Econometrica Supplementary Material

SUPPLEMENT TO "POLITICIZED SCIENTISTS: CREDIBILITY COST OF POLITICAL EXPRESSION ON TWITTER"

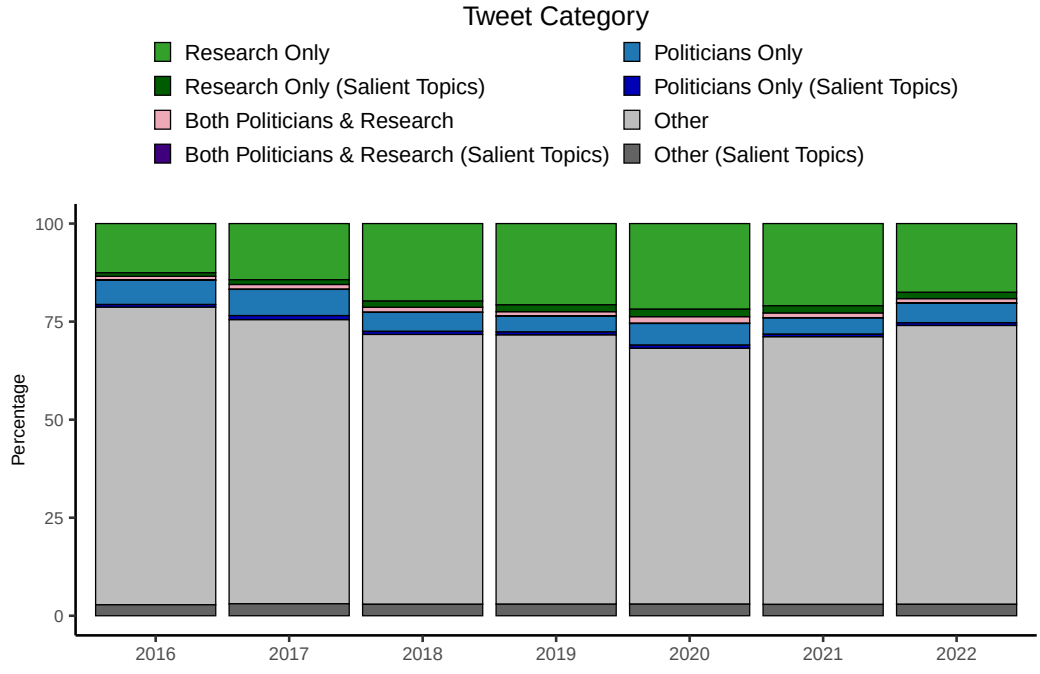
ELEONORA ALABRESE
University of Bath, CAGE, SAFE,

FRANCESCO CAPOZZA
WZB Berlin, BSoE, CESifo

PRASHANT GARG
Imperial College London

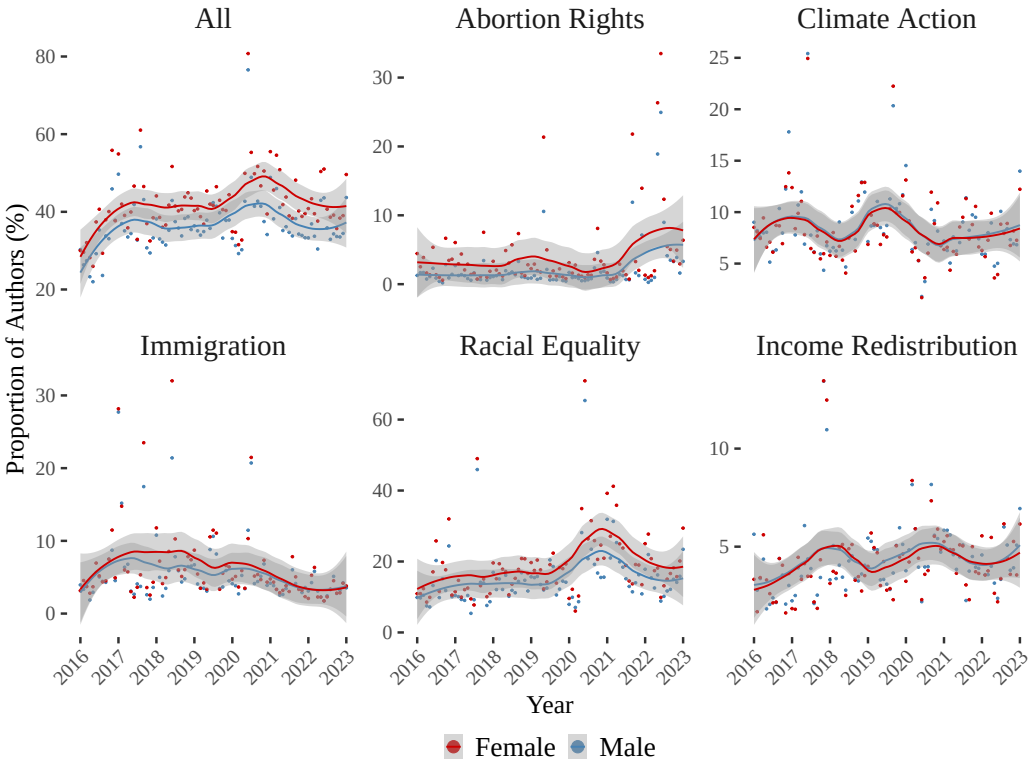
1. ONLINE FIGURES

FIGURE 1.—Yearly Distribution of Tweets by Academics Mentioning Politicians, Research Papers, and Salient Topics



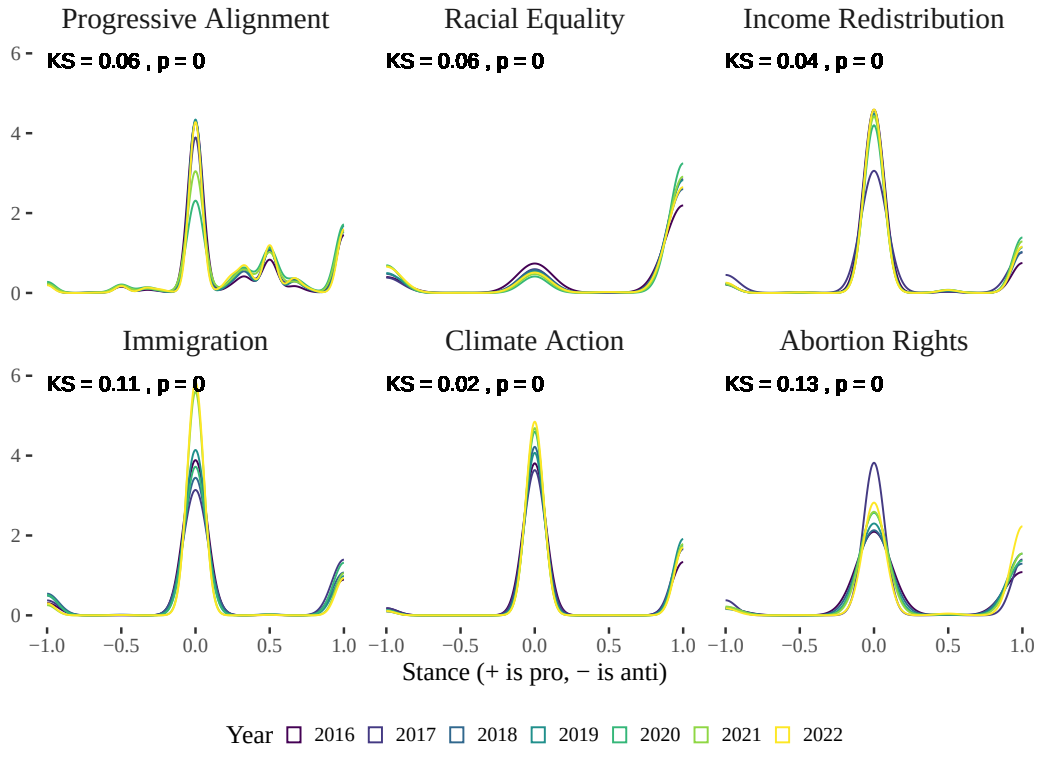
Note: This figure depicts the yearly distribution of tweets by academics from 2016 to 2022, highlighting the proportion of tweets that mention politicians, research papers, both, and other content. It helps to understand the interaction between political discourse and academic content over time. Each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

FIGURE 2.—Proportion of Academics with Political Opinions Over Time by Topic and Gender



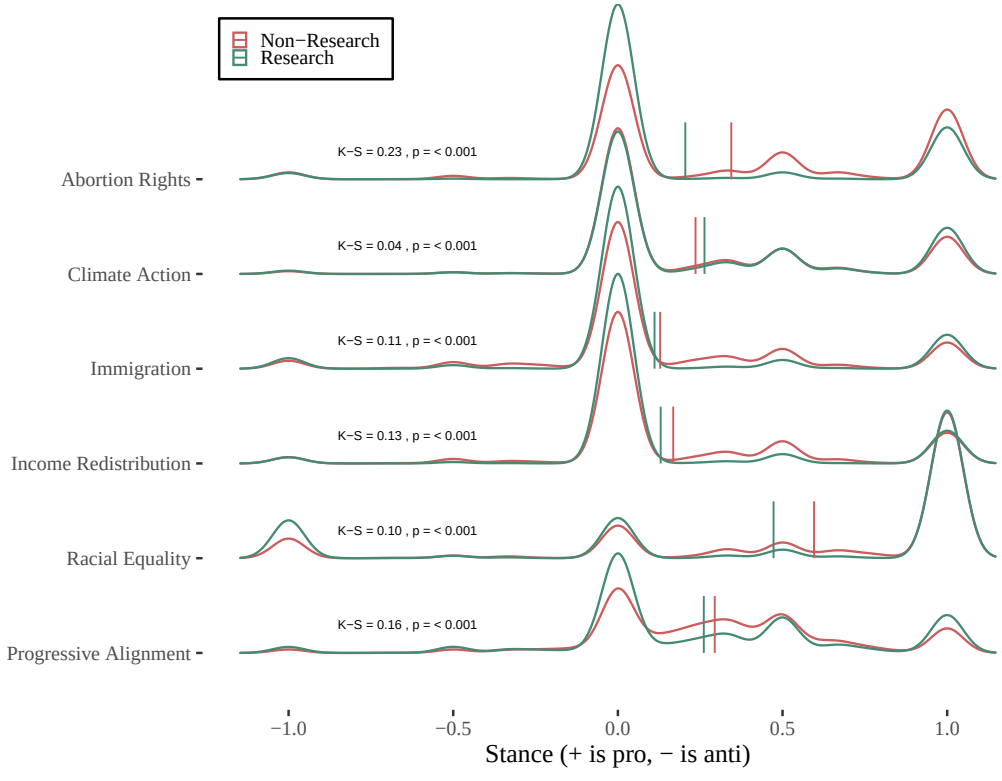
Note: We passed the full OpenAlex academic name as it appears on their papers to an LLM to classify the gender as 'Male', 'Female', or 'Unclear'. Close to 99% of names were labeled Male or Female. Using this binary classification of gender, we can explore sub-population differences in political expression.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

FIGURE 3.—Evolution of Ideological Polarization among Academics



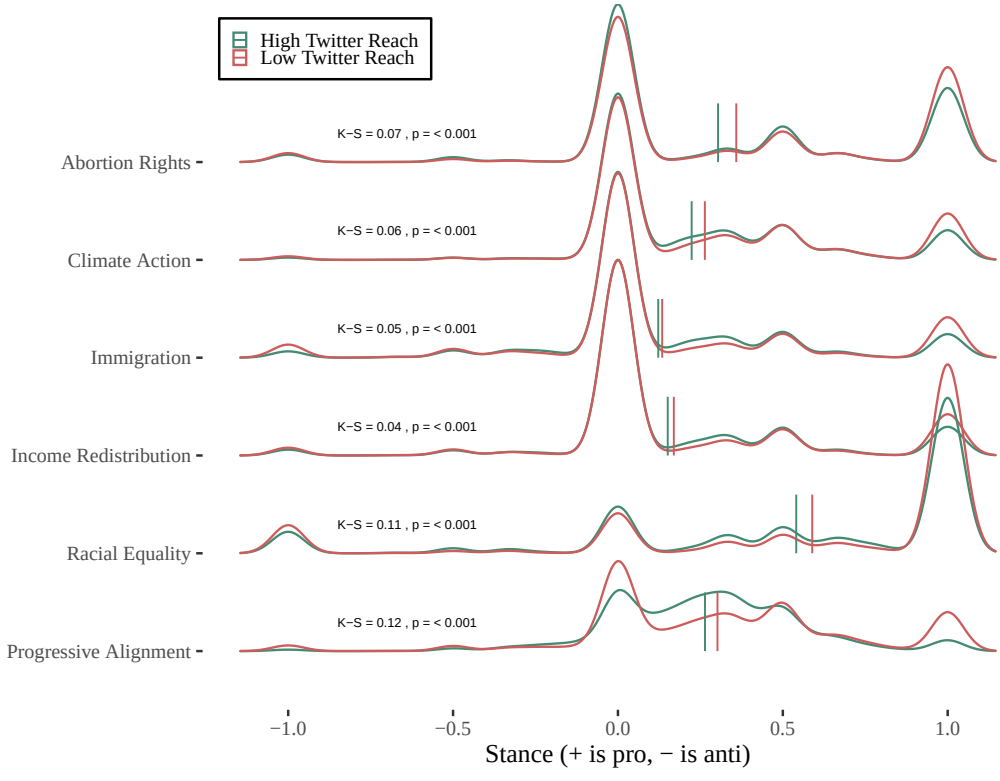
Note: This figure investigates the dynamics of ideological polarization among academics over time, focusing on key political issues. Each panel presents yearly distributions of stances of U.S. academics on various topics, testing for distribution equality between early (2016-2017) and late (2021-2022) 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 4.—Cross-sectional Ideological Polarization based on whether Academic Tweets are Research Related



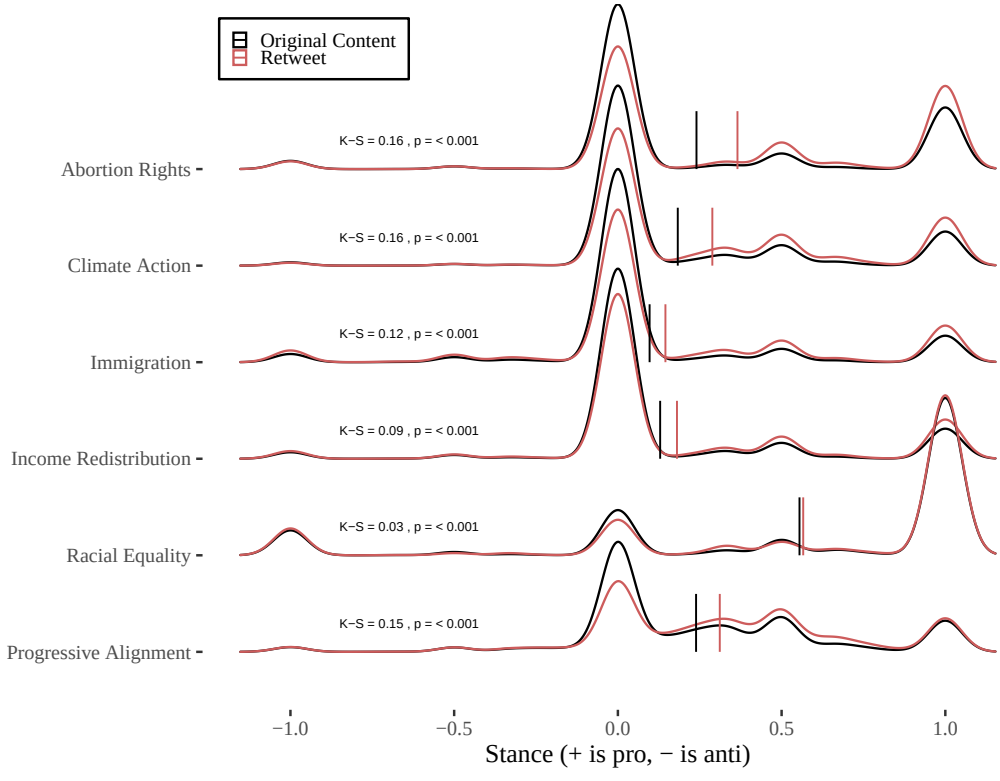
Note: The figure presents the density distributions of net stances across various political topics among U.S. academics from 2016 to 2022, comparing tweets that mention research papers (in green) with those that do not (in red). Topics include Income Redistribution, Climate Action, Immigration, Abortion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

FIGURE 5.—Cross-sectional Ideological Polarization based on High vs. Low Twitter Reach



Note: The figure presents the density distributions of net stances across various political topics among U.S. academics from 2016 to 2022, comparing academics with high Twitter reach (in green) and low Twitter reach (in red). High and low Twitter reach is defined based on whether the follower count is above or below the median of the filtered dataset (median = 522; 1st quartile = 219; 3rd quartile = 1,302; max = 4,587,745). Topics include Income Redistribution, Climate Action, Immigration, Abortion Rights, and Racial Equality, with "Progressive Alignment" representing the average stance across these topics. The x-axis represents the net stance, where positive values indicate a pro stance and negative values indicate an anti stance. The y-axis lists the different topics, with density distributions shown as ridgelines. Vertical mean lines are included for each distribution, colored according to the Twitter reach category. Kolmogorov-Smirnov (K-S) test results are annotated for each topic, indicating statistically significant differences between the distributions of high and low Twitter reach (p-values < 0.001). Low reach tweets tend to exhibit more polarized stances compared to high reach tweets, with the largest divergence observed in Abortion Rights and Racial Equality.

FIGURE 6.—Cross-sectional Ideological Polarization based on Retweets vs. Original Content



Note: The figure presents the density distributions of net stances across various political topics among U.S. academics from 2016 to 2022, comparing retweets (in red) with original content (in black). Original content includes original tweets, replies and any retweets with additional comments (i.e., quoted retweets). Topics include Income Redistribution, Climate Action, Immigration, Abortion Rights, and Racial Equality, with "Progressive Alignment" representing the average stance across these topics. The x-axis represents the net stance, where positive values indicate a pro stance and negative values indicate an anti stance. The y-axis lists the different topics, with density distributions shown as ridgelines. Vertical mean lines are included for each distribution, colored according to the content type. Kolmogorov-Smirnov (K-S) test results are annotated for each topic, indicating statistically significant differences between the distributions of retweets and original content (p-values < 0.001). Retweets tend to exhibit more polarized stances compared to original content, with the largest divergence observed in Abortion Rights and Climate Action.

FIGURE 7.—Vignettes of scientists profiles

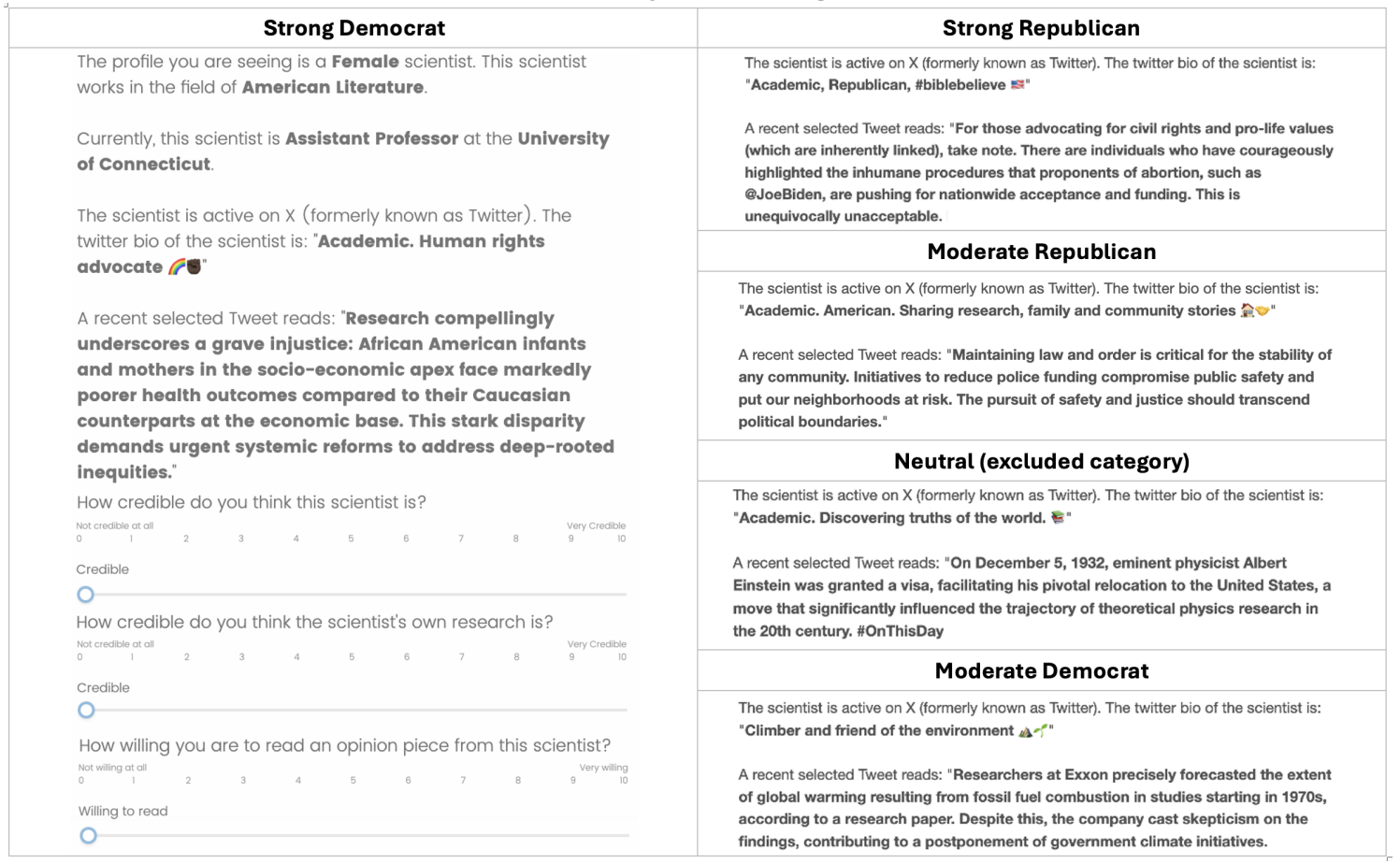
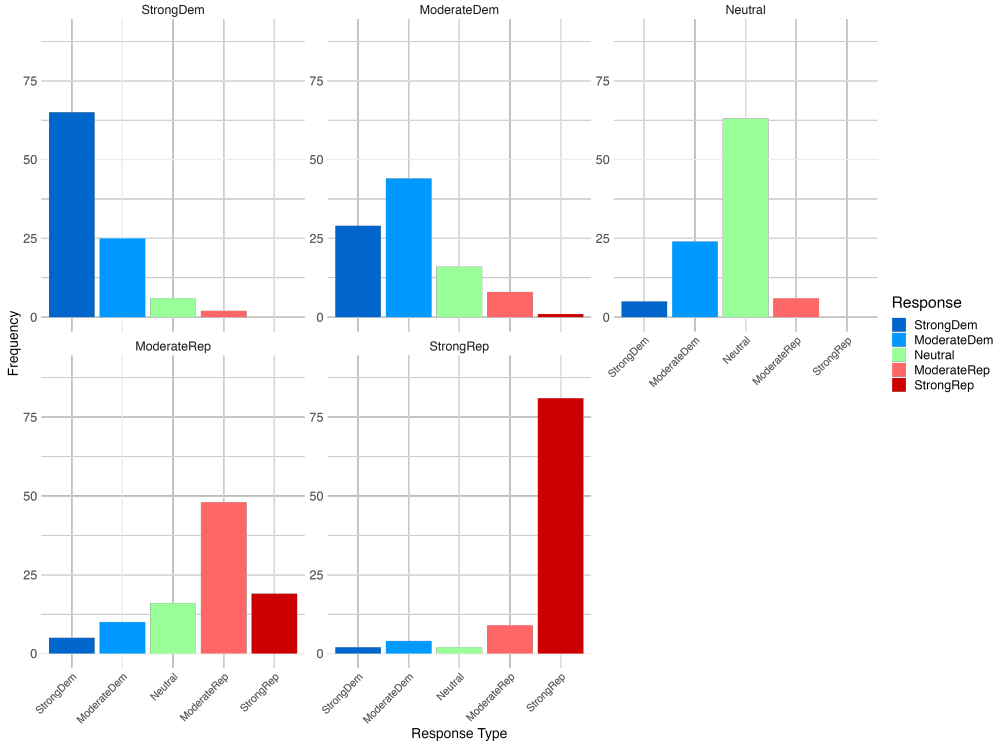
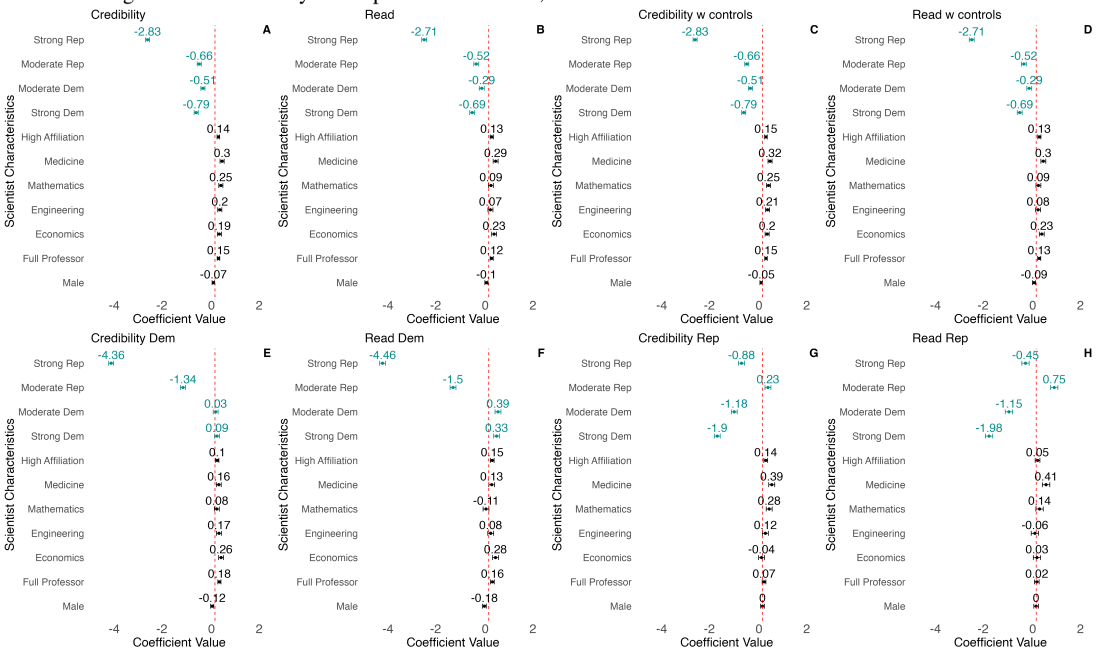


FIGURE 8.—Frequency of Responses by Intended Political Leaning of Twitter Signal



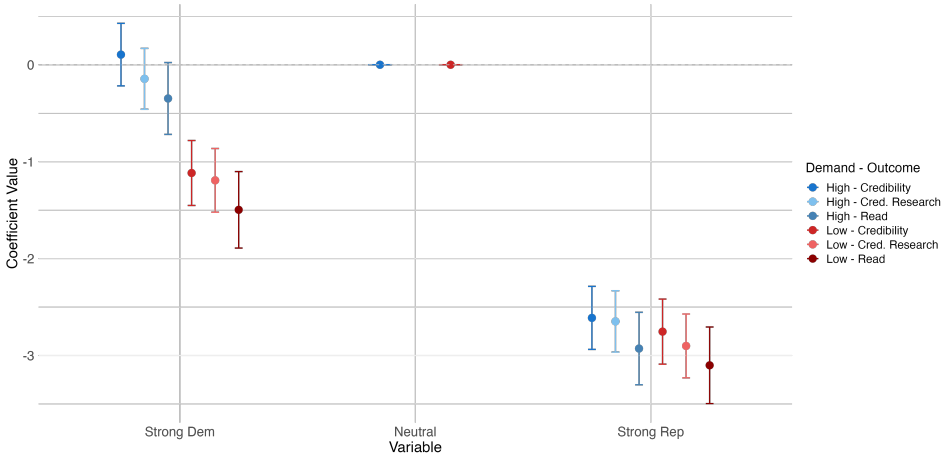
Note: The figure presents the results of a validation of the political signals used in the main experiment. In the validation, we asked 98 respondents, recruited on Prolific, to classify the political leaning of five vignettes. Each vignette displayed one of five different Twitter bios and Twitter posts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

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



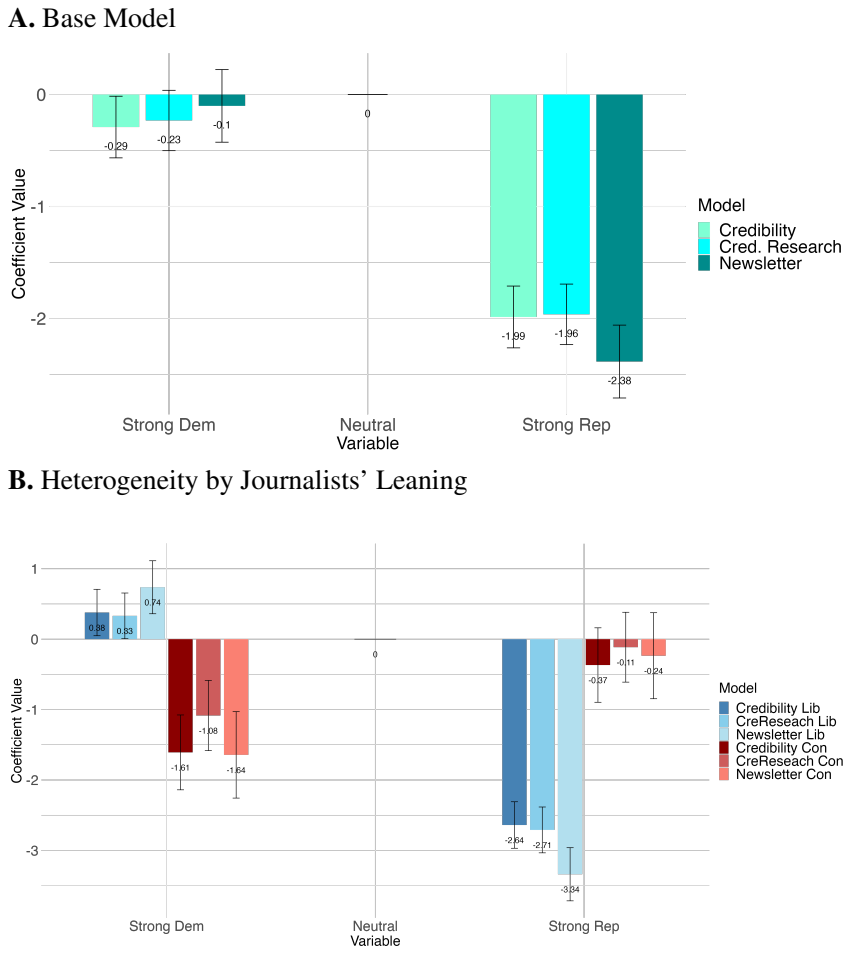
Note: Coefficients are obtained by regressing scientists' characteristics on respondents' perceived credibility or willingness to read from scientists. All the standard errors are clustered at the individual level. Political leaning is indicated by "Strong Republican," "Moderate Republican," "Strong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

FIGURE 10.—Bounding the impact of scientists' political expression on perceived credibility and willingness to read: Credibility and public willingness to read peak at neutral, while both left- and right-leaning scientists face a credibility penalty regardless of the demand condition.



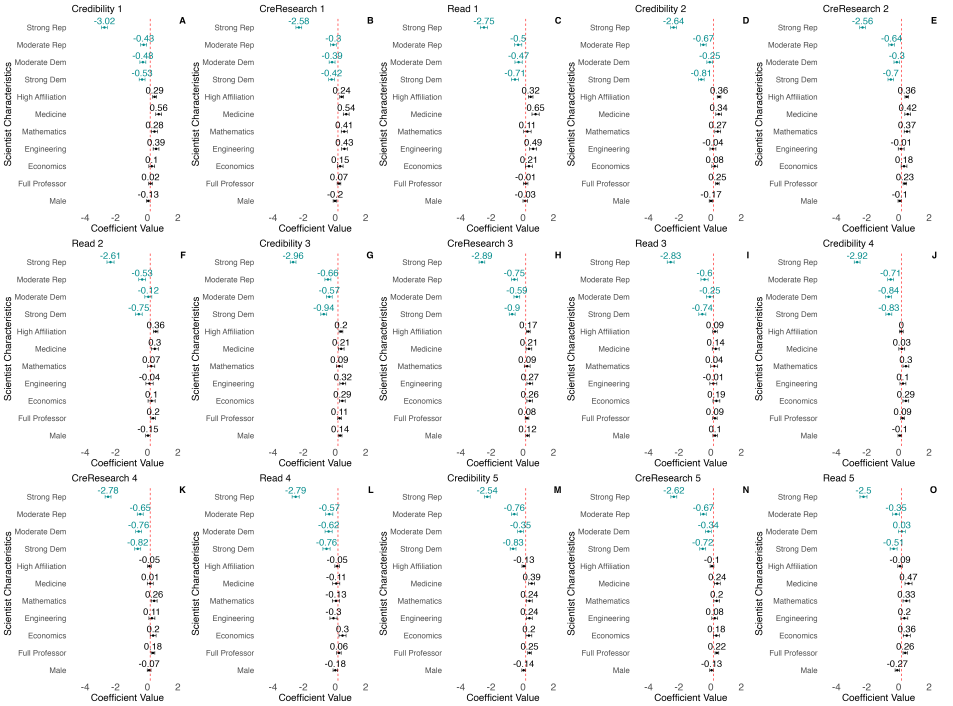
Note: Coefficients are estimated by regressing respondents' perceived credibility and willingness to read opinions from scientists on the scientists' attributes. The x-axis represents different political affiliations of scientists, captured using indicator variables for "Strong Republican" and "Strong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

FIGURE 11.—Impact of scientists' political expression on perceived credibility and willingness to read from the general public. Credibility and public willingness to read peak at neutral, with a penalty for scientists displaying political affiliations to the 'left' and 'right' of neutral (***Journalists***).



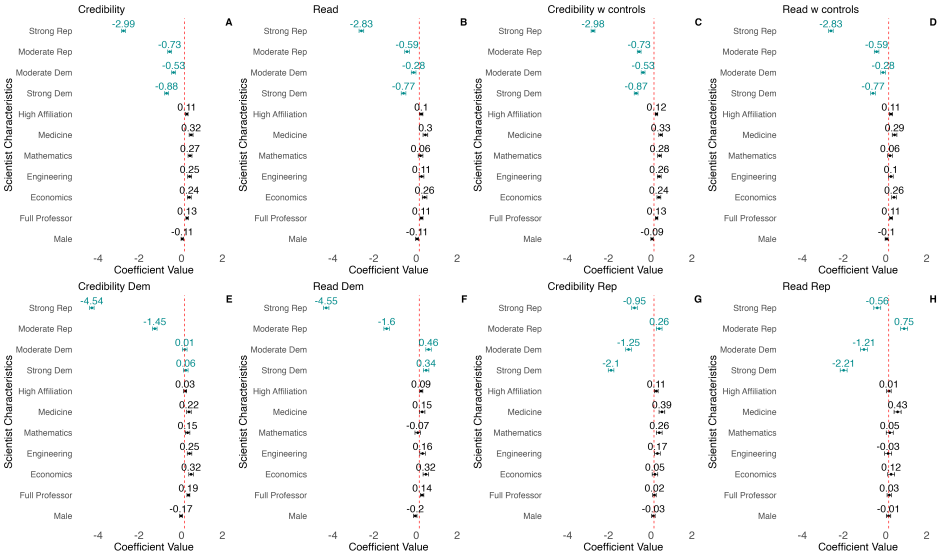
Note: Coefficients are obtained by regressing scientists' characteristics on journalists' perceived credibility or willingness to feature content from scientists. The x-axis represents different political affiliations of scientists, estimated by indicator variables for "Strong Republican" and "Strong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

FIGURE 12.—Excluding carryover effects on scientists' credibility and willingness to read.



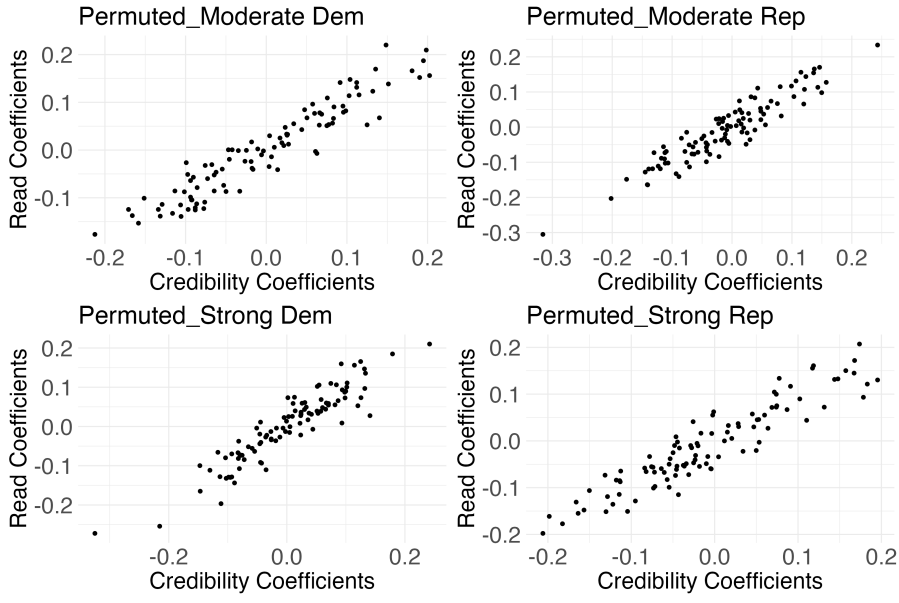
Note: Coefficients were obtained by regressing scientists' characteristics on respondents' perceived credibility or likelihood of reading from similar scientists. We repeat the procedure for each profile the respondents have seen in the study. All the standard errors are clustered at the individual level.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

FIGURE 13.—Effect of scientists' attributes on respondents' perceived credibility, excluding speeders.



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

FIGURE 14.—Permutation Test



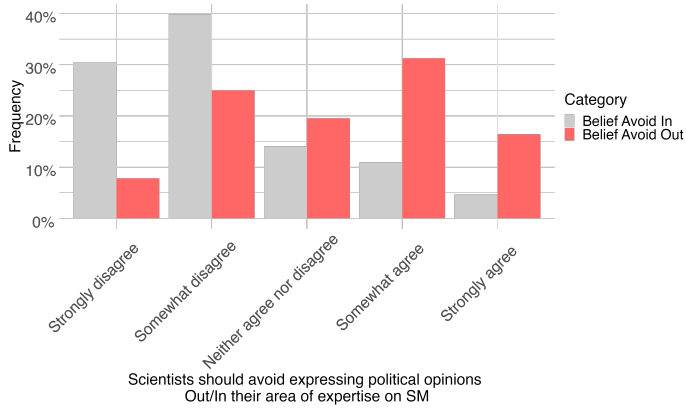
Note: This figure reports the results of a permutation test conducted to assess the robustness of our estimates and ensure that our observed political effects are not due to some unusual feature of the data. To address this, we randomly re-shuffled all political labels across profiles within each respondent,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

FIGURE 15.—Vignettes of economists profiles

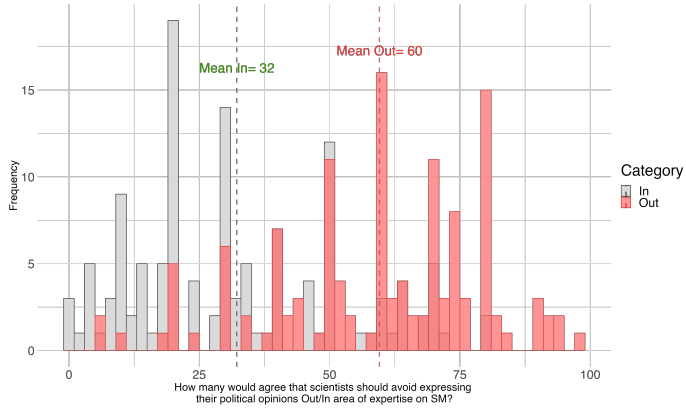
Passive Control 1/6	**Treatment Left (signal)** 1/3
The economist is active on X (formerly known as Twitter). The twitter bio of the economist is: "**Passionate about Research**". This is an example of a tweet: "**In our recent paper, we show that Nash equilibrium uniquely satisfies key axioms across 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 16.—Scientists' Own Beliefs and Belief's on Other Scientists Beliefs around Academics Publicly Expressing Political Views

A. Scientists Should Avoid Expressing Political Opinions

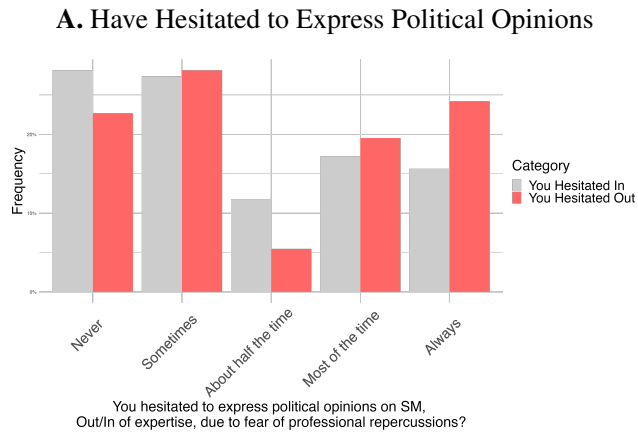


B. How many Scientists Agree on Avoiding to Express Political Opinions



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 17.—Scientists' Experience Hesitating to Express Political Opinions and their Perception around Positive and Negative Consequences from Public Political Expression



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.

2. ONLINE TABLES

TABLE I

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
High Twitter Reach	25,688	50.1	87.8	53.1
Low Twitter Reach	25,583	49.9	74.8	36.3
Field: With Concepts Data	25,719	49.0	81.4	51.7
Field: Humanities	103	0.4	86.4	57.8
Field: STEM	11,819	45.95	79.5	42.5
Field: Social Sciences	6,032	23.5	86.0	64.9
Field: Medicine	7,765	30.19	80.6	38.3

Note: 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. High and low Twitter reach is defined based on whether the follower count is above or below the median of the filtered dataset (median = 522; 1st quartile = 219; 3rd quartile = 1,302; max = 4,587,745). "With Concepts Data" refers to those for whom we have concepts data. Above 40% of our full sample of academics ever talked about one of the topics of interest during the period of observation.

TABLE II

SUMMARY STATISTICS OF TOPIC AND STANCE DETECTION

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

Note: Table shows tweet-level summary statistics of topic and stance detection steps. The dataset and classification methods are described in detail in Section 4. We reproduce here the essential methods for variables used in this paper. The data contains the entirety of these academics' Twitter activities from January 1, 2016, to December 31, 2022. This included original tweets, retweets, quoted retweets, and replies, totaling around 116 million tweets. Topic detection was the primary step in our methodology of stance classification, aiming first to categorize tweets into one of the predefined topics: (1) Abortion Rights, (2) Climate Action, (3) Immigration, (4) Racial Equality, (5) Income Redistribution. This approach is further demonstrated in Garg and Fetzer (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 (including Trump or Biden). The "% Mention Trump/Biden" column represents the percentage of tweets mentioning either Joe Biden or Donald Trump. The "% Mention Research" column represents the percentage of tweets mentioning scientific research papers.

TABLE III

EXAMPLE NGRAMS FOR TOPIC DETECTION

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

Note: 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 IV

EVALUATION METRICS: GPT 3.5 TURBO, GPT-4, AND TOPIC DETECTION

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

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

TABLE V

EXAMPLES OF TWEETS BY STANCE

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

Note: The table presents examples of tweets by stance (pro, anti, neutral) for the five topics: Income Redistribution, Climate Action, Immigration, Abortion Rights, and Racial Equality. These tweets are drawn from the complete timelines of academics, which include (1) original tweets, (2) retweets, (3) quote retweets, and (4) replies. Consequently, some tweets may reflect content shared or quoted by academics rather than authored directly by them.

TABLE VI

SUMMARY STATISTICS MAIN STUDY

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

Outcome	Mean
Credibility	6.35
Credibility Research	6.27
Read	5.63

Note: 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.

TABLE VII

CHARACTERISTICS OF THE SCIENTISTS' PROFILES

Attributes	**Categories**	**Options**
Gender	Male, Female	We specify the gender
Research Field	Social Sciences, STEM, Medicine, and Humanities	We mention: Economics, Material Engineering, Mathematics, Medicine, American Literature
Seniority	Senior, Junior	We mention that scientists are: Full Professor or Assistant Professor
University Affiliation	High-ranked, Low-ranked	We use affiliations to Harvard University, Berkeley, University of Chicago, University of Arkansas, University of Connecticut
Twitter Bio and Twitter Post	Strongly Dem, Moderately Dem, Strongly Rep, Moderately Rep, Neutral	Academic. Human rights advocate [rainbow and fist emoji] - "Greta has been arrested for the first time. This signals a moment for more of us to rise and face arrest if necessary, for the future of our planet. Such actions have the power to change the course of events.", Academic. Friend of the environment [wave emoji] - "Researchers at Exxon precisely forecasted the extent of global warming resulting from fossil fuel combustion in studies starting in 1970s, according to a research paper. Despite this, the company cast skepticism on the findings, contributing to a postponement of government climate initiatives. ", Academic. Republican. #biblebelieve [American flag] - "For those advocating for civil rights and pro-life values (which are inherently linked), take note. There are individuals who have courageously highlighted the inhumane procedures that proponents of abortion, such as @JoeBiden, are pushing for nationwide acceptance and funding. This is unequivocally unacceptable", Academic. American. Sharing research, family and community stories [house and handshake emoji] - "I'm not inclined towards the right or the left, but the excessive wokeness of the left has nudged me to the right. Interestingly, when right-wing extremists commit mass shootings against minorities, it doesn't compel me to shift towards the left. Somehow, that's not considered 'too far.'", Academic. Discovering truths of the world [books emoji] - "On December 5, 1932, Albert Einstein received a visa, enabling his journey to the United States. #OnThisDay"
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."

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

TABLE VIII

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

Note: 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 IX

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

Note: 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 X

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

Note: 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 XI

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

Note: 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 XII

SUMMARY STATISTICS OF JOURNALISTS

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

Outcome	Mean
Credibility	6.24
Credibility of Research	6.14
Newsletter	5.92

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

TABLE XIII

JOURNALISTS' BELIEFS

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

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

TABLE XIV

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

Note: 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 XV

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

Note: 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 XVI

SUMMARY STATISTICS OF SCIENTISTS

	Survey 1	Survey 2
Institute: University	0.63	0.65
Institute: Research Institute (including public agencies)	0.17	0.16
Institute: Private institute	0.18	0.14
Institute: Non profit	0.02	0.02
Institute: Hospital/clinic/facility	0.01	0.02
Seniority: Less than 1 year	0.08	0.11
Seniority: Between 1 year and 3 years	0.19	0.18
Seniority: Between 3 years and 5 years	0.26	0.2
Seniority: More than 5 years	0.48	0.51
Position: Postdoctoral researcher	0.43	0.49
Position: University faculty	0.28	0.32
Position: Industry professional	0.29	0.19
Field: Arts & Humanities	0.05	0.10
Field: Life Sciences & Biomedicine	0.34	0.20
Field: Physical Sciences	0.11	0.09
Field: Social Sciences	0.34	0.43
Field: Technology	0.16	0.17
Employment: Working full time now	0.89	0.81
Employment: Working part time now	0.05	0.08
Employment: Unemployed	0.03	0.02
Employment: Retired	0.01	0.01
Male	0.51	0.45
Female	0.46	0.52
Non-binary	0.03	0.03
Republican	0.02	0.06
Democrat	0.42	0.37
Independent	0.18	0.20
Other	0.28	0.22
Not sure	0.10	0.14

Note: The Scientists samples recruited on Prolific. The characteristics are broken down into different dimensions.

TABLE XVII
SUMMARY OF SCIENTISTS' RESPONSES TO OPEN-ENDED QUESTIONS

Question	Summary of Responses	Example Response
In your own words, **what qualifies a scientist as 'politicized'** when they actively engage in political discourse? Where do you draw the line between sharing an opinion and promoting an ideology?	Scientists are often seen as "politicized" when their engagement shifts from presenting evidence-based insights to actively promoting specific ideologies or agendas. Intent, evidence basis, and context are key factors in distinguishing opinions from ideology.	*A scientist becomes 'politicized' when they share opinions that are politically laden and fall outside their area of expertise; the key distinction lies in intent.*
In a previous survey, scientists found it broadly acceptable to share political views related to their expertise. In your own words, **what are the boundaries of that expertise** (e.g., own literature, sub-field, discipline)?	The boundaries of expertise include a scientist's research area, sub-field, and relevant literature. While it is acceptable to share views directly related to one's expertise, caution and evidence-based claims are essential to maintain credibility.	*The boundaries of a scientist's expertise encompass their research, broader sub-field, and established knowledge, provided their claims are supported by evidence and consensus.*
Would you like to **share any personal experiences** regarding the costs or benefits of sharing political views online or in public?	Respondents expressed mixed views, highlighting potential professional risks (e.g., backlash, reputation loss, job security) but also noting opportunities for raising awareness and fostering discourse on important issues within their expertise.	*Sharing political views online can help inform the public about important issues, but it can also lead to backlash or harm professional relationships, making caution essential.*

3. ONLINE PRESENCE OF SCIENTIFIC PUBLICATIONS

Using Scopus, we retrieved 114,868 articles (2011–2020) from top journals (*Science*, *Nature*, *PNAS*, *Cell*, *NEJM*, *Lancet*); 107,008 articles with unique DOIs were tracked by Altmetric.[1] Our analysis reveals a consistent upward trend in online presence across diverse media, indicating that scientists increasingly engage broader audiences beyond traditional academia. Figure 1 (Panel A) shows a marked surge in coverage via blogs, newspapers, and Twitter.

Twitter mentions are especially significant: 42,701 articles (40%) were mentioned in blogs, 47,987 (45%) in news articles, and 102,795 (96%) in tweets, underscoring Twitter's pivotal role in scientific communication. The first panel of Figure 1 (Panel A) presents the absolute number of appearances across media; the second, the proportion of articles with any coverage; and the third, the average number of appearances per article.

Overall, all metrics show an upward trend. Blog posts (orange) remain relatively stable in absolute numbers, proportions, and average mentions—possibly reflecting their declining relevance—whereas newspaper coverage (red) increased steadily in the first half of the period, plateaued later, and spiked in 2020. Scientific discourse on Twitter (light blue) has surged since 2013, with nearly all papers mentioned on the platform and an average peak of almost 250

[1]Altmetric tracks online dissemination of scientific articles across platforms (Alabrese, 2022, Peng et al., 2022); accessed November 10, 2021. See API documentation.

tweets per paper in 2020. Figure 1, Panel B, further illustrates that, from 2011 to 2020, the distribution of Twitter mentions has become less skewed towards zero, with a thicker right tail and more high-mention outliers, highlighting Twitter's emerging prominence as a medium for scientific dissemination and engagement.

4. LLM VALIDATION

Validation of Topic and Stance Detection Methods Our stance detection method leverages LLMs, with validation detailed in Garg and Fetzer (2024). Comparing GPT-3.5 Turbo's classifications against 40,317 human-coded labels (from 5,000 unique tweets labeled by 137 annotators) for topics like Abortion Rights and Donald Trump, the model achieved F-scores between 79 and 92. Table IV reproduces these results. Comparisons with GPT-4, which showed slight improvements on Abortion-related content, confirm our method's robustness. Topic detection was validated using the SemEval-2016 dataset, with GPT-4–generated dictionaries for topics (e.g., Feminist Movement, Hillary Clinton, Legalization of Abortion, Donald Trump) yielding F-scores from 67.01 to 74.87 (see Table IV).

Gender We inferred gender using GPT-3.5 Turbo to classify OpenAlex author names as 'Male', 'Female', or 'Unclear', resulting in a distribution of 49% Male, 49% Female, and <1% Unclear. Garg and Fetzer (2024) validated this approach with 147,269 unique names from sources such as the U.S. Social Security Applications (1880–2019), UK Baby Names (2011–2018), British Columbia's 100 Years of Popular Baby Names (1918–2018), and Australian Baby Names (1944–2019), achieving a count-weighted F1 score of 0.9868.

Field OpenAlex assigns each author's work to 19 hierarchical root-level 'Concepts'. For our analysis, we simplified these into four broad categories: STEM, Medicine, Social Sciences, and Humanities. Each author's primary field is determined by the highest average score across root concepts (based on their 2016–2022 publications). STEM covers Biology, Chemistry, Computer Science, Engineering, Environmental Science, Geography, Geology, Materials Science, Mathematics, and Physics; Medicine is standalone; Social Sciences include Business, Economics, History, Political Science, Psychology, and Sociology; Humanities encompass Art, Philosophy, Literature, Religion, Music, Theater, Dance, and Film. Table I summarizes these classifications, with about half of the authors tweeting on political topics having an identified field and a detailed distribution across these categories.

REFERENCES

ALABRESE, ELEONORA (2022): "Bad Science: Retractions and Media Coverage," *CESifo Working Paper No. 10195*. [29]

GARG, PRASHANT AND THIEMO FETZER (2024): "Political Expression of Academics on Twitter," *Forthcoming, Nature Human Behaviour*. [17, 18, 30]

PENG, HAO, DANIEL M. ROMERO, AND EMOKE-Á.GNES HORVÁT (2022): "Dynamics of Cross-platform Attention to Retracted Papers," *Proceedings of the National Academy of Sciences*, 119 (25), e2119086119. [29]