	-.09	**	(.04)	-.04		(.04)
Republicans (v. Democrats)	.09		(.07)	.16	**	(.07)	-.02		(.07)	-.06		(.04)	.00		(.05)
Deference to Scientific Authority	.26	***	(.04)	.32	***	(.03)	.32	***	(.03)	.25	***	(.02)	.23	***	(.02)
Conflict Aversion	-.14	***	(.03)	-.03		(.02)	-.02		(.02)	-.02		(.02)	-.01		(.02)
Interactions															
Civil Disagreement (v. Agreement) * DSA	.04		(.05)	-.02		(.05)	-.01		(.05)	.03		(.03)	.02		(.03)
Uncivil Disagreement (v. Agreement) * DSA	.02		(.05)	-.08		(.05)	-.04		(.05)	-.03		(.03)	-.08	**	(.03)
Constant	1.32	***	(.18)	2.70	***	(.17)	2.81	***	(.17)	1.73	***	(.11)	1.70	***	(.11)
Observations	1,988			1,988			1,975			1,986			1,985		
Adjusted R^2	.11			.20			.23			.26			.18		
Residual Standard Error	1.275 (df = 1977)			1.145 (df = 1977)			1.142 (df = 1964)			0.754 (df = 1975)			0.793 (df = 1974)		
F Statistic	26.404*** (df = 10; 1977)			50.234*** (df = 10; 1977)			60.988*** (df = 10; 1964)			70.347*** (df = 10; 1975)			44.671*** (df = 10; 1974)		

Note: *p<0.1; **p<0.05; ***p<0.01

Table B.6: Interactive Effects of Manipulation and Deference to Scientific Authority on Outcomes (3/3)

	Trust in Scientists			Trust in Scientific Methods			Better or Worse			Benefits v. Harms			Utility for Daily Life			Utility for Policymaking		
Civil Disagreement (v. Agreement)	-.22	*	(.13)	-.31	**	(.13)	-.27	**	(.13)	-.24	*	(.13)	-.24		(.15)	-.22		(.15)
Uncivil Disagreement (v. Agreement)	-.32	**	(.13)	-.36	***	(.13)	-.39	***	(.13)	-.32	**	(.13)	-.04		(.15)	-.02		(.15)
Brain (v. Blood)	-.23	***	(.05)	-.19	***	(.05)	-.20	***	(.05)	-.22	***	(.05)	-.18	***	(.05)	-.16	***	(.05)
Space (v. Blood)	-.04		(.05)	-.06		(.05)	-.10	**	(.05)	-.10	**	(.05)	-.04		(.05)	-.01		(.05)
Independents (v. Democrats)	-.16	***	(.04)	-.17	***	(.05)	-.16	***	(.05)	-.10	**	(.05)	-.14	***	(.05)	-.21	***	(.05)
Republicans (v. Democrats)	-.14	***	(.05)	-.13	**	(.05)	-.10	**	(.05)	-.01		(.05)	-.23	***	(.05)	-.27	***	(.06)
Deference to Scientific Authority	.33	***	(.02)	.32	***	(.03)	.28	***	(.02)	.27	***	(.03)	.36	***	(.03)	.37	***	(.03)
Conflict Aversion	-.02		(.02)	-.05	***	(.02)	-.02		(.02)	-.05	**	(.02)	-.01		(.02)	-.02		(.02)
Interactions																		
Civil Disagreement (v. Agreement) * DSA	.03		(.03)	.04		(.04)	.05		(.03)	.05		(.04)	.06		(.04)	.05		(.04)
Uncivil Disagreement (v. Agreement) * DSA	.03		(.03)	.05		(.04)	.06	*	(.03)	.06	*	(.04)	.01		(.04)	.00		(.04)
Constant	1.56	***	(.12)	1.77	***	(.13)	2.40	***	(.12)	2.31	***	(.13)	1.26	***	(.14)	1.03	***	(.14)
Observations	1,987			1,987			1,988			1,987			1,987			1,987		
Adjusted R^2	.28			.26			.24			.21			.26			.26		
Residual Standard Error	0.822 (df = 1976)			0.868 (df = 1976)			0.834 (df = 1977)			0.867 (df = 1976)			0.941 (df = 1976)			0.973 (df = 1976)		
F Statistic	79.497*** (df = 10; 1976)			69.582*** (df = 10; 1976)			63.397*** (df = 10; 1977)			52.884*** (df = 10; 1976)			71.030*** (df = 10; 1976)			70.687*** (df = 10; 1976)		

Note: *p<0.1; **p<0.05; ***p<0.01

Table B.7: Interactive Effects of Manipulation and Conflict Aversion on Outcomes (1/3)

	Interest			Information Seeking			Eng. w/ Study Authors			Eng. w/ Commenting Scientist			Eng. on Social Media		
Civil Disagreement (v. Agreement)	.24		(.22)	.29		(.22)	.34		(.25)	.46	*	(.25)	.27		(.24)
Uncivil Disagreement (v. Agreement)	-.16		(.22)	-.15		(.22)	-.20		(.24)	-.06		(.25)	-.10		(.24)
Brain (v. Blood)	-.20	***	(.07)	-.14	**	(.07)	.13	*	(.08)	.10		(.08)	.02		(.07)
Space (v. Blood)	-.13	**	(.07)	-.09		(.07)	-.06		(.07)	-.07		(.07)	-.05		(.07)
Independents (v. Democrats)	-.18	***	(.06)	-.13	**	(.06)	-.13	*	(.07)	-.18	**	(.07)	-.19	***	(.07)
Republicans (v. Democrats)	.05		(.07)	.06		(.07)	.03		(.08)	.06		(.08)	.04		(.08)
Deference to Scientific Authority	.29	***	(.02)	.28	***	(.02)	.27	***	(.02)	.25	***	(.02)	.26	***	(.02)
Conflict Aversion	-.09	**	(.04)	-.09	**	(.04)	-.19	***	(.05)	-.18	***	(.05)	-.09	*	(.05)
Interactions															
Civil Disagreement (v. Agreement) * Conflict Aversion	-.12	*	(.06)	-.12	**	(.06)	-.14	**	(.07)	-.16	**	(.07)	-.13	*	(.07)
Uncivil Disagreement (v. Agreement) * Conflict Aversion	-.03		(.06)	-.03		(.06)	.00		(.07)	-.04		(.07)	-.05		(.07)
Constant	1.48	***	(.18)	1.39	***	(.18)	1.60	***	(.20)	1.62	***	(.20)	1.23	***	(.20)
Observations	1,987			1,988			1,987			1,986			1,987		
Adjusted R^2	.13			.12			.11			.11			.10		
Residual Standard Error	1.191 (df = 1976)			1.198 (df = 1977)			1.347 (df = 1976)			1.350 (df = 1975)			1.298 (df = 1976)		
F Statistic	29.504*** (df = 10; 1976)			27.160*** (df = 10; 1977)			25.379*** (df = 10; 1976)			24.917*** (df = 10; 1975)			22.236*** (df = 10; 1976)		

Note: *p<0.1; **p<0.05; ***p<0.01

Table B.8: Interactive Effects of Manipulation and Conflict Aversion on Outcomes (2/3)

	Sharing			Acceptance of Study Findings			Evaluation of Research			Trust in Study Authors			Trust in Commenting Scientist		
Civil Disagreement (v. Agreement)	.27		(.23)	-.81	***	(.21)	-.52	**	(.21)	-.19		(.14)	-.14		(.15)
Uncivil Disagreement (v. Agreement)	-.16		(.23)	-.72	***	(.21)	-.50	**	(.21)	-.32	**	(.14)	-.34	**	(.14)
Brain (v. Blood)	-.13	*	(.07)	-.71	***	(.06)	-.95	***	(.06)	-.36	***	(.04)	-.21	***	(.04)
Space (v. Blood)	-.19	***	(.07)	-.08		(.06)	-.24	***	(.06)	.08	*	(.04)	-.03		(.04)
Independents (v. Democrats)	-.19	***	(.07)	-.01		(.06)	-.14	**	(.06)	-.09	**	(.04)	-.04		(.04)
Republicans (v. Democrats)	.09		(.07)	.16	**	(.07)	-.01		(.07)	-.05		(.04)	.00		(.05)
Deference to Scientific Authority	.28	***	(.02)	.29	***	(.02)	.30	***	(.02)	.25	***	(.01)	.21	***	(.01)
Conflict Aversion	-.08	*	(.05)	-.06		(.04)	-.02		(.04)	-.01		(.03)	.02		(.03)
Interactions															
Civil Disagreement (v. Agreement) * Conflict Aversion	-.13	**	(.07)	.09		(.06)	.04		(.06)	.00		(.04)	-.01		(.04)
Uncivil Disagreement (v. Agreement) * Conflict Aversion	-.05		(.06)	.02		(.06)	-.03		(.06)	-.05		(.04)	-.06		(.04)
Constant	1.04	***	(.19)	2.93	***	(.17)	2.88	***	(.17)	1.67	***	(.11)	1.71	***	(.12)
Observations	1,988			1,988			1,975			1,986			1,985		
Adjusted R^2	.12			.20			.23			.26			.18		
Residual Standard Error	1.274 (df = 1977)			1.145 (df = 1977)			1.142 (df = 1964)			0.754 (df = 1975)			0.794 (df = 1974)		
F Statistic	26.815*** (df = 10; 1977)			50.168*** (df = 10; 1977)			61.089*** (df = 10; 1964)			70.062*** (df = 10; 1975)			43.673*** (df = 10; 1974)		

Note: *p<0.1; **p<0.05; ***p<0.01

Table B.9: Interactive Effects of Manipulation and Conflict Aversion on Outcomes (3/3)

	Trust in Scientists			Trust in Scientific Methods			Better or Worse			Benefits v. Harms			Utility for Daily Life			Utility for Policymaking		
Civil Disagreement (v. Agreement)	-.12		(.15)	-.11		(.16)	-.24		(.15)	.02		(.16)	-.07		(.17)	-.20		(.18)
Uncivil Disagreement (v. Agreement)	-.12		(.15)	.03		(.16)	-.03		(.15)	-.03		(.16)	.06		(.17)	.05		(.18)
Brain (v. Blood)	-.23	***	(.05)	-.18	***	(.05)	-.19	***	(.05)	-.21	***	(.05)	-.17	***	(.05)	-.15	***	(.05)
Space (v. Blood)	-.04		(.05)	-.06		(.05)	-.10	**	(.05)	-.10	**	(.05)	-.04		(.05)	-.01		(.05)
Independents (v. Democrats)	-.16	***	(.04)	-.17	***	(.05)	-.16	***	(.05)	-.11	**	(.05)	-.14	***	(.05)	-.20	***	(.05)
Republicans (v. Democrats)	-.14	***	(.05)	-.13	**	(.05)	-.10	**	(.05)	-.01		(.05)	-.23	***	(.05)	-.27	***	(.06)
Deference to Scientific Authority	.35	***	(.01)	.35	***	(.02)	.32	***	(.01)	.31	***	(.02)	.39	***	(.02)	.39	***	(.02)
Conflict Aversion	-.01		(.03)	-.03		(.03)	-.02		(.03)	-.03		(.03)	.00		(.03)	-.03		(.04)
Interactions																		
Civil Disagreement (v. Agreement) * Conflict Aversion	-.01		(.04)	-.01		(.04)	.04		(.04)	-.02		(.04)	.01		(.05)	.05		(.05)
Uncivil Disagreement (v. Agreement) * Conflict Aversion	-.03		(.04)	-.06		(.04)	-.04		(.04)	-.02		(.04)	-.02		(.05)	-.02		(.05)
Constant	1.46	***	(.12)	1.56	***	(.13)	2.25	***	(.13)	2.13	***	(.13)	1.17	***	(.14)	.99	***	(.15)
Observations	1,987			1,987			1,988			1,987			1,987			1,987		
Adjusted R^2	.28			.26			.24			.21			.26			.26		
Residual Standard Error	0.823 (df = 1976)			0.868 (df = 1976)			0.834 (df = 1977)			0.868 (df = 1976)			0.942 (df = 1976)			0.973 (df = 1976)		
F Statistic	79.447*** (df = 10; 1976)			69.548*** (df = 10; 1976)			63.470*** (df = 10; 1977)			52.505*** (df = 10; 1976)			70.670*** (df = 10; 1976)			70.645*** (df = 10; 1976)		

Note: *p<0.1; **p<0.05; ***p<0.01

Figure B.2: Visualization of Significant Interactive Effects of Deference to Scientific Authority and Experimental Condition

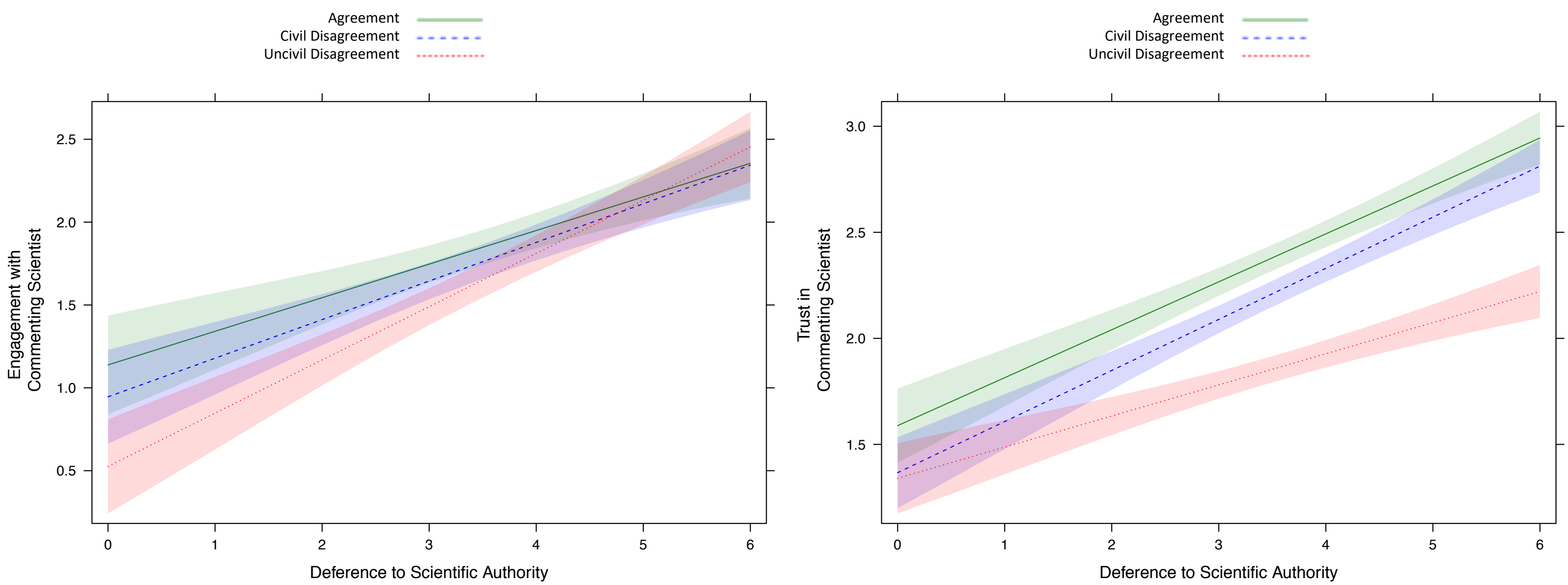
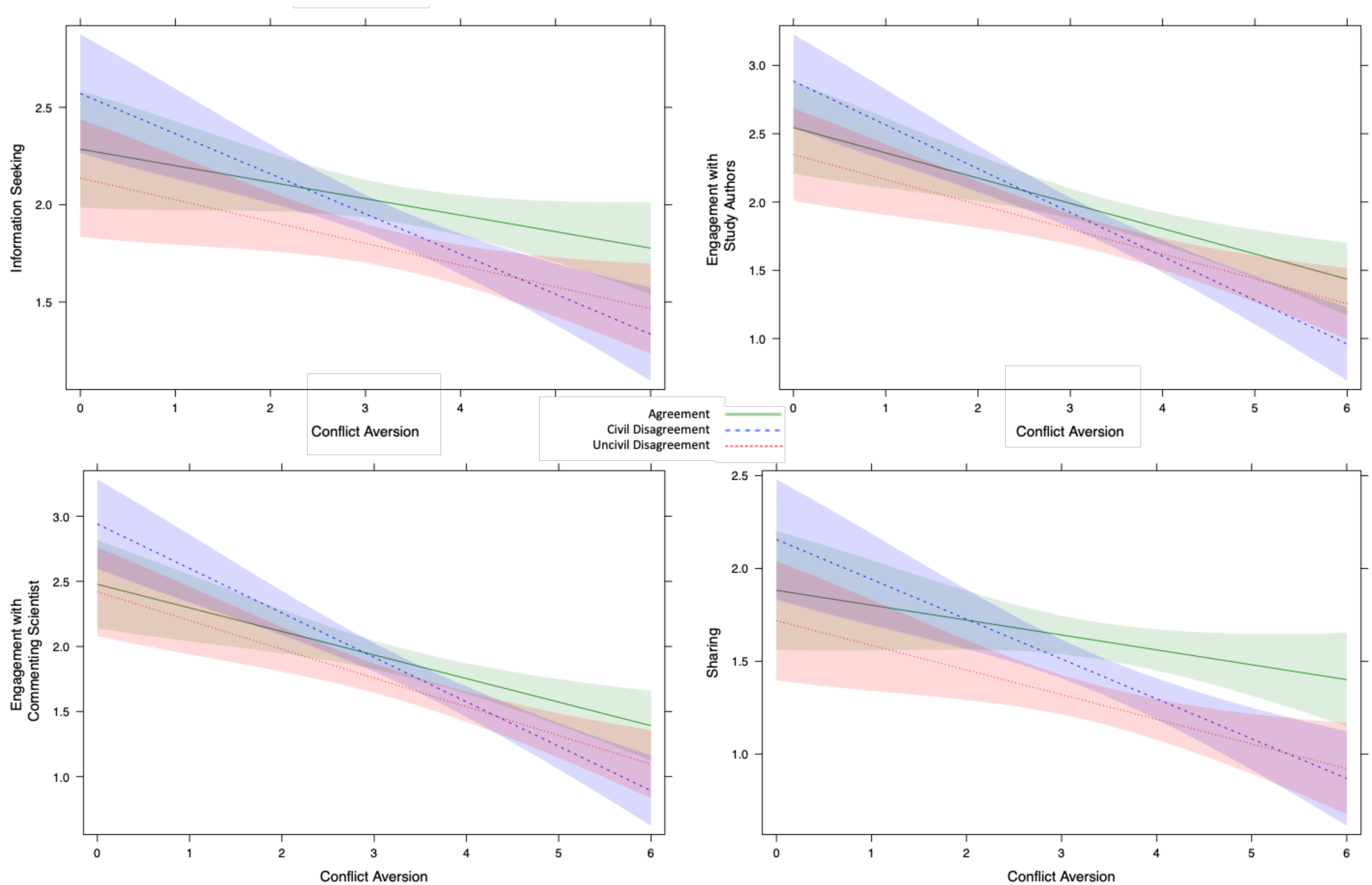


Figure B.3: Visualization of Significant Interactive Effects of Conflict Aversion and Experimental Condition



APPENDIX C

Pre-test Descriptive Information

Pre-test consensus estimate was measured by asking participants, "To the best of your knowledge, what percent (%) of climate scientists say that human activity is causing climate change? (0 - 100)" (M = 67.86, SD = 25.05).

Pre-test belief in climate change was measured by asking respondents, "How strongly do you believe that climate change is or is not happening?" Respondents reported their beliefs on a 5-point scale from "I strongly believe that climate change IS NOT happening" (1) to "I strongly believe that climate change IS happening" (5) (M = 4.10, SD = 1.17).

Pre-test belief in human causation was measured by asking respondents, "Assuming climate change IS happening, to what extent do you think climate change is human-induced as opposed to a result of Earth's natural changes?" Participants reported their beliefs on a 5-point scale from "Climate change is completely caused by natural changes" (1) to "Climate change is completely caused by human activity" (5) (M = 3.35, SD = 1.13).

Pre-test worry was measured by asking participants, "How worried are you about climate change?" Responses were captured on a 5-point scale from "Not at all worried" (1) to "Extremely worried" (5). We also asked, "How concerned are you about climate change?" Responses were captured on a 5-point scale from "Not at all concerned" (1) to

"Extremely concerned" (5). These measures of worry and concern about climate change were averaged to create a measure of *pre-test worry and concern* (M = 3.31, SD = 1.34, r = .92, p = .00).

Pre-test support for public action was measured with the question, "What do you think of peoples' efforts to address climate change? Do you think that people should be putting more, less, or about the same amount of effort toward addressing climate change?" Participants responded on a 5-point scale from "People should put MUCH LESS effort toward addressing climate change" (1) to "People should put MUCH MORE effort toward addressing climate change" (5) (M = 4.09, SD = 1.16).

Finally, we asked participants about their *pre-test support for government action* with the question, "How strongly do you support or oppose government action to address climate change?" Responses were recorded on a 7-point scale from "Strongly support" (1) to "Strongly oppose (7) (M = 5.32, SD = 1.71).

ANOVA Results

To look at condition differences with post-hoc Tukey tests, we first ran a series of ANOVA models with experimental condition and political ideology as predictors, along with gender, age, education, and concern about COVID-19. The omnibus F-tests for experimental condition and political ideology are reported below.

Consensus estimates were significantly associated with both experimental condition $F(3, 1979) = 111.06$, p = .00, $\eta_p^2 = .144$ and political ideology $F(1, 1979) = 64.6$, p = .00, $\eta_p^2 = .031$.

Belief in global warming was significantly associated with both experimental condition $F(3, 1986) = 3.45$, $p = .02$, $\eta_p^2 = .005$ and political ideology $F(1, 1986) = 305.35$, $p = .00$, $\eta_p^2 = .133$.

Belief in human causation was significantly associated with both experimental condition $F(3, 1986) = 5.64$, $p = .00$, $\eta_p^2 = .008$ and political ideology $F(1, 1986) = 247.59$, $p = .00$, $\eta_p^2 = .111$.

Worry and concern about climate change was not associated with experimental condition $F(3, 1986) = 2.33$, $p = .07$. However, it was significantly associated with political ideology $F(1, 1986) = 530.10$, $p = .00$, $\eta_p^2 = .211$.

Support for public action on climate change was not associated with experimental condition $F(3, 1985) = 1.41$, $p = .24$. However, it was significantly associated with political ideology $F(1, 1985) = 341.63$, $p = .00$, $\eta_p^2 = .147$.

Support for government action on climate change was not associated with experimental condition $F(3, 1985) = 2.01$, $p = .11$. However, it was significantly associated with political ideology $F(1, 1985) = 231.80$, $p = .00$, $\eta_p^2 = .105$.

Coding Open-Text Responses

I coded two open-text questions for this study. The first asked participants what they thought informed their views on climate change. The second asked participants what they thought the survey was about.

To code responses to these items, I developed very basic dictionaries to capture language of interest. I did this by first looking at a random draw of 200 responses and making note of the language respondents used to express the quantities of interest. I then created simple dictionaries from this language. I then ran the dictionaries over the text using approximate matching (agrepl in R). Following this, I human coded a random draw of 100 responses from each question and compared them to the dictionary coding. In both cases, the correlation between the human coding and dictionary coding was quite high (.92 for both, $p < .001$).

What influences your attitudes about climate change?

For the question about what influences one's climate attitudes, I was specifically interested in how often scientific agreement was mentioned. It became clear from looking at the initial 200 responses that respondents did not often refer explicitly to consensus information (e.g., "if 97% of scientists say humans cause climate change, then i 100% believe it"), but more frequently cited "scientists" as influences on their attitudes (e.g., "what the experts have to say about it" or "Scientists, health issues, ice Melting, sea rising"). I therefore coded any mentions of scientists, experts, or scientific agreement as indicating that the opinions of many scientists informed one's climate attitudes (see dictionary in Table C.1). However, I did not include other mentions of scientific research, studies, or evidence in this coding. Though these are of course related to scientific agreement, these responses did not refer explicitly to the opinions of experts, like was summarized in the consensus message, but could instead refer to models, individual studies, or other scientific facts.

In some cases, individuals talked about disagreeing with scientists in their responses. For example, one respondent wrote, "Common sense and the realization that most of these so-called scientists have agendas. Do you think they'll get any funding if they say, \"Everything is fine -- nothing to see here folks.\"? (sic)". The dictionary results were not in any way corrected to deal with this type of negation. This appeared to be the main source of inconsistencies between the human coding and the dictionary coding. However, given that the correlation between human coding and the dictionary results remained high even without correcting dictionary results for these cases, I did not pursue any kind of correction to the dictionary results to account for people disagreeing with experts in their responses.

Though not quantitatively coded, other common influences on climate attitudes included personal experience or witnessed changes in weather (e.g., “Watching the devastating weather conditions around the world”); news, documentaries, and other media (e.g., I watch a lot of documentaries on nature and the natural world, including geology, and I have seen quite a bit of good documentaries showing the problems going on with climate change right now, especially at the polar caps.”); and environmental organizations and related appeals (e.g., “the polar bears are starving”). Others used this opportunity to express disagreement (e.g., “I am part of the 3% that believe it is a bunch of crap,” or “The 97% figure is a gross exaggeration, put forward by leftist to advance their anti-capitalist agenda”), conspiracy beliefs (e.g., “It's a front for the 1% agenda to form NWO”), or the belief that climatic changes are fated in some way (“Listen, God has control of the climate. It has nothing to do with man. If God wants to change the climate, then he will change the climate. It's in God's hand”). A few responses were humorous (e.g., “solid waste management and oil industry”).

What is this survey about?

In responses to the question about what this survey was about, I was particularly interested in whether people identified that the survey was about climate change, in spite of the distractor questions. Inspection of an initial 200 responses revealed that in most responses that correctly identified that the survey was about climate change, participants included the phrases “climate change” or “global warming” (e.g., “various subjects, but more about climate change opinion”). In some cases, the responses were quite precise as to the intention of the study (e.g., “Seeing if these statements will change my opinion on climate change”). The dictionary for coding this item were therefore limited to the phrases “climate change” and “global warming” (see Table C.1). References to “the environment” were not included, as this sometimes appeared alongside mention of climate change and other times along mentions of travel destinations (distractor questions included questions and images about travel).

There was evidence of reactance in responses to this question. For example, one respondent wrote that this survey was, “Ostensibly about climate change. In reality it is about a false statement that is used to manipulate opinions.” Others wrote about being forced or manipulated to hold a view on climate change (e.g., “Media trying to force me into thinking the climate change is all caused by humans” or “convincing me to believe your opinion that climate change is real”). Others inferred that politics was a central question (e.g., “I think and HOPE it's to show old republicans that anyone with a brain knows that climate change is real”).

Though not quantitatively coded, others identified the topic of the survey as related to travel and social media, which were the substance of the distractor tasks. Others took the opportunity to thank us for providing the survey. A few responses were humorous (e.g., “Foolish chat-bots...Climate change!!!”).

Table C.1: Dictionaries for Open-Text Responses

Salience	“scientists”, “experts”, “consensus”, “percent”, “97%”*
Demand Characteristics	“climate change”, “global warming”
Note: I used approximate grep searches (agrepl) to approximately match keywords, thus allowing me to count misspelled keywords with the dictionary. *the 97% keyword was identified only using exact matching, because respondents occasionally referred to other percentages for unrelated reasons.	

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