Politicized Scientists: Credibility Cost of Political Expression on Twitter

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I and twenty-two other Nobel economists signed a letter endorsing Kamala Harris for President.

We believe Harris's policies will result in a stronger economic performance, with economic growth that is more robust, more sustainable, and more equitable.

Traduci post

Da cnn.com

5:50 PM · 23 ott 2024 · **1,9 Mln** visualizzazioni

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Tony Yates @t0nyyates · 19 giu

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PS if you are an economist and endorse this letter, and are prepared to do so openly, let me know.

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What are the risks?

Trust in science matter

> In *post-truth* era where difference bw facts and opinions shrinks (Bursztyn et al., 2023; McIntyre, 2018), **trust in science crucial for informed decision-making and effective public policy**

> **Examples**: COVID public health responses (Algan et al., 2021; Calónico et al., 2023); persuit of environmental goals (Druckman and McGrath, 2019); overall progress (Cervellati et al., 2023)

Erosion of trust

> Erosion of trust in science observed in recent years (Lupia et al., 2024; Nichols, 2017).

> **Factors** fueling anti-science sentiment: misinformation (West and Bergstrom, 2021), conspiracy theories (Douglas, 2021; Rutjens and Većkalov, 2022), "reproducibility crisis" (Hendriks et al., 2020), science-related populism (Mede and Schäfer, 2020), political ideology (Cologna et al., 2025) perceived political bias (Altenmüller et al., 2024)

> Polarization rises concerns: **U.S. conservatives** report lower trust in scientists, stronger anti-science attitudes, lower confidence in scientists' intentions and methods (Azevedo and Jost, 2021; Funk et al., 2020; Li and Qian, 2022; Mede, 2022)

Research question

Can scientists public political expression polarize audience perceptions?

1. How vocal are scientists around political issues online?
2. Does scientists' online political expression impact public perceptions?

Study two common concepts of political polarization (Barberá, 2020)
- ideological polarization (divergence in expressed political views)
- affective polarization (dislike for the partisan outgroup)

This Paper

Uses descriptive evidence (Twitter/**X**) and online experiments (US pop, international journalists and scientists)

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   Strong Rep scientists are 40% less credible than neutral scientists

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2. Large *credibility penalty* for scientists engaging in political discourse, with respondents primarily losing trust in the "other side"
   Strong Rep scientists are 40% less credible than neutral scientists

3. Salient research content and pure political signal both impact credibility

Political Tweets

Contribution

- Public perceptions of scientists and their communication Altenmüller et al. (2024); Kotcher et al. (2017); Petersen et al. (2021); Van Der Bles et al. (2020, 2019); Zhang (2023) → Impact of scientists' political commentary
- Measures stances using text-as-data Ash (2016); Cagé et al. (2020); Draca and Schwarz (2024); Gentzkow et al. (2019); Grimmer (2010); Hansen et al. (2018); Jelveh et al. (2024); Jensen et al. (2012) → U.S. academics slant and disagreement around salient issues on social media
- U.S. trends in ideological and affective polarization Alesina et al. (2020); Boxell et al. (2024); Canen et al. (2021); Flaxman et al. (2016); Gentzkow and Shapiro (2011); Iyengar et al. (2019); Levy (2021) → Individuals gravitate toward scientists with aligned views and dismiss misaligned as less credible
- Social identity Alford et al. (2011); Braghieri et al. (2024); Brown et al. (2022); Burnitt et al. (2024); Bursztyn et al. (2020); Charness and Chen (2020); Garcia-Hombrados et al. (2024); Grossman and Helpman (2021); Huber and Malhotra (2017) → Scientists' political identity diminishes their credibility, the credibility of their research, and public engagement
- Online media and its effect Ajzenman et al. (2023a,b); Angeli et al. (2022); Beknazar-Yuzbashev et al. (2022); Guriev et al. (2023); Jiménez Durán (2022); Zhuravskaya et al. (2020) → Risks of social media increased centrality in academia

Outline

1. Introduction
2. Scientists' Voice
3. Impact on Credibility
4. Take aways

Do scientists express political views online?

Context: Science and scientists online

- Impact is important for scientists and SM can yeld professional benefits (Chan et al., 2023; Klar et al., 2020; Qiu et al., 2024)
- Reflected in Altmetric data showing significant online dissemination of scientific research
  Online Coverage X Distribution
- Scientists post beyond research and **public can easily access** more information on them
  Type of Tweets
- One possible reason for low credibility is perceived political bias Altenmüller et al. (2024)
- **Need to study academics online political expression and its impact**

Data

> Dataset from network of $\approx 100K$ US academics on $\mathbf{X}$ (from Garg and Fetzer, 2025)

> Mongeon et al. (2023) links researchers' OpenAlex and $\mathbf{X}$ accounts with high accuracy

> OpenAlex data includes *publications, citations, affiliations, co-authors, and fields*

> $\mathbf{X}$ data on academics from Jan 2016 to Dec 2022

> Include *tweets, retweets, quotes, and replies*, total **115M posts**

Methodology (Step 1)

Topic detection → Stance detection → Ideological polarization

Dynamic keyword dictionaries

$\forall$ topic using GPT-4

topics: Abortion, Climate Immigration, Race, Redistribution

Topic Detection

Methodology (Step 2)

Topic detection → **Stance detection** → Ideological polarization

Pro/anti/neutral stances

$\forall$ tweet x topic using GPT-3.5

Stance Detection

Methodology (Step 3)

Topic detection → Stance detection → **Ideological polarization**

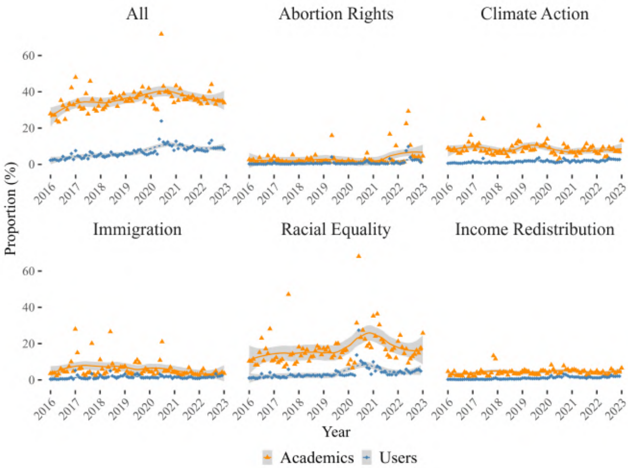
↓

Slant S_u (net pro stance)

$\forall$ user x topic x time period

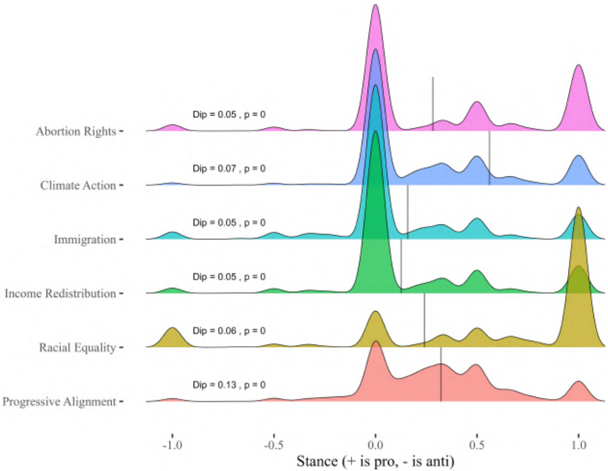
Ideological Polarization

Scientists are more vocal than users, especially on *climate* and *race*



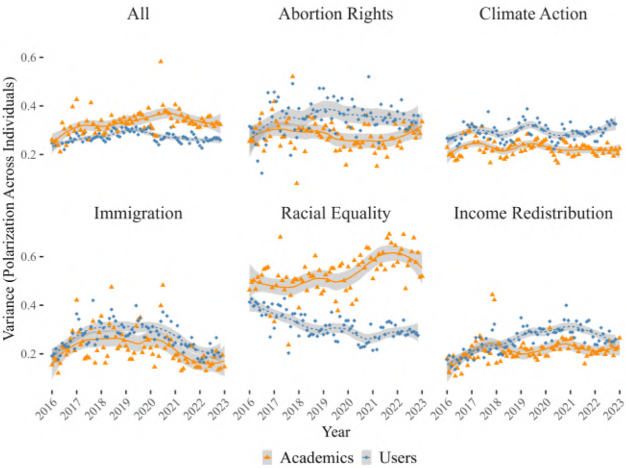
By Gender and Field

Scientists appear ideologically polarized across topics



Research v Not | High v Low reach | Original v Not | Academics v Users | Over Time

Scientists disagree more about *race*, less on other topics



By Gender and Field

Can political expression affect scientists' credibility?

Context: Reputational cost

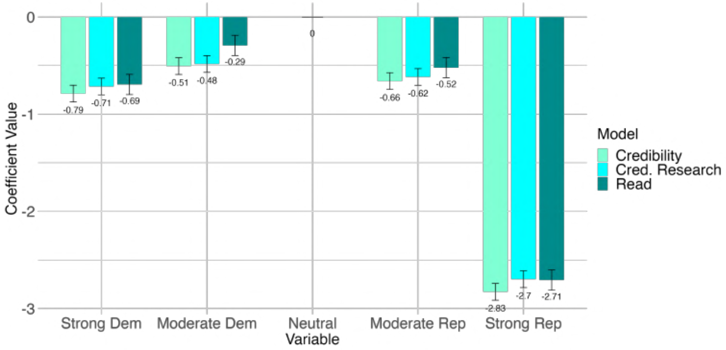
- SM can offers academic benefits, reflected in greater dissemination of research online
- Scientists are vocal on salient issues, expressing diverse opinions
- Cheap-talk models (Morris, 2001; Ottaviani and Sørensen, 2006) argue **reputational loss** arises from misaligned communication, leading to *political correctness* and *information loss*
- Our goal: **Asses the reputational cost** for scientists engaging in political discourse
- We experimentally test it by **revealing scientists' political positions online**

Experimental design

- **Conjoint experiment** (eg. Hainmueller et al., 2015)
- 1700 US respondents recruited on Prolific (eg. Enke et al., 2023) Representativeness
- 5 synthetic vignettes varying: *gender*, *research field*, *seniority*, *university* Attributes
- Political affiliation: description resembling **X biographies** and a recent **post** categorized from **Strong Democrat** to **Strong Republican**
- Outcomes: **Credibility** profiles/research, **willingness to read** from similar scientists

Main Vignettes

Large *credibility penalty* for scientists who display political affiliations

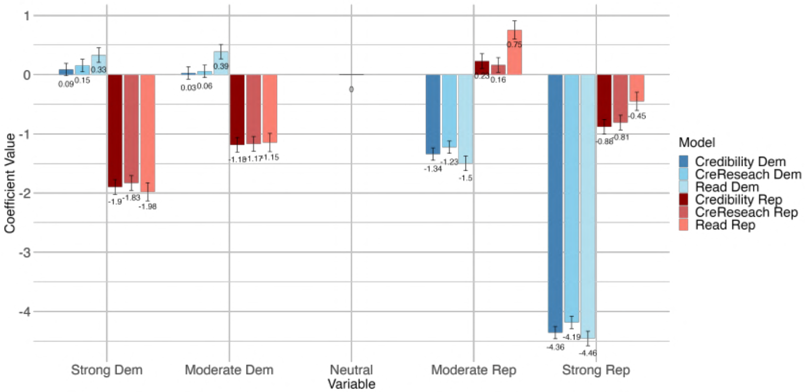


Note: Coefficients of regressing scientists' attributes on respondents' perceived credibility or willingness to read from scientists. Standard errors clustered at the individual. Scientists' leaning range from "Strongly Republican" to "Strongly Democrat", with "Neutral" as excluded category. Other attributes include scientist affiliation, field of research, seniority and gender. (N = 1704, 940 Dem/Lean Dem, 745 Rep/Lean Rep, 19 Other.)

→ Strong Rep and Strong Dem scientists are -40% and -10% credible than neutral (-40% vs -10% read)

→ Moderate Rep and Moderate Dem scientists are -9% and -7% credible than neutral (-9% vs -5% read)

Affective Polarization: penalty varies by audience partisanship



→ Dem/leaning Dem penalize Rep scientists (*Strong* -60-64%, *Moderate* -20-22%)

→ Rep/leaning Rep penalize Dem scientists (*Moderate* -17-18%, *Strong* -26-29%)

→ Reward *Moderate Rep* (+7-11%) and penalize *Strong Rep* (-8-5%) less than *Dem* scientists Full model

Separating the effect of salient research from pure political signal

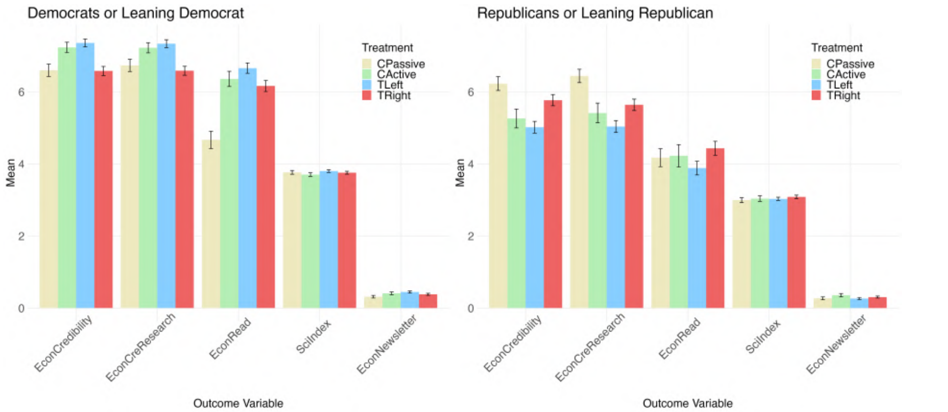
> **Between individual design** assigns respondents to 1 of 4 groups:

- **CPassive**: *NO* politically salient research + *NO* political signal
- **CActive**: politically salient research + *NO* political signal
- **TLeft (Right)**: politically salient research + Left (Right) political signal (in **X** bio)

> Outcomes: **Credibility**, **willingness to read**, trust in science, **newsletter** sign-up

Vignettes task n.2

Separating the effect of salient research from pure political signal



→ Dem/leaning Dem: Higher outcomes with politically aligned research; left signal improves, right signal reduces

→ Rep/leaning Rep: Lower outcomes with misaligned research; left signal reduces more than right

Ingroup vs Outgroup | Dem regressions | Rep regessions | Full sample

Robustness and more

- Carryover effects — Estimates by profile order
- Exclude those who spent < 1 min on survey — No speeders
- Replication main results — Main experiment
- Experimenter Demand — Bounding demand
- Replication on sample of **journalists** — Journalists' experiment | J' statistics | J' beliefs
- Impact of *other* attributes by profile type — Credibility | Credibile Research | WTR
- Correcting for hetheroskedasticity — Robust Std Err
- Multiple Hyphotesis Testing (Benjamini et al., 2006) — Multiple Hyphotesis Testing
- **Validating** political signals (bio+post) — Validation Perceived Leaning | Placebo
- **Scientists'** survey — Beliefs Penalty | Norm | Experience | Costs v Benefits | Open-end

Take aways

We find:

> Social media is increasingly important for scientific dissemination

> Scientists also express diverging political views online (*Ideological* polarization)

> Online political engagement harms scientists' perceived credibility

> With strong effects against partisan out-group (*Affective* polarization)

Take aways

We find:

- Social media is increasingly important for scientific dissemination
- Scientists also express diverging political views online (*Ideological* polarization)
- Online political engagement harms scientists' perceived credibility
- With strong effects against partisan out-group (*Affective* polarization)

Which implies a trade-off between *visibility* and *credibility*:

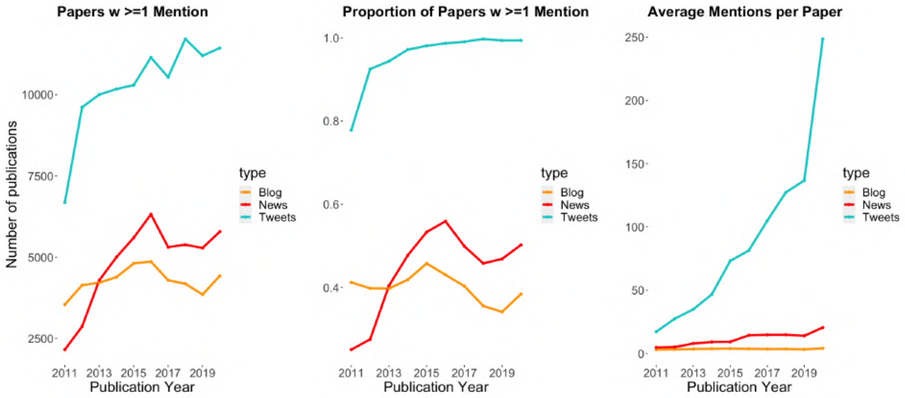
- **Political engagement** to influence decision making
  $\downarrow$ credibility and effective communication and polarize audience
- **No political engagement** anticipating credibility penalty
  information loss — possibly mediated by personal career gains

Thank you!

webpage: www.eleonora-alabrese.com

Figure: GitHub

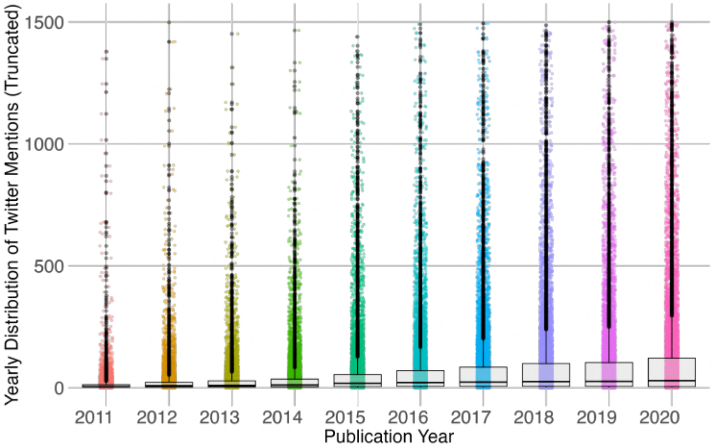
Increasing trends in online mentions of scientific publications



Note: Scopus library searched for published articles in renowned general interest journals (Science, Nature, PNAS, Cell, NEJM, Lancet), retrieving 114,868 scientific articles published between 2011 and 2020. Among these 107,008 had unique DOIs tracked by Altmetric.

42.7K DOIs in **blogs (40%)**, 47.9K in **news (45%)**, 102.8K in **tweets (96%)** X Distribution Back

Increasing presence of scientific publications on Twitter



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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

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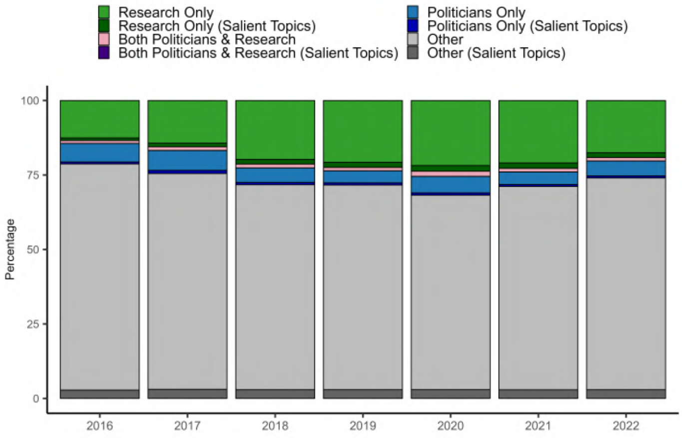
Tweets mentioning politicians, research papers, and salient topics



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Topic detection

1 **Dynamic keyword dictionaries:**

- Abortion Rights, Climate Action, Immigration, Racism, Income Redistribution
- Prompt GPT-4 (5 topics x 3 ngrams x 7 years x 2 vernacular types)

  "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."
- Twitter Fine Tuning is "Focus on language, phrases, or hashtags commonly used on Twitter" or empty

2 **Keywords applied to all posts:** tweet $\in$ *topic* if contains keyword of *topic* dictionary

3 Analysis limited to **topical tweets** and **their authors** (6M tweets, 52K scientists)

Type of Tweets Ngram Examples Back

Stance detection

4 **Stance detection:**

- Tweets categorized into four stances: pro, anti, neutral, or unrelated.
- Prompt GPT-3.5: "Classify this tweet's stance towards <topic> as 'pro', 'anti', 'neutral', or 'unrelated'. Tweet: <tweet>."
- Sampling procedure to reduce costs of labeling (up to 3 tweets per author-topic)
- Validated against 40,000 human-coded labels with **avg. F-score 86.4**
- Comparisons with opinion polls in Garg and Fetzer (2025)

Statistics on Tweets | Statistics on Scientists | Evaluation GPT | Examples | Back

Ideological polarization

5 **Ideological polarization:**

- Calculate **Slant (net pro stance)** for each user, topic, and time-period, offering insights into overall sentiment towards a topic

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

- Measure ranging from -1 (completely anti) to 1 (completely pro)

- $Var(S_{um})$ across users reflects **disagreement (ideological polarization)** on a topic

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Summary statistics (Tweet level)

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

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

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Summary statistics (Scientist level)

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

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. 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.

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Evaluation metrics: GPT 3.5 Turbo

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

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

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Example

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.

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Examples of Tweets

Stance	Example Tweet
Income Redistribution	
Pro	when someone runs an experiment asking "what happens if you give people some money" the answer is, without fail, "their life gets better." No amount of research validating and re-validating this will ever be enough for the politicians who demand suffering as penance for poverty. https://t.co/bhHbqG2
Anti	Civilrights/prolife colleagues (same thing), FYI. '@daviddaleiden is a national hero for exposing these barbaric practices that abortion zealots like @JoeBiden want all Americans to approve and fund.' https://t.co/Og9rp3Vxsw
Neutral	Do corporate tax cuts boost growth? Our paper is out @ European Economic Review. We meta-analyse 441 estimates from 42 studies; results imply: the attention corporate taxation has received as a source of growth has often been exaggerated. https://t.co/U1X4VI
Climate Action	
Pro	Do you remember the famous 97% study - that 97% of climate science supported the consensus on human-caused climate change? Well, we have just published an update for 2012-2021 papers in the same journal, Environmental Research Letters. The figure is now... drumroll please...99.9%!
Anti	The concept of global warming was created by and for the Chinese in order to make U.S. manufacturing non-competitive.
Neutral	The most significant contribution among the highest emitters is from air and land transport, with 41% and 21% among the top 1% of EU households. Air transport is by far the most income-elastic, unequal and carbon-intensive consumption category in our study. https://t.co/eU2RXG8Hzw
Immigration	
Pro	Our new research in @LancetGH provides evidence of the health effects of hostile environment policies to migrants: restrictive entry and integration policies are associated with worse mental and general health, and an increased risk of death. https://t.co/js4GmbnKG9
Anti	National sovereignty and border security are paramount. Open borders policies invite chaos and undermine the rule of law. A nation must control its borders to protect its citizens and uphold its values.
Neutral	Finally ready to share my paper on individualistic Scandinavian emigrants, and how their departure during the Age of Mass Migration generated lasting cultural change towards collectivism and convergence across migrant-sending districts. https://t.co/adYS5rJGiA
Abortion Rights	
Pro	Texas' latest abortion ban, SB8, gives people the right to sue those who provide or help others get an abortion after 6 weeks. Bans like these are not based in science and the consequences could potentially be disastrous. Here's what our research says.
Anti	Let's Make Abortion UNTHINKABLE! Who's with me? prolife unborn bhfyp alllivesmatter hope endabortion prolifegen https://t.co/EojMrSJVKN
Neutral	In the wake of a gene-editing experiment gone wrong, the president of the National Catholic Bioethics Center said that the Church must stand firm against the unborn being "sacrificed on the altar of scientific research." https://t.co/6XUBBg9KOD
Racial Equality	
Pro	An article came out in @TheLancet today that is flying under the radar but is absolutely critical to read. It provides rare CAUSAL evidence showing structural racism causes poor health outcomes for Black Americans. Here's the science in a quick thread.
Anti	My study of northern backlash against the Great Migration has no policy prescription, but it has a smoking gun. Police are the only public investment to increase in metro areas w/ more black migration. Good faith pursuit of racial justice starts by questioning this institution. https://t.co/uQaYdGQnPn
Neutral	We document the appearance of a new race gap in traffic deaths that emerged after 2014. In fact, this was the first time that the rate of traffic deaths for Black Americans exceeded that of White Americans since at least the early 1970s. Our paper tries to unravel this mystery. https://t.co/jTluzYirqn

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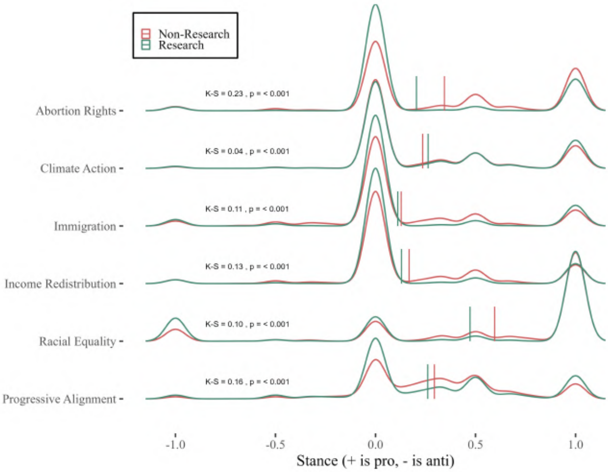
Scientists appear less ideologically polarized when *mentioning research*



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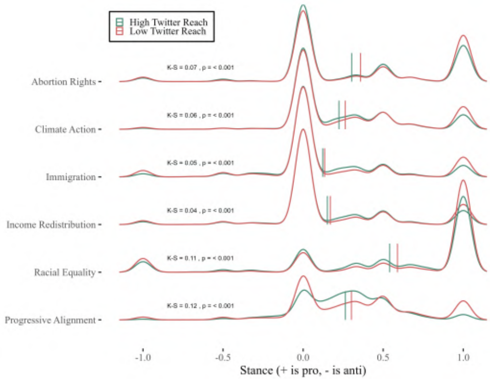
Scientists with *higher reach* appear more ideologically polarized



Note: 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).

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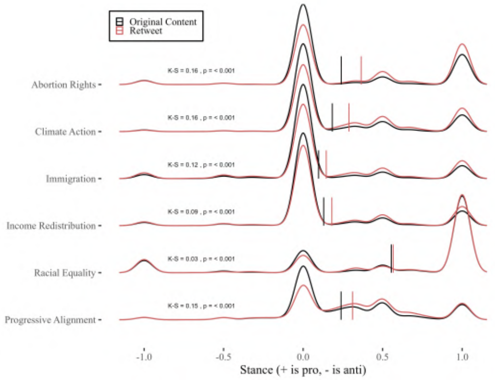
Scientists *original content* appears less ideologically polarized



Note: Original content includes original tweets, replies and any retweets with additional comments (i.e., quoted retweets).

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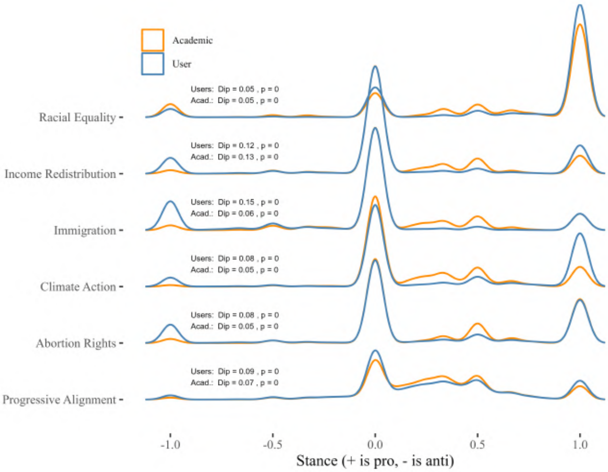
Scientists appear *less* ideologically polarized *than users*



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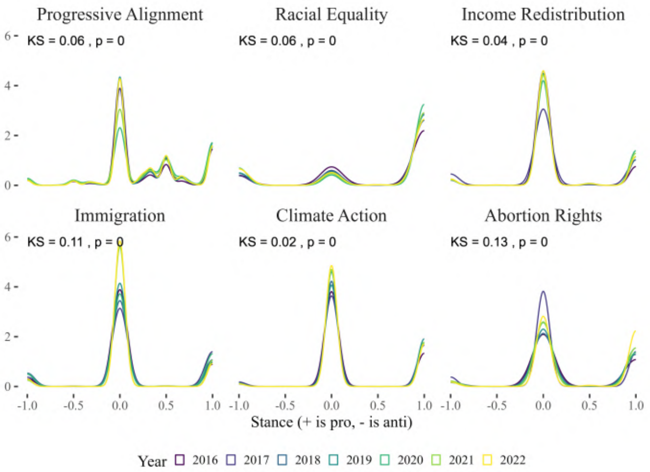
Density of net-pro stance across topics and *time*



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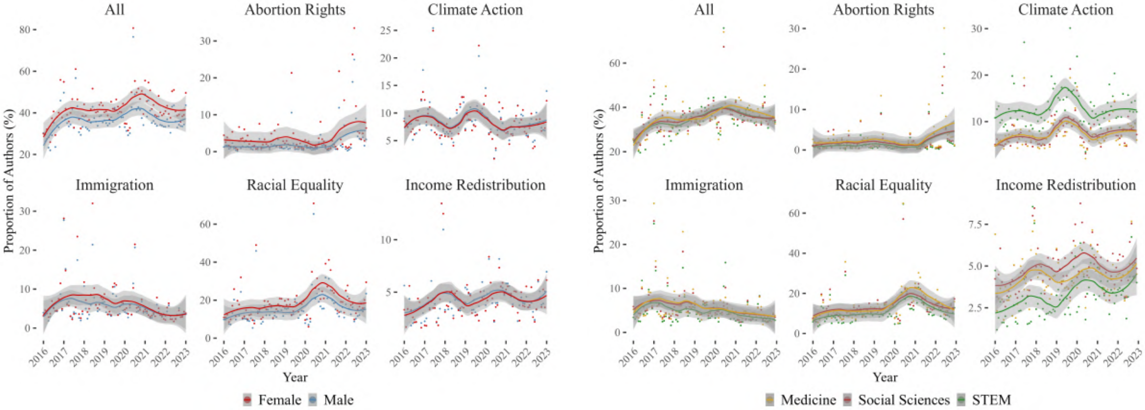
Small differences in expression by *gender* and *discipline*



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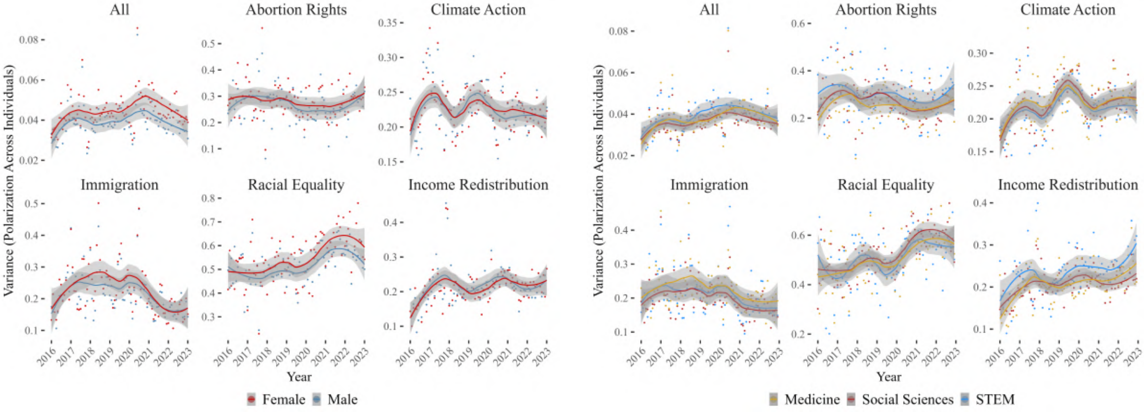
Small differences in variance by *gender* and *discipline*



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Representativeness

	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	

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Summary of attributes

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	Strong Dem, Moderate Dem, Strong Rep, Moderate 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."

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Strong Democrat

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

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

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

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

How credible do you think this scientist is?

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

Credible

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

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

Credible

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

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

Willing to read

Strong Republican

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

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

Moderate Republican

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

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

Neutral (excluded category)

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

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

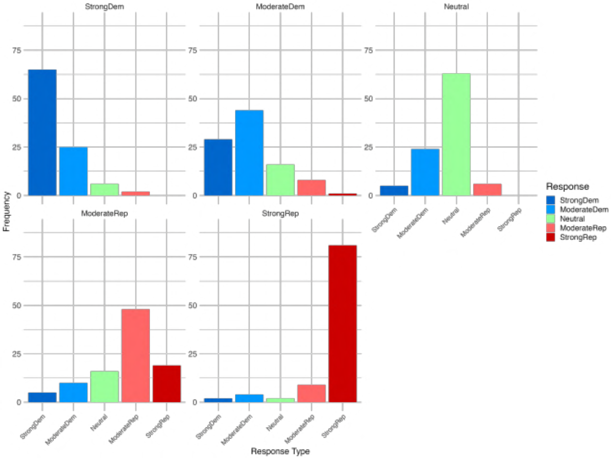
Moderate Democrat

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

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

Validation Perceived Leaning Back

Validation of political affiliation attributes



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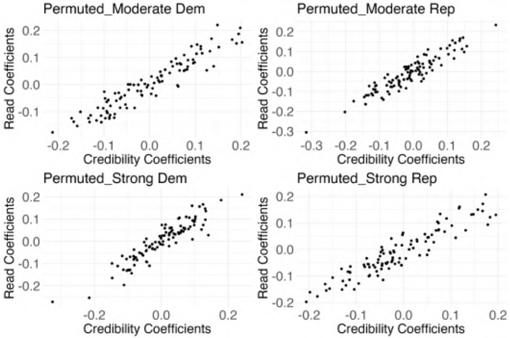
Permutation Test



Note: Placebo test conducted to ensure that the observed political effects are not due to unusual feature of the data. We randomly re-shuffled political labels across profiles within each respondent, creating a permuted version of the "Political" affiliation of the scientists' profiles, repeating the procedure 100 random times. For each permutation, we ran regressions using these mis-labeled political indicators to estimate their impact on public perceptions. Each dot represent the effect of the placebo political affiliation of scientists on their perceived credibility (x-axis) and on respondents' willingness to read (y-axis) for each permutations. Permuted labels do not systematically influence outcomes, as all coefficients remain close to zero and smaller than our estimates.

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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."**

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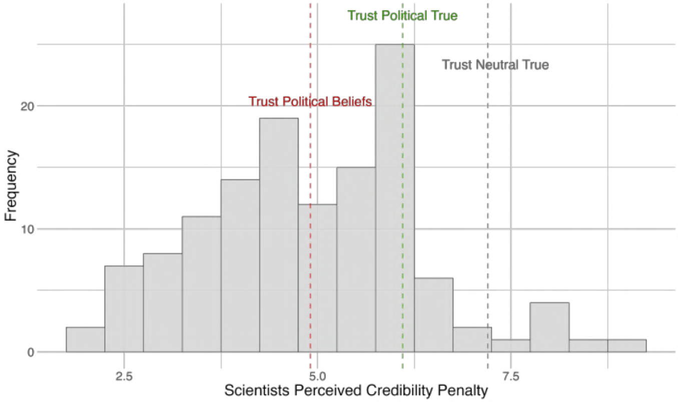
Scientists' Beliefs about Credibility Penalty



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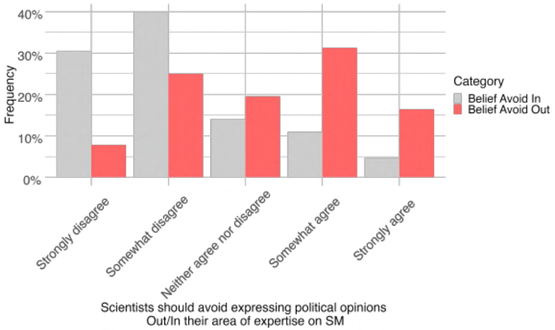
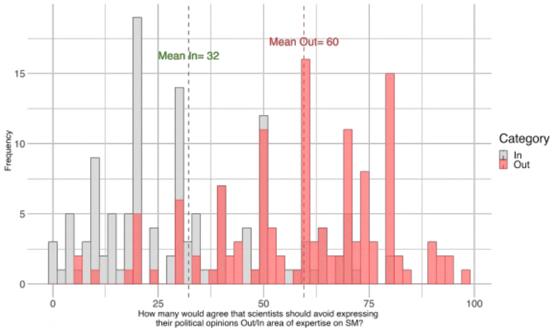
Scientists' beliefs around academics publicly expressing political views

A. Scientists Should Avoid Expressing Political Opinions



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



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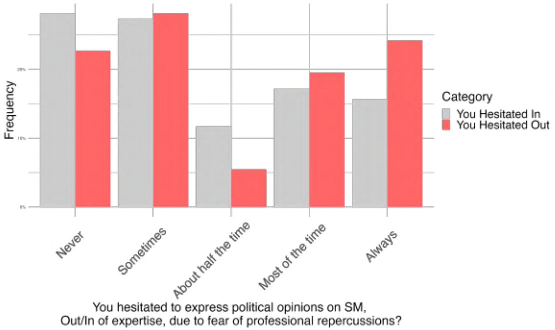
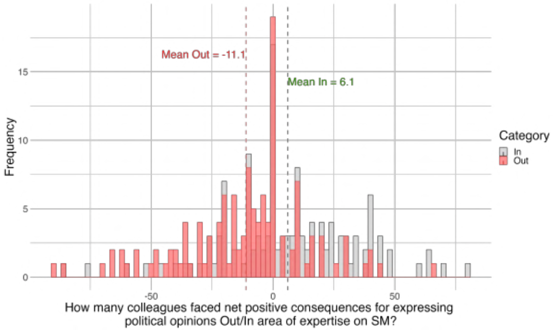
Scientists' perception on consequences of public political expression

A. Have Hesitated to Express Political Opinions



B. Perceived (Net) Consequences of Expressing Political Opinions



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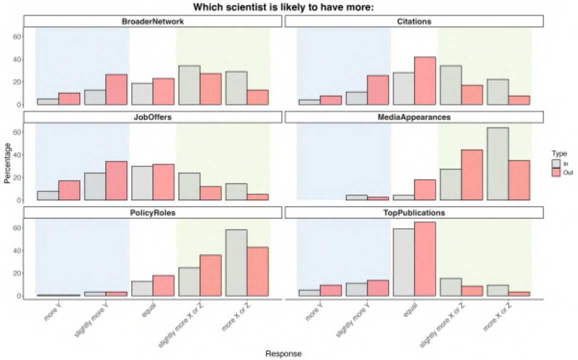
Scientists' perceived costs and benefits of public political expression



Note: Respondents compared the outcomes for Scientist X (grey), who shares opinions on politically charged topics related to their research, and Scientist Z (red), who shares opinions on politically charged topics unrelated to their research, against Scientist Y, who refrains from such expression (respectively, either related or unrelated to their research). A distribution skewed towards X or Z (green area) reflects perceived benefits from political expression, while a denser left tail towards Y (blue area) indicates perceived costs.

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Scientists' views from open-end 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 subfield, 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.*

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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

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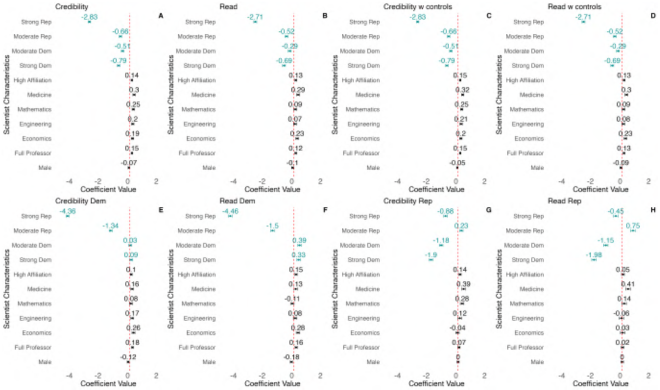
Large *credibility penalty* (full model)



Note: Regressions of scientists' attributes on perceived credibility or willingness to read. SE at individual level. Political leaning: "Strong Republican," "Moderate Republican," "Strong Democrat," or "Moderate Democrat," excluding "Neutral." High Affiliation: top institutions like Harvard, UC Berkeley, or Chicago, versus others like Arkansas or Connecticut. Research fields: Medicine, Mathematics, Engineering, and Economics, excluding Literature. "Full professor" coded as one, "assistant professors" as zero. "Male" coded as one for male scientists. Controls: age, gender, income, ethnicity, education, employment status, religion, region, and political leaning. Sample: 1740, with 940 Dem/Lean Dem, 745 Rep/Lean Rep, 19 Other.

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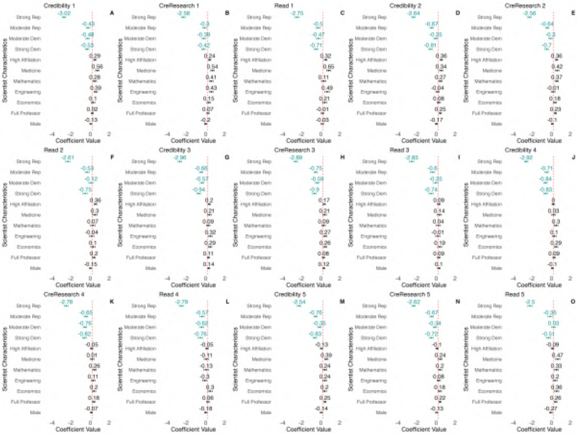
Carryover effects on scientists' credibility and willingness to read



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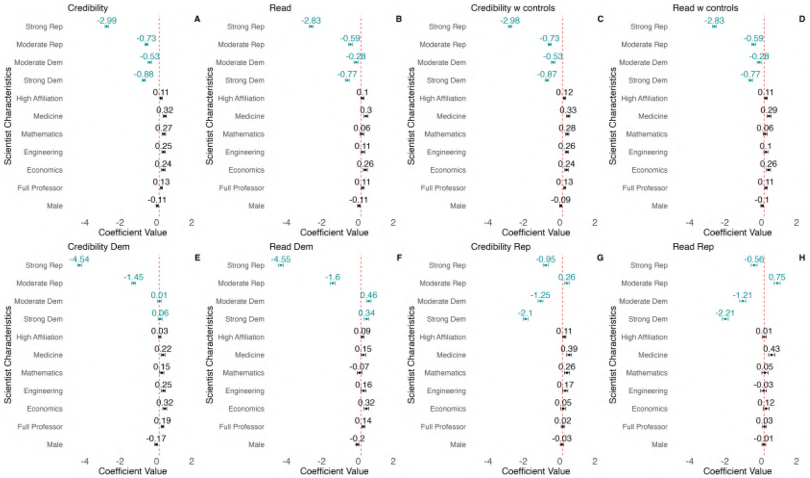
Effect of scientists' attributes excluding speeders (N = 1431)



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Regression with Robust standard errors

	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)
Moderate 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)
Moderate 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)
Strong 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.

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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)
Moderate 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)
Moderate 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)
Strong 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 an of reading from similar scientists. The p-values in Columns 4, 5 and 6 are corrected for Multiple Hypothesis Testing using FDR procedure.

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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

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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

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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

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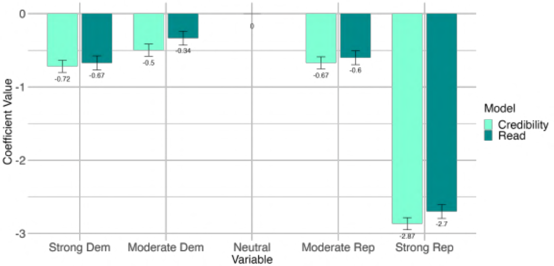
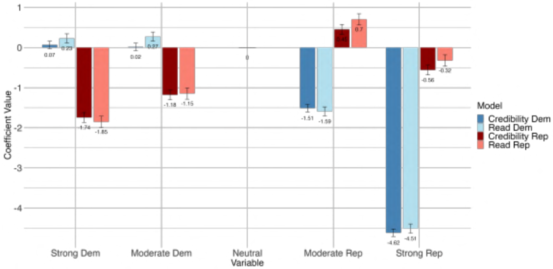
Replication (N=1990)

A. Base Model



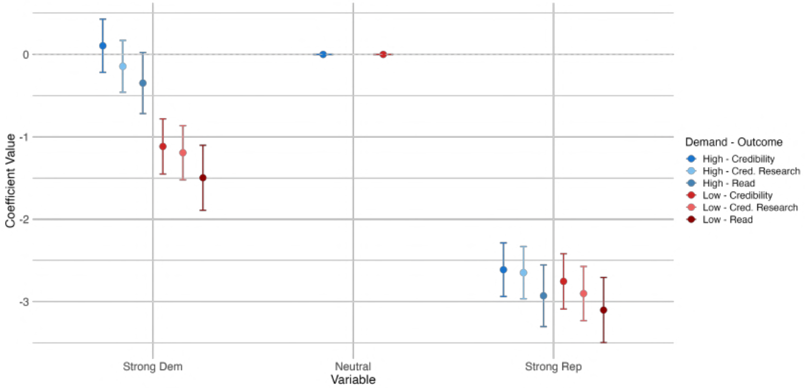
B. Heterogeneity by Respondents' Leaning



Note: N = 1990, 1118 Dem. or Lean Dem., 855 Rep. or Lean Rep., 17 Other leaning.

Back

Experimenter Demand



Note: 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 outcomes peak for Neutral scientists, while left- and right-leaning scientists face credibility penalties, regardless of the demand condition (N = 346).

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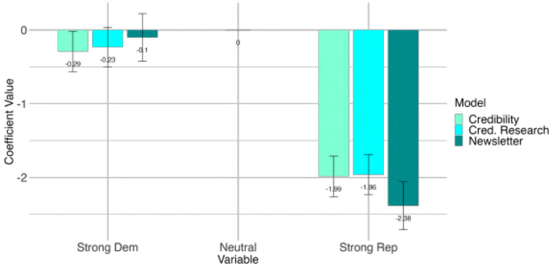
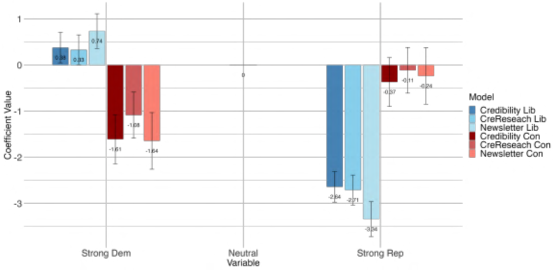
Sample of international journalists

A. Base Model



B. Heterogeneity by Respondents' Leaning



Note: N = 135, 36 conservative, 84 Liberal, 15 Moderate.

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Summary statistics for 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

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Beliefs of journalists

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

Notes: We summarize journalists' answers to the questions listed below. Answers were recorder on a 5-item Likert scale, and grouped in 3 categories. We ask journalists the 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***).

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Mechanism: Separating the effect of salient research from pure 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

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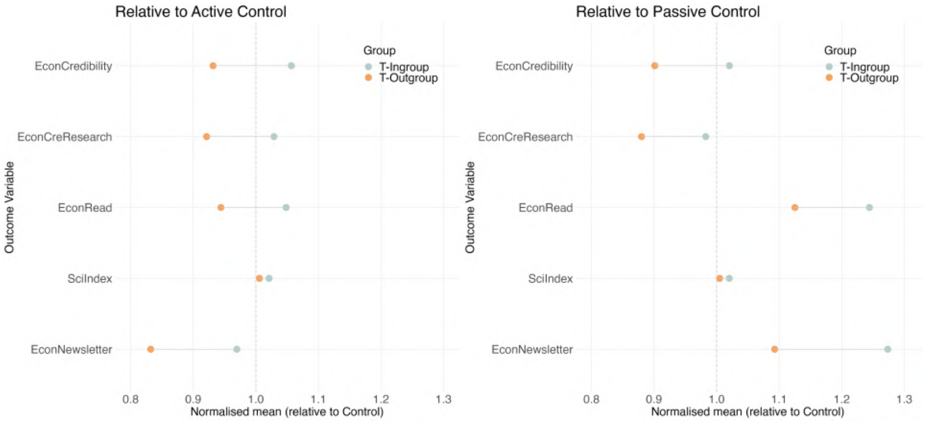
Separating the effect of salient research from pure political signal (normalized)



→ In-group respondents (aligned with signal) perceive better outcomes than out-group respondents Back

Mechanism: Separating effect of salient research from pure political signal (*Democrats*)

	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)
Observations	940	940	940	940	940
Controls	X	X	X	X	X

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Mechanism: Separating effect of salient research from pure political signal (*Republicans*)

	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

Back

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