Politicized Scientists:
Credibility Cost of Political Expression on Twitter

Eleonora Alabrese
University of Bath

Francesco Capozza
WZB and CESifo

Prashant Garg
Imperial College London

November 2024

Daron Acemoglu @DAcemogluMIT

I am disappointed with mainstream US media, including the New York Times. The headlines are all about Biden's debate performance. Yes, he's old. Yes, it would've been great to have had a more inspiring younger candidate. Yes, he had a bad night, certainly compared to his State of the Union address. But that is not the main story. The main story is that Trump is a very serious threat to US democracy.

Traduci post

10:36 PM · 29 giu 2024 · **938.605** visualizzazioni

523 · 1.251 · 5.084 · 469

Daron Acemoglu @DAcemogluMIT · 29 giu

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The Economists' letter genre is alive and well. Surely the decisive nail in the coffin for the 2024 Tories.

Da theguardian.com

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

1 · 2 · 1.614


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Is this a good idea?

Motivation

- In "post-truth" era the difference bw facts and opinions shrinks (Bursztyn et al. 2023, McIntyre 2018)
- Trust in science crucial for informed decision-making and effective public policy
- COVID-19 highlights influence of scientific expertise on public health responses (Algan et al. 2021, Calónico et al. 2023)
- Doubts about climate change hinder progress toward environmental goals (Druckman & McGrath 2019)
- Erosion of trust in scientific authority observed in recent years (Nichols 2017)
- Polarization exacerbates concerns w conservatives lowering trust in scientists (Azevedo & Jost 2021, Funk et al. 2020, Li & Qian 2022, Mede 2022)

Research Questions

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 (Altmetrics and $\mathbf{X}$) and online experiment (1700 US)

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   44% US academics vs 7% random users express political opinions on $\mathbf{X}$

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2. Large *credibility penalty* for scientists engaging in political discourse
   Strong Rep scientists are 40% less credible than neutral scientists

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   44% US academics vs 7% random users express political opinions on **X**
2. Large *credibility penalty* for scientists engaging in political discourse
   Strong Rep scientists are 40% less credible than neutral scientists
3. Salient research content and pure political signal both impact credibility

Examples of Political Tweets | Contribution

Outline

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

Do scientists express political views online?

Data

> Dataset from network of $\approx 98K$ US academics on $\mathbf{X}$ (from Garg & Fetzer 2024)

> 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 (detailed in Garg & Fetzer 2024)

> 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

Stance detection ↓

Pro/anti/neutral stances

$\forall$ tweet x topic using GPT-3.5

Stance Detection

Methodology (Step 3)

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

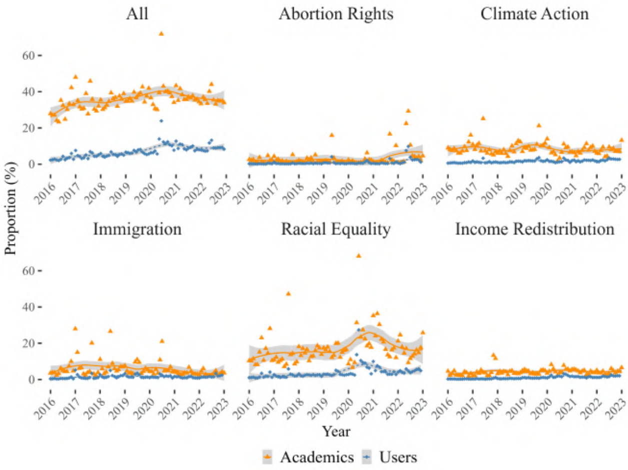
↓

Net pro stance S_u

$\forall$ user x topic x time period

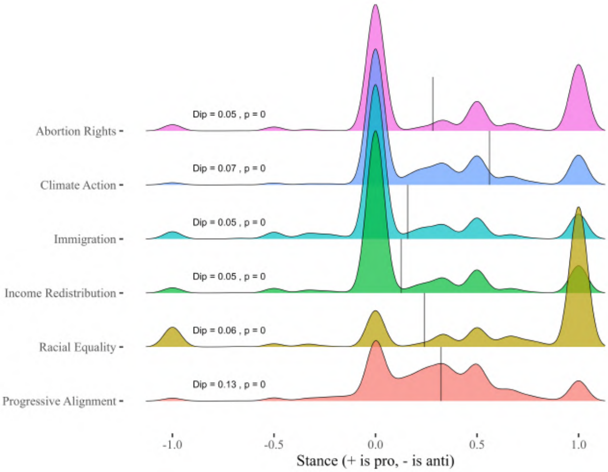
Ideological Polarization

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



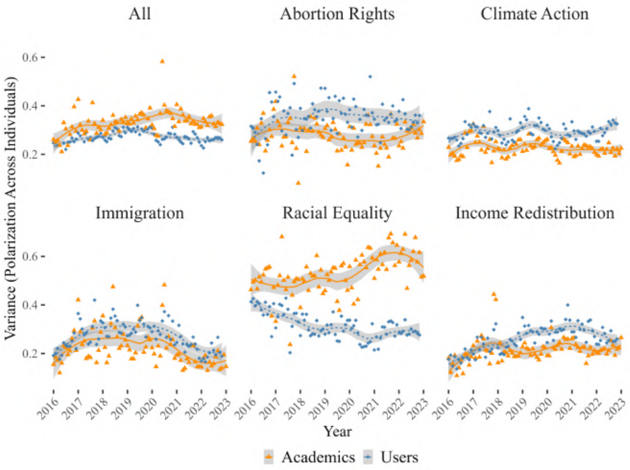
By Gender and Field

Scientists appear ideologically polarized across topics



Density Net-pro over Time

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



By Gender and Field

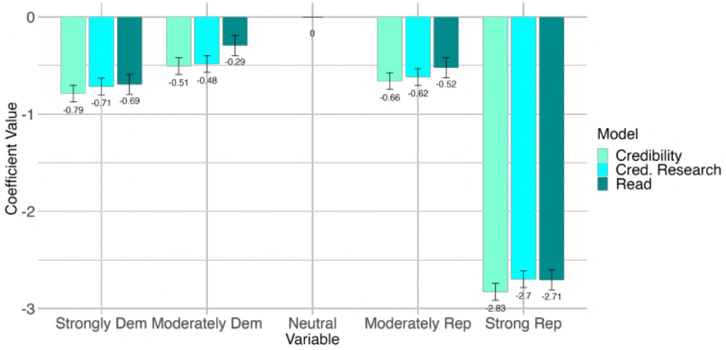
Can political expression affect scientists' credibility?

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 **Strongly Democrat** to **Strongly Republican**
- Mechanism task 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 (from **X** bio)

Vignettes task 1 Validation Perceived Leaning Vignettes task 2

Large *credibility penalty* for scientists who display political affiliations

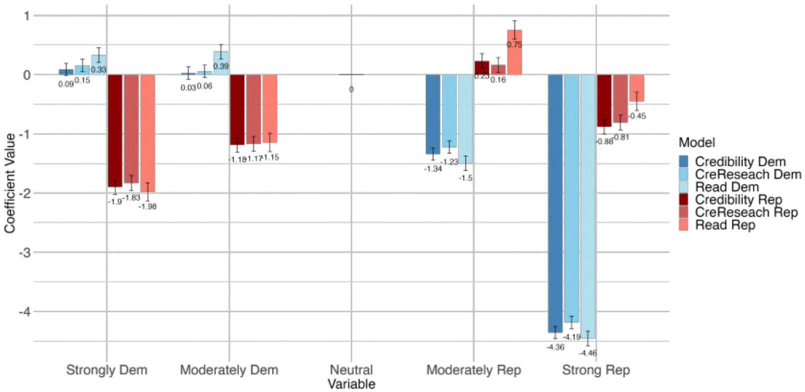


Note: Coefficients of regressing scientists' attributes on respondents' perceived credibility or willingness to read from scientists. Standard errors clustered at the individual. Scientists' leaning range from "Strongly Republican" to "Strongly Democrat", with "Neutral" as excluded category. Other attributes include scientist affiliation, field of research, seniority and gender. (N = 1990, 1118 Dem/Lean Dem, 855 Rep/Lean Rep, 17 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

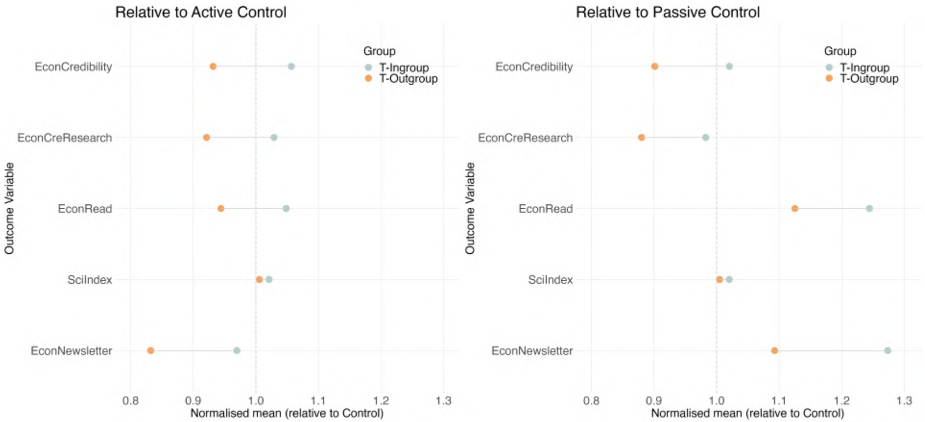


→ Dem/lean Dem penalize Rep scientists (*Strong* -60-64%, *Moderate* -20-22%)

→ Rep/lean 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 pure political signal from salient research



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

Group averages by respondents leaning

Robustness and more

- > Carryover effects — Estimates by profile order
- > Exclude those who spent < 1min on survey — No speeders
- > Replication main results — Main experiment
- > Main result on sample of journalists
- > 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 + tweet) — Validation Perceived Leaning
- > Survey of **scientists** — Beliefs Credibility Penalty | Expression Norm | Expression Consequences

Take aways

We find...

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

Which implies...

- Polarizing views on science highlight a possible **trade-off** bw *visibility* and *credibility*
- Political expression **risks undermining trust** and **exacerbating polarization**
- Need to carefully **balance** research **dissemination** and **political expression** online

Thank you!

webpage: www.eleonora-alabrese.com

Contribution

> Observational literature measuring polarization

Alesina et al. (2020), Boxell et al. (2024), Colleoni et al. (2014), Flaxman et al. (2016), Gentzkow & Shapiro (2011), Iyengar et al. (2019), Stewart et al. (2019)

→ We measure political voice of scientists using social media posts

> Experimental literature on polarization

Chopra et al. (2024), Huddy et al. (2015), Levy (2021), Mosleh et al. (2021)

→ We measure impact of scientists' voice on their perceived credibility

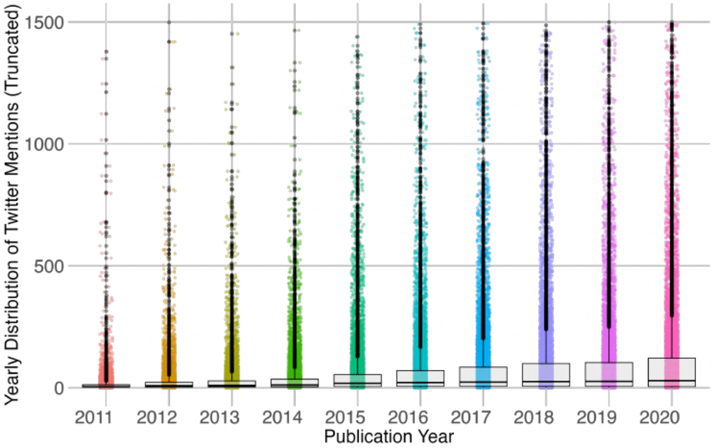
> Literature on scientists perceptions and scientific communication

Blastland et al. (2020), Garg & Fetzer (2024), Kotcher et al. (2017), Petersen et al. (2021), Van Der Bles et al. (2019, 2020), Zhang (2023)

→ Illuminate on balance bw research dissemination and online expression

This paper

Increasing presence of scientific publications on Twitter



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Topic detection

1 **Dynamic keyword dictionaries:** (Garg & Fetzer 2024, Garg & Martin 2024)

- 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:** (Garg & Fetzer 2024)

- 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 & Fetzer (2024), Garg & Martin (2024)

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

Measure of ideological polarization

5 **Ideological polarization:**

- Analysis involves calculating **net pro stance** for each user, 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 all users reflects **disagreement in political voice** on a topic

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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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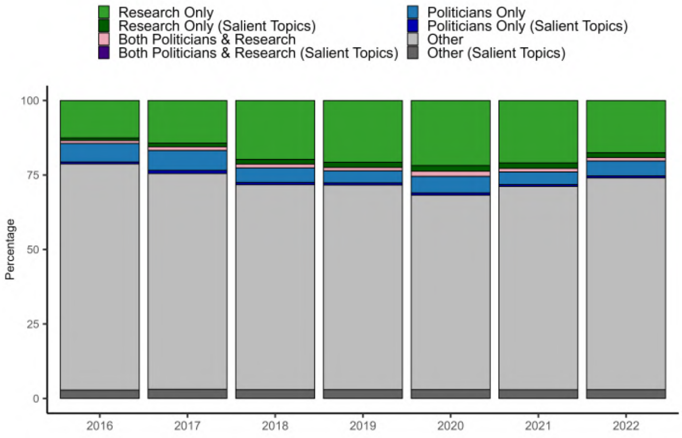
Tweets mentioning politicians, research papers, and salient topics



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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
Field: With Concepts Data	25,719	49.0	81.4	51.7
Field: Humanities	103	0.4	86.4	57.8
Field: STEM	19,584	76.1	80.2	41.8
Field: Social Sciences	6,032	23.5	86.0	64.9
Field: Medicine	7,765	30.2	81.0	38.3

Notes: Table shows individual-level summary statistics on key characteristics of scientists. For some key categories relevant to our experiment, we show a breakdown by the number of observations, the proportion of those who tweeted about any of our topics, and among them, the proportion of those who are *politicized* (i.e., whether they have made at least one pro or anti tweet on one of our five topics in the cross-section from 2016 to 2022). The "Filtered" column refers to the subset of scientists who have tweeted about a political topic (pro, anti, or neutral). The "% Politicized" refers to the subset of scientists who have made at least one pro or anti tweet. "With Concepts Data" refers to those for whom we have concepts data. Around 44% of our full sample of academics ever talked about one of the topics of interest during the period of observation.

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Evaluation metrics: GPT 3.5 Turbo

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

Notes: Table shows results of validation of stance detection step. We obtain human labels for stance detection task from ACM SemEval-2016 Task 6 (Mohammad et al. 2016). Humans labelled tweets are pro-, anti- and neutral-, on topics ranging from Abortion Rights to Donald Trump. The stance detection's effectiveness was validated against 4200 human labels from SemEval-2016 Task 6, yielding F-scores of 84-92, which are considered very high for classification tasks. For further details on validation and comparisons with opinion poll measures, see Garg and Fetzer (2024).

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Climate

- **Anti:** The concept of global warming was created by and for the Chinese in order to make U.S. manufacturing non-competitive.
- **Pro:** Donald Trump believes climate change is a hoax. Donald Trump is an idiot.

Abortion

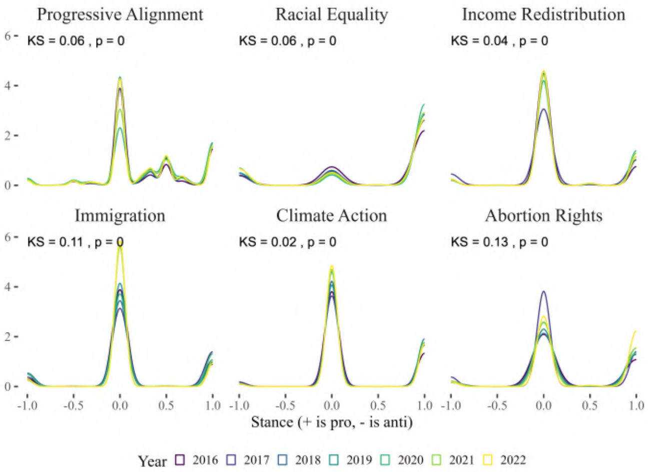
- **Pro:** A pregnant mother in Poland, where abortion is mostly outlawed, went to the hospital in need of a life-saving abortion. Doctors refused and she died. In Bolivia, Catholic leaders are coercing a pregnant child into giving birth. This is what prolife laws do.
- **Anti:** Let's Make Abortion UNTHINKABLE! Who's with me? prolife unborn bhfyp alllivesmatter hope endabortion prolifegen

Abortion + Science

- **Anti:** 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."
- **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:

Back 'this paper' Back 'methods'

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



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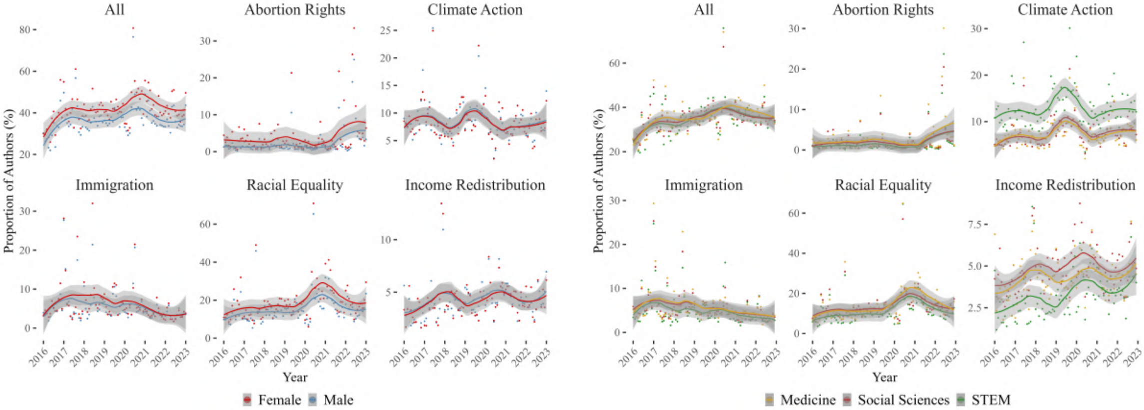
Small differences in expression by *gender* and *discipline*



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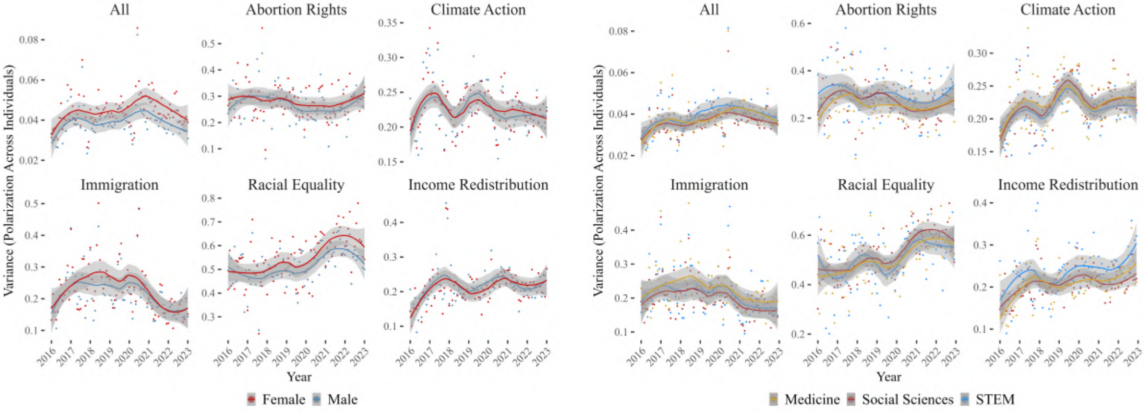
Small differences in variance by *gender* and *discipline*



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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

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Strong Democrat	Strong Republican

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.**

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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	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."

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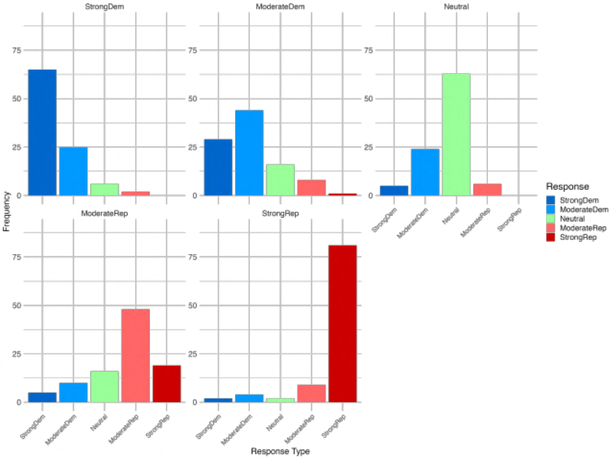
Validation of political affiliation attributes



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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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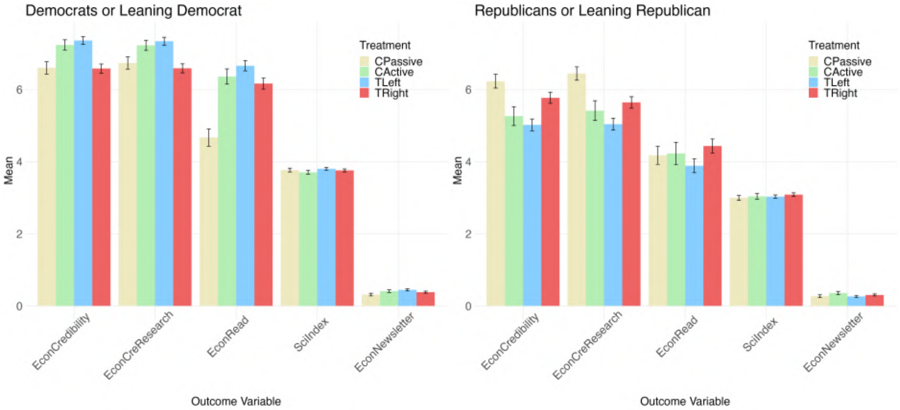
Separating the effect of salient research from pure political signal

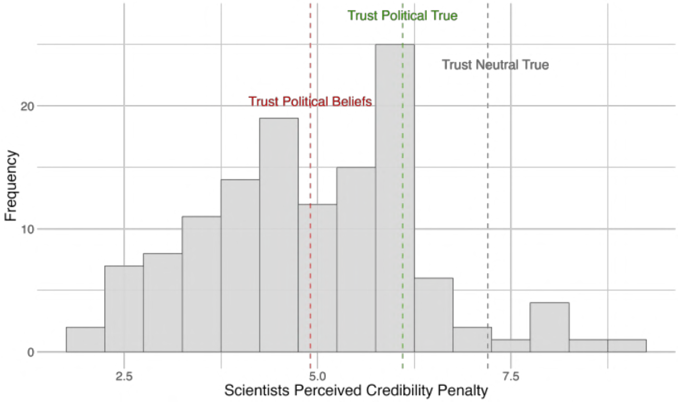


→ Dem/lean Dem: Higher outcomes with politically aligned research; left signal improves, right signal reduces

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

Dem regressions Rep regressions Full sample Back

Scientists' Beliefs about Credibility Penalty



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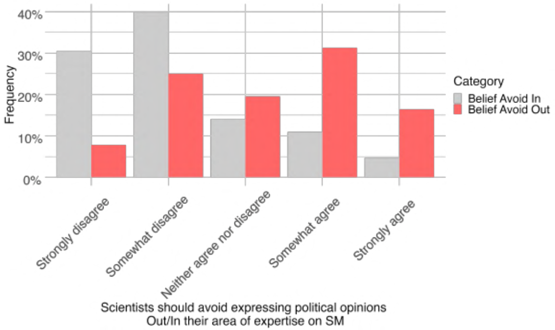
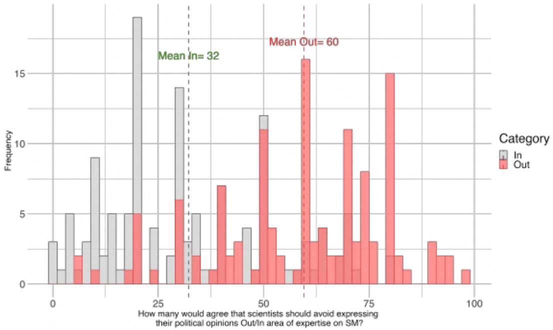
Scientists' beliefs around academics publicly expressing political views

A. Scientists Should Avoid Expressing Political Opinions



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



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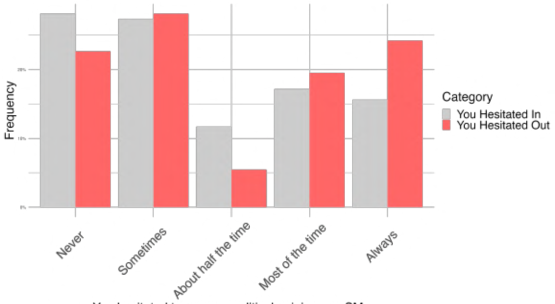
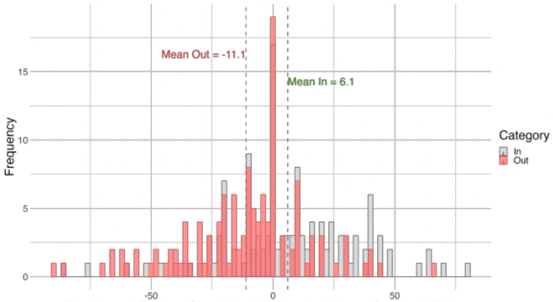
Scientists' perception on consequences of public political expression

A. Have Hesitated to Express Political Opinions



B. Perceived (Net) Consequences of Expressing Political Opinions



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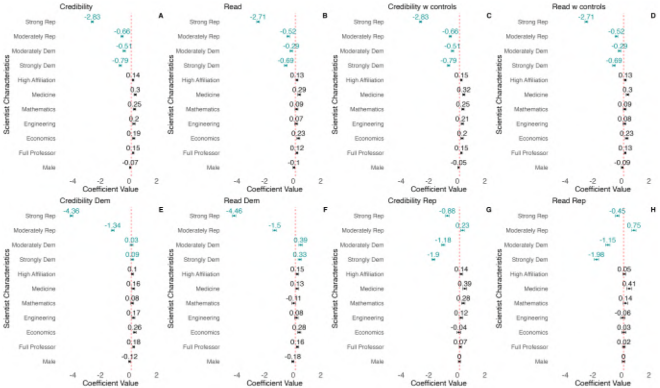
Large *credibility penalty* (full model)



Note: Regressions of scientists' attributes on perceived credibility or willingness to read. SE at individual level. Political leaning: "Strongly Republican," "Moderately Republican," "Strongly Democrat," or "Moderately 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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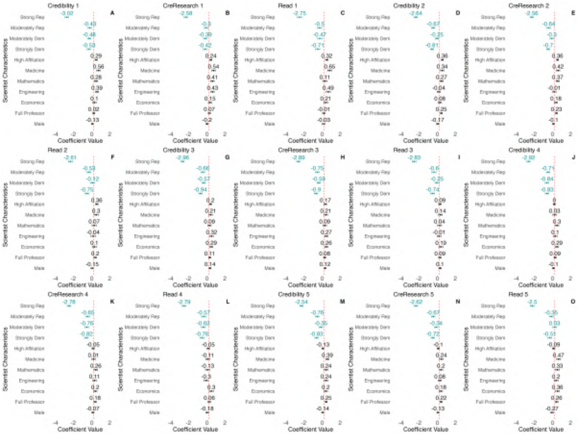
Carryover effects on scientists' credibility and willingness to read



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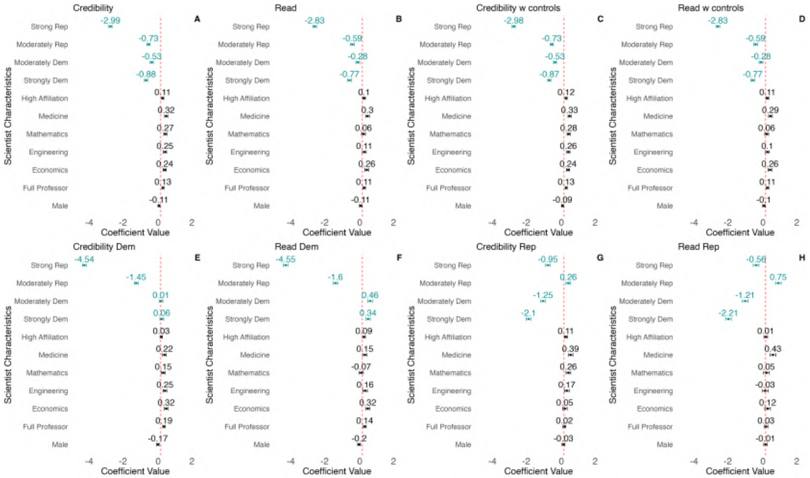
Effect of scientists' attributes excluding speeders (N = 1431)



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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)
Moderately Dem	−0.505***	−0.483***	−0.293***	−0.505***	−0.483***	−0.293***
	(0.086)	(0.086)	(0.104)	(0.073)	(0.073)	(0.094)
Moderately Rep	−0.660***	−0.617***	−0.521***	−0.660***	−0.617***	−0.521***
	(0.086)	(0.086)	(0.104)	(0.076)	(0.075)	(0.095)
Strong Rep	−2.828***	−2.698***	−2.708***	−2.828***	−2.698***	−2.708***
	(0.086)	(0.086)	(0.104)	(0.089)	(0.088)	(0.105)
Strongly Dem	−0.788***	−0.715***	−0.694***	−0.788***	−0.715***	−0.694***
	(0.086)	(0.086)	(0.104)	(0.081)	(0.081)	(0.100)
Constant	6.994***	6.876***	6.243***	6.994***	6.876***	6.243***
	(0.096)	(0.095)	(0.115)	(0.088)	(0.089)	(0.108)
Observations	8,520	8,520	8,520	8,520	8,520	8,520

Notes: Coefficients are obtained by regressing scientists' characteristics on respondents' perceived credibility, perceived credibility of scientists' research and likelihood of reading from similar scientists. All the standard errors are clustered at the individual level and are robust to heteroskedasticity in Columns 4 to 6.

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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)
Moderately Dem	−0.505***	−0.483***	−0.293***	−0.505***	−0.483***	−0.293***
	(0.086)	(0.086)	(0.104)	(0.073)	(0.073)	(0.094)
Moderately Rep	−0.660***	−0.617***	−0.521***	−0.660***	−0.617***	−0.521***
	(0.086)	(0.086)	(0.104)	(0.076)	(0.075)	(0.095)
Strong Rep	−2.828***	−2.698***	−2.708***	−2.828***	−2.698***	−2.708***
	(0.086)	(0.086)	(0.104)	(0.089)	(0.088)	(0.105)
Strongly Dem	−0.788***	−0.715***	−0.694***	−0.788***	−0.715***	−0.694***
	(0.086)	(0.086)	(0.104)	(0.081)	(0.081)	(0.100)
Constant	6.994***	6.876***	6.243***	6.994***	6.876***	6.243***
	(0.096)	(0.095)	(0.115)	(0.088)	(0.089)	(0.108)
Observations	8,520	8,520	8,520	8,520	8,520	8,520

Notes: Coefficients are obtained by regressing scientists' characteristics on respondents' perceived credibility, perceived credibility of scientists' research and 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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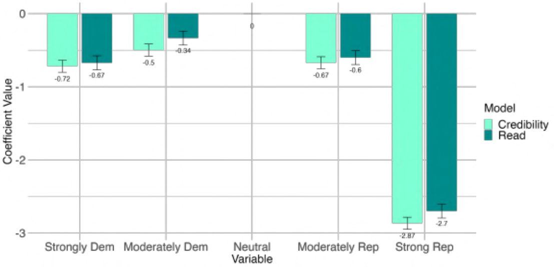
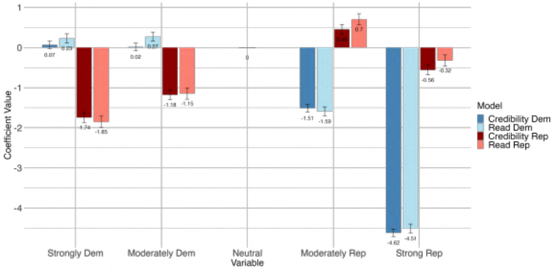
Replication (N=1990)

A. Base Model



B. Heterogeneity by Respondents' Leaning



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

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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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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

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