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Abstract

As social media is increasingly popular, we examine the reputational costs of its increased centrality among academics. Analyzing posts of 98,000 scientists on Twitter (2016–2022) reveals substantial and varied political discourse. We assess the impact of such online political expression with online experiments on a representative sample of 3,700 U.S. respondents and 135 journalists who rate vignettes of synthetic academic profiles with varied political affiliations. Politically neutral scientists are viewed as the most credible. Strikingly, on both the 'left' and 'right' sides of politically neutral, there is a monotonic penalty for scientists displaying political affiliations: the stronger their posts, the less credible their profile and research are perceived, and the lower the public's willingness to read their content, especially among oppositely aligned respondents. A survey of 128 scientists shows awareness of this penalty and a consensus on avoiding political expression outside their expertise.

Keywords: Social Media, Scientists' Credibility, Polarization, Online Experiment
JEL Classification: A11, C93, D72, D83, D91, I23, Z10, Z13

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1 Introduction

In an era of "post-truth," trust in science is a cornerstone of informed decision-making and effective public policy (McIntyre, 2018; Angelucci and Prat, 2024; Bursztyn et al., 2023b; Arold, 2024; Ash et al., 2024). The COVID-19 pandemic has starkly highlighted this reality, illustrating how confidence in scientific expertise shapes public health responses. Similarly, doubts regarding climate change within certain societal groups hinder progress toward environmental goals.[1] Skepticism extends beyond these domains, impacting economic development, education, and broader societal trust.

Credibility is critical for science, yet it currently faces a period of relatively low public trust, particularly among conservatives in the U.S.[2] A key reason for this distrust may be the perception of political bias among scientists (Altenmüller et al., 2024), an issue amplified by the ease with which the public can now access information about scientists, including their social media posts.[3] Hence, this paper proceeds in two linked parts. First, we leverage Large Language Models (LLMs) to measure the extent to which scientists express political views on social media.[4]

Next, we identify the reputational costs scientists may face as persuasive public opinion makers involved in evidence-based decision-making (Aina, 2023) and influencing individual preferences and behaviors (Algan et al., 2021; Burnitt et al., 2024; Martinez-Bravo and Stegmann, 2022), by examining whether their online political engagement affects public perceptions. Specifically, we use an online experiment to evaluate how revealing scientists' political leanings shapes public perceptions of their credibility and contributes to audience polarization.

[1] Higher trust in science is linked to earlier adoption of preventive measures during COVID-19 (Algan et al., 2021; Bartoš et al., 2022; Bowles et al., 2023; Eichengreen et al., 2021). In contrast, skepticism has been associated with adopting unverified remedies, such as those documented in Argentina (Calónico et al., 2023; Albornoz et al., 2024). In the context of climate change, Druckman and McGrath (2019) highlights how differing beliefs about credible evidence significantly affect policy support.

[2] Nichols (2017) highlights the growing hostility toward expertise in the U.S., while Lupia et al. (2024) documents a decline in trust in science among U.S. respondents. Factors contributing to anti-science sentiment include misinformation (West and Bergstrom, 2021; Roozenbeek et al., 2020), historical failings (Scharff et al., 2010), the reproducibility crisis (Hendriks et al., 2020; Garg and Fetzer, 2024a), conspiracy theories (Rutjens and Većkalov, 2022; Douglas, 2021), science-related populism (Mede and Schäfer, 2020; Mede et al., 2021), and political ideology (Cologna et al., Forthcoming). Conservatives and right-leaning individuals in U.S. report lower trust in scientists, stronger anti-science attitudes, and less confidence in scientists' intentions and methods (Mede, 2022; Funk et al., 2020; Li and Qian, 2022; Azevedo and Jost, 2021).

[3] Acquisti and Fong (2020) and Gift and Gift (2015) show that online disclosure of personal information, including political cues, can influence labor market outcomes.

[4] LLMs provide a cost-effective way to analyze large-scale text data while capturing the contextual and dynamic nuances of language, closely approximating the accuracy of human coding.

Our findings reveal evidence of both *ideological* polarization (divergent political positions among academics) and *affective* polarization (public aversion to scientists associated with opposing partisan groups) (Lelkes, 2016; Barberá, 2020).

The central questions of our study are: *To what extent do scientists express polarized political opinions on social media? And what impact does this political expression have on their perceived credibility?*

Impact is increasingly crucial for academics, with social media playing a growing role in both research dissemination and public engagement. Consistent with studies suggesting that social media engagement can offer benefits to academics (Chan et al., 2023; Klar et al., 2020; Qiu et al., 2024; Boken et al., 2023), Altmetric data[5] reveal a significant rise in the online presence of scientific research from prominent journals between 2011 and 2020, particularly on social media.[6] Our study extends this perspective, exploring how scientists use social media not only to share research but also to engage in politically salient discussions, assessing the implications for credibility and the public polarization around science.

First, our analysis extends the descriptive work of Garg and Fetzer (2024b) by examining the extent of online political discourse and issue-based disagreement among scientists (university-based researchers) compared to the general population. Analyzing political slants on social media offers three key advantages: (i) it captures a large, cross-disciplinary sample of academics, (ii) provides a nuanced view of ideological positions on specific issues beyond a simple left-right spectrum, and (iii) focuses on publicly visible content, avoiding the limitations of classifications based on surveys or based on published work.

Our descriptive analysis reveals that 44% of 97,737 U.S. academics on Twitter expressed political opinions by making at least one non-neutral post on any of five politically salient topics between 2016 and 2022, compared to only 7% of the general non-academic U.S. Twitter base.[7] Political engagement is relatively consistent among disciplines and across topics. Notably, 29% of academics' tweets on politically salient issues

[5]Altmetric is a comprehensive service that monitors the impact of research articles across various outlets, including newspapers, blogs, social media platforms, policy briefs, patents, and more, alongside traditional citations. Recent studies have used Altmetric data to track the online dissemination of scientific articles, including retractions (Alabrese, 2022; Peng et al., 2022).

[6]While increased social media usage overall may contribute to this trend, our data indicate a specific rise in the visibility of scientific content.

[7]The issues analyzed are: (i) abortion rights, (ii) climate action, (iii) immigration, (iv) income redistribution, and (v) racial equality. These topics are identified as the most salient in U.S. political debates by Gallup and Pew Research.

are research-related,[8] reflecting a significant intersection between research and political discourse. However, academics tend to adopt more neutral positions in research-related tweets, while expressing more explicit stances in non-research tweets.[9] Positions have also shifted over time, with racial equality standing out: disagreement among academics is not only more pronounced than in the general public but is also widening.[10]

According to Morris (2001), engaging in "politically incorrect" communication can result in reputational loss, as audiences may draw adverse inference about the speaker.[11] As reputational concerns can lead to information loss,[12] the second part of our paper assesses this reputational cost in an online experiment with a representative sample of 1,700 U.S. respondents. Respondents were asked to rate vignettes featuring synthetic academic profiles, varying in scientists' political affiliations —based on real tweets— and other characteristics, following Kessler et al. (2019).[13]

Findings reveal a significant *credibility penalty* for scientists engaging in political discourse across the political spectrum. Scientists on both the "left" and "right" experience a monotonic credibility decline when displaying a political affiliation: Strong Republican (Democrat) scientists are 39% (11%) less credible than neutral ones, while moderate Republican (Democrat) scientists are 9% (7%) less credible. This penalty extends to reduced public willingness to engage with scientists' work, with respondents 42% (10.7%) less willing to read opinions from a strong Republican (Democrat) scientist and 8% (4.5%) from a moderate Republican (Democrat) scientist compared to a neutral one.

Credibility penalties reflect a strong partisan bias, as respondents tend to view scientists aligned with opposing political views as less credible. Specifically, Democrat

[8]Conversely, only 7% of all research-based tweets mention these salient issues.

[9]This distinction highlights the sensitivity of our classification in capturing the intensity of political expression.

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

[11]Despite the potential costs, scientists can find value in the public use of social media. For example, studies suggest professional advantages for scientists active on Twitter, including a citation premium (Chan et al., 2023; Klar et al., 2020) and recruitment advantages for candidates in the academic job market (Qiu et al., 2024).

[12]The broader welfare implications of expert communication are complex. Chakraborty et al. (2020) differentiate 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 advocacy. This synergy persists unless the conflict between voter and expert preferences becomes excessively large.

[13]Conjoint designs have been used to study medical decisions (Chan, 2022), repugnant transactions (Elías et al., 2019; Sullivan, 2021), financial decisions (Macchi, 2023), dating preferences (Low, 2014), and charitable donations (List and Lucking-Reiley, 2002). In general, there has been an increase in the use of unincentivized measures in economics research (Ameriks et al., 2020; Bernheim et al., 2022; Stango and Zinman, 2023; Almås et al., 2023; Andre et al., 2022, 2024).

respondents rate neutral and Democrat-leaning scientists similarly but lose trust in Republican-leaning scientists. Meanwhile, Republican respondents generally favor moderately Republican-leaning scientists but lose some confidence in those with the most conservative stances—though to a lesser extent than for Democrat-leaning scientists. This suggests that academics' political discourse can serve as a channel for polarizing public perceptions of scientists as well as engagement with scientific discourse.

Regarding other tested characteristics, we found that scientists affiliated with high-ranked institutions or those who are senior are considered more credible, while gender and field have no significant impact. Notably, political affiliation is the most salient attribute shaping public perceptions of scientists.

We also conducted a number of checks. We fully replicated the main findings with a separate sample of 2,000 U.S. respondents. Moreover, results exhibit minimal carryover effects across profiles and remain robust after excluding "speeders" and correcting for multiple hypothesis testing. Additionally, a permutation test and a validation task with new respondents confirmed that participants accurately identified the political affiliation of scientists in the vignettes.

To extend the validity of our findings, we tested whether the *credibility penalty* for politically engaged scientists is also observed among journalists. Among 135 international journalists surveyed, we observed asymmetric effects: Republican scientists were rated 33% less credible than neutral scientists, and their opinion pieces were 40% less likely to be included in newsletters. Democrat scientists, by contrast, were rated only 5% less credible and 2% less likely to feature in newsletters.[14] Partisan bias was evident: liberal journalists were 7, 9, and 5 times less likely to find a Republican scientist's credibility, research, and newsletter inclusion favorable compared to a Democrat, while conservative journalists showed a comparable bias against Democrat scientists, being 4, 9, and 7 times less likely to rate their credibility, research, and newsletter inclusion favorably, relative to Republicans.

According to the sender-receiver framework in Gentzkow and Shapiro (2006), a sender who fails to align their message with the receiver's prior beliefs incurs a greater credibility penalty, particularly when ex-post verification of the sender's quality is challenging. For scientists, this penalty may arise when discussing politically charged research topics that conflict with readers' views or when signaling a research-unrelated political cue that differ from the audience's political leaning. To investigate this, we conducted an

[14]These effects for Democrat scientists are statistically indistinguishable from zero, likely due to the large representation of liberal journalists.

additional experimental task, isolating the effect of audience perceptions of scientists' credibility driven by (i) tweeting about politically salient research versus (ii) signaling a direct political affiliation, while holding the message and expertise constant (restricting profiles to economists).

Both sharing politically salient research and signaling political affiliation shape public perceptions. Democrats find economists sharing politically aligned research more credible (compared to non-politically salient research), especially when paired with a left-leaning signal, while credibility drops sharply with a right-leaning signal. Conversely, Republicans assign lower credibility to economists sharing misaligned research, particularly when coupled with a left-leaning signal, though the effect is less pronounced with a right-leaning signal. This indicates that merely tweeting about politically charged research can reduce credibility for some audiences, while signaling political affiliation either enhances credibility (if aligned with the audience's leaning) or markedly diminishes it (if misaligned). A similar pattern emerges in newsletter demand—a behavioral measure of audience engagement curated following (Chopra et al., 2022, 2024)—where alignment with the audience's political leaning strongly drives sign-ups. These findings suggest affective polarization, where the public primarily engages with scientific communication aligned with their views and distances itself from misaligned content.

What do scientists think? We finally surveyed 128 international scientists on Prolific to assess whether they anticipate the credibility penalty observed in our experiment and to explore their views on political expression online. Scientists expected a larger credibility penalty than we found and viewed expressing opinions within their expertise as more acceptable than commenting on unrelated topics—a norm they believed was widely shared among academics. Many reported hesitating to share political views on social media, potentially contributing to information loss in public discourse (Morris, 2001; Ottaviani and Sørensen, 2006). While they foresee mild net reputational costs for opinions outside their expertise, they anticipate small net reputational benefits for sharing views within their field. However, perceptions of costs and benefits largely overlap. While this work studies the costs associated with academics' political engagement, an empirical evaluation of both costs and benefits remains an important avenue for future research.

Contribution to the Literature Our findings enrich our understanding of public perceptions of scientists and their communication (Altenmüller et al., 2024; Blastland et al., 2020; Norris, 2020). Existing research examines the effects of communicating uncertainty and political transparency on public trust in science (Van Der Bles et al., 2019, 2020; Petersen et al., 2021), and shows that scientific endorsements can polarize perceptions around publishers and science overall (Zhang, 2023). Relatedly, Kotcher et al. (2017) found that climate scientists' advocacy only minimally affected their credibility, except when they supported nuclear power. In contrast, our results indicate that scientists' political commentary online reduces their credibility.

More broadly, we contribute to the literature on the communication of politically salient topics in the U.S.—or the lack thereof, as in the case of the "spiral of silence" (Huang and Ho, 2023)—both offline (Braghieri, 2024) and online (Bursztyn et al., 2023a), focusing on decisions to voice controversial opinions and their downstream effects. To the best of our knowledge, this work is the first to examine U.S. academics' online communication on politically charged topics and its impact on public perceptions.

We relate to the literature that measures ideological stances and political views using text-as-data from sources like official documents (Ash, 2016; Hansen et al., 2018; Grimmer, 2010), online news (Cagé et al., 2020), product descriptions (Fetzer et al., 2024), political speeches (Jensen et al., 2012; Gentzkow et al., 2019), academic papers (Garg and Fetzer, 2024a; Jelveh et al., 2024), and survey data (Draca and Schwarz, 2024). Our study builds on the measures of academics' political expression on Twitter developed by (Garg and Fetzer, 2024b), who find that scientists' political expression differs from the general public in both topic and tone, with public narratives often skewed by academics with high reach but lower academic impact. Focusing on U.S. academics, we here examine their slant and disagreement around salient issues on social media, causally identifying the reputational risks of such political engagement.

Our findings align with broader U.S. trends in ideological and affective polarization, documenting the emergence of echo chambers that deepen public divides (Fiorina and Abrams, 2008; Alesina et al., 2020; Iyengar et al., 2019; Gentzkow and Shapiro, 2011; Levy, 2021; Chopra et al., 2024; Mosleh et al., 2021; Colleoni et al., 2014; Flaxman et al., 2016; Stewart et al., 2019; Boxell et al., 2024; Garg and Martin, 2024; Canen et al., 2021; Kahan et al., 2011). Our findings that individuals gravitate toward scientists whose views align with their own and dismiss misaligned views as less credible, highlight the need for strategies to mitigate polarization while enhancing scientific discourse.

Additionally, our work connects to the literature on social identity, originally explored by Tajfel and Turner (2003) and later incorporated into economic analysis by Akerlof and Kranton (2000) and Shayo (2009, 2020). Recent research examined the impact of social identity on various economic outcomes, such as trade policy (Grossman and Helpman, 2021), teamwork (Charness and Chen, 2020), acceptance of bonus payments (Bursztyn et al., 2020), policy adoption (Garcia-Hombrados et al., 2024), and casual interactions (Braghieri et al., 2024). Furthermore, party affiliation increasingly influences individuals' choices in both political and non-political domains, including in decisions on whom to marry (Alford et al., 2011), whom to date (Huber and Malhotra, 2017), where to live (Brown et al., 2022), and what to eat (Burnitt et al., 2024). Our findings show that scientists' social identity —specifically their political identity— diminishes their credibility, the credibility of their research, and the public's willingness to engage with their communication.

While our study is not a real-time Twitter experiment, it connects with recent experimental work that assesses interventions to reduce the spread of fake news, toxic speech, and discrimination (Guriev et al., 2023; Jiménez Durán, 2022; Beknazar-Yuzbashev et al., 2022; Angeli et al., 2022; Ajzenman et al., 2023a,b). Our research also contributes to the broader literature on the political effects of the internet and social media, which examines the impact on voting, protests, polarization, and misinformation (see Zhuravskaya et al., 2020, for a review). Our focus, however, is on potential risks of the increased centrality of social media among academics.

The remainder of this paper is organized as follows. Section 2 examines the political engagement of a large sample of U.S. academics on Twitter. Section 3 experimentally tests the implications of this engagement for public perceptions of scientists' credibility and willingness to engage with their content. Section 4 reviews a survey of scientists regarding their views on online political expression. Finally, Section 5 concludes.

2 Scientists' Online Political Expression

2.1 Science in the Media

Given the increasing importance of impact for academics, does social media play a growing role in scientific dissemination? To contextualize this, we analyze the diffusion of scientific research online using data from the Scopus library, covering over 100,000 articles published between 2011 and 2020 in general interest journals. We track their online mentions through Altmetric,[15] which extensively monitors the online dissemination of scientific articles across a variety of platforms (Alabrese, 2022; Peng et al., 2022).

The analysis reveals a consistent increase in the online presence of scientific publications, suggesting that scientists may be engaging more with broader audiences. Figure 1 shows a steady rise in coverage across blogs, newspapers, and Twitter, with Twitter mentions particularly notable: over 96% of published articles are referenced on the platform (details in Appendix Section C). Figure A.1 further illustrates the evolution of Twitter mentions, showing a distribution less skewed towards zero, a thicker right tail, and a growing number of high-mention outliers over time. This indicates increasing variability in the attention scientific articles receive on Twitter, highlighting its importance as a platform for scientific communication.

2.2 Academics on Twitter: Sample and Method

As the dissemination of scientific work on Twitter grows, it is important to examine how academics use the platform beyond research sharing. To this end, we analyze trends in political discourse and ideological polarization among 97,737 U.S. academics on Twitter from 2016 to 2022, focusing on the nature and extent of their political engagement.[16] These university-based researchers were identified through Mongeon et al. (2023), who matched authors' OpenAlex identifiers to corresponding Twitter/X accounts using Crossref Event Data with high precision and moderate recall.[17]

Building on the work of Garg and Fetzer (2024b), we leverage their merged dataset of Twitter timelines and OpenAlex records, which employed large language models (LLMs) to detect whether tweets addressed specific topics and to classify their stances as pro, anti, or neutral towards each topic.[18] The Twitter data includes complete timelines, capturing academics' (1) original tweets, (2) retweets, (3) quote retweets, and (4) replies, comprising approximately 116 million tweets in total. Our analysis focuses on five politically salient issues central to U.S. political debate, as identified by Gallup: Abortion

[15] We retrieved 114,868 articles from journals such as *Science*, *Nature*, *PNAS*, *Cell*, *NEJM* and *Lancet*, of which 107,008 were tracked by Altmetric (accessed on November 10, 2021).

[16] Our sample of academics represents a significant subset of the 683,050 research-active academics in the U.S. (based on the National Center for Education Statistics, 2020).

[17] OpenAlex is a comprehensive bibliographic database built on Microsoft Academic Graph, providing detailed information on publications, citations, affiliations, co-authors, research concepts, and more. Crossref is the largest global registry of Digital Object Identifiers (DOIs) and its Event Data links scholarly work to platforms that engage with academic content.

[18] Comprehensive individual-level, time-series data are publicly available here.

Rights, Climate Action, Racial Equality, Immigration, and Income Redistribution.[19]

The procedure involves two key steps. The first is *topic detection*. OpenAI's GPT-4 was used to generate dynamic keyword dictionaries, designed to capture the evolving discourse on each topic. The model was prompted with:

> *Provide a list of [**ngrams**] related to the topic of [**topic**] in the year [**year**]. [**Twitter Fine Tuning**]. Provide the [**ngrams**] as a comma-separated list.*

The **[Twitter Fine Tuning]** either explicitly instructed the model to *'Focus on language, phrases, or hashtags commonly used on Twitter'*, ensuring the dictionary remains contextually relevant to the platform's discourse or was left empty. This process generated 210 prompts, covering all combinations of 5 topics, 3 ngram types, 7 years, and 2 vernacular adjustments. Keywords from these prompts were aggregated at the topic level by taking the union across all dimensions, resulting in five comprehensive keyword dictionaries. These dictionaries were applied to the entire corpus of tweets. Tweets containing any keyword from a topic's dictionary were labeled as belonging to that topic. For example, tweets mentioning "Paris Agreement" were categorized under "Climate Action". This keyword detection step amounts to a sample of 5.31% of all initial tweets.

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

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

This process not only identifies the position of each tweet on a specified topic but also enhances precision and relevance by filtering out unrelated tweets. To manage labeling costs, a sampling approach was used: for each month, year and topic, up to three random tweets per author were included. This ensured adequate coverage to reliably determine an academic's position within each time period.[20] Table B.4 provides examples for each stance across the topics analyzed. Further details on methodology and validation are available in Section D.

[19] Gallup's list of pressing issues for U.S. citizens is available here.

[20] Most cases (99.55%) involve only one tweet per topic per month, with 0.45% involving two tweets and just 0.004% involving three. Increasing the limit would have minimal impact, altering total observations by less than 0.007%.

Our analysis focuses on topical tweets and the subset of scientists who posted non-neutral topic tweets, comprising 6,151,793 tweets from 42,747 scientists (Tables B.1 and B.2). Table B.1 summarizes the key characteristics of the full sample, showing that most scientists are employed in STEM fields, followed by Medicine and Social Sciences. Among U.S.-based academics, 54% discussed at least one of the topics during the observation period, and 81% of those expressed non-neutral stances.[21]

We also examine variation in the proportion of *politicized* scientists—those expressing pro or anti stances on any of the five topics between 2016 and 2022—for key characteristics relevant to our experiment. The share of politicized scientists remains relatively stable across levels of academic recognition (as measured by cumulative citations), ranging from 41% to 46%.[22] Disciplinary differences are notable: academics in Humanities (58%) and Social Sciences (65%) are more vocal compared to those in STEM (43%) and Medicine (38%). Gender differences are also present, with 50% of female scientists being vocal compared to 40% of male scientists. Section 2.3.2 provides further details on these patterns.

2.3 Academics Political Engagement on Twitter

Figure 2 illustrates trends in the political discourse of academics (orange) versus general users (blue) on Twitter from early 2016 to late 2022.[23] The "All" panel (top left) shows that more than a third of the 97,737 tracked U.S. academics expressed a non-neutral opinion in each given month on any of the specified political topics. [24] It also highlights a substantial gap in political expression with an equally sized random sample of general U.S. Twitter users.[25]

To investigate this further, we break down the overall trend by individual topics. The

[21] Climate Action was the most discussed topic (2.09% of all tweets), followed by Racial Equality (1.50%) and Immigration (0.86%).

[22] Citation counts are classified into four categories: fewer than 100; 101–500; 501–1,000; and more than 1,000, reflecting the sample's distribution (25th percentile: 36, median: 190, mean: 1,205, 75th percentile: 849).

[23] The figure presents monthly aggregated scatter plots of expressed (pro or anti) stances for each topic, with trends smoothed using locally estimated scatterplot smoothing (LOESS) with a span of 0.5. Shaded areas represent standard errors.

[24] While monthly averages are reported in the Figure, the cross-sectional proportion in the previous section (44%) reflects the share of U.S. academics posting at least once on any topic at any time. The cross-sectional measure is therefore higher as it aggregates over the full period, capturing occasional contributors, and is preferred for its comprehensiveness.

[25] This comparison is based on data from roughly 100,000 U.S. general Twitter users described in Garg and Fetzer (2024b); Garg and Martin (2024).

largest contributors to the gap in political discourse between academics and the general population are Climate Action and Racial Equality, which are also the most frequently discussed topics throughout the sample period. We further observe considerable variation in engagement trends and noticeable spikes for specific issues. For example, discourse around Climate Action declined at the onset of the COVID-19 pandemic. Racial Equality, however, remained highly salient among academics, with a significant surge in mid-2020 following the George Floyd incident and the widespread protests against racial injustice. Abortion Rights saw a spike in discussions in 2022, driven by changes in abortion laws. Conversations around Immigration peaked around the 2016 presidential election and have diminished over time.

2.3.1 Overlap with Politics and Research

Examining how academics discuss both political and research-related topics helps us understand the interplay between scientific discourse and political engagement, particularly on salient issues. To investigate this overlap, we applied a methodology similar to that outlined in Section 2.2. Using the GPT-4o model, we constructed a dictionary to detect mentions of [**scientific research papers**] for identifying research-focused discussions. Additionally, we generated dictionaries for [**Donald Trump**] and [**Joe Biden**] the two presidents within our sample period—as well as for [**Politicians**] and [**Political Candidates**]. These were combined to create a comprehensive dictionary for identifying mentions of political figures and candidates. Table B.3 provides examples of ngrams generated for each category, illustrating the diversity and scope of our topic detection approach.

We analyzed the yearly distribution of the full sample of academics' tweets across four categories: mentions of politicians[26] (blue), research papers (green), both politicians and research papers (pink), and other content (gray). Figure A.2 depicts this distribution, with each bar showing the proportion of tweets in each category for a given year. On average, about 10% of tweets mention politicians, approximately 20% reference research papers, and around 1% mention both politicians and research papers in the same tweet. The proportion of tweets mentioning politicians or research papers remained relatively stable over the years, with notable fluctuations potentially tied to significant events. For instance, the wider colored areas in 2020 may reflect increased discussions on racial equality sparked by the George Floyd incident or a surge in research-related tweets

[26]This includes political figures and candidates, among which Joe Biden and Donald Trump

prompted by the COVID-19 pandemic. Darker shades within these categories indicate tweets discussing specifically any of the five salient political topics—Abortion Rights, Climate Action, Racial Equality, Immigration, and Income Redistribution—which are predominantly concentrated in the residual content category.

These trends align with the cross-sectional summary statistics in Table B.2. In the full sample, 9.8% of tweets mention politicians (including Trump and Biden), and 19.2% mention research papers; focusing on the five salient topics, these proportions increase to 16.0% and 28.9%, respectively. Notably, Climate Action tweets mention research papers (44.5%) far more than politicians (15%), with a research-to-politician mention ratio of approximately 3 to 1, reflecting the emphasis on scientific discourse. Conversely, Abortion Rights and Immigration tweets are more likely to mention politicians (25.6 and 28%) than research papers (15% and 21.4%), with ratios of approximately 1.7 to 1 and 1.3 to 1, respectively, highlighting the political salience of these issues.

Overall, the data suggest that scientists engage in discussions about research, political figures, and politically salient issues, with a notable but not overwhelming overlap. Given that politically salient tweets typically generate high engagement and that research-related discourse is becoming more prevalent on Twitter (see Figure A.1), it is important to examine the potential impact of this communication on public perceptions.

2.3.2 Differences by Gender and Discipline

We further study whether the online political expression of academics varies by gender and discipline. Gender was determined using a binary classification based on LLM,[27] and gender-based differences are presented in Figure A.3 broken down by political topics. Overall, academics with female-labeled names express slightly more political opinions, especially on Abortion Rights, Immigration, and Racial Equality, with more notable increases post-2020. In contrast, topics such as Climate Action and Income Redistribution show no significant gender differences.

We also analyzed differences in political expression across disciplines using OpenAlex's "Concepts" to classify fields of study.[28] Each research work is assigned a score from 0 to 1 for each of the 19 root concepts, indicating the likelihood that the work be-

[27] Full academic names were processed through an LLM to categorize them as "Male," "Female," or "Unclear," with nearly 99% of names classified as Male or Female. Details in Appendix Section D.

[28] OpenAlex describes "Concepts" as hierarchical, tree-like structures with 19 root-level concepts and six layers of descendants, totaling about 65,000 concepts. Each research work is classified with high accuracy. More details are available here and in Appendix Section D.

longs to a specific concept. For each researcher, we averaged these scores across all their publications from 2016 to 2022 and identified their primary concept as the one with the highest average score. We then grouped these primary concepts into three broad categories for comparison: (1) Medicine, (2) Social Sciences, and (3) STEM.[29] Figure A.4 shows the proportion of academics in each field category who expressed a non-neutral opinion on one of the five politically salient issues. Overall, similar dynamics are observed across disciplines, with a general trend of U.S. academics expressing political views beyond their area of expertise (top left graph). However, STEM scientists are most vocal about Climate Action, while Social Scientists are more active on Income Redistribution. Notably, gaps between disciplines have narrowed over time for both issues. This pattern contrasts with common stereotypes about the politicization of scientists (Altenmüller et al., 2024).

2.3.3 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. Given the significant political engagement of scientists and the stark contrast with the general public, it becomes important to investigate academics' *ideological polarization* — defined as the divergence in political views or issue positions among individuals.

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. For each topic and user in a given month, we calculated their net stance 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. 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 indi-

[29] Medicine stands alone. Social Sciences include Business, Economics, History, Political Science, Psychology, and Sociology. STEM encompasses Biology, Chemistry, Engineering, Environmental Science, Geography, Geology, Materials Science, Mathematics, and Physics (excludes Medicine). Humanities, including Art, Philosophy, Literature, Religion, Music, Theater, Dance, and Film, are excluded from the plot due to the small sample size.

vidual, 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 3 shows the cross-sectional distribution of net pro stances S_{um} for each topic, comparing academics and general users over the entire sampled period. For all topics except Racial Equality, neutral views are the most common. Nonetheless, the figure highlights the presence of multiple peaks, confirmed by Hartigan's Dip Test (Hartigan and Hartigan, 1985), which reports p-values of 0, indicating strong multimodality for both groups. This pattern suggests distinct political camps and highlights significant polarization. Although both samples display multiple peaks in their distributions, general users are more likely to cluster at extreme stances compared to academics, particularly around the most conservative positions (-1) on all issues except Racial Equality. Academics, on the other hand, tend to be more concentrated in the moderate liberal/progressive range. Interestingly, for Racial Equality, the topic with the fewest neutral stances, users exhibit a higher degree of consensus, with a greater concentration of completely pro stances compared to academics.

Figure A.5 compares academics' net pro stance distributions across years. To study changes in distribution over time, we test the equality of two early and late distributions (specifically 2016-2017 vs. 2021-2022) using the Kolmogorov-Smirnov (KS) test (Massey Jr, 1951). Results suggest shifts in opinions over time, particularly on topics like Immigration and Abortion Rights, for which KS is highest, highlighting the dynamic nature of ideological polarization among academics.

We also examine differences in net stances between tweets mentioning scientific research and those that do not. Figure A.6 displays the distributions of net pro stances across topics, comparing research-related and non-research-related tweets among academics. The KS tests in the figure indicate statistically significant differences between the two distributions for each topic. Non-research tweets tend to be less neutral and generally more liberal across most topics, except for Climate Action, where differences are smaller, and research-related tweets are slightly more progressive.[30] The largest divergence is observed in the topic of Abortion Rights, where non-research tweets have a greater concentration toward a pro-abortion stance (+1), while research-related tweets

[30] Tweets on Climate Action are also the most likely to explicitly reference research (44%), see Table B.2.

cluster significantly more around neutrality (0). This suggests that academics are more likely to adopt explicitly pro-choice positions in tweets unrelated to research, whereas tweets referencing research tend to remain more balanced. This distinction aligns with expectations: research-related tweets likely reflect professional norms of moderation, while non-research tweets allow for more direct political expression. These patterns validate the sensitivity of our measure as it captures the reasonable difference between the more neutral stances expected in research-related discourse and the more explicit positions in non-research tweets.

2.3.4 Evolution of Scientists' Disagreement

We finally examine the evolution of disagreement among scientists, taking the variance of the net pro stances S_{um} across all users and academics for each topic, monthly. This approach provides a refined understanding of time trends, offering a continuous aggregate measure of opinion diversity for each topic. Variance is particularly well-suited for capturing the range of opinions, as it is unaffected by the average stance and highly sensitive to extreme positions, which are central to our investigation. Additionally, it enables comparative analysis across topics and time periods (McCarty et al., 2016).

We selected the variance because it serves as a robust and interpretable summary statistic for large datasets, facilitating longitudinal and cross-topic comparisons. Despite its advantages, utilizing the variance presents limitations. It does not explain the underlying reasons for the observed disagreement (Fiorina et al., 2005), and its sensitivity to extreme views may sometimes overstate the extent of disagreement if only a small number of individuals hold extreme positions. Moreover, the variance might not highlight areas of consensus, which could provide valuable insights into a group's ideological alignment (Hopkins, 2018). To mitigate these concerns, we interpret this variance in relative terms, observing how it fluctuates over time, across topics, and samples. Lower variances indicate greater consensus on specific issues or during particular periods, relative to other times or topics. This approach allows us to identify not only areas of divergence but also points of agreement that emerge within different samples and over time, offering a comprehensive view of the evolving ideological landscape in academia.

The top left panel in Figure 4, titled "All," aggregates all topics to provide an overall measure of political disagreement. Similar to trends in political engagement, political disagreement shows a mild increase from 2016 to 2022, raising concerns about its potential impact on scientific consensus-building and public trust in scientific expertise.

While scientists initially appear to exhibit greater ideological distance than general users, a breakdown by topic reveals a more nuanced picture. For most topics, the general U.S. Twitter population exhibits more disagreement than academics. However, Racial Equality is an exception: academics show a growing and increasingly pronounced disagreement compared to the general public. As this topic is the second most discussed among both groups, the heightened polarization among academics on this issue disproportionally affects the aggregate trend. For other issues, including Immigration, Income Redistribution, and Abortion, the general public demonstrates higher ideological disagreement. This gap widens around the pandemic and then narrows toward the end of the period. In the case of Climate Action, disagreement between academics and the general public persists throughout the sample period, with the gap widening further by the end of 2022.

3 Scientists' Political Expression and Public Perceptions

Having examined the scope of online political discourse and issue-based disagreement among scientists, and compared these patterns with general social media users, we now explore the potential risks associated with scientists' political engagement. Specifically, we investigate whether such academic engagement influences public perceptions of scientists' credibility and contributes to audience polarization.

To assess the impact of scientists' political discourse on public perceptions, we conducted a conjoint experiment with 1,704 respondents from a broadly representative sample of the U.S. population, recruited via Prolific—a platform extensively used for experimental research (Bursztyn et al., 2023a; Enke et al., 2023).[31]

Our sample adequately represents the U.S. population across key dimensions, including political affiliation, region, ethnicity, and gender. However, as is typical with Prolific samples, respondents have slightly higher income levels, and are somewhat younger and more educated compared to the general population. Table B.6 provides details on the representativeness of our sample. To ensure data quality, all participants were required to pass an attention check.

[31] All studies and surveys presented in this paper were pre-registered on AsPredicted with numbers 166935, 179009, 181452, and 18629.

3.1 Experimental Design

Our conjoint experiment adheres to the best practices recommended in the literature (Hainmueller et al., 2015). We designed five hypothetical vignettes representing distinct scientist profiles, each varying randomly across key attributes: gender (male or female), research field (Social Sciences, STEM, Medicine, or Humanities), seniority (senior or junior), university affiliation (high-ranking or low-ranking), and, most importantly, political affiliation.

Political affiliation—our primary attribute of interest—is conveyed through a biographic description (similar to those found on Twitter) and a real high-engagement tweet.[32] This design minimizes concerns about the external validity of our manipulation. The political profiles span five categories: Strong Democrat, Moderate Democrat, Neutral (serving as the benchmark), Moderate Republican, and Strong Republican. Table B.7 provides a summary of all the attributes varied across the vignettes.

The scientist profiles were generated by randomizing each attribute, ensuring that each of the five political profiles was associated with a unique set of characteristics. All vignettes maintained a consistent format and were presented to respondents in a randomized order to prevent order effects (see Figure A.7 for a visual representation).

*The profile you are seeing is a [**Gender**] scientist.*
*This scientist works in the field of [**Research Field**]*
*Currently, this scientist is a [**Seniority**] at the [**University Affiliation**].*
The scientist is active on X (formerly known as Twitter).
*The Twitter bio of the scientist is: "[**Twitter Bio**]".*
*A recent selected Tweet reads: "[**Twitter Post**]".*

Participants were then asked to rate the credibility of the scientists and their research on a scale from 0 (not credible) to 10 (very credible), as well as to indicate their willingness to read an opinion piece from a scientist with similar attributes from 0 (not willing at all) to 10 (very willing).[33] To incentivize respondents, they were informed that they would receive an opinion piece from a real scientist whose characteristics matched their

[32] High-engagement tweets are more likely to be seen by users who do not follow the account due to their increased visibility through Twitter's recommendation algorithms and user engagement metrics (e.g., likes, retweets, and comments).

[33] Hainmueller et al. (2015) demonstrate that treatment effect estimates are generally consistent whether using single or paired vignettes. Thus, we opted for the less cognitively demanding single-vignette approach.

stated preferences over the scientists.[34] This approach, designed to avoid deception, is consistent with the methodology outlined by Kessler et al. (2019).

The experimental design included 960 unique profiles generated from a 2 (gender) X 4 (research field) X 2 (seniority) X 2 (university affiliation) * 5 (Twitter bio and post) factorial combinations. Using a clustered bootstrap procedure that resampled respondents with replacement, we calculated a minimum detectable effect size of 0.05 standard deviations at 99% power, with a significance level set at 5%.

Our design addresses common concerns in conjoint experiments (Hainmueller et al., 2015), particularly regarding attribute-order effects and experimenter demand effects. To mitigate attribute-order effects, we positioned the primary attribute of interest—political affiliation—at the bottom of the profile page. To reduce experimenter demand effects, we emphasized multiple salient profile attributes and incentivized respondents informing them they would receive an opinion piece from a real scientist resembling their top-rated profile. Further discussion on the experimenter demand effect is available in Section 3.2.2. Detailed instructions for the experiment are available in Appendix Section E.

3.1.1 Validating Twitter Political Signals

To validate our characterization of Twitter political affiliations, we surveyed 98 new participants on Prolific. These participants were asked to classify the political signals—comprising the Twitter biographies and tweets used in the main experiment to denote scientists' political affiliation—into one of five categories: Strong Republican, Moderate Republican, Neutral, Moderate Democrat, or Strong Democrat.

Figure A.8 presents the results of our validation exercise. Each subplot corresponds to a specific intended political affiliation. The bars in each subplot show the proportion of respondents who selected each classification option. Our findings confirm that most respondents accurately identified the intended political signals. For each designated political affiliation, the highest proportion of responses matched the correct label. This indicates that the majority of participants accurately perceived the intended political orientation. Furthermore, when errors occurred, they were primarily shifted to the adjacent political category. This further supports the reliability of our classifications. The high accuracy of these perceptions validates our initial categorization and reinforces the credibility of our experimental design.

[34] Evidence shows that there is no difference between hypothetical and incentivized measurements across different outcomes (Hainmueller et al., 2015; Brañas-Garza et al., 2021, 2023; Enke et al., 2022).

3.2 Impact on Public Perceptions

We now turn to the effects of scientists' political expressions on their perceived credibility and the public's willingness to engage with their work. Figure 5 illustrates a monotonic penalty associated with scientists' online political expression. Perceptions of scientists' credibility, the credibility of their research, and the public's willingness to read an opinion piece are highest for the neutral profile. These outcomes decline significantly as political affiliations become more extreme, both on the 'left' and 'right' of neutral.

Scientists who express any political stance are, on average, viewed as less credible than those who remain neutral (Panel A, lighter shades). This finding supports the stereotype that scientists should remain impartial and avoid politicization (Altenmüller et al., 2024). The credibility penalty increases with the intensity of political affiliation: Strong Republican scientists are perceived as 39% less credible than neutral scientists, while Strong Democrat scientists face an 11% credibility penalty. Moderate Republican and Moderate Democrat scientists experience smaller penalties of 9% and 7%, respectively, compared to neutral scientists.

Similarly, respondents are less willing to read opinions from scientists with political stances (Panel A, darker shades). This willingness decreases in a monotonic fashion: respondents are 42% less willing to read from Strong Republican scientists and 10.7% less willing to engage with Strong Democrat scientists, relative to neutral profiles. Moderate Republican and Moderate Democrat scientists face smaller declines of 8% and 4.5%, respectively. Both findings remain robust even when controlling for respondents' characteristics (Figure A.9, Panel C and D).

Figure A.9, along with Tables B.8 to B.10, illustrate that additional attributes of the scientists have a causal effect on how respondents perceive the credibility of scientists and their research, as well as their willingness to read an opinion piece from them. Specifically, scientists affiliated with prestigious institutions (such as Harvard University, UC Berkeley, and UChicago) are seen as more credible and are more likely to attract readership compared to those affiliated with less prestigious universities (like the University of Arkansas or the University of Connecticut).

When examining each scientist's political affiliation separately, the advantage of high institutional affiliation holds for all profiles except the politically neutral scientist. Notably, prestigious affiliations result in a credibility penalty for scientists with a Strong Republican profile. Seniority also matters: Full Professors are generally perceived as more credible and are more likely to be read compared to Assistant Professors. Interestingly, the gender of the scientist does not significantly impact credibility perceptions. However, in the case of neutral stances, male scientists are slightly less likely to be read than their female counterparts.

3.2.1 Heterogeneity by Respondent Leaning

To determine whether scientists' online political expression contributes to polarization, we analyzed how audience perceptions of different scientist profiles vary based on respondents' political leanings. Figure 5 highlights significant heterogeneity linked to respondents' political identities, revealing a clear pattern of affective polarization.

Respondents identifying as *Democrat* or *leaning Democrat* perceive Republican-leaning scientists as significantly less credible than their Democrat or neutral counterparts. Specifically, Moderate Republican scientists face an 18.3% credibility penalty, while Strong Republican scientists experience a substantial 60% credibility penalty (Panel B, dark blue). Similarly, these respondents are 23.2% less willing to read opinions from Moderate Republicans and 69% less willing to engage with Strong Republicans (Panel B, light blue). The severity of these penalties thus increases with more extreme affiliations.

On the other hand, respondents identifying as *Republican* or *leaning Republican* view Democrat-leaning scientists as less credible, imposing a 16% penalty on Moderate Democrats and a 26% penalty on Strong Democrats (Panel B, dark red). Their willingness to read from Democrat scientists also drops by 18% to 30%, depending on the degree of Democratic affiliation (Panel B, light red). As with Democrat respondents, stronger political stances from scientists result in greater penalties.

Interestingly, Republican respondents view scientists with Moderate Republican stances as 3.1% more credible than neutral scientists and are 11.6% more willing to read from them. This asymmetric pattern is consistent with findings by González-Bailón et al. (2023), which show that conservatives are more likely to remain in information bubbles. While Strongly Republican scientists are seen as 12% less credible than neutral scientists by Republican respondents, they are still considered more credible than Democrat-leaning scientists. Likewise, Republican respondents are only 7% less willing to read Strong Republican opinions, showing a less pronounced penalty compared to Democrat scientists.

Overall, the gap in willingness to engage with scientists holding opposing political identities is between 18% to 23% for scientists with moderate stances and rises to 30% up to 69% for those with extreme stances. The magnitudes of these results are broadly in line with the lower bound of those found in the literature measuring affective polarization using willingness to interact with the opponent. For example, Ajzenman et al. (2023b) find that sharing political identity increases follow-backs on Twitter by 119% relative to opposite political identities. Additionally, Rathje et al. (2021) show that if a social media post contains a term referring to the political out-group the odds of a social media post being shared increase by 67%.

The monotonic pattern in penalties, where the effect is larger for Strong Republican and Strong Democrat scientists compared to their moderately affiliated counterparts, particularly among respondents with opposing political leanings, highlights the polarization in perceptions based on the political affiliations of both scientists and respondents. This pattern is evidence of *affective polarization*, where individuals' evaluations of scientists are strongly influenced by their political identity.

3.2.2 Robustness Checks

We conducted several robustness checks to address potential concerns: (1) a full replication of our main results; (2) an analysis confirming that disciplines do not show differential penalties when the salient political tweet aligns with their field of expertise; (3) exclusion of respondents who completed the survey unusually quickly; (4) corrections for heteroskedasticity; (5) a placebo test involving random permutations of political affiliations; and (6) adjustments for multiple hypothesis testing.

Replication We replicate the results of our main experiment with a new sample of 2,000 respondents recruited on Prolific where we only elicited two outcomes: perceived credibility of the scientist and willingness to read an opinion piece from them. This replication aims to assess the robustness of our findings to the elicitation procedures. Figure A.10 shows that the main results of the conjoint experiment are virtually unchanged. The results show that the measurement exercise is not sensitive to changes in the elicited outcomes.

Role of Expertise While we do not explicitly test the role of expertise, we can evaluate whether there is a concordance between the scientists' disciplines in the vignettes and the topics of their tweets. Based on the selected tweets used to represent scientists' political affiliations (see vignettes in Figure A.7), the Strong Republican scientist might be perceived as an expert in Medicine, the Moderate Republican as an expert in Economics, and the Strong Democrat as an expert in either Economics or Medicine. The Moderate Democrat scientist could be seen as an expert in STEM.

By randomizing the discipline attributes across vignettes, we can test whether a match between a scientist's discipline and the topic mentioned in the tweet affects perceived credibility. Table B.8, Table B.9, and Table B.10 show no evidence that scientists whose discipline aligns with the tweet topic — and who could thus be perceived as experts — are viewed as more or less credible compared to those without such a match. This holds also true for both the perceived credibility of their research and the public's willingness to engage with their opinion pieces.

Carryover Effects A crucial assumption for identifying the effects in our experimental design is the stability of these effects, specifically the absence of carryover effects across different profiles. Carryover effects would imply that a respondent's evaluation of a particular scientist's political affiliation could be influenced by the profiles they encountered before or after that profile, thereby introducing bias. Although such effects are unlikely due to the randomization of profile order, we tested for their presence to ensure robustness. We analyzed respondents' answers separately for each round of the experiment. As shown in Figure A.13, the results remain consistent across all rounds, suggesting that carryover effects are not present. This consistency supports the validity of our measurement and alleviates concerns regarding order effects.

Excluding 'Speeders' A common concern in online experiments is that some respondents may rush through the task without paying adequate attention, introducing noise into the data. To address this, we repeated our main analysis after excluding respondents who completed the survey in less than one minute, compared to a median completion time of 7.2 minutes. As shown in Figure A.14, the results remain virtually unchanged, indicating that our findings are robust and not driven by the inclusion of 'speeders'.

Heteroskedasticity To ensure the robustness of our estimates, we corrected the standard errors to account for potential heteroskedasticity. We re-estimated our main regressions, excluding control variables, and used standard errors that are robust to heteroskedasticity. As presented in Table B.12, the results remain unaffected by this change in specification.

Permutation Test A potential concern is whether our baseline 'neutral' scientist is truly perceived as neutral or may be subtly signaling a political identity, which could bias our estimates of the effects of political affiliation. To test this, we conducted a permutation test. First, we randomly reassigned the five political affiliation labels across profiles for each respondent. Next, we ran our main regression analysis using these misassigned labels and recorded the coefficients. This procedure was repeated 100 times. As illustrated in Figure A.15, the regression coefficients from the randomly mislabelled affiliations clustered closely around zero (in both positive and negative directions), unlike the significant effects observed in our main model. This result supports the validity of our findings, alleviating concerns about the neutrality of the baseline profile.

Multiple Hypothesis Testing One advantage of a conjoint experiment is the ability to simultaneously test multiple hypotheses across various attribute categories. However, this raises concerns about whether our results would hold after correcting for multiple hypothesis testing. To address this, we re-estimated our main models (without controls) and adjusted the p-values using the 'false discovery rate' method proposed by Benjamini et al. (2006). Specifically, we corrected for 11 treatments, calculated as the 16 attribute categories minus 5 baseline attributes. As shown in Table B.13, the estimates with corrected p-values retain their exact significance, confirming the robustness of our results even after accounting for multiple hypothesis testing.

Experimenter Demand Although we encouraged truthful responses and placed scientists' political affiliation last among vignette attributes, concerns about experimenter demand effects may still arise. We believe, however, that our results suggest only a limited influence, if any. First, while demand effects could affect effect size, they would not alter the relative order or monotonic relationship across intensities of political signals, especially given the diverse responses across subgroups. Second, the effect of political affiliation equally holds in our second experimental task, which presents respondents with only one academic profile, allowing for between-group comparisons. Third, the significant impact of other attributes on public perceptions indicates that respondents weigh multiple characteristics beyond political affiliation alone. Finally, our design carefully balances the need to mitigate demand effects with the clarity of the political signal, allowing confident interpretation of our findings (see validation in 3.1.1).

Nonetheless, we further tested for potential demand effects by conducting a robustness experiment with 354 U.S. respondents on Prolific. In this simplified task, respondents rated the credibility of a neutral scientist's profile, their research, and their willingness to read an opinion piece from them, followed by either a Strong Republican or Strong Democrat academic profile. To explicitly induce demand effects, we cross-randomized respondents, nudging them to rate the second vignette either higher or lower (following de Quidt et al. (2018)). By estimating the impact of political affiliation under these induced conditions, we could bound the potential demand effects. Figure A.11 illustrates these effects are moderate or null, as estimations show that credibility and willingness to read peak for neutral scientists, while left- and right-leaning scientists face credibility penalties, regardless of the demand condition, qualitatively confirming our main findings.

3.2.3 Impact on Journalists Perceptions

To enhance the external validity of our findings, we conducted a simplified version of our experiment with a sample of 135 international journalists, recruited via Prolific. Table B.14 provides details on the sample characteristics: half of the journalists have more than five years of experience, 78% work as reporters or editors, and over half are based in the U.S. or the UK. The journalists are employed in various roles, including daily newspapers, online newspapers, and freelance work, with around 60% affiliated with outlets that have a political orientation.

In this streamlined experiment, we presented journalists with three scientist profiles. We reduced the number of profiles compared to the main experiment, to account for the limited sample size and maintain statistical power. The profiles signaled three distinct political ideologies — Strong Republican, Strong Democrat, and Neutral — using only the Twitter biographies from the main experiment, without tweets. Journalists were asked to evaluate the credibility of the scientists and their research. Additionally, they indicated their willingness to feature an opinion piece from a scientist with similar characteristics. To incentivize thoughtful responses, we informed journalists that an opinion piece from the scientist they rated highest would be included in a newsletter shown to 100 readers. If their selected piece ranked among the top five in the newsletter, the journalist would receive a monetary bonus.

We replicated our main results, as illustrated in Figure A.12, which shows that neutral scientists are rated highest, while those with non-neutral political attributes face significant penalties. Specifically, journalists perceive the Strong Republican scientist and their research as 33% and 32% less credible, respectively, compared to the neutral scientist

(Panel A, light shades). Additionally, journalists are 40% less willing to feature an opinion piece from a Strong Republican scientist in a newsletter (Panel A, dark shade). In contrast, the Strong Democrat scientist is viewed as 5% less credible, and their research is rated 4% less credible than that of a neutral scientist. Journalists are also 2% less willing to include an opinion piece from a Strong Democrat scientist in a newsletter. The more pronounced penalty for Republican scientists is largely driven by the high proportion of liberal respondents among the journalists (62% of the sample). For liberal journalists, the credibility and willingness-to-read penalties for Republican scientists range from 42% to 56% (Panel B, blue). Conversely, for conservative journalists, the penalties for Democrat scientists range from 18% to 28% (Panel B, red).

Finally, we explored the factors that might influence journalists' preferences. We gathered their beliefs about standard practices regarding the reporting of scientists' political identities, their expectations of readers' reactions to articles featuring scientists' political opinions, and their likelihood of engaging with scientists who have known political views or are politically active on social media. Table B.15 summarizes these findings. First, over half of the journalists believe that a scientist's political leaning should be disclosed in an article and that featuring a politically active scientist could impact the newspaper's credibility. Second, they expect mixed reactions from their readership: some readers may be less engaged with content from a scientist with well-known political views, while others may be more engaged, likely reflecting the audience's diverse political views. Third, despite potential credibility concerns, journalists still express a willingness to reach out to scientists with known political views or those politically active on social media. This indicates that journalists may play a role in amplifying scientists' political opinions, thereby influencing public perceptions of scientists' credibility.

3.3 Research vs. Pure Political Signal

Scientists often communicate their political views either by discussing research relevant to politically charged issues or by expressing opinions outside their area of expertise. Here, we investigate whether the effect on audience perceptions of scientists' credibility is driven by tweeting about politically salient research or by signaling political identity.

Experimental Design To explore this, we conducted an additional experimental task, following the presentation of the five synthetic profiles from the conjoint experiment. In this task, respondents were shown a profile of an economist, chosen because the field of economics frequently addresses politically salient issues. We randomized respondents into four experimental conditions, varying whether the economist discusses a recent publication on a politically sensitive topic (or not) and whether they provide a clear left- or right-leaning signal. Importantly, expertise is held constant, as economists only discuss topics within their field.

Specifically, we structured two control groups: an *active control* group and a *passive control* group. In the active control group, the economist posts about new research on the negative impact of policies on migrants' health—a politically charged issue aligned with a left-leaning perspective.[35] The passive control group features an economist with no political affiliation, discussing economic theory research that is not politically charged. We then created two treatment conditions by manipulating the economist's political identity through their Twitter bio: either *Left* ("advocate for equality") or *Right* ("proud patriot") (see vignettes in Figure A.16). In both treatment conditions, the economist discusses the same politically salient research as in the active control group.

Following the economist profile presentation, we measured how credible respondents found the economist and their research, and their willingness to read an opinion piece by the economist. We also invited respondents to join a newsletter on socio-economic issues in the U.S., featuring pieces from economists similar to the one they had just seen. The newsletter was offered at no cost, with no required subscription, and could be delivered directly via Prolific message (similar to Chopra et al. (2024)). A screenshot of the newsletter can be found in Figure A.17. Finally, we assessed respondents' overall trust in scientists using three Likert scale questions, which we averaged into a composite index.

Results Figure 6 presents the results of this experimental task. Scientists tweeting about non-politically salient research are perceived similarly by both Democrat and Republican respondents. However, the top left panel shows that Democrat respondents perceive economists and their research as 8.6% and 6.3% more credible, respectively, when the tweets cover politically aligned research compared to non-salient research. A left-leaning political signal further enhances credibility by an additional 1.7%, whereas a right-leaning signal decreases it by 8.6%, bringing credibility perceptions back to the baseline level of non-political research. Similarly, willingness to read the economist's

[35] We selected research that aligns with one political side (Democrat) and is opposed by the other (Republican) to easily interpret the effects based on respondents' political orientations. We expect these effects to be symmetric to research content.

piece increases by 33% with politically aligned research, with the left signal adding another 7.1%, while the right signal reduces it by 4.5%.

The top right panel reveals that Republican respondents perceive economists discussing misaligned politically salient research as 12% less credible compared to the non-salient benchmark. This credibility penalty is intensified by an additional 5% with a left-leaning signal but is mitigated by 5% with a right-leaning signal. Willingness to read the economist's opinion piece is highest when paired with a congruent right-leaning signal and lowest with a left-leaning signal.

For both Democrat and Republican sub-samples, newsletter sign-up and overall trust in science display similar patterns, albeit with less pronounced changes. We validated the willingness to read the economist's opinion outcome by correlating it with the demand for the newsletter, finding a significantly positive correlation ($\beta = 0.064$, p-value < 0.001). To further confirm the validity of our newsletter demand outcome, we recontacted respondents a few weeks later, providing the link to the newsletter. Of the 595 respondents who expressed interest, we successfully recontacted 440 within one month, and 86% of them clicked the link to access the newsletter.

The bottom panels of Figure 6 show normalized group averages relative to either the active or passive control. In-group respondents (those whose political leanings aligned with the scientist's signal) perceived the scientist and their research as significantly more credible, expressed greater willingness to read their opinions, and were more likely to sign up for the newsletter, compared to out-group respondents. Equivalent regression results in Tables B.16 and B.17 support these visual findings and demonstrate the robustness of our estimates to the inclusion of individual-level controls.

4 Scientists' Views on Online Political Expression

Having measured academics' online political expression and assessed the reputational risks for public perceptions, we now turn to directly gathering scientists' self-reported views through a brief survey. We recruited 128 scientists globally on Prolific.[36]

Table B.18 provides details on the sample characteristics. Regarding employment, 94% of the scientists are currently employed, with over 60% working at universities. The sample includes 43% postdoctoral researchers, 28% faculty members, and 29% industry

[36]We specifically targeted Prolific respondents who identified as working in "Research," holding a "PhD degree," and being fluent in English.

professionals. In terms of fields, 34% of the scientists are in life sciences and biomedicine, another 34% in social sciences, and the rest work in physical sciences and technology.

Our survey focused on three main areas. First, we investigated whether scientists anticipate a credibility penalty for expressing political opinions on social media. Second, we explored their first- and second-order beliefs about the acceptability of online political expression, both within and outside their area of expertise, using the framework from Bursztyn and Yang (2022).[37] Lastly, we examined their personal experiences with publicly expressing political views on social media.

Do scientists anticipate a credibility penalty for expressing political opinions on social media? To investigate this, we first provided participants with the following: "*We conducted a survey [...]. We measured trust in scientists, particularly focusing on whether this trust changes when scientists express political opinions on social media. The sample reported a level of trust of 7.2 out of 10 for scientists who* ***do not express*** *political opinions on social media.*"

We then asked them: "*What do you think is the reported level of trust for scientists who* ***do express*** *political opinions on social media?*"[38] In line with the theoretical premises of cheap-talk models in the presence of reputational concerns (Morris, 2001; Ottaviani and Sørensen, 2006), Figure A.18 illustrates that scientists indeed anticipate a trust penalty for expressing political opinions on social media. Interestingly, they overestimate the magnitude of this penalty, predicting an average trust loss of 30%, which is considerably higher than the actual experimentally measured average loss of 16.6%.

Second, we assessed scientists' views on the appropriateness of expressing political opinions online. Panel A of Figure A.19 indicates that respondents generally believe it is acceptable to publicly express political opinions on topics within their area of expertise but consider it inappropriate to do so for topics *outside* their field. This finding aligns with Garg and Fetzer (2024b), who show that academics are more likely to adopt prosocial views on topics where they hold expertise. In terms of their beliefs about the views of other scientists, Panel B of Figure A.19 reveals a congruent social norm: scientists believe that their peers also find it acceptable to express political opinions on social media when the opinions pertain to their research field, but not when they address unrelated topics.

Finally, we examined scientists' personal experiences with expressing political views on social media. Panel A of Figure A.20 shows that hesitation varies, with scientists

[37] This includes scientists' own views and their perceptions of how other scientists view the acceptability of expressing political opinions online.

[38] To incentivize accuracy, participants received a bonus of 0.5 GBP for a correct answer.

significantly more reluctant to share opinions on topics outside their area of expertise. This reluctance aligns with theoretical findings on information loss due to reputational concerns (Morris, 2001; Ottaviani and Sørensen, 2006). Similarly, this survey evidence complements the perception of a 'spiral-of-silence' affecting academics (e.g. in political science (Norris, 2020)). Panel B of Figure A.20 highlights that scientists generally anticipate reputational costs for expressing views on issues unrelated to their research, whereas they expect net benefits when opinions are tied to their field. Specifically, they believe more colleagues have experienced *negative* repercussions for sharing political views beyond their area of expertise while expressing opinions within their field has led more to favorable outcomes. Nevertheless, perceptions of these costs and benefits show considerable overlap, reflecting variation in individual experiences. Although we cannot determine the precise motivations behind scientists' political expression using Twitter data, the survey suggests that academics perceive greater advantages when their opinions align with their research expertise. As Gentzkow and Shapiro (2006) suggests, scientists may even adjust their communication to resonate with an audience's prior beliefs, especially when those beliefs are strong.

5 Conclusion

This study demonstrates that scientists' public expression of political views on social media significantly influences perceptions of their credibility.

First, we document that a substantial portion of U.S. academics engage in political discourse online. Between 2016 and 2022, approximately 44% of 97,737 academics actively discussed political issues on Twitter—a rate over six times higher than that of a random sample of U.S. Twitter users. Scientists frequently discuss topics like climate change and racial equality, exhibiting notably divergent viewpoints, especially around racial issues.

Secondly, we experimentally identify the effects of scientists' online political expression on public perceptions. Using conjoint experiments with 3,700 U.S. representative respondents and 135 international journalists who rated synthetic academic profiles with varied political affiliations, we find a monotonic credibility penalty for scientists expressing political views on either the left or right side of a neutral profile. The more extreme their political posts, the less credible they and their research are perceived, and the lower the public's willingness to engage with their content—particularly among respondents with opposing political views.

In a complementary survey of 128 international scientists, we find that scientists anticipate an even larger credibility penalty than what our experiment revealed. They also believe it is acceptable to express political opinions related to their field of expertise but not on unrelated topics, reflecting an established social norm within academia.

Our results highlight a significant challenge to the Mertonian norm of Universalism (Merton, 1973), which advocates for evaluating scientific work on its merits rather than the scientist's identity or views. Scientists' online political expression can undermine both their personal and scientific credibility, hinder public engagement with scientific discourse, and potentially exacerbate affective polarization within U.S. society.

Studying the reputational cost of scientists' online political engagement reveals a trade-off. On one hand, anticipating a "credibility" penalty may discourage scientists from sharing their views, leading to information loss in policy debates and potentially diminishing societal benefits—mediated by the personal career advantages academics gain from social media engagement. On the other hand, expressing political views can harm scientists' credibility, limiting their ability to influence decision-making and shape public preferences and behavior. While a welfare analysis of these dynamics is beyond the scope of this paper, our findings highlight the interplay between these forces and call for further research to understand their overall implications.

References

Acquisti, Alessandro, and Christina Fong. 2020. "An Experiment in Hiring Discrimination Via Online Social Networks." *Management Science* 66 (3): 1005–1024.

Aina, Chiara. 2023. "Tailored Stories." *Mimeo*.

Ajzenman, Nicolás, Bruno Ferman, and Pedro C. Sant'Anna. 2023a. "Discrimination in the Formation of Academic Networks: a Field Experiment on Econtwitter." *IZA Discussion Paper No. 15878*.

Ajzenman, Nicolas, Bruno Ferman, and Pedro C. Sant'Anna. 2023b. "Rooting for the Same Team: Shared Social Identities in a Polarized Context." *SSRN Working Paper No. 4326148*.

Akerlof, George A., and Rachel E. Kranton. 2000. "Economics and Identity." *The Quarterly Journal of Economics* 115 (3): 715–753.

Alabrese, Eleonora. 2022. "Bad Science: Retractions and Media Coverage." *CESifo Working Paper No. 10195*.

Albornoz, Facundo, Nicolas Bottan, Guillermo Cruces, Bridget Hoffmann, and María Lombardi. 2024. "Backlash Against Expert Recommendations: Reactions to COVID-19 Advice in Latin America." *Journal of Economic Behavior & Organization* 228 106752. https://doi.org/10.1016/j.jebo.2024.106752.

Alesina, Alberto, Armando Miano, and Stefanie Stantcheva. 2020. "The Polarization of Reality." *AEA Papers and Proceedings* 110 324–328.

Alford, John R., Peter K. Hatemi, John R. Hibbing, Nicholas G. Martin, and Lindon J. Eaves. 2011. "The Politics of Mate Choice." *The Journal of Politics* 73 (2): 362–379.

Algan, Yann, Daniel Cohen, Eva Davoine, Martial Foucault, and Stefanie Stantcheva. 2021. "Trust in scientists in times of pandemic: Panel evidence from 12 countries." *Proceedings of the Academy of Sciences* 118 (40): 1–8. 10.1073/pnas.2108576118.

Almås, Ingvild, Orazio Attanasio, and Pamela Jervis. 2023. "Economics and Measurement: New Measures to Model Decision Making." *National Bureau of Economic Research No. w30839*.

Altenmüller, Marlene S., Tobias Wingen, and Anna Schulte. 2024. "Explaining Polarized Trust in Scientists: a Political Stereotype-approach." *Science Communication* 46 (1): 92–115.

Ameriks, John, Joseph Briggs, Andrew Caplin, Matthew D. Shapiro, and Christopher Tonetti. 2020. "Long-term-care Utility and Late-in-life Saving." *Journal of Political Economy* 128 (6): 2375–2451.

Andre, Peter, Ingar Haaland, Christopher Roth, Mirko Wiederholt, and Johannes Wohlfart. 2024. "Narratives About the Macroeconomy." *SAFE Working Paper No. 426*.

Andre, Peter, Carlo Pizzinelli, Christopher Roth, and Johannes Wohlfart. 2022. "Subjective Models of the Macroeconomy: Evidence From Experts and Representative Samples." *The Review of Economic Studies* 89 (6): 2958–2991.

Angeli, Deivis, Matt Lowe et al. 2022. "Virtue Signals." *Working Paper*.

Angelucci, Charles, and Andrea Prat. 2024. "Is Journalistic Truth Dead? Measuring How Informed Voters Are About Political News." *American Economic Review* 114 (4): 887–925.

Arold, Benjamin W. 2024. "Evolution Vs. Creationism in the Classroom: the Lasting Effects of Science Education." *The Quarterly Journal of Economics* 2331–2375.

Ash, Elliott. 2016. "The Political Economy of Tax Laws in the US States." *Working Paper*.

Ash, Elliott, Sergio Galletta, Dominik Hangartner, Yotam Margalit, and Matteo Pinna. 2024. "The Effect of Fox News on Health Behavior During Covid-19." *Political Analysis* 32 (2): 275–284.

Azevedo, Flávio, and John T. Jost. 2021. "The Ideological Basis of Antiscientific Attitudes: Effects of Authoritarianism, Conservatism, Religiosity, Social Dominance, and System Justification." *Group Processes & Intergroup Relations* 24 (4): 518–549.

Barberá, Pablo. 2020. "Social Media, Echo Chambers, and Political Polarization." *Social Media and Democracy: the State of the Field, Prospects for Reform* 34.

Bartoš, Vojtěch, Michal Bauer, Jana Cahlíková, and Julie Chytilová. 2022. "Communicating Doctors' Consensus Persistently Increases Covid-19 Vaccinations." *Nature* 606 (7914): 542–549.

Beknazar-Yuzbashev, George, Rafael Jiménez Durán, Jesse McCrosky, and Mateusz Stalinski. 2022. "Toxic Content and User Engagement on Social Media: Evidence From a Field Experiment." *SSRN Working Paper No. 4307346*.

Bénabou, Roland, and Jean Tirole. 2006. "Incentives and Prosocial Behavior." *American Economic Review* 96 (5): 1652–1678.

Benjamini, Yoav, Abba M. Krieger, and Daniel Yekutieli. 2006. "Adaptive Linear Step-up Procedures That Control the False Discovery Rate." *Biometrika* 93 (3): 491–507.

Bernheim, B. Douglas, Daniel Björkegren, Jeffrey Naecker, and Michael Pollmann. 2022. "Causal Inference From Hypothetical Evaluations." *National Bureau of Economic Research No. w29616*.

Blastland, Michael, Alexandra LJ Freeman, Sander van der Linden, Theresa M. Marteau, and David Spiegelhalter. 2020. "Five Rules for Evidence Communication." *Nature* 587 (7834): 362–364.

Boken, Johannes, Mirko Draca, Nicola Mastrorocco, and Arianna Ornaghi. 2023. "The Returns to Viral Media: the Case of Us Campaign Contributions." *Warwick Economics Research Papers Series No. 1472*.

Bowles, Jeremy, Kevin Croke, Horacio Larreguy, John Marshall, and Shelley Liu. 2023. "Sustaining Exposure to Fact-checks: Misinformation Discernment, Media Consumption, and Its Political Implications." *SSRN Working Paper No. 4582703*.

Boxell, Levi, Matthew Gentzkow, and Jesse M. Shapiro. 2024. "Cross-country Trends in Affective Polarization." *The Review of Economics and Statistics* 106 (2): 557–565.

Braghieri, Luca. 2024. "Political Correctness, Social Image, and Information Transmission." *American Economic Review* 114 (12): 3877–3904. 10.1257/aer.20210039.

Braghieri, Luca, Peter Schwardmann, and Egon Tripodi. 2024. "Talking Across the Aisle." *Mimeo*.

Brañas-Garza, Pablo, Lorenzo Estepa-Mohedano, Diego Jorrat, Victor Orozco, and Ericka Rascón-Ramírez. 2021. "To Pay or Not to Pay: Measuring Risk Preferences in Lab and Field." *Judgment and Decision Making* 16 (5): 1290–1313.

Brañas-Garza, Pablo, Diego Jorrat, Antonio M. Espín, and Angel S.ánchez. 2023. "Paid and Hypothetical Time Preferences Are the Same: Lab, Field and Online Evidence." *Experimental Economics* 26 (2): 412–434.

Brown, Jacob R., Enrico Cantoni, Ryan D. Enos, Vincent Pons, and Emilie Sartre. 2022. "The Increase in Partisan Segregation in the United States." *NICEP Research Discussion paper 2023-09*.

Burnitt, Christopher, Jarrett Gars, and Mateusz Stalinski. 2024. "The Politics of Food." *Mimeo*.

Bursztyn, Leonardo, Michael Callen, Bruno Ferman, Saad Gulzar, Ali Hasanain, and Noam Yuchtman. 2020. "Political Identity: Experimental Evidence on Anti-americanism in Pakistan." *Journal of the European Economic Association* 18 (5): 2532–2560.

Bursztyn, Leonardo, Georgy Egorov, Ingar Haaland, Aakaash Rao, and Christopher Roth. 2023a. "Justifying Dissent." *The Quarterly Journal of Economics* 138 (3): 1403–1451.

Bursztyn, Leonardo, Aakaash Rao, Christopher Roth, and David Yanagizawa-Drott. 2023b. "Opinions As Facts." *The Review of Economic Studies* 90 (4): 1832–1864.

Bursztyn, Leonardo, and David Y. Yang. 2022. "Misperceptions About Others." *Annual Review of Economics* 14 (1): 425–452.

Cagé, Julia, Nicolas Hervé, and Marie-Luce Viaud. 2020. "The Production of Information in an Online World." *The Review of Economic Studies* 87 (5): 2126–2164.

Calónico, Sebastian, Rafael Di Tella, and Juan Cruz Lopez del Valle. 2023. "The Political Economy of a "Miracle Cure": the Case of Nebulized Ibuprofen and Its Diffusion in Argentina." *National Bureau of Economic Research No. w31781*.

Campbell, Eryn, John Kotcher, Teresa Myers, John Cook, Amanda C. Borth, and Edward Maibach. 2023. "What Motivates People to Defend Science: Evidence From the 2017 March for Science." *Plos One* 18 (11): e0290222.

Canen, Nathan J., Chad Kendall, and Francesco Trebbi. 2021. "Political Parties As Drivers of Us Polarization: 1927-2018."Technical report, National Bureau of Economic Research.

Chakraborty, Archishman, Parikshit Ghosh, and Jaideep Roy. 2020. "Expert-captured Democracies." *American Economic Review* 110 (6): 1713–1751.

Chan, Alex. 2022. "Discrimination Against Doctors: a Field Experiment." *Working Paper*.

Chan, Ho Fai, Ali Sina Önder, Sascha Schweitzer, and Benno Torgler. 2023. "Twitter and Citations." *Economics Letters* 231 111270.

Charness, Gary, and Yan Chen. 2020. "Social Identity, Group Behavior, and Teams." *Annual Review of Economics* 12 (1): 691–713.

Chopra, Felix, Ingar Haaland, and Christopher Roth. 2022. "Do People Demand Fact-checked News? Evidence From US Democrats." *Journal of Public Economics* 205 104549.

Chopra, Felix, Ingar Haaland, and Christopher Roth. 2024. "The Demand for News: Accuracy Concerns Versus Belief Confirmation Motives." *The Economic Journal* 134 (661): 1806–1834.

Colleoni, Elanor, Alessandro Rozza, and Adam Arvidsson. 2014. "Echo Chamber or Public Sphere? Predicting Political Orientation and Measuring Political Homophily in Twitter Using Big Data." *Journal of Communication* 64 (2): 317–332.

Cologna, Viktoria, Niels Mede, Sebastian Berger et al. Forthcoming. "Trust in Scientists and Their Role in Society Across 68 Countries." *Nature Human Behaviour*. https://doi.org/10.31219/osf.io/6ay7s.

Douglas, Karen M. 2021. "Are Conspiracy Theories Harmless?" *The Spanish Journal of Psychology* 24 e13.

Draca, Mirko, and Carlo Schwarz. 2024. "How Polarised Are Citizens? Measuring Ideology From the Ground Up." *The Economic Journal* 134 (661): 1950–1984.

Druckman, James N., and Mary C. McGrath. 2019. "The Evidence for Motivated Reasoning in Climate Change Preference Formation." *Nature Climate Change* 9 (2): 111–119.

Eichengreen, Barry, Cevat Giray Aksoy, and Orkun Saka. 2021. "Revenge of the Experts: Will Covid-19 Renew or Diminish Public Trust in Science?" *Journal of Public Economics* 193 104343.

Elías, Julio J., Nicola Lacetera, and Mario Macis. 2019. "Paying for Kidneys? a Randomized Survey and Choice Experiment." *American Economic Review* 109 (8): 2855–2888.

Enke, Benjamin, Thomas Graeber, and Ryan Oprea. 2023. "Confidence, Self-selection, and Bias in the Aggregate." *American Economic Review* 113 (7): 1933–1966.

Enke, Benjamin, Ricardo Rodriguez-Padilla, and Florian Zimmermann. 2022. "Moral Universalism: Measurement and Economic Relevance." *Management Science* 68 (5): 3590–3603.

Esteban, Joan-Maria, and Debraj Ray. 1994. "On the Measurement of Polarization." *Econometrica* 62 (4): 819–851.

Fetzer, Thiemo, John Peter Lambert, Bennet Feld, and Prashant Garg. 2024. "AI-Generated Production Networks: Measurement and Applications to Global Trade." Discussion Paper 19708, CEPR Press, Paris & London, https://cepr.org/publications/dp19708.

Fiorina, Morris P., and Samuel J. Abrams. 2008. "Political Polarization in the American Public." *Annual Review Political Science* 11 563–588.

Fiorina, Morris P., J. Abrams Samuel, and C. Pope Jeremy. 2005. *Culture War? the Myth of a Polarized America*. New York: Pearson Longman.

Flaxman, Seth, Sharad Goel, and Justin M. Rao. 2016. "Filter Bubbles, Echo Chambers, and Online News Consumption." *Public Opinion Quarterly* 80 (S1): 298–320.

Funk, Cary, Alec Tyson, Brian Kennedy, and Courtney Johnson. 2020. "Science and Scientists Held in High Esteem Across Global Publics." *Pew Research Center* 29.

Garcia-Hombrados, Jorge, Marcel Jansen, Á.ngel Martínez, Berkay Ö.zcan, Pedro Rey-Biel, and Antonio Roldán-Monés. 2024. "Ideological Alignment and Evidence-based Policy Adoption." *IZA Discussion Paper No. 17007*.

Garg, Prashant, and Thiemo Fetzer. 2024a. "Causal Claims in Economics." Discussion Paper 19701, CEPR Press, Paris & London, https://cepr.org/publications/dp19701.

Garg, Prashant, and Thiemo Fetzer. 2024b. "Political Expression of Academics on Social Media." *Research Square Preprint*. 10.21203/rs.3.rs-4480504/v1.

Garg, Prashant, and Ralf Martin. 2024. "Who Influences Whom About What?" *Mimeo*.

Gentzkow, Matthew, and Jesse M. Shapiro. 2006. "Media Bias and Reputation." *Journal of Political Economy* 114 (2): 280–316.

Gentzkow, Matthew, and Jesse M. Shapiro. 2011. "Ideological Segregation Online and Offline." *The Quarterly Journal of Economics* 126 (4): 1799–1839.

Gentzkow, Matthew, Jesse M. Shapiro, and Matt Taddy. 2019. "Measuring Group Differences in High-dimensional Choices: Method and Application to Congressional Speech." *Econometrica* 87 (4): 1307–1340.

Gift, Karen, and Thomas Gift. 2015. "Does Politics Influence Hiring? Evidence From a Randomized Experiment." *Political Behavior* 37 653–675.

González-Bailón, Sandra, David Lazer, Pablo Barberá et al. 2023. "Asymmetric Ideological Segregation in Exposure to Political News on Facebook." *Science* 381 (6656): 392–398.

Grimmer, Justin. 2010. "A Bayesian Hierarchical Topic Model for Political Texts: Measuring Expressed Agendas in Senate Press Releases." *Political Analysis* 18 (1): 1–35.

Grossman, Gene M., and Elhanan Helpman. 2021. "Identity Politics and Trade Policy." *The Review of Economic Studies* 88 (3): 1101–1126.

Guriev, Sergei, Emeric Henry, Théo Marquis, and Ekaterina Zhuravskaya. 2023. "Curtailing False News, Amplifying Truth." *SSRN Working Paper No. 4616553*.

Hainmueller, Jens, Dominik Hangartner, and Teppei Yamamoto. 2015. "Validating Vignette and Conjoint Survey Experiments Against Real-world Behavior." *Proceedings of the National Academy of Sciences* 112 (8): 2395–2400.

Hansen, Stephen, Michael McMahon, and Andrea Prat. 2018. "Transparency and Deliberation Within the Fomc: a Computational Linguistics Approach." *The Quarterly Journal of Economics* 133 (2): 801–870.

Hartigan, John A., and Pamela M. Hartigan. 1985. "The Dip Test of Unimodality." *The Annals of Statistics* 13 (1): 70–84.

Hendriks, Friederike, Dorothe Kienhues, and Rainer Bromme. 2020. "Replication Crisis= Trust Crisis? the Effect of Successful vs Failed Replications on Laypeople's Trust in Researchers and Research." *Public Understanding of Science* 29 (3): 270–288.

Hopkins, Daniel J. 2018. *The Increasingly United States: How and Why American Political Behavior Nationalized*. University of Chicago Press.

Huang, Yihong, and Yuen Ho. 2023. "Breaking the Spiral of Silence." *Mimeo*.

Huber, Gregory A., and Neil Malhotra. 2017. "Political Homophily in Social Relationships: Evidence From Online Dating Behavior." *The Journal of Politics* 79 (1): 269–283.

Iyengar, Shanto, Yphtach Lelkes, Matthew Levendusky, Neil Malhotra, and Sean J. Westwood. 2019. "The Origins and Consequences of Affective Polarization in the United States." *Annual Review of Political Science* 22 129–146.

Jelveh, Zubin, Bruce Kogut, and Suresh Naidu. 2024. "Political Language in Economics." *The Economic Journal* 134 (662): 2439–2469.

Jensen, Jacob, Suresh Naidu, Ethan Kaplan, Laurence Wilse-Samson, David Gergen,

Michael Zuckerman, and Arthur Spirling. 2012. "Political Polarization and the Dynamics of Political Language: Evidence From 130 Years of Partisan Speech." *Brookings Papers on Economic Activity* 1–81.

Jiménez Durán, Rafael. 2022. "The Economics of Content Moderation: Evidence From Hate Speech on Twitter." *Stigler Center for the Study of the Economy the State Working Paper No. 324*.

Kahan, Dan M., Hank Jenkins-Smith, and Donald Braman. 2011. "Cultural Cognition of Scientific Consensus." *Journal of Risk Research* 14 (2): 147–174.

Kessler, Judd B., Corinne Low, and Colin D. Sullivan. 2019. "Incentivized Resume Rating: Eliciting Employer Preferences Without Deception." *American Economic Review* 109 (11): 3713–3744.

Klar, Samara, Yanna Krupnikov, John Barry Ryan, Kathleen Searles, and Yotam Shmargad. 2020. "Using Social Media to Promote Academic Research: Identifying the Benefits of Twitter for Sharing Academic Work." *PLoS One* 15 (4): e0229446.

Kotcher, John E., Teresa A. Myers, Emily K. Vraga, Neil Stenhouse, and Edward W. Maibach. 2017. "Does Engagement in Advocacy Hurt the Credibility of Scientists? Results from a Randomized National Survey Experiment." *Environmental Communication* 11 (3): 415–429. 10.1080/17524032.2016.1275736.

Lelkes, Yphtach. 2016. "Mass Polarization: Manifestations and Measurements." *Public Opinion Quarterly* 80 (S1): 392–410.

Levy, Ro'ee. 2021. "Social Media, News Consumption, and Polarization: Evidence From a Field Experiment." *American Economic Review* 111 (3): 831–870.

Li, Nan, and Yachao Qian. 2022. "Polarization of Public Trust in Scientists Between 1978 and 2018: Insights From a Cross-decade Comparison Using Interpretable Machine Learning." *Politics and the Life Sciences* 41 (1): 45–54.

List, John A., and David Lucking-Reiley. 2002. "The Effects of Seed Money and Refunds on Charitable Giving: Experimental Evidence From a University Capital Campaign." *Journal of Political Economy* 110 (1): 215–233.

Low, Corinne. 2014. "Pricing the Biological Clock: Reproductive Capital on the US Marriage Market." *Wharton School of Business 17*.

Lupia, Arthur, David B. Allison, Kathleen Hall Jamieson, Jennifer Heimberg, Magdalena Skipper, and Susan M. Wolf. 2024. "Trends in US public confidence in science and opportunities for progress." *Proceedings of the National Academy of Sciences* 121 (11): e2319488121. 10.1073/pnas.2319488121.

Macchi, Elisa. 2023. "Worth Your Weight: Experimental Evidence on the Benefits of Obesity in Low-income Countries." *American Economic Review* 113 (9): 2287–2322.

Martinez-Bravo, Monica, and Andreas Stegmann. 2022. "In Vaccines We Trust? the Effects of the CIA's Vaccine Ruse on Immunization in Pakistan." *Journal of the European Economic Association* 20 (1): 150–186.

Massey Jr, Frank J. 1951. "The Kolmogorov-Smirnov Test for Goodness of Fit." *Journal of the American Statistical Association* 46 (253): 68–78.

McCarty, Nolan, Keith T. Poole, and Howard Rosenthal. 2016. *Polarized America: the Dance of Ideology and Unequal Riches*. MIT Press.

McIntyre, Lee. 2018. *Post-truth*. MIT Press.

Mede, Niels G. 2022. "Legacy Media As Inhibitors and Drivers of Public Reservations Against Science: Global Survey Evidence on the Link Between Media Use and Anti-science Attitudes." *Humanities and Social Sciences Communications* 9 (1): 1–11.

Mede, Niels G., and Mike S. Schäfer. 2020. "Science-related Populism: Conceptualizing Populist Demands Toward Science." *Public Understanding of Science* 29 (5): 473–491.

Mede, Niels G., Mike S. Schäfer, and Tobias F.üchslin. 2021. "The Scipop Scale for Measuring Science-related Populist Attitudes in Surveys: Development, Test, and Validation." *International Journal of Public Opinion Research* 33 (2): 273–293.

Merton, Robert K. 1973. *The Sociology of Science: Theoretical and Empirical Investigations*. University of Chicago Press.

Mongeon, Philippe, Timothy D. Bowman, and Rodrigo Costas. 2023. "An Open Data Set of Scholars on Twitter." *Quantitative Science Studies* 4 (2): 314–324.

Morris, Stephen. 2001. "Political Correctness." *Journal of Political Economy* 109 (2): 231–265.

Mosleh, Mohsen, Cameron Martel, Dean Eckles, and David G. Rand. 2021. "Shared Partisanship Dramatically Increases Social Tie Formation in a Twitter Field Experiment." *Proceedings of the National Academy of Sciences* 118 (7): e2022761118.

Nichols, Tom. 2017. *The Death of Expertise: the Campaign Against Established Knowledge and Why It Matters*. Oxford University Press.

Norris, Pippa. 2020. "Closed Minds? Is a 'Cancel Culture'stifling Academic Freedom and Intellectual Debate in Political Science?" *HKS Working Paper No. RWP20-025*.

Ottaviani, Marco, and Peter Norman Sørensen. 2006. "Reputational Cheap Talk." *The Rand Journal of Economics* 37 (1): 155–175.

Peng, Hao, Daniel M. Romero, and Emoke-Á.gnes Horvát. 2022. "Dynamics of Cross-platform Attention to Retracted Papers." *Proceedings of the National Academy of Sciences* 119 (25): e2119086119.

Petersen, Michael Bang, Alexander Bor, Frederik J.ørgensen, and Marie Fly Lindholt. 2021. "Transparent Communication About Negative Features of Covid-19 Vaccines Decreases Acceptance But Increases Trust." *Proceedings of the National Academy of Sciences* 118 (29): e2024597118.

Qiu, Jingyi, Yan Chen, Alain Cohn, and Alvin E. Roth. 2024. "Social Media and Job Market Success: a Field Experiment on Twitter." *SSRN Working Paper No. 4778120*.

de Quidt, Jonathan, Johannes Haushofer, and Christopher Roth. 2018. "Measuring and Bounding Experimenter Demand." *American Economic Review* 108 (11): 3266–3302.

Rathje, Steve, Jay J. Van Bavel, and Sander Van Der Linden. 2021. "Out-group Animosity Drives Engagement on Social Media." *Proceedings of the National Academy of Sciences* 118 (26): e2024292118.

Roozenbeek, Jon, Claudia R. Schneider, Sarah Dryhurst, John Kerr, Alexandra LJ Freeman, Gabriel Recchia, Anne Marthe Van Der Bles, and Sander Van Der Linden. 2020. "Susceptibility to Misinformation About Covid-19 Around the World." *Royal Society Open Science* 7 (10): 201199.

Russell, Adrienne, and Matthew Tegelberg. 2020. "Beyond the Boundaries of Science: Resistance to Misinformation by Scientist Citizens." *Journalism* 21 (3): 327–344.

Rutjens, Bastiaan T., and Bojana Većkalov. 2022. "Conspiracy Beliefs and Science Rejection." *Current Opinion in Psychology* 46 101392.

Scharff, Darcell P., Katherine J. Mathews, Pamela Jackson, Jonathan Hoffsuemmer, Emeobong Martin, and Dorothy Edwards. 2010. "More Than Tuskegee: Understanding Mistrust About Research Participation." *Journal of Health Care for the Poor and Underserved* 21 (3): 879.

Shayo, Moses. 2009. "A Model of Social Identity With an Application to Political Economy: Nation, Class, and Redistribution." *American Political Science Review* 103 (2): 147–174.

Shayo, Moses. 2020. "Social Identity and Economic Policy." *Annual Review of Economics* 12 (1): 355–389.

Stango, Victor, and Jonathan Zinman. 2023. "We Are All Behavioural, More, or Less: a Taxonomy of Consumer Decision-making." *The Review of Economic Studies* 90 (3): 1470–1498.

Stewart, Alexander J., Mohsen Mosleh, Marina Diakonova, Antonio A. Arechar, David G. Rand, and Joshua B. Plotkin. 2019. "Information Gerrymandering and Undemocratic Decisions." *Nature* 573 (7772): 117–121.

Sullivan, Colin D. 2021. "Eliciting Preferences Over Life and Death: Experimental Evidence From Organ Transplantation."

Tajfel, Henri, and John C. Turner. 2003. "The Social Identity Theory of Intergroup Behavior." *Social Psychology* 4 73–98.

Van Der Bles, Anne Marthe, Sander van der Linden, Alexandra LJ Freeman, and David J. Spiegelhalter. 2020. "The Effects of Communicating Uncertainty on Public Trust in Facts and Numbers." *Proceedings of the National Academy of Sciences* 117 (14): 7672–7683.

Van Der Bles, Anne Marthe, Sander Van Der Linden, Alexandra LJ Freeman, James Mitchell, Ana B. Galvao, Lisa Zaval, and David J. Spiegelhalter. 2019. "Communicating Uncertainty About Facts, Numbers and Science." *Royal Society Open Science* 6 (5): 181870.

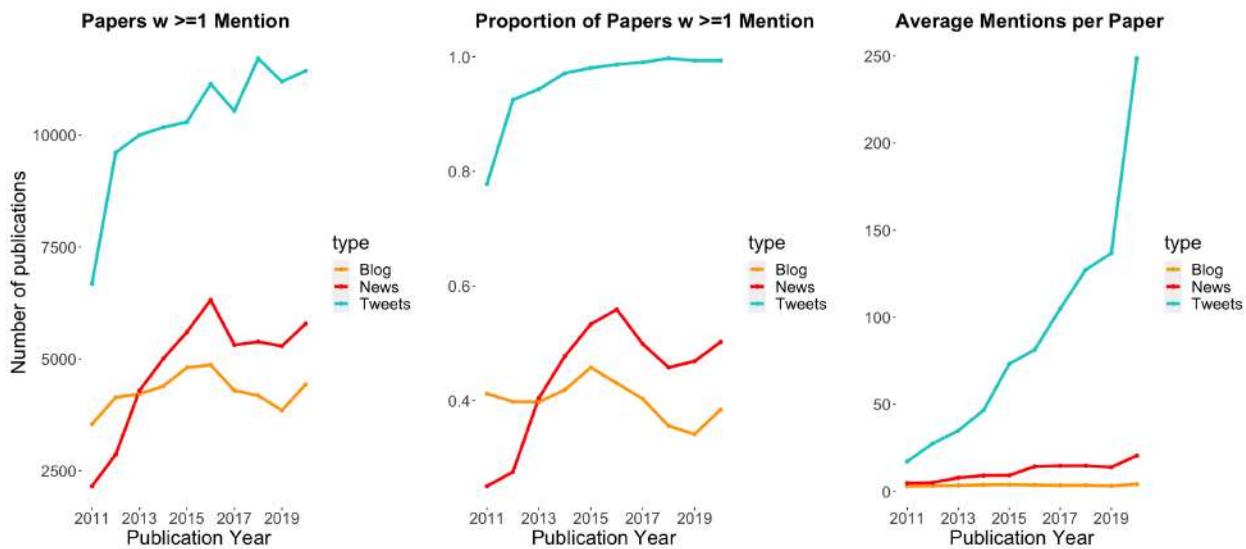
West, Jevin D., and Carl T. Bergstrom. 2021. "Misinformation in and About Science." *Proceedings of the National Academy of Sciences* 118 (15): e1912444117.

Zhang, Floyd Jiuyun. 2023. "Political Endorsement by Nature and Trust in Scientific Expertise During Covid-19." *Nature Human Behaviour* 7 (5): 696–706.

Zhuravskaya, Ekaterina, Maria Petrova, and Ruben Enikolopov. 2020. "Political Effects of the Internet and Social Media." *Annual Review of Economics* 12 415–438.

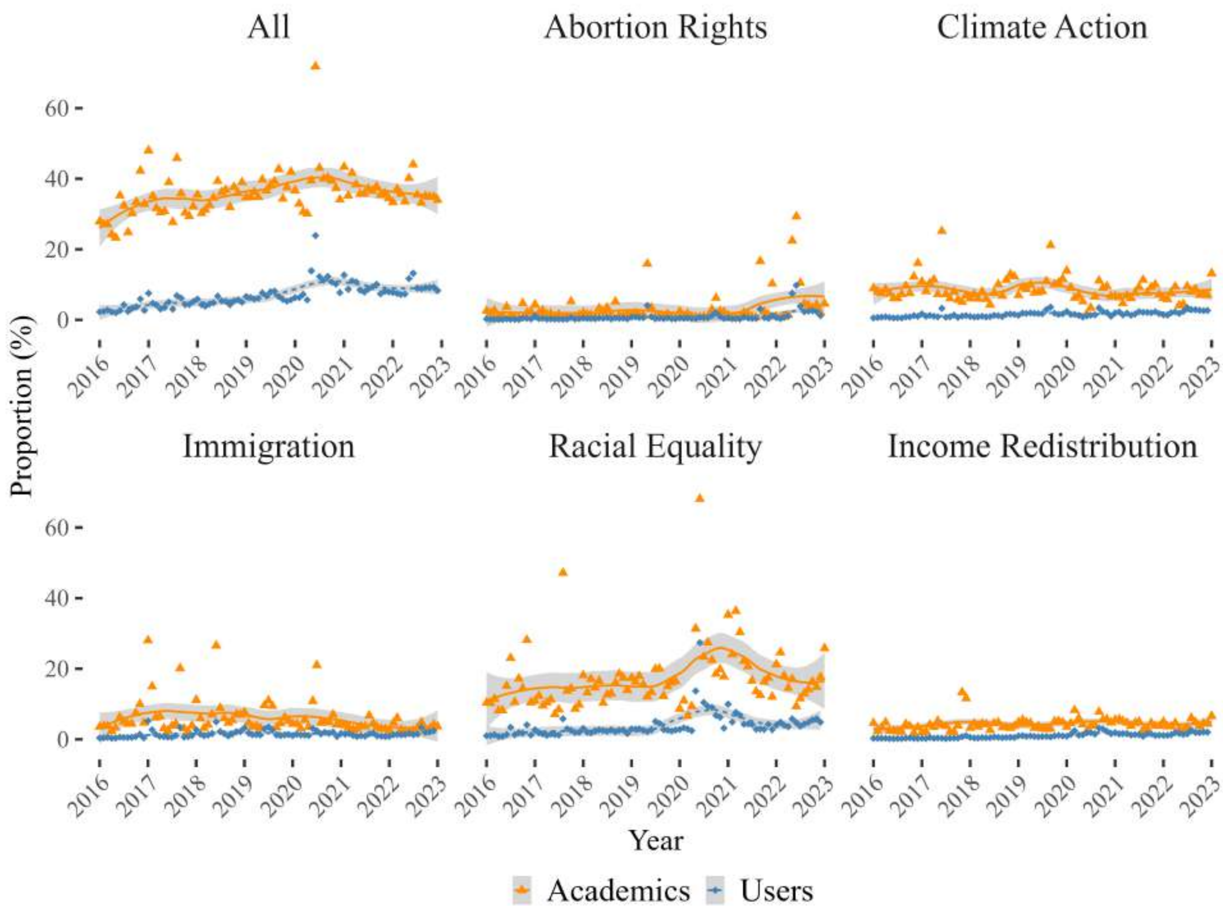
Figures

Figure 1: Online presence of research articles published in general interest journals between 2011 and 2020



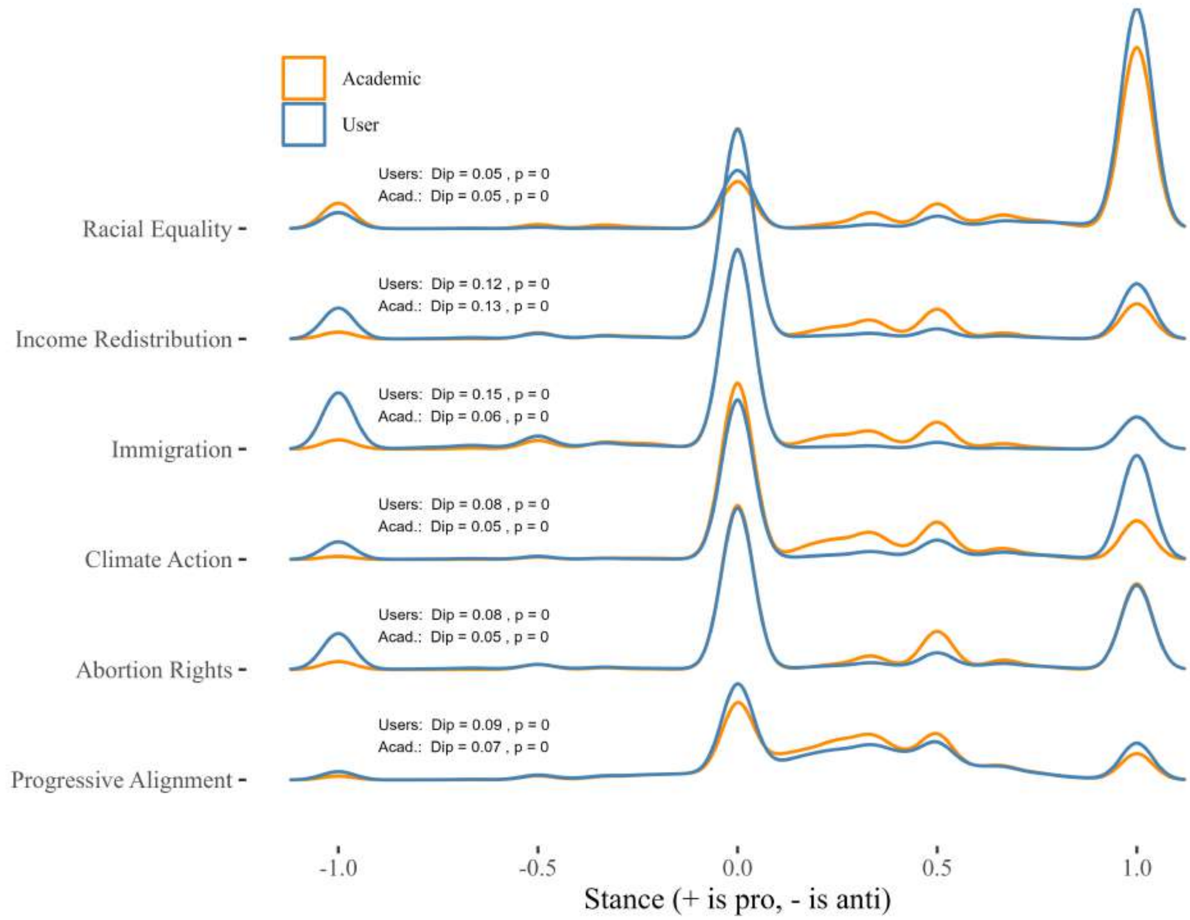
Note: Figure provides trends in online coverage of scientific articles published in *Science*, *Nature*, *PNAS*, *Cell*, *NEJM*, and *Lancet* between 2011 and 2020. Online appearances across blog posts, newspaper articles, or Twitter are retrieved from Altmetric (accessed on November 10th, 2021). The 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 2: Proportion of US Users and Academics with a Political Opinion Over Time



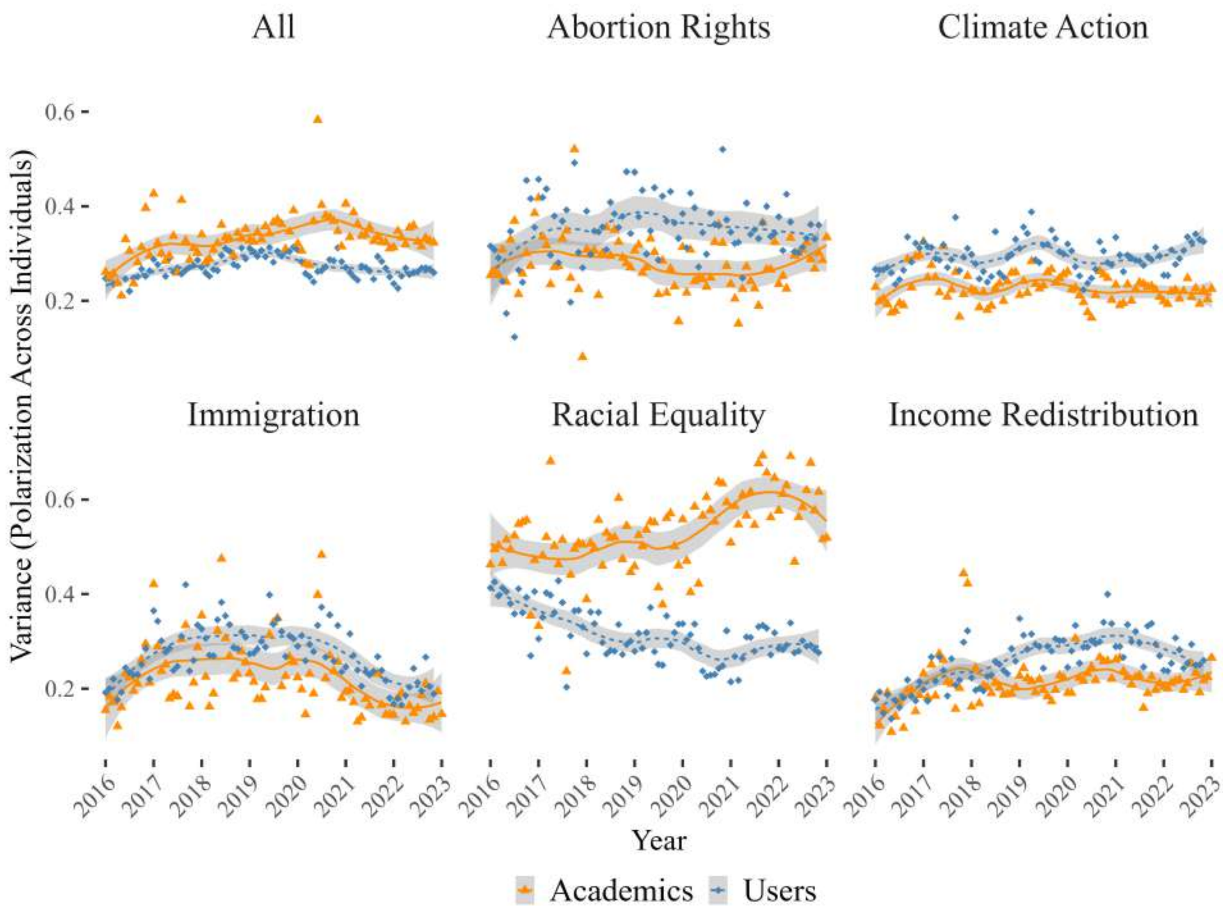
Note: The figure illustrates trends in politicization of conversations by academics and general users on Twitter from 2016 to 2022. Monthly aggregated scatter plots display expressed stance for each topic, with a LOESS applied for trend visualization. Standard errors are depicted in the shaded region. 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.

Figure 3: Cross-sectional Ideological Polarization across US Users and Academics, 2016-2022



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.

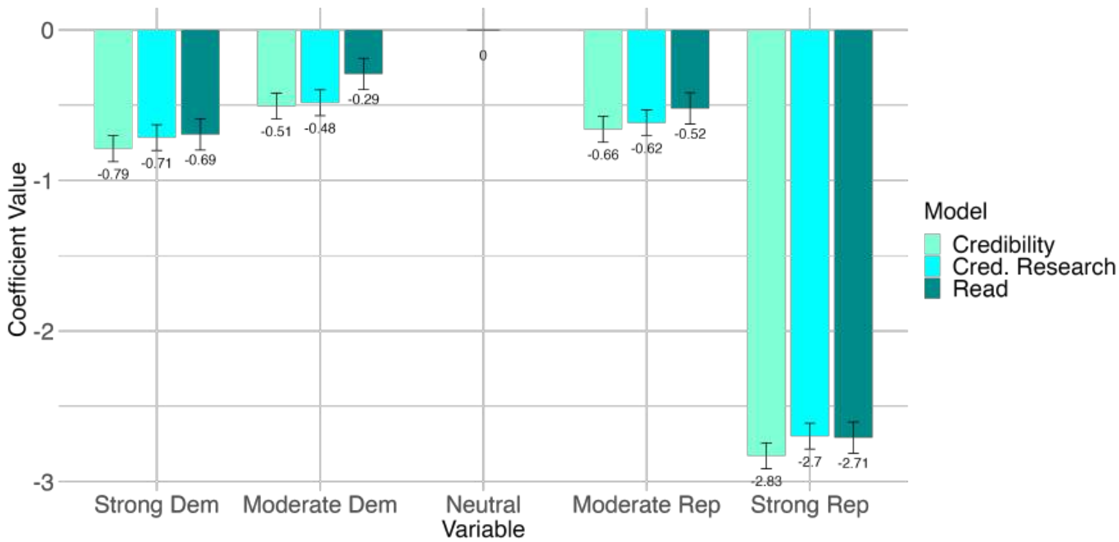
Figure 4: Issue Disagreement Across Academics By Topics Over Time



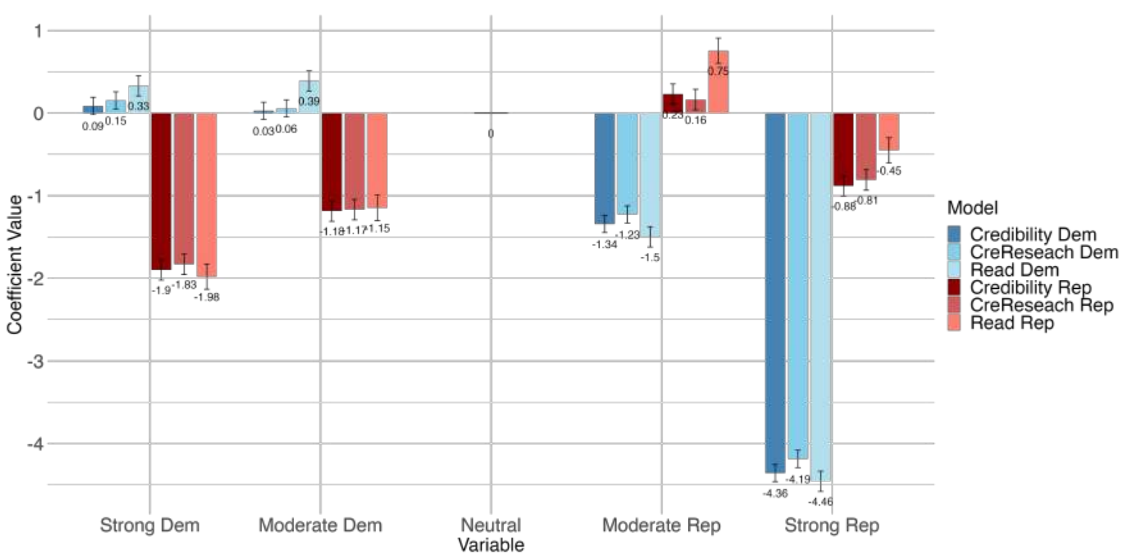
Note: The figure measures ideological polarization by computing the variance of net stance held by a population on predefined political topics. Variance across users reflects the dispersion of political opinion on each topic, providing a continuous measure of ideological disagreement. Aggregating across 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.

Figure 5: Impact of scientists' political expression on perceived credibility and willingness to read from the general public. Credibility and public willingness to read peak at neutral, with a monotonic penalty for scientists displaying political affiliations to the 'left' and 'right' of neutral.

A. Base Model

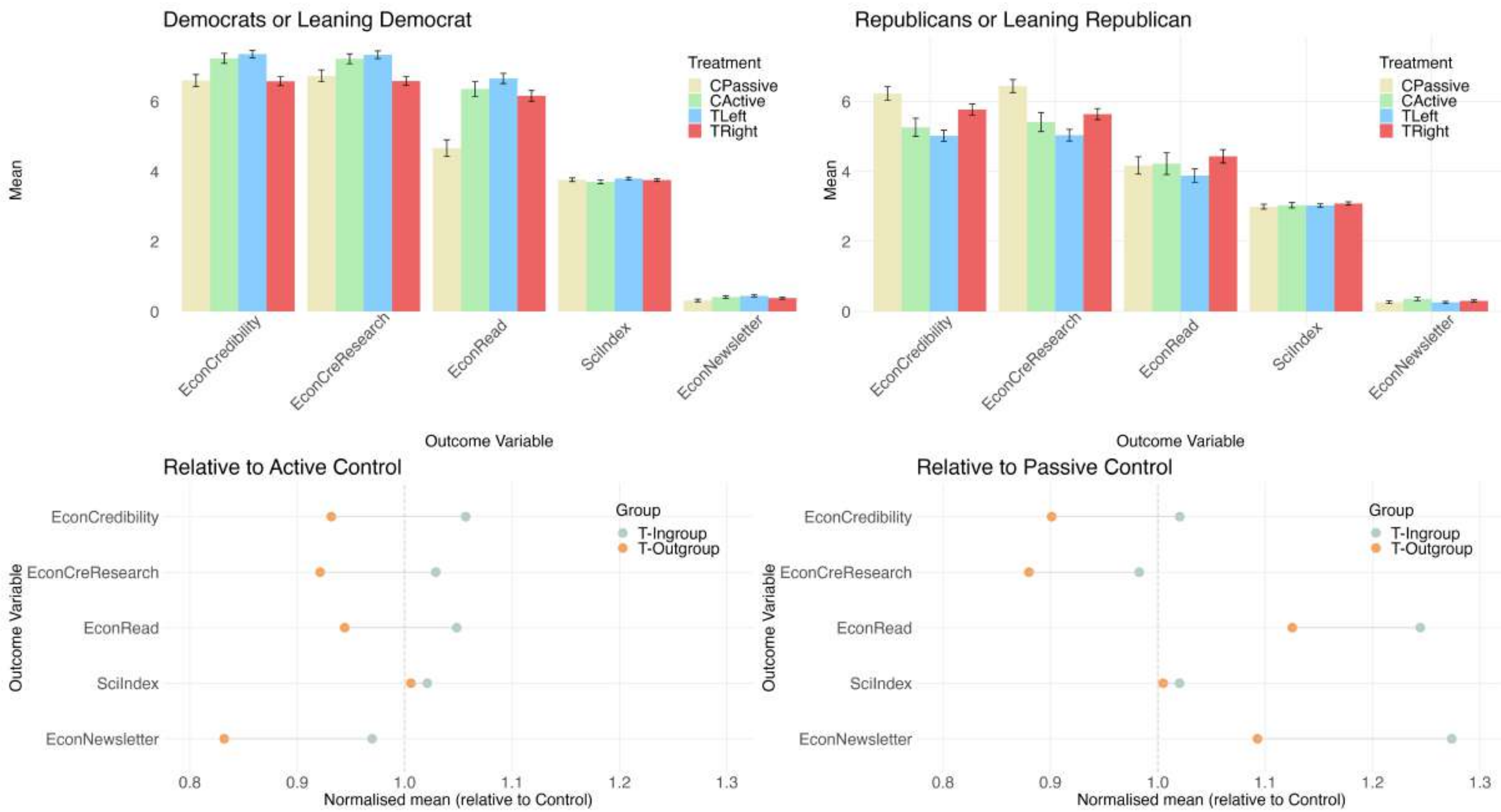


B. Heterogeneity by Respondents' Partisanship



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 6: 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.)

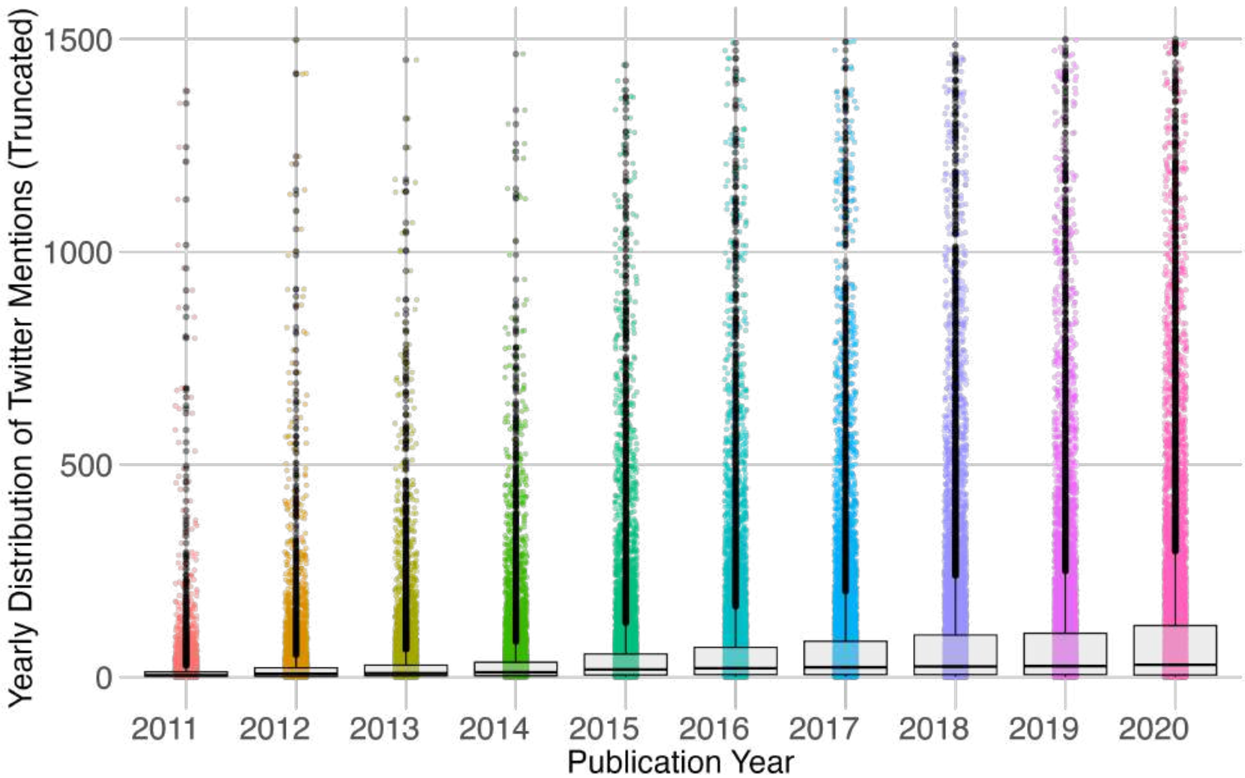
For online publication

Politicized Scientists: Credibility Cost of Political Expression on Twitter

Eleonora Alabrese, Francesco Capozza, and Prashant Garg

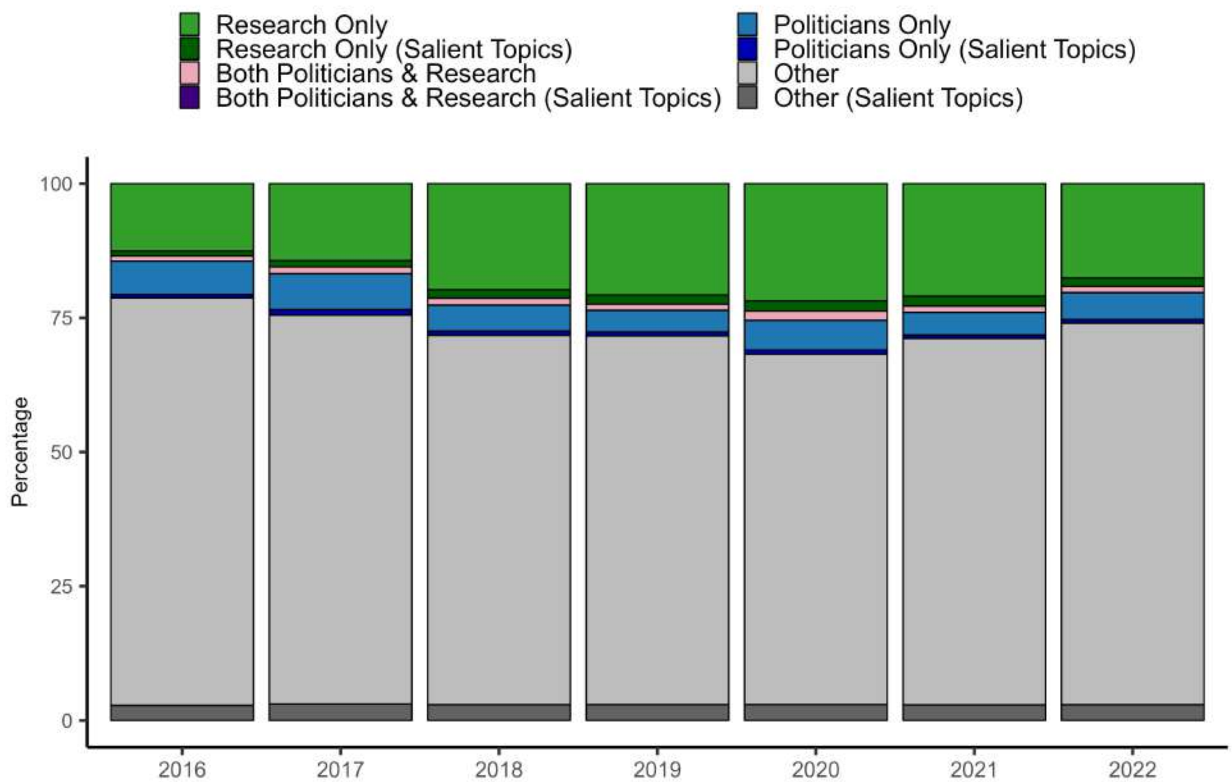
A Appendix Figures

Figure A.1: Distribution of Twitter mentions for research articles published in general interest journals between 2011 and 2020



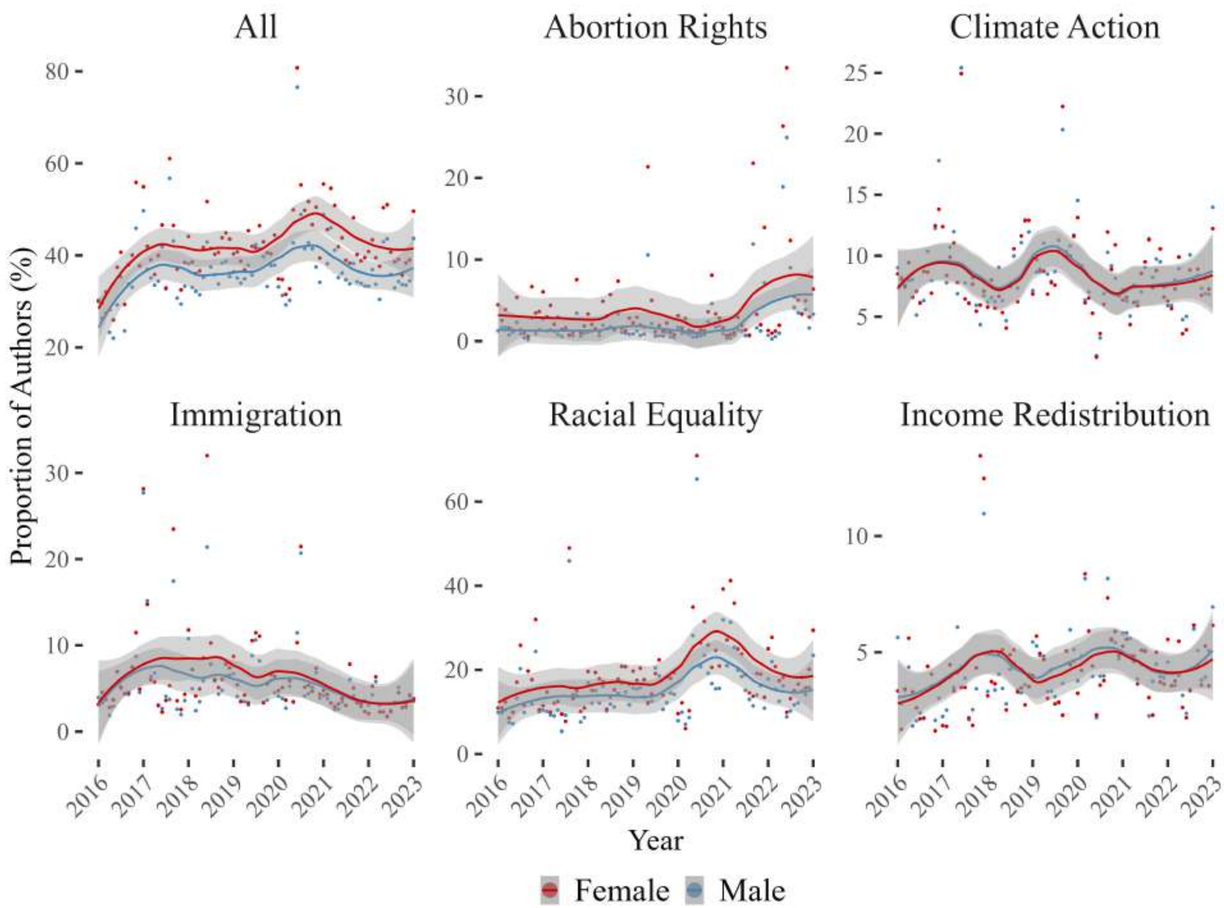
Note: Figure provides trends in Twitter coverage of scientific articles published in *Science*, *Nature*, *PNAS*, *Cell*, *NEJM*, and *Lancet* between 2011 and 2020. The data present the distribution of Twitter mentions per article, retrieved from Altmetric (accessed on November 10th, 2021). The figure indicates growing online presence, with the distribution of Twitter mentions becoming less skewed towards zero, with a ticker right tale and a rise in high-mention outliers over time.

Figure A.2: Yearly Distribution of Tweets by Academics Mentioning Politicians, Research Papers, and Salient Topics



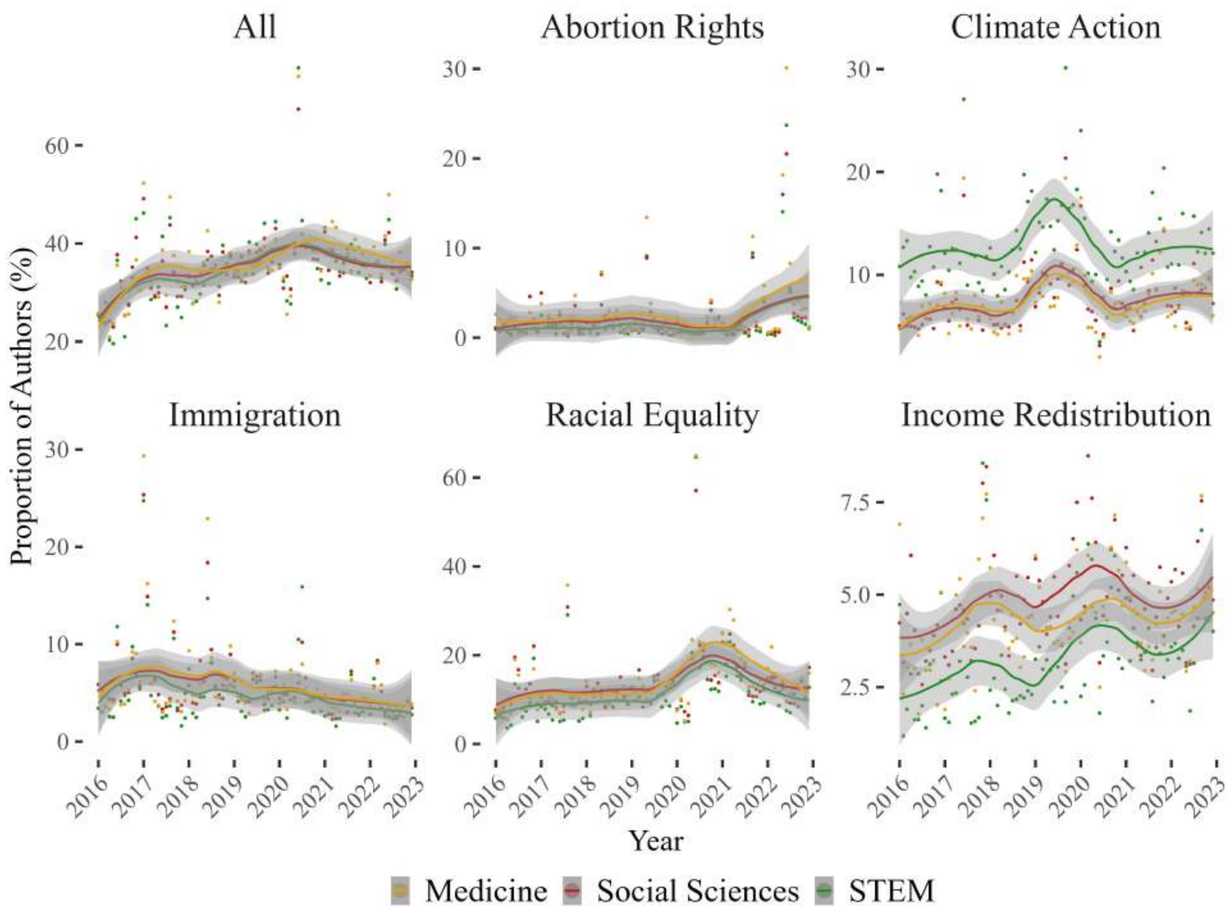
Note: This figure depicts the yearly distribution of tweets by academics from 2016 to 2022, highlighting the proportion of tweets that mention politicians, research papers, both, and other content. It helps to understand the interaction between political discourse and academic content over time. Each bar represents the total percentage of tweets for a given year, with colors indicating the categories: green for tweets mentioning research papers, blue for tweets mentioning politicians, purple for tweets mentioning both politicians and research papers, and grey for other tweets. Darker shades within each color represent tweets related to the five salient topics (Abortion Rights, Climate Action, Racial Equality, Immigration, and Income Redistribution). The "*Politicians Only (Salient Topics)*" category includes tweets that mention politicians and one of the salient topics, the "*Research Only (Salient Topics)*" category includes tweets that mention research papers and one of the salient topics, and the "*Both Politicians & Research (Salient Topics)*" category includes tweets that mention both politicians and research papers within the salient topics. The overlaps between categories, represented by the pink sections, are relatively small across all years, typically around 1% (with the salient topics subset being even smaller, at 0.01%). The overall proportion of tweets mentioning politicians remains around 10%, while approximately 20% of tweets mention research papers. Notable spikes in tweets mentioning politicians and research papers are observed in certain years, reflecting significant political or scientific events such as the 2016 and 2020 US presidential elections, the George Floyd incident in 2020, and the COVID-19 pandemic.

Figure A.3: Proportion of Academics with Political Opinions Over Time by Topic and Gender



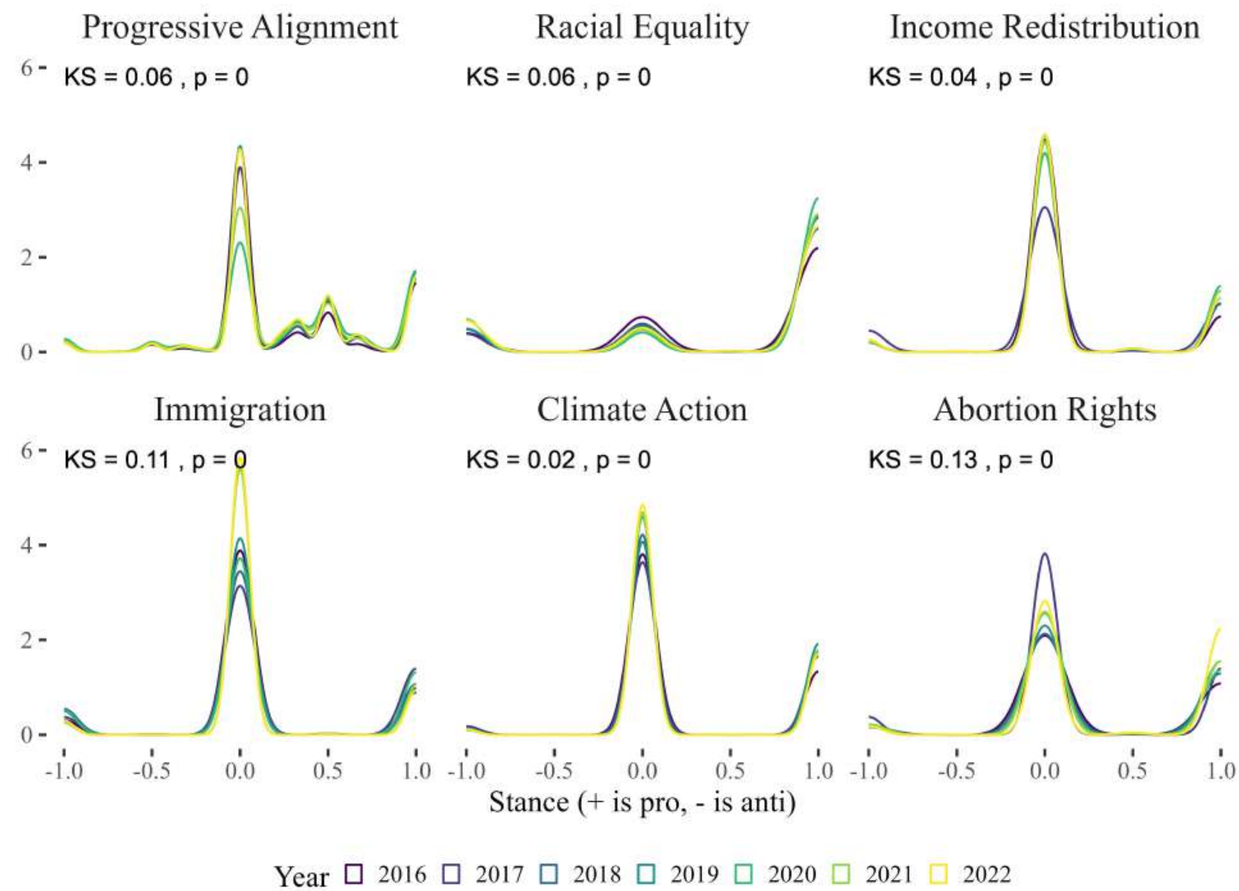
Note: We passed the full OpenAlex academic name as it appears on their papers to an LLM to classify the gender as 'Male', 'Female', or 'Unclear'. Close to 99% of names were labeled Male or Female. Using this binary classification of gender, we can explore sub-population differences in political expression. This is displayed in the figure broken down by political topics. In general, we find academics with names classified as female to express slightly more political opinions overall, especially on topics Abortion Rights, Immigration, and Racial Equality. Most statistically significant differences occur post-2020 (when confidence intervals overlap the least). The topics of Climate Action and Income Redistribution display the least differences.

Figure A.4: Proportion of Academics with Political Opinions Over Time by Topic and Discipline



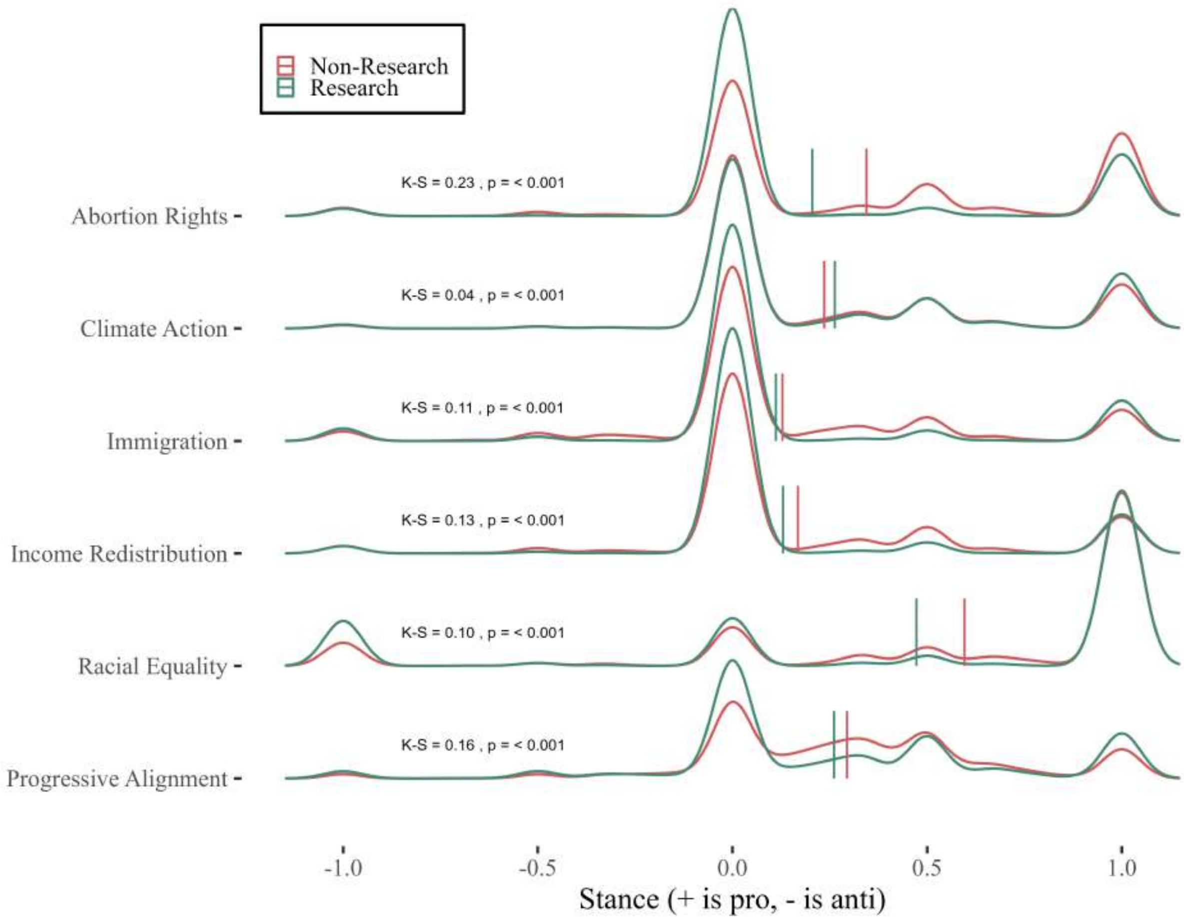
Note: OpenAlex describes "Concepts" as abstract ideas that a work is about: "Concepts are hierarchical, like a tree. There are 19 root-level concepts, and six layers of descendants branching out from them, containing about 65 thousand concepts all told". OpenAlex classifies each work with a high level 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.

Figure A.5: Evolution of Ideological Polarization among Academics



Note: This figure investigates the dynamics of ideological polarization among academics over time, focusing on key political issues. Each panel presents yearly distributions of stances of U.S. academics on various topics, testing for distribution equality between early (2016-2017) and late (2021-2022) years. Topics include Income Redistribution, Climate Action, Immigration, Abortion Rights, and Racial Equality, with "Progressive Alignment" representing the average stance across all topics. The x-axis shows the net stance, with positive values indicating a pro-stance and negative values an anti-stance. Density distributions are depicted as overlapping yearly ridgelines, with different colors representing different years. Each plot includes the Kolmogorov-Smirnov (KS) test results, testing distributions equality between 2016-2017 and 2021-2022, the KS statistic and corresponding p-value are provided. The figure demonstrates significant shifts in ideological stances over time, particularly on Immigration and Abortion Rights, which show larger KS statistics, indicating substantial distributional changes, whereas Climate Action shows smaller shifts.

Figure A.6: Cross-sectional Ideological Polarization based on Whether Academic Tweets are Research Related



Note: The figure presents the density distributions of net stances across various political topics among U.S. academics from 2016 to 2022, comparing tweets that mention research papers (in aquamarine4) with those that do not (in indianred). 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 lists the different topics, with density distributions shown as ridgelines. Vertical mean lines are included for each distribution, colored according to the tweet type. Kolmogorov-Smirnov (K-S) test results are annotated for each topic, indicating statistically significant differences between the distributions of research-related and non-research-related tweets (p-values < 0.001). The largest divergence is observed in Abortion Rights, where non-research tweets show a larger mass toward the pro stance (+1), while research-related tweets are more centered around neutrality (0). Generally, non-research tweets tend to be more liberal across most topics, except for Climate Action, where research-related tweets are more progressive. This suggests that the context of discussion influences the expression of political stances among academics.

Figure A.7: Vignettes of scientists profiles

Strong Democrat

The profile you are seeing is a **Female** scientist. This scientist works in the field of **American Literature**.

Currently, this scientist is **Assistant Professor** at the **University of Connecticut**.

The scientist is active on X (formerly known as Twitter). The twitter bio of the scientist is: "**Academic. Human rights advocate** 🌈✊🏿"

A recent selected Tweet reads: "**Research compellingly underscores a grave injustice: African American infants and mothers in the socio-economic apex face markedly poorer health outcomes compared to their Caucasian counterparts at the economic base. This stark disparity demands urgent systemic reforms to address deep-rooted inequities.**"

How credible do you think this scientist is?

Not credible at all ... Very Credible
0 1 2 3 4 5 6 7 8 9 10

Credible

How credible do you think the scientist's own research is?

Not credible at all ... Very Credible
0 1 2 3 4 5 6 7 8 9 10

Credible

How willing you are to read an opinion piece from this scientist?

Not willing at all ... Very willing
0 1 2 3 4 5 6 7 8 9 10

Willing to read

Strong Republican

The scientist is active on X (formerly known as Twitter). The twitter bio of the scientist is: "**Academic, Republican, #biblebelieve** 🇺🇸"

A recent selected Tweet reads: "**For those advocating for civil rights and pro-life values (which are inherently linked), take note. There are individuals who have courageously highlighted the inhumane procedures that proponents of abortion, such as @JoeBiden, are pushing for nationwide acceptance and funding. This is unequivocally unacceptable.**

Moderate Republican

The scientist is active on X (formerly known as Twitter). The twitter bio of the scientist is: "**Academic. American. Sharing research, family and community stories** 🏡🤝"

A recent selected Tweet reads: "**Maintaining law and order is critical for the stability of any community. Initiatives to reduce police funding compromise public safety and put our neighborhoods at risk. The pursuit of safety and justice should transcend political boundaries.**"

Neutral (excluded category)

The scientist is active on X (formerly known as Twitter). The twitter bio of the scientist is: "**Academic. Discovering truths of the world.** 📚"

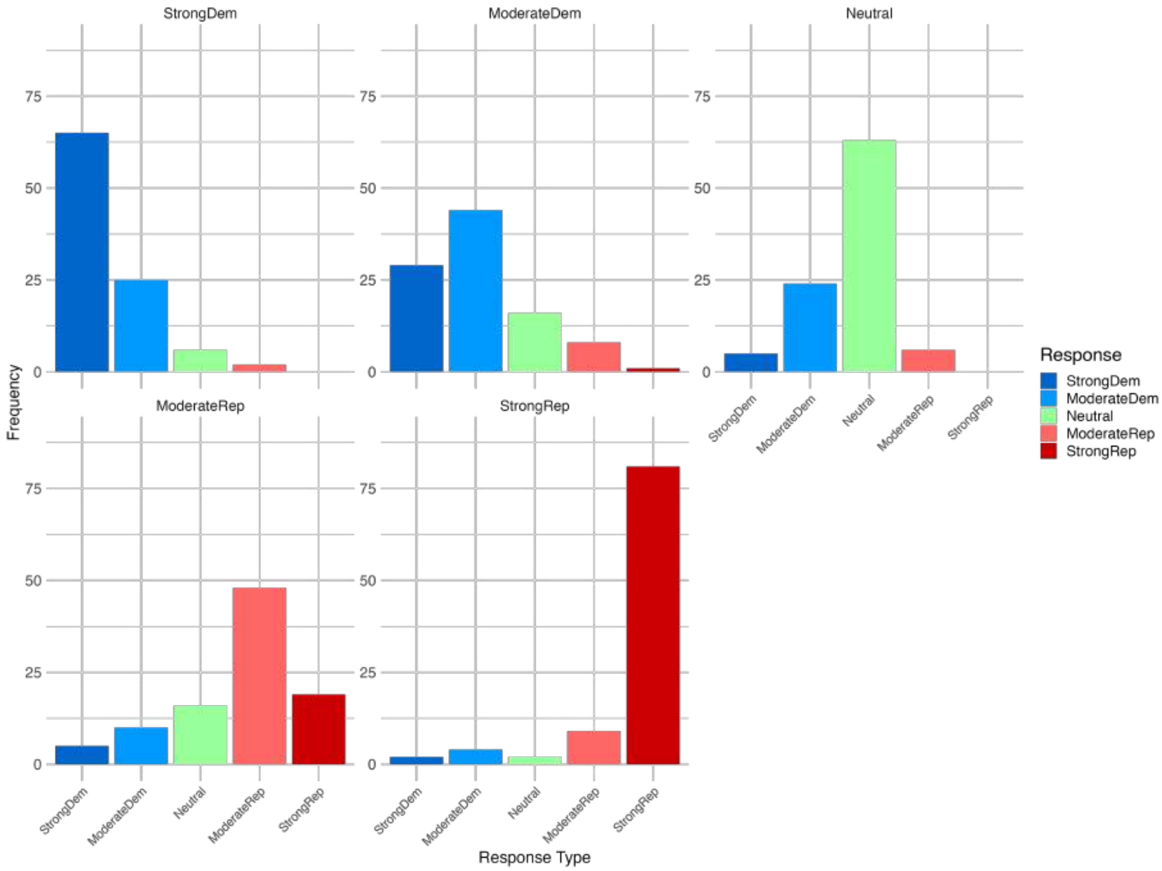
A recent selected Tweet reads: "**On December 5, 1932, eminent physicist Albert Einstein was granted a visa, facilitating his pivotal relocation to the United States, a move that significantly influenced the trajectory of theoretical physics research in the 20th century. #OnThisDay**

Moderate Democrat

The scientist is active on X (formerly known as Twitter). The twitter bio of the scientist is: "**Climber and friend of the environment** ⛰️🌱"

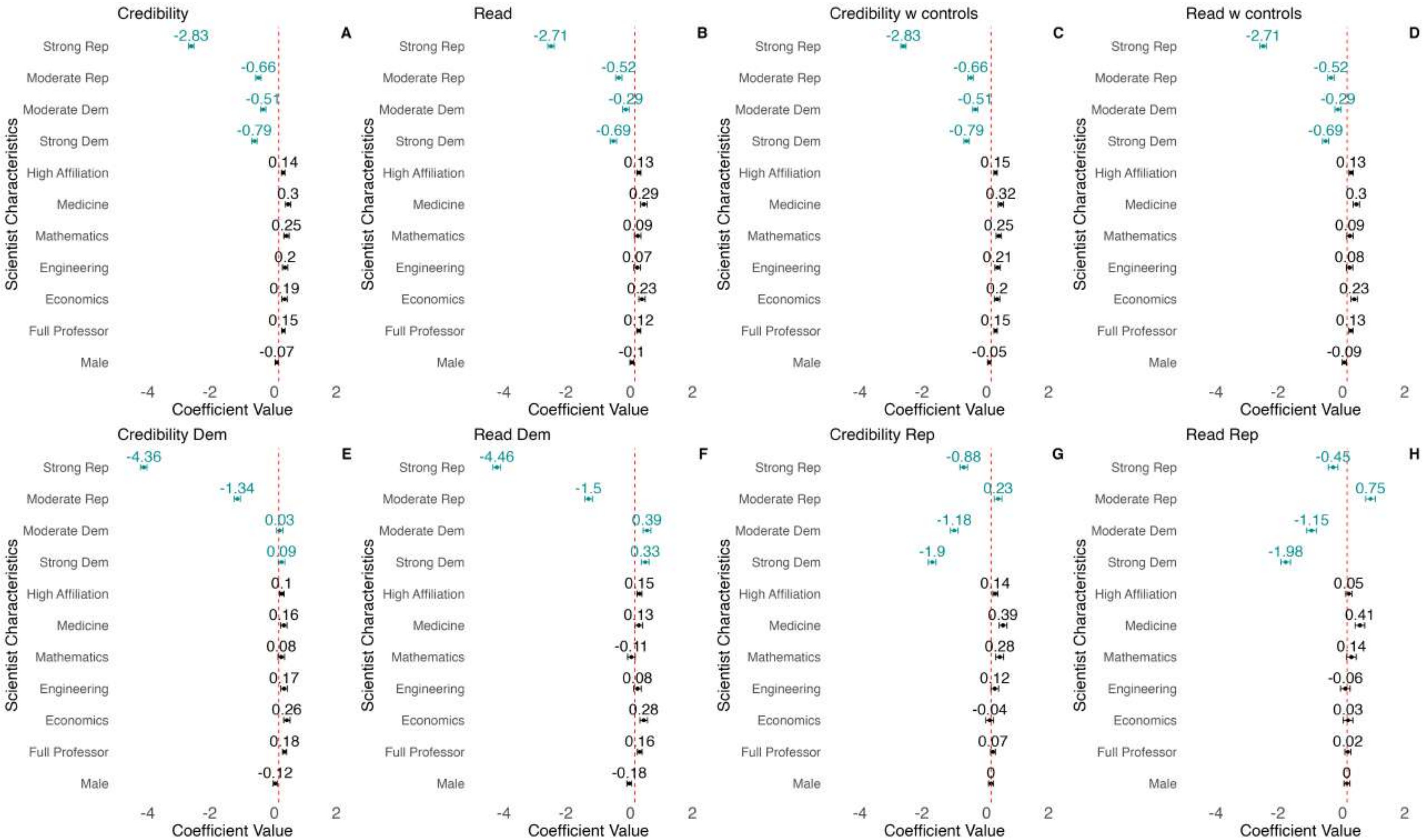
A recent selected Tweet reads: "**Researchers at Exxon precisely forecasted the extent of global warming resulting from fossil fuel combustion in studies starting in 1970s, according to a research paper. Despite this, the company cast skepticism on the findings, contributing to a postponement of government climate initiatives.**

Figure A.8: Frequency of Responses by Intended Political Leaning of Twitter Signal



Note: The figure presents the results of a validation of the political signals used in the main experiment. In the validation, we asked 98 respondents, recruited on Prolific, to classify the political leaning of five vignettes. Each vignette displayed one of five different Twitter bios and Twitter posts combinations, which were used in the main experiment. Respondents were presented with each of the five vignettes in random order and asked to classify each into one of five categories: "Strongly Republican," "Moderately Republican," "Strongly Democrat," "Moderately Democrat," and "Neutral." Each plot displays a histogram of responses for each political signal (vignette) used in the main experiment. For each histogram, the mode answer correctly identifies the political leaning of the vignette profile, thereby validating our main exercise.

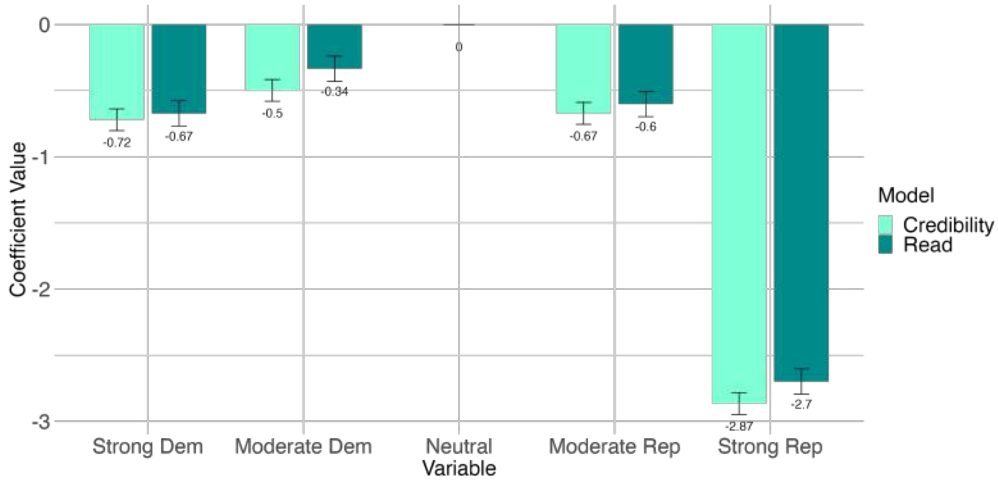
Figure A.9: Effect of scientists' characteristics on respondents' perceived credibility. Any perceived political leaning of scientists reduces their credibility. Effects are heterogeneous, with Democrats showing reduced credibility for Republican scientists, and vice versa.



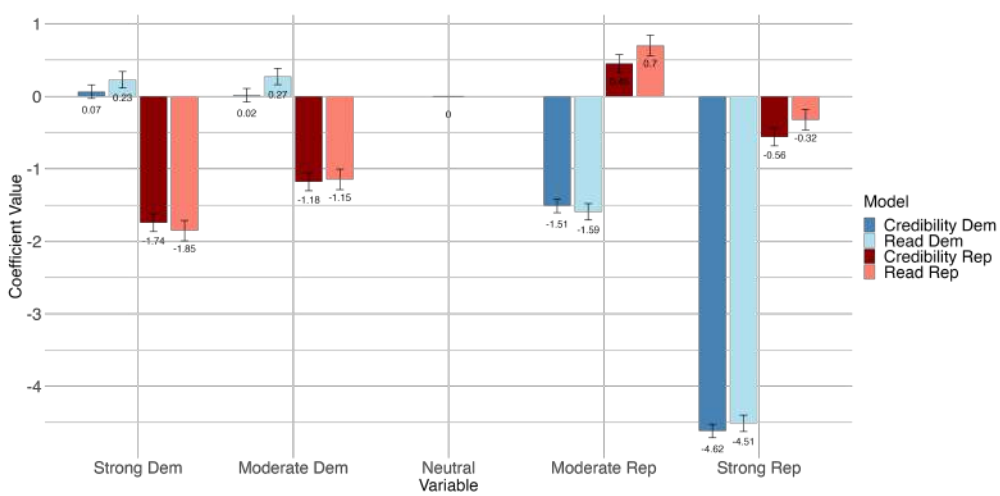
Note: Coefficients are obtained by regressing scientists' characteristics on respondents' perceived credibility or willingness to read from scientists. All the standard errors are clustered at the individual level. Political leaning is indicated by "Strong Republican," "Moderate Republican," "Strong Democrat," or "Moderate Democrat," with "Neutral" as the excluded category. High Affiliation signifies institutions such as Harvard, UC Berkeley, or Chicago, versus Arkansas or Connecticut. Research fields include Medicine, Mathematics, Engineering, and Economics, with Literature excluded. Full professor indicates full professors versus assistant professors. Male is coded as one for male scientists. Controls encompass respondents' age, gender, income, ethnicity, education, employment status, religion, region, and political leaning. (N = 1704, 940 Dem. or Lean Dem., 745 Rep. or Lean Rep., 19 Other leaning.)

Figure A.10: Impact of scientists' political expression on perceived credibility and willingness to read from the general public. Credibility and public willingness to read peak at neutral, with a monotonic penalty for scientists displaying political affiliations to the 'left' and 'right' of neutral (***Replication***).

A. Base Model

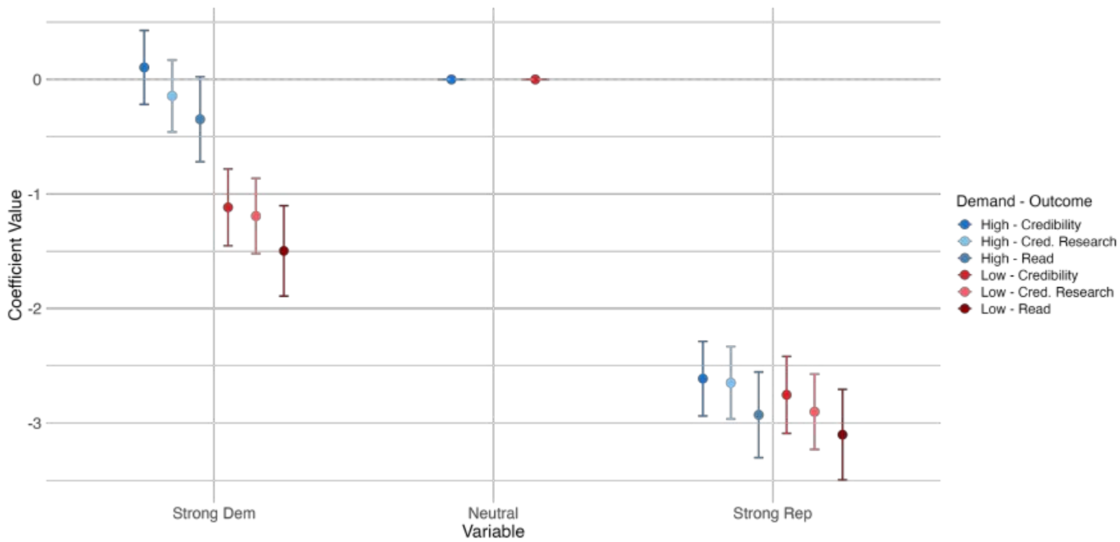


B. Heterogeneity by Respondents' Partisanship



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. (N = 1990, 1118 Dem. or Lean Dem., 855 Rep. or Lean Rep., 17 Other leaning.)

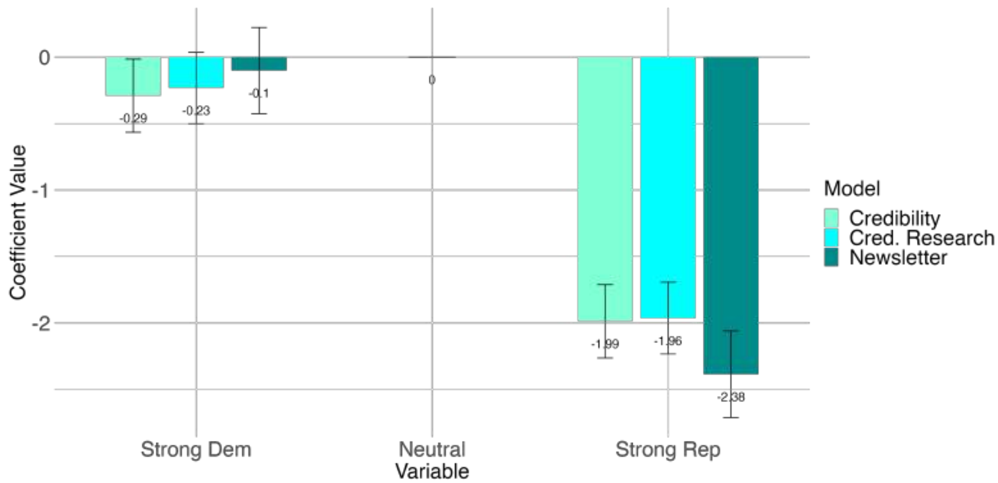
Figure A.11: Bounding the impact of scientists' political expression on perceived credibility and willingness to read: Credibility and public willingness to read peak at neutral, while both left- and right-leaning scientists face a credibility penalty regardless of the demand condition.



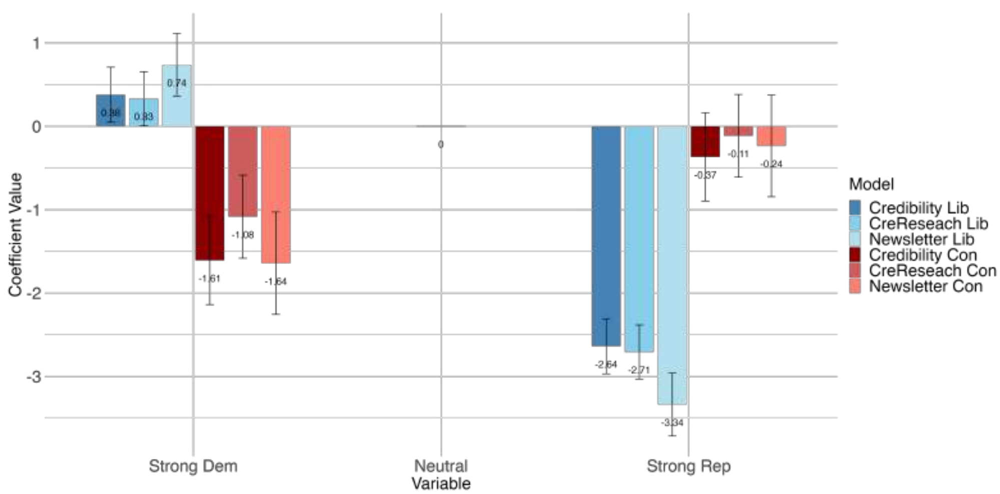
Note: Coefficients are estimated by regressing respondents' perceived credibility and willingness to read opinions from scientists on the scientists' attributes. The x-axis represents different political affiliations of scientists, captured using indicator variables for "Strong Republican" and "Strong Democrat," with "Neutral" as the excluded category. The y-axis displays the estimated coefficients, indicating the impact of political affiliation on credibility and willingness to engage. Respondents were randomly assigned a Neutral scientist profile alongside either a Republican or Democrat profile and were further randomly nudged to rate the latter either higher (blue) or lower (red) relative to the Neutral profile. The results show that credibility and willingness to read peak for Neutral scientists, while left- and right-leaning scientists face credibility penalties, regardless of the demand condition. Standard errors are clustered at the respondent level. (N = 346).

Figure A.12: Impact of scientists' political expression on perceived credibility and willingness to read from the general public. Credibility and public willingness to read peak at neutral, with a penalty for scientists displaying political affiliations to the 'left' and 'right' of neutral (***Journalists***).

A. Base Model

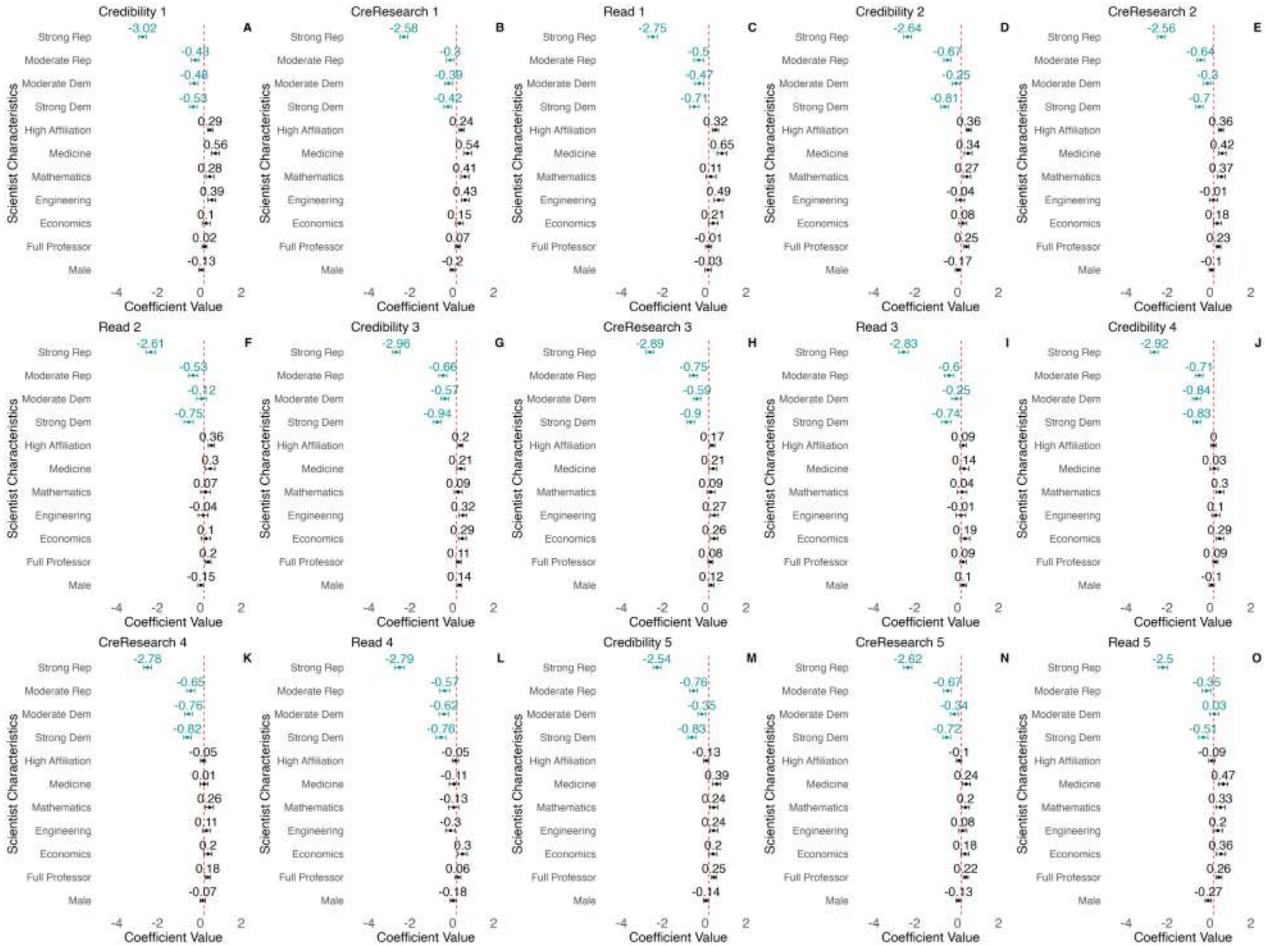


B. Heterogeneity by Journalists' Leaning



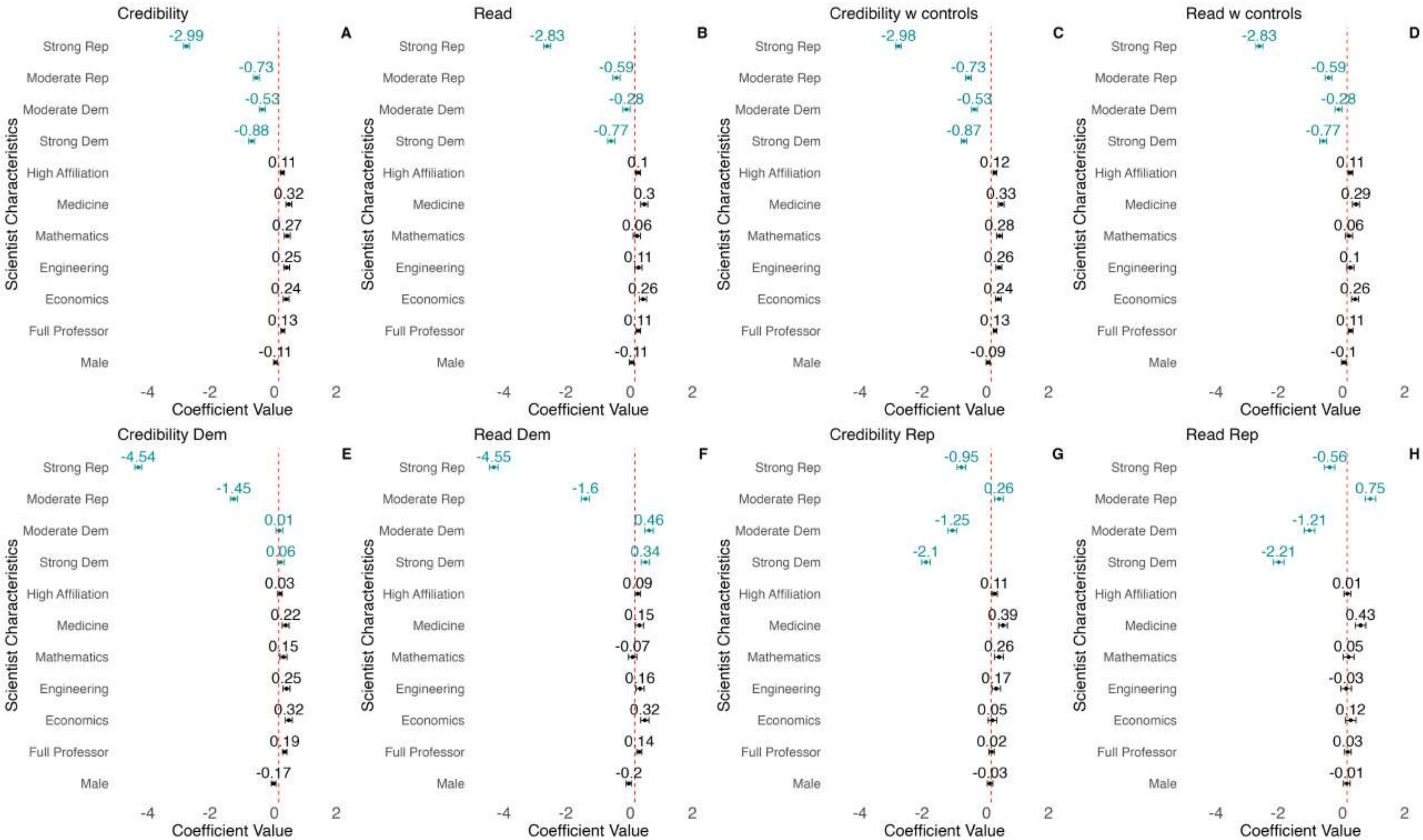
Note: Coefficients are obtained by regressing scientists' characteristics on journalists' perceived credibility or willingness to feature content from scientists. The x-axis represents different political affiliations of scientists, estimated by indicator variables for "Strong Republican" and "Strong Democrat", with "Neutral" as the excluded category. The y-axis shows the coefficient values indicating the impact on credibility and willingness to feature the profile in a newsletter. 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. (N = 135, 36 Conservative, 84 Liberal, 15 Moderate leaning.)

Figure A.13: Excluding carryover effects on scientists' credibility and willingness to read.



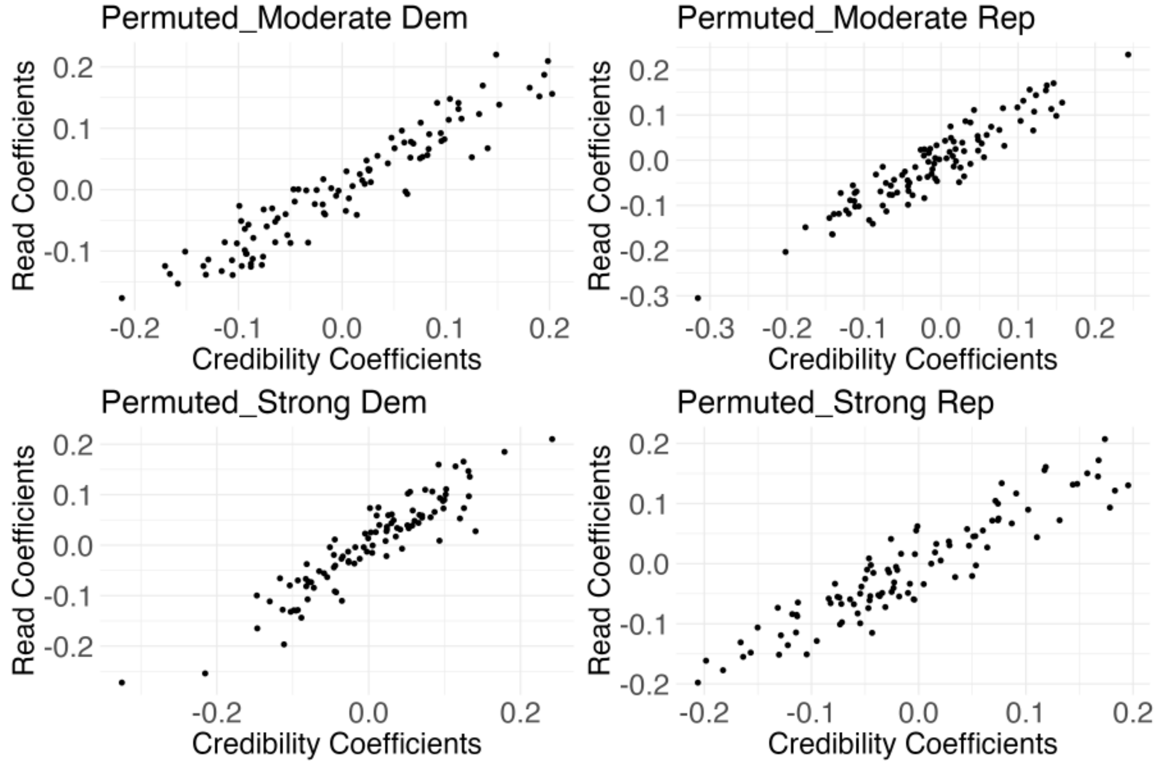
Note: Coefficients were obtained by regressing scientists' characteristics on respondents' perceived credibility or likelihood of reading from similar scientists. We repeat the procedure for each profile the respondents have seen in the study. All the standard errors are clustered at the individual level. Political leaning is indicated by "Strong Republican," "Moderate Republican," "Strong Democrat," or "Moderate Democrat," with "Neutral" as the excluded category. High Affiliation signifies institutions such as Harvard, UC Berkeley, or Chicago, versus Arkansas or Connecticut. Research fields include Medicine, Mathematics, Engineering, and Economics, with Literature excluded. Full professor indicates full professors versus assistant professors. Male is coded as one for male scientists. (N=1704)

Figure A.14: Effect of scientists' attributes on respondents' perceived credibility, excluding speeders.



Note: Coefficients were obtained by regressing scientists' characteristics on respondents' perceived credibility or likelihood of reading from similar scientists. All the standard errors are clustered at the individual level. Political leaning is indicated by "Strong Republican," "Moderate Republican," "Strong Democrat," or "Moderate Democrat," with "Neutral" as the excluded category. High Affiliation signifies institutions such as Harvard, UC Berkeley, or Chicago, versus Arkansas or Connecticut. Research fields include Medicine, Mathematics, Engineering, and Economics, with Literature excluded. Full professor indicates full professors versus assistant professors. Male is coded as one for male scientists. Controls encompass respondents' age, gender, income, ethnicity, education, employment status, religion, region, and political leaning. (N = 1431)

Figure A.15: Permutation Test



Note: This figure reports the results of a permutation test conducted to assess the robustness of our estimates and ensure that our observed political effects are not due to some unusual feature of the data. To address this, we randomly re-shuffled all political labels across profiles within each respondent, creating a permuted version of the "Political" affiliation of the synthetic scientists' profiles. For each permuted dataset, we ran regressions using these mis-labeled dummy variables to estimate their impact on perceived credibility and willingness to read, repeating the procedure with 100 random permutations. Each scatter plot illustrates the coefficients of the placebo political affiliation of scientists on their perceived credibility (x-axis) and on respondents' willingness to read (y-axis) for the different political profile permutations. The consistent patterns across these plots indicate that the permuted labels do not systematically influence our main effects, as all coefficients remain close to zero and smaller than our estimates, demonstrating that our original findings are not driven by any peculiarities in the data, thereby affirming the robustness of our results.

Figure A.16: Vignettes of economists profiles

Passive Control 1/6	**Treatment Left (signal)** 1/3
The economist is active on X (formerly known as Twitter). The twitter bio of the economist is: "**Passionate about Research**". This is an example of a tweet: **"In our recent paper, we show that Nash equilibrium uniquely satisfies key axioms across different games, challenging refinement theories. Our findings have implications for zero-sum, potential, and graphical games."**	The economist is active on X (formerly known as Twitter). The twitter bio of the economist is: "**Passionate about Research and Advocate for Equality** 🌍". This is an example of a tweet: **"Our latest study in Lancet Global Health provides evidence on the health impacts of hostile environment policies toward migrants: restrictive entry and integration policies are linked to poorer mental and general health, and a higher risk of death."**
Active Control 1/6	**Treatment Right (signal)** 1/3
The economist is active on X (formerly known as Twitter). The twitter bio of the economist is: "**Passionate about Research**". This is an example of a tweet: **"Our latest study in Lancet Global Health provides evidence on the health impacts of hostile environment policies toward migrants: restrictive entry and integration policies are linked to poorer mental and general health, and a higher risk of death."**	The economist active on X (formerly known as Twitter). The twitter bio of the economist is: "**Passionate about Research and Proud Patriot** 🦅". This is an example of a tweet: **"Our latest study in Lancet Global Health provides evidence on the health impacts of hostile environment policies toward migrants: restrictive entry and integration policies are linked to poorer mental and general health, and a higher risk of death."**

Figure A.17: Screenshot of the newsletter

Project

We are a team of economists and we share opinion pieces and blog posts with people who have expressed interest in receiving a newsletter covering topics related to U.S. economy. At the end of the month, we will post the top three articles and opinion pieces from economists that cover topics related to U.S. economy. These articles and blog posts are based on real academic articles.

To access the articles, please click on the title and you will re-directed to article's page.

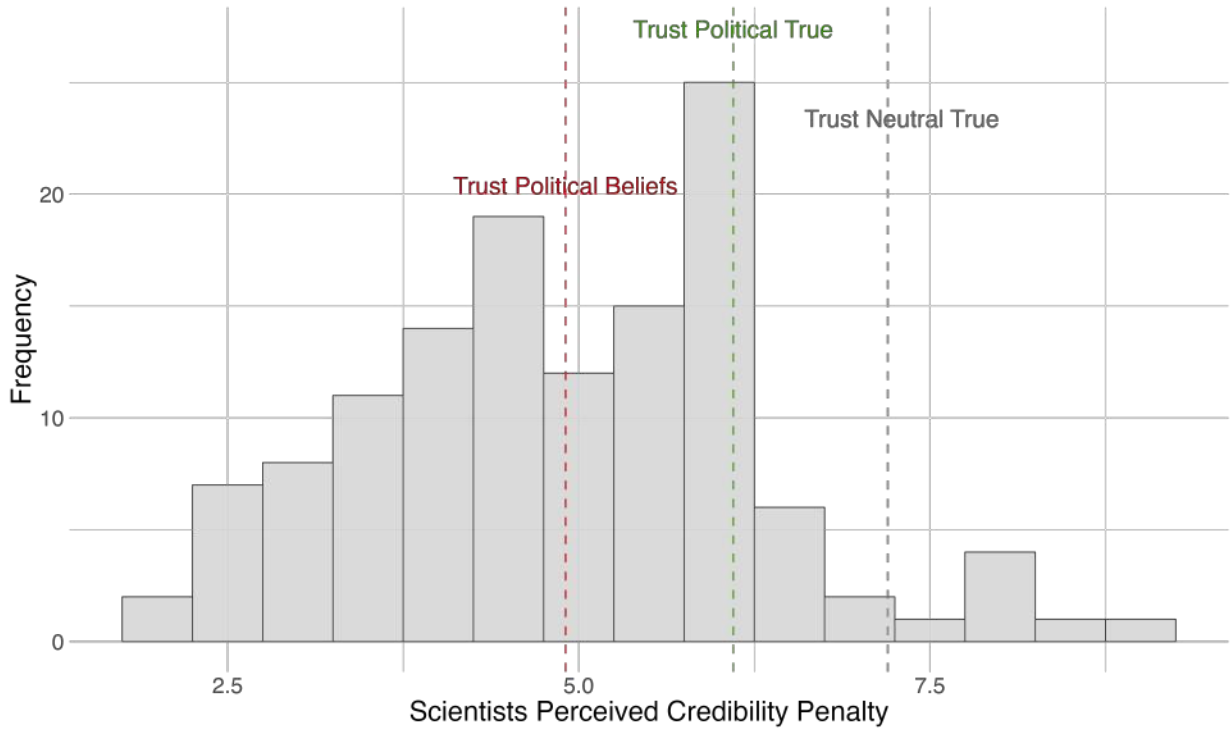
July 2024

Article 1: US election risks and the impact of Trump's re-election odds on financial markets

Article 2: Investments in hospital infrastructure reduced mortality in the US South

Article 3: Import competition and US sentiment toward China

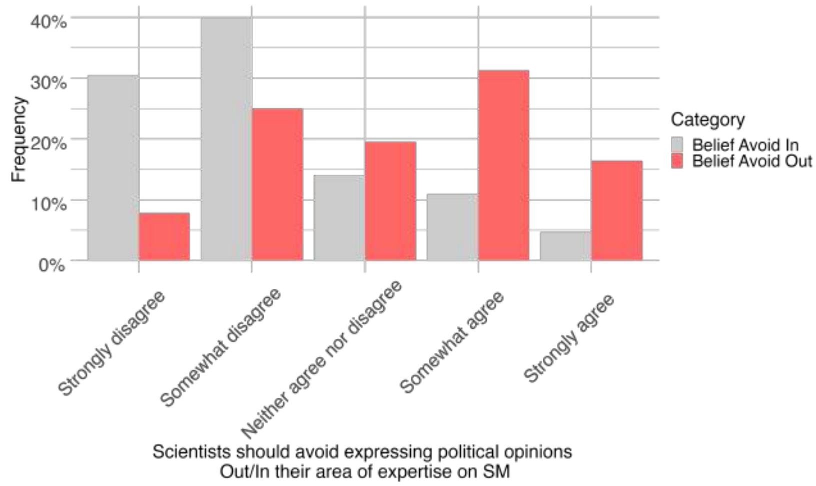
Figure A.18: Scientists' Beliefs about Credibility Penalty



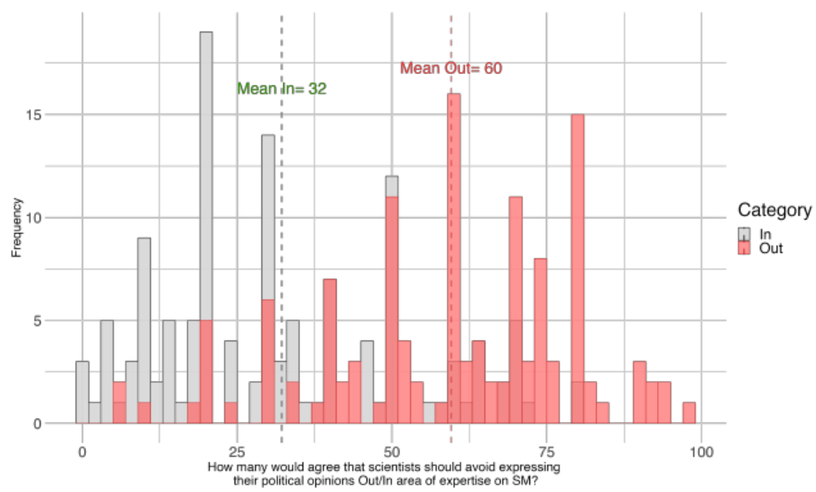
Note: This figure reports the distribution of responses from 128 scientists recruited on Prolific to the following question: *"What do you think is the reported level of trust for scientists who do express political opinions on social media?"*. Prior to asking the question, we informed the academic respondents that we had surveyed a representative sample of the U.S. on their perceived credibility of scientists, distinguishing between those who had expressed political opinions online and those who had not. We anchored our scientists' beliefs on the public perceived credibility for scientists who *do not* express political opinions online (indicated by the grey dashed line). The average answer of our sample of scientists is shown by the red dashed line and is significantly lower than the true value obtained in the main survey of a representative sample of U.S. respondents, which is indicated by the green dashed line.

Figure A.19: Scientists' Own Beliefs and Belief's on Other Scientists Beliefs around Academics Publicly Expressing Political Views

A. Scientists Should Avoid Expressing Political Opinions



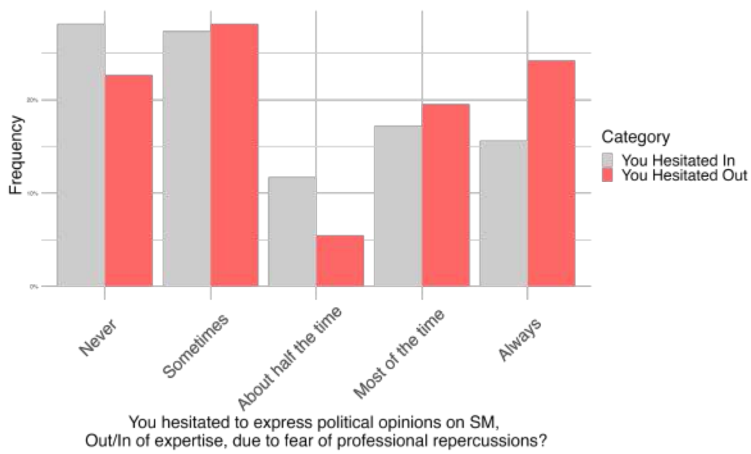
B. How many Scientists Agree on Avoiding to Express Political Opinions



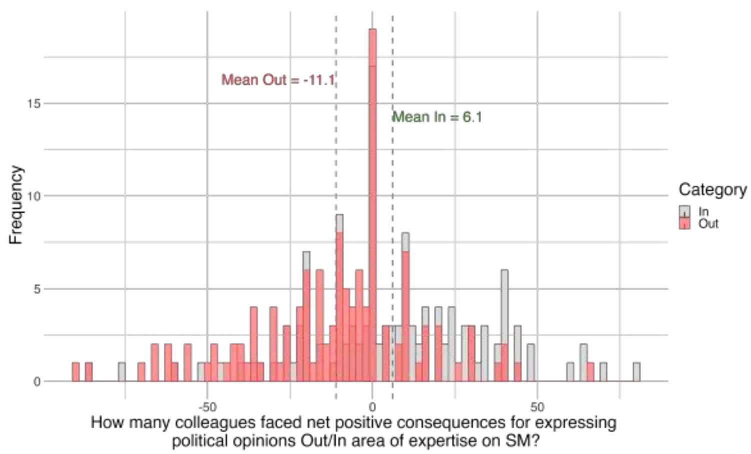
Note: The figure illustrates scientists' own beliefs and their beliefs about other scientists' views on the public expression of political opinions on social media, based on a sample of 128 scientists recruited on Prolific. Panel A shows scientists' responses to their level of agreement with the following statements: *"Scientists and researchers should avoid expressing their political opinions* ***outside*** *their area of expertise on social media."* (red bars) and *"Scientists and researchers should avoid expressing their political opinions* ***within*** *their area of expertise on social media."* (grey bars). For either statement, scientists could choose one of five options: "Strongly disagree," "Somewhat disagree," "Neither agree nor disagree," "Somewhat agree," and "Strongly agree." Our respondents think that expressing political views on social media is more acceptable within their own area of expertise than outside it. Panel B illustrates scientists' responses to the following questions: *Out of 100 scientists and researchers, how many do you think would agree with the statement: "Scientists and researchers should avoid expressing their political opinions* ***outside*** *their area of expertise on social media?"* (red bars) and *Out of 100 scientists and researchers, how many do you think would agree with the statement: "Scientists and researchers should avoid expressing their political opinions* ***about*** *their area of expertise on social media?"* (grey bars). Our respondents believe that other scientists also think that publicly expressing political views outside their own area of expertise is less acceptable than within their own area of expertise.

Figure A.20: Scientists' Experience Hesitating to Express Political Opinions and their Perception around Positive and Negative Consequences from Public Political Expression.

A. Have Hesitated to Express Political Opinions



B. Perceived Consequences of Expressing Political Opinions



Note: The figure illustrates scientists' hesitation to express political views online and their perceptions of colleagues facing consequences from public political expression, based on a sample of 128 scientists recruited on Prolific. Panel A shows responses to whether they hesitated to express political opinions on social media due to professional concerns, either *"outside* their area of expertise (red bars) or *"within* their area of expertise (grey bars). Respondents chose from: "Always," "Most of the time," "About half the time," "Sometimes," and "Never." Panel B illustrates responses to the perceived consequences for colleagues expressing political opinions. Scientists estimated how many out of 100 colleagues faced *negative consequences* and *positive consequences* for opinions expressed outside (about) their area of expertise. Red bars represent the difference in responses for areas outside one's expertise, and grey bars represent the same for areas within one's expertise. Scientists anticipate net reputational costs for expressing political opinions outside their field compared to net benefits within their field. On average, scientists believe more colleagues faced *negative* consequences for expressing political opinions outside their area of expertise and more colleagues benefited from expressing views within their area of expertise. However, there is significant variation in responses, with perceptions of costs and benefits largely overlapping for opinions expressed outside versus inside one's area of expertise.

B Appendix Tables

Table B.1: Summary Statistics of Scientist level characteristics

Variables	**N**	**% (Filtered)**	**% Politicized (Filtered)**	**% Politicized (Full data)**
Scientists (Full)	97,737	-	-	43.7
Scientists (Filtered)	52,541	100	81.4	-
Male	28,998	55.2	78.3	40.0
Female	22,442	42.7	85.4	49.6
Other	1,101	2.1	79.3	-
Citations: 1-100	19,285	36.7	82.3	41.4
Citations: 101-500	14,097	26.8	80.9	46.0
Citations: 501-1000	5,859	11.1	80.5	44.2
Citations: 1000+	13,299	25.3	80.9	45.0
Field: With Concepts Data	25,719	49.0	81.4	51.7
Field: Humanities	103	0.4	86.4	57.8
Field: STEM	11,819	45.95	79.5	42.5
Field: Social Sciences	6,032	23.5	86.0	64.9
Field: Medicine	7,765	30.19	80.6	38.3

Notes: Table shows individual-level summary statistics on key characteristics of scientists. For some key categories relevant to our experiment, we show a breakdown by the number of observations, the proportion of those who tweeted about any of our topics, and among them, the proportion of those who are *politicized* (i.e., whether they have made at least one pro or anti tweet on one of our five topics in the cross-section from 2016 to 2022). The "Filtered" column refers to the subset of scientists who have tweeted about a political topic (pro, anti, or neutral). The "% Politicized" refers to the subset of scientists who have made at least one pro or anti tweet. "With Concepts Data" refers to those for whom we have concepts data. Above 40% of our full sample of academics ever talked about one of the topics of interest during the period of observation.

Table B.2: Summary statistics of Topic and Stance Detection

Topics	N. Tweets (Full data)	% All Tweets (Full data)	N. Tweets (Sampled)	% All Tweets (Sampled)	% Pro	% Neutral	% Anti	% Mention Politician	% Mention Trump/Biden	% Mention Research
Climate Action	2,423,954	2.09%	97,587	0.08	28	70	2	11.57	3.40	44.50
Immigration	995,558	0.86%	79,892	0.06	20	73	7	21.46	6.57	21.41
Racial Equality	1,738,049	1.50%	79,986	0.07	15	12	73	14.24	3.26	25.99
Abortion Rights	287,346	0.254%	31,351	0.03	37	58	5	21.53	4.07	15.03
Income Redistribution	706,886	0.61%	61,683	0.05	21	74	5	15.34	3.57	25.06
Topical Tweets	6,151,793	5.31%	350,499	0.30	-	-	-	16.01	4.19	28.91
All Tweets	115,744,660	100%	-	-	-	-	-	8.55	1.21	19.22

Notes: Table shows tweet-level summary statistics of topic and stance detection steps. The dataset and classification methods are described in detail in Section D. We reproduce here the essential methods for variables used in this paper. The data contains the entirety of these academics' Twitter activities from January 1, 2016, to December 31, 2022. This included original tweets, retweets, quoted retweets, and replies, totaling around 116 million tweets. Topic detection was the primary step in our methodology of stance classification, aiming first to categorize tweets into one of the predefined topics: (1) Abortion Rights, (2) Climate Action, (3) Immigration, (4) Racial Equality, (5) Income Redistribution. This approach is further demonstrated in Garg and Fetzer (2024b). OpenAI's GPT-4 was used to generate dynamic keyword dictionaries to capture the evolving discourse on these subjects. For stance detection, we employed OpenAI's GPT-3.5 Turbo. Tweets were classified into one of four stances: pro, anti, neutral, or unrelated. This was done using the prompt "Classify this tweet's stance towards <topic> as 'pro', 'anti', 'neutral', or 'unrelated'. Tweet: <tweet>.'" A sampling procedure was employed to reduce the total costs of this tweet-by-tweet labeling task. For each year by month, up to three random tweets per author per topic were included in the sample. This ensured we have enough tweets to determine the stance of an author in a given time period. The stance detection results refer to the sampled tweet sample. The final three columns on "% Mention" show results from an additional topic detection step. The "% Mention Politician" column represents the percentage of tweets mentioning any politician or political candidate (including Trump or Biden). The "% Mention Trump/Biden" column represents the percentage of tweets mentioning either Joe Biden or Donald Trump. The "% Mention Research" column represents the percentage of tweets mentioning scientific research papers.

Table B.3: Example ngrams for Topic Detection

Topic	Example ngrams
Abortion	abortion, abortion rights, planned parenthood, pro-choice, pro-life
Climate Action	renewable energy, protect the environment, climatehoax, global warming
Immigration	deportation, immigration, undocumented, migrants, ice detention centers
Racial Equality	race relations, black lives matter, xenophobia, affirmative action, #sayhername
Income Redistribution	welfare state, taxation, #ubi, income level, social safety net
Donald Trump	maga, trump administration, trump tower, Russia investigation, #trumptrain
Joe Biden	#buildbackbetter, bidenharris2020, Afghanistan troop withdrawal, biden's first 100 days
Politicians	candidate forum, presidential candidates, vote, swing state, campaign ads
Research	research impact, sample size, researchgate, clinical trials, peer review

Notes: Table shows example ngrams used in the topic detection step of our methodology. We used OpenAI's GPT-4 family of models to generate dynamic keyword dictionaries to capture the evolving discourse on these subjects. The prompt used was "Provide a list of <ngrams> related to the topic of <topic> in the year <year>. <twitter fine tuning>. Provide the <ngrams> as a comma-separated list." This process was repeated for each combination of topic, ngram, year, and vernacular type, resulting in 180 prompts. The generated keywords were combined at the topic level and applied to the full corpus of tweets. Tweets containing keywords from a topic's dictionary were labeled as belonging to that topic. These example ngrams are chosen to illustrate the diversity of responses we can obtain.

Table B.4: Examples of Tweets by Stance

Stance	Example Tweet
Income Redistribution	
Pro	when someone runs an experiment asking "what happens if you give people some money" the answer is, without fail, "their life gets better." No amount of research validating and re-validating this will ever be enough for the politicians who demand suffering as penance for poverty. https://t.co/bhHbqG2
Anti	Civilrights/prolife colleagues (same thing), FYI. '@daviddaleiden is a national hero for exposing these barbaric practices that abortion zealots like @JoeBiden want all Americans to approve and fund.' https://t.co/Og9rp3Vxsw
Neutral	Do corporate tax cuts boost growth? Our paper is out @ European Economic Review. We meta-analyse 441 estimates from 42 studies; results imply: the attention corporate taxation has received as a source of growth has often been exaggerated. https://t.co/U1X4Vl
Climate Action	
Pro	Do you remember the famous 97% study - that 97% of climate science supported the consensus on human-caused climate change? Well, we have just published an update for 2012-2021 papers in the same journal, Environmental Research Letters. The figure is now... drumroll please...99.9%!
Anti	The concept of global warming was created by and for the Chinese in order to make U.S. manufacturing non-competitive.
Neutral	The most significant contribution among the highest emitters is from air and land transport, with 41% and 21% among the top 1% of EU households. Air transport is by far the most income-elastic, unequal and carbon-intensive consumption category in our study. https://t.co/eU2RXG8Hzw
Immigration	
Pro	Our new research in @LancetGH provides evidence of the health effects of hostile environment policies to migrants: restrictive entry and integration policies are associated with worse mental and general health, and an increased risk of death. https://t.co/js4GmbnKG9
Anti	National sovereignty and border security are paramount. Open borders policies invite chaos and undermine the rule of law. A nation must control its borders to protect its citizens and uphold its values.
Neutral	Finally ready to share my paper on individualistic Scandinavian emigrants, and how their departure during the Age of Mass Migration generated lasting cultural change towards collectivism and convergence across migrant-sending districts. https://t.co/adYS5rJGiA
Abortion Rights	
Pro	Texas' latest abortion ban, SB8, gives people the right to sue those who provide or help others get an abortion after 6 weeks. Bans like these are not based in science and the consequences could potentially be disastrous. Here's what our research says.
Anti	Let's Make Abortion UNTHINKABLE! Who's with me? prolife unborn bhfyp alllivesmatter hope endabortion prolifegen https://t.co/EojMrSJVKN
Neutral	In the wake of a gene-editing experiment gone wrong, the president of the National Catholic Bioethics Center said that the Church must stand firm against the unborn being "sacrificed on the altar of scientific research." https://t.co/6XUBBg9KOD
Racial Equality	
Pro	An article came out in @TheLancet today that is flying under the radar but is absolutely critical to read. It provides rare CAUSAL evidence showing structural racism causes poor health outcomes for Black Americans. Here's the science in a quick thread.
Anti	My study of northern backlash against the Great Migration has no policy prescription, but it has a smoking gun. Police are the only public investment to increase in metro areas w/ more black migration. Good faith pursuit of racial justice starts by questioning this institution. https://t.co/uQaYdGQnPn
Neutral	We document the appearance of a new race gap in traffic deaths that emerged after 2014. In fact, this was the first time that the rate of traffic deaths for Black Americans exceeded that of White Americans since at least the early 1970s. Our paper tries to unravel this mystery. https://t.co/jTluzYirqn

Notes: The table presents examples of tweets by stance (pro, anti, neutral) for the five topics: Income Redistribution, Climate Action, Immigration, Abortion Rights, and Racial Equality.

Table B.5: Evaluation Metrics: GPT 3.5 Turbo, GPT-4, and Topic Detection

Task	**Target**	**GPT 3.5 Turbo (F_{avg})**	**GPT 4 (F_{avg})**	**Topic Detection (F_{avg})**
A	Feminism	92.44	81.89	67.01
A	Hillary Clinton	89.57	87.53	67.35
A	Abortion	79.52	84.36	74.87
B	Donald Trump	84.18	80.00	71.84

Notes: The table presents validation results for stance detection using both GPT-3.5 Turbo and GPT-4 models, comparing their performance on the ACM SemEval-2016 Task 6 dataset. GPT-3.5 Turbo achieved F_{avg} scores ranging from 79.52 to 92.44, with GPT-4 showing slightly better performance on Abortion (84.36) but generally similar results. Topic detection was validated using dictionaries generated from GPT-4, capturing evolving lexical patterns for the same topics. True positives, true negatives, false positives, and false negatives were calculated to measure the accuracy of topic detection, achieving F_{avg} scores of 67.01 to 74.87, indicating high recall and precision in filtering relevant tweets. For further comparisons and details on stance and topic detection validation, see Garg and Fetzer (2024b).

Table B.6: Summary Statistics Main Study

	Population	Sample
Income: $<$ 30,000	0.51	0.17
Income: 30-59,999	0.26	0.25
Income: 60-99,999	0.14	0.27
Income: 100-149,999	0.06	0.19
Income: $>$ 149,999	0.04	0.11
Age: 18-34	0.30	0.29
Age: 35-44	0.16	0.18
Age: 45-54	0.16	0.16
Age: 55-64	0.17	0.24
Age: $>$ 64	0.21	0.13
Ethnicity: White	0.7	0.73
Edu: Up to Highschool	0.39	0.26
Edu: Some college	0.22	0.20
Edu: Bachelor or Associate	0.28	0.35
Edu: Masters or above	0.11	0.19
Region: West	0.24	0.17
Region: North-east	0.17	0.22
Region: South	0.38	0.40
Region: Mid-west	0.21	0.21
Male	0.49	0.49
Republican	0.28	0.28
Democrat	0.32	0.31
Outcome	**Mean**	
Credibility	6.35	
Credibility Research	6.27	
Read	5.63	

Notes: The population average demographics are computed using the 2022 American Community Survey (ACS) 1-year estimates. The ACS sample includes only individuals above the age of 18. The population share of Republicans is obtained from the average share of people identifying as Republicans across multiple surveys conducted in 2024 by Gallup. (https://news.gallup.com/poll/15370/party-affiliation.aspx).

Table B.7: Characteristics of the Scientists' Profiles

Attributes	Categories	Options
Gender	Male, Female	We specify the gender
Research Field	Social Sciences, STEM, Medicine, and Humanities	We mention: Economics, Material Engineering, Mathematics, Medicine, American Literature
Seniority	Senior, Junior	We mention that scientists are: Full Professor or Assistant Professor
University Affiliation	High-ranked, Low-ranked	We use affiliations to Harvard University, Berkeley, University of Chicago, University of Arkansas, University of Connecticut
Twitter Bio and Twitter Post	Strongly Dem, Moderately Dem, Strongly Rep, Moderately Rep, Neutral	Academic. Human rights advocate [rainbow and fist emoji] - "Greta has been arrested for the first time. This signals a moment for more of us to rise and face arrest if necessary, for the future of our planet. Such actions have the power to change the course of events.", Academic. Friend of the environment [wave emoji] - "Researchers at Exxon precisely forecasted the extent of global warming resulting from fossil fuel combustion in studies starting in 1970s, according to a research paper. Despite this, the company cast skepticism on the findings, contributing to a postponement of government climate initiatives. ", Academic. Republican. #biblebelieve [American flag] - "For those advocating for civil rights and pro-life values (which are inherently linked), take note. There are individuals who have courageously highlighted the inhumane procedures that proponents of abortion, such as @JoeBiden, are pushing for nationwide acceptance and funding. This is unequivocally unacceptable", Academic. American. Sharing research, family and community stories [house and handshake emoji] - "I'm not inclined towards the right or the left, but the excessive wokeness of the left has nudged me to the right. Interestingly, when right-wing extremists commit mass shootings against minorities, it doesn't compel me to shift towards the left. Somehow, that's not considered 'too far.'", Academic. Discovering truths of the world [books emoji] - "On December 5, 1932, Albert Einstein received a visa, enabling his journey to the United States. OnThisDay https://t.co/XmFcvInjMF."
Twitter Bio and Twitter Post (Cross-randomization)	Dem, Rep, Active Control, Pure Control	Passionate about Research and Advocate for Equality [Earth emoji] - "Our latest study in Lancet Global Health provides evidence on the health impacts of hostile environment policies toward migrants: restrictive entry and integration policies are linked to poorer mental and general health, and a higher risk of death.", Passionate about Research and Proud Patriot [Eagle emoji] - "Our latest study in Lancet Global Health provides evidence on the health impacts of hostile environment policies toward migrants: restrictive entry and integration policies are linked to poorer mental and general health, and a higher risk of death.", Passionate about Research - "Our latest study in Lancet Global Health provides evidence on the health impacts of hostile environment policies toward migrants: restrictive entry and integration policies are linked to poorer mental and general health, and a higher risk of death.", Passionate about Research - "In our recent paper, we show that Nash equilibrium uniquely satisfies key axioms across different games, challenging refinement theories. Our findings have implications for zero-sum, potential, and graphical games."

This table provides an overview of the characteristics of the scientists we manipulate in the conjoint experiment and in the last task.

Table B.8: Scientists' Profile Credibility by Scientists' Political Affiliation

	Credibility of Scientists by Profile Type:				
	Strong *Rep*	Moderate *Rep*	Neutral	Moderate *Dem*	Strong *Dem*
Male	−0.060	−0.165	−0.014	−0.116	0.021
	(0.150)	(0.117)	(0.097)	(0.110)	(0.129)
Full Professor	−0.024	0.214*	0.313***	−0.045	0.267**
	(0.150)	(0.117)	(0.097)	(0.110)	(0.129)
Economics	0.356	0.288	−0.029	0.410**	−0.105
	(0.234)	(0.187)	(0.154)	(0.171)	(0.201)
Engineering	0.247	0.141	0.075	0.384**	0.168
	(0.230)	(0.189)	(0.151)	(0.172)	(0.212)
Mathematics	0.094	0.362**	0.007	0.549***	0.169
	(0.238)	(0.184)	(0.153)	(0.174)	(0.204)
Medicine	0.084	−0.004	0.134	0.871***	0.389*
	(0.230)	(0.189)	(0.154)	(0.170)	(0.208)
High Affiliation	0.254*	0.274**	0.088	0.337***	−0.229*
	(0.152)	(0.120)	(0.099)	(0.111)	(0.132)
Constant	4.210***	6.294***	7.067***	6.244***	6.396***
	(0.208)	(0.174)	(0.139)	(0.156)	(0.189)
Observations	1,704	1,704	1,704	1,704	1,704

Notes: Coefficients were obtained by regressing scientists' characteristics on respondents' perceived credibility. All the standard errors are clustered at the individual level. Each column represents a different scientist based on the political affiliation. High Affiliation signifies institutions such as Harvard, UC Berkeley, or Chicago, versus Arkansas or Connecticut. Research fields include Medicine, Mathematics, Engineering, and Economics, with Literature excluded. Full professor indicates full professors versus assistant professors. Male is coded as one for male scientists. The significance levels are as follows: *p<0.1; **p<0.05; ***p<0.01.

Table B.9: Scientists' Research Credibility by Scientists' Political Affiliation

	Credibility of Scientists Research by Profile Type:				
	Strong *Rep*	Moderate *Rep*	Neutral	Moderate *Dem*	Strong *Dem*
Male	−0.123	−0.154	−0.031	−0.127	0.093
	(0.149)	(0.116)	(0.096)	(0.111)	(0.130)
Full Professor	−0.007	0.288**	0.271***	0.047	0.218*
	(0.149)	(0.116)	(0.096)	(0.111)	(0.129)
Economics	0.331	0.297	0.090	0.326*	−0.147
	(0.233)	(0.186)	(0.153)	(0.173)	(0.202)
Engineering	0.216	0.075	0.002	0.411**	0.156
	(0.230)	(0.188)	(0.150)	(0.174)	(0.213)
Mathematics	0.289	0.341*	0.033	0.539***	0.120
	(0.238)	(0.182)	(0.152)	(0.176)	(0.204)
Medicine	0.175	−0.037	0.179	0.747***	0.289
	(0.230)	(0.187)	(0.152)	(0.172)	(0.209)
High Affiliation	0.169	0.274**	0.109	0.330***	−0.276**
	(0.152)	(0.119)	(0.098)	(0.113)	(0.132)
Constant	4.241***	6.186***	6.933***	6.138***	6.399***
	(0.207)	(0.173)	(0.138)	(0.157)	(0.189)
Observations	1,704	1,704	1,704	1,704	1,704

Notes: Coefficients were obtained by regressing scientists' characteristics on respondents' perceived credibility of scientist's own research. All the standard errors are clustered at the individual level. Each column represents a different scientist based on the political affiliation. High Affiliation signifies institutions such as Harvard, UC Berkeley, or Chicago, versus Arkansas or Connecticut. Research fields include Medicine, Mathematics, Engineering, and Economics, with Literature excluded. Full professor indicates full professors versus assistant professors. Male is coded as one for male scientists. The significance levels are as follows: *p$<$0.1; **p$<$0.05; ***p$<$0.01.

Table B.10: Willingness to Read by Scientists' Political Affiliation

	Willingness to Read Opinion of Scientists by Profile Type:				
	Strong *Rep*	Moderate *Rep*	Neutral	Moderate *Dem*	Strong *Dem*
Male	0.073	−0.196	−0.317**	−0.122	0.068
	(0.168)	(0.144)	(0.126)	(0.139)	(0.155)
Full Professor	−0.035	0.213	0.162	0.012	0.270*
	(0.168)	(0.144)	(0.126)	(0.139)	(0.155)
Economics	0.223	0.325	−0.033	0.411*	0.194
	(0.262)	(0.230)	(0.200)	(0.217)	(0.242)
Engineering	0.033	−0.023	−0.001	0.009	0.372
	(0.258)	(0.233)	(0.197)	(0.218)	(0.256)
Mathematics	−0.133	0.169	0.012	0.276	0.094
	(0.268)	(0.226)	(0.199)	(0.220)	(0.245)
Medicine	0.116	0.043	0.061	0.676***	0.531**
	(0.258)	(0.232)	(0.200)	(0.216)	(0.251)
High Affiliation	0.196	0.244*	0.097	0.301**	−0.182
	(0.171)	(0.148)	(0.129)	(0.141)	(0.158)
Constant	3.575***	5.684***	6.485***	5.781***	5.488***
	(0.233)	(0.214)	(0.181)	(0.197)	(0.227)
Observations	1,704	1,704	1,704	1,704	1,704

Notes: Coefficients were obtained by regressing scientists' characteristics on respondents' likelihood of reading from similar scientists. All the standard errors are clustered at the individual level. Each column represents a different scientist based on the political affiliation. High Affiliation signifies institutions such as Harvard, UC Berkeley, or Chicago, versus Arkansas or Connecticut. Research fields include Medicine, Mathematics, Engineering, and Economics, with Literature excluded. Full professor indicates full professors versus assistant professors. Male is coded as one for male scientists. The significance levels are as follows: *p<0.1; **p<0.05; ***p<0.01.

Table B.11: Summary Statistics Robustness Study

	Population	Sample
Income: $<$ 30,000	0.51	0.17
Income: 30-59,999	0.26	0.26
Income: 60-99,999	0.14	0.27
Income: 100-149,999	0.06	0.19
Income: $>$ 149,999	0.04	0.11
Age: 18-34	0.30	0.31
Age: 35-44	0.16	0.26
Age: 45-54	0.16	0.19
Age: 55-64	0.17	0.14
Age: $>$ 64	0.21	0.10
Ethnicity: White	0.7	0.69
Edu: Up to Highschool	0.39	0.26
Edu: Some college	0.22	0.19
Edu: Bachelor or Associate	0.28	0.40
Edu: Masters or above	0.11	0.15
Region: West	0.24	0.21
Region: North-east	0.17	0.21
Region: South	0.38	0.37
Region: Mid-west	0.21	0.21
Male	0.49	0.49
Republican	0.28	0.29
Democrat	0.32	0.33

Notes: The population average demographics are computed using the 2022 American Community Survey (ACS) 1-year estimates. The ACS sample includes only individuals above the age of 18. The population share of Republicans is obtained from the average share of people identifying as Republicans across multiple surveys conducted in 2024 by Gallup. (https://news.gallup.com/poll/15370/party-affiliation.aspx).

Table B.12: Regression with Robust SE

	Dependent variable:					
	Credibility	Cred.Research	Read	Credibility	Cred.Research	Read
	(1)	(2)	(3)	(4)	(5)	(6)
Male	−0.067	−0.068	−0.097	−0.067	−0.068	−0.097
	(0.054)	(0.054)	(0.066)	(0.054)	(0.054)	(0.066)
Full Professor	0.147***	0.165***	0.124*	0.147***	0.165***	0.124*
	(0.054)	(0.054)	(0.066)	(0.055)	(0.055)	(0.066)
Economics	0.185**	0.184**	0.226**	0.185**	0.184**	0.226**
	(0.086)	(0.086)	(0.103)	(0.086)	(0.086)	(0.103)
Engineering	0.202**	0.172**	0.072	0.202**	0.172**	0.072
	(0.086)	(0.086)	(0.104)	(0.088)	(0.087)	(0.105)
Mathematics	0.246***	0.272***	0.092	0.246***	0.272***	0.092
	(0.086)	(0.086)	(0.104)	(0.085)	(0.086)	(0.104)
Medicine	0.299***	0.279***	0.290***	0.299***	0.279***	0.290***
	(0.086)	(0.086)	(0.104)	(0.086)	(0.087)	(0.103)
High Affiliation	0.142**	0.120**	0.128*	0.142**	0.120**	0.128*
	(0.056)	(0.056)	(0.067)	(0.056)	(0.056)	(0.067)
Moderately Dem	−0.505***	−0.483***	−0.293***	−0.505***	−0.483***	−0.293***
	(0.086)	(0.086)	(0.104)	(0.073)	(0.073)	(0.094)
Moderately Rep	−0.660***	−0.617***	−0.521***	−0.660***	−0.617***	−0.521***
	(0.086)	(0.086)	(0.104)	(0.076)	(0.075)	(0.095)
Strong Rep	−2.828***	−2.698***	−2.708***	−2.828***	−2.698***	−2.708***
	(0.086)	(0.086)	(0.104)	(0.089)	(0.088)	(0.105)
Strongly Dem	−0.788***	−0.715***	−0.694***	−0.788***	−0.715***	−0.694***
	(0.086)	(0.086)	(0.104)	(0.081)	(0.081)	(0.100)
Constant	6.994***	6.876***	6.243***	6.994***	6.876***	6.243***
	(0.096)	(0.095)	(0.115)	(0.088)	(0.089)	(0.108)
Observations	8,520	8,520	8,520	8,520	8,520	8,520

Notes: Coefficients are obtained by regressing scientists' characteristics on respondents' perceived credibility, perceived credibility of scientists' research and likelihood of reading from similar scientists. All the standard errors are clustered at the individual level and are robust to heteroskedasticity in Columns 4 to 6. Political leaning is indicated by "Strongly Republican," "Moderately Republican," "Strongly Democrat," or "Moderately Democrat," with "Neutral" as the excluded category. High Affiliation signifies institutions such as Harvard, UC Berkeley, or Chicago, versus Arkansas or Connecticut. Research fields include Medicine, Mathematics, Engineering, and Economics, with Literature excluded. Full professor indicates full professors versus assistant professors. Male is coded as one for male scientists. The significance levels are as follows: *p<0.1; **p<0.05; ***p<0.01.

Table B.13: Regression with Multiple Hypothesis Testing Correction

	Dependent variable:					
	Credibility (1)	Cred.Research (2)	Read (3)	Credibility (4)	Cred.Research (5)	Read (6)
Male	-0.067	-0.068	-0.097	-0.067	-0.068	-0.097
	(0.054)	(0.054)	(0.066)	(0.054)	(0.054)	(0.066)
Full Professor	0.147^{***}	0.165^{***}	0.124^{*}	0.147^{**}	0.165^{***}	0.124^{*}
	(0.054)	(0.054)	(0.066)	(0.055)	(0.055)	(0.066)
Economics	0.185^{**}	0.184^{**}	0.226^{**}	0.185^{**}	0.184^{**}	0.226^{**}
	(0.086)	(0.086)	(0.103)	(0.086)	(0.086)	(0.103)
Engineering	0.202^{**}	0.172^{**}	0.072	0.202^{**}	0.172^{**}	0.072
	(0.086)	(0.086)	(0.104)	(0.088)	(0.087)	(0.105)
Mathematics	0.246^{***}	0.272^{***}	0.092	0.246^{***}	0.272^{***}	0.092
	(0.086)	(0.086)	(0.104)	(0.085)	(0.086)	(0.104)
Medicine	0.299^{***}	0.279^{***}	0.290^{***}	0.299^{***}	0.279^{***}	0.290^{***}
	(0.086)	(0.086)	(0.104)	(0.086)	(0.087)	(0.103)
High Affiliation	0.142^{**}	0.120^{**}	0.128^{*}	0.142^{**}	0.120^{**}	0.128^{*}
	(0.056)	(0.056)	(0.067)	(0.056)	(0.056)	(0.067)
Moderately Dem	-0.505^{***}	-0.483^{***}	-0.293^{***}	-0.505^{***}	-0.483^{***}	-0.293^{***}
	(0.086)	(0.086)	(0.104)	(0.073)	(0.073)	(0.094)
Moderately Rep	-0.660^{***}	-0.617^{***}	-0.521^{***}	-0.660^{***}	-0.617^{***}	-0.521^{***}
	(0.086)	(0.086)	(0.104)	(0.076)	(0.075)	(0.095)
Strong Rep	-2.828^{***}	-2.698^{***}	-2.708^{***}	-2.828^{***}	-2.698^{***}	-2.708^{***}
	(0.086)	(0.086)	(0.104)	(0.089)	(0.088)	(0.105)
Strongly Dem	-0.788^{***}	-0.715^{***}	-0.694^{***}	-0.788^{***}	-0.715^{***}	-0.694^{***}
	(0.086)	(0.086)	(0.104)	(0.081)	(0.081)	(0.100)
Constant	6.994^{***}	6.876^{***}	6.243^{***}	6.994^{***}	6.876^{***}	6.243^{***}
	(0.096)	(0.095)	(0.115)	(0.088)	(0.089)	(0.108)
Observations	8,520	8,520	8,520	8,520	8,520	8,520

Notes: Coefficients were obtained by regressing scientists' characteristics on respondents' perceived credibility, scientists' research perceived credibility or likelihood of reading from similar scientists. The p-values in Columns 4, 5 and 6 are corrected for Multiple Hypothesis Testing using FDR procedure. All the standard errors are clustered at the individual level. Political leaning is indicated by "Strongly Republican," "Moderately Republican," "Strongly Democrat," or "Moderately Democrat," with "Neutral" as the excluded category. High Affiliation signifies institutions such as Harvard, UC Berkeley, or Chicago, versus Arkansas or Connecticut. Research fields include Medicine, Mathematics, Engineering, and Economics, with Literature excluded. Full professor indicates full professors versus assistant professors. Male is coded as one for male scientists. The significance levels are as follows: *p<0.1; **p<0.05; ***p<0.01.

Table B.14: Summary Statistics of Journalists

	Sample
Seniority: Less than 1 year	0.10
Seniority: Between 1 year and 3 years	0.23
Seniority: Between 3 years and 5 years	0.14
Seniority: More than 5 years	0.53
Position: Reporter	0.45
Position: Editor	0.33
Position: Opinion Writer	0.14
Position: Columnist	0.08
Job: Daily Newspaper	0.16
Job: Weekly Newspaper	0.04
Job: Freelance	0.28
Job: Online Newspaper	0.35
Job: Blog	0.04
Job: TV	0.12
Political: Conservative	0.27
Political: Liberal	0.62
Political: Moderate	0.11
Employment: Working full time now	0.74
Employment: Working part time now	0.17
Employment: Unemployed	0.02
Employment: Retired	0.03
Country: U.S. and UK	0.59
Country: Other	0.47
Male	0.37
Female	0.59
Non-binary	0.04
Outcome	**Mean**
Credibility	6.24
Credibility of Research	6.14
Newsletter	5.92

Notes: The Journalist sample recruited on Prolific. The characteristics are broken down into different dimensions.

Table B.15: Journalists' Beliefs

	Sample
Disclosure Leaning: Disagree	0.33
Disclosure Leaning: Neither Disagree nor Agree	0.15
Disclosure Leaning: Agree	0.52
Source Credibility: Disagree	0.16
Source Credibility: Neither Disagree nor Agree	0.14
Source Credibility: Agree	0.70
Readership Reaction: More Backlash	0.39
Readership Reaction: More Engagement	0.18
Readership Reaction: Balanced Mix of Both	0.43
Contact Politicized Scientist: Unlikely	0.21
Contact Politicized Scientist: Neither Unlikely nor Likely	0.27
Contact Politicized Scientist: Likely	0.52
Feature SM Active Scientist: Unlikely	0.21
Feature SM Active Scientist: Neither Unlikely nor Likely	0.24
Feature SM Active Scientist: Likely	0.55

Notes: We summarize the journalists' answers to different questions listed below. All the answers were recorder on a 5-item Likert scale. For convenience, we grouped the answers in three categories. We ask them to state the degree of agreement to the following statements: "*A scientist's political leaning should be disclosed when their research is reported*" (Disclosure Leaning) and "*Featuring politically active scientists might affect the newspaper's credibility with its audience*" (Source Credibility). Then, we asked the following questions: "*How do you expect your readership to respond if a scientist's political views are prominently featured in your content?*" (Readership Reaction), "*How likely are you to reach out to a scientist for an interview or expert opinion if their political views are well-known?*" (Contact Politicized Scientist) and "*How likely are you to feature a scientist if they have a politically active social media presence?*" (Feature SM Active Scientist).

Table B.16: Mechanism: Separating the Effect of Communicating Salient Research from a Pure Scientists' Political Signal

	Dependent variable:				
	Credibility	Credible Research	Willing to Read	Yes Newsletter	Trust in Science Idx
Active Control	0.010	−0.120	1.049***	0.089**	0.004
	(0.193)	(0.194)	(0.239)	(0.040)	(0.060)
Treatment Left	−0.096	−0.285*	0.972***	0.062*	0.045
	(0.166)	(0.167)	(0.207)	(0.035)	(0.052)
Treatment Right	−0.121	−0.370**	0.978***	0.039	0.056
	(0.167)	(0.168)	(0.207)	(0.035)	(0.052)
Male	0.048	0.032	−0.123	−0.030	0.021
	(0.111)	(0.112)	(0.138)	(0.023)	(0.034)
Full Professor	0.230**	0.239**	0.375***	0.047**	0.052
	(0.111)	(0.111)	(0.137)	(0.023)	(0.034)
High Affiliation	−0.044	−0.017	0.063	−0.008	−0.090**
	(0.113)	(0.114)	(0.141)	(0.024)	(0.035)
Constant	7.335***	8.082***	5.382***	0.622***	4.067***
	(0.974)	(0.979)	(1.210)	(0.203)	(0.301)
Observations	1,704	1,704	1,704	1,704	1,704
Controls	X	X	X	X	X

Notes: Coefficients were obtained by regressing scientists' characteristics on respondents' credibility perceptions, likelihood of reading from similar scientists, willingness to receive a related newsletter, and their general trust in scientists. Each column represents a different outcome variable. High Affiliation signifies institutions such as Harvard, UC Berkeley, or Chicago, versus Arkansas or Connecticut. Research fields include Medicine, Mathematics, Engineering, and Economics, with Literature excluded. Full professor indicates full professors versus assistant professors. Male is coded as one for male scientists. Controls encompass respondents' age, gender, income, ethnicity, education, employment status, religion, region, and political leaning. The significance levels are as follows: *p<0.1; **p<0.05; ***p<0.01.

Table B.17: Mechanism: Separating the Effect of Communicating Salient Research from a Pure Scientists' Political Signal (*Democrat* vs. *Republican* respondents)

	Panel A: *Democrats or Leaning Democrat*				
	Credibility	Credible Research	Willing to Read	Yes Newsletter	Trust in Science Idx
Active Control	0.646***	0.489**	1.730***	0.081	−0.056
	(0.232)	(0.231)	(0.304)	(0.055)	(0.074)
Treatment Left	0.773***	0.594***	1.985***	0.110**	0.048
	(0.205)	(0.205)	(0.269)	(0.049)	(0.066)
Treatment Right	0.071	−0.071	1.571***	0.055	0.018
	(0.205)	(0.204)	(0.269)	(0.049)	(0.066)
Male	−0.097	−0.131	−0.233	−0.033	0.063
	(0.136)	(0.136)	(0.178)	(0.033)	(0.043)
Full Professor	0.077	0.097	0.231	0.062*	0.022
	(0.134)	(0.134)	(0.176)	(0.032)	(0.043)
High Affiliation	−0.049	−0.082	−0.140	−0.023	−0.092**
	(0.138)	(0.138)	(0.181)	(0.033)	(0.044)
Constant	7.496***	7.781***	3.577*	0.015	3.285***
	(1.637)	(1.632)	(2.146)	(0.392)	(0.523)
Controls	X	X	X	X	X
Observations	940	940	940	940	940

	Panel B: *Republican or Leaning Republican*				
	Credibility	Credible Research	Willing to Read	Yes Newsletter	Trust in Science Idx
Active Control	−0.818**	−0.879***	0.229	0.084	0.073
	(0.328)	(0.335)	(0.386)	(0.060)	(0.100)
Treatment Left	−1.152***	−1.337***	−0.335	−0.034	0.026
	(0.279)	(0.285)	(0.328)	(0.051)	(0.085)
Treatment Right	−0.479*	−0.825***	0.103	−0.003	0.080
	(0.278)	(0.284)	(0.328)	(0.051)	(0.085)
Male	0.104	0.102	−0.074	−0.038	−0.049
	(0.185)	(0.189)	(0.218)	(0.034)	(0.056)
Full Professor	0.354*	0.350*	0.516**	0.034	0.088
	(0.186)	(0.190)	(0.219)	(0.034)	(0.056)
High Affiliation	−0.138	−0.007	0.201	0.008	−0.098*
	(0.191)	(0.195)	(0.225)	(0.035)	(0.058)
Constant	6.780***	7.484***	6.058***	0.897***	3.711***
	(1.384)	(1.414)	(1.629)	(0.251)	(0.420)
Observations	745	745	745	745	745
Controls	X	X	X	X	X

Notes: Coefficients were obtained by regressing scientists' characteristics on respondents' credibility perceptions, likelihood of reading from similar scientists, willingness to receive a related newsletter, and their general trust in scientists. Each column represents a different outcome variable. High Affiliation signifies institutions such as Harvard, UC Berkeley, or Chicago, versus Arkansas or Connecticut. Research fields include Medicine, Mathematics, Engineering, and Economics, with Literature excluded. Full professor indicates full professors versus assistant professors. Male is coded as one for male scientists. The significance levels are as follows: *p<0.1; **p<0.05; ***p<0.01.

Table B.18: Summary Statistics of Scientists

	Sample
Institute: University	0.63
Institute: Research Institute (including public agencies)	0.17
Institute: Private institute	0.18
Institute: Non profit	0.02
Institute: Hospital/clinic/facility	0.01
Seniority: Less than 1 year	0.08
Seniority: Between 1 year and 3 years	0.19
Seniority: Between 3 years and 5 years	0.26
Seniority: More than 5 years	0.48
Position: Postdoctoral researcher	0.43
Position: University faculty	0.28
Position: Industry professional	0.29
Field: Arts & Humanities	0.05
Field: Life Sciences & Biomedicine	0.34
Field: Physical Sciences	0.11
Field: Social Sciences	0.34
Field: Technology	0.16
Employment: Working full time now	0.89
Employment: Working part time now	0.05
Employment: Unemployed	0.03
Employment: Retired	0.01
Male	0.51
Female	0.46
Non-binary	0.03
Republican	0.02
Democrat	0.42
Independent	0.18
Other	0.28
Not sure	0.10

Notes: The Scientists sample recruited on Prolific. The characteristics are broken down into different dimensions.

C Online Presence of Scientific Publications

Using the Scopus library, we conducted a comprehensive search for all published papers in renowned general interest journals, including *Science*, *Nature*, *PNAS*, *Cell*, *NEJM*, and *Lancet*, spanning the period from 2011 to 2020. This search yielded a total of 114,868 scientific articles. Among these publications, 107,008 had unique DOIs and were consequently tracked by Altmetric, providing a rich dataset for analysis.[1]

The analysis revealed a consistent upward trend in the online presence of scientific publications across a diverse array of media platforms. This trend underscores an evolving landscape wherein scientists are increasingly embracing opportunities to engage with broader audiences beyond the confines of traditional academic circles. Figure 1 visually represents these trends, depicting a notable surge in online coverage across various channels such as blog posts, newspaper articles, and Twitter.

Of particular significance is the substantial increase in Twitter mentions, with nearly all of the published papers receiving references on this platform. Specifically, 42,701 papers were mentioned in blog posts (40%), 47,987 papers in news articles (45%), and a striking 102,795 papers in tweets (96%). These findings underscore the growing prominence of Twitter as a pivotal medium for scientific communication and dissemination.

In further detail, the first panel of Figure 1 illustrates the absolute number of appearances of scientific papers across different media platforms. The second panel shows the proportion of all published articles that received any media coverage, highlighting the widespread dissemination of scientific findings. Lastly, the third panel presents the average number of appearances per published paper, providing insights into the frequency and extent of media exposure for individual scientific publications with any online presence.

There is a general upward trend across all metrics. First, blog posts (orange) exhibit relative stability in absolute terms, as well as in proportion to publications and average mentions per paper, perhaps manifesting the decreased relevance of blogs. Conversely, newspaper coverage (red) demonstrates a consistent increase across the first half of the period and across all three metrics, plateauing in more recent years, but with a notable uptick observed in 2020.

Notably, scientific discourse on Twitter (light blue) has shown a remarkable surge

[1] Altmetric is a service that most extensively tracks the online dissemination of scientific articles across platforms (Alabrese, 2022; Peng et al., 2022). Accessed on November 10th, 2021. See API documentation here.

in presence, evident from the outset of the period, with nearly all papers making an appearance on the platform as early as 2013 and maintaining this trend consistently. The number of mentions per paper on Twitter has seen a significant increase, reaching a peak in 2020 with an average of almost 250 tweets per published paper with a presence on the platform.

Zooming in on Twitter, the appendix figure A.1 illustrates the evolution of the distribution of Twitter mentions for research articles published each year from 2011 to 2020. The figure highlights a growing presence of research on social media, with the distribution of Twitter mentions becoming less skewed towards zero, a thicker right tail, and an increase in high-mention outliers over time. These observations highlight the evolving landscape of scientific communication, with Twitter (now X) emerging as a prominent platform for dissemination and engagement.

D LLM Validation

Validation of topic and stance detection methods Our stance detection methodology represents a frontier application of LLMs for classification tasks. Validation efforts, as detailed by Garg and Martin (2024) and Garg and Fetzer (2024b), compared the stances predicted by GPT-3.5 Turbo to those labeled by humans. Human raters categorized tweets as pro-, anti-, or neutral on various topics, including Abortion Rights and Donald Trump. The model's effectiveness was tested against 40,317 hand-coded labels from 137 human annotators, achieving high F-scores ranging from 79 to 92, which are considered robust for such classification tasks. We reproduce these results in Table B.5. Additional comparisons involving GPT-4, which demonstrated slight performance improvements on Abortion-related content, further confirm the method's reliability. The consistency of stance labels across models, with GPT-4o yielding the highest agreement rates and F-scores, underscores the robustness of our approach.

Topic detection was similarly validated using the SemEval-2016 dataset. Dictionaries for topics such as the Feminist Movement, Hillary Clinton, Legalization of Abortion, and Donald Trump were generated using GPT-4, and tweets were matched accordingly. Validation metrics were computed based on true positives, true negatives, false positives, and false negatives. F-scores for topic detection ranged from 67.01 to 74.87, indicating solid performance. These validation results are presented alongside stance detection metrics in Table B.5, highlighting the overall effectiveness of our methodology.

Gender We inferred gender using OpenAI's GPT-3.5 Turbo, which categorized author names from OpenAlex as 'Male', 'Female', or 'Unclear'. This classification resulted in a distribution of 49% Male, 49% Female, and less than 1% Unclear. Garg and Fetzer (2024b) validated this approach with a dataset of 147,269 unique names from authoritative sources,[2] achieving a high F1 score of 0.9868 in a count-weighted evaluation.

Field OpenAlex uses a machine-learning algorithm to evaluate the thematic 'Concepts' associated with each author's body of work, organized into 19 root-level concepts arranged hierarchically. For our comparative analysis, we simplified these into four broad categories: Social Science, Medicine, STEM, and Humanities. Each author's primary

[2]These sources include the U.S. Social Security Card Applications (1880–2019), UK Baby Names in England and Wales Statistical Bulletins (2011–2018), British Columbia's 100 Years of Popular Baby Names (1918–2018), and Australian Baby Names from the Attorney-General's Department (1944–2019).

field of study was assigned based on the highest average score across these root concepts, representing the dominant theme of their publications from 2016 to 2022. STEM includes disciplines such as Biology, Chemistry, Computer Science, Engineering, Environmental Science, Geography, Geology, Materials Science, Mathematics, and Physics; with Medicine classified as a standalone category given its size. Social Sciences encompass fields like Business, Economics, History, Political Science, Psychology, and Sociology. Humanities cover areas such as Art, Philosophy, Literature, Religion, Music, Theater, Dance, and Film. Some authors did not have "concepts" linked to their work, which prevented classification. Table B.1 summarizes these classifications, showing that half of the authors who posted tweets on political topics have their field of study identified, with a detailed distribution across the broad categories.

E Instructions: Study of general population

Thank you for participating in this survey. Completing it will take about 5 minutes.

This study is part of a scientific research project. More detailed instructions will be provided. This study has received ethical approval, therefore the information you will find in the survey is truthful.

By clicking NEXT you explicitly give us your consent that:
We can collect your anonymous, non-sensitive personal data (like age, income, etc).
We can use this personal data for scientific purposes.
We can store your personal data on our safe-guarded university servers for up to 10 years.
We can make anonymized data available to other researchers online.
You are an American citizen.
You are at least 18 years old.

We promise to protect your data according to the new General Data Protection Regulation (GDPR) laws.

In case you have doubts on the experiment, do not hesitate to contact us.

Paste your Prolific ID:

—- page break —-

In surveys like ours, some participants do not carefully read the questions. This means that there are a lot of random answers that can compromise the results of research studies. To show that you read our questions carefully, please choose both “Extremely interested” and “Not at all interested” below: [Extremely interested, Very Interested, A little bit interested, Slightly interested, Not interested at all]

E.1 Demographics

What is your age? [Dropdown list from 18 to 99]

What is the gender you identify yourself with? [Male, Female, Other]

What is your household's gross income in 2020 in US dollars? [Less than $15,000, $15,000 - $24,999, $25,000 - $49,999, $50,000 - $74,999, $75,000 - $99,999, $100,000 - $149,999, $150,000 - $200,000, More than $200,000]

Which of the following best describes your ethnic identity? [African American/Black, Asian American/Asian, Caucasian/White, Native American, Hawaiian/Pacific Islander, Other, Prefer not to say]

What is your highest level of completed education? [Eight grade or less, Some high school, High school degree/GED, Some college, 2-year college degree, 4-year college degree, Master's degree, Doctoral degree, Professional degree (JD, MD, MBA)]

What is your employment status? [Employed full-time, Employed part-time, Unemployed looking for work, Unemployed not looking for work, Retired, Student, Disabled]

If employed, what best describes your work? [Management/Executive, Professional (e.g., doctor, lawyer, engineer), Clerical/Office/Administrative, Skilled trades (e.g., electrician, plumber), Service industry (e.g., hospitality, retail), Healthcare practitioner/Technical, Education/Training]

Please indicate to what extent you consider yourself religious [Not at all religious, Slightly religious, Moderately religious, Strongly religious, Very Strongly religious]

In which region do you currently reside? [Northeast (CT, ME, MA, NH, RI, VT, NK, NY, PA), Midwest (IL, IN, MI, OH, WI, IA, KS, MN, MO, NE, ND, SD), South (DE, DC, FL, GA, MD, NC, SC, VA, WV, AL, KY, MS, TN, AR, LA, OK, TX), West (AZ, CO, ID, NM, MT, UT, NV, WY, AK, CA, HI, OR, WA)]

In politics, as of today, how do you consider yourself? [Republican, Democrat, Independent]

E.2 Vignettes

You are going to see the profiles of 5 different scientists. These scientists are active in different fields, they have different demographic characteristics and academic affiliations.
You are going to rate how credible you find each of these scientists and how willing you are to read their opinions.
These profiles are hypothetical but it is in your best interest to rate them based on what you really think. In fact, we are going to send to you via message the opinions of a scientist whose characteristics are closest to your highest-rated profile.

[The same structure of the questions will apply for all the 5 vignettes]

The profile you are seeing is a [Gender] scientist. This scientist works in the field of [Research Field]
Currently, this scientist is a [Seniority] at the [University Affiliation].
The scientist is active on X (formerly known as Twitter). The Twitter bio is the following: "[Twitter Bio]". An example of the scientist's post on X is available here: "[Twitter Post]".

How credible do you think this scientist is? [Slider 0-10]

How credible do you think this scientist's own research is? [Slider 0-10]

How willing you are to read an opinion piece from this scientist? [Slider 0-10]

E.3 Intermezzo

You are going to start a new task where you are going to see the profile of an economist. At the end of the task, you will be able to choose to receive a link to access a newsletter via Prolific message. The newsletter discusses several political and social issues in the U.S., based on research of economists similar to the one you will see on the next page.

E.4 Scientist's Profile

E.4.1 Passive Control Bio

The profile you are seeing is a [Gender] economist.

Currently, this economist is [Seniority] at the [Affiliation].

The economist is active on X (formerly known as Twitter). The twitter bio of the economist is: **"Passionate about Research"**

This is an example of a tweet: **"In our research paper, we show that Nash equilibrium uniquely satisfies key axioms across different games, challenging refinement theories. Our findings have implications for zero-sum, potential and graphical games."**

E.4.2 Active Control Bio

The profile you are seeing is a [Gender] economist.

Currently, this economist is [Seniority] at the [Affiliation].

The economist is active on X (formerly known as Twitter). The twitter bio of the economist is: **"Passionate about Research"**

This is an example of a tweet: **"Our latest study in Lancet Global Health provides evidence on the health impacts of hostile environment policies toward migrants: restrictive entry and integration policies are linked to poorer mental and general health, and a higher risk of death."**

E.4.3 Democrat Bio

The profile you are seeing is a [Gender] economist.

Currently, this economist is [Seniority] at the [Affiliation].

The economist is active on X (formerly known as Twitter). The twitter bio of the economist is: **"Passionate about Research and Advocate for Equality (World Globe**

emoji)"

This is an example of a tweet: **"Our latest study in Lancet Global Health provides evidence on the health impacts of hostile environment policies toward migrants: restrictive entry and integration policies are linked to poorer mental and general health, and a higher risk of death."**

E.4.4 Republican Bio

The profile you are seeing is a [Gender] economist.

Currently, this economist is [Seniority] at the [Affiliation].

The economist is active on X (formerly known as Twitter). The twitter bio of the economist is: **Passionate about Research and Proud Patriot [Eagle emoji]**

This is an example of a tweet: **"Our latest study in Lancet Global Health provides evidence on the health impacts of hostile environment policies toward migrants: restrictive entry and integration policies are linked to poorer mental and general health, and a higher risk of death."**

E.5 Outcomes

How credible do you think this economist is? [Slider 0-10]

How credible do you think this economist's own research is? [Slider 0-10]

How willing you are to read an opinion piece from this economist? [Slider 0-10]

——————— page break ———————

You have the opportunity to receive a real newsletter that combines opinion pieces on economic and social issues from economists who are similar to the profile you have seen just now.

This newsletter will be released to you via Prolific message. We will send you the link to access the newsletter. You can express your interest by clicking YES.

There are no costs involved in the newsletter and no subscription is needed.

Would you like to receive the link to the newsletter?[Yes/No]

———————— page break ————————

In general, how much do you trust scientists to find out accurate information about the world? [Extremely, Very, Moderately, Slightly, Not at all]

In general, how much do you trust scientists to do their work with the intention of benefiting the public? [Extremely, Very, Moderately, Slightly, Not at all]

In general, how much do you think that scientists should be involved in the policy-making process? [Extremely, Very, Moderately, Slightly, Not at all]

F Instructions: Survey of journalists

Thank you for participating in this survey. Completing it will take about 5 minutes.

This study is part of a scientific research project. More detailed instructions will be provided. This study has received ethical approval, therefore the information you will find in the survey is truthful.

By clicking NEXT you explicitly give us your consent that:
We can collect your anonymous, non-sensitive personal data (like age, income, etc).
We can use this personal data for scientific purposes.
We can store your personal data on our safe-guarded university servers for up to 10 years.
We can make anonymized data available to other researchers online.
You are at least 18 years old.

We promise to protect your data according to the new General Data Protection Regulation (GDPR) laws.

In case you have doubts on the experiment, do not hesitate to contact us.

Paste your Prolific ID:

—- page break —-

In surveys like ours, some participants do not carefully read the questions. This means that there are a lot of random answers that can compromise the results of research studies. To show that you read our questions carefully, please choose both “Extremely interested” and “Not at all interested” below: [Extremely interested, Very Interested, A little bit interested, Slightly interested, Not interested at all]

—- page break —-

Which best describes your gender?[Male, Female, Non-Binary]

Which of the following best describes your current employment status?[Working full time now, Working part time now, Temporarily laid off, Unemployed, Retired, Receiving benefits or insurance, Taking care of home or family, Student, Other]

In which country do you live?

How many years have you spent in the field?[Less than 1 year, Between 1 year and 3 years, Between 3 years and 5 years, More than 5 years]

For what type of journal/news source do you work?[Daily newspaper/Weekly newspaper/Freelance/Online newspaper/Blog/TV]

What type of role do you have (or you had in your last employment)?[Reporter/Editor/Opinion writer/Columnist]

What is the political leaning of your employer?[Conservative/Liberal/Progressive/Not political]

Where do you place yourself on this scale? [Strongly conservative...Strongly Liberal]

—- page break —-

You will see the profiles of 3 different economists. These economists are active in research and have diverse demographic characteristics and academic affiliations.

You will rate how credible you find each of these scientists and their research, as well as how willing you are to read their opinions.

These profiles are hypothetical, but it is in your best interest to rate them based on your genuine preferences. In fact, we will include the opinions of the scientist whose characteristics most closely match your highest-rated profile in a newsletter about socio-economic issues in the U.S. that will be shared with 100 randomly selected U.S. respondents. If they rate the post you suggest as the highest, you will be entitled to receive a monetary bonus.

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The profile you are seeing is a [Gender] economist.

Currently, this economist is [Seniority] at the [Affiliation].

The economist is active on X (formerly known as Twitter). The twitter bio of the economist is: **"Strongly Dem/Strongly Rep/Neutral"**

How credible do you think this economist is? [0 to 10]

How credible do you think the economist's own research is? [0 to 10]

How willing you are to include an opinion piece from this economist to a newsletter? [0 to 10]

—- page break —-

Please state how much do you agree with the following statements.

A scientist's political stance should be disclosed when their research is reported [Strongly disagree...Strongly agree]

Featuring politically active scientists might affect their newspaper's credibility with its audience. [Strongly disagree...Strongly agree]

You anticipate backlash or increased engagement from their readership if a scientist's political views were prominently featured. [Slider from 0 (mostly backlash) to 100 (mostly engagement)]

Would you be more or less likely to reach out to a scientist for an interview or expert opinion based on the scientist's known political stance? [Extremely unlikely...Extremely likely]

Does an active or political social media presence make you more or less likely to feature that scientist? [Extremely unlikely...Extremely likely]

G Instructions: Survey of scientists

Thank you for participating in this survey. Completing it will take about 5 minutes.

This study is part of a scientific research project. More detailed instructions will be provided. This study has received ethical approval, therefore the information you will find in the survey is truthful.

By clicking NEXT you explicitly give us your consent that:
We can collect your anonymous, non-sensitive personal data (like age, income, etc).
We can use this personal data for scientific purposes.
We can store your personal data on our safe-guarded university servers for up to 10 years.
We can make anonymized data available to other researchers online.
You are at least 18 years old.

We promise to protect your data according to the new General Data Protection Regulation (GDPR) laws.

In case you have doubts on the experiment, do not hesitate to contact us.

Paste your Prolific ID:

—- page break —-

In surveys like ours, some participants do not carefully read the questions. This means that there are a lot of random answers that can compromise the results of research studies. To show that you read our questions carefully, please choose both "Extremely interested" and "Not at all interested" below: [Extremely interested, Very Interested, A little bit interested, Slightly interested, Not interested at all]

—- page break —-

Which best describes your gender?[Male, Female, Non-Binary]

Which of the following best describes your current employment status?[Working full time now, Working part time now, Temporarily laid off, Unemployed, Retired, Receiving benefits or insurance, Taking care of home or family, Student, Other]

In which field do you work?[Arts & Humanities, Life Sciences & Biomedicine, Physical Sciences, Social Sciences, Technology]

How many years have you spent in the field (after your postgraduate studies)?[Less than 1 year, Between 1 year and 3 years, Between 3 years and 5 years, More than 5 years]

What is your current position?[Postdoctoral researcher, University faculty, Industry professional]

For which institute do you work?[University, Research Institute (including public agencies), Private institute, Non profit, Hospital/clinic/facility]

To what extent do you consider yourself religious?[Very religious, Somewhat religious, Moderately religious, Slightly religious, Not at all religious]

Do you consider yourself a Republican, Democrat, Independent, or Other?[Republican, Democrat, Independent, Other, Not sure]

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We conducted a survey with a sample representing the U.S. population, matching broad census characteristics. We measured their trust in scientists, particularly focusing on whether this trust changes when these scientists express political opinions on social media.

The trust level was measured on a scale from 0 (no trust) to 10 (full trust). The sample reported a trust level of 7.2 out of 10 for scientists who do not express political opinions on social media.

What do you think is the reported level of trust for scientists who do express political opinions on social media?

If you guess correctly, you will receive a 0.5 GBP bonus (Use the scale from 0 to 10).

Slider from 0 to 10.

How much do you agree with the following statement?

"Scientists and researchers should avoid expressing their political opinions outside their area of expertise on social media."[Strongly disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, Strongly agree]

"Scientists and researchers should avoid expressing their political opinions about their area of expertise on social media."[Strongly disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, Strongly agree]

Out of 100 scientists and researchers, how many do you think would agree with the statement: "Scientists and researchers should avoid expressing their political opinions outside their area of expertise on social media."? Slider 0-100

Out of 100 scientists and researchers, how many do you think would agree with the statement: "Scientists and researchers should avoid expressing their political opinions about their area of expertise on social media."? Slider 0-100

To what extent do you agree with the statement?

"Expressing political opinions outside own area of expertise on social media can affect public trust in scientists."[Strongly disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, Strongly agree]

"Expressing political opinions about own area of expertise on social media can affect public trust in scientists."[Strongly disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, Strongly agree]

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Have you ever expressed your political opinions outside your area of expertise on social media?[Always, Most of the time, About half the time, Sometimes, Never]

Have you ever expressed your political opinions about your area of expertise on social media?[Always, Most of the time, About half the time, Sometimes, Never]

Do you believe that expressing political opinions on social media outside your area of expertise can impact your professional reputation?[No Impact, Moderate impact, Moderate to Severe impact, Severe Impact, Strong impact]

Do you believe that expressing political opinions on social media about your area of expertise can impact your professional reputation? [No Impact, Moderate impact, Moderate to Severe impact, Severe Impact, Strong impact]

Have you ever hesitated to express your political opinions on social media outside your area of expertise due to concerns about professional repercussions? [Always, Most of the time, About half the time, Sometimes, Never]

Have you ever hesitated to express your political opinions on social media about your area of expertise due to concerns about professional repercussions? [Always, Most of the time, About half the time, Sometimes, Never]

Have you observed other scientists expressing their political opinions outside their area of expertise on social media? [Always, Most of the time, About half the time, Sometimes, Never]

Have you observed other scientists expressing their political opinions about their area of expertise on social media? [Always, Most of the time, About half the time, Sometimes, Never]

Out of 100 colleagues, how many of them do you believe have faced negative consequences for expressing their political opinions outside their area of expertise on social media? Slider 0-100

Out of 100 colleagues, how many of them do you believe have faced negative consequences for expressing their political opinions about their area of expertise on social media? Slider 0-100

Out of 100 colleagues, how many of them do you believe have benefited from expressing their political opinions outside their area of expertise on social media? Slider 0-100

Out of 100 colleagues, how many of them do you believe have benefited from expressing their political opinions about their area of expertise on social media? Slider 0-100

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How much do you agree with the following statement?

"It is ethical for scientists to express their political opinions on social media about their field of expertise." [Strongly disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, Strongly agree]

"It is ethical for scientists to express their political opinions on social media outside their field of expertise."[Strongly disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, Strongly agree]

"There should be guidelines or policies regarding political expression of scientists on social media." [Strongly disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, Strongly agree]

"Scientists have a responsibility to remain neutral and unbiased in their public communications." [Strongly disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, Strongly agree]

"Expressing political opinions on social media can affect the public's trust in scientific research." [Strongly disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, Strongly agree]