CESifo WORKING PAPERS

11254
2024

July 2024

Politicized Scientists: Credibility Cost of Political Expression on Twitter

Eleonora Alabrese, Francesco Capozza, Prashant Garg

CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editor: Clemens Fuest
https://www.cesifo.org/en/wp
An electronic version of the paper may be downloaded
· from the SSRN website: www.SSRN.com
· from the RePEc website: www.RePEc.org
· from the CESifo website: https://www.cesifo.org/en/wp

CESifo *Working Paper No. 11254*

Politicized Scientists: Credibility Cost of Political Expression on Twitter

Abstract

The study measures scientists' polarization on social media and its impact on public perceptions of their credibility. Analyzing 98,000 scientists on Twitter from 2016 to 2022 reveals significant divergence in expressed political opinions. An experiment assesses the impact of online political expression on a representative sample of 1,700 U.S. respondents, who rated vignettes with synthetic academic profiles varying scientists' political affiliations based on real tweets. 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. The penalty varies with respondents' political leanings.

JEL-Codes: A110, C930, D720, D830, D910, I230, Z100, Z130.

Keywords: Twitter, trust in science, ideological polarization, affective polarization, online experiment.

Eleonora Alabrese
University of Bath / United Kingdom
ea2143@bath.ac.uk

Francesco Capozza
WZB Berlin Social Science Center, Berlin
School of Economics / Germany
francesco.capozza@wzb.eu

Prashant Garg
Imperial College London / United Kingdom
prashant.garg@imperial.ac.uk

July 26, 2024
We obtained IRB approval from WZB Berlin Social Science Center number 235. The studies were pre-registered on the platform as.predicted with the number 166935, 179009, and 181452. The University of Bath and WZB financially supported this research. The funders have/had no role in study design, data collection and analysis, decision to publish, or manuscript preparation. We thank Nicolas Ajzenman, Aurelien Baillon, Sacha Becker, George Beknazar-Yuzbashev, Apurav Yash Bhatiya, Abel Brodeur, Anna Dreber, Ruben Durante, Thiemo Fetzer, Andy Guess, Felix Holzmeister, Rafael Jimenez-Duran, Giuseppe Musillo, Andrew Oswald, Tom Palfrey, Barbara Piotrowska, Martina Pocchiari, Andreas Stegmann, and Jean Tirole. The authors declare no competing interests.

1 Introduction

In an era of "post-truth", trust in science stands as a cornerstone for informed decision-making and effective public policy (McIntyre 2018, Bursztyn et al. 2023, Simonov et al. 2020, Ash et al. 2024). The COVID-19 pandemic has starkly highlighted this reality, illustrating how confidence in scientific expertise shapes public health responses (Algan et al. 2021, Bartoš et al. 2022, Bowles et al. 2023), while skepticism can lead to the adoption of unverified remedies, as seen in contexts like Argentina (Calónico et al. 2023). Similarly, doubts regarding climate change within certain societal groups hinder progress toward environmental goals (Druckman and McGrath 2019). However, in recent years, there has been a troubling erosion of trust in scientific authority (Nichols 2017). This skepticism extends beyond these domains, impacting economic development, education, and broader societal trust.

Factors fueling anti-science sentiments include misinformation (West and Bergstrom 2021, Roozenbeek et al. 2020), historical shortcomings (Scharff et al. 2010), the "reproducibility crisis" (Hendriks et al. 2020), conspiracy theories (Rutjens and Većkalov 2022, Douglas 2021), and science-related populism (Mede and Schäfer 2020, Mede et al. 2021), posing a significant challenge to the epistemic authority of science. Political polarization exacerbates these concerns. Conservatives and right-leaning individuals, in the U.S. and other countries, exhibit lower trust in scientists, hold stronger anti-science attitudes, and express low confidence that scientists act in the public's best interest, provide benefits to society, and apply reliable methods (Mede 2022, Funk et al. 2020, Li and Qian 2022, Azevedo and Jost 2021).

Given the increased dissemination of scientific content online, this study explores the evolving role of social media in shaping public perceptions of scientific credibility. We explore whether such political expressions polarize audience perceptions, showing evidence of both *ideological* polarization (divergence in political views or issue positions) and *affective* polarization (dislike for the partisan outgroup) (Lelkes 2016, Barberá 2020). Our central question is: *Do scientists express polarized political opinions on social media, and if so, does this public political expression impact public perceptions of their credibility?*

Our findings reveal three insights into the evolving dynamics of scientists' online engagement and its implications. First, we note a significant rise in the online dissemination of scientific research between 2011 and 2020, particularly on social media. This trend, reflected across various metrics from Altmetric data,[1] encompasses a comprehensive search of published papers in renowned general interest and life science journals and highlights the growing importance of social media as a channel for scientific communication. While the rise in social media use overall may contribute to this trend, our data suggests a significant increase in the presence of scientific content online.

Building on this observation, our analysis extends the descriptive work of Garg and Fetzer (2024) to explore the extent of polarization and issue disagreement in online discourse among scientists. We find that 44% of a sample of 97,737 U.S. academics on Twitter have expressed political opinions —they have made at least one non-neutral post on any of our salient topics in the period from 2016 to 2022— compared to 7% of the general non-academic Twitter user base. We document significant ideological polarization among academics on five politically salient topics.[2] We also show the evolution of issue disagreement across academics. Racism is an issue where disagreement among academics is increasingly greater than disagreement between the general public.[3]

The advantage of measuring scientists' ideological polarization via Twitter is threefold. First, we can analyze a large sample of academics across disciplines, providing a comprehensive view. Second, by examining specific topical political issues, we offer a multidimensional perspective beyond the traditional left-right spectrum. Third, our approach avoids reliance on survey classification or authors' published work, which may not be readily accessible to the public. Instead, publicly accessible social media timelines of academics better reflect the public audience's potential exposure.

To study the implications of scientists' online political engagement on public perception, we conducted an online experiment. This experiment assessed the impact of online

[1]Recent work on the visibility of scientific retraction used Altmetric to track the online dissemination of scientific articles across platforms(Alabrese 2022, Peng et al. 2022).

[2]These topics were originally selected from a set of politically salient issues as mentioned in Pew Research (survey link). The issues considered are: (i) abortion rights, (ii) climate action, (iii) immigration, (iv) income redistribution, (v) racial equality.

[3]This trend of increased political activism among scientists has been anecdotally documented in relation to the March for Science (Russell and Tegelberg 2020, Campbell et al. 2023).

political expression by presenting a representative sample of 1,700 U.S. respondents with vignettes featuring synthetic academic profiles varying the scientists' political affiliations based on real tweets. Our findings reveal a significant 'credibility penalty' for scientists engaging in political discourse. Scientists on both the 'left' and 'right' of the political spectrum experience a monotonic penalty when displaying a political affiliation. This penalty manifests as reduced public perception of credibility for both the scientists and their work, as well as decreased public willingness to engage with scientific content.

Regarding additional attributes, the gender of a scientist does not affect public perceptions, while those affiliated with high-ranked institutions or senior scientists are considered more credible. Importantly, political affiliation is the most salient attribute affecting perceptions of scientists. These perceptions vary considerably depending on the partisan affiliations of their audience, with scientists perceived as part of the political outgroup regarded as particularly less credible. This result aligns with Garcia-Hombrados et al. (2024), who found that Spanish policymakers are less willing to implement policies suggested by think tanks from opposing political ideologies.

In an additional experimental task, we disentangle the effect of tweeting about a politically salient topic from signaling direct political affiliation on the credibility of a scientist (in this case, an economist). Both the communication of politically salient research and the pure signal of political affiliation affect public perceptions. Specifically, we find that Democrats perceive higher credibility for economists and their research when exposed to politically aligned research (compared to non-politically salient research), especially when coupled with a congruent political signal, and lower credibility with an opposing signal. Republicans exhibit significantly reduced perceived credibility when exposed to misaligned politically salient research (relative to the non-politically salient benchmark), particularly when the economist has a left-leaning signal, though less so with a right-leaning signal.

Finally, we surveyed an international sample of 128 scientists recruited on Prolific and asked them about their perceptions regarding the political expression of academics on social media. First, scientists anticipate a penalty in overall trust among the public for academics expressing political opinions on social media, and they even overestimate

this penalty compared to our experimental findings. Second, scientists perceive that expressing political opinions on topics related to their expertise is more socially acceptable than expressing opinions on topics outside their field of expertise. They also believe that this view is shared among other scientists. On average, the scientists anticipate net reputational costs for publicly expressing political opinions outside their field and net reputational benefits for expressing political opinions within their own field.

Drawing from the Mertonian norm of Universalism (Merton 1973), which advocates for evaluating scientific work on its merits rather than the scientist's identity, our findings reveal a significant challenge. Mertonian Universalism, rooted in Plato's discussions on rhetoric differentiating ethos (the scientist), logos (the work), and pathos (persuasion), suggests that work should be assessed independently of the scientist (Cooper et al. 1997). However, our study shows that political expression by scientists impacts both their personal and perceived scientific credibility. In an era of declining trust in scientific expertise, understanding factors shaping public perceptions of scientists' credibility is vital. Our findings call for reassessing science communication strategies to maintain credibility, considering how online political engagement might affect the accessibility of scientific information and influence decision-making.

Contribution to the Literature Our findings enrich discussions on public perceptions of scientists and the credibility of their communication (Blastland et al. 2020). Existing work focuses particularly on how uncertainty and political transparency in scientific communication impact public trust (Van Der Bles et al. 2019, 2020, Petersen et al. 2021). Previous research has also explored the ramifications of political endorsements by scientific publications on public confidence, noting that such endorsements can significantly polarize perceptions, as shown in the differential impacts of *Nature*'s political endorsement on Trump and Biden supporters' trust in the journal itself and the broader scientific community (Zhang 2023). Kotcher et al. (2017) examined the effects of climate scientists' advocacy on their credibility through a Facebook-based experiment, and found that credibility remained high across various advocacy conditions except when supporting nuclear power, with no significant impact on trust in the broader scientific

community. In contrast, our findings suggest that political commentary on social media broadly impacts scientists' credibility across disciplines.

More broadly, we contribute to the literature that studies the communication (or lack thereof) of politically salient topics in the U.S. offline (Braghieri 2021) and online (Bursztyn et al. 2023) in terms of the decision to express politically controversial opinions and their downstream consequences. In particular, we study the social media communication patterns of U.S. based scientists, especially in terms of politically salient topics, and its consequences among the public.

We build upon research that explains polarized trust in scientists through a political stereotype approach (Altenmüller et al. 2024), which uses Twitter to highlight how people across the political spectrum hold stereotypes about scientists' political orientation and the influence of these stereotypes on their trust in science. This insight aligns with our findings on the impact of scientists' partisanship on their perceived credibility and the public's willingness to engage with their content. In this work, we directly measure the actual political expression of scientists on social media and causally identify the impact of scientists' online communication on people's perceptions.

We contribute to the literature measuring ideological stances and political views using text-as-data such as official documents and minutes (Ash 2016, Hansen et al. 2018, Grimmer 2010), online news (Cagé et al. 2020), political speeches (Jensen et al. 2012, Gentzkow et al. 2019), papers (Jelveh et al. 2024), and survey data (Draca and Schwarz 2024). We use measures of academics' political expression using Twitter data from 100,000 U.S. based academics constructed by (Garg and Fetzer 2024), who describe patterns in academics' expressions globally. They show that these expressions often diverge from general public opinion in both topic focus and style. Additionally, they highlight the divergence between academics with high public reach and those with significant academic impact, noting that public narratives can be skewed by the former group, with implications for public perceptions of academia. Our study builds on this by studying some of those implications. We focus on the U.S. sample, employ the same granular dataset, and extend the text-analysis measures (topic detection and stance detection) developed in their research. We provide a systematic analysis of ideological polarization

and issue disagreement among U.S. scientists on social media. We extend these insights by causally estimating the impact of scientists' political expressions on social media, demonstrating how this can undermine credibility and contribute to the formation of echo chambers, especially among audiences with strong partisan identities (Kahan et al. 2011).

We also connect to the literature on ideological polarization and on affective polarization by characterizing scientists' political affiliation using vignettes with synthetic experimental profiles, measuring its impact on public credibility and engagement. Crucially, the perceived political affiliation of scientists is identified through real high-engagement tweets. Our identified impact of scientists' online political expression aligns with broader patterns of ideological and affective polarization in the U.S. and documents the emerging echo chambers that can further polarize public views (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 2024a). By demonstrating the impact of scientists' perceived partisanship on their public credibility and the public's willingness to engage with their content, our findings emphasise the complex relationship between scientific communication and societal perceptions. This highlights the need for strategies that mitigate polarization while enhancing the visibility and influence of scientific discourse in society.

While our study is not a real-time Twitter experiment, it relates to recent experimental work on Twitter evaluating which interventions are more effective in reducing the spread of fake news, toxic speech, and discrimination (Guriev et al. 2023, Jiménez Durán 2021, Beknazar-Yuzbashev et al. 2022, Angeli et al. 2022, Ajzenman et al. 2023a,b). Additionally, our research is relevant to the broad literature on the political effects of the internet and social media, which discusses how these platforms impact voting, protests, political polarization, and the spread of misinformation (see Zhuravskaya et al. 2020, for a review). However, we focus on the specific impact of scientists' political expressions on social media.

2 Scientists' Political Posts and Ideological Polarization

Drawing upon data from the Scopus library, we first examine over 100,000 scientific articles published between 2011 and 2020 in general interest journals and track their online mentions via Altmetric.[4] Altmetric is a service that most extensively tracks the online dissemination of scientific articles across platforms (Alabrese 2022, Peng et al. 2022). Notably, there has been a consistent rise in online appearances of scientific publications across various media platforms, signaling a growing trend of scientists engaging with broader audiences beyond traditional academic circles. Figure 1 illustrates these trends, revealing a steady increase in online coverage across blog posts, newspaper articles, and Twitter. Particularly noteworthy is the substantial rise in Twitter mentions, with over 96% of published papers being referenced on the platform (for more details, see Appendix Section C). This surge underscores the growing significance of Twitter as a medium for scientific communication and dissemination.

2.1 Sample of academics on Twitter

Amidst the surge in online engagement, there is discernible evidence of ideological polarization within the scientific community's discourse on Twitter. We analyzed trends in politicization and ideological polarization among 97,737 U.S. academics on Twitter from 2016 to 2022. The sample of academics was derived from Mongeon et al. (2023), who matched authors from OpenAlex with Twitter users identified in Crossref Event Data. Garg and Fetzer (2024) collected the Twitter timelines and OpenAlex data post-merge and employed large language models (LLMs) to process these timelines for topic detection and stance labeling.[5] This sample consists of a researcher's OpenAlex identifier matched to their Twitter/X user identifiers with a high level of precision and moderate recall. OpenAlex builds upon Microsoft Academic Graph and provides data on a researcher's publications, citations to the publications, affiliations listed on the publica-

[4] A total of 114,868 scientific articles from journals such as *Science*, *Nature*, *PNAS*, *Cell*, *NEJM*, and *Lancet* were retrieved. Of these, 107,008 were tracked by Altmetric (accessed on November 10, 2021).

[5] The underlying full-scale individual-by-time-level measures data are available at https://www.academicexpression.online/data-download.

tion, co-authors, fields and concepts each publication covers, and other academic data. The Twitter data contain full timelines generated by the academics, including (1) original posts (tweets), (2) shared posts from others (retweets), (3) quoted retweets, and (4) comments (replies). In this section, any mention of tweets will refer to all four types of tweets mentioned above.

The timelines of the academics were processed by Garg and Fetzer (2024) using large language models (LLMs) to retrieve the topics mentioned in the tweets and to detect the stance of the tweet authors towards the topic. For instance, the method detected whether a tweet is about "Abortion Rights" and whether the tweet is in favor (pro), against (anti), or neutral towards Abortion Rights. We focus on five topics that are salient in U.S. political debates: abortion rights, climate action, racism, immigration, and income redistribution. This approach enables a deeper understanding of the diverse political stances of academics, transcending the traditional left-right spectrum. The use of LLMs is important in enabling efficient and accurate large-scale labeling of millions of tweets. The method is described in detail in Appendix Section D.

Appendix Table B.1 provides 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). Around 44% of our full sample of academics ever talked about one of the topics of interest during the period of observation.

Focusing on these *politicized* scientists who have expressed an opinion for or against any of these topics, we show the distribution across four categories of citations representing different levels of academic recognition.[6] The proportion of politicized scientists remains consistent across different cutoff levels, ranging from 41% to 46%. There are some differences in the field of the authors. Those belonging to the humanities or social sciences tend to be more politicized (58% and 65%, respectively) compared to those in

[6]This classification was chosen because, in our sample, the 25th percentile of citation count was 36, the median was 190, the mean was 1205, and the 75th percentile was 849. We see that the shares do not vary significantly across this sub-population either.

STEM or medicine (42% and 38%, respectively). In terms of gender, female scientists are more likely to be politicized (50%) compared to their male counterparts (40%).

2.2 Politicization of academics on Twitter

Figure 2 shows trends in the politicization of conversations by academics and general users on Twitter from the beginning of 2016 to the end of 2022. The figure plots the monthly aggregated scatter plots of expressed stances for each topic. To aid visual detection of trends, we also apply locally estimated scatterplot smoothing (LOESS) using a span of 0.5. The standard errors are depicted in the shaded region. In the panel titled "All," we see that around 40% of the 97,737 tracked US academics expressed an opinion on any of our predefined political issues. Using a dataset of approximately 100,000 US general users described in Garg and Fetzer (2024), Garg and Martin (2024b), we find around 7% of individuals expressed a political opinion in a given time period. Contrasting the expressed stances of academics to those of a random set of US users, this figure reveals significant gaps in political expression between these two populations.

To explore this further, we break the overall trend down by topic. We observe significant variation in trends and spikes across topics. The topics with the largest gaps throughout the sample period are Climate Action and Racism. For Climate Action, there was a significant decline during the onset of the COVID-19 pandemic. Mid-2020 was a rallying moment on Racism for both academics and the general population, reflecting the outcry against racial intolerance after the George Floyd incident. For the remaining topics, we find a somewhat stable increasing trend. Topics like Abortion Rights and Immigration occasionally see sudden spikes, which are generally short-lived. This is more so for Abortion Rights, with the most recent spike occurring around the change in Abortion Laws in 2022. For Immigration, the spikiness has reduced in magnitude but maintained its regularity. There was a large focus on Immigration during the 2016 presidential election.

2.3 Patterns by gender and discipline

We examine how the proportion of academics discussing political topics varies according to their gender and field of study. We obtained data on the gender of academics from Garg and Fetzer (2024), who 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 as Male or Female. Using this binary classification of gender, we can explore sub-population differences in political expression. This is displayed in Figure A.1 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 Racism. Most statistically significant differences occur post-2020 (when confidence intervals overlap the least). The topics Climate Action and Income Redistribution display the least differences.

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 in total." OpenAlex classifies each work with a high level of accuracy.[7] We combine the 19 root level concepts into 4 broad categories for ease of comparison: (1) Medicine, (2) Social Sciences, and (3) STEM.[8] Each work by an author can belong to multiple concepts, with a score from 0 to 1 given to each concept, where values closer to 1 reflect the likelihood that 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 identify the primary concept of that academic as the root-level concept with the highest average score. Figure A.2 depicts the proportion of academics within each concept category that express an opinion about a political topic. We find differences in trends and spikes between the four categories. In the overall trend, we see similarities in the dynamics across the broad fields. On differences, STEM scientists are more supportive of Climate Action, while

[7] More details can be found at https://docs.openalex.org/api-entities/concepts

[8] (1) Medicine consists of itself. (2) Social Sciences include Business, Economics, History, Political science, Psychology, Sociology. (3) STEM includes Biology, Chemistry, Engineering, Environmental science, Geography, Geology, Materials science, Mathematics, Medicine, Physics. Humanities include Art, Philosophy, Literature, Religion, Music, Theater, Dance, Film. Note we remove Humanities from this plot given that we have around 100 academics, which makes the dynamics noisier.

Social Scientists are more supportive of Income Redistribution. Likewise, this result contrasts people's stereotypes about the politicization of the scientists (Altenmüller et al. 2024). Considering the apolitical nature of publications in STEM and Medicine, it is important to explore the implications of scientists engaging in political discourse.

2.4 Mentions of Politicians and Scientific Research in Academic Tweets

We examined the yearly distribution of tweets by academics from 2016 to 2022, focusing on mentions of politicians, research papers, and other content. Figure A.3 illustrates this distribution, with each bar representing the total percentage of tweets for a given year. The colors indicate the categories: blue for tweets mentioning politicians, green for tweets mentioning research papers, and grey for other tweets. Within these categories, darker shades highlight tweets that discuss one of the five salient political topics: Abortion Rights, Climate Action, Racism, Immigration, and Income Redistribution. Overall, around 10% of tweets mention politicians, and approximately 30% mention research papers. This is consistent with the cross-sectional summary statistics provided in Table B.2, where the full sample shows 8.6% of tweets mentioning politicians and 19.2% mentioning research papers. The proportion of topical tweets, focusing on the five salient topics, shows higher engagement with 16.0% mentioning politicians and 28.9% mentioning research papers.

The visualization reveals that the proportion of tweets mentioning politicians and research papers remains relatively stable across the years, with notable spikes reflecting significant political or scientific events. For example, the spike in 2016 can be attributed to the US presidential election, which heightened political discourse. Similarly, the spikes in 2020 correspond to the George Floyd incident, leading to increased discussions on racism, and the COVID-19 pandemic, which prompted more tweets related to scientific research. Notably, Climate Action tweets frequently mention research papers (44.5%), possibly due to the high level of scientific discourse surrounding environmental issues.

2.5 Ideological Polarization of Academics on Twitter

Given the substantial gaps in political expression between groups, it is important to document ideological polarization—defined as the net stance in political views or issue positions among individuals. To measure this, we first classify the scientists' tweets into three discrete categories: "pro," "anti," and "neutral." We follow the theoretical approach of Esteban and Ray (1994). The net stance for a user in a given month is defined as the number of pro-stance tweets minus the number of anti-stance tweets, divided by the total number of political tweets (pro, anti, or neutral) posted by that user during the month. This is expressed by the equation:

$$S_{um} = \frac{pro_{um} - anti_{um}}{pro_{um} + anti_{um} + neutral_{um}} \tag{2.1}$$

Here, S_{um} represents the proportion of tweets about a topic that exhibits a net pro stance by user u during time-period m relative to all tweets about that topic by the same user. The numerator quantifies the tweets expressing a net pro stance within a specific time frame. This continuous measure ranges from -1 (completely anti) to 1 (completely pro) at an author-by-time level.

Our method effectively highlights the range of opinions from strong opposition to firm support on issues such as climate action. It sensitively distinguishes between moderate and extreme pro-climate action stances, which is crucial in environments where public opinions may skew towards prosocial expressions (Bénabou and Tirole 2006).

Building upon our analysis of scientists' politicization, we investigate the potential disagreement in publicly expressed views of academics. In Figures 3 and A.4, we explore the distribution of academics' political net pro stances S_{um} for each year and topic. Figure 3 shows the distribution of net pro stances for each political topic over the entire period from 2016 to 2022. The presence of multiple peaks—excluding multimodal distributions using Hartigan's Dip Test (Hartigan and Hartigan 1985)—in each of the presented distributions suggests distinct ideological camps, indicating significant polarization. Appendix Figure A.4 compares yearly topic distributions. We also test the equality of two early and late distributions (specifically 2016-2017 vs. 2021-2022) using the Kolmogorov-

Smirnov (KS) test to highlight changes in stance distribution over time (Massey Jr 1951). The analysis suggests shifts in opinions over time, particularly on topics like Immigration and Abortion Rights, underscoring the dynamic nature of ideological polarization among academics. These figures complement the variance-based analysis in the next paragraph by providing a disaggregated view of how political stances are distributed and how they evolve, emphasizing both the extent and nature of polarization in the academic community.

2.6 Disagreement among Scientists across Political Stances

The variance of S_{um} across all users in a given month reflects the disagreement of political opinion expressed on a given topic, providing a continuous measure of disagreement for each topic. Using variance allows us to focus on the spread of opinions without being influenced by the average stance, making it exceptionally responsive to extreme positions which are our primary interest. Furthermore, this measure facilitates comparative analysis across different topics and time periods (McCarty et al. 2016).

We chose variance due to its ability to capture broad trends across a large dataset, and suitability for longitudinal and cross-topic comparisons. While variance offers transparency and is easily comprehensible, making our research accessible to a broader audience, it also has limitations. Using a single metric might not fully capture the reasons behind observed disagreement but does not explore the underlying causes or debate quality (Fiorina et al. 2005). Also, being sensitive to extreme views might sometimes exaggerate the perception of disagreement if only a few hold extreme positions. Moreover, this approach may not directly highlight areas of consensus, which could provide additional insights into the group's ideological stance (Hopkins 2018). However, we can address part of this concern in a relative manner since we have time and topic variation in our measure: lower variances can imply higher consensus on certain topics or during specific time periods, relative to other topics or time periods. This allows us to identify not only divisions but also points of agreement that emerge among different topics or for the same topic over time, thus offering a more comprehensive view of the ideological

landscape in academia.

Aggregating all topics yields an overall measure of political disagreement, as shown in the panel titled "All" in Figure 4. Similar to the increasing trend in the expression of opinion, we see an increase in political disagreement observed between 2016 and 2022. This raises concerns about its potential impact on scientific consensus-building and public trust in scientific expertise. The rest of the figure breaks it down by topic. We find large variations across topics. Generally, the general population of US Twitter users tends to show more disagreement than academics, except on the topic of Race, where academics display an increasingly wider debate amongst themselves, relative to the debate amongst the general population. Given that Race is the most frequently discussed political topic among academics and general users alike, this disproportionately affects the overall trend in the panel "All". On the rest of the topics, we see more ideological disagreement across the general public, with that gap widening the most around the pandemic period for topics Immigration, Income Redistribution, and Abortion, but also closing around the end of 2022. For Climate Action, the gap persists throughout the sample period and has only grown at the end of 2022.

3 Scientists' Political Expression Hurts their Credibility: Experimental Evidence

To investigate the impact of scientists' politicization on their perceived credibility, we conducted a conjoint experiment with 1,704 respondents from a representative sample of the US population recruited on the online platform Prolific, which is widely used to conduct experimental research (Bursztyn et al. 2023, Enke et al. 2023). The methodology of the conjoint experiment follows what is usually recommended in the literature (Hainmueller et al. 2015). The sample adequately represents the U.S. general population across dimensions of political affiliation, region, ethnicity, and gender. The sample is broadly representative of the general population along income (our respondents have higher income than the population), along age (the sample is slightly younger than the general

population), and education (the sample is slightly more educated than the general population). Table B.5 shows the representativeness of the sample. All the respondents that we have surveyed had to pass an attention check.

3.1 Experimental Design

We created 5 hypothetical vignettes and exposed them to the respondents. Table B.6 provides a summary of the characteristics of the vignettes. These vignettes presented the description of scientists, with variations in attributes including gender (male and female), research field (Social Sciences, STEM, Medicine, and Humanities), seniority (senior and junior), university affiliation (high-ranking universities and low-ranking universities), and their inferred political affiliations. Specifically, the key attribute of interest was the political affiliation (or lack thereof) of the scientists, categorized as Strongly Democrat, Moderately Democrat, Neutral, Moderately Republican, and Strongly Republican. We signaled the affiliations of the scientists by adding a biographic description that resembles those found on Twitter as well as a high-engagement tweets in order to increase the external validity of the treatment manipulation. All the tweets cover topics that are related to scientific content but they do not discuss a specific research paper. These profiles were generated by randomizing the existing characteristics of real scientists. All the vignettes follow the same structure and we randomize the order in which we display the vignettes at the individual level (see Figure A.5 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 is the following: "[**Twitter Bio**]".*
> *An example of the scientist's post on X is available here: "[**Twitter Post**]".*

Participants were then asked to rate the credibility of these scientists, their research and indicate their willingness to read an opinion piece from scientists with similar char-

acteristics.[9] To incentivize the respondents, they were informed that they would receive an opinion piece from an actual scientist whose characteristics matched their most-voted scientific profile, This methodology, designed to prevent deception, follows the approach outlined by Kessler et al. (2019).

Our design addresses common concerns in conjoint experiments (Hainmueller et al. 2015), especially on profile-order effects and experimenter demand effects. To mitigate profile-order effects, we positioned the attribute of primary interest, political affiliation, at the bottom of the page. To minimize experimenter demand, we highlighted other salient profile dimensions and provided incentives by informing respondents they would receive opinions from a real scientist resembling their top-rated profile. The full set of instructions can be found in Appendix Section E.

The experimental design comprised 160 unique profiles, derived from 2 (gender) X 4 (field of study) X 2 (seniority) X 2 (institutional affiliation) X 5 (political affiliations) factorial combinations. Using a clustered bootstrap procedure that resamples respondents with replacement, we estimated a minimum detectable effect size of 0.05 of a standard deviation at 99% power in our main specification and a significance threshold of 5%.

3.2 Validating Twitter political signals

We successfully validated our classification of Twitter political signals by conducting a survey with 98 new participants on Prolific, who were asked to classify each political signal (the combinations of the Twitter bios and tweets used in the main experiment) into one of five categories ranging from Strong Republican to Strong Democrat.

Figure A.6 illustrates the results of this validation exercise. Each subplot represents one of the intended political signals, with the bars indicating the frequency of each classification by the new respondents. The results demonstrate that most respondents accurately perceived the political Twitter signals as intended. For each intended signal, the highest frequency of responses corresponds to the correct label, affirming that

[9] Hainmueller et al. (2015) show that the estimates of treatment effects using single vignettes and paired vignettes are usually identical. Therefore, we implemented the approach less cognitively demanding for the respondents.

the majority of participants correctly identified the political orientation of the signals. Additionally, the second most frequent classifications also show a significant number of respondents choosing the next closest category, further supporting the robustness of our intended classifications. The high accuracy in respondents' perceptions confirms the effectiveness of our initial categorization and reinforces the validity of the signals used in the main experiment.

4 Impact on perceived credibility and willingness to read

Figure 5 demonstrates a monotonic penalty that scientists face due to online political expression. The drop in credibility and willingness to read increases as their political affiliation becomes stronger. Scientists who display political stances are on average perceived to be less credible than scientists who have neutral stances (Panel A, light shades). This result is in line with the stereotype about scientists that they should be impartial and not politicized (Altenmüller et al. 2024). This credibility penalty is larger for scientists with strong signals of political affiliation, demonstrating a clear monotonic trend. Strongly Republican scientists are 39% less credible than neutral scientists, whereas Strongly Democrat scientists are 11% less credible than neutral scientists. Moreover, Moderately Republican and Moderately Democrat scientists are respectively 9% and 7% less credible than neutral scientists.

Respondents are on average less willing to read the opinions of scientists displaying political stances (Panel A, dark shades). Similarly, respondents are 42% less willing to read opinions from a Strongly Republican scientist and 10.7% less willing to read opinions from a Strongly Democrat scientist, relative to a neutral scientist. Furthermore, respondents are less willing to read from Moderately Republican and Moderately Democrat scientists by respectively 8% and 4.5% than neutral scientists. Both results are robust to the inclusion of control variables of the respondents (Figure A.7, Panel C and D).

Figure A.7 (as well at Tables from B.7 to Table B.9) documents that some additional attributes of the scientists causally affect the respondents' perceived credibility of the scientists and their research, as well as the respondents' willingness to read an opinion

piece from the scientists. In particular, scientists with high affiliation (affiliated with Harvard University, UC Berkeley, and UChicago) are perceived to be more credible and are more likely to be read than scientists with low affiliation (University of Arkansas, University of Connecticut). When focusing on each scientist's political affiliation individually, high affiliation matters for all except the politically-neutral scientist, while profiles with prestigious affiliations are penalized in the case of a Strong Republican profile. Similarly, seniority plays a role, as Full Professors are often perceived to be more credible and more likely to be read than Assistant Professors. Surprisingly, the gender of the scientist does not impact respondents' perceptions; however, male scientists are less likely to be read in the case of a Neutral political affiliation.

4.1 Heterogeneity by respondent political leaning

The results in Figure 5 reveal significant heterogeneity in terms of the respondents' political affiliations, illustrating a clear pattern of affective polarization. Respondents who report being *Democrat* or *leaning towards Democrats* perceive Republican-leaning scientists as less credible than Democrat and neutral scientists. In this case, Moderately Republican scientists experience a 18.3% penalty in credibility and Strongly Republican scientists a 60% penalty in credibility (Panel B, dark blue). The respondents are also 23.2% less willing to read the opinions of Moderately Republican scientists and 69% less willing to read those of Strongly Republican scientists (Panel B, light blue). This demonstrates that stronger Republican stances result in greater penalties from Democrat-leaning respondents.

Conversely, respondents who report being *Republican* or *leaning towards Republicans* perceive Democrat scientists as less credible, with a penalty of 16% for Moderately Democrat scientists and 26% for Strongly Democrat scientists (Panel B, dark red). Moreover, these respondents are 18% to 30% less willing to read from them relative to scientists with neutral stances (Panel B, light red). Here too, stronger Democrat stances lead to greater penalties from Republican-leaning respondents.

Interestingly, scientists with Moderate Republican stances are considered 3.1% more

credible than neutral scientists and 11.6% more likely to be read by Republican respondents. This asymmetric pattern seems to mirror the key result from González-Bailón et al. (2023), where conservatives are more likely to end up in an information bubble. Republican respondents find Strongly Republican scientists 12% less credible than neutral scientists but still more credible than Democrat scientists. A similar pattern emerges for their willingness to read, where Republican respondents are 7% less willing to read the opinions of Strongly Republican scientists.

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

4.2 Robustness Checks

We have conducted a replication exercise with 2,000 respondents on Prolific where we tested the robustness of the elicitation procedure as well as a set of robustness checks to probe the identification assumptions and the estimation procedures used in the analysis. All the additional tests that we have conducted fully confirm our main findings.

Replication We replicate the results of our main experiment with another 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. The aim of this replication was to assess the robustness of our findings with respect to the elicitation procedures. Figure A.8 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 number of outcomes that are elicited.

Carryover Effects An important identification assumption is the stability or the avoidance of carryover effects across different choices in our experimental design. Non-stable effects across choice tasks would suggest that respondents value a particular degree of,

say, the political affiliation of the scientist in a certain task more or less depending on what type of profiles they have seen before or after that particular profile. While such effects are unlikely given the randomization of profiles across experimental rounds, we still took some actions to rule out these effects. We regressed respondent answers for each profile individually taking into account the order in which the profiles are displayed to the respondents. Our results in Figure A.9 are very similar across all rounds suggesting the absence of carryover effects across profiles, which alleviates the concerns of the validity of our measurement.

Excluding 'Speeders' One concern of online experiments is that the respondents do not pay enough attention to the task and they rush through it which leads to a more noise in the data. To rule out the concern that our results are driven by 'speeders', we repeat the same steps of the main analysis after excluding those respondents who have spent less than 1 minute on the survey (the median completion time was 7.2 minutes). Figure A.10 confirms that the main results are virtually unchanged with respect main specification and are robust to the exclusion of 'speeders'.

Heteroskedasticity-Robust Standard Errors We assess the robustness of our estimates to changes in the estimation procedures by correcting the standard errors to make them robust to heteroskedasticity. We repeat the estimation procedure of the two main regressions without controls using standard errors robust to heteroskedasticity. Table B.11 shows that the results are unchanged with this change in the specification.

Permutations Test Another concern is that we estimate the effects of the political affiliation on credibility and willingness to read relative to a baseline level which is a 'neutral' scientist. It could be that the neutral scientist is not perceived to be neutral but signalling a political identity. If this was the case, then we would find an effect of the political affiliation on our outcomes of interest when we would randomly assign the different labels of political identities in our vignettes. To address this concern, we performed a permutation test. First, the five labels are randomly re-shuffled across profiles

within each respondents. Second, we run the regressions with the mis-labelled dummy variables and we store the coefficients of these regressions. Third, we repeat the procedure 100 times. Figure A.11 shows that randomly mislabelling the political identity of the scientists leads to regression coefficients smaller than our main model, which rules out this presence of this concern.

Multiple Hypothesis Testing An important feature of a conjoint experiment is to allow the test of several hypotheses, as many as the levels of the attributes, at the same time. This feature might raise concerns that our results do not survive to multiple hypothesis testing correction. We repeat the estimation procedure of the two main regressions without controls after correcting the p-values for multiple hypothesis testing ('false discovery rate'). To do so, we apply the methodology proposed by Benjamini et al. (2006). According to this procedure, we will correct for 11 treatments, which are 16 attributes of the profile of the scientists minus 5 baseline attributes. Table B.12 reports the estimates with the corrected p-values, which are still significant at the same significance level.

4.3 Mechanisms

Scientists may signal their political views while discussing their own research or expressing opinions beyond their expertise. In this section, we ask: is tweeting about a politically salient research topic or signaling one's political identity driving the effect on audience perception of scientists' credibility? To investigate this question, we conducted an additional experimental task after showing the respondents five different synthetic profiles (the conjoint experiment above).

In this task, we presented respondents with an additional profile of an economist. We selected an economist as our example because this discipline often covers politically salient issuesWe cross-randomized our respondents into four different experimental conditions, varying whether the economist describes their recent publication on a politically salient issue (or not) while providing (or not) a clear left or right-leaning signal. Crucially, we hold expertise constant across treatments as these economists talk about topics in their field of expertise.

Specifically, we have two control groups: an active control and a passive control group. In the *active control* group, the economist has no clear political signal and posts about their new research on the negative impact of policies on migrants' health (a politically salient topic favorable to a left-leaning narrative).[10] To further benchmark our estimates, in the *passive control* group, the economist has no clear political affiliation and posts about their research on economic theory (a non-politically charged topic). Additionally, we have two treatment conditions where we manipulate the political identity of the economist via their Twitter bio: either *Left* ("advocate for equality") or *Right* ("proud patriot") (see vignettes in Figure A.12). In both the Left and Right treatment conditions, the economist posts about their politically salient research (as in the active control group).

After showing the economist profile according to one of the four experimental conditions, we then elicited how credible respondents perceived the economist and their research to be, and whether they were willing to read an opinion piece from the economist. Finally, we asked respondents if they wanted to join a newsletter discussing socioeconomic issues in the U.S., featuring opinion pieces from economists similar to the one they had just seen. We mentioned that the newsletter could be joined at no cost, with no subscription required, and they could receive it directly via Prolific message (see Chopra et al. (2024) for a similar approach). We concluded the experiment by measuring respondents' overall trust in scientists with three Likert scale questions, which we averaged into an index.

Figure 6 shows the result of this experimental task. Looking at the top left panel, we find that Democrats show higher perceived credibility of economists and their research when exposed to politically aligned research (with respect to non-salient research). The left political signal further improves respondents' perceptions, while the right signal worsens them. Similarly, willingness to read is higher with politically aligned research; the left signal raises it, while the right signal decreases it. Looking at the top right panel, Republicans exhibited significantly reduced perceived credibility when exposed

[10] We chose research clearly favored by one political side (Democrat) and opposed by the other (Republican) to easily interpret changes in group estimates depending on respondents' political leanings. We expect effects to be symmetric with respect to the research content.

to misaligned politically salient research (relative to the non-salient benchmark), especially with a left signal, though less so with a right signal. Similarly, willingness to read is highest with a congruent right signal and lowest with a left signal. For both subsamples, newsletter sign-up and overall trust in science vary similarly, but changes were less pronounced.

Additionally, looking at the bottom panels, where we normalize our group averages relative to the respective active or passive control, we observed that in-group respondents (when scientist signal and respondents' leaning align) perceived significantly higher credibility of scientists and their research, were more willing to read their opinion, and were more likely to sign up for the newsletter, relative to out-group respondents. Equivalent regressions in Tables B.13 and B.14 corroborate our visual representation, while proving robustness of estimates to the inclusion of individual controls.

5 Scientists' beliefs on public expression of political views

Do scientists anticipate a credibility penalty if they express a political opinion on social media? To answer this question, we recruited 128 scientists from around the world via the online platform Prolific for our survey.[11] The characteristics of the sample are detailed in Table B.15. 94% of the scientists are currently employed and more than 60% of them are currently employed at the university. 43% of the scientists are postdoctoral researchers, 28% of them are faculty members, and 29% of them are industry professionals. In addition, 34% of scientists work in life sciences and biomedicine, 34% of them work in social sciences, and the remaining respondents work in physical sciences and technology.

We explored these scientists' beliefs about the impact of publicly expressing political opinions on public trust in scientists, as well as their first- and second-order beliefs about the acceptability of expressing political views on social media.[12] We also investigated

[11] We focused on Prolific respondents who reported working in "Research", holding a "PhD degree", and being fluent in English.

[12] This includes their personal views and their beliefs about other scientists' views on public expression of political opinions online.

their personal experiences with public political expression on social media.

We first informed the scientists: "*We conducted a survey [...]. We measured trust in scientists, particularly focusing on whether this trust changes when these 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?*"[13] Figure A.13 shows that scientists anticipate a trust penalty for those who express political opinions on social media, and they even overestimate the size of this penalty. The scientists report, on average, to expect a loss of trust in the public of 30%, while the actual loss is around 16.6%.

Second, regarding scientists' views on the appropriateness of expressing political opinions online, Panel A of Figure A.14 shows that our respondents believe it is acceptable to publicly express political opinions on topics related to their area of expertise, while it is not acceptable to do so for topics *outside* their area of expertise. This complements the findings from Garg and Fetzer (2024), which show that academics tend to have more pro-social views on topics if they are actually experts in those topics. Regarding their beliefs about other scientists' views on the matter, Panel B of Figure A.14 documents the existence of a congruent social norm: scientists believe other academics agree that it is acceptable to express political views on social media regarding topics related to one's research, but not for topics outside one's research area.

Finally, we investigated scientists' personal experiences with public expression on social media. Panel A of Figure A.15 shows that scientists hesitate to express their political views on social media to varying degrees, with more hesitation reported outside one's area of research. Panel B of Figure A.15 indicates that scientists anticipate net reputational costs for expressing political opinions outside their field compared to net benefits for expressing opinions within their field. Specifically, scientists believe that, on average, more colleagues have faced largely *negative* consequences for expressing their political opinions outside their area of expertise on social media, while more colleagues have benefited from expressing views related to their areas of expertise. However, there

[13]The answer was incentivized with a 0.5 GBP bonus for a correct answer.

is significant variation in responses, as perceptions of costs (and benefits) for opinions expressed outside vs. inside one's area of expertise largely overlap. While we cannot investigate the reasons behind the decision of the scientists to express their political opinions using Twitter data, the evidence from the survey we have conducted suggests that scientists perceive net benefits from expressing political opinion in their topic.

6 Conclusion

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

We first document that a substantial portion of U.S. academics engage in political discourse on social media. Approximately 44% of 97,737 academics between 2016 and 2022 actively discussed political topics on Twitter, a rate about six times higher than that of a random sub-sample of Twitter users. Scientists particularly discuss issues such as climate change and racism, showing significant ideological polarization, especially around race. Significant ideological polarization is evident in the divergent viewpoints expressed by scientists on these contentious topics.

Secondly, we investigate the impact of scientists' political voice on social media on public perceptions. Through a conjoint experiment with 1,704 U.S. representative respondents rating synthetic academic profiles with varied political affiliations, we find, to the 'left' and 'right' sides of politically neutral, a monotonic penalty for scientists displaying political affiliations: the stronger their political posts, the less credible their profile and their research are perceived, and the lower the public's willingness to engage with their content. Scientists' gender does not affect perceived credibility, but affiliation with a top university and being a full professor improves public perceptions.

These findings suggest that politicized scientific communication online erodes public perceptions of scientists' credibility, undermines public engagement with scientific discourse, and potentially exacerbates affective polarization within U.S. society.

In a complementary survey with 128 scientists, we find that scientists anticipate a credibility penalty for expressing political opinions online, with the anticipated penalty

being larger than that detected in our experiment. Scientists also believe it is acceptable to express political opinions related to their field of expertise but not beyond it, indicating a social norm within the academic profession.

Our study emphasizes the critical need for scientists to carefully balance research dissemination online with political expression on social media, urging a reassessment of communication strategies. Additionally, the results prompt consideration of downstream effects, including the potential impact of scientists' online political engagement on the accessibility of scientific information and its influence on informed decision-making.

References

Ajzenman, N., B. Ferman, and P. C Sant'Anna (2023a). Discrimination in the formation of academic networks: a field experiment on# econtwitter.

Ajzenman, N., B. Ferman, and P. C Sant'Anna (2023b). Rooting for the same team: shared social identities in a polarized context.

Alabrese, E. (2022). Bad science: Retractions and media coverage.

Alesina, A., A. Miano, and S. Stantcheva (2020). The polarization of reality. In *AEA Papers and Proceedings*, Volume 110, pp. 324–328. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Algan, Y., D. Cohen, E. Davoine, M. Foucault, and S. Stantcheva (2021). Trust in scientists in times of pandemic: Panel evidence from 12 countries. *Proc. Natl. Acad. Sci. U. S. A. 118*(40), 1–8.

Altenmüller, M. S., T. Wingen, and A. Schulte (2024). Explaining polarized trust in scientists: A political stereotype-approach. *Science Communication 46*(1), 92–115.

Angeli, D., M. Lowe, et al. (2022). Virtue signals.

Ash, E. (2016). The political economy of tax laws in the us states. *Unpublished Manuscript, University of Warwick, Coventry*.

Ash, E., S. Galletta, D. Hangartner, Y. Margalit, and M. Pinna (2024). The effect of fox

news on health behavior during covid-19. *Political Analysis 32*(2), 275–284.

Azevedo, F. and J. 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, P. (2020). Social media, echo chambers, and political polarization. *Social media and democracy: The state of the field, prospects for reform 34*.

Bartoš, V., M. Bauer, J. Cahlíková, and J. Chytilová (2022). Communicating doctors' consensus persistently increases covid-19 vaccinations. *Nature 606*(7914), 542–549.

Beknazar-Yuzbashev, G., R. Jiménez Durán, J. McCrosky, and M. Stalinski (2022). Toxic content and user engagement on social media: Evidence from a field experiment. *Available at SSRN 4307346*.

Bénabou, R. and J. Tirole (2006). Incentives and prosocial behavior. *American economic review 96*(5), 1652–1678.

Benjamini, Y., A. M. Krieger, and D. Yekutieli (2006). Adaptive linear step-up procedures that control the false discovery rate. *Biometrika 93*(3), 491–507.

Blastland, M., A. L. Freeman, S. van der Linden, T. M. Marteau, and D. Spiegelhalter (2020). Five rules for evidence communication. *Nature 587*(7834), 362–364.

Bowles, J., K. Croke, H. Larreguy, J. Marshall, and S. Liu (2023). Sustaining exposure to fact-checks: Misinformation discernment, media consumption, and its political implications. *Media Consumption, and its Political Implications (September 25, 2023)*.

Boxell, L., M. Gentzkow, and J. M. Shapiro (2024). Cross-country trends in affective polarization. *Review of Economics and Statistics*, 1–9.

Braghieri, L. (2021). Political correctness, social image, and information transmission. *Work. Pap., Stanford Univ., Stanford, CA*.

Bursztyn, L., G. Egorov, I. Haaland, A. Rao, and C. Roth (2023). Justifying dissent. *The Quarterly Journal of Economics 138*(3), 1403–1451.

Bursztyn, L., A. Rao, C. Roth, and D. Yanagizawa-Drott (2023). Opinions as facts. *The Review of Economic Studies 90*(4), 1832–1864.

Cagé, J., N. Hervé, and M.-L. Viaud (2020). The production of information in an online

world. *The Review of economic studies 87*(5), 2126–2164.

Calónico, S., R. Di Tella, and J. C. Lopez del Valle (2023). The political economy of a "miracle cure": The case of nebulized ibuprofen and its diffusion in argentina. Working Paper 31781, National Bureau of Economic Research.

Campbell, E., J. Kotcher, T. Myers, J. Cook, A. C. Borth, and E. Maibach (2023). What motivates people to defend science: Evidence from the 2017 march for science. *Plos one 18*(11), e0290222.

Chopra, F., I. Haaland, and C. Roth (2024). The demand for news: Accuracy concerns versus belief confirmation motives. *The Economic Journal 134*(661), 1806–1834.

Colleoni, E., A. Rozza, and A. 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.

Cooper, J. M., D. S. Hutchinson, et al. (1997). *Plato: complete works*. Hackett Publishing.

Douglas, K. M. (2021). Are conspiracy theories harmless? *The Spanish journal of psychology 24*, e13.

Draca, M. and C. Schwarz (2024). How polarised are citizens? measuring ideology from the ground up. *The Economic Journal*, ueae010.

Druckman, J. N. and M. C. McGrath (2019). The evidence for motivated reasoning in climate change preference formation. *Nature Climate Change 9*(2), 111–119.

Enke, B., T. Graeber, and R. Oprea (2023). Confidence, self-selection, and bias in the aggregate. *American Economic Review 113*(7), 1933–1966.

Esteban, J.-M. and D. Ray (1994). On the measurement of polarization. *Econometrica: Journal of the Econometric Society*, 819–851.

Fiorina, M. P. and S. J. Abrams (2008). Political polarization in the american public. *Annu. Rev. Polit. Sci. 11*, 563–588.

Fiorina, M. P., J. Abrams Samuel, and C. Pope Jeremy (2005). Culture war? the myth of a polarized america.

Flaxman, S., S. Goel, and J. M. Rao (2016). Filter bubbles, echo chambers, and online news consumption. *Public opinion quarterly 80*(S1), 298–320.

Funk, C., A. Tyson, B. Kennedy, and C. Johnson (2020). Science and scientists held in high esteem across global publics. *Pew research center 29*.

Garcia-Hombrados, J., M. Jansen, Á. Martínez, B. Özcan, P. Rey-Biel, and A. Roldán-Monés (2024). Ideological alignment and evidence-based policy adoption.

Garg, P. and T. Fetzer (2024). Political expression of academics on social media. *Research Square preprint*.

Garg, P. and R. Martin (2024a). Shocking views on climate action. *Working Paper*.

Garg, P. and R. Martin (2024b). Who influences whom about what? *Working Paper*.

Gentzkow, M. and J. M. Shapiro (2011). Ideological segregation online and offline. *The Quarterly Journal of Economics 126*(4), 1799–1839.

Gentzkow, M., J. M. Shapiro, and M. Taddy (2019). Measuring group differences in high-dimensional choices: method and application to congressional speech. *Econometrica 87*(4), 1307–1340.

González-Bailón, S., D. Lazer, P. Barberá, M. Zhang, H. Allcott, T. Brown, A. Crespo-Tenorio, D. Freelon, M. Gentzkow, A. M. Guess, et al. (2023). Asymmetric ideological segregation in exposure to political news on facebook. *Science 381*(6656), 392–398.

Grimmer, J. (2010). A bayesian hierarchical topic model for political texts: Measuring expressed agendas in senate press releases. *Political analysis 18*(1), 1–35.

Guriev, S., E. Henry, T. Marquis, and E. Zhuravskaya (2023). Curtailing false news, amplifying truth. *Amplifying Truth (October 29, 2023)*.

Hainmueller, J., D. Hangartner, and T. Yamamoto (2015). Validating vignette and conjoint survey experiments against real-world behavior. *Proceedings of the National Academy of Sciences 112*(8), 2395–2400.

Hansen, S., M. McMahon, and A. Prat (2018). Transparency and deliberation within the fomc: A computational linguistics approach. *The Quarterly Journal of Economics 133*(2), 801–870.

Hartigan, J. A. and P. M. Hartigan (1985). The dip test of unimodality. *The annals of Statistics*, 70–84.

Hendriks, F., D. Kienhues, and R. Bromme (2020). Replication crisis= trust crisis? the ef-

fect of successful vs failed replications on laypeople's trust in researchers and research. *Public Understanding of Science 29*(3), 270–288.

Hopkins, D. J. (2018). *The increasingly United States: How and why American political behavior nationalized*. University of Chicago Press.

Iyengar, S., Y. Lelkes, M. Levendusky, N. Malhotra, and S. J. Westwood (2019). The origins and consequences of affective polarization in the united states. *Annual review of political science 22*, 129–146.

Jelveh, Z., B. Kogut, and S. Naidu (2024). Political language in economics. *The Economic Journal*, ueae026.

Jensen, J., S. Naidu, E. Kaplan, L. Wilse-Samson, D. Gergen, M. Zuckerman, and A. Spirling (2012). Political polarization and the dynamics of political language: Evidence from 130 years of partisan speech [with comments and discussion]. *Brookings Papers on Economic Activity*, 1–81.

Jiménez Durán, R. (2021). The economics of content moderation: Evidence from hate speech on twitter. *Available at SSRN 4044098*.

Kahan, D. M., H. Jenkins-Smith, and D. Braman (2011). Cultural cognition of scientific consensus. *Journal of risk research 14*(2), 147–174.

Kessler, J. B., C. Low, and C. D. Sullivan (2019). Incentivized resume rating: Eliciting employer preferences without deception. *American Economic Review 109*(11), 3713–3744.

Kotcher, J. E., T. A. Myers, E. K. Vraga, N. Stenhouse, and E. 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.

Lelkes, Y. (2016). Mass polarization: Manifestations and measurements. *Public Opinion Quarterly 80*(S1), 392–410.

Levy, R. (2021). Social media, news consumption, and polarization: Evidence from a field experiment. *American economic review 111*(3), 831–870.

Li, N. and Y. 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.

Massey Jr, F. J. (1951). The kolmogorov-smirnov test for goodness of fit. *Journal of the American statistical Association 46*(253), 68–78.

McCarty, N., K. T. Poole, and H. Rosenthal (2016). *Polarized America: The dance of ideology and unequal riches*. mit Press.

McIntyre, L. (2018). *Post-truth*. MIt Press.

Mede, N. 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, N. G. and M. S. Schäfer (2020). Science-related populism: Conceptualizing populist demands toward science. *Public Understanding of science 29*(5), 473–491.

Mede, N. G., M. S. Schäfer, and T. Füchslin (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, R. K. (1973). *The sociology of science: Theoretical and empirical investigations*. University of Chicago press.

Mohammad, S., S. Kiritchenko, P. Sobhani, X. Zhu, and C. Cherry (2016). Semeval-2016 task 6: Detecting stance in tweets. In *Proceedings of the 10th international workshop on semantic evaluation (SemEval-2016)*, pp. 31–41.

Mongeon, P., T. D. Bowman, and R. Costas (2023). An open data set of scholars on twitter. *Quantitative Science Studies 4*(2), 314–324.

Mosleh, M., C. Martel, D. Eckles, and D. 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, T. (2017). *The death of expertise: The campaign against established knowledge and why it matters*. Oxford University Press.

Peng, H., D. M. Romero, and E.-Á. Horvát (2022). Dynamics of cross-platform attention to retracted papers. *Proceedings of the National Academy of Sciences 119*(25), e2119086119.

Petersen, M. B., A. Bor, F. Jørgensen, and M. F. Lindholt (2021). Transparent communi-

cation about negative features of covid-19 vaccines decreases acceptance but increases trust. *Proceedings of the National Academy of Sciences 118*(29), e2024597118.

Roozenbeek, J., C. R. Schneider, S. Dryhurst, J. Kerr, A. L. Freeman, G. Recchia, A. M. Van Der Bles, and S. Van Der Linden (2020). Susceptibility to misinformation about covid-19 around the world. *Royal Society open science 7*(10), 201199.

Russell, A. and M. Tegelberg (2020). Beyond the boundaries of science: Resistance to misinformation by scientist citizens. *Journalism 21*(3), 327–344.

Rutjens, B. T. and B. Većkalov (2022). Conspiracy beliefs and science rejection. *Current Opinion in Psychology 46*, 101392.

Scharff, D. P., K. J. Mathews, P. Jackson, J. Hoffsuemmer, E. Martin, and D. Edwards (2010). More than tuskegee: understanding mistrust about research participation. *Journal of health care for the poor and underserved 21*(3), 879.

Simonov, A., S. Sacher, J. Dubé, and S. Biswas (2020). The persuasive effect of fox news: Non-compliance with social distancing during the covid-19 pandemic (working paper 27237).

Stewart, A. J., M. Mosleh, M. Diakonova, A. A. Arechar, D. G. Rand, and J. B. Plotkin (2019). Information gerrymandering and undemocratic decisions. *Nature 573*(7772), 117–121.

Van Der Bles, A. M., S. Van Der Linden, A. L. Freeman, J. Mitchell, A. B. Galvao, L. Zaval, and D. J. Spiegelhalter (2019). Communicating uncertainty about facts, numbers and science. *Royal Society open science 6*(5), 181870.

Van Der Bles, A. M., S. van der Linden, A. L. Freeman, and D. 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.

West, J. D. and C. T. Bergstrom (2021). Misinformation in and about science. *Proceedings of the National Academy of Sciences 118*(15), e1912444117.

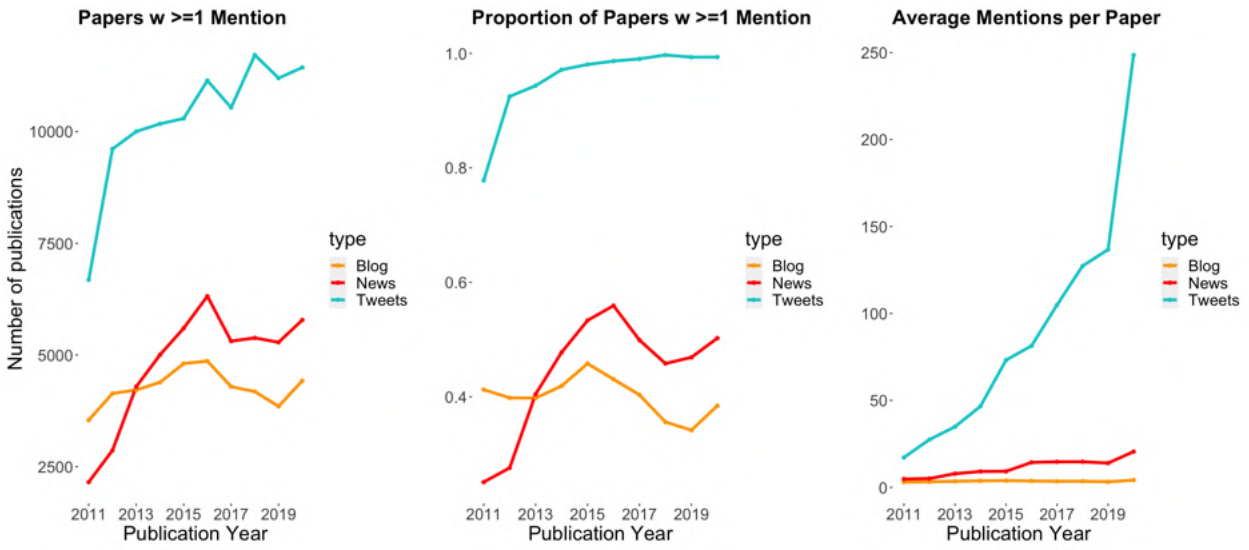
Zhang, F. J. (2023). Political endorsement by nature and trust in scientific expertise during covid-19. *Nature Human Behaviour 7*(5), 696–706.

Zhuravskaya, E., M. Petrova, and R. Enikolopov (2020). Political effects of the internet

and social media. *Annual review of economics 12*, 415–438.

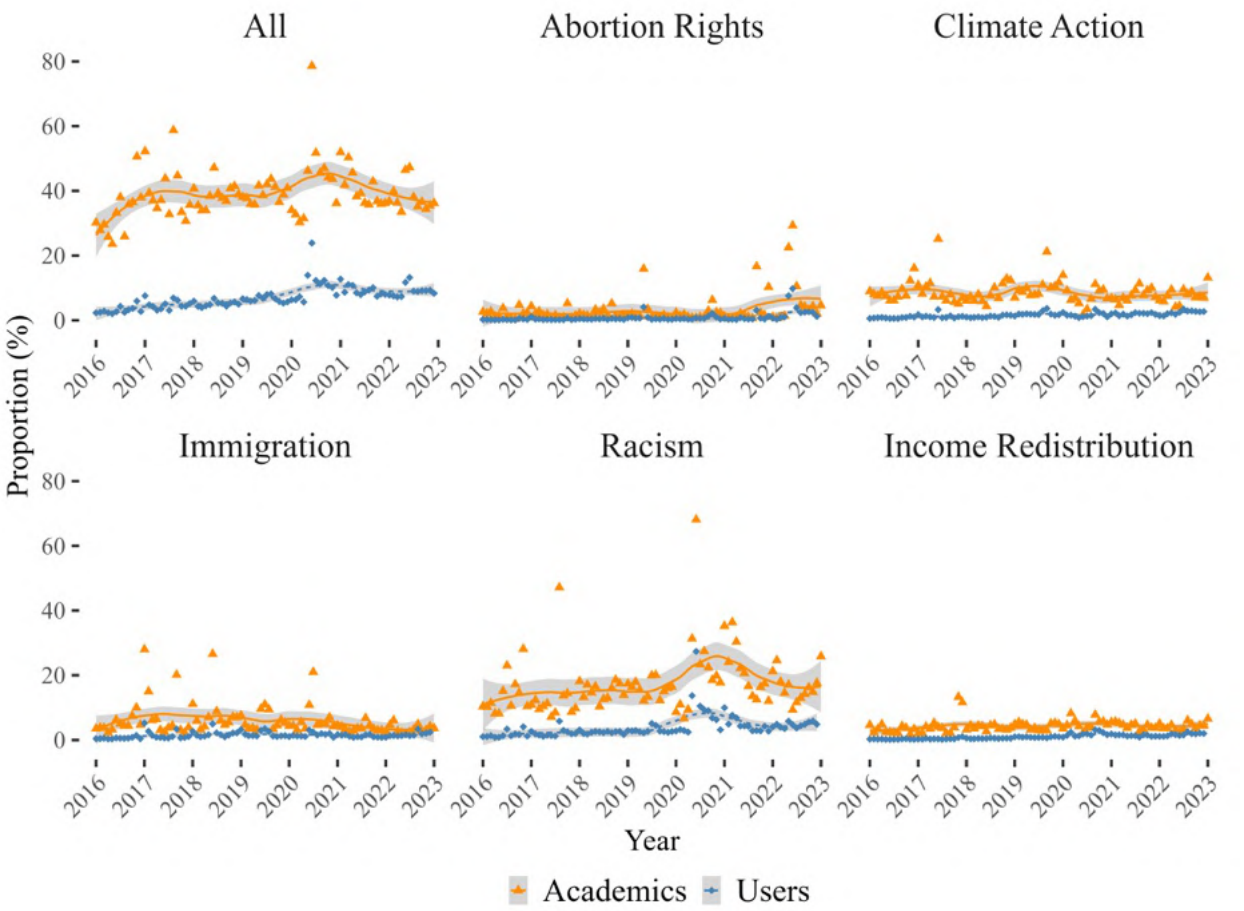
Figures

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



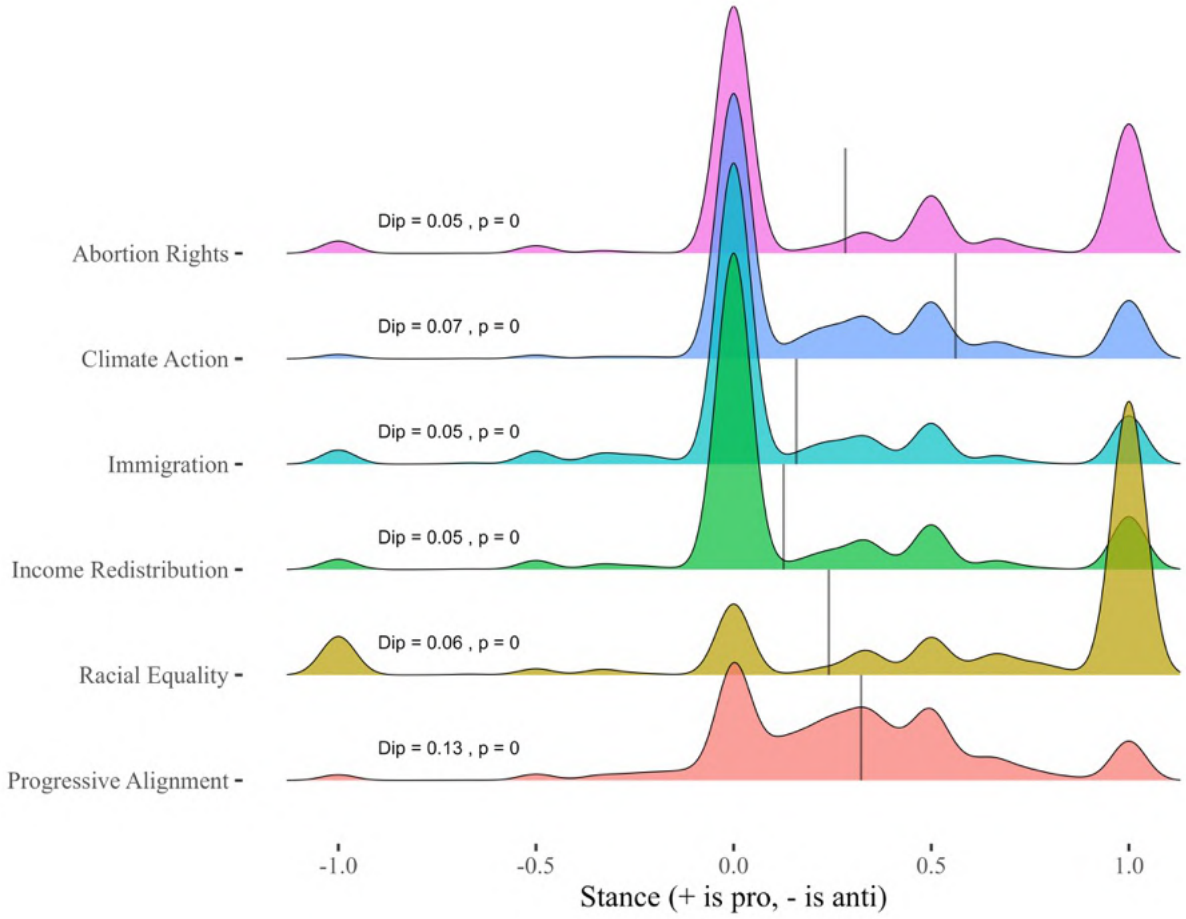
Note: Figure provides trends in online coverage of scientific articles published in *Science*, *Nature*, *PNAS*, *Cell*, *NEJM*, and *Lancet* between 2011 and 2020. Online appearances across blog posts, newspaper articles, or Twitter are retrieved from Altmetric (accessed on November 10th, 2021). The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



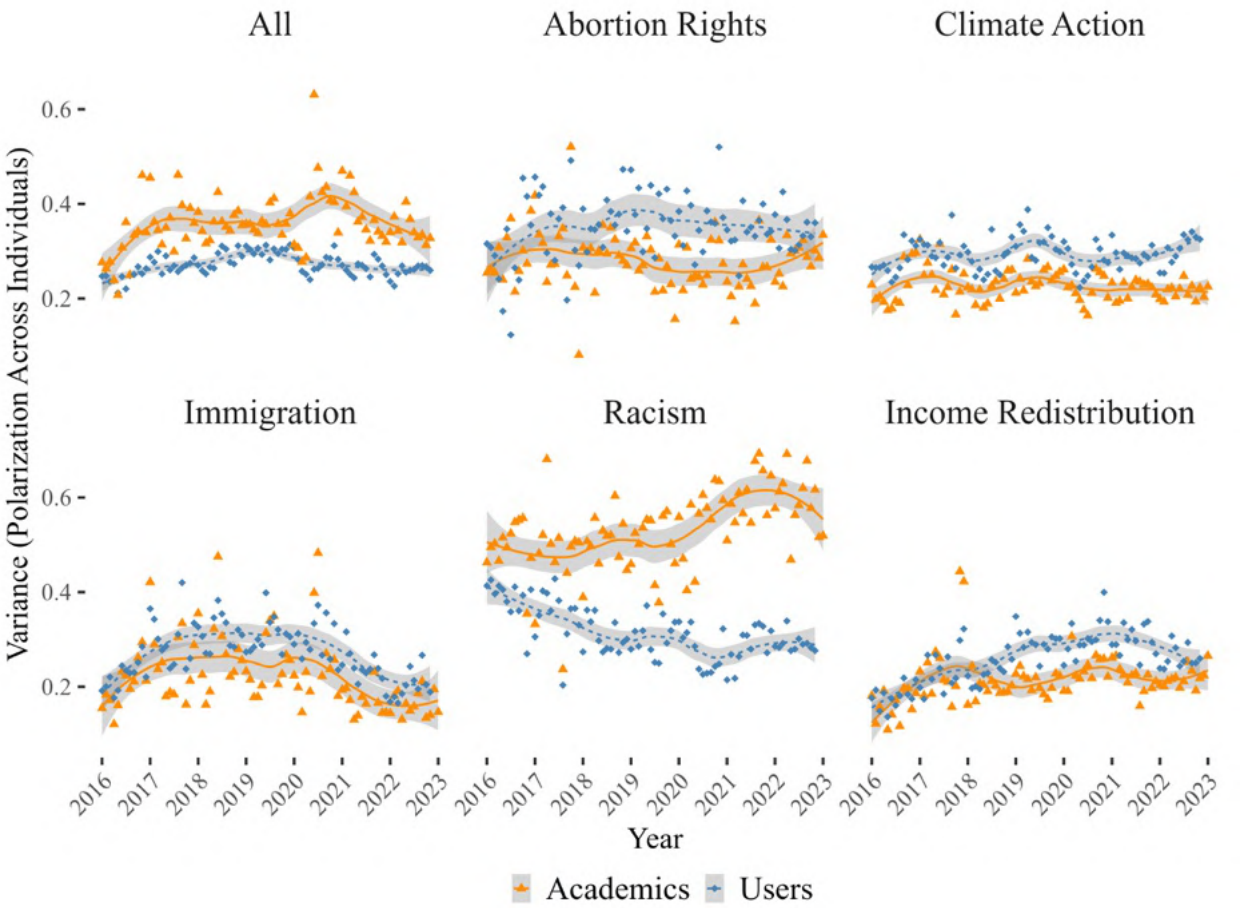
Note: The figure illustrates trends in politicization of conversations by academics and general users on Twitter from 2016 to 2022. Monthly aggregated scatter plots display expressed stance for each topic, with a LOESS applied for trend visualization. Standard errors are depicted in the shaded region. 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 Racism showing the largest disparities. Climate Action witnessed significant declines during the COVID-19 pandemic onset. Mid-2020 saw a surge in attention to Racism, 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 Academics over 2016-2022



Note: The figure illustrates the density distribution of net stance across various political topics among U.S. academics 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 academics 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. These results indicate that academics are not homogeneously distributed in their political stances but rather form clusters. The presence of multiple peaks suggests four ideological camps: very liberal, somewhat liberal, neutral/self-censored, and conservative. This clustering indicates significant ideological polarization within the academic community, providing visual and statistical evidence of the cross-sectional diversity of political views expressed by academics.

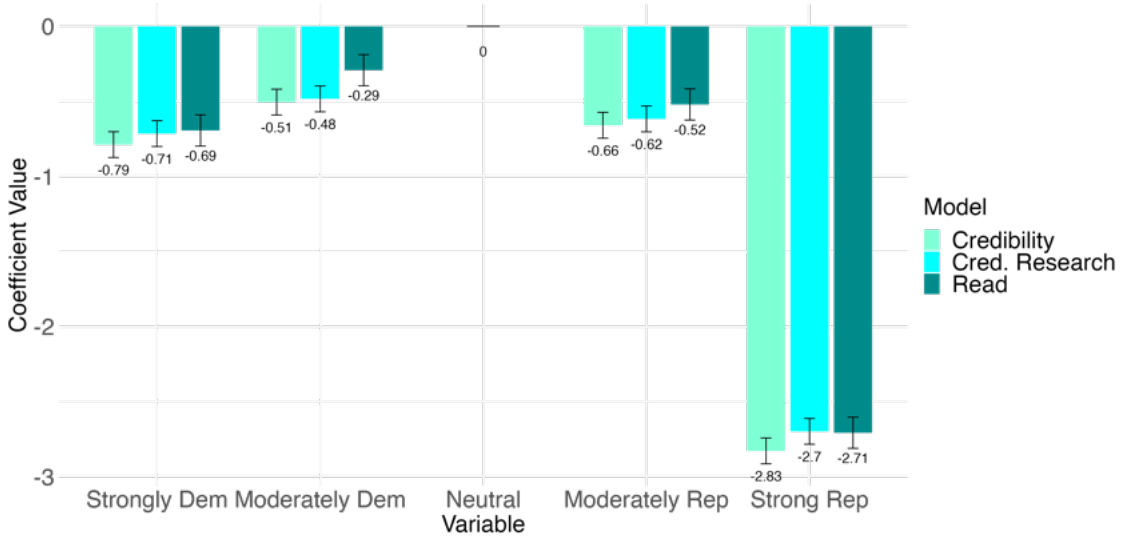
Figure 4: Issue Disagreement Across Academics By Topics Over Time



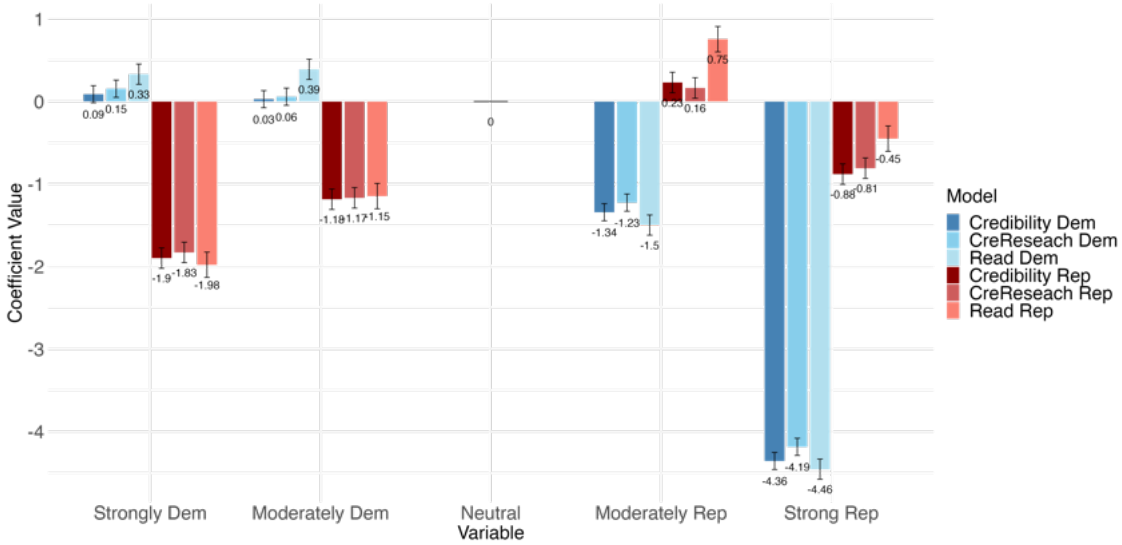
Note: The figure measures ideological polarization by computing the variance of net stance held by a population on predefined political topics. Variance across users reflects the dispersion of political opinion on each topic, providing a continuous measure of ideological disagreement. Aggregating across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

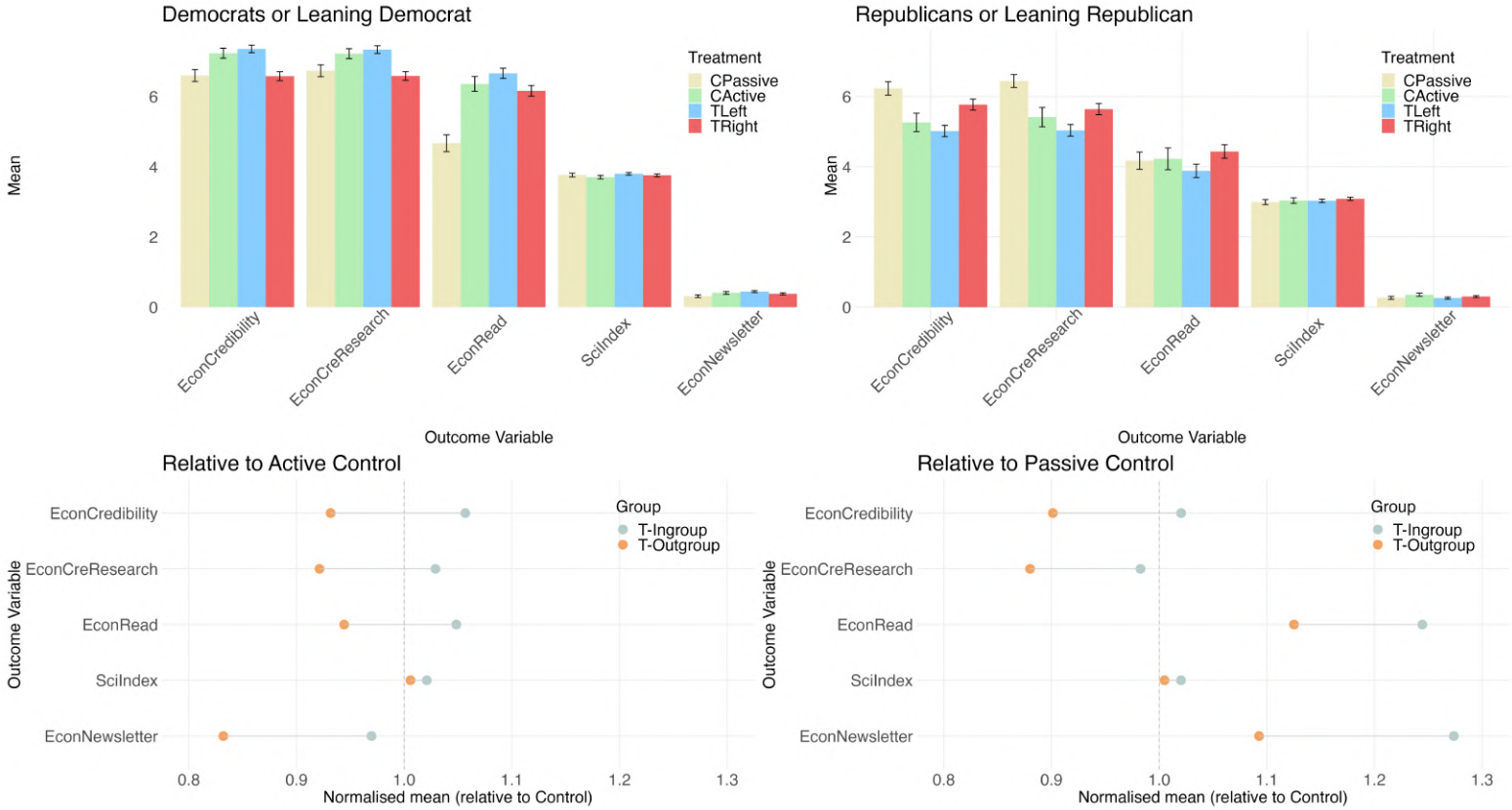


B. Heterogeneity by Respondents' Partisanship



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 "Strongly Republican", "Moderately Republican", "Strongly Democrat", or "Moderately 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.)

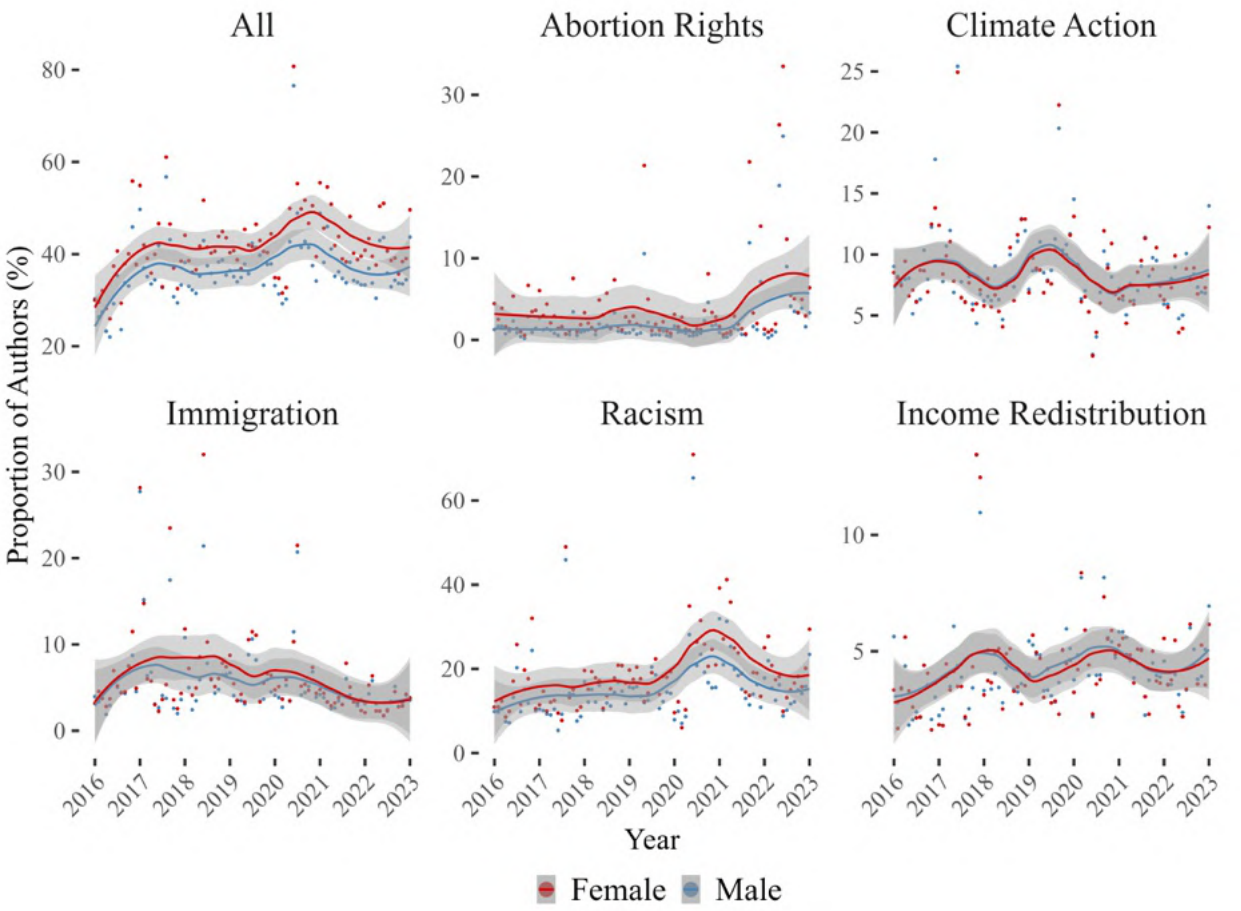
For online publication

Politicized Scientists: Credibility Cost of Political Expression on Twitter

Eleonora Alabrese, Francesco Capozza, and Prashant Garg

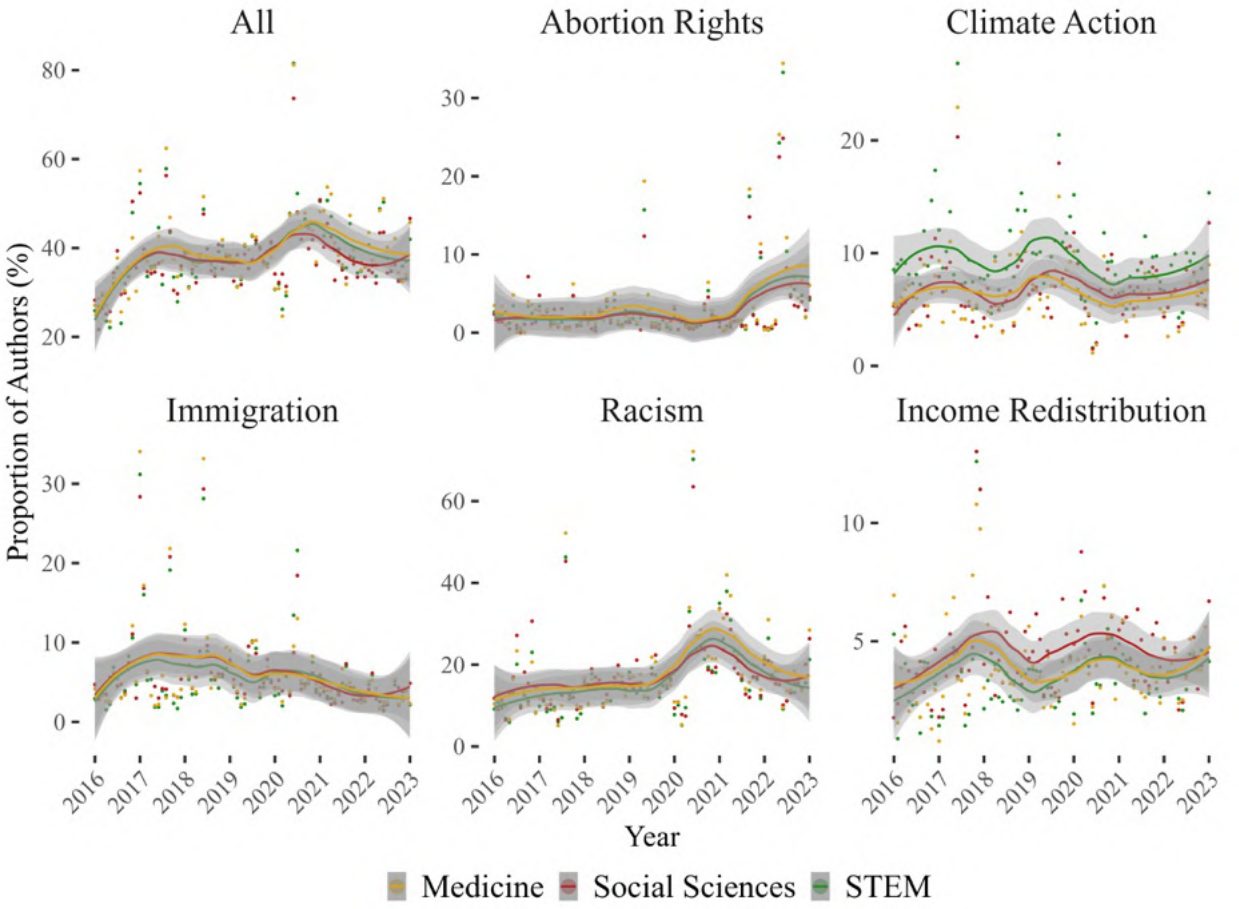
A Appendix Figures

Figure A.1: Proportion of Academics with Political Opinions Over Time by Topic and Gender



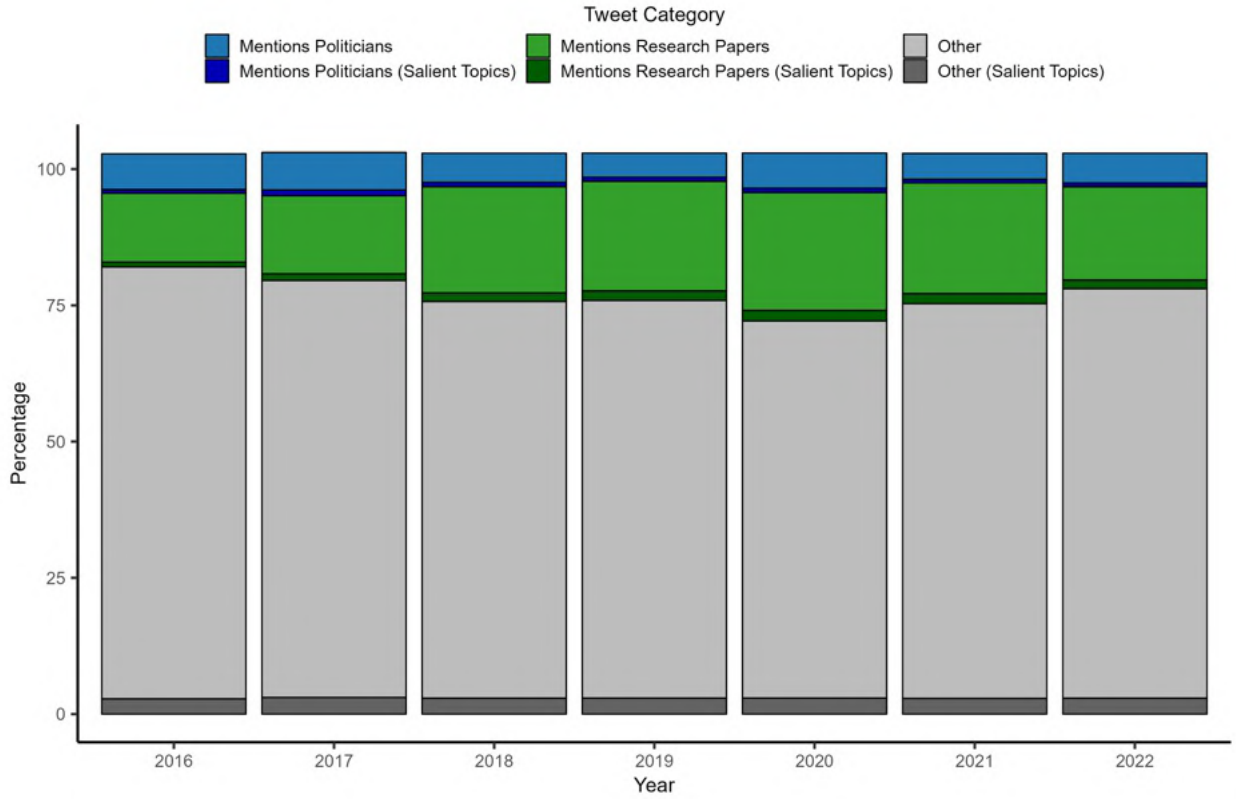
Note: We passed the full OpenAlex academic name as it appears on their papers to an LLM to classify the gender as 'Male', 'Female', or 'Unclear'. Close to 99% of names were labeled Male or Female. Using this binary classification of gender, we can explore sub-population differences in political expression. 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 Racism. 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.2: Proportion of Academics with Political Opinions Over Time by Topic and Concepts



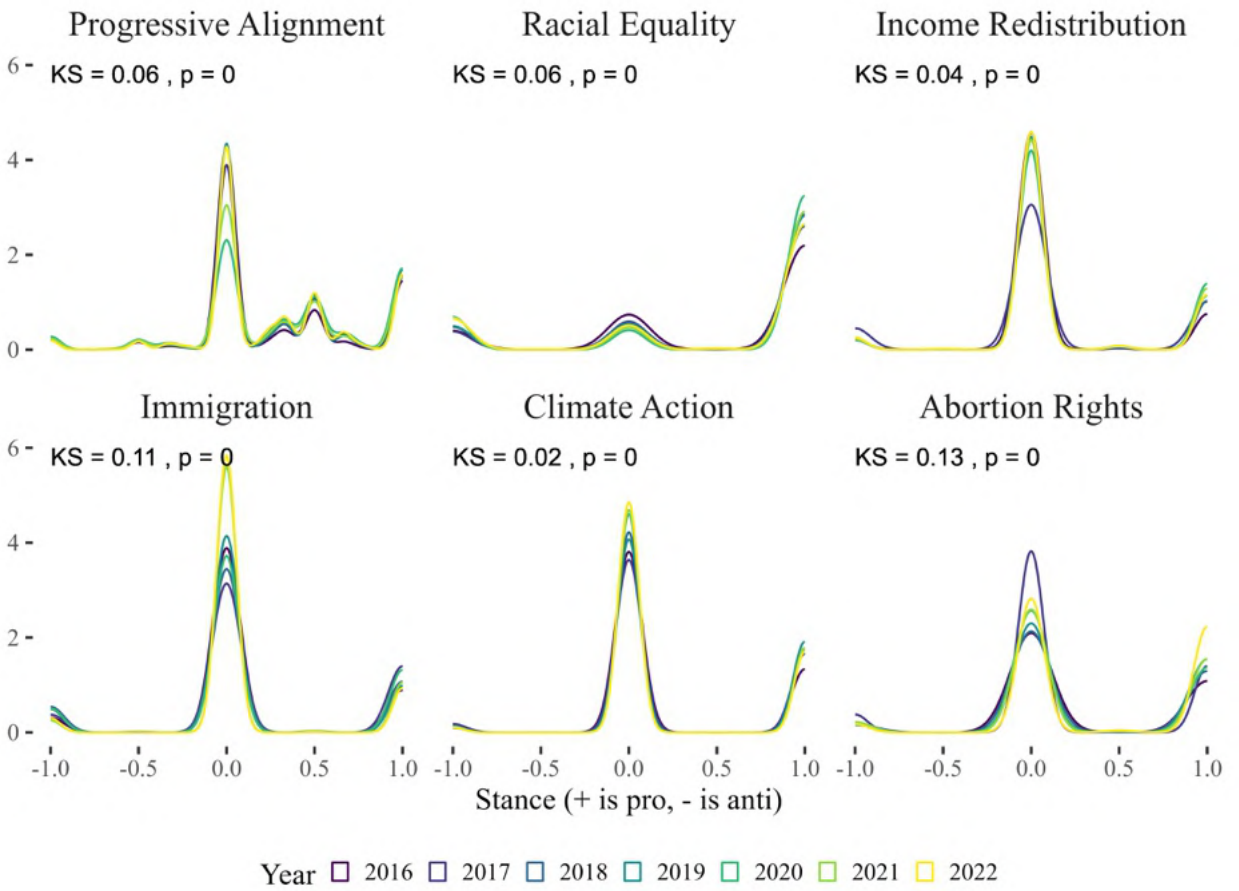
Note: Note: OpenAlex describes "Concepts" as abstract ideas that a work is about: "Concepts are hierarchical, like a tree. There are 19 root-level concepts, and six layers of descendants branching out from them, containing about 65 thousand concepts all told". OpenAlex classifies each work with a high 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. We find differences in trends and spikes between the four categories. In the overall trend, we see humanities being more vocal, but other scientists approach their "vocalness" over time. Given the non-political nature of STEM and Medicine publications, it is important to understand what happens when scientists working on apolitical concepts become political in public.

Figure A.3: 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, and other content. Each bar represents the total percentage of tweets for a given year, with colors indicating the categories: blue for tweets mentioning politicians, green for tweets mentioning research papers, and grey for other tweets. Darker shades within each color represent tweets related to the five salient topics (Abortion Rights, Climate Action, Racism, Immigration, and Income Redistribution). The "Mentions Politicians (Salient Topics)" category includes tweets that mention both politicians and one of the salient topics, and the "Mentions Research Papers (Salient Topics)" category includes tweets that mention both research papers and one of the salient topics. The overall proportion of tweets mentioning politicians is around 10%, while approximately 30% 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. This visualization helps to understand the interaction between political discourse and academic content over time.

Figure A.4: 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.5: Vignettes of scientists profiles

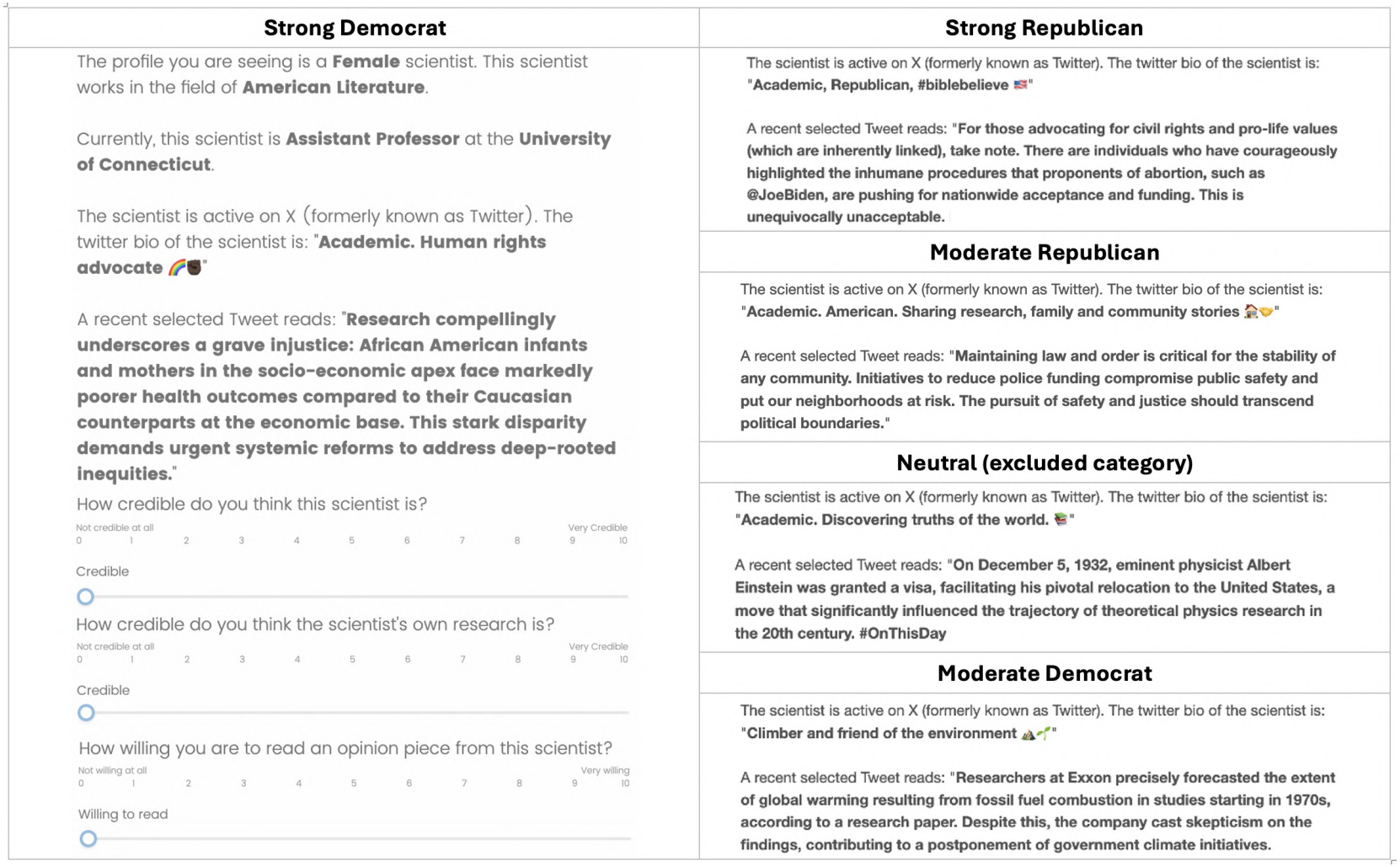
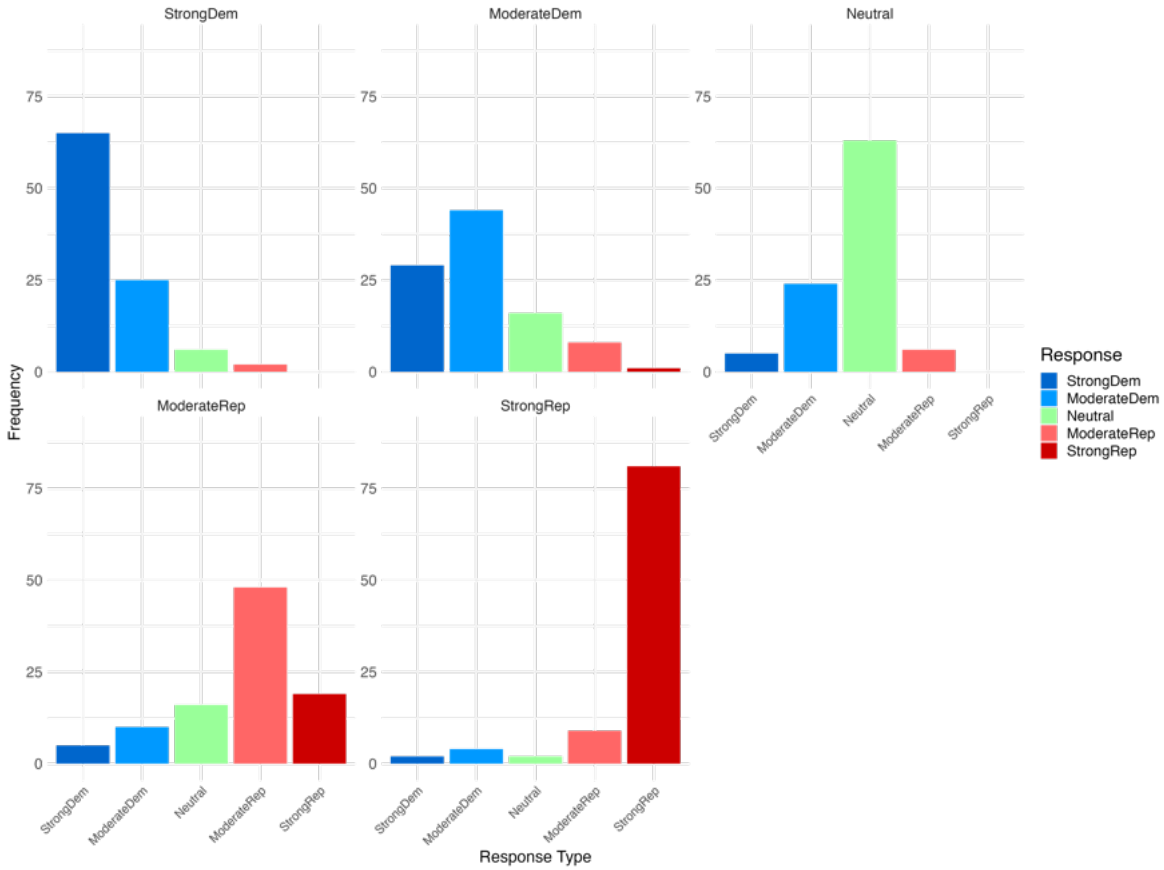
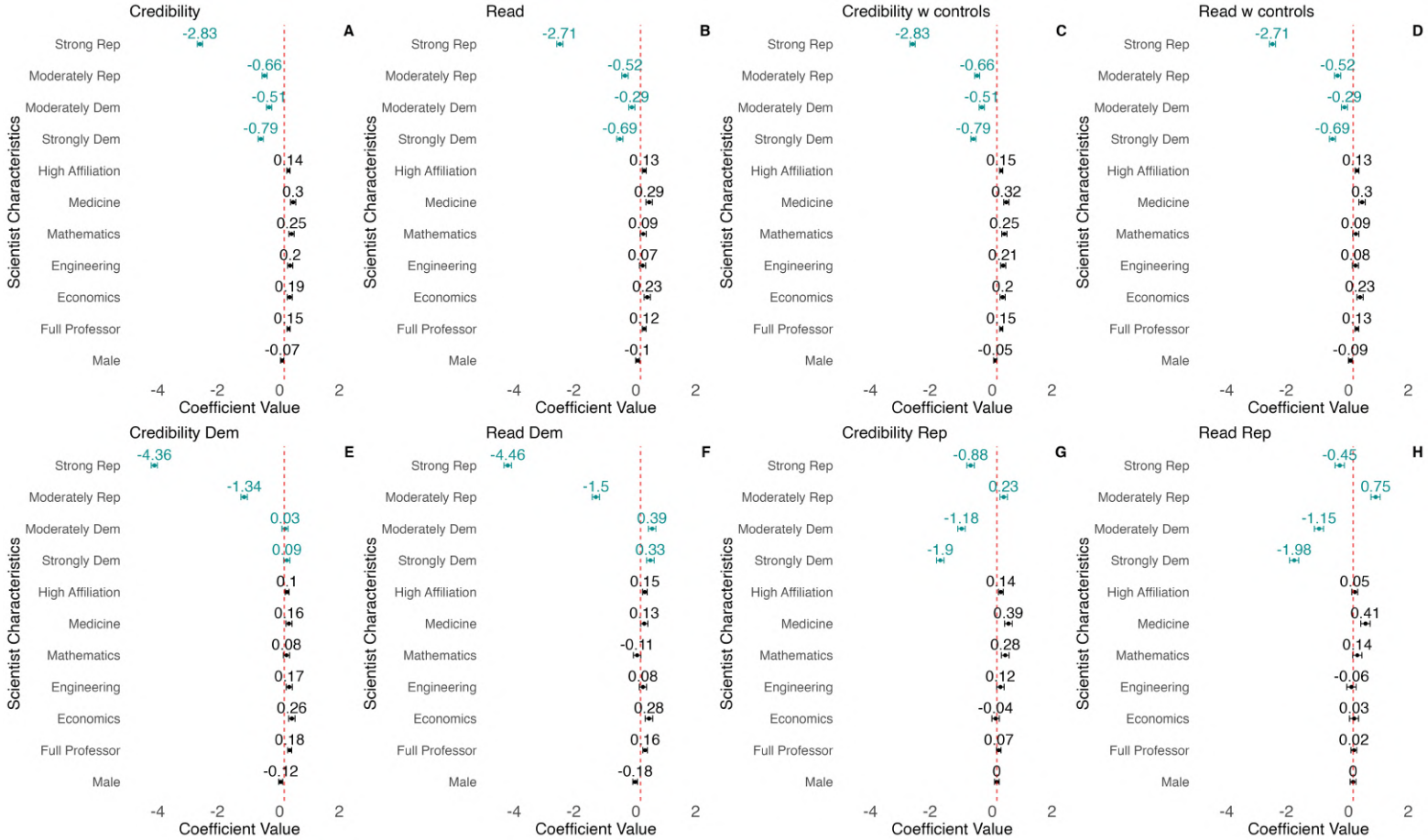


Figure A.6: Frequency of Responses by Intended Political Leaning of Twitter Signal



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.

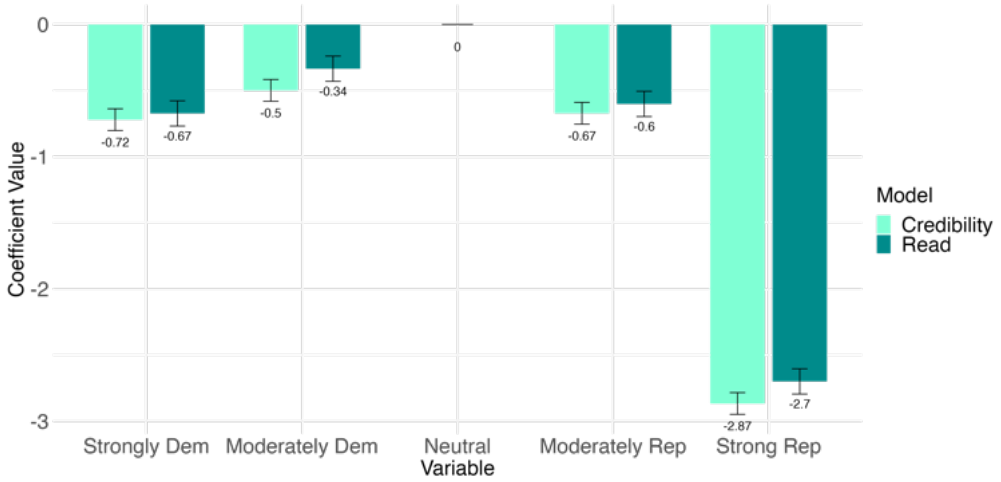
Figure A.7: Effect of scientists' characteristics on respondents' perceived credibility. Any perceived political leaning of scientists reduces their credibility. Effects are heterogeneous, with Democrats showing reduced credibility for Republican scientists, and vice versa.



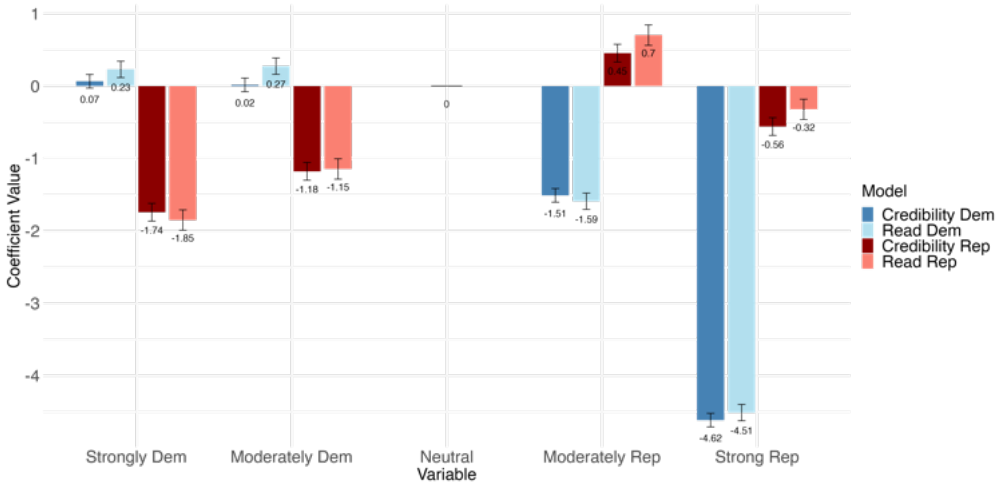
Note: Coefficients are obtained by regressing scientists' characteristics on respondents' perceived credibility or willingness to read from scientists. All the standard errors are clustered at the individual level. Political leaning is indicated by "Strongly Republican," "Moderately Republican," "Strongly 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. 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.8: 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

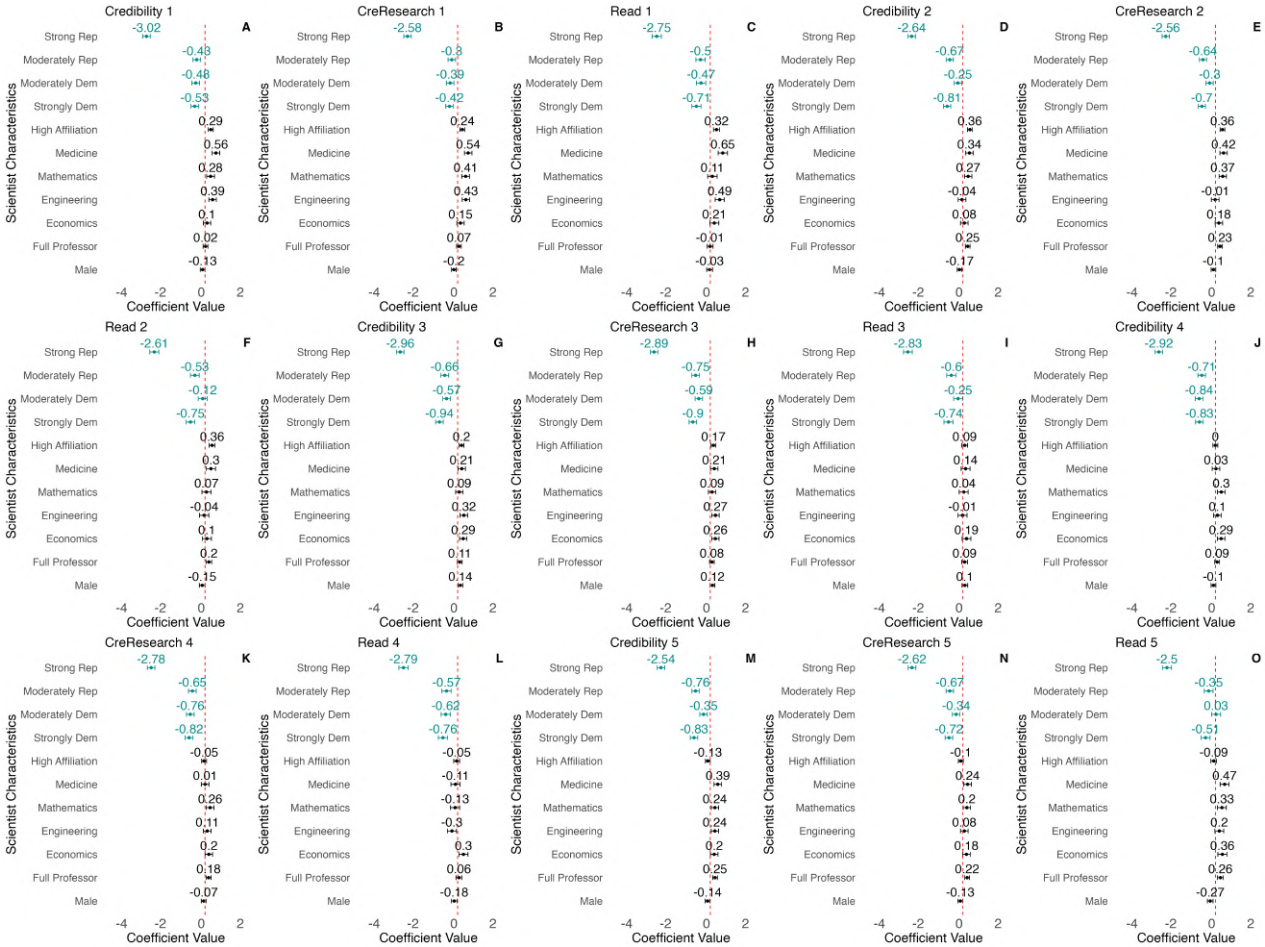


B. Heterogeneity by Respondents' Partisanship



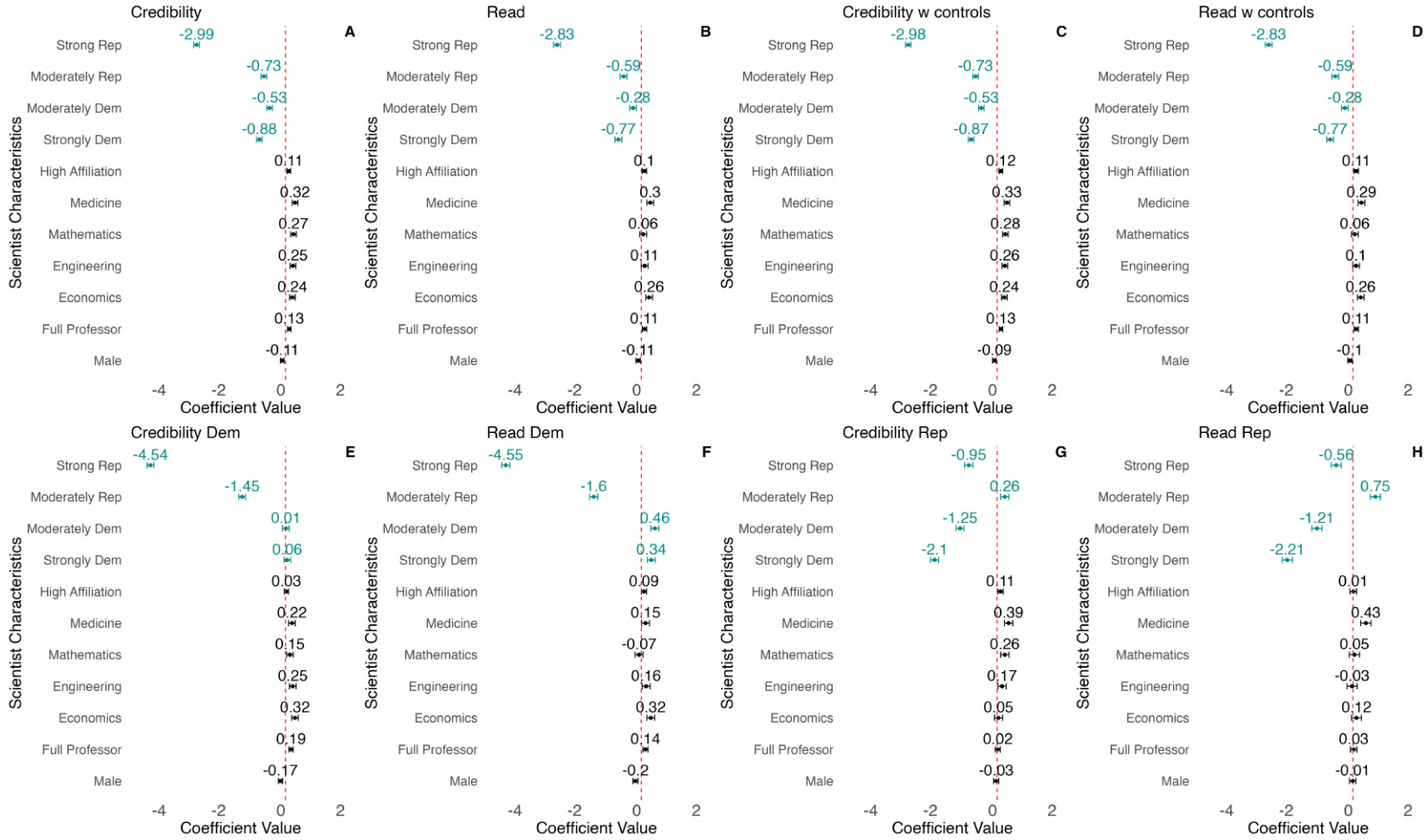
Note: Coefficients are obtained by regressing scientists' characteristics on respondents' perceived credibility or willingness to read content from scientists. The x-axis represents different political affiliations of scientists, estimated by indicator variables for "Strongly Republican", "Moderately Republican", "Strongly Democrat", or "Moderately 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.9: Effect of carryovers on scientists' credibility and willingness to read.



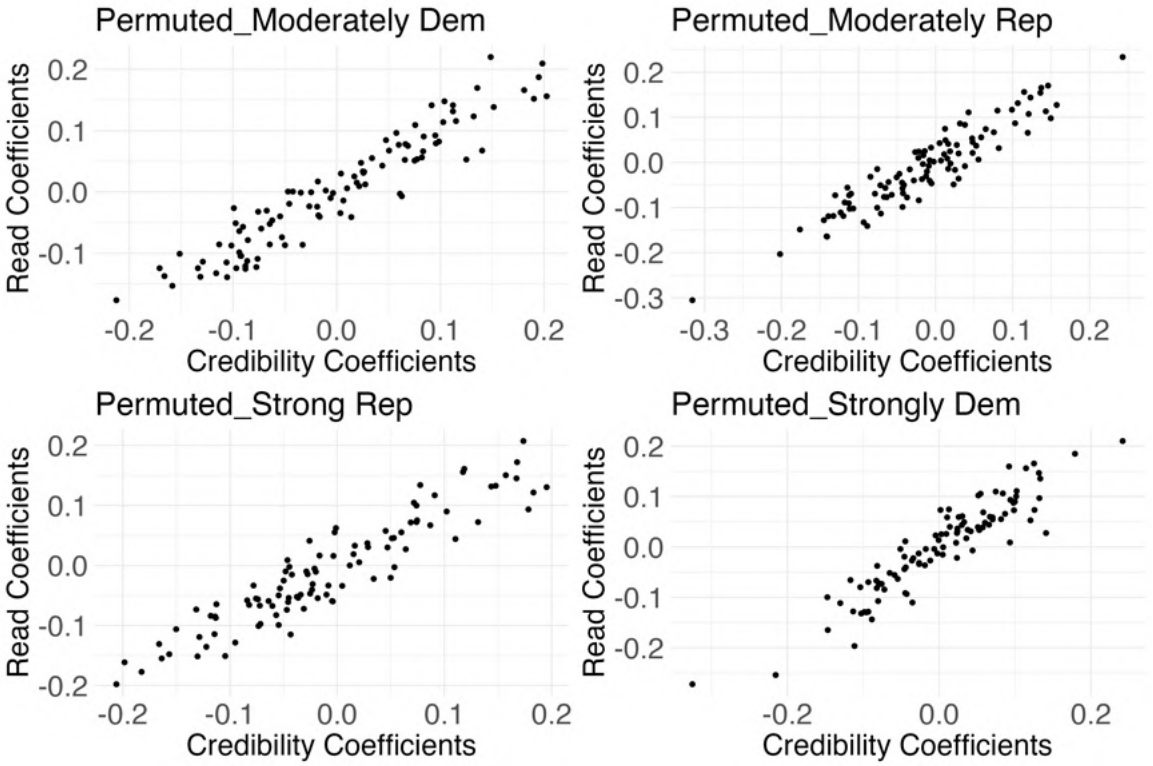
Note: Coefficients were obtained by regressing scientists' characteristics on respondents' perceived credibility or likelihood of reading from similar scientists. We repeat the procedure for each profile the respondents have seen in the study. All the standard errors are clustered at the individual level. Political leaning is indicated by "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. (N=1704)

Figure A.10: Effect of scientists' characteristics 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 "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. Controls encompass respondents' age, gender, income, ethnicity, education, employment status, religion, region, and political leaning. (N = 1431)

Figure A.11: Permutation Tests

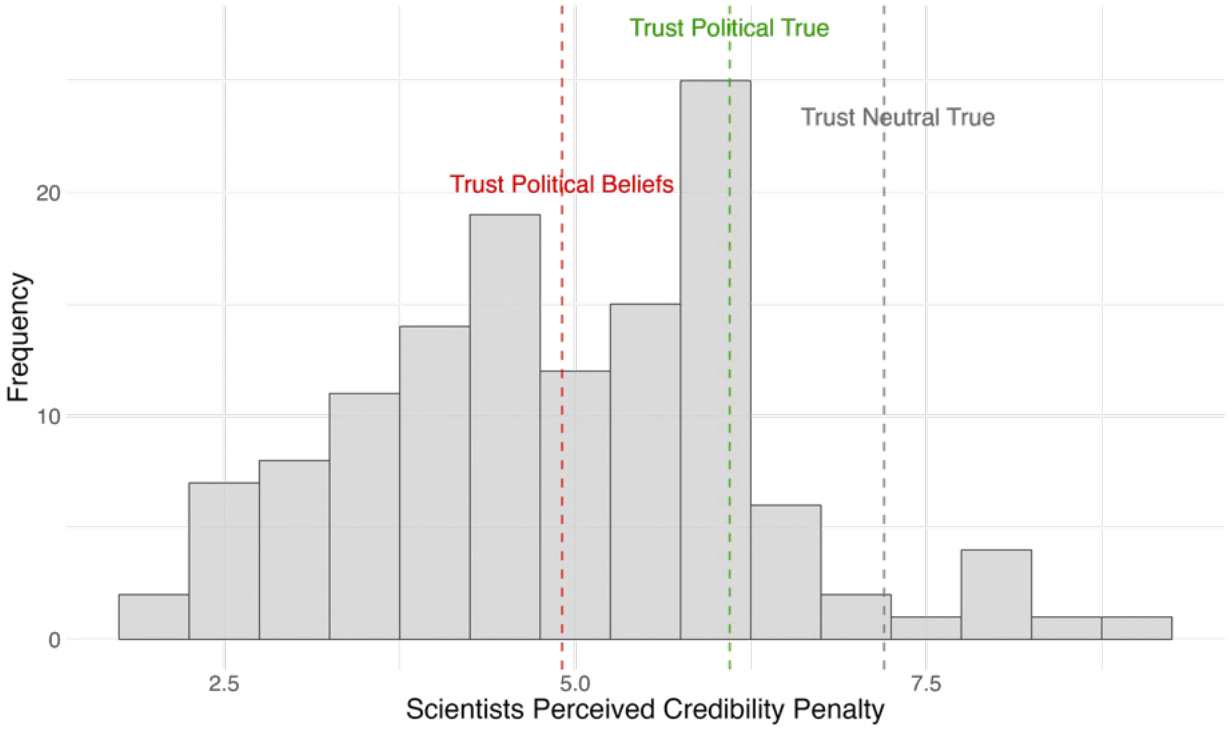


Note: This figure reports the results of a permutation test conducted to assess the robustness of our estimates and ensure that our observed political effects are not due to some unusual feature of the data. To address this, we randomly re-shuffled all political labels across profiles within each respondent, 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.12: 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."**

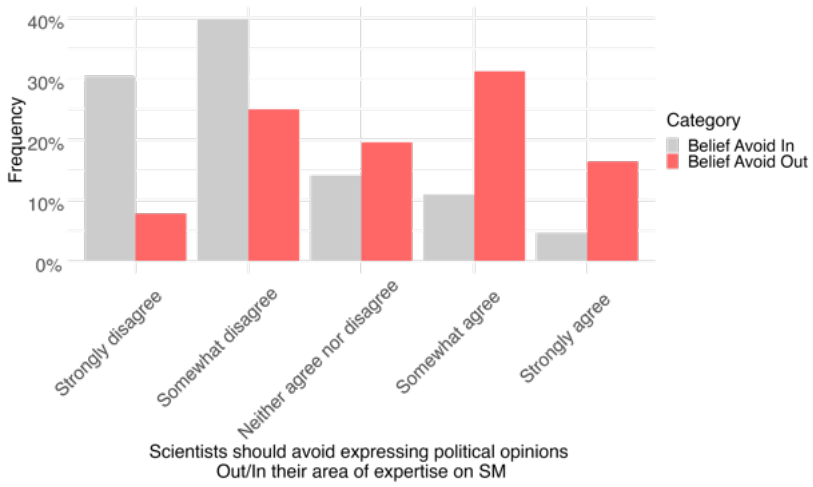
Figure A.13: Scientists' Beliefs about Credibility Penalty



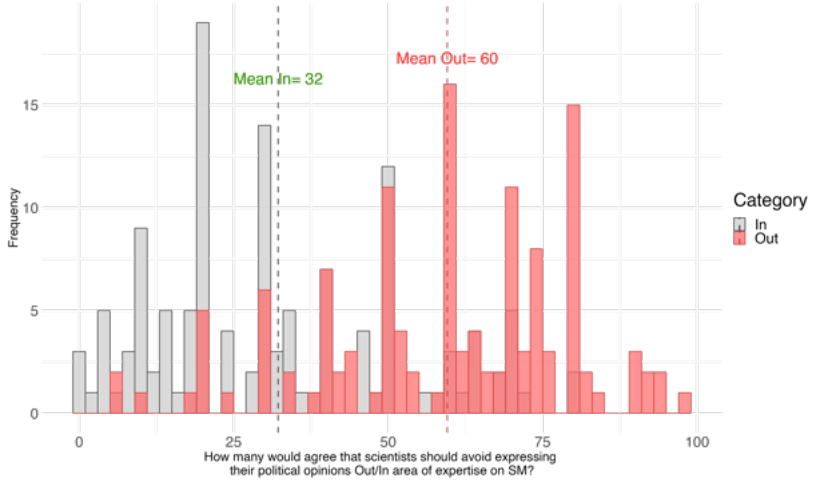
Note: This figure reports the distribution of responses from 128 scientists recruited on Prolific to the following question: *"What do you think is the reported level of trust for scientists who do express political opinions on social media?"*. Prior to asking the question, we informed the academic respondents 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.14: Scientists' Own Beliefs and Belief's on Other Scientists Beliefs around Academics Publicly Expressing Political Views

A. Scientists Should Avoid Expressing Political Opinions



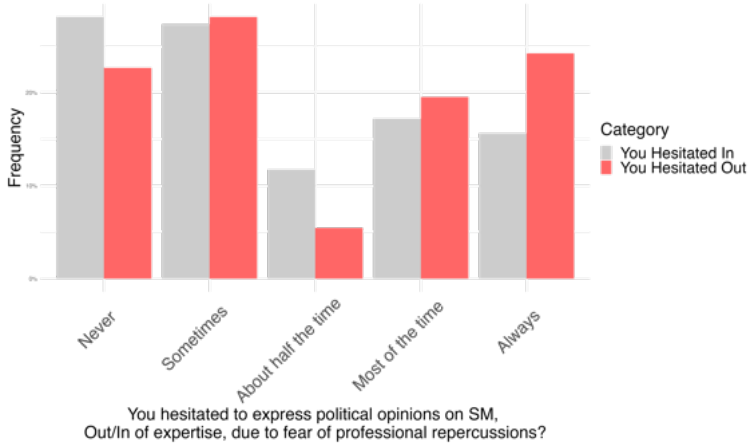
B. How many Scientists Agree on Avoiding to Express Political Opinions



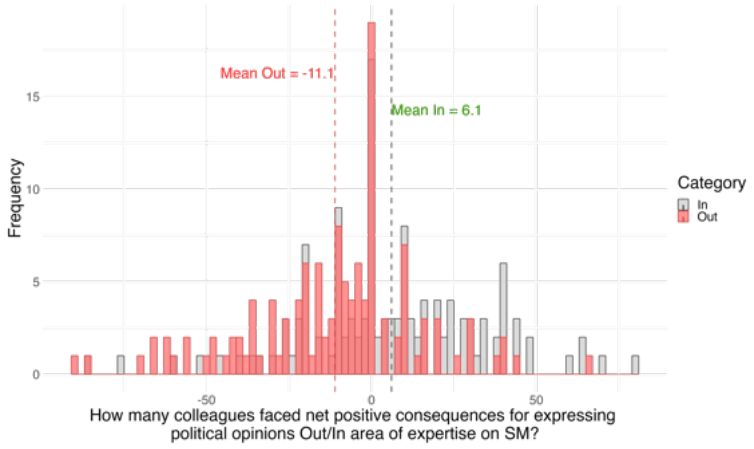
Note: The figure illustrates scientists' own beliefs and their beliefs about other scientists' views on the public expression of political opinions on social media, based on a sample of 128 scientists recruited on Prolific. Panel A shows scientists' responses to their level of agreement with the following 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.15: 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	19,584	76.1	80.2	41.8
Field: Social Sciences	6,032	23.5	86.0	64.9
Field: Medicine	7,765	30.2	81.0	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. Around 44% 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
Racism	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 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) Racism, (5) Income Redistribution. This approach is further demonstrated in Garg and Fetzer (2024). 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. 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
Racism/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: Evaluation Metrics: GPT 3.5 Turbo

Task	Target	GPT 3.5 Turbo (F_{avg})
A	Feminism	92.44
A	Hillary Clinton	89.57
A	Abortion	79.52
B	Donald Trump	84.18

Notes: Table shows results of validation of stance detection step. We obtain human labels for stance detection task from ACM SemEval-2016 Task 6 (Mohammad et al. 2016). Humans labelled tweets are pro-, anti- and neutral-, on topics ranging from Abortion Rights to Donald Trump. The stance detection's effectiveness was validated against 40,317 hand-coded labels from 137 humans, yielding F-scores of 79-92, which are considered very high for classification tasks. For further details on validation and comparisons with opinion poll measures, see Garg and Fetzer (2024).

Table B.5: 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

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.6: 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, Iowa State, 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.7: 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.8: 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.9: 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.10: 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.11: 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.12: Regression with Multiple Hypothesis Testing Correction

	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 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.13: 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.14: 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.15: 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,

[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.

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 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. These observations underscore the evolving landscape of scientific communication, with Twitter (now X) emerging as a prominent platform for dissemination and engagement.

D Details on Classification

The analysis begins with a dataset derived from a social network of approximately 97,737 academics on Twitter, as outlined by Mongeon et al. (2023). This dataset, which is the largest of its kind to our knowledge, links researchers' OpenAlex IDs with their Twitter user IDs with high accuracy. It draws from the OpenAlex database, which includes comprehensive academic information such as publications, citations, affiliations, co-authors, and research fields.

The above dataset includes identifiers of academics' Twitter account linked to identifiers of their scholar profile from OpenAlex. Garg and Fetzer (2024) then collect all twitter data available from each profile, including tweets, retweets, comments, follow graph and user-level metadata. While their full dataset includes scholars from all 174 countries, we focus only on US, for which there is the most coverage, and because it is the setting for our experiment. The US sample contains the entirety of these academics' Twitter activities from January 1, 2016, to December 31, 2022, totaling around 116 million tweets. Garg and Fetzer (2024) also conducted the text analysis methods that we reproduce here, focusing on the essential methods for variables used in this paper. The summary statistics provided in this section include the US only sample and includes additional measures that are relevant to this paper, e.g., mentions of scientific research papers or political candidates.

Topic detection Topic detection was primary step in our methodology of stance classification, aiming first to categorize tweets into one of the predefined topical topics: (1) Abortion Rights, (2) Climate Action, (3) Immigration, (4) Racism, (5) Income Redistribution. This approach is further demonstrated in Garg and Fetzer (2024). OpenAI's GPT-4 was used 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.'" The '<*Twitter Fine Tuning*>' directive either explicitly instructed the model to *'Focus on language, phrases, or hashtags commonly used on Twitter'* or was

left empty, ensuring the dictionary remains contextually relevant to the platform's discourse. Hence, the prompt was generated for each combination of topic, ngram, year and vernacular type. This gave 180 prompts (5 topics times 3 ngrams times 6 years and 2 vernacular types). As an illustrative example of the possible combinations is the prompt: *'Provide a list of bigrams related to the topic of climate change in the year 2017. Focus on language, phrases, or hashtags commonly used on Twitter. Provide the bigrams as a* comma-separated *list.'*. Each prompt was sent individually to GPT-4, which gave back keywords for that specific combination. Those keywords were combined at topic level by taking a union across other dimensions. In the end, we are left with five keyword dictionaries, one for each topic. The keywords for each dictionary were applied to the full corpus of tweets. If a tweet contained a keyword from a topic's dictionary, we label that tweet as belonging to that topic. For instance, tweets containing term "Paris Agreement" became part of the "Climate Action" topic. After the topic detection step, we reduced the sample to 5.31% of all tweets. We limit our analysis to the sample of tweets that are topical and sample of authors that have made these topical tweets. This gives us 6,151,793 tweets by 42,747 scientists, as reported in tables B.2 and B.1.

We used a similar process[2] to detect topics for "scientific research papers" to get the dictionary for that. We generated dictionaries for "Donald Trump", and "Joe Biden", the two presidents within our sample, and took the union of the two dictionaries, giving us a single dictionary for Trump or Biden. For politicians/political candidates in general, we generated dictionaries for "Politicians", "Political Candidates", "Donald Trump", and "Joe Biden", and took the union of these four dictionaries, giving us a comprehensive dictionary for politicians and political candidates. The results of this topic detection are also reported in tables B.2 and visualised in figure A.3. Table B.3 presents a selection of example ngrams generated for each topic, illustrating the diversity and scope of ngrams our topic detection method can produce.

Stance detection For stance detection, Garg and Fetzer (2024) employed OpenAI's GPT-3.5 Turbo. Tweets were classified into one of four stances: pro, anti, neutral, or

[2]The only difference is we use GPT-4o instead of GPT-4 since at time of implementation it was the latest model.

unrelated. This was done using the prompt "Classify this tweet's stance towards <topic> as 'pro', 'anti', 'neutral', or 'unrelated'. Tweet: <tweet>.'" This classification was instrumental in assessing each tweet's position on the specified topics, aided by a refined prompt strategy that improved accuracy and relevance. A sampling procedure was employed to reduce the total costs of this tweet-by-tweet labelling task. For each year by month, up to three random tweets per authors per topic were included in the sample. This ensured there are enough tweets to determine the stance of an author in a given time period. See table B.2 for the summary of the topical and stance detection steps.

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>.'" This classification was instrumental in assessing each tweet's position on the specified topics, aided by a refined prompt strategy that improved accuracy and relevance. A sampling procedure was employed to reduce the total costs of this tweet-by-tweet labelling 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. This sampling procedure did not reduce the number of academics.

Out of the initial sample of 97,737 academics, we retained only those who had tweeted about a political topic, resulting in 52,541 academics. These 52,541 academics had tweeted in a pro, anti, or neutral way on at least one of the five topics. See table B.2 for the summary of the topical and stance detection steps.

The stance detection methodology is a frontier application of LLMs for classification purposes. Garg and Martin (2024b) and Garg and Fetzer (2024) provide validation of the stance detection procedure used by comparing the stances predicted by GPT 3.5 Turbo and those labelled by humans. We reproduce the validation exercise here for completeness. Humans labelled tweets are pro-, anti- and neutral-, on topics ranging from Abortion Rights to Donald Trump. The stance detection's effectiveness was validated against 40,317 hand-coded labels from 137 humans, yielding F-scores of 79-92, which are considered very high for classification tasks. We reproduce the results in table B.4. For

further details on validation and comparisons with opinion poll measures, see Garg and Martin (2024b) and Garg and Fetzer (2024).

Gender Gender was inferred using OpenAI's GPT-3.5 Turbo on the Author names from OpenAlex, categorizing them as 'Male', 'Female', or 'Unclear', resulting in 49% Male, 49% Female, and less than 1% Unclear. This approach acknowledges the limitations of name-based gender inference and of binary classification, but is included for simplicity.

Field OpenAlex employs a machine-learning algorithm that evaluates the thematic 'Concepts' of each author's works. With 19 root-level concepts organized hierarchically, we simplified these into four broad categories: Social Science, Medicine, STEM, and Humanities, for comparative analysis. Each author's primary field of study was determined based on the highest average score across these root concepts, reflecting the predominant theme in their works from 2016 to 2022. We classified the root-level concepts into broader concepts using the following sets: (1) STEM contains Biology, Chemistry, Computer Science, Engineering, Environmental Science, Geography, Geology, Materials Science, Mathematics, Medicine[3], Physics. (2) Social Sciences contains Business, Economics, History, Political Science, Psychology, Sociology. (3) Medicine contains Medicine. (4) Humanities contains Art, Philosophy, Literature, Religion, Music, Theater, Dance, Film. A portion of authors did not have associated "concepts" linked to their work. Table B.1 provides a summary statistic on authors that we have the concepts associated with—half of the authors that have tweeted on political topics have concepts classified, and the distribution across broad fields. Future work will use the new "Topics" feature released by OpenAlex.

[3]Note: Medicine appears in both STEM and in the broader category Medicine.

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 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]

—- page break —-

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 dis-

agree, Somewhat agree, Strongly agree]

—- page break —-

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

—- page break —-

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]