

1	POLITICIZED SCIENTISTS:	1
2	CREDIBILITY COST OF POLITICAL EXPRESSION ON TWITTER	2
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9	As social media becomes prominent within academia, we examine its rep-	9
10	utational costs for academics. Analyzing Twitter posts from 98,000 scientists	10
11	(2016–22), we uncover substantial political expression. Online experiments with	11
12	4,000 U.S. respondents and 135 journalists, rating synthetic academic profiles	12
13	with different political affiliations, reveal that politically neutral scientists are seen	13
14	as the most credible. Strikingly, political expressions result in monotonic penal-	14
15	ties: Stronger posts reduce perceived credibility of scientists and their research and	15
16	audience engagement more, particularly among oppositely aligned respondents.	16
17	Two surveys with scientists highlight their awareness to penalties, their perceived	17
18	benefits, and a consensus on limiting political expression outside their expertise.	18
19	KEYWORDS: Twitter, Scientists' Credibility, Polarization, Online Experiment.	19
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1. INTRODUCTION 1

2 In a "post-truth" era, trust in science is a cornerstone of informed decision-making and
3 effective public policy (McIntyre, 2018, Angelucci and Prat, 2024, Bursztyn et al., 2023b,
4 Arold, 2024, Ash et al., 2024). The COVID-19 pandemic highlighted this reality, illustrating
5 how confidence in scientific expertise shapes public health responses. Similarly, climate
6 skepticism hinders progress toward environmental goals.¹ Skepticism extends beyond these
7 domains, affecting economic development, education, and societal trust more broadly.
8

9 Credibility is essential to science, yet public trust is at a relative low, particularly among
10 U.S. conservatives.² A key driver of distrust is the perception of political bias among scientists
11 (Altenmüller et al., 2024), amplified by the accessibility of their social media activity,
12 where nearly half of academic content engagement comes from non-academics (Mohammadi et al., 2018, Maleki and Holmberg, 2024).

13 This paper proceeds in two parts. First, we use Large Language Models (LLMs) to measure
14 the extent and nuance of scientists' political expression on social media. Second, we
15 assess whether their online political engagement affects public perceptions, focusing on
16 the reputational costs for scientists as public opinion makers (Aina, 2023) shaping individual
17 preferences and behaviors (Algan et al., 2021, Burnitt et al., 2024, Martinez-Bravo and Stegmann, 2022). Using an online experiment, we evaluate how revealing scientists'
18 political views on social media influences perceptions of their credibility and contributes to
19 audience polarization.
20

21
22 _____
23 ¹Higher trust in science is linked to earlier adoption of preventive measures during COVID-19 (Algan et al.,
24 Allcott et al., 2020, Bartoš et al., 2022, Bowles et al., 2023, Eichengreen et al., 2021), whereas skepticism
25 has driven reliance on unverified remedies, such as those documented in Argentina (Calónico et al., 2023, Al-
26 bornoz et al., 2024). On climate change, Druckman and McGrath (2019) highlights how differing beliefs about
27 credible evidence influence policy support.

28 ²Nichols (2017) discusses hostility toward expertise in the U.S., while Lupia et al. (2024) documents declining
29 trust in science among U.S. respondents. Factors include misinformation (West and Bergstrom, 2021, Roozenbeek
30 et al., 2020), historical failings (Scharff et al., 2010), the reproducibility crisis (Hendriks et al., 2020), conspiracy
31 theories (Rutjens and Večkalov, 2022, Douglas, 2021), science-related populism (Mede and Schäfer, 2020, Mede
32 et al., 2021), and political ideology (Cologna et al., 2025), with U.S. conservatives reporting lower trust in scien-
tists, stronger anti-science attitudes, and less confidence in their intentions and methods (Mede, 2022, Funk et al.,
2020, Li and Qian, 2022, Azevedo and Jost, 2021).

1 Our findings reveal evidence of both *ideological* polarization (divergent political posi- 1
2 tions among academics) and *affective* polarization (public aversion to scientists associated 2
3 with opposing partisan groups) (Lelkes, 2016, Barberá, 2020). The central questions of our 3
4 study are: *To what extent do scientists express polarized political opinions on social media?* 4
5 *And what impact does this political expression have on their perceived credibility?* 5

6 Impact is increasingly crucial for academics, with social media playing a growing role in 6
7 research dissemination and public engagement. Studies suggest that social media engage- 7
8 ment can benefit academics (Chan et al., 2023, Klar et al., 2020, Qiu et al., 2024, Boken 8
9 et al., 2023), and Altmetric data reveal a significant rise in the online presence of scientific 9
10 research from prominent journals between 2011 and 2020, particularly on social media.³ 10
11 Our study extends this perspective, examining how scientists use social media not just to 11
12 share research but to engage in politically salient discussions, assessing the implications 12
13 for credibility and public polarization. 13

14 First, we build on Garg and Fetzer (2024) by analyzing the extent of online political dis- 14
15 course and issue-based disagreement among U.S. scientists (university-based researchers) 15
16 compared to general social media users. Examining political slants on social media of- 16
17 fers three key advantages: (i) capturing a large, cross-disciplinary sample of academics, (ii) 17
18 providing a nuanced view of ideological positions beyond a left-right spectrum, and (iii) fo- 18
19 cusing on publicly visible content, avoiding the limitations of survey-based or publication- 19
20 based classifications. 20

21 Our descriptive analysis reveals that 44% of 97,737 U.S. academics on Twitter expressed 21
22 political opinions by making at least one non-neutral post on any of five politically salient 22
23 topics—(i) abortion rights, (ii) climate action, (iii) immigration, (iv) income redistribu- 23
24 tion, and (v) racial equality—between 2016 and 2022, compared to only 7% of the general 24
25 non-academic U.S. Twitter base.⁴ Political engagement is consistent among disciplines 25
26 and topics. Notably, 29% of academics' tweets on these issues are research-related, but 26
27 only 7% of all research-based tweets mention these topics, reflecting a significant intersec- 27
28
28

29 ³While this trend may partly reflect overall social media growth, our data suggest a specific surge in the vis- 29
30 ibility of scientific research online. Altmetric tracks research impact across diverse outlets—newspapers, blogs, 30
31 social media platforms, policy briefs, patents, and traditional citations. 31

32 ⁴These topics are identified as the most salient in U.S. political debates by Gallup and Pew Research. 32

tion between research and political discourse. Academics adopt more neutral positions in research-related tweets but express more explicit stances in non-research tweets. Original posts are also less explicit than retweets, and high-reach academics tend to adopt more moderate stances.⁵ Positions have also shifted over time, with racial equality standing out: disagreement among academics is both more pronounced and widening compared to general users.⁶

According to Morris (2001), engaging in “politically incorrect” communication can result in reputational loss, as audiences may draw adverse inferences about the speaker. Since such reputational concerns can lead to information loss, the second part of our paper quantifies this cost through an online experiment with a representative sample of 1,700 U.S. respondents.⁷ In the experiment, respondents rated vignettes featuring synthetic academic profiles, which varied in political affiliation—based on real tweets—and other attributes, following Kessler et al. (2019). They assessed each scientist’s personal credibility, the credibility of their research, and their willingness to engage with their content. This conjoint design allows us to isolate and precisely estimate the effects of political expression on public perceptions, offering more experimental control than a Twitter-based approach.⁸

Findings reveal a significant *credibility penalty* for scientists who engage in political discourse, regardless of political orientation. Scientists expressing either left- or right-leaning views face a monotonic decline in *personal credibility* (first outcome): Strong Republicans are rated 39% less credible than neutral scientists, Strong Democrats 11% less; Moderate

⁵These patterns highlight the sensitivity of our classification in capturing the intensity of political expression.

⁶This trend of increased political activism among scientists has been linked to events like the March for Science (Russell and Tegelberg, 2020, Campbell et al., 2023).

⁷The broader welfare implications of expert communication are complex. Chakraborty et al. (2020) distinguish between partisan endorsements (post-platform choice) and policy advocacy (pre-platform choice). While endorsements may reduce voter welfare by distorting platforms, these distortions can incentivize experts to provide informative policy advice—unless the conflict between expert and voter preferences is too large. Moreover, despite potential reputational costs, scientists can also benefit professionally from social media, including citation premiums (Chan et al., 2023, Klar et al., 2020) and improved recruitment outcomes in the academic job market (Qiu et al., 2024).

⁸Conjoint designs have been used to study medical decisions (Chan, 2022), repugnant transactions (Elías et al., 2019, Sullivan, 2021), financial choices (Macchi, 2023), dating preferences (Low, 2014), and charitable donations (List and Lucking-Reiley, 2002).

1 Republicans and Democrats are rated 9% and 7% less credible, respectively. This penalty 1
2 extends to the *credibility of their academic work* (second outcome), indicating that rep- 2
3 utational costs go beyond personal perception and exceed standard in-group bias. It also 3
4 translates into lower public *willingness to engage with their work* (third outcome): respon- 4
5 dents are 42% less willing to read opinion pieces from Strong Republicans, 10.7% less for 5
6 Strong Democrats, and 8% and 4.5% less for Moderate Republicans and Democrats, re- 6
7 spectively, compared to neutral scientists. All effects are statistically significant at the 1% 7
8 level. 8

9 Credibility penalties reflect a strong partisan bias: respondents mainly perceive scientists 9
10 aligned with opposing political views as less credible. Democrat respondents rate neutral 10
11 and Democrat-leaning scientists similarly but lose trust in Republican-leaning ones. Repub- 11
12 lican respondents generally prefer moderately Republican scientists to neutral, while still 12
13 penalizing strongly conservative profiles—though less so than they penalize Democrat- 13
14 leaning scientists. These patterns suggest that scientists’ political discourse can serve as a 14
15 channel for polarizing public perceptions and reducing engagement with scientific content, 15
16 depending on audience ideology. 16

17 Among other tested attributes, scientists from highly ranked institutions and those in se- 17
18 nior positions are perceived as more credible, while gender and field have no significant 18
19 effect. Notably, political affiliation emerges as the most salient factor shaping public per- 19
20 ceptions of scientists. 20

21 We conducted several robustness checks. First, we replicated our main findings with a 21
22 separate sample of 2,000 U.S. respondents, confirming that results hold under a different 22
23 outcome structure. We also found minimal carryover effects across profiles, and results 23
24 remain stable after excluding “speeders” and adjusting for multiple hypothesis testing. A 24
25 permutation test and a validation task with new respondents confirmed that participants 25
26 accurately identified the intended political affiliations of scientists in the vignettes. Finally, 26
27 we bounded potential experimenter demand effects and found that any such influence is 27
28 minimal and cannot account for our results. 28

29 To assess external validity, we tested whether the *credibility penalty* for politically en- 29
30 gaged scientists extends to journalists—an important audience, as they regularly cover sci- 30
31 entific research and interview scientists (Alabrese, 2022). Among 135 international jour- 31
32 nalists surveyed, we observed clear asymmetries: Republican scientists were rated 33% less 32

1 credible than neutral ones, and their opinion pieces were 40% less likely to be included in 1
2 newsletters. By contrast, Democrat scientists were rated only 5% less credible and 2% less 2
3 likely to be featured—effects that are statistically indistinguishable from zero, likely due to 3
4 the overrepresentation of liberal journalists. Partisan bias was evident: Liberal journalists 4
5 were 7, 9, and 5 times less likely to rate a Republican scientist’s credibility, research, and 5
6 newsletter inclusion favorably compared to a Democrat. Conservative journalists showed 6
7 a comparable bias in the opposite direction, being 4, 9, and 7 times less likely to favor 7
8 Democrat scientists across the same dimensions.⁹ 8

9 According to the sender-receiver framework in [Gentzkow and Shapiro \(2006\)](#), a sender 9
10 who fails to align their message with the receiver’s prior beliefs incurs a greater credibility 10
11 penalty—especially when the quality of the sender cannot be easily verified *ex post*. For 11
12 scientists, this penalty may arise in two ways: when discussing politically charged research 12
13 topics that conflict with readers’ views (leading audiences to infer political bias) or when 13
14 signaling a political identity cue unrelated to research (which may elicit affective polarization). 14
15 To investigate these channels, we conducted an additional experimental task after the 15
16 conjoint experiment. This between-subject task isolates the credibility effects of (i) tweeting 16
17 about politically salient research that may implicitly signal ideological bias versus (ii) 17
18 explicitly signaling political affiliation through unrelated political cues. We held the re- 18
19 search message constant, varied the political signal in an otherwise uninformative bio, and 19
20 restricted all profiles to economists to keep expertise constant. 20

21 Both mechanisms—sharing politically salient research and signaling political iden- 21
22 tity—independently shape public perceptions. First, we find that merely tweeting about 22
23 politically charged research influences credibility: Democrats view economists more favor- 23
24 ably when the research aligns with their political views, while Republicans rate economists 24
25 lower when the research content is misaligned. These credibility shifts occur even in the 25
26 absence of any explicit political signaling. Second, adding a political identity cue amplifies 26
27 these effects. Among Democrats, a left-leaning bio further increases credibility, while a 27
28 right-leaning one sharply reduces it. For Republicans, the pattern reverses: left-leaning sig- 28
29 nals exacerbate the credibility penalty for misaligned research, while right-leaning signals 29
30

31 ⁹This aligns with findings from [Boxell and Conway \(2022\)](#), who show that 16% of slant variation across outlets 31
32 can be explained by journalist preferences. 32

1 moderate it. These effects extend to newsletter demand—a behavioral measure of audience 1
2 engagement curated following (Chopra et al., 2022, 2024)—where alignment between the 2
3 audience’s political views and the scientist’s signal strongly predicts sign-ups. Together, 3
4 these findings confirm that both inferred ideological bias (based on research content) and 4
5 affective polarization (based on identity cues) contribute to audience reactions, shaping 5
6 who the public trusts and engages with. 6

7 What do scientists think? We surveyed 128 international scientists on Prolific to assess 7
8 whether they anticipate the credibility penalty observed in our experiment and to under- 8
9 stand their views on political expression online. Scientists expected a larger penalty than 9
10 what we observed and considered it more acceptable to express political opinions within 10
11 their area of expertise than outside it—a norm they believe to be widely shared among 11
12 academics. Many reported hesitating to share political views on social media, suggesting 12
13 a potential for information loss in public discourse (Morris, 2001, Ottaviani and Sørensen, 13
14 2006). While they anticipated mild reputational costs for commenting on topics outside 14
15 their field, they saw modest reputational benefits when engaging within their expertise. 15
16 However, perceptions of costs and benefits largely overlapped. To examine this further, we 16
17 conducted a follow-up survey with 118 additional international scientists. Respondents per- 17
18 ceived clear professional benefits of political expression for media appearances and policy 18
19 roles, smaller benefits for network size and citations, and ambiguous or slight costs for top 19
20 journal publications and academic job offers. 20

21
22 *Contribution to the Literature* Our findings deepen our understanding of how the pub- 22
23 lic perceives scientists and their communication (Altenmüller et al., 2024, Blastland et al., 23
24 2020, Norris, 2020). Prior work has explored how uncertainty and political transparency 24
25 affect trust in science (Van Der Bles et al., 2019, 2020, Petersen et al., 2021). For exam- 25
26 ple, Kotcher et al. (2017) found that climate scientists’ advocacy generally did not reduce 26
27 credibility, except when promoting nuclear power. Zhang (2023) showed that political en- 27
28 dorsements by scientific journals—such as Nature’s support for Joe Biden—can polarize 28
29 perceptions of publishers and science more broadly, particularly among Republicans. 29

30 We extend the most directly related work by Zhang (2023) in several key ways. Rather 30
31 than focusing on editorial decisions by publishers—which may reflect institutional rather 31
32 than individual scientist preferences—we provide robust, large-scale observational evi- 32

1 dence on political discourse among scientists themselves, across disciplines and over time. 1
2 We then causally identify the reputational impact of scientists' political expression through 2
3 online experiments, allowing us to distinguish between credibility effects driven by re- 3
4 search on politically charged topics and those driven by personal political signals. Beyond 4
5 this, our study contributes along several additional dimensions: we incorporate behavioral 5
6 outcomes such as newsletter sign-ups; extend external validity by testing effects among 6
7 journalists; and explore scientists' motivations for political expression through survey evi- 7
8 dence. 8

9 More broadly, we contribute to the literature on the communication—or absence—of po- 9
10 litically salient topics in the U.S., including the “spiral of silence” (Huang and Ho, 2023), 10
11 both offline (Braghieri, 2024) and online (Bursztyn et al., 2023a). This literature focuses 11
12 on decisions to voice controversial opinions and their downstream effects. To our knowl- 12
13 edge, this is the first study to examine U.S. academics' online communication on politically 13
14 charged topics and its impact on public perceptions. We also contribute to work on polit- 14
15 ically motivated reasoning in the acquisition (Chopra et al., 2024, Faia et al., 2024) and 15
16 interpretation (Gentzkow et al., 2023, Thaler, 2024) of information, by showing how polit- 16
17 ical affiliation mediates responses to scientists' views. 17

18 We further relate to the growing literature using text-as-data to measure political ideol- 18
19 ogy from sources such as official documents (Ash, 2016, Hansen et al., 2018, Grimmer, 19
20 2010), online news (Cagé et al., 2020), product descriptions (Fetzer et al., 2024), political 20
21 speeches (Jensen et al., 2012, Gentzkow et al., 2019), academic publications (Garg and Fet- 21
22 zer, 2025, Jelveh et al., 2024, Brown and Gupta, 2023), and surveys (Draca and Schwarz, 22
23 2024). Our study builds directly on (Garg and Fetzer, 2024), who show that scientists' po- 23
24 litical expression differs from that of the general public in both topic and tone, with public 24
25 narratives often shaped by highly visible but less academically impactful scientists. We ex- 25
26 tend this work by analyzing polarization in political discourse among U.S. academics and 26
27 causally identifying the reputational risks of political engagement, which vary sharply by 27
28 audience ideology. 28

29 Our findings contribute to broader evidence on ideological and affective polarization in 29
30 the U.S., documenting how echo chambers can deepen public divides (Canen et al., 2020, 30
31 2021, Fiorina and Abrams, 2008, Alesina et al., 2020, Iyengar et al., 2019, Gentzkow and 31
32 Shapiro, 2011, Levy, 2021, Chopra et al., 2024, Mosleh et al., 2021, Colleoni et al., 2014, 32

1 Flaxman et al., 2016, Stewart et al., 2019, Boxell et al., 2024, Kahan et al., 2011). Finding 1
2 that individuals gravitate toward scientists whose views align with their own—and discount 2
3 misaligned voices as less credible—highlights the need for strategies to reduce polarization 3
4 while preserving the integrity and reach of scientific discourse. 4

5 Additionally, our work contributes to the literature on social identity, originally devel- 5
6 oped by Tajfel and Turner (2003) and later incorporated into economic analysis by Akerlof 6
7 and Kranton (2000) and Shayo (2009, 2020). Recent research has examined how social 7
8 identity shapes economic behavior in areas such as trade policy (Grossman and Helpman, 8
9 2021), teamwork (Charness and Chen, 2020), bonus acceptance (Bursztyn et al., 2020), pol- 9
10 icy adoption (Garcia-Hombrados et al., 2024), and everyday interactions (Braghieri et al., 10
11 2024). Party affiliation increasingly influences individual choices beyond politics, includ- 11
12 ing decisions about marriage (Alford et al., 2011), dating (Huber and Malhotra, 2017), 12
13 residential location (Brown et al., 2022), career path (Chinoy and Koenen, 2024), medical 13
14 treatment (Kim, 2024), and even food preferences (Burnett et al., 2024). Our findings show 14
15 that scientists' social identity—specifically their political identity—reduces their perceived 15
16 credibility, the credibility of their research, and the public's willingness to engage with their 16
17 communication. 17

18 While our study is not a real-time Twitter experiment, it relates to recent experimental 18
19 work on interventions to reduce misinformation, toxicity, and discrimination online (Guriev 19
20 et al., 2023, Jiménez Durán, 2022, Beknazár-Yuzbashev et al., 2022, Angeli et al., 2022, 20
21 Ajzenman et al., 2023a,b). We also contribute to the broader literature on the political 21
22 effects of the internet and social media, including their role in shaping voting behavior, 22
23 protests, polarization, and misinformation (see Zhuravskaya et al., 2020, for a review). Our 23
24 focus, however, is on the reputational risks of the growing role of social media in academic 24
25 communication. 25

26 The remainder of the paper is organized as follows. Section 2 examines the political en- 26
27 gagement of a large sample of U.S. academics on Twitter. Section 3 experimentally tests 27
28 how political expression affects public perceptions of scientists' credibility and engage- 28
29 ment with their content. Section 4 presents survey evidence on scientists' own views about 29
30 political expression online. Section 5 concludes. 30

31 31
32 32

1 2. SCIENTISTS' ONLINE POLITICAL EXPRESSION 1

2 Given the growing emphasis on academic impact, we assess whether social media is 2
 3 increasingly vital for scientific dissemination. We track the online diffusion of over 100,000 3
 4 Scopus-indexed articles published from 2011 to 2020 in top general interest and life-science 4
 5 journals using Altmetric data (Alabrese, 2022, Peng et al., 2022).¹⁰ Figure 1, Panel A, 5
 6 shows a steady rise in online presence, particularly on Twitter, where over 96% of articles 6
 7 are mentioned. Panel B further shows that the distribution of Twitter mentions has become 7
 8 less skewed towards zero with a thicker right tail and more high-mention outliers over time, 8
 9 indicating increasing variability in social media attention. 9

10 These trends highlight Twitter's growing role in scientific communication while also in- 10
 11 creasing public visibility into scientists' social media activity. Since about half of those 11
 12 engaging with academic content on Twitter are non-academics (Mohammadi et al., 2018, 12
 13 Maleki and Holmberg, 2024) and that perceptions of political bias among scientists con- 13
 14 tribute to distrust in science (Altenmüller et al., 2024), in this section we leverage Large 14
 15 Language Models (LLMs) to cost-effectively measure the extent and nuance of scientists' 15
 16 political expression on social media. 16

17

18 2.1. *Academics on Twitter: Sample and Method* 18

19 We analyze political discourse and ideological polarization among 97,737 U.S. aca- 19
 20 demics on Twitter from 2016 to 2022, a substantial subset of the 683,050 U.S. research- 20
 21 active academics (National Center for Education Statistics, 2020). These academics gather 21
 22 significant attention to their online content, averaging 6,093 likes ($SD = 6093$) and 1,101 22
 23 retweets ($SD = 1100.9$) per post (medians: 1,376 likes, 272 retweets), with even higher 23
 24 averages for politically salient tweets (e.g., 7,168 likes and 1,210 retweets, $SD = 7168$ and 24
 25 1,209.8; median: 1,978 likes, 405 retweets). These university-based researchers were iden- 25
 26 tified by Mongeon et al. (2023) by matching authors' OpenAlex IDs to Twitter/X accounts 26
 27 via Crossref Event Data. Their method achieved high precision and moderate recall by 27
 28 identifying authors who tweeted their own research. Building on Garg and Fetzer (2024), 28
 29 we use their merged dataset of Twitter timelines and OpenAlex records, employing LLMs 29
 30

31 ¹⁰Of the 114,868 articles published between 2011 and 2020 in *Science*, *Nature*, *PNAS*, *Cell*, *NEJM*, and *Lancet*, 31
 32 107,008 were tracked by Altmetric as of November 10, 2021. See Appendix 3 for details. 32

10

1 to detect whether tweets address specific salient topics and to classify stances of posts as 1
2 pro, anti, or neutral towards those topics.¹¹ 2

3 Our dataset comprises approximately 116 million tweets (original tweets, retweets, quote 3
4 retweets, and replies) from these academics, and our analysis focuses on five politically 4
5 salient issues: Abortion Rights, Climate Action, Racial Equality, Immigration, and Income 5
6 Redistribution.¹² The procedure involves two key steps. The first is *topic detection*. Open 6
7 nAI's GPT-4 was used to generate dynamic keyword dictionaries designed to capture the 7
8 evolving discourse on each topic. The model was prompted with: 8

9 Provide a list of [ngrams] related to the topic of [topic] in 9
10 the year [year]. [Twitter Fine Tuning]. 10

11 Provide the [ngrams] as a comma-separated list. 11

12 The [Twitter Fine Tuning] either explicitly instructed the model to 'Focus 12
13 on language, phrases, or hashtags commonly used on Twitter', 13
14 ensuring the dictionary remains contextually relevant to the platform's discourse or was 14
15 left empty. This process, spanning 5 topics × 3 n-gram types × 7 years × 2 vernacular ad- 15
16 justments (210 prompts), yields five comprehensive keyword dictionaries applied to the full 16
17 corpus of tweets. Tweets containing any keyword from a topic's dictionary were labeled 17
18 as belonging to that topic (e.g., tweets mentioning "Paris Agreement" are labeled under 18
19 Climate Action). The topic detection captures 5.31% (around 6.15 million) of the initial 19
20 116 million tweets. Climate Action was the most discussed topic (2.09% of all tweets), 20
21 followed by Racial Equality (1.50%) and Immigration (0.86%).¹³ 21

22 The second step is *stance detection*. Using OpenAI's GPT-3.5 Turbo, topical tweets were 22
23 classified into three discrete categories: "pro," "anti," and "neutral." The classification used 23
24 the following prompt: 24

25 Classify this tweet's stance towards [topic] as 'pro', 'anti', 25
26 'neutral', or 'unrelated'. Tweet: [tweet]. 26

27 27

28 28

29 ¹¹Comprehensive individual-level, time-series data are publicly available [here](#). 29

30 ¹²We identified salient issue based on Gallup survey. Gallup's list is available [here](#). 30

31 ¹³Using GPT-4 on all tweets would be prohibitive, so we focus on using GPT-3.5 Turbo on the set of topical 31
32 posts for stance detection. 32

1 This process not only identifies the position of each tweet on a specified topic but also 1
2 enhances precision and relevance by filtering out unrelated tweets. To reduce costs, we 2
3 sampled up to three random tweets per author, month, and topic (99.55% had one tweet; 3
4 0.45% had two; 0.004% had three), ensuring adequate coverage and reliable stance esti- 4
5 mation. See Appendix Table V for examples on each topic-stance, posts-level summary 5
6 statistics in Appendix Table II and details on validation in Appendix Section 4. 6

7 Appendix Table I summarizes the key characteristics of our sample of academics. Most 7
8 scientists are in STEM, followed by Medicine and Social Sciences. 54% of U.S.-based 8
9 academics discussed at least one topic, and 81% of those expressed non-neutral stances. 9
10 Our analysis thus focuses on 42,747 scientists who posted non-neutral topical tweets. 10

11 We call *politicized* the scientists who express a non-neutral stance on any salient topic. 11
12 Our focus on non-neutral communication offers several advantages: first, it maps naturally 12
13 from our methodology; second, it broadly identifies the presence of academic discourse 13
14 related to political issues. Such discourse may enable the public to infer scientists' political 14
15 leaning and update the perception of their credibility—a central concern addressed in the 15
16 second part of this paper. 16

17 Appendix Table I further breaks down the proportion of politicized scientists by key char- 17
18 acteristics. The proportion remains relatively stable across categories of academic recogni- 18
19 tion (between 41% and 46%).¹⁴ Disciplinary differences are more notable, with higher 19
20 proportions in Humanities (58%) and Social Sciences (65%) versus STEM (43%) and 20
21 Medicine (38%). Some gender differences also emerge, with 50% of female scientists and 21
22 40% of male scientists being vocal. More details are provided in Section 2.2.2. 22

24 2.2. Academics Political Engagement on Twitter 24

25 Figure 2 compares political discourse trends between academics (orange) and a random 25
26 sample of approximately 100,000 U.S. Twitter users (blue) between 2016 and 2022.¹⁵ The 26
27

28

¹⁴Cumulative citation categories: <100; 101–500; 501–1,000; >1,000. Categories are derived from the follow- 28
29 ing distribution: 25th percentile = 36, median = 190, mean = 1205, 75th percentile = 849. 29

30 ¹⁵Twitter users were originally sampled by Siegel et al. (2021). Their method randomly generated user IDs and 30
31 filtered for active accounts with geographic metadata indicating U.S. residency, based on time zone or location 31
32 fields referencing U.S. states or major cities. 32

1 top-left panel ("All") shows that well over one-third of the 97,737 tracked U.S. academics 1
 2 express a non-neutral opinion on any specified salient topic in each month, revealing a 2
 3 substantial gap compared to general users.¹⁶ 3

4 Breaking the trend down by topic, Climate Action and Racial Equality—the most fre- 4
 5 quently discussed issues—are the largest contributors to the gap. Notably, Climate Action 5
 6 discourse declined at the onset of the COVID-19 pandemic, while Racial Equality remained 6
 7 highly salient, surging in mid-2020 following the George Floyd incident and widespread 7
 8 protests. Abortion Rights discussions spiked in 2022 due to changes in abortion laws, and 8
 9 Immigration conversations peaked around the 2016 presidential election and diminished 9
 10 over time. 10

11 2.2.1. *Overlap with Politics and Research* 11

12 To understand the interplay between scientific discourse and political engagement, we 13
 13 analyzed how academics discuss both research and politically salient issues. Following 14
 14 the methodology in Section 2.1, we used GPT-4o to generate dictionaries for detecting 15
 15 mentions of [*scientific research papers*]. Additionally, we generated diction- 16
 16 naries for [*Donald Trump*], [*Joe Biden*], [*Politicians*], and [*Political 17
 17 Candidates*]. These were combined to create a comprehensive dictionary for identify- 18
 18 ing mentions of political figures (see Appendix Table III for examples). 19

19 We then examined the yearly distribution of academics' tweets across four categories: 20
 20 tweets mentioning politicians (blue), research papers (green), both (pink), and other content 21
 21 (grey). Appendix Figure 1 shows that, on average, 10% of tweets mention politicians, 20% 22
 22 reference research papers, and about 1% mention both. These proportions remain relatively 23
 23 stable over the years, with fluctuations likely tied to significant events (e.g., larger coloured 24
 24 areas in 2020 may reflect discussions post-George Floyd or a COVID-19-induced surge in 25
 25 research tweets). Darker shades mark tweets addressing the five salient issues—Abortion 26
 26 Rights, Climate Action, Racial Equality, Immigration, and Income Redistribution—which 27
 27 largely fall in the residual grey category. 28

28 These findings align with the cross-sectional summary statistics in Appendix Table II: 29
 29 overall, 9.8% of tweets mention politicians and 19.2% mention research papers; when re- 30
 30

31 32 ¹⁶Monthly aggregated scatter plots are smoothed using LOESS (span=0.5) with shaded standard errors.

1 stricted to the five salient topics, these rise to 16.0% and 28.9%, respectively. Notably,
2 Climate Action tweets mention research papers 44.5% of the time versus 15% for politi-
3 cians (a roughly 3:1 ratio), while Abortion Rights and Immigration tweets favor mentions
4 of politicians (25.6% and 28%) over research papers (15% and 21.4%), with ratios of ap-
5 proximately 1.7:1 and 1.3:1.

6 Overall, the data suggest that scientists engage in discussions about research, political
7 figures, and politically salient issues, with a moderate overlap between these domains.
8 Given that politically salient tweets generate high engagement and research-related dis-
9 course is increasingly prevalent on Twitter (see Figure 1), it is important to assess the
10 impact of this communication on public perceptions.

11
12
13 *2.2.2. Differences by Gender and Discipline*

14 We examine variation in academics' online political expression by gender and discipline.
15 Gender was determined via a binary LLM classification (Appendix Figure 2).¹⁷ Academics
16 with female-labeled names express slightly more political opinions—especially on Abor-
17 tion Rights, Immigration, and Racial Equality (with notable increases post-2020)—while
18 no significant gender differences appear for Climate Action and Income Redistribution.
19

20 We also assess disciplinary differences using OpenAlex "Concepts." Each publication
21 is scored on 19 root concepts; for each researcher, we average these scores over the en-
22 tire period and assign the primary concept to one of three groups: Medicine, Social Sci-
23 ences (Business, Economics, History, Political Science, Psychology, Sociology), or STEM
24 (Biology, Chemistry, Engineering, Environmental Science, Geography, Geology, Materials
25 Science, Mathematics, Physics). Figure 3 shows that, overall, U.S. academics express po-
26 litical views beyond their field. However, STEM scientists are most vocal about Climate
27 Action, while Social Scientists are more active on Income Redistribution. Notably, gaps
28 between disciplines have narrowed over time, contrasting with common stereotypes of sci-
29 entist politicization (Altenmüller et al., 2024).

30
31
32 ¹⁷Names were classified as "Male" or "Female" with 99% accuracy (see Appendix Section 4).

1 2.2.3. Scientists' Ideological Polarization on Twitter

Our analysis thus far shows that, of the 97,737 academics sampled, 52,541 engaged in tweeting about political issues, with 81% of these expressing non-neutral stances on at least one of the five salient topics. We define *ideological polarization* as the divergence in political views or issue positions among individuals.

For each topic and user in a given month, we calculated their slant as the difference between the number of pro-stance tweets and anti-stance tweets, divided by the total number of tweets (pro, anti, or neutral) they posted during that month on that topic.¹⁸ This is expressed as:

$$S_{um} = \frac{pro_{um} - anti_{um}}{pro_{um} + anti_{um} + neutral_{um}}$$

In this formula, S_{um} denotes the net pro stance share of tweets by user u in time-period m , relative to all their tweets on a topic. This approach provides, for each individual, a continuous measure of slant ranging from -1 (completely anti) to 1 (completely pro) for each topic, at any point in time. Our method captures the spectrum of opinions, from strong opposition to firm support, while distinguishing between more moderate or explicit positions—an essential feature in environments where public opinions may lean toward socially desirable expressions (Bénabou and Tirole, 2006).

Figure 4 displays the net pro stance distributions S_{um} for each topic across academics and general users over the entire sampled period. Except for Racial Equality, neutral views dominate; however, multiple peaks—confirmed by Hartigan’s Dip Test ([Hartigan and Hartigan, 1985](#)) ($p=0$)—indicate strong multimodality and distinct political camps. General users cluster more at extreme conservative stances (e.g., -1) than academics, who concentrate in the moderate liberal/progressive range. Notably, for Racial Equality, with few neutral stances, users show higher consensus by clustering more at the fully pro stance compared to academics. Appendix Figure 3 further compares early (2016–2017) and late (2021–2022) net pro stance distributions. Results suggest shifts in opinions over time, particularly on topics like Immigration and Abortion Rights, for which KS is highest

³¹ Specifically, we measured individual academics' slant following the theoretical framework of Esteban and Ray (1994), categorizing tweets into 'pro', 'anti', and a residual 'neutral' category.

1 (Massey Jr, 1951), highlighting the dynamic nature of ideological polarization among aca- 1
2 demics. 2

3 We also examine differences in net stances between tweets mentioning scientific re- 3
4 search or not and how differences in Twitter reach and post type influence academics' net 4
5 stances. Appendix Figure 4 shows that academic research-related tweets are significantly 5
6 more moderate than non-research tweets (except for Climate Action, where differences 6
7 are smaller and research tweets are slightly more progressive). The largest divergence be- 7
8 tween research and non-research-related tweets is seen in Abortion Rights: non-research 8
9 tweets skew more pro-choice (+1) while research tweets cluster more near neutrality (0). 9
10 Further, Appendix Figure 5 indicates that academics with lower Twitter reach (below the 10
11 median of 522 followers) exhibit more extreme stances, whereas high-reach academics ap- 11
12 pear more moderate. Finally, Appendix Figure 6 reveals that retweets display consistently 12
13 more extreme stances than original tweets—particularly for Abortion Rights and Climate 13
14 Action—suggesting that original posts tend to be more measured while retweets amplify 14
15 polarized views. 15

16 Findings align with expectations: research-related tweets likely reflect professional 16
17 norms of moderation, while non-research tweets allow for more direct political expres- 17
18 sion. Similarly, academics adopt a more measured tone in their original posts, potentially 18
19 exercising greater caution with content directly attributable to them. Overall, these patterns 19
20 highlight the sensitivity of our measure in capturing differences between more neutral or 20
21 explicit positions. 21

22 22

23 2.2.4. *Evolution of Scientists' Disagreement* 23

24 24

25 We finally examine the evolution of disagreement among scientists by computing the 25
26 monthly variance of net pro stances S_{um} for each topic. Variance provides a continuous 26
27 measure of opinion diversity that is insensitive to the average stance yet highly sensitive 27
28 to extremes, facilitating longitudinal and cross-topic comparisons (McCarty et al., 2016). 28
29 Although variance is robust and interpretable for large datasets, it does not reveal the causes 29
30 of disagreement (Fiorina et al., 2005) and may overstate divergence if few hold extreme 30
31 views; it also may not capture consensus well (Hopkins, 2018). Therefore, we interpret 31
32 variance in relative terms—lower variances indicate greater consensus—and examine its 32

1 fluctuations over time and topics to identify both divergence and emerging agreement in 1
 2 the evolving ideological landscape. 2

3 The top left panel in Figure 5 ("All") aggregates all topics, showing a mild increase in 3
 4 disagreement from 2016 to 2022, which could raise concerns about scientific consensus 4
 5 and public trust. While scientists appear to exhibit greater ideological distance than general 5
 6 users overall, a topic breakdown reveals nuances. For most topics, the general U.S. Twitter 6
 7 population shows higher disagreement than academics. However, for Racial Equality, aca- 7
 8 demics display a growing and more pronounced disagreement compared to the public—a 8
 9 disparity that disproportionately affects the aggregate trend given its high prominence. For 9
 10 Immigration, Income Redistribution, and Abortion, public disagreement is higher, with the 10
 11 gap widening during the pandemic before narrowing toward the end of the period. In the 11
 12 case of Climate Action, disagreement between academics and the general public persists 12
 13 throughout, with the gap widening further by the end of 2022. 13

14
 15 3. SCIENTISTS' POLITICAL EXPRESSION AND PUBLIC PERCEPTIONS 14
 16

17 Having examined the scope of online political discourse and issue-based disagreement 16
 18 among scientists—and compared these patterns to those of general X users—we now assess 17
 19 the risks of such engagement. Specifically, we study how scientists' political expression af- 18
 20 fects public perceptions of their credibility and contributes to audience polarization. We ran 19
 21 a conjoint experiment with 1,704 respondents from a broadly representative U.S. sample, 20
 22 recruited via Prolific—a platform widely used for experimental research (Bursztyn et al., 21
 23 Enke et al., 2023).¹⁹ 22

24 Our sample broadly reflects the U.S. population in terms of key dimensions, including 23
 25 political affiliation, region, ethnicity, and gender. As is typical with Prolific, respondents 24
 26 tend to be slightly younger, more educated, and have higher incomes than the general pop- 25
 27 ulation. Importantly, prior work shows that Prolific's Republican sample is representative 26
 28 of the broader Republican population (Braghieri et al., 2024, Kashner and Stalinski, 2024). 27
 29 Appendix Table VI provides full demographic comparisons. To ensure data quality, all par- 28
 30 ticipants passed an attention check before beginning the main task. 29

31 ¹⁹All studies and surveys in this paper were pre-registered on AsPredicted with numbers 166935, 179009, 31
 32 181452, 186295, and 206927. 32

1 We opted for an online experiment over a field experiment on X due to several advan- 1
 2 tages, despite a minor conceptual mismatch with Section 2. First, the conjoint design on 2
 3 Prolific lets us systematically vary scientists' attributes—something hard to achieve on X. 3
 4 Second, a field experiment would require creating fake scientist profiles to engage with 4
 5 users, a method both impractical and likely to raise authenticity concerns. Third, typical 5
 6 field outcomes like follow-backs and retweets (Ajzenman et al., 2023a,b) are too narrow 6
 7 for capturing perceived credibility. 7

8

9 3.1. Experimental Design

10 Following best practices for conjoint experiments (Hainmueller et al., 2015), we created 10
 11 five hypothetical scientist profiles, randomly varying key attributes: gender (male/female), 11
 12 research field (Social Sciences, STEM, Medicine, Humanities), seniority (junior/senior), 12
 13 university prestige (high/low), and political affiliation. 13

14 The latter—our main attribute—is conveyed through a Twitter-style bio and a high- 14
 15 engagement tweet,²⁰ spanning five categories: Strong Democrat, Moderate Democrat, Neu- 15
 16 tral (baseline), Moderate Republican, and Strong Republican. 16

17 The five political profiles were created by randomizing the remaining attributes, ensuring 17
 18 each had a unique combination of characteristics. Vignettes followed a consistent format 18
 19 and were shown in random order to avoid order effects (see Appendix Table VII and Figure 19
 20 7 for a visual representation). 20

21

22 *The profile you are seeing is a [Gender] scientist.* 22

23 *This scientist works in the field of [Research Field]* 23

24 *Currently, this scientist is a [Seniority] at the [University Affiliation].* 24

25 *The scientist is active on X (formerly known as Twitter).* 25

26 *The Twitter bio of the scientist is: "[Twitter Bio]".* 26

27 *A recent selected Tweet reads: "[Twitter Post]".* 27

28

29 Participants rated the credibility of the scientist and their research separately on a 29
 30 0–10 scale, and indicated their willingness to read an opinion piece by a similar scien- 30

31

32 ²⁰High-engagement tweets (those with many likes, retweets, and comments) are used for their greater visibility. 32

1 tist (0–10).²¹ To encourage truthful responses, participants were told they would receive an 1
 2 article from a real scientist matching their ratings.²² The design included 960 unique pro- 2
 3 files, generated from all combinations of 2 (gender) × 4 (field) × 2 (seniority) × 2 (university 3
 4 affiliation) × 5 (political profile). 4

5 Our within-subject conjoint design covers the full political spectrum and provides greater 5
 6 power to detect the effect of each attribute. A between-subject design, by contrast, would 6
 7 allow only limited variation—for example, varying the Twitter bio while holding the tweet 7
 8 constant. However, to complement our main task, we also ran a between-subject task in 8
 9 which respondents rated the credibility of an economist (discipline held constant). In this 9
 10 additional task—detailed in Section 3.4—the tweet (promoting a research paper) was fixed, 10
 11 while political leaning was signaled only through the bio (left or right). This design allowed 11
 12 us to isolate whether credibility penalties stem from politically salient research topics or 12
 13 from identity cues unrelated to scientific content. 13

14 Our design addresses common concerns in conjoint experiments (Hainmueller et al., 14
 15 2015), particularly attribute-order effects and experimenter demand effects. To mitigate 15
 16 order effects, we placed the primary attribute—political affiliation—at the bottom of the 16
 17 profile. To reduce demand effects, we highlighted multiple salient attributes and informed 17
 18 respondents that they would receive an opinion piece from a real scientist matching their 18
 19 top-rated profile. We explicitly discuss and bound potential demand effects in Section 3.2.2. 19
 20 To enhance profile plausibility, we informed participants that all tweets were from real sci- 20
 21 entists and stated in the consent form that no false information was used. Full experimental 21
 22 instructions are provided in the supplementary Instructions material. 22

23

24 3.1.1. *Validating Twitter Political Signals*

25 To validate our political affiliation signals, we surveyed 98 new Prolific participants who 25
 26 categorized each combination of Twitter bios and tweets from the main experiment into 26
 27 one of five labels: Strong Republican, Moderate Republican, Neutral, Moderate Democrat, 27
 28

29 ²¹Hainmueller et al. (2015) shows that single- and paired-vignette designs yield similar estimates; we use the 29
 30 simpler single-vignette approach. 30

31 ²²Prior work finds no significant difference between hypothetical and incentivized responses (Hainmueller 31
 32 et al., 2015, Brañas-Garza et al., 2021, 2023, Enke et al., 2022). 32

1 or Strong Democrat. Appendix Figure 8 shows that most responses matched the intended
2 labels, with misclassifications largely limited to adjacent categories. This high accuracy
3 confirms that our signals were reliably perceived, supporting the credibility of our design.
4

5 3.2. Impact on Public Perceptions 6

7 Figure 6 shows that scientists' online political expression leads to a monotonic penalty:
8 neutral profiles receive the highest ratings for personal credibility, research credibility, and
9 willingness to read opinion pieces, with outcomes declining significantly as political affili-
10 ations become more extreme on either the left or right.
11

11 Scientists expressing any political stance are viewed as less credible than neutral ones
12 (Panel A), supporting the stereotype that scientists should remain impartial (Altenmüller
13 et al., 2024). Relative to neutral scientists, Strong Republicans are rated 39% less credible
14 and Strong Democrats 11% less. Moderate Republicans and Moderate Democrats incur
15 smaller penalties—9% and 7%, respectively. An identical pattern holds for research credi-
16 bility, indicating that political discourse impacts both personal and scientific credibility.
17

17 Similarly, willingness to read declines monotonically: respondents are 42% less willing
18 to read from Strong Republicans and 10.7% less willing to read from Strong Democrats.
19 Moderate Republicans and Moderate Democrats see more limited declines of 8% and 4.5%,
20 respectively. All results remain robust when controlling for respondent characteristics (Ap-
21 pendix Figure 9, Panels C and D).
22

22 While political affiliation is the most salient attribute, a few additional characteristics
23 also marginally affect public perceptions. Scientists from prestigious institutions (e.g., Har-
24 vard, UC Berkeley, UChicago) are rated as more credible and attract higher readership than
25 those from less prestigious ones (e.g., University of Arkansas, University of Connecticut),
26 as shown in Appendix Figure 9 and Appendix Tables VIII to X. When examining each
27 political profile separately, the benefit of a prestigious institutional affiliation holds for all
28 except the neutral academic, and it even results in a penalty for Strong Democrat profiles.
29 Moreover, Full Professors are generally seen as more credible and are more likely to be
30 read than Assistant Professors.
31

31 Other attributes are never statistically significant. Specifically, gender does not appear
32 to affect credibility—though neutral male scientists are (non-significantly but consistently)
32

1 less likely to be read than their female counterparts, partly consistent with findings in Siev- 1
 2 ertsen and Smith (2025). 2

3 3

4 4

5 5

6 3.2.1. *Heterogeneity by Respondent Leaning* 6

7 7

8 To determine whether scientists' online political expression may contribute to polarizing 8
 9 audience views, we analyzed how perceptions of different scientist profiles vary based on 9
 10 respondents' political leanings. Panel B of Figure 6 reveals significant heterogeneity tied 10
 11 to political identity, showing a clear pattern of affective polarization. 11

12 Respondents identifying as *Democrat* or *leaning Democrat* assign substantially lower 12
 13 credibility to the Republican-leaning scientists: the Moderate Republican scientist faces an 13
 14 18.3% credibility penalty and the Strong Republican a 60% penalty (Panel B, dark blue), 14
 15 with willingness-to-read dropping by 23.2% and 69%, respectively (light blue). These re- 15
 16 spondents view the Neutral and Democrat-leaning scientists similarly. 16

17 Conversely, respondents identifying as *Republican* or *leaning Republican* rate the 17
 18 Democrat-leaning scientists as 16% (Moderate) to 26% (Strong) less credible (Panel B, 18
 19 dark red), and are 18%–30% less willing to read their opinions (light red). Notably, they 19
 20 view the Moderate Republican scientist as 3.1% more credible than the Neutral one and are 20
 21 11.6% more willing to read them. While the Strong Republican scientist is rated 12% lower 21
 22 in credibility than the Neutral one, they remain more credible than the Democrat-leaning 22
 23 scientists, with only a 7% drop in willingness-to-read. 23

24 Overall, the gap in willingness to engage with scientists holding opposing political iden- 24
 25 tities ranges from 18%–23% for moderate stances and increases to 30%–69% for extreme 25
 26 ones. These results, consistent with Ajzenman et al. (2023b) and Rathje et al. (2021), show 26
 27 a monotonic pattern: stronger political signals lead to larger penalties among politically 27
 28 opposed respondents, reflecting affective polarization. Crucially, the drop in personal cred- 28
 29 ibility extends to perceived research credibility and translates into lower willingness to 29
 30 engage with their content. Barrios et al. (2024) documents a comparable effect—a 30% 30
 31 decline in trust in an economics paper due to a conflict of interest—aligning closely with 31
 32 our findings. 32

1 3.2.2. *Robustness Checks*

2 We conducted several robustness checks to address potential concerns: (1) sample and
3 procedure robustness, (2) variation in perceived expertise, (3) differential respondent atten-
4 tion, (4) misperception of political profiles, (5) multiple hypothesis testing, and (6) experi-
5 menter demand effects.

6

7 *Replication* We replicated the main experiment with 2,000 new Prolific respondents,
8 eliciting only two outcomes—credibility and willingness to read. Results are virtually iden-
9 tical, confirming robustness to procedural changes and to a new, representative U.S. sample
10 (available upon request).

11

12 *Role of Expertise* As discipline is randomized across profiles, we test whether matching
13 a scientist’s expertise to the topic of their post affects perceptions (e.g., the Strong Repub-
14 ican may be a medical expert; the Moderate Democrat a STEM expert). Appendix Tables
15 **VIII–X** show no significant effect of such alignment on credibility or willingness to engage.

16 *Carryover Effects* A crucial assumption for our design is the absence of carryover ef-
17 fects across profiles. Such effects would imply that a respondent’s evaluation of one profile
18 is influenced by those seen before or after, introducing bias. Although unlikely due to ran-
19 domization, we explicitly test this by analyzing responses within each round. Appendix
20 Figure 12 confirms that results are consistent across rounds, ruling out order effects.

21

22 *Excluding ‘Speeders’* A common concern in online experiments is that some respon-
23 dents rush through tasks without paying adequate attention, introducing noise. We therefore
24 exclude respondents who completed the survey in under one minute (median time: 7.2 min-
25 utes). Appendix Figure 13 shows results remain stable, indicating inattentive respondents
26 are not driving our findings.

27

28 *Permutation Test* We further test whether the baseline ‘neutral’ scientist inadvertently
29 signals political identity. We randomly reassigned labels across the five profiles seen by
30 each respondent and re-estimated our main result, repeating the procedure 100 times. Ap-
31 pendix Figure 14 shows the resulting coefficients cluster around zero, supporting the neu-
32 trality of the baseline.

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1 *Multiple Hypothesis Testing* One advantage of a conjoint experiment is the ability to 1
 2 simultaneously test multiple attributes, though this requires correction for multiple hypoth- 2
 3 esis testing. We adjust for multiple comparisons using the false discovery rate method 3
 4 (Benjamini et al., 2006), correcting for 11 treatments (16 attribute categories minus five 4
 5 baselines). Appendix Table XI shows that estimates remain statistically significant after 5
 6 correction. 6

7

8 *Experimenter Demand* Our design minimizes demand effects by placing political affil- 8
 9 iation last among randomized attributes and incentivizing truthful responses via a tailored 9
 10 newsletter. Yet, we bound potential residual effects by conducting a separate experiment 10
 11 with 354 U.S. respondents. After rating a neutral profile, subjects were shown either a 11
 12 Strong Republican or Strong Democrat profile. Before rating the second, they were nudged 12
 13 to rate it either higher or lower to induce demand (de Quidt et al., 2018). Appendix Figure 13
 14 10 shows that these nudges had little effect: neutral scientists remain the most credible and 14
 15 readable, while left- and right-leaning profiles incur penalties. 15

16

17 3.3. *Impact on Journalists Perceptions*

18

19 To assess external validity, we conducted a simplified experiment with 135 international 19
 20 journalists recruited via Prolific. The sample includes experienced professionals employed 20
 21 in various roles and outlets (50% with over 5 years of experience, 78% as reporters or edi- 21
 22 tors, and over half based in the U.S. or the UK), with roughly 60% affiliated with politically 22
 23 oriented outlets (see detailed summary statistics in Appendix Table XII). 23

24

25 In this streamlined experiment, journalists viewed three scientist profiles—signaling 24
 26 Strong Republican, Strong Democrat, and Neutral ideologies via Twitter biographies (with- 25
 27 out tweets).²³ They evaluated the credibility of the scientists and their research and indi- 26
 28 cated their willingness to feature an opinion piece from a scientist with such characteristics. 27
 29 To incentivize thoughtful responses, journalists were informed that an opinion piece from 28
 30 their highest-rated scientist would appear in a newsletter shown to 100 readers, with a mon- 29
 31 etary bonus awarded if their selected piece ranked among the top five preferred by readers. 30

31

32 ²³We reduced the number of profiles to account for the limited sample size while maintaining statistical power. 31

1 Appendix Figure 11 replicates our main findings in this new sample of international 1
2 journalists: neutral scientists are rated highest, while ideologically non-neutral profiles in- 2
3 cur significant penalties. Specifically, journalists perceive the Strong Republican scientist 3
4 and their research as 33% and 32% less credible, respectively, and are 40% less willing to 4
5 feature their opinion piece, relative to a neutral scientist (Panel A). By contrast, the Strong 5
6 Democrat scientist is rated 5% less credible (4% for their research) and elicits a 2% lower 6
7 willingness to feature their opinion piece; however, these smaller effects are not statistically 7
8 significant. The more pronounced effects for Republican profiles are mainly driven by the 8
9 liberal majority among journalists (62%): among liberal respondents, penalties for Repub- 9
10 lican scientists range from 42% to 56% (Panel B), while conservative journalists impose 10
11 penalties of 18% to 28% on Democrat scientists. 11

12 We further explored factors shaping journalists' preferences by surveying their views 12
13 on disclosing scientists' political leanings (when known), expectations of reader reactions 13
14 to featuring politically engaged scientists, and willingness to engage with such scientists 14
15 who are politically active on social media. Appendix Table XIII shows that over half 15
16 of the journalists believe a scientist's political leaning should be disclosed and that fea- 16
17 turing politically active scientists can affect a newspaper's credibility. While they antici- 17
18 pate mixed reader reactions, most remain inclined to reach out to politically active scien- 18
19 tists—suggesting that journalists may play a role in amplifying scientists' political opinions 19
20 and shaping public perceptions of scientific credibility. 20

21 21
22 22

23 3.4. Disentangling Mechanisms 23

24 24
25 Scientists may share political views while discussing their research on politically charged 25
26 issues or when expressing opinions unrelated to their work. We aim to disentangle whether 26
27 these two types of communication have different effects on public perception. Specifically, 27
28 we test whether perceived credibility is influenced by (1) tweeting about research on po- 28
29 litically salient topics, which may signal ideological bias (Altenmüller et al., 2024), or (2) 29
30 signaling political identity through content unrelated to research (Ajzenman et al., 2023b, 30
31 Rathje et al., 2021, Levy, 2021). While other mechanisms may matter, our design isolates 31
32 these two core, policy-relevant channels. 32

1 *Experimental Design* To disentangle the two channels, we added a final task immedi- 1
 2 ately after the main experiment in Section 3.1. Respondents were randomly assigned to 2
 3 one of four conditions that varied whether an economist (who regularly discusses politi- 3
 4 cally salient issues) tweets about recent research on a politically sensitive topic (vs. a non- 4
 5 sensitive one), and whether their Twitter bio includes a clear political signal (vs. a neutral 5
 6 one). Expertise is held constant across all profiles. 6

7 In the *passive control*, the economist discusses game theory research on a non-political 7
 8 issue. In the *active control*, the economist tweets about research on the negative impact of 8
 9 policies on migrants' health—a topic with a potentially left-leaning narrative.²⁴ The differ- 9
 10 ence between active and passive control isolates the effect of politically sensitive research 10
 11 content on perceived ideological bias. Both profiles feature neutral Twitter bios. Two treat- 11
 12 ment arms add a political signal in the Twitter bio—either *Left* ("advocate for equality") or 12
 13 *Right* ("proud patriot")—while keeping the same politically salient research as in the active 13
 14 control (see Appendix Figure 15). This isolates the effect of explicit political identity. 14

15 After viewing one of the four profiles, respondents rated the economist's personal and 15
 16 research credibility and their willingness to read an opinion piece from a similar economist. 16
 17 They were also invited to subscribe to a free newsletter on U.S. socio-economic issues 17
 18 featuring similar economists, delivered via Prolific message (see screenshot in Instructions 18
 19 Material). Finally, we measured respondents' general trust in scientists using three Likert 19
 20 items, averaged into a composite index. 20

21
 22 *Results* Figure 7 shows that both channels—research content and political identity 22
 23 cues—influence audience perceptions, with effects varying by respondents' political lean- 23
 24 ings. Among Democrats, perceptions remain stable when the economist discusses non- 24
 25 political research content. However, politically aligned research increases perceived cred- 25
 26 ibility by 8.6% (economist) and 6.3% (research), and raises willingness to read by 33%. 26
 27 Adding a left-leaning bio further increases credibility by 1.7% and willingness to read by 27
 28 7.1%. A right-leaning bio, by contrast, reduces credibility by 8.6%—bringing it back to the 28
 29 non-political baseline—and lowers willingness to read by 4.5%. Republican respondents 29

30
 31 ²⁴The research topic was chosen to clearly align with one political side and oppose the other, facilitating inter- 31
 32 pretation. Symmetrical effects are expected with right-leaning aligned research. 32

1 show the opposite pattern: when the economist discusses politically misaligned research, 1
2 credibility drops by 12% relative to the non-salient benchmark. This penalty increases by 2
3 5% with a left-leaning signal and is reduced by 5% with a right-leaning one. Willingness 3
4 to read follows a similar trajectory. 4

5 Newsletter sign-ups and overall trust in science show similar, though less pronounced, 5
6 patterns. Correlating newsletter demand and willingness to read validates the latter out- 6
7 come ($\beta = 0.064$, $p < 0.001$). Recontacting respondents a few weeks later further confirms 7
8 engagement: of 595 participants who expressed interest in the newsletter, 440 were suc- 8
9 cessfully recontacted, and 86% clicked the newsletter link to join. 9

10 The bottom of Figure 7 presents average outcomes for treated respondents relative to ei- 10
11 ther the active or passive control, allowing a clearer comparison between in-group and out- 11
12 group conditions. In-group respondents—those whose political leanings match the political 12
13 signal—rate scientists more favorably across all outcomes. Regression results in Appendix 13
14 Tables XIV and XV confirm these findings. 14

15 These results highlight two main insights. First, audience responses vary sharply by po- 15
16 litical alignment: for the same content, credibility and engagement increase when the po- 16
17 litical signal aligns with the respondent’s views—clear evidence of affective polarization. 17
18 Second, both channels independently shape perceptions of scientists’ credibility. 18

19

20 4. SCIENTISTS’ VIEWS ON ONLINE POLITICAL EXPRESSION 20

21 Having quantified academics’ political expression and its reputational risks, we now ex- 21
22 amine scientists’ self-reported views using two surveys. We recruited 128 scientists glob- 22
23 ally via Prolific.²⁵ Appendix Table XVI describes the sample: 94% are employed (over 23
24 60% at universities), including 43% postdoctoral researchers, 28% faculty, and 29% indus- 24
25 try professionals; 34% work in life sciences/biomedicine, 34% in social sciences, and the 25
26 remainder in physical sciences or technology. 26

27 The first survey covered three areas. First, we asked whether scientists expect a credi- 27
28 bility penalty for expressing political opinions on social media. Second, we elicited first- 28
29 and second-order beliefs about the acceptability of political expression within and beyond 29
30

31 _____
32 ²⁵Prolific respondents were screened for employment in “Research,” PhD-level education, and English fluency. 32

1 their expertise, following Bursztyn and Yang (2022).²⁶ Third, we asked about personal 1
 2 experiences with publicly expressing political opinions. 2

3 To gauge the expected credibility penalty, we told respondents that scientists who **do** 3
 4 **not** express political opinions receive a trust score of 7.2/10, then asked: “*What is the* 4
 5 *reported trust level for scientists who do express political opinions on social media?*”²⁷ As 5
 6 shown in Figure 8, respondents expect a 30% trust loss—nearly double the experimentally 6
 7 observed loss of 16.6%, consistent with cheap-talk models under reputational concerns 7
 8 (Morris, 2001, Ottaviani and Sørensen, 2006). 8

9 Relative to professional norms, Panel A of Appendix Figure 16 shows that scientists 9
 10 consider political expression acceptable when related to their expertise, but not beyond it.²⁸ 10
 11 Panel B shows they believe peers share this norm. Finally, Panel A of Appendix Figure 17 11
 12 indicates that scientists are significantly more hesitant to comment on topics outside their 12
 13 field,²⁹ while Panel B shows they expect negative repercussions for out-of-field comments 13
 14 and net benefits for in-field ones, though the differences are small. 14

15 To further examine the perceived professional costs and benefits of expressing political 15
 16 views online, we again surveyed 118 international scientists via Prolific. This survey dis- 16
 17 entangles the perceived impact of political expression on outcomes such as network size, 17
 18 citations, academic job offers, media appearances, policy roles, and top publications. 18

19 Figure 9 compares three profiles: Scientist X (grey), who expresses political views re- 19
 20 lated to their research; Scientist Z (red), who expresses views on unrelated topics; and Sci- 20
 21 entist Y, identical to X or Z but refraining from political expression. Distributions shifted 21
 22 toward X or Z (green areas) indicate perceived benefits, while a denser left tail for Y (blue 22
 23 areas) signals perceived costs. The results reveal clear perceived benefits for media appear- 23
 24 ances and policy roles, milder benefits for network size and citations, and ambiguous or 24
 25 slight costs for top publications and job offers. 25

26 26

27 27

28 ²⁶That is, both scientists’ own views and their perceptions of peers’ views. 28

29 ²⁷Participants earned a £0.50 bonus for a correct response. 29

30 ²⁸This aligns with Garg and Fetzer (2024), who find that academics adopt more pro-social views on topics 30
 31 where they hold expertise. 31

32 ²⁹This complements evidence of a ‘spiral of silence’ in academia (e.g., Norris (2020)). 32

1 Finally, we posed three open-ended questions to capture scientists' views on what con- 1
2 stitutes "politicized" behavior, the boundaries of expertise for political commentary, and 2
3 personal experiences with its costs and benefits. Appendix Table XVII summarizes these 3
4 responses, highlighting recurring concerns about credibility, expertise boundaries, and the 4
5 trade-offs of political engagement. While our Twitter data cannot fully capture scientists' 5
6 motivations, survey responses consistently suggest that academics perceive greater benefits 6
7 when political opinions align with their research expertise. 7

8 5. CONCLUSION 8

9 This study demonstrates that scientists' public expression of political views on social 10
10 media significantly shapes public perceptions of their credibility. 11

11 First, we show that political discourse is common among U.S. academics: between 2016 12
12 and 2022, roughly 44% of 97,737 scientists actively discussed political issues on Twi- 13
13 ter—over six times the rate observed among a random sample of U.S. Twitter users. Topics 14
14 like climate change and racial equality are frequently discussed, often with divergent view- 15
15 points. 16

16 Second, using conjoint experiments with 4,000 U.S. representative respondents and 135 17
17 international journalists rating synthetic academic profiles with varied political affiliations, 18
18 we identify a monotonic credibility penalty for scientists who express political views. The 19
19 more extreme the position—on either left or right—the less credible the scientist and their 20
20 research are perceived, and the lower the willingness to engage with their content, espe- 21
21 cially among ideologically opposed respondents. 22

22 Complementary surveys of 128 international scientists reveal that they expect an even 23
23 larger credibility penalty than what we observe experimentally. Scientists broadly view po- 24
24 litical expression as acceptable when related to their expertise, but not beyond it—reflecting 25
25 a prevailing norm within academia. At the same time, they recognize potential professional 26
26 benefits from political engagement, particularly when aligned with their research. 27

27 Studying the reputational costs of scientists' online political engagement reveals a funda- 28
28 mental trade-off. Expressing political views can undermine scientists' credibility, limiting 29
29 their ability to shape public preferences and influence decision-making while potentially 30
30 deepening affective polarization. At the same time, anticipating this credibility penalty may 31
31 discourage scientists from participating in policy debates—leading to information loss and 32

1 diminishing the societal value of expert engagement. These effects are further mediated by 1
 2 scientists' perceptions of personal career benefits from engaging on social media. 2

3 Our results highlight a significant challenge to the Mertonian norm of Universalism 3
 4 (Merton, 1973), which holds that scientific work should be judged on its merits, not on the 4
 5 scientist's identity or beliefs. While a full welfare analysis is beyond our scope, the find- 5
 6 ings highlight an important trade-off with clear policy implications. It may be disheartening 6
 7 yet unavoidable that political opponents react negatively to research tweets on politically 7
 8 charged topics—as seen in the Active Control from Section 3.4—but such tweets still serve 8
 9 to transmit knowledge. By contrast, scientists' use of uninformative cues, such as partisan 9
 10 emojis in bios, may unnecessarily narrow their audience, intensify affective polarization, 10
 11 and hinder the flow of information in public debate. 11

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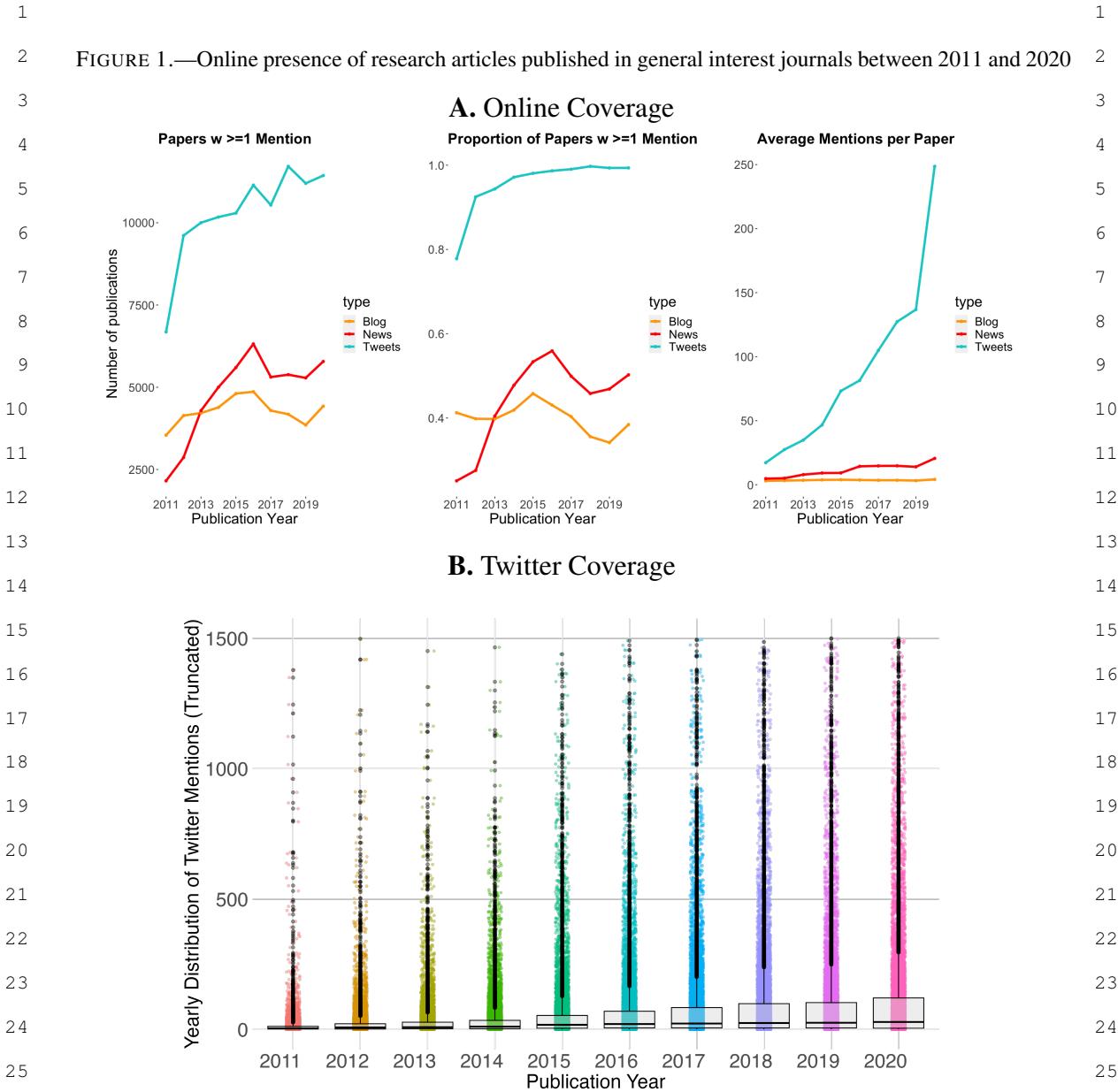
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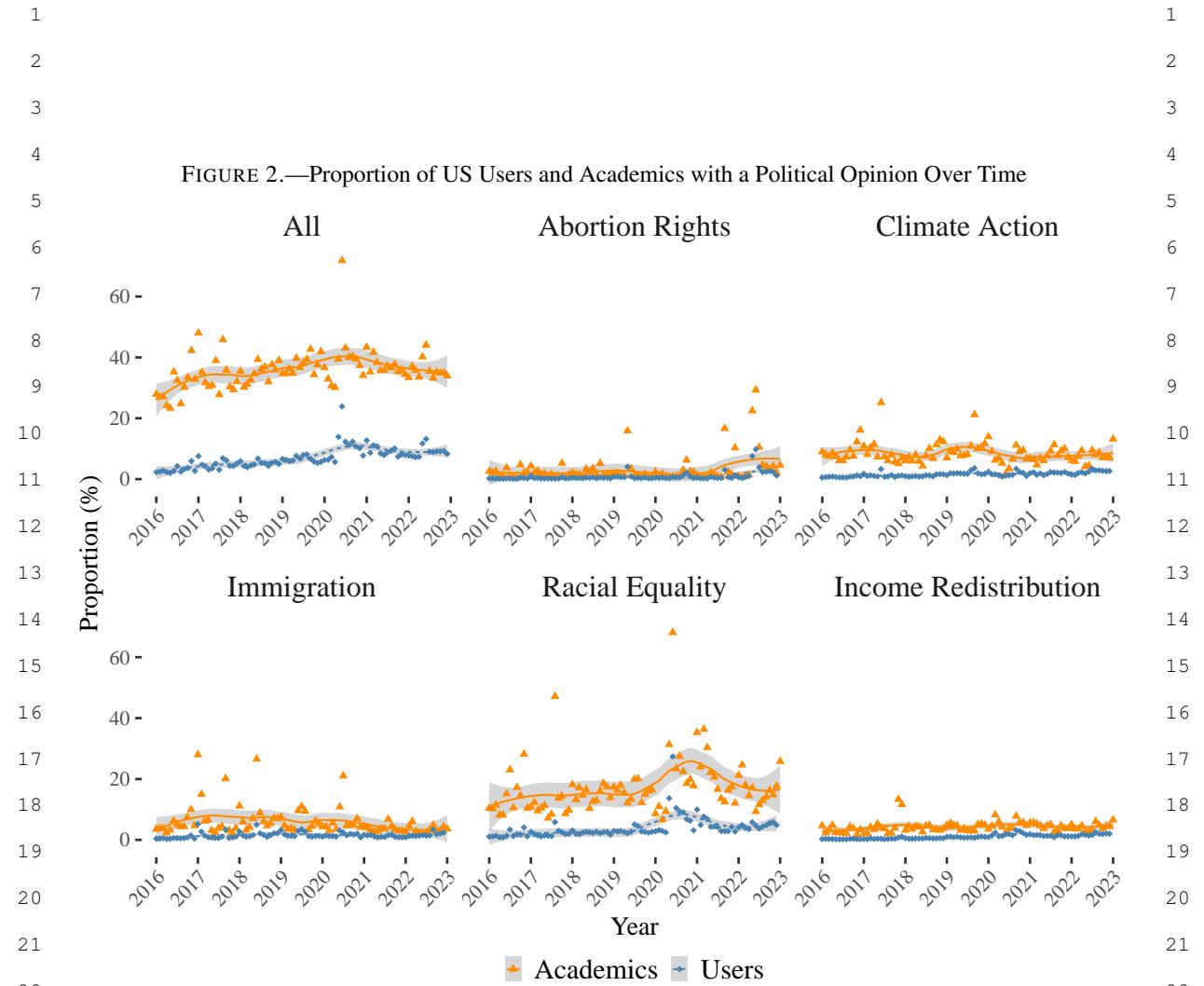
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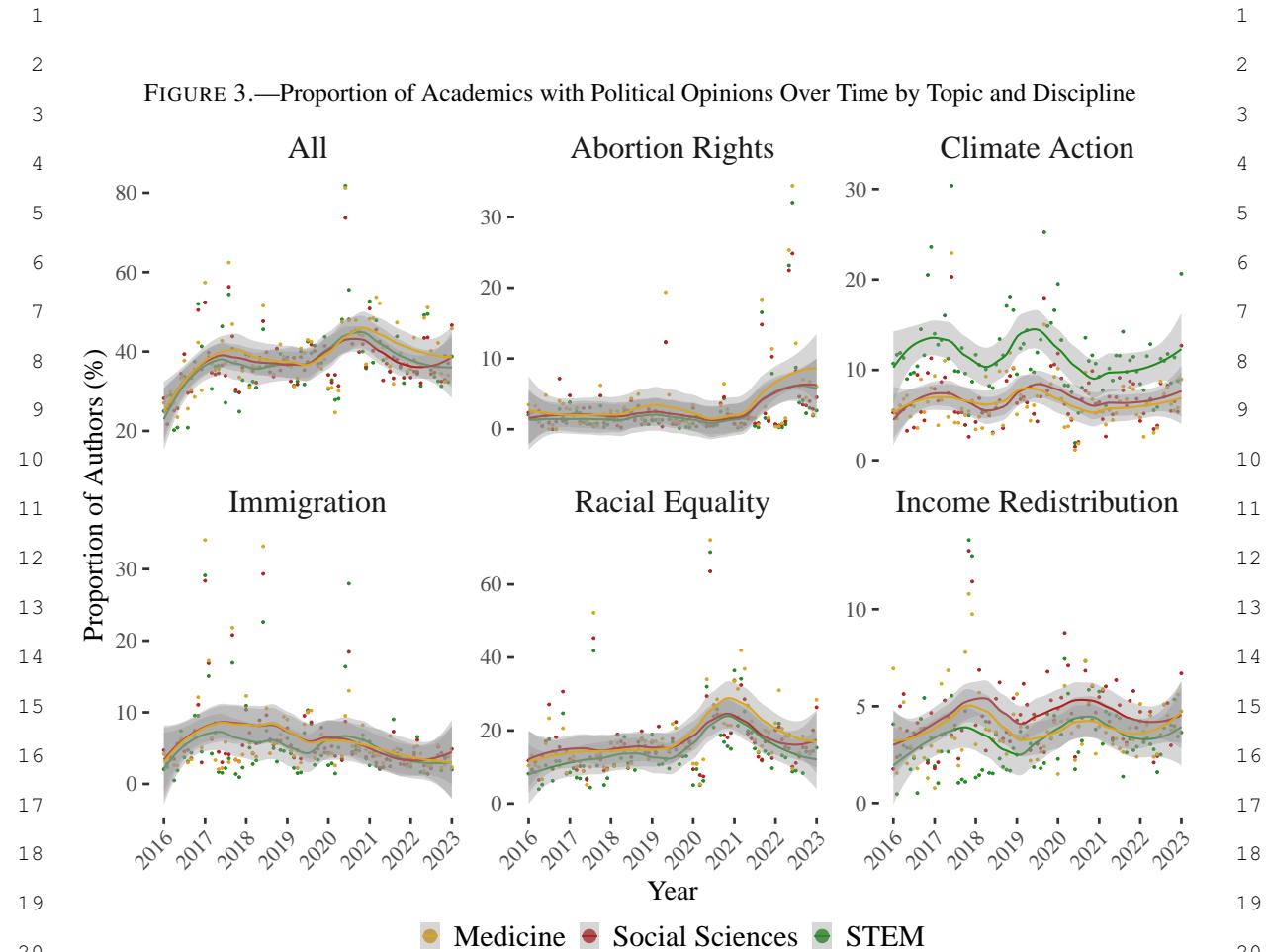
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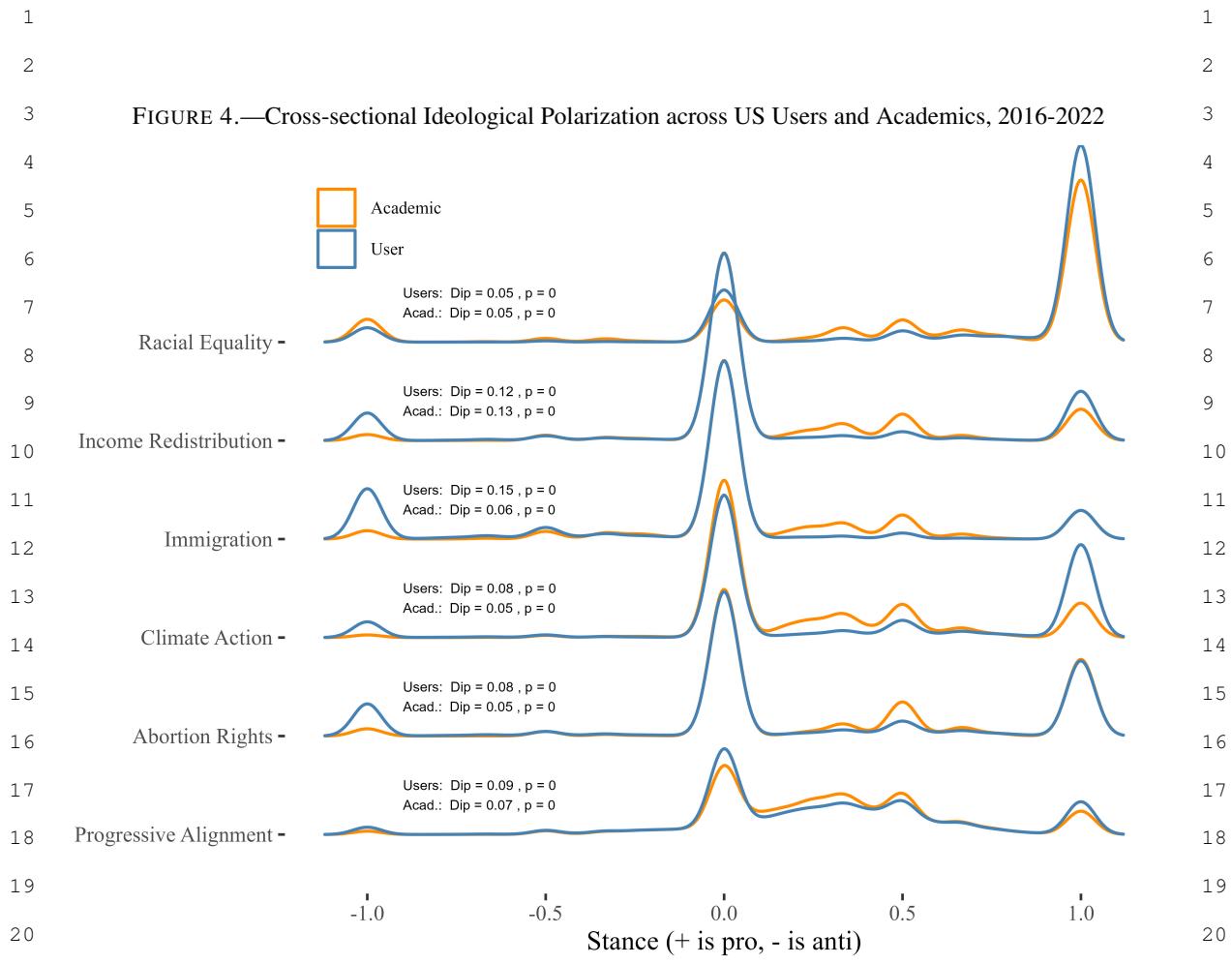
Note: Figure A provides trends in online coverage of scientific articles published in *Science*, *Nature*, *PNAS*, *Cell*, *NEJM*, and *Lancet* between 2011 and 2020. Online appearances across blog posts, newspaper articles, or Twitter are retrieved from Altmetric (accessed on November 10th, 2021). The figure suggests that scientific articles with any online appearances have increased over time, in absolute number (first row), as a proportion of all articles published (second row), and per average number of appearances per published paper (third row). Figure B provides trends in Twitter coverage of scientific articles published in *Science*, *Nature*, *PNAS*, *Cell*, *NEJM*, and *Lancet* between 2011 and 2020. The data present the distribution of Twitter mentions per article, retrieved from Altmetric (accessed on November 10th, 2021). The figure indicates growing online presence, with the distribution of Twitter mentions becoming less skewed towards zero, with a tick right tail and a rise in high-mention outliers over time.



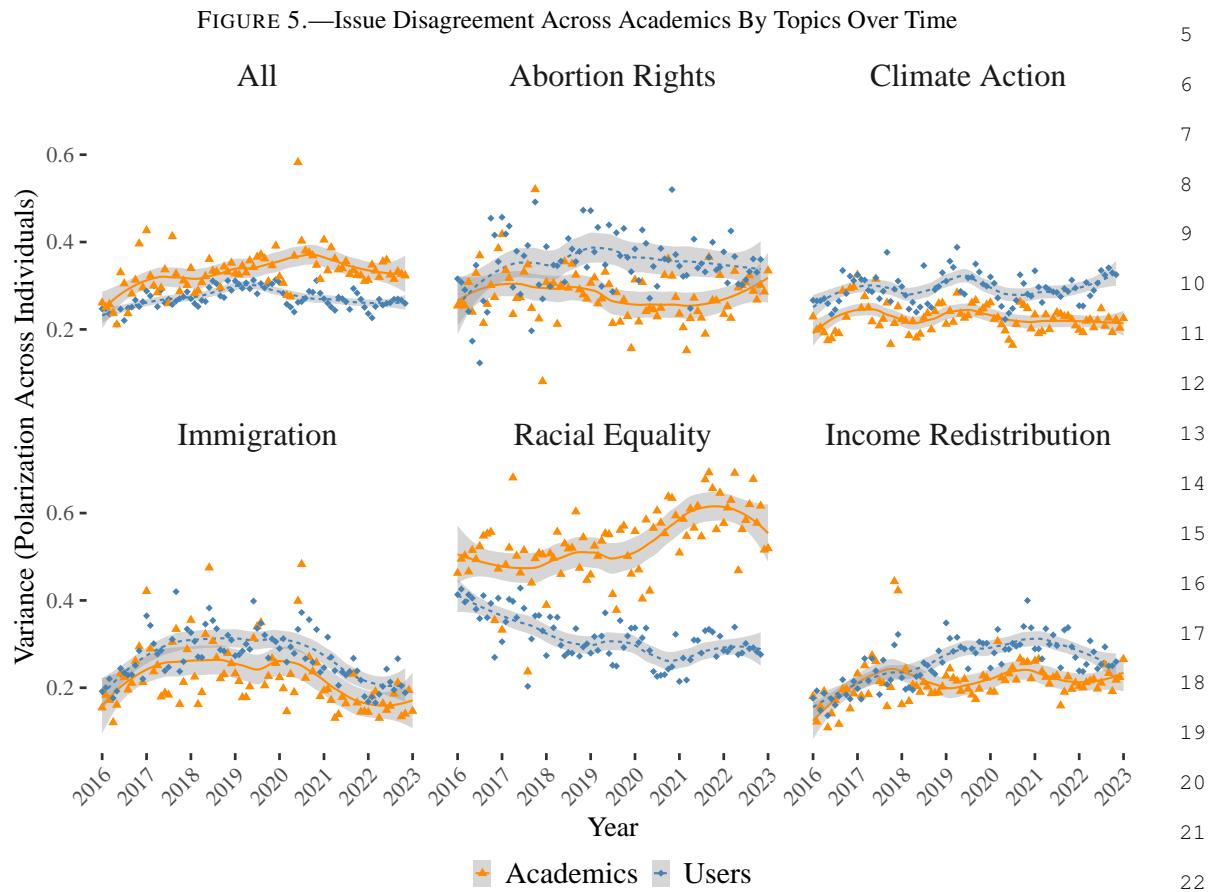
Note: The figure illustrates trends in politicization of conversations by academics and general users on Twitter from 2016 to 2022. Monthly aggregated scatter plots display expressed stance for each topic, with a LOESS applied for trend visualization. Standard errors are depicted in the shaded region. In the "All" panel, around 40% of tracked US academics expressed opinions on predefined political issues, compared to 5-10% of general users. Variations and spikes are observed across topics, with Climate Action and Racial Equality showing the largest disparities. Climate Action witnessed significant declines during the COVID-19 pandemic onset. Mid-2020 saw a surge in attention to Racial Equality, reflecting the outcry after the George Floyd incident. Other topics exhibit stable increasing trends, with occasional short-lived spikes, notably in Abortion Rights around changes in laws in 2022. Immigration discussions, while less frequent, maintained regularity, with heightened attention during the 2016 presidential election.



Note: OpenAlex describes "Concepts" as abstract ideas that a work is about: "Concepts are hierarchical, like a tree. There are 19 root-level concepts, and six layers of descendants branching out from them, containing about 65 thousand concepts all told". OpenAlex classifies each work with a high level of accuracy. We combine the 19 root-level concepts into 3 broad categories for ease of comparison: (1) Medicine, (2) Social Sciences, and (3) STEM. We omit Humanities from the time-series depiction given we have only around 100 humanities' academics, which would create unreliable trends. Each work by an author can belong to multiple concepts and a score from 0 to 1 is given to each concept, where values closer to 1 reflect the likelihood the work belongs to that concept. For each academic, we take the average score for all the root-level concepts across all their works from 2016-2022. We then pick the primary concept of that academic as the root level concept with the highest average score. This depicts the proportion of academics within each concept category expressing an opinion about a political topic. Our analysis reveals distinct patterns and spikes across concept categories for two issues: Climate Action and Income Redistribution. STEM academics consistently show significantly higher engagement with Climate Action, almost doubling the frequency of expressions from other fields in any given period. On Income Redistribution, however, STEM academics were notably less vocal than those in Medicine or Social Sciences before 2020, after which the differences narrowed.



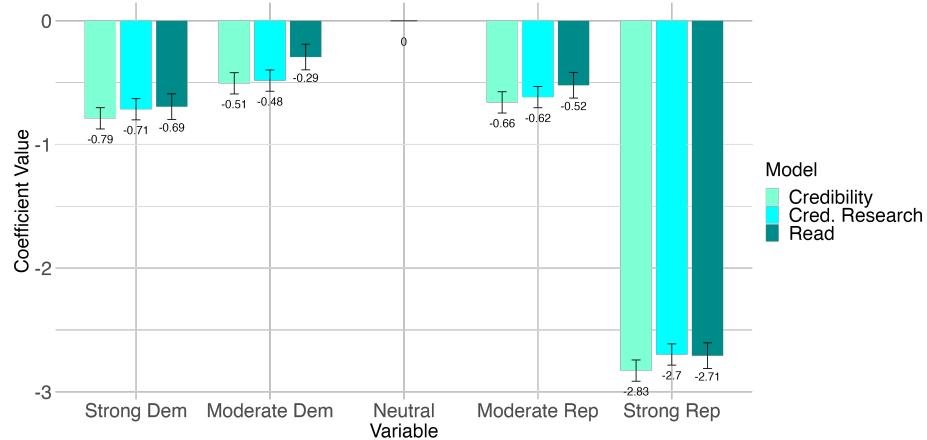
Note: The figure illustrates the density distribution of net stance across various political topics among U.S. academics (in orange) and general users (in blue) from 2016 to 2022. Topics include Income Redistribution, Climate Action, Immigration, Abortion Rights, and Racial Equality, with "Progressive Alignment" representing the average stance across these topics. The x-axis represents the net stance, where positive values indicate a pro-stance and negative values indicate an anti-stance. The y-axis indicates different topics, with density distributions shown as ridgelines. Each ridgeline highlights where individuals tend to cluster in their expressed opinions. Black vertical lines within each distribution represent the mean net stance for each topic. Hartigan's Dip Test identifies multimodal distributions, suggesting distinct ideological camps. The dip statistic and corresponding p-value are annotated for each topic, demonstrating statistically significant multimodalities for both groups. Compared to academics, general users tend to cluster more around extreme viewpoints, especially towards the conservative (-1) side on most issues. Academics, on the other hand, have a larger mass in the moderate liberal/progressive range. An exception to this is the issue of race, where general users show more consensus, with a larger mass towards pro-racial equality. Both groups exhibit statistically significant multimodal distributions (p-values of 0), with users showing slightly higher dip statistics on average, indicating more pronounced ideological polarization.



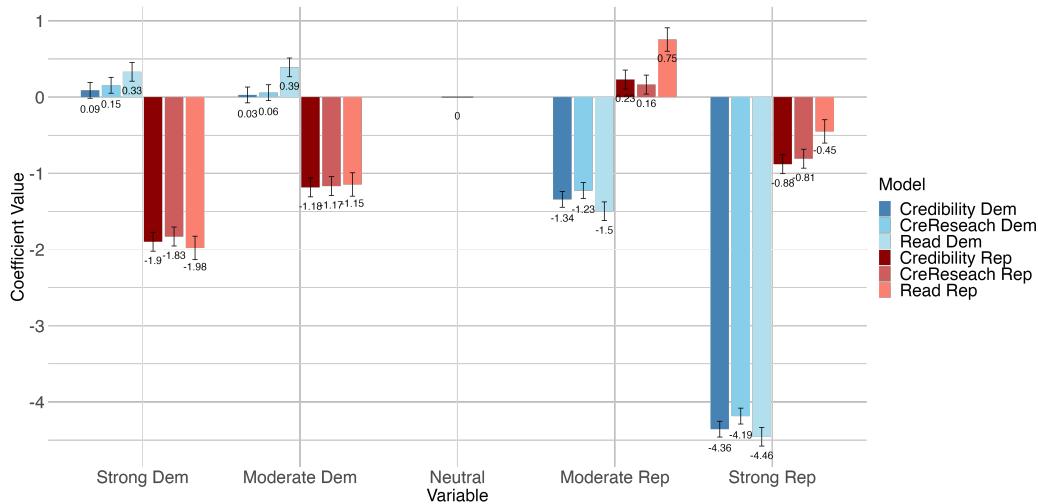
Note: The figure measures ideological polarization by computing the variance of net stance held by a population on predefined political topics. Variance across users reflects the dispersion of political opinion on each topic, providing a continuous measure of ideological disagreement. Aggregating across topics yields an overall measure of political variance. Similar to the increasing trend in expression of opinion, polarization increases between 2016 and 2022, raising concerns about its impact on scientific consensus-building and public trust in scientific expertise. Race exhibits wider debate among academics relative to the general population. Disparities in ideological disagreement are observed across topics, with gaps widening, particularly around the pandemic period for Immigration, Income Redistribution, and Abortion, but also closing by the end of 2022. The gap persists for Climate Action throughout the sample period and grows at the end of 2022.

1 FIGURE 6.—Impact of scientists' political expression on perceived credibility and willingness to read from the
 2 general public. Credibility and public willingness to read peak at neutral, with a monotonic penalty for scientists
 3 displaying political affiliations to the 'left' and 'right' of neutral.

A. Base Model



B. Heterogeneity by Respondents' Partisanship



Note: Coefficients are obtained by regressing scientists' characteristics on respondents' perceived credibility or willingness to read content from scientists. The x-axis represents different political affiliations of scientists, estimated by indicator variables for "Strong Republican", "Moderate Republican", "Strong Democrat", or "Moderate Democrat", with "Neutral" as the excluded category. The y-axis shows the coefficient values indicating the impact on credibility and willingness to read. The data reveals a peak in credibility for neutral scientists, with a decline for both left- and right-leaning scientists. Standard errors are clustered at the individual level. Additional regressors include indicator variables to control for other scientist characteristics: institutional affiliation (Harvard, UC Berkeley, or Chicago, versus Arkansas or Connecticut), field of research (Medicine, Mathematics, Engineering, Economics, or Literature), seniority of role (Full professor or Assistant Professor), and gender (male or female). (N = 1704, 940 Dem. or Lean Dem., 745 Rep. or Lean Rep., 19 Other leaning.)

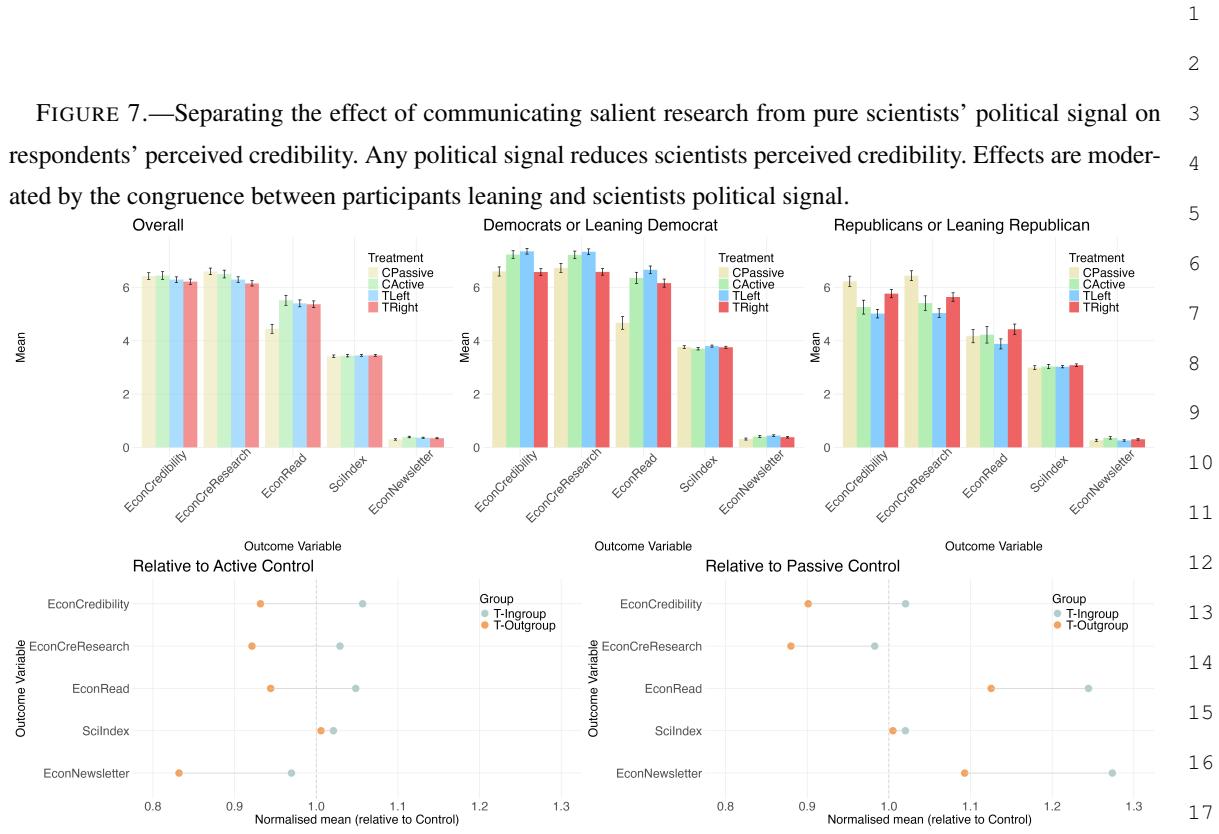
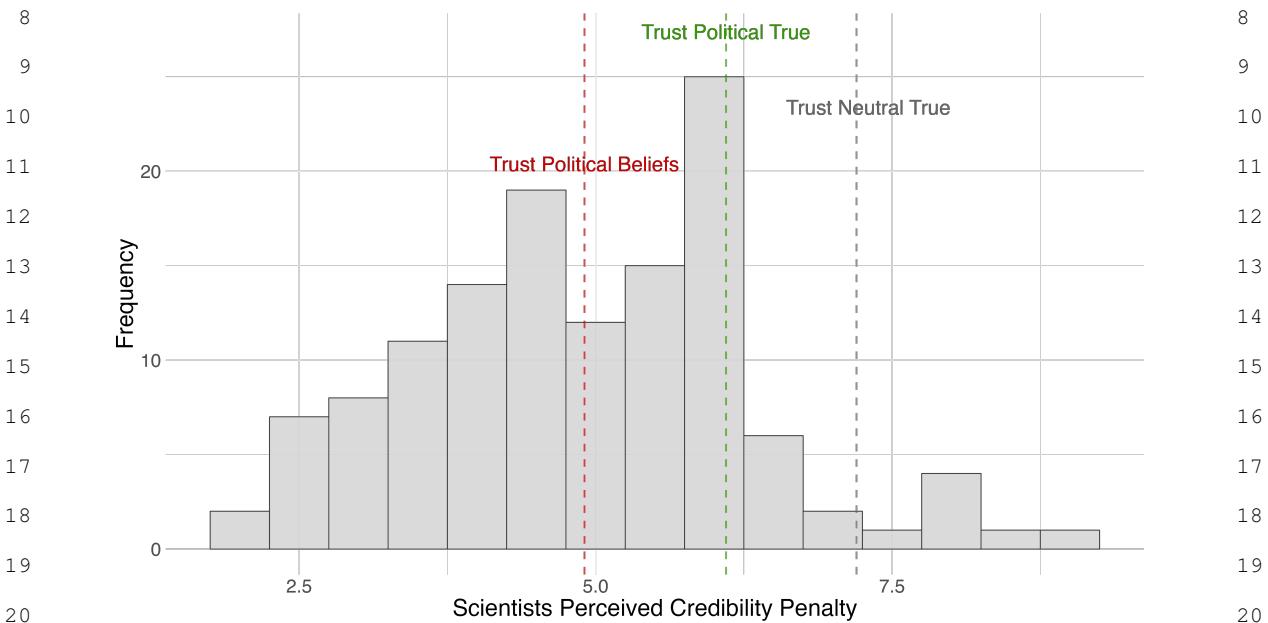


FIGURE 7.—Separating the effect of communicating salient research from pure scientists' political signal on respondents' perceived credibility. Any political signal reduces scientists perceived credibility. Effects are moderated by the congruence between participants leaning and scientists political signal.

Note: Figures show results of our second experimental task where respondents are divided into four groups: in the *passive control* group, respondents are exposed to an economist who neither advertises own research in a politically salient issue nor signals any political affiliation; respondents in the *active control* group are exposed to the profile of an economist advertising own research in a politically salient issue with no political signal; respondents in the *treatment left (right)* group are exposed to an economist advertising their research in a politically salient issue together with a left (right) political signal. The politically salient research is favourable to a democrat leaning narrative. After viewing one of the four profiles, we collect the following outcome variables for each respondent: their perceived credibility of the economist, their perceived credibility of the economist's research, their willingness to read an opinion from the economist, their intention to sign up for a newsletter containing opinions from a similar profile, and a composite index of general trust in science. Democrats show higher credibility when exposed to politically aligned research. The left political signal increases perceived credibility, while the right signal reduces it. Similarly, willingness to read is higher with politically aligned research; the left signal increases it, while the right signal decreases it. Republicans exhibit significantly reduced perceived credibility when exposed to misaligned politically salient research, especially with a left signal, though less so with a right signal. Willingness to read is highest with a congruent right signal and lowest with a left signal. For both sub-samples, newsletter sign-up and overall trust in science move similarly, but changes are less pronounced. Additionally, normalising our group averages relative to the active or passive control, at the bottom, we observe that in-group respondents (when scientist signal and respondents leaning align) perceive significantly higher credibility of scientists and their research, are more willing to read their opinion, and are more likely to sign up to the newsletter, relative to out-group respondents. (N = 1704, 940 Dem. or Lean Dem., 745 Rep. or Lean Rep., 19 Other leaning.)

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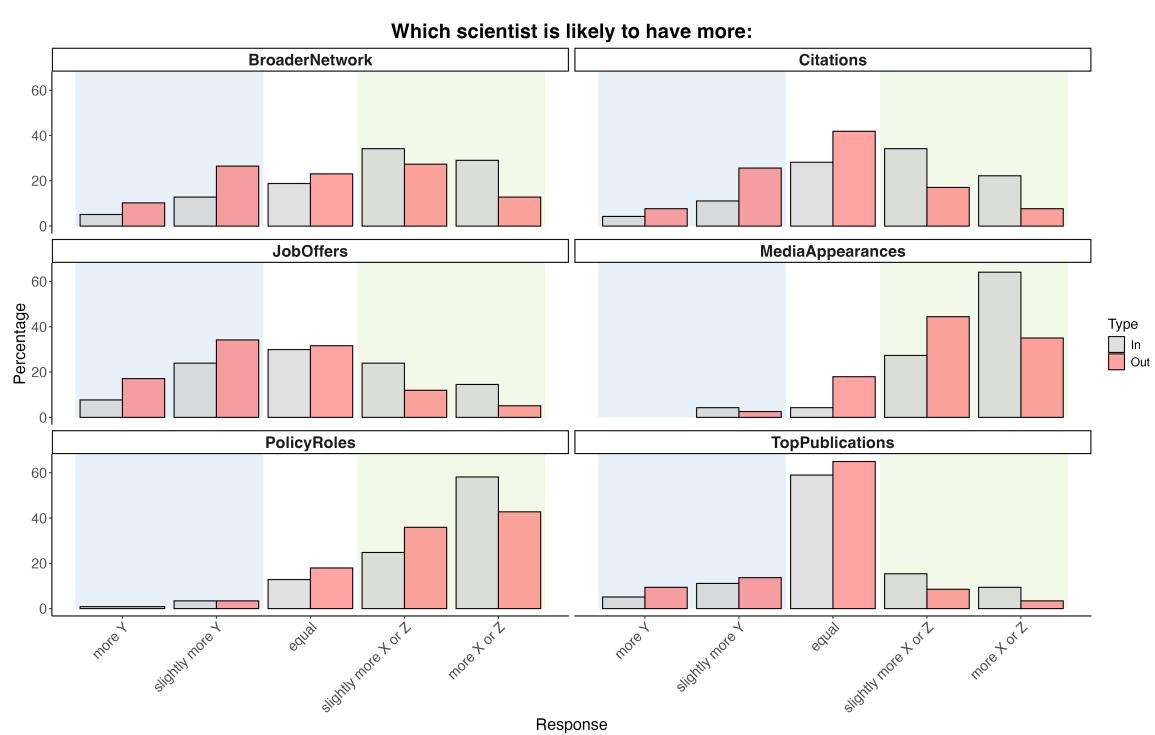
FIGURE 8.—Scientists' Beliefs about Credibility Penalty



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22 Note: This figure reports the distribution of responses from 128 scientists recruited on Prolific to the following question:
23 "What do you think is the reported level of trust for scientists who do express political opinions on social media?". Prior to
24 asking the question, we informed the academic respondents that we had surveyed a representative sample of the U.S. on their
25 perceived credibility of scientists, distinguishing between those who had expressed political opinions online and those who had
26 not. We anchored our scientists' beliefs on the public perceived credibility for scientists who do not express political opinions
27 online (indicated by the grey dashed line). The average answer of our sample of scientists is shown by the red dashed line and
28 is significantly lower than the true value obtained in the main survey of a representative sample of U.S. respondents, which is
29 indicated by the green dashed line.
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6 FIGURE 9.—Scientists' Perceived Costs and Benefits from Public Political Expression
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Note: The figure illustrates scientists' perceptions of professional benefits based on public political expression. Respondents compared the outcomes for Scientist X (grey), who shares opinions on politically charged topics related to their research, and Scientist Z (red), who shares opinions on politically charged topics unrelated to their research, against Scientist Y, who refrains from such expression (respectively, either related or unrelated to their research). The evaluated benefits include network size, citations, academic job offers, media appearances, policy roles, and top publications. A distribution skewed towards X or Z (green area) reflects perceived benefits from political expression, while a denser left tail towards Y (blue area) indicates perceived costs. Results suggest clear benefits for media appearances and policy roles, milder benefits for network size and citations, and ambiguous or slight perceived costs for top publications and academic job offers.