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Partisan Disparities in the Production and Uptake of Science

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Abstract

Scientific institutions are designed to produce and evaluate claims through shared evidentiary and disciplinary standards, yet they are embedded in an increasingly polarized society. This fundamental tension raises the question of whether scientists' partisan alignment is associated with the production, circulation, and uptake of scientific knowledge. Here the authors integrate campaign-finance records, faculty rosters, voter-registration data, an original survey of approximately 7,000 active U.S. scientists, bibliometric data, and measures of uptake in policy documents, patents, and news coverage to map the partisan composition of the scientific workforce, the knowledge it produces, and its uptake within and beyond science. The authors find that U.S. science is politically asymmetric without being ideologically homogeneous: scientists who make political contributions are overwhelmingly Democratic-aligned, and this asymmetry has widened over time, yet the broader workforce includes many Independents and substantial ideological heterogeneity within partisan groups. Among scientists with strong, behaviorally observed partisan alignments, Democratic-and Republican-authored papers are systematically distinguishable in semantic content across all fields, even after conditioning on fine-grained topic and year. Differences in total scientific citation rates are modest and have narrowed over time, whereas citations occur more often within the same partisan author communities than expected under topic-and year-preserving null models. Uptake beyond science also varies by partisan authorship and domain, with the clearest directional selectivity among ideological think tanks. These findings reveal an uneven profile of partisan association across U.S. science, visible in published content and directional attention, but comparatively limited in aggregate scientific recognition. This profile is consistent with a scientific system in which shared evaluative standards coexist with political structure in the production and circulation of knowledge, with implications for science's capacity to remain a common evidentiary resource in a polarized society.

Scientific research has long been regarded as a distinctive source of knowledge, valued for its capacity to produce claims that can be evaluated by evidence, disciplinary standards, and shared epistemic norms that transcend political divides [*1–4*]. Its role has become increasingly consequential as many pressing societal challenges, from public health and climate change to technological innovation and national security, are deeply linked with scientific progress. Yet science is produced by people and institutions embedded in a polarized society. Amid growing partisan divisions in trust toward science and scientists [*5–15*], a fundamental question remains open: Is partisan alignment of scientists systematically associated with the production, circulation, and uptake of scientific knowledge? This question probes the fundamental nexus between knowledge and institutions that shapes epistemic diversity, the flow of ideas across communities, public trust, and the evidentiary foundations of democratic governance [*16*].

A priori, there are reasons to expect both partisan imprint and partisan insulation within science. Values, identities, and worldviews can shape which problems feel urgent, which risks are emphasized, which populations are centered, and which collaborators and institutions feel proximate [*4*, *17*]. Funding systems, policy or market demand, and public interest may further channel attention toward some questions and away from others [*18*, *19*]. At the same time, science is organized around norms and incentives that push against partisan imprint [*1*, *20*]: claims are evaluated through peer review, replication, and disciplinary standards [*21*]; professional rewards are tied to credibility and impact [*22*]; and many research questions carry no directly contested partisan valence. Whether partisan identity is merely an external correlate of scientists' politics or a latent axis organizing scientific production and use, therefore, has remained an open empirical question.

Existing evidence is incomplete in two ways. First, prior work on the political orientations of scientists largely relies on surveys of specific disciplines, policy domains, or academic institutions [*23–29*]. More recent studies using Federal Election Commission (FEC) campaign contribution records [*30*] and voter registration records [*31*, *32*] show that American scientists disproportionately support Democrats and that this partisan skew has intensified over time. But we lack an across-science account that triangulates partisan identity across behavioral, administrative, and survey measures. Second, and more importantly, we lack an integrated account of whether partisan alignment is associated with how science is produced and used, spanning across research content, citation flows, and societal uptakes.

At the same time, the science of science literature has shown that large-scale bibliometric and network data can reveal regularities in how scientific fields evolve, how collaborations form, how knowledge diffuses, and how scientific work travels into public domains [*13*, *33–38*]. Yet the political identity of scientists is largely absent as an explicit axis in these studies. We know that policymakers with different partisan commitments cite science differently in policy [*13*], that trust in science is polarized along partisan lines [*5*, *6*, *9*, *11*], and that scientists' visible political behavior can affect their perceived credibility [*30*, *39–42*]. However, we know much less about whether scientists' partisan identity is itself associated with the structure of scientific production and use [*43–45*].

Here we combine large-scale datasets capturing scientists, scientific publications, and the public use of science together with ideological commitments of the scientists to systematically examine partisan disparities in the production and uptake of science in the United States. We integrate seven large-scale data sources from disparate domains, including individual-level campaign finance data [*46*], faculty roster data [*47*], voter registration records [*48*], bibliometric data from Dimensions [*49*] and OpenAlex [*50*], patent and media citation data from SciSciNet [*51*], and policy-citation data from Overton [*52*]. We identify the partisan alignments of roughly 430,000 scientists using FEC campaign contribution records and link these alignments to their publications (Materials and Methods), allowing us to examine the nature of their work and its uptake within and beyond science. We further augment this data integration with an original survey of active U.S.-based scientists (Materials and Methods). Together, these sources allow us to assemble the first systematic mapping between the political composition of the scientific workforce and the linked system through which scientific knowledge is produced, circulated, and used.

Political participation, partisan alignment, and ideology of U.S. scientists

We first analyze individual-level FEC campaign contribution records matched to disambiguated author publication and affiliation data to identify scientists who made at least one political donation to either Republican or Democratic candidates for public office (Materials and Methods). Classifying scientists' partisan alignment by the party affiliation of the candidates they supported, we find that political participation among scientists has increased sharply in recent decades. The number of scientists making campaign contributions rose steadily from the early 2000s onward, with a pronounced spike in the 2020 election cycle (Fig. 1A). Among these politically active scientists, partisan alignment is highly asymmetric (Fig. 1B), with the vast majority contributing exclusively to Democratic candidates.

This asymmetry has evolved substantially over time (Fig. 1C). In the early 1980s, scientists donating to Democratic versus Republican candidates were divided roughly 60% to 40%. Over time, however, the share supporting Democratic candidates steadily widened. By 2020, approximately 95% of partisan donating scientists contributed almost exclusively to Democratic candidates.

To estimate the size and composition of this politically active subset within the professoriate, we use faculty-roster data from the Academic Analytics Research Center (AARC), which captures a census of over 300,000 faculty at 362 Ph.D.-granting institutions in the United States. Among tenure-line faculty active between 2012 and 2022, 23.5% contributed to either Democratic or Republican candidates. In a typical year, roughly 10% of faculty contributed, with a pronounced spike in 2020. Full professors consistently contributed at the highest rates, compared with assistant or associate professors, with 25.9% of full professors contributing in 2020 [Fig S5]. These contribution rates are in line with, if slightly lower than, relevant benchmarks among U.S. citizens according to the American National Election Study ANES (Fig. S3). Among these faculty contributors who gave to either Democrats or Republicans, a highly asymmetric pattern remains: approximately 95% contributed almost exclusively to Democrats, compared with approximately 5% who contributed almost exclusively to Republicans (Fig. S4).

These results are consistent with prior evidence of a strong Democratic skew among politically active scientists, now presented at a larger scale and across the scientific workforce [see Ref.

[*53*] for a review]. But campaign finance records do not describe the entire ideological distribution of the scientific workforce. Their value is that they identify a substantial, politically active, and disproportionately senior subset whose partisan identities can be measured behaviorally, observed longitudinally, and linked directly to scientific output with high fidelity (see SM). They are also limited, however, because they do not observe scientists who do not donate. To characterize this broader landscape, we fielded an original survey of approximately 7,000 active U.S.-based scientists, asking respondents about party identification as well as social and economic ideological positions (Materials and Methods). The survey reveals that the scientific workforce is politically asymmetric but not ideologically monolithic. While Republican identification remains uncommon across fields (Fig. 1D]) a substantial share of scientists identify as political Independents, and many scientists, including many partisan identifiers, do not consistently hold liberal or conservative positions across economic and social dimensions.

Indeed, combining ideological self-placement with party identification reveals considerable heterogeneity beneath partisan labels. While 69.6% of Democratic-identifying scientists hold consistently liberal views, 29.8% are ideologically mixed. Among Independents, 65.2% fall into this mixed category. Even among the smaller set of Republican-identifying scientists, 44.2% are neither consistently liberal nor consistently conservative, compared with 51.6% who are consistently conservative.

Scientists who identify as Independents are particularly interesting because they have received limited attention in the literature, which has often focused on ratios of Democrats to Republicans [*53*], and because they are difficult to observe in campaign finance records. Figure 1D situates Independents within a two-dimensional ideological space defined by their self-placement on social and economic liberal–conservative scales. The modal Independent scientist describes themselves as “middle of the road” on both dimensions. Although Independents overlap substantially with self-identified Democrats, their distribution is more centrist on average, suggesting that Independent identification among scientists reflects meaningful ideological moderation rather than merely expressive distance from party labels. Indeed, Independents constitute the largest partisan group in Physical Sciences & Engineering (Fig. 1F) and are more ideologically moderate than Democratic identifiers on both economic and social dimensions (Fig. 1D).

Finally, we turn to a left-right ideological scale which we derive from scientists’ views on political issues such as the role of the government, markets, and inequality, rather than their self-placement)Materials and Methods; Fig. S1). Figure 1G shows the distribution of this scale across party and ideological subgroups. Although Independents overlap considerably with self-identified Democrats and Republicans, their distribution is more centrist on average than either. More broadly, the distributions shift in expected ways across party and self-described ideology, but every subgroup exhibits wide within-group variation and substantial overlap with adjacent groups, underscoring that scientists are ideologically diverse rather than monolithic in their views.

To further validate this broader picture, we match a sample of scientists to voter-registration records (Materials and Methods; Figs. S6 and S7). These administrative data confirm a key survey observation: while Democratic scientists outnumber Republican scientists, a large share of scientists are registered as Independent, unaffiliated, or nonpartisan (Fig. 1E) Thus, the prominence of Independents is not merely a feature of survey self-report. At the same time, voter registration records do not measure ideological self-placement or issue-specific beliefs, highlighting the complementary role of the survey in revealing moderation and mixed ideological profiles beneath party labels. Indeed, each of these approaches to measuring scientists' political and ideological alignments is subject to its own measurement procedures, revealing different parts of the landscape beyond what campaign finance measures capture.

Together, these measures offer a more precise picture than any single source could provide. Among scientists who make political donations, partisan alignment is highly asymmetric and overwhelmingly Democratic across all major fields. Yet survey and voter-registration evidence shows that the broader scientific workforce is not ideologically monolithic: Independents are numerous, ideological self-placement varies across fields, and many partisan identifiers hold mixed views across issue domains.

This layered political landscape raises a central question: when partisan alignment is strong enough to be observed behaviorally, is it associated with the content and uptake of scientific work? We next focus on scientists who give almost exclusively to either Democratic or Republican candidates (Materials and Methods), allowing us to test whether strong partisan alignment is associated with research content and with the uptake of scientific work within and beyond science.

Political alignment predicts differences in scientific content

To compare the research produced by Democratic- and Republican-aligned scientists, we represent each paper as a SPECTER2 [*54*] embedding and use the Cramér multivariate two-sample test to evaluate whether the two sets of papers occupy different regions of semantic space [*55*]. We define partisan paper sets inclusively. Any paper with at least one Democratic-aligned author enters the Democratic-authored set, and any paper with at least one Republican-aligned author enters the Republican-authored set. Papers with both Democratic- and Republican-aligned authors therefore appear in both sets, which by construction reduces between-set differences and makes our estimates conservative. Due to computational constraints of the Cramér test, we estimate the statistic using balanced bootstrap resamples of partisan-authored papers within each field (Materials and Methods).

We find that, across all 26 high-level OpenAlex fields, Democratic- and Republican-authored papers differ systematically in semantic content (Fig. 2A). To assess whether these differences simply reflect partisan scientists working in different areas of science, we benchmark the observed Cramér statistics against permutation-based null models that preserve publication year and increasingly fine-grained topical structure. Blocking by publication year accounts for temporal changes in partisan authorship and secular movement in the semantic frontier of science. Blocking by subfield (252 across 26 fields) and then by OpenAlex topic (4,516 across 26 fields) further preserves increasingly detailed intellectual context.

The topic controls attenuate the partisan separation, indicating that part of the observed difference reflects compositional differences across measured research topics. Yet the OpenAlex topic taxonomy does not exhaust the difference. Even under the most stringent topic-preserving null model that we consider, Democratic- and Republican-authored papers remain semantically distinguishable in every field (Fig. 2A; $p < 0.001$ in all fields, Table S2). Expressed as a common-language effect size, the probability that an observed Cramér statistic exceeds the topic-preserving null ranges from 74.9% in earth and planetary sciences to 99.3% in the social sciences. Thus, partisan differences in scientific content are not confined to overtly political domains, although their magnitude varies considerably across fields.

The Cramér tests establish that partisan-authored work occupies different regions of semantic space, but not what those differences mean. To characterize the partisan dimension within each field, we fit field-specific regularized logistic models that predict Democratic- versus Republican-aligned authorship from a paper's SPECTER2 embedding, controlling for publication year and OpenAlex topic (Materials and Methods). To isolate the partisan axis within each field, we train the discriminant model on papers with unambiguous partisan authorship, defined as papers whose contribution-matched authors are all Democratic-aligned or all Republican-aligned. Evaluation uses held-out test sets that preserve each field's natural mix of Democratic-only, Republican-only, and mixed Democratic–Republican papers, with mixed papers entering both classes at half weight so that performance is not improved by forcing cross-partisan work to one side.

The resulting discriminant scores locate papers along field-specific partisan semantic axes. We find that correlations between these axes across fields are low (ranging from -.032 to .425, with a median of .121), indicating that partisan differentiation is locally expressed within fields rather than reflecting a single left–right dimension running through science as a whole (Fig. S9). In other words, partisan alignment appears to organize different research programs in different fields, rather than imposing a common ideological vocabulary across science.

Overall, the models reveal systematic but heterogeneous separation between Democratic- and Republican-authored work. Author alignment is most separable by content in agricultural and biological sciences, dentistry, decision sciences, and arts and humanities, and least separable in physics and astronomy, chemical engineering, immunology and microbiology, and nursing (Fig. 2B). To interpret these field-specific differences, we identify papers in the Democratic- and Republican-associated tails of each discriminant distribution and conduct a differential keyword analysis of their abstracts. This analysis recovers the lexical and thematic content most strongly associated with each side of the partisan semantic axis after accounting for topic and year (Fig. 2C; Fig. S10). The resulting terms, shown for the four highest- and four lowest-AUC fields, point to differences in research emphasis (e.g., ecology and biodiversity versus crop yield and livestock), framing (disparities and access versus procedures and complications), applications (Medicaid coverage versus asset prices), and populations studied (women and LGBTQ youth versus surgical patients). In other words, partisan alignment is associated not only with broad topic sorting, but with finer-grained research-program choices within measured topics.

These findings do not imply that partisan identity determines scientific conclusions, nor that scientists with different political commitments would reach different answers when evaluating the same evidence. Rather, they show that, among scientists with strong behaviorally observed partisan alignments, Democratic- and Republican-authored work differs systematically in semantic content. Part of this difference reflects topical specialization; part remains within measured topics, suggesting that partisan alignment is associated with the fine-grained organization of scientific inquiry.

Political alignment and uptake within science

Having shown that partisan alignment is associated with differences in scientific content, we next examine the uptake of this work in science. We distinguish between two dimensions of uptake: rate, or how many citations a paper receives, and direction, or where those citations come from.

Using weighted Poisson fixed-effects models of scientific citation counts, we compare papers with at least one Democratic-aligned author to papers with at least one Republican-aligned author, with politically mixed papers contributing to both groups (Materials and Methods). The models condition on fine-grained OpenAlex research topic, publication year, team size, funding, the number of partisan contributing authors, and reference-list length, allowing us to compute standardized predicted citation counts holding the covariate distribution fixed. We find that papers with Republican-aligned authorship receive roughly 8% fewer citations than otherwise comparable papers with Democratic-aligned authorship (approximately 40.7 versus 37.4 predicted citations; R-D = -3.3, $p < 0.001$), a modest but statistically significant difference (Fig. 3A) SM reports alternative specifications, showing consistent conclusions (Tables S8 and S9).

This citation gap, however, appears to have narrowed over time. We estimate a pooled model interacting authorship party with publication year, recovering the standardized R−D difference in predicted citations within each year (Fig. 3B) Earlier cohorts show the largest gap, which then narrows over the 2000s and 2010s, with year-specific differences attenuating from roughly the mid-2000s onward and closing by approximately 2015. Overall, these citation-rate results point to a modest yet diminishing difference in paper-level scientific impact associated with partisan authorship, rather than a large or uniform pattern of differential uptake.

Turning to the direction of scientific uptake, we examine partisan homophily in citation networks for each high-level OpenAlex field. Because a paper may have both Democratic- and Republican-aligned authors, we assign party inclusively at the paper level and measure homophily at the edge level (Materials and Methods). We compare each field's observed share to a permutation null in which paper-level partisan labels are reassigned within publication year and OpenAlex topic. This design preserves temporal structure and topical specialization while breaking any remaining association between partisan alignment and citations. Across all 26 fields, the observed networks exhibit more same-party citation than expected under this null (Fig. 3C), with excesses ranging from roughly 2 to 9 percentage points. Therefore, among the subset of papers we analyze, citations are more likely to connect papers from the same partisan author community than shared topics and cohort effects alone would predict.

The contrast between citation rates and citation direction is noteworthy. While partisan alignment is associated with only modest differences in the number of scientific citations papers receive, it is more clearly visible in the pathways through which scientific attention flows.

Partisan alignment may index research-program proximity that remains finer-grained than topic labels. Consistent with the content results, partisan alignment appears as patterned attention within science, rather than large differences in citation impact.

Political alignment and uptake beyond science

To what extent do the partisan differences observed within science translate into societal uptakes? Scientific discoveries travel into public life through multiple channels, including policymaking, marketplace applications, and public perception [*36*]. In examining whether partisan alignment is associated with these societal uptakes, we again distinguish between the rate of uptake and the direction of uptake. The rate analyses ask whether papers authored by different partisan author communities receive different levels of attention in public domains. The direction analyses ask whether politically identifiable policy actors draw on different parts of the scientific record.

We examine the uptake of science across three public domains, tracing how scientific papers are cited in policy documents, patents, and news media, respectively. For each domain, we compute a relative consumption index (RCI) [*36*], defined as the share of a group's papers taken up by that domain normalized by the corresponding share for the corpus of papers for that group as a whole. We estimate RCI estimated by author-party composition and scientific field: values above one denote uptake exceeding the expected rate for papers by contributing scientists, whereas values below one indicate uptake short of it (Materials and Methods).

Comparing papers with any Democratic author against those with any Republican author—a conservative contrast since politically mixed teams count toward both groups, we uncover three key patterns (Fig. 4A). First, Republican-authored papers see greater use in patenting than Democratic-authored counterparts, whereas Democratic-authored papers see greater use in news media and policy documents. Second, the sharpest partisan difference appears to be in news media. Papers with a Republican author are picked up by news below the corpus average in the health (RCI = 0.57), life (0.76), and physical (0.55) sciences, and the D–R gap appears widest for news in most fields. Third, public uptake is strongly domain-specific but directionally persistent across science: patents disproportionately draw on Republican-authored work, while news and policy disproportionately draw on Democratic-authored work, and these tendencies recur across disciplines despite large differences in the overall prevalence of each form of uptake.

Turning to the direction of uptake, we analyze policy citations from ideological think tanks and congressional committees, asking whether Democratic and Republican policymakers differentially use science from ideologically aligned authors. We use the same estimation strategy as our scientific citation analyses, comparing policy-citation rates for papers with at least one Republican-aligned author to those with at least one Democratic-aligned author separately for each institutional context (Materials and Methods).

We find that ideological think tanks [*13*] exhibit clear and symmetric directional selectivity. Right-leaning think tanks cite Republican-affiliated papers at significantly higher rates than Democratic-affiliated papers (Fig. 4C), whereas left-leaning think tanks show the mirror-image pattern, citing Democratic-affiliated papers at significantly higher rates than Republican-affiliated papers (Fig. 4B). This pattern is robust across various fixed-effects specifications (Table S7).

Congressional committees, on the other hand, show a weaker signal. Under our main specification, the overall citation rate does not differ significantly between Republican- and Democratic-affiliated papers in either Republican- or Democratic-controlled committees (Fig. 4D, 4E). The point estimates for predicted policy citations in both committees nonetheless fall in the direction of partisan selection, with each leaning toward papers sharing its party. In Democratic-controlled committees, this difference reaches statistical significance under alternative fixed-effects specifications (Table S7). Overall, the evidence suggests at most weakly directional signals, consistent in sign with partisan selection but far smaller in magnitude and less robust in specification than the think-tank patterns. Partisan selectivity in policy uptake thus appears concentrated in the explicitly ideological think-tank sector rather than in the government setting.

These results show that partisan alignment is visible not only in the production and circulation within science, but also in its public and political uptake. The strongest evidence appears among ideological think tanks, institutions explicitly organized around political worldviews. It is important to note that this alignment does not require policymakers or policy professionals to know authors' campaign donation histories or political orientations. Rather, author alignment may reflect research programs, frames, networks, institutions, and evidentiary styles that different political actors find more useful or credible. In this sense, partisan alignment connects the supply side of science to its demand side: the organization of scientific production is associated with the parts of the scientific record that travel into public and political life.

Discussion

Taken together, our findings establish two key features of the political organization of contemporary U.S. science. First, science is politically asymmetric without being ideologically homogeneous. Scientists who make political contributions are overwhelmingly Democratic-aligned, and this asymmetry has widened over time. However, survey and voter-registration evidence reveal a substantial population of Independents, meaningful ideological moderation among many of them, and considerable ideological heterogeneity even within partisan groups. Second, among scientists with strong, behaviorally observable partisan alignments through campaign contributions, political identity is associated with the content and circulation of scientific work, but unevenly so. Partisan differences are detectable in published content and in the direction of scientific and political attention, whereas differences in total scientific citation rates are modest and have narrowed over time.

This uneven profile is central to interpreting the results. Discussions of politics and science often conflate the political identities of scientists, the organization of scientific work, and the validity of scientific claims. Our evidence concerns the first two, not the third. It does not show that scientific conclusions are determined by authors' politics, that papers should be evaluated by partisan identity, or that scientists with different commitments would reach different conclusions from the same evidence. It shows that a scientific system can retain broadly shared standards for assessing claims while exhibiting political structure in the published record and in some of the pathways through which that record receives attention.

The political landscape documented here must therefore be understood in both directions. Campaign-finance records reveal a substantial and disproportionately senior subset of scientists whose partisan identities are observed behaviorally and can be linked to scientific output. That subset is highly asymmetric. But it is not equivalent to the scientific workforce as a whole, which includes many Independents and substantial ideological variation beneath partisan labels. Describing scientists as a uniform partisan bloc overstates the evidence, while ignoring the asymmetry among politically active scientists misses a key feature of contemporary science. Both observations are necessary to characterize the institution accurately. The prominence of independents also opens a distinct research agenda. Because independents are difficult to identify in campaign-finance data and are often treated as a residual category in research on the partisan valence of the academy, little is known about where they are situated within science, how their political and ideological heterogeneity relates to scientific work, or how they are perceived by external audiences. Studying this population may be especially important for understanding representation, trust in scientists, and the broader social contract through which science secures public legitimacy and support.

The semantic results identify field-specific differentiation in published scientific content. Some of the separation between Democratic- and Republican-authored work reflects differences in topic composition. Yet fine-grained controls for field, year, and measured topic do not eliminate it, and the dimensions separating the two groups correlate only weakly across fields. Partisan differentiation is expressed differently across scientific domains rather than as a single ideological vocabulary running through science. Beyond this substantive finding, the field-specific axes provide a reusable measurement framework. Trained on authors with behaviorally observed partisan alignments, they offer a route to studying partisan differentiation in the broader scientific record. In this sense, the axes make partisan disparities in scientific content measurable in field-specific terms.

The source and meaning of this residual differentiation remain unresolved. Abstract-level semantics cannot determine whether it arises from finer-grained research problems, study populations, applications, methods, framing, substantive findings, or combinations of these features. Nor can the present design determine whether political alignment precedes entry into particular research programs, develops through institutional and professional environments, or reflects common antecedents such as training, geography, and funding. These results therefore open two linked lines of inquiry: identifying the dimensions of scientific work along which partisan differentiation appears, and explaining the processes through which that differentiation develops.

The citation results provide an important contrast between the amount and direction of scientific recognition. The modest citation deficit associated with Republican authorship is concentrated among earlier cohorts and closes by approximately 2015. Within the partisan-labeled citation network, however, citations connect papers associated with the same partisan author community more often than expected after preserving measured topic and year. Partisan alignment is therefore more visible in the direction of attention within this observed network than in large or persistent differences in aggregate citation counts.

This pattern should be interpreted with care. The analysis establishes that measured topic and cohort do not fully account for citation patterns within the partisan-labeled subnetwork. The analysis does not represent the complete scientific citation network, and the observed overlap may reflect other factors such as institutional location, geography, training lineage, methodological community, journal audience, funding environment, professional networks, or other forms of scientific proximity not captured by topic labels. It does not show that scientists consciously cite on the basis of party, and most authors are unlikely to know the political contribution histories of the researchers they cite.

One provisional account of this uneven empirical profile concerns the reach of scientific norms. Peer review, replication, and disciplinary standards principally govern the assessment of scientific claims. They exert less direct control over the distribution of scientists' attention and published work across research areas, the networks through which their attention circulates, or the external institutions that later mobilize research. Partisan associations might therefore be comparatively attenuated in paper-level recognition while remaining more visible in scientific content, directional attention, and external uptake. The findings are consistent with this account, but they do not uniquely establish it. Selection into fields and institutions, funding environments, geographic and professional sorting, and demand-side incentives could generate overlapping patterns. The present study's primary contribution is to empirically establish these regularities; distinguishing among the mechanisms capable of producing them remains a task for future theory and research.

Uptake beyond science likewise differs by partisan authorship without showing a uniform partisan advantage. Republican-authored papers receive relatively greater patent uptake, whereas Democratic-authored papers generally receive greater news and policy uptake, with substantial variation across fields. These differences may reflect research content, sectoral relevance, institutional location, professional networks, or audience demand. Directional policy selectivity is clearest among ideological think tanks: organizations on the left and right disproportionately cite work associated with aligned author communities. Congressional committees show considerably weaker patterns. Political sorting in uptake is therefore most evident among institutions explicitly organized around ideological commitments, not uniformly across policymaking.

Overall, these findings should be interpreted together with emerging evidence on the broader science-politics system. Earlier work showed that Democratic and Republican policy actors often cite different science, with limited overlap in the papers that receive attention across partisan coalitions [*13*, *56*]. Evidence on science funding, by contrast, complicates any simple account in which one party consistently supports science and the other opposes it, and shows that historically, Republican control of some institutions has coincided with higher federal science funding [*19*]. The present study adds the production and circulation layer, showing that partisan alignment is associated with the research programs and attention networks through which scientific knowledge is produced, circulated, and made visible.

These findings thus suggest that the science-politics interface is a coupled system linking resources, production, attention, and uptake, with partisan conflict over science emerging across the system rather than at a single point in the pipeline from discovery to policy. Political actors may selectively draw from science, but they do not draw from an undifferentiated stock of evidence. Scientific knowledge is produced through research programs, institutions, and networks that make some bodies of evidence more proximate to some audiences than others. Political coalitions may therefore not merely disagree over how to interpret shared evidence; they may encounter, cite, and legitimate different parts of the scientific enterprise.

This has direct implications for democratic governance. A pluralistic democracy does not require political actors to agree on values, priorities, or policy goals [*57*]. But it does require capacity to reason from shared evidence [*58*]. If scientific production, scientific attention, funding priorities, and policy uptake are partially sorted, then evidence fragmentation need not arise only from the rejection of scientific standards. It can also arise when different communities draw from different parts of the scientific record, filtered through distinct research programs, networks, and institutional pathways. In such a system, the challenge extends beyond the validity of individual claims to whether scientific evidence can remain sufficiently shared to support collective decision-making.

Several limitations qualify these conclusions. The linked analyses focus on scientists whose partisan identities can be inferred from campaign contributions. This revealed-partisanship subset is substantial, politically active, and disproportionately senior, but it does not represent the full scientific workforce. Hence, while our study represents to our knowledge the largest analysis of its kind, estimates from it should not be interpreted as science-wide averages. The citation-network analysis likewise characterizes only the partisan-labeled portion of the network. Moreover, although our analysis focuses on the United States, the questions raised here transcend national boundaries [*59*]: all governments must support, organize, and draw on scientific expertise, even as political polarization and the funding and organization of science vary across countries [*10*]. Broadening the geographical ambit of this work is therefore an important direction for future research. Finally, our design is observational. It does not establish whether partisan alignment causes differences in scientific content or uptake, identify which dimensions of papers generate the semantic distinctions, or adjudicate the correctness of scientific claims.

Ultimately, science's capacity to function as a shared and self-correcting knowledge institution depends on both the reliability of individual claims and the organization of the system through which those claims are produced, circulated, and encountered. Our results show that partisan alignment is associated with detectable differences in the scientific record and in some of the pathways through which that record receives attention. Understanding those associations is essential to sustaining science as both a self-correcting enterprise and a common resource for a democratic society.

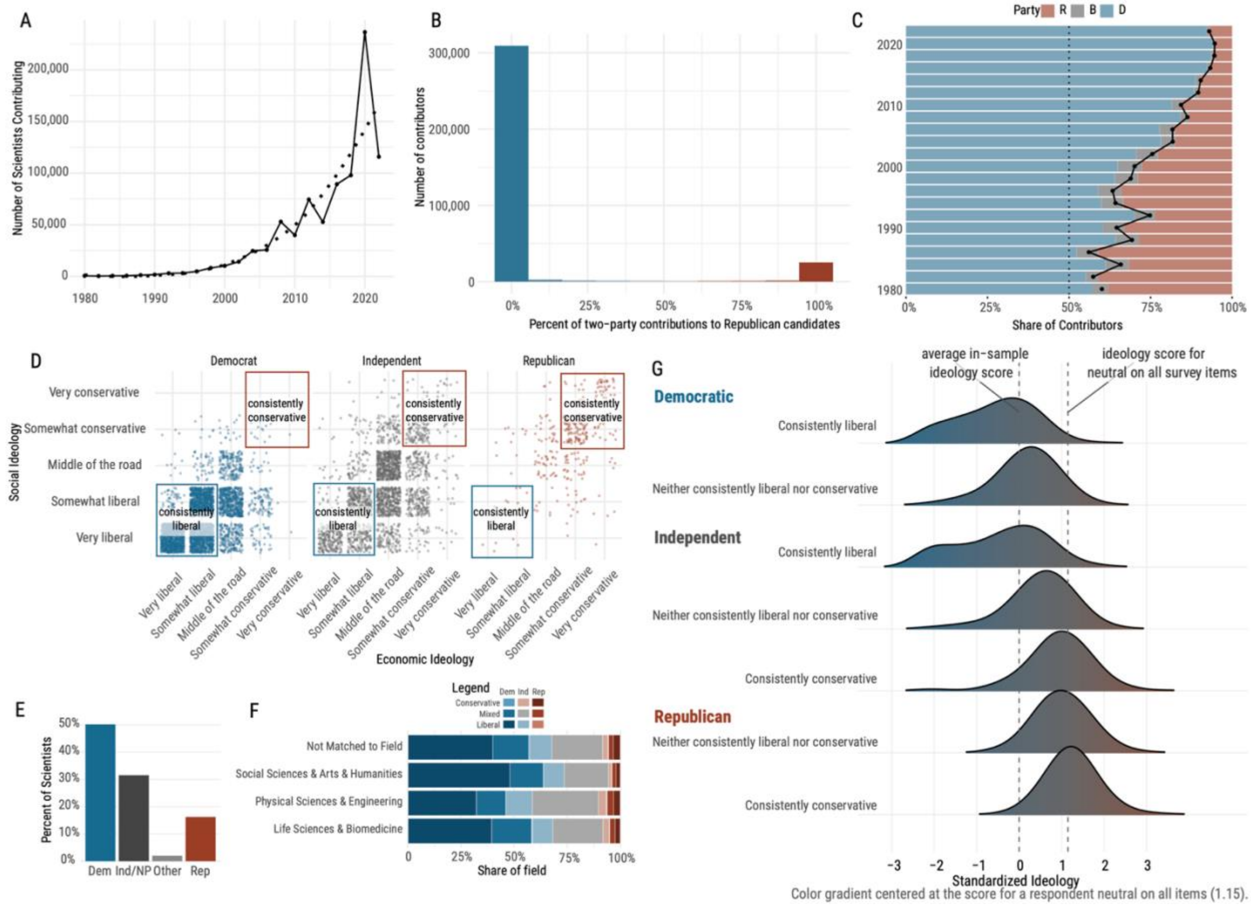

Figure 1: Partisanship of American scientists. (A) The number of FEC campaign contributors matched to scientists per year, 1980-2022. **(B)** Histogram of the number of scientists matched to their campaign contributions by the percent of two-party contributions to Republican candidates. **(C)** The share of contributing scientists by party affiliation from 1980-2022. Scientists contributing more than 90 percent of their two-party contributions to a single party are classified as affiliated with that party, while scientists contributing less than 90 percent to a single party are labelled as bipartisan. **(D)** Ideological self-placement on social and economic dimensions by party identification. Scientists who identified themselves as very- or somewhat-liberal on both dimensions are labelled "consistently liberal;" those who identified themselves as very- or somewhat-conservative on both dimensions are labelled "consistently conservative." **(E)** Party of voter registration for more than 600,000 scientists (see Figs. S6 and S7). **(F)** Party and ideological self-identification from a survey of active U.S.-based scientists (see SM) by top-level field of research. **(G)** Distribution of standardized ($\mu = 0$, $\sigma = 1$) IRT-based ideology measure derived from survey attitudes toward markets, government, and inequality by self-reported party and ideology (conservative Democrats and liberal Republicans excluded due to small sample size). The color gradient is centered at the score for a respondent answering "neither agree nor disagree" on all items.

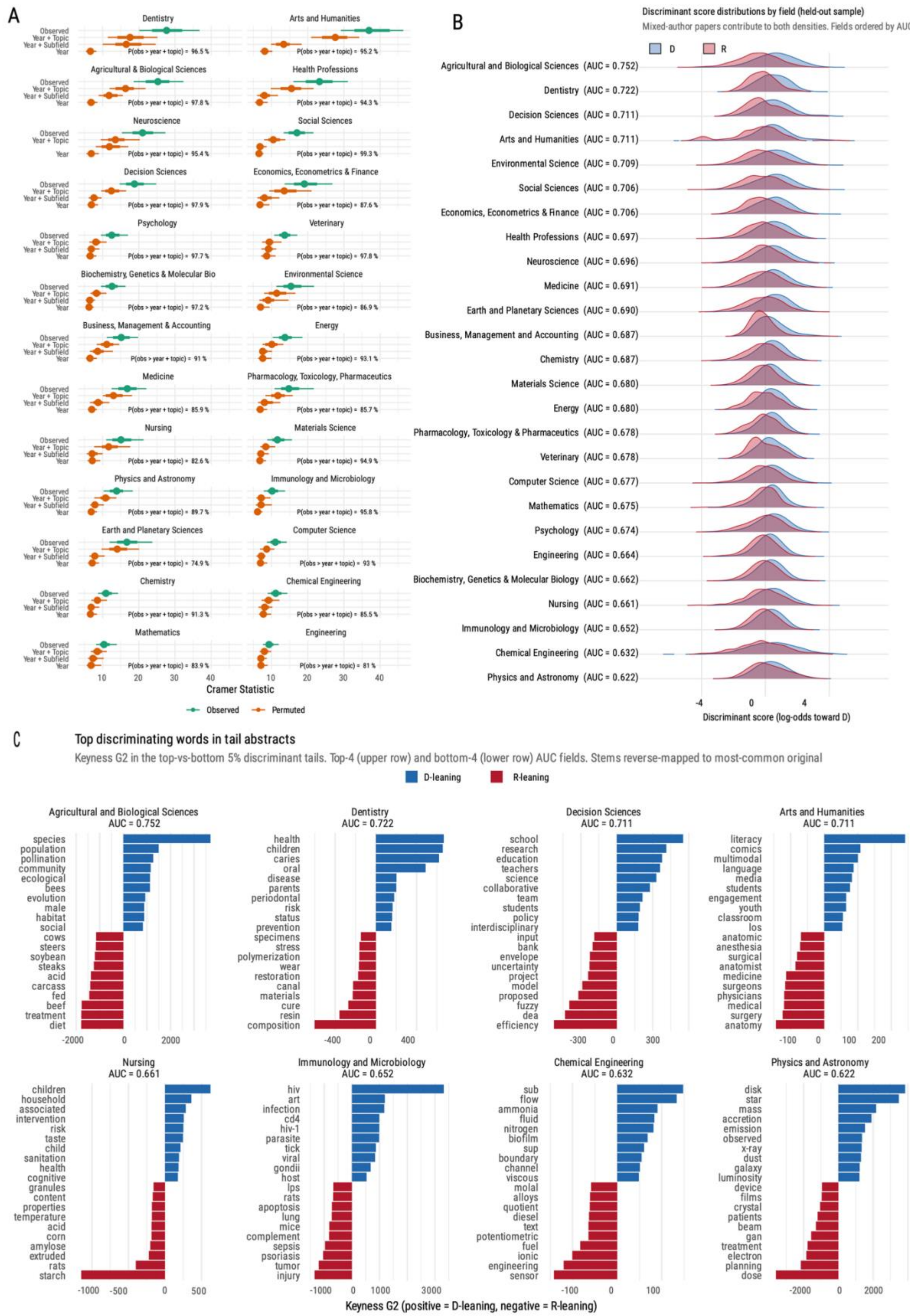
A
Dentistry
P(obs > year + topic) = 96.5 %
Arts and Humanities
P(obs > year + topic) = 95.2 %
Agricultural & Biological Sciences
P(obs > year + topic) = 97.8 %
Health Professions
P(obs > year + topic) = 94.3 %
Neuroscience
P(obs > year + topic) = 95.4 %
Social Sciences
P(obs > year + topic) = 99.3 %
Decision Sciences
P(obs > year + topic) = 97.9 %
Economics, Econometrics & Finance
P(obs > year + topic) = 87.6 %
Psychology
P(obs > year + topic) = 97.7 %
Veterinary
P(obs > year + topic) = 97.8 %
Biochemistry, Genetics & Molecular Bio
P(obs > year + topic) = 97.2 %
Environmental Science
P(obs > year + topic) = 86.9 %
Business, Management & Accounting
P(obs > year + topic) = 91 %
Energy
P(obs > year + topic) = 93.1 %
Medicine
P(obs > year + topic) = 85.9 %
Pharmacology, Toxicology, Pharmaceutics
P(obs > year + topic) = 85.7 %
Nursing
P(obs > year + topic) = 82.6 %
Materials Science
P(obs > year + topic) = 94.9 %
Physics and Astronomy
P(obs > year + topic) = 89.7 %
Immunology and Microbiology
P(obs > year + topic) = 95.8 %
Earth and Planetary Sciences
P(obs > year + topic) = 74.9 %
Computer Science
P(obs > year + topic) = 93 %
Chemistry
P(obs > year + topic) = 91.3 %
Chemical Engineering
P(obs > year + topic) = 85.5 %
Mathematics
P(obs > year + topic) = 83.9 %
Engineering
P(obs > year + topic) = 81 %
Observed
Year + Topic
Year + Subfield
Year
Cramer Statistic
Observed
Permuted
B
Discriminant score distributions by field (held-out sample)
Mixed-author papers contribute to both densities. Fields ordered by AUC
D
R
Agricultural and Biological Sciences (AUC = 0.752)
Dentistry (AUC = 0.722)
Decision Sciences (AUC = 0.711)
Arts and Humanities (AUC = 0.711)
Environmental Science (AUC = 0.709)
Social Sciences (AUC = 0.706)
Economics, Econometrics & Finance (AUC = 0.706)
Health Professions (AUC = 0.697)
Neuroscience (AUC = 0.696)
Medicine (AUC = 0.691)
Earth and Planetary Sciences (AUC = 0.690)
Business, Management and Accounting (AUC = 0.687)
Chemistry (AUC = 0.687)
Materials Science (AUC = 0.680)
Energy (AUC = 0.680)
Pharmacology, Toxicology & Pharmaceutics (AUC = 0.678)
Veterinary (AUC = 0.678)
Computer Science (AUC = 0.677)
Mathematics (AUC = 0.675)
Psychology (AUC = 0.674)
Engineering (AUC = 0.664)
Biochemistry, Genetics & Molecular Biology (AUC = 0.662)
Nursing (AUC = 0.661)
Immunology and Microbiology (AUC = 0.652)
Chemical Engineering (AUC = 0.632)
Physics and Astronomy (AUC = 0.622)
Discriminant score (log-odds toward D)
C
Top discriminating words in tail abstracts
Keyness G2 in the top-vs-bottom 5% discriminant tails. Top-4 (upper row) and bottom-4 (lower row) AUC fields. Stems reverse-mapped to most-common original
D-leaning
R-leaning
Agricultural and Biological Sciences
AUC = 0.752
species population pollination community ecological bees evolution male habitat social cows steers soybean steaks acid carcass fed beef treatment diet
Dentistry
AUC = 0.722
health children caries oral disease parents periodontal risk status prevention specimens stress polymerization wear restoration canal materials cure resin composition
Decision Sciences
AUC = 0.711
school research education teachers science collaborative team students policy interdisciplinary input bank envelope uncertainty project model proposed fuzzy dea efficiency
Arts and Humanities
AUC = 0.711
literacy comics multimodal language media students engagement youth classroom los anatomic anesthesia surgical anatomist medicine surgeons physicians medical surgery anatomy
Nursing
AUC = 0.661
children household associated intervention risk taste child sanitation health cognitive granules content properties temperature acid corn amylose extruded rats starch
Immunology and Microbiology
AUC = 0.652
hiv art infection cd4 hiv-1 parasite tick viral gondii host lps rats apoptosis lung mice complement sepsis psoriasis tumor injury
Chemical Engineering
AUC = 0.632
sub flow ammonia fluid nitrogen biofilm sup boundary channel viscous molal alloys quotient diesel text potentiometric fuel ionic engineering sensor
Physics and Astronomy
AUC = 0.622
disk star mass accretion emission observed x-ray dust galaxy luminosity device films crystal patients beam gan treatment electron planning dose
Keyness G2 (positive = D-leaning, negative = R-leaning)

Figure 2: Political alignment and differences in scientific content. **(A)** Bootstrap distribution (k=100) of the Cramér statistic two-sample test of observed differences in SPECTER2 embeddings of scientific papers with Republican and Democratic authors compared to permuted null distributions of the test statistic with successively more stringent temporal and topical blocking (year, year + subfield, year + topic). The probability of the observed statistic exceeding the permuted statistic for the most stringent null (year + topic) is shown for each field. **(B)** Distribution of partisan discriminant scores by academic field, ordered by weighted AUC on a held-out sample matching the field partisan authorships natural composition. Each ridgeline shows the density of paper-level log-odds scores for the held-out sample of papers with Democratic-contributing and Republican-contributing (red) authors, with papers with both Democratic and Republican authors contributing to both samples. **(C)** Top 10 Democratic-leaning and top 10 Republican-leaning differential keywords (by G^2 statistic) for the four highest- and four lowest-AUC fields.

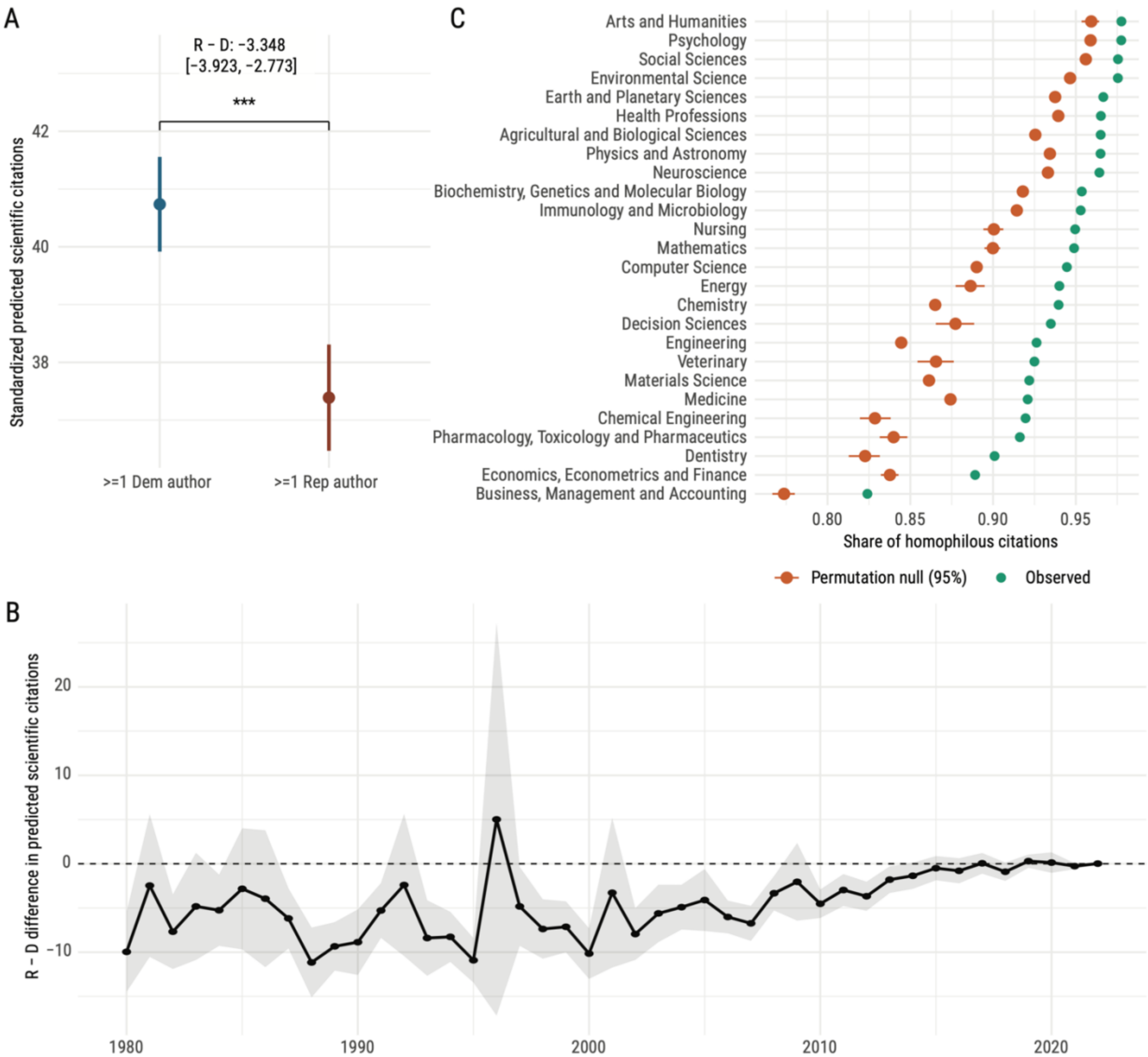

Figure 3: Political alignment and uptake within science. **(A)** Standardized predicted scientific citation counts for papers with at least one Democratic-aligned author and papers with at least one Republican-aligned author, from a weighted Poisson fixed-effects model with OpenAlex topic and year fixed effects; the bracket reports the standardized R − D difference with its delta-method 95% confidence interval. **(B)** Standardized R − D difference in predicted citations by publication year, from a single pooled model interacting authorship party with year; shading shows the delta-method 95% confidence interval. **(C)** Observed partisan homophily in the citation network—the share of citations joining papers that share at least one party—within each OpenAlex field, compared to a permutation null in which paper-level party labels are reshuffled within publication-year × topic strata.

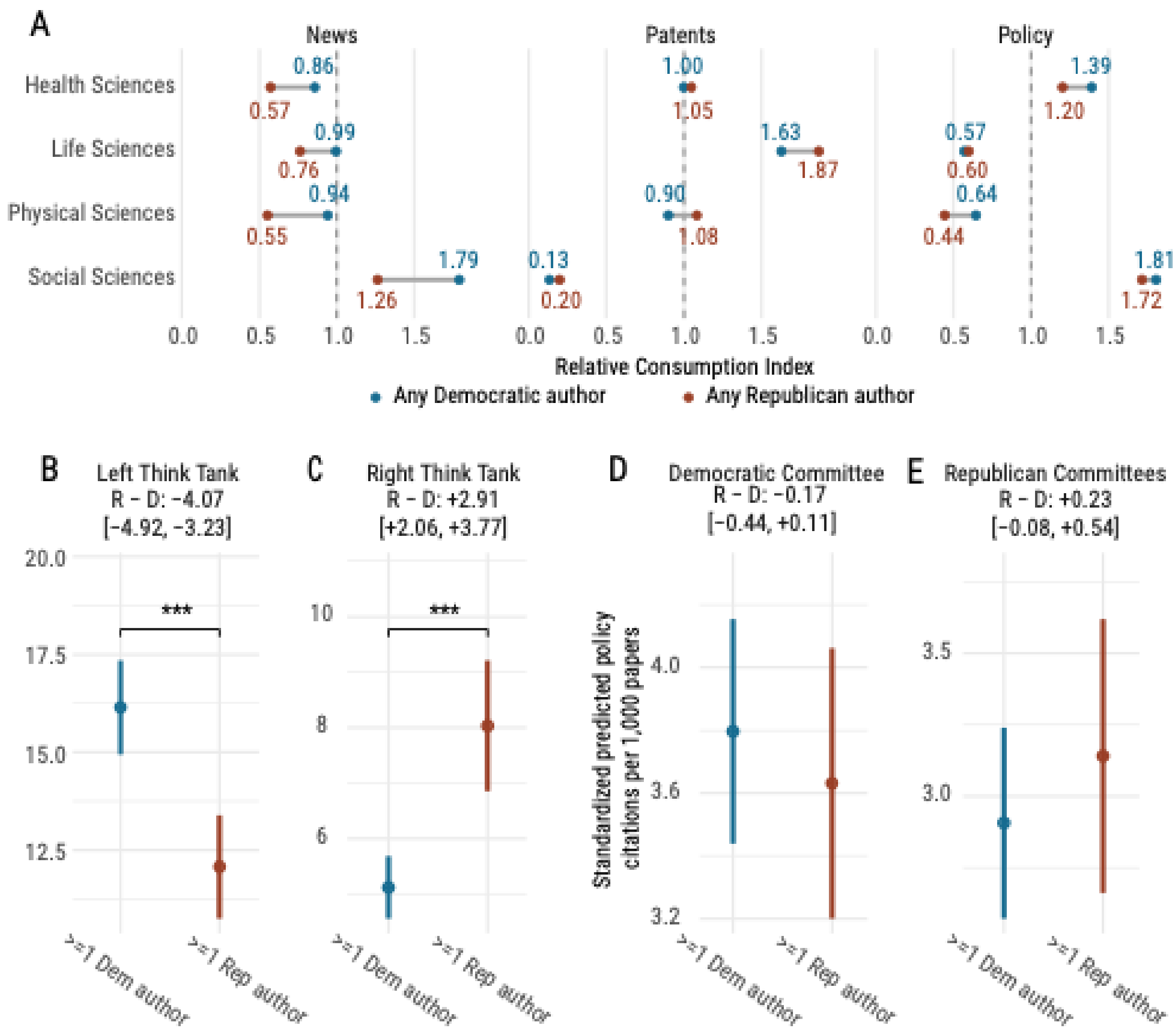

Figure 4: Political alignment and societal uptake. (A) Relative Consumption Index (RCI) for science with at least one Democratic-aligned author (blue) and at least one Republican-aligned author (red), across news, patents, and policy, by high-level OpenAlex research domain. Politically mixed papers contribute to both groups. RCI is the share of papers in each party-by-domain cell receiving any uptake of a given type, divided by the partisan author linked corpus-wide share receiving that uptake; the dashed ring marks RCI = 1 (the corpus-wide average), with values greater than 1 indicating over-consumption and less than 1 indicating under-consumption. **(B–E)** Standardized predicted policy-document citations per 1,000 papers for papers with at least one Democratic-aligned author (blue) versus at least one Republican-aligned author (red), from weighted Poisson fixed-effects models with OpenAlex topic and year fixed effects; predictions are standardized over the observed covariate distribution by G-computation, estimated separately for **(B)** left-leaning think tanks, and **(C)** right-leaning think tanks. **(D)** Democratic-controlled congressional committees, **(E)** Republican-controlled congressional committees, **(**Panel headers report the standardized R−D difference with its delta-method 95% confidence interval; brackets and asterisks denote significance of the R−D contrast (*** $p < 0.001$).

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Author contributions:
Conceptualization: ACF, DW
Data curation: ACF, YY, JG
Formal analysis: ACF
Funding acquisition: DW
Investigation: ACF, DW
Methodology: ACF
Project administration: ACF
Resources: DW
Software: ACF, YY, JG
Supervision: DW
Validation: ACF
Visualization: ACF
Writing – original draft: ACF
Writing – review & editing: ACF, DW

Competing interests:
The authors declare no competing interest.

Supplementary Materials for

Partisan disparities in the production and uptake of science

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The PDF file includes:

- Materials and Methods
- Supplementary Text
- Figs. S1 to S11
- Tables S1 to S9
- References

Materials and Methods

Data Sources and Sample Construction

FEC Campaign Contribution Records

We identify politically active scientists using individual-level Federal Election Commission (FEC) campaign contribution records from the Database on Ideology, Money in Politics, and Elections (DIME) (*46*). The DIME database contains 76,830,440 contribution records for 2,072,608 unique donors (identified by Bonica contributor IDs, or CIDs) who are flagged as possible scientists based on their reported occupation and employer. After cleaning to retain only records with valid geographic information (latitude and longitude), 2,308,782 records remain for 1,913,024 unique donors. For each donor, the cleaned data contain the CID, name, state, geocode, and institutional affiliation (GRID ID), where GRID identifiers are inferred from the donor's reported employer name, state, and city using the Dimensions searching API endpoint. For each contributor, we observe the total number of contributions, the breakdown of contributions to Democratic and Republican candidates, and the Republican share of two-party contributions.

Matching FEC Contributors to Scientists

We match FEC contributors to disambiguated scientists in the Dimensions (*60*, *49*) bibliometric database (Version 20230121). The Dimensions author data contain 8,455,104 records for 4,038,518 unique authors in the United States (defined as authors with at least one U.S. affiliation). Each author record includes a Dimensions researcher ID (PID), name, state, geocode (based on current affiliation), GRID identifiers for all past affiliations, and publication records.

The matching procedure is conducted in several steps. First, we match on exact last name and exact first initial of first name, producing candidate donor–author pairs. Second, we evaluate each candidate pair against two complementary criteria: institutional overlap (shared GRID identifiers) and geographic proximity (geodesic distance between donor and author geocodes). Matches are classified into three types based on these criteria:

(d) GRID match: If the donor and author share at least one GRID identifier (shared GRID ≥ 1), the match is retained regardless of geographic distance. This is the highest-confidence match type, as it indicates that both the name and institutional affiliation align.

(e) Geographic match, no shared GRID: For candidate pairs without a shared GRID, we retain matches where the geodesic distance between the donor's and author's geocodes is 100 km or less. Within this category, we distinguish: (e1) one-to-one matches, where one CID donor maps to exactly one PID author; and (e2) one-to-many matches, where one CID donor maps to multiple PID authors.

This procedure yields 581,536 unique donor–author pairs, linking 383,502 unique donors (20 percent of the 1,913,024 potential scientist donors) to 432,269 unique Dimensions authors (11 percent of the 4,038,518 U.S.-based authors). By match type, 255,507 pairs are matched on shared GRID (regardless of distance), 133,757 are one-CID-to-one-PID matches within 100 km, and 192,272 are one-CID-to-many-PID matches within 100 km. The geographic distance distribution for GRID-matched pairs extends beyond 100 km because GRID overlap is assessed across all historical affiliations, while geocodes reflect only current affiliation. For non-GRID matches, the one-to-many pairs exhibit a wider distance distribution than one-to-one pairs.

The one-to-many matching cases—where a single donor maps to multiple candidate scientists—arise from two sources: genuine ambiguity (multiple scientists sharing a name and geographic proximity) and imperfect entity disambiguation in the underlying databases. Both Dimensions and DIME face well-known challenges in disambiguating individuals from administrative records: Dimensions may split a single scientist into multiple researcher IDs or merge distinct scientists into one, and DIME may similarly over- or under-consolidate contributor records. To the extent that such misattributions are effectively random with respect to the outcomes of interest, they introduce classical measurement error in the partisan classification, which would attenuate estimated partisan differences toward zero and render our results conservative. Even in the non-random case where geographically proximate scientists at the same institution share political leanings, mismatched scientists may be more likely to hold the same party affiliation as the true donor than chance alone would predict, limiting the magnitude of any bias.

We handle these many-to-one matches in several different ways throughout our analysis depending on the application. In Fig. 1(A,B) where we count the number of unique donating scientists, we use the number of unique CID records which we were able to link to Dimensions to avoid double counting. In Fig. S5, we count individuals in AARC faculty rosters as contributors if they match to one or more CIDs. Where a single party ID is needed for a scientist (PID) and that scientist is linked to multiple donors (CIDs), we assign the modal party ID across the linked contributor records; ties are broken randomly. Where a single donor (CID) is matched to multiple scientists (PIDs), each matched scientist independently inherits that donor's party classification.

Partisan Classification

Scientists are classified into three partisan categories based on their aggregate contribution behavior across all election cycles (1980–2022). Scientists contributing more than 90 percent of their two-party contributions to Democratic candidates are classified as Democratic (D); those contributing more than 90 percent to Republican candidates are classified as Republican (R); and those falling below 90 percent for either party are classified as bipartisan (B). Contributors with unknown, unclassifiable party affiliations, or only third-party or non-candidate donations are excluded. For the content, collaboration, and citation analyses, we focus on these scientists with strong partisan signals (those classified as D or R through campaign contributions) which captures scientists giving nearly exclusively to one party. For paper-level analyses in Figs. 2 and 3, a paper is considered D-authored if we have classified at least one of its authors as Democratic and R-authored if we have classified at least one of its authors as Republican according to the above criteria. Any paper with at least one Democratic author is included in the Democratic set, and any paper with at least one Republican author is included in the Republican set, such that papers with both Democratic and Republican authors are included in both, which should make our tests of the differences between these sets of partisan papers more conservative. We apply this same inclusive definition to the paper-level regression analyses in Figs. 3 and 4: politically mixed papers enter both the Democratic and Republican sets through the stacked, weighted specification described below (see Citation Models), with Democratic authorship as the reference category.

Matching Voter Records to Dimensions Researcher Profiles

We linked individual voter records to scientific researcher profiles by combining the L2 voter file (dated October 2020 – January 2021, n = 204,969,857 across all 50 states and DC) with the Dimensions researcher profile dump of 1 May 2021. The Dimensions data was first restricted to researchers whose primary affiliation is in the United States (10,029,206 affiliation rows; 6,977,645 unique researcher IDs) and reduced to a name-keyed lookup table of 6,970,428 (researcher ID, last name, first name) combinations after deduplication and removal of records missing a usable name. Names on both sides were placed in a common standardized form: characters were mapped to ASCII equivalents using the unidecode package, lowercased, with hyphens and apostrophes converted to spaces and surrounding whitespace trimmed. On the voter side, the standardized first and middle names were then concatenated into a single first-name string (e.g., a voter recorded as “Deborah” with middle initial “J” yielded the matching string “deborah j”), so that the rules below could compare voter and researcher first-name representations symmetrically.

Candidate voter–researcher pairs were generated by an exact blocking join on standardized last name and the first letter of the standardized first-name string. Within each block, every pair was evaluated against five accept rules, applied in the following priority order:

- Type 0 (perfect match): the full standardized first-name strings are identical.
- Type 1 (exact first + exact middle): after splitting each first-name string into a head token and a tail-token remainder, the heads agree and the tails agree.
- Type 2 (exact first, missing middle): the heads agree, and the tail is empty on at least one side.
- Type 3 (exact first, middle initial agrees): the heads agree, and one side’s tail is a single letter that equals the first letter of the other side’s tail.
- Type 4 (first initial, exact middle): the heads disagree, but one side’s head is a single letter equal to the first letter of the other side’s head, and the tails agree.

Pairs satisfying any of these five rules were retained as candidate matches; all other pairs were treated as non-matches and discarded. For each retained (voter, researcher) pair, we computed the great-circle (Haversine) distance, with R = 6371 km, between the voter’s residential coordinates and each of the researcher’s institutional locations recorded in Dimensions, and we kept only the pairing in which the closest institutional location was within 100 km of the voter.

Voters were then assigned at most one researcher in three sequential stages. First, for any voter with at least one within-100-km candidate researcher in the same state, we kept the candidate with the lowest match-type number, breaking ties by smallest voter–researcher distance. Second, for voters with no within-state candidate, we accepted a cross-state candidate only if it was a perfect first-name-string match (type 0), again taking the closest by distance. Third, for voters still unmatched after the first two stages, we relaxed the cross-state restriction and kept any remaining within-100-km candidate, ranked by match type and then distance. This produced a many-voters-to-one-researcher map in which each voter is assigned at most one researcher, but a single common-name researcher could be claimed by several voters. To obtain a one-to-one linkage, we performed a second-pass greedy deduplication on the researcher side: for each researcher ID, we retained only the voter with the lowest match type, breaking ties first by distance and then by voter ID. The final linked dataset contains 2,336,270 unique voter–researcher pairs, in which each voter and each researcher appears exactly once, drawn from the 6,977,645 U.S.-affiliated researchers in the Dimensions pool (a 33.5% researcher coverage rate) and roughly 205 million voter records. Of these matches, 1,534,363 unique voter–researcher pairs are in the 30 states with partisan voter registration, which we confine our analysis to rather than using L2's proprietary predicted party. There are 638,549 linked voter-researcher pairs that are type 0 matches (perfect string matches), which we report in the main text. The pipeline is implemented in DuckDB SQL driven by Python.

Researchers without an explicit country = "United States" tag in Dimensions were excluded even when their state field corresponded to a U.S. state, in order to keep the matchable pool unambiguous. The greedy researcher-side deduplication is locally optimal but does not guarantee a globally optimal one-to-one assignment in the sense of Hungarian or stable matching; in practice, the cost of imposing global optimality is substantial relative to the gain at this scale. Distance is computed using Haversine on a spherical Earth, which differs from the geodesic distance by less than half a percent at the spatial scales relevant here and is immaterial for the 100-km cutoff.

Bibliometric Data (Dimensions and OpenAlex)

Publication, co-authorship, and citation data are drawn from the Dimensions database (*60*, *49*). Each paper is linked to its authors via Dimensions researcher IDs and to metadata including DOI, publication date, journal, number of authors, number of funding acknowledgments, number of references, and scientific citation counts. Papers are classified using the OpenAlex (*50*) hierarchical topic taxonomy, which provides four levels of granularity: domain, field (26 fields), subfield (252 subfields), and topic (4,516 topics). Where a paper is assigned multiple OpenAlex topics, one is randomly selected for analyses requiring a unique topic assignment. Scientists are also classified by ANZSRC (Australian and New Zealand Standard Research Classification) Fields of Research at the broadest level (field_l0_name) for descriptive analyses using the modal category of their papers.

SPECTER2 Embeddings

We represent the semantic content of each paper using SPECTER2 (*54*), a transformer-based model that maps scientific paper abstracts into 768-dimensional dense vector representations. These embeddings capture semantic similarity in a continuous space, allowing us to compare the distributional properties of research produced by scientists of different partisan alignments. Embeddings are stored as 768-column numeric matrices (V1–V768) keyed by DOI.

Policy Citation Data (Overton)

Policy citations of scientific papers are obtained from the Overton database (*51*), which tracks references to scientific publications in policy documents, including congressional committee reports and think tank publications. We classify policy-citing institutions along two dimensions: (i) congressional committees are classified by the party holding committee control (Republican-controlled or Democratic-controlled); (ii) think tanks are classified as right-leaning or left-leaning based on their ideological orientation using coding from Furnas et al. (*13*).

AARC Faculty Roster Data

To estimate contribution rates among the academic workforce, we use the Academic Analytics Research Center (AARC) faculty roster (https://aarcresearch.com/), which provides a census of over 300,000 tenure-line faculty (assistant, associate, and full professors) at 362 PhD-granting institutions in the United States. Faculty are matched to Dimensions researcher IDs and then linked to FEC contribution records by election cycle (even years, 2012–2022). Contribution rates are computed as the share of faculty making at least one contribution in a given cycle, broken down by academic rank.

Survey of U.S.-Based Scientists

The survey data used in this study are drawn from a large-scale survey of active U.S.-based scientists originally fielded for a companion study on the evaluation of international scientific collaboration (*61*). The survey was implemented in Qualtrics and ruled exempt by the Northwestern University Institutional Review Board (STU00222562).

Sampling frame and fielding. We identified corresponding authors from articles published in Web of Science-indexed journals between January 2022 and September 2024. From this dataset, we randomly selected 245,000 U.S.-affiliated scholars. After cleaning inactive and duplicate email addresses, we distributed 218,195 invitations and received 9,830 completed responses, representing a response rate of approximately 4.5 percent, consistent with prior survey studies of scientists. Following screening for informed consent, U.S. location, and active research status, the final analysis sample comprises 7,154 scientists.

Because respondents were recruited into a study of scientific collaboration rather than a study of scientists' politics, and ideology items appeared only at the end of the survey, this design helps mitigate concerns about self-selection by respondents motivated primarily by political identity.

Key measures. The survey includes party identification (Democrat, Republican, Independent), ideological self-placement on separate 5-point economic and social liberal–conservative scales (from "very liberal", "somewhat liberal", "middle of the road", "somewhat conservative", to "very conservative"), standard demographic items, and a 5-question battery soliciting opinions about the size and scope of government originally developed by Heinz et al. (*62*) and used in prior studies for ideological scaling (*63*, *64*) below:

Thinking about your own personal opinions, what do you think about the following?

- The protection of consumer interests is best insured by vigorous competition among sellers rather than by federal government regulation on behalf of consumers.
- There is too much power concentrated in the hands of a few large companies for the good of the country.
- One of the most important roles of government is to help those who cannot help themselves, such as the poor, the disadvantaged, and the unemployed.
- All Americans should have access to quality medical care regardless of ability to pay.
- The differences in income among occupations should be reduced.

Response options (all items): (1) Strongly agree, (2) Somewhat agree, (3) Neither agree nor disagree, (4) Somewhat disagree, (5) Strongly disagree

Linkage to Dimensions. Survey respondents were linked to the Dimensions bibliometric database by first merging with the Web of Science sampling frame, then matching respondents' Web of Science identifiers to Dimensions paper identifiers using DOIs as a crosswalk. Author disambiguation within linked papers was performed using Jaro-Winkler string distance on respondents' names. This procedure linked 143,063 of the contact-list email addresses (approximately 65 percent) to Dimensions researcher profiles. Of the 7,154 respondents in the analysis sample, 73.1 percent were matched to Dimensions researcher IDs, enabling linkage to bibliometric and grant-related metadata including total publications, h-index, grant history, current research organization, and scientific field classification.

Weighting. Respondents differ from non-respondents on several professional dimensions: respondents are on average older, more productive, and more grant-active than non-respondents (mean h-index 21.7 vs. 17.3; mean total grants 2.89 vs. 1.85). To address this imbalance, we developed post-stratification weights based on a stratification framework in which respondents were grouped into strata defined by combinations of quartiles for h-index, year of first publication, and scientific field, with a fifth category for missingness. Weights were calculated using the postStratify function from the survey package in R, targeting the distribution of these variables in the full Web of Science contact list. The effective sample size after weighting is 5,912. After applying weights, covariate balance improves substantially: Cramér's V statistics fall below 0.025 for all categorical variables, and standardized mean differences are negligible for most continuous variables.

ANES Benchmark Data

We benchmark scientist contribution rates against the general population using the American National Election Study (ANES) Cumulative Data File (time-series release, February 2026). The key variables are: VCF0721 (self-reported campaign donation: 1 = No, 2 = Yes), VCF0004 (election year), VCF0009z (full sample weight combining face-to-face and web modes), VCF0110 (education level, where 4 = college degree or higher), VCF0114 (income percentile group), VCF0115 (occupation type, where 1 = professional), and VCF0303 (3-category party identification including leaners: 1 = Democrat, 2 = Independent, 3 = Republican).

We compute weighted donation rates per year for four populations: (i) the overall public, (ii) respondents with a college degree or higher, (iii) respondents in the top two income groups (68th percentile and above), and (iv) college-educated professionals. Among donors, we compute weighted partisan shares (Democrat, Independent, Republican) per year for each subgroup. Analyses are restricted to 1990 onward to ensure consistent variable availability.

Analytical Methods

Item-Response Theory Ideology Measurement

To estimate unidimensional ideal points for scientist respondents to our survey based on their responses to the five questions about the market, government, and redistribution listed above, we use the eRm (Extended Rasch Modelling) package's implementation of Partial Credit IRT models for ordinal categorical data (*65*). We follow the same approach used in (*64*, *66*). Item characteristic curves for the five questions we scale are shown in Fig S1. We standardize the resulting scores to a mean of zero and a standard deviation of 1.

Cramér Multivariate Two-Sample Test

To evaluate whether the distribution of research content differs between Democratic- and Republican-aligned scientists, we employ the Cramér multivariate two-sample test (*55*), a nonparametric test of equality of multivariate distributions. For each of the 26 OpenAlex fields, we proceed as follows: We define the Democratic paper set as all papers with at least one Democratic-aligned author and the Republican paper set as all papers with at least one Republican-aligned author; papers with both D and R authors appear in both sets, which mechanically reduces between-set differences and renders our estimates conservative.

Because the Cramér test is computationally intensive in high dimensions, we approximate its sampling distribution via bootstrap resampling. In each of 100 bootstrap replicates, we draw 500 papers (with replacement) from each party's paper set and compute the Cramér statistic on the resulting 500 × 768 embedding matrices using the R *cramer* package (cramer.test with just.statistic = TRUE).

Permutation-Based Null Models for Content Differences

To assess whether observed content differences could arise from the distribution of partisan authorship across time and topics, we construct permutation-based null models with successively stringent blocking. In each permutation, party labels are randomly reassigned to papers within defined strata, preserving the marginal distribution of partisanship within each stratum while severing any association between party and embedding content. We implement four blocking levels: (i) no blocking (unconditional), (ii) within publication year, (iii) within year × OpenAlex subfield, and (iv) within year × OpenAlex topic. For each blocking level, 100 permuted datasets are generated, and the Cramér bootstrap procedure is repeated on each permuted dataset. The statistical significance of the observed content difference is assessed as the probability that the observed Cramér statistic exceeds the permuted statistic under the most stringent null (year × topic).

Partisan Discriminant Analysis (Logistic Regression on Embeddings)

To quantify and characterize partisan signatures in the content of scientific writing, we fit field-specific L2-regularized (ridge) logistic regressions predicting the partisan affiliation of a paper's contributing authors from the paper's SPECTER2 embedding. We classify papers under an inclusive scheme: a paper is Democratic-authored if any of its authors is Democratic-aligned and Republican-authored if any of its authors is Republican-aligned, so mixed-authorship papers belong to both groups. Within each OpenAlex field, we partition the universe of papers at the DOI level, uniformly holding out 20% of D-only, 20% of R-only, and 20% of mixed papers as a test set whose composition matches the field's natural population shares of the three categories. The training pool consists of the remaining 80% of D-only and R-only papers; mixed papers are withheld from training because their dual membership would supply contradictory labels for identical content. From this pool we draw a balanced sample of up to 25,000 papers per party, capped at the smaller of the two single-party training pools.

The model matrix consists of 768 embedding dimensions (penalized), publication year (unpenalized), and one-hot-encoded OpenAlex topic dummies (unpenalized; topics with fewer than 20 papers are collapsed into an "other" category). We use a pure ridge penalty (glmnet mixing parameter $\alpha = 0$) and select the penalty λ by 5-fold cross-validation maximizing AUC on the training set (cv.glmnet from the glmnet package). Discriminability is evaluated on the held-out test set using a weighted Mann-Whitney AUC. Single-party test papers enter as ordinary observations (D-only as $y = 1$, R-only as $y = 0$, weight 1). Mixed test papers enter as paired observations, once with $y = 1$ at weight 0.5 and once with $y = 0$ at weight 0.5, so that each contributes equally to both classes; this reflects their genuine ambiguity rather than forcing a single label.

The resulting per-paper discriminant scores are interpretable as the log-odds of Democratic authorship conditional on topic and year. Positive scores indicate content more characteristic of Democratic-authored work; negative scores indicate content more characteristic of Republican-authored work. All random sampling and fold assignment use a fixed seed (8675309) for reproducibility. Held-out weighted AUC for each field is shown in Fig. 2B; detailed per-field metrics are listed in Table S1.

Differential Keyword Analysis

To characterize what substantively distinguishes the partisan tails, we extract the top and bottom 5 percent of papers on each field's discriminant axis and perform a differential keyword analysis. We tokenize abstracts, apply word stemming, and compute log-likelihood ratio keyness statistics (G^2) using the textstat_keyness function from the quanteda package, comparing the most Democratic-leaning papers against the most Republican-leaning papers. We report the top 10 keywords loading in each partisan direction in Fig. S10. For visualization, stems are reverse-mapped to their most frequent original word form by tokenizing the tail abstracts both with and without stemming.

Stylometric Word-Level Analysis

As a complementary approach, we use the stylest package to perform Bayesian multinomial text analysis identifying words that discriminate between D and R papers within each OpenAlex field (*67*). For each field, we sample 10,000 papers and select an optimal vocabulary cutoff via stylest_select_vocab (minimizing cross-validated misclassification rate). We then fit the stylistic model within each field and produce the predicted party of Democratic authorship for each term, displaying the top and bottom 10 among the 1,000 most common abstract words per field (see Fig. S11). We report the percent misclassification rate (PMR) for each field.

Citation Network Homophily

For the citation network, party is assigned at the paper level using an inclusive definition derived from the author-level classification described in the Partisan Classification section: a paper is Democratic-affiliated if at least one identified author is Democratic-aligned and Republican-affiliated if at least one is Republican-aligned, so that bipartisan papers belong to both sets rather than to a separate exclusive category. Papers with no identified partisan authors are excluded, and a directed citation graph is built from paper-to-paper reference data using igraph. Because nodes can belong to two overlapping sets, we measure homophily at the edge level rather than with single-label nominal assortativity: within each OpenAlex field, we compute the share of citations among partisan papers whose endpoints share at least one party, and we compare it to a permutation null in which paper-level party membership is shuffled within publication-year × OpenAlex-topic strata, preserving each stratum's party composition and the citation structure (1,000 permutations). Across all fields, the observed homophilous share exceeds the null, with the excess ranging from roughly 2 to nearly 9 percentage points, indicating same-party citation preference beyond what party composition and topic structure alone would produce.

Citation Models

Across the citation analyses, we use a common estimation strategy, described once here. Partisan authorship is assigned at the paper level from the author-level classification (Partisan Classification section) using an inclusive definition: a paper enters the Democratic-affiliated set if at least one identified author is Democratic-aligned and the Republican-affiliated set if at least one is Republican-aligned, so politically mixed papers belong to both sets rather than to a separate exclusive category. We implement this by stacking each paper once per party it contains and assigning each row a weight of 1/(number of party rows for that paper); every paper thus contributes total weight one, and a mixed paper contributes weight one-half to each set. Authorship party enters as a two-level factor (Democratic, Republican) with Democratic as the reference.

We estimate counts with weighted Poisson pseudo-maximum-likelihood (PPML) fixed-effects models (fepois, fixest package). Fixed-effects Poisson is consistent for the conditional mean under high-dimensional fixed effects, accommodates the observation weights above, and—combined with cluster-robust standard errors—requires no assumption about the conditional variance, with overdispersion absorbed by the standard errors rather than modeled; the negative-binomial fixed-effects estimator does not share this consistency property. All models include OpenAlex research-topic and publication-year fixed effects. We condition on research topic rather than publication venue because venue is itself a downstream outcome of evaluation, and conditioning on it would absorb the mechanism of interest (the journal-fixed-effects specification, which attenuates the estimated differences, is reported in Tables S7 and S9). Standard errors are two-way cluster-robust, clustered on paper (DOI) and on the topic-by-year interaction—the former because a mixed paper's stacked rows share an identical outcome and are not independent, the latter to allow citation shocks common to a topic in a given year.

Our quantity of interest throughout is the standardized difference in predicted citations between Republican- and Democratic-affiliated papers, obtained by G-computation: from the fitted model, we predict counts setting authorship to Republican and to Democratic across the estimation sample, average over the observed covariate distribution, and take the difference (R − D), with delta-method standard errors from the clustered covariance.

Policy Citation Models

We model the count of citations a paper receives from each of four institutional contexts in separate models, using the estimation strategy described above: (i) Republican-controlled congressional committees, (ii) Democratic-controlled congressional committees, (iii) right-leaning think tanks, and (iv) left-leaning think tanks. Controls comprise log(times_cited + 1), log(num_funds + 1), log(num_authors), log(num_references + 1), and log(num_DR_auth). Full model results and standardized contrasts are reported in Tables S4 and S5 (main specification, topic fixed effects); journal- and subfield-fixed-effects specifications are reported in Tables S6 and S7.

Scientific Citation Models

We first model the total number of scientific citations a paper receives, using the estimation strategy described above. Controls comprise log(num_DR_auth), log(num_funds + 1), log(num_authors), and log(num_references + 1). To assess change over time, we estimate a single pooled model interacting authorship party with publication year (1980 onward) rather than separate per-year models, which are unstable in years with few Republican-affiliated papers; publication year enters through the interaction, so this model absorbs topic fixed effects only, and we recover the standardized R − D difference within each year by G-computation.

Relative Consumption Index by Author, Party, and Field

Public uptake of partisan-authored research. We measure the public uptake of partisan-authored papers using a Relative Consumption Index (RCI) adapted from (*37*). The paper universe comprises DOIs in our partisan-author corpus with at least one author identified as Democratic (D) or Republican (R); DOIs were normalized to lowercase with the doi.org URL prefix stripped before all joins. We adopted an inclusive party classification: a paper is D-inclusive if it has any Democratic author and R-inclusive if it has any Republican author, so politically mixed teams contribute to both groups. This makes the D–R contrast conservative, since the shared mixed-team mass (331,305 DOIs) pulls the two groups' rates toward each other. The inclusive groups contain 5,927,572 (D) and 739,011 (R) DOIs, drawn from 6,335,278 unique partisan DOIs.

Each paper was assigned a single primary field, the OpenAlex domain_display_name of its highest-scoring topic (Health, Life, Physical, or Social Sciences). We defined three binary uptake indicators per paper: news (SciSciNet newsfeed_count > 0), patents (SciSciNet patent_count > 0), and policy (num_pcites > 0 from the Overton-derived policy-citation counts); papers absent from a given source were coded zero. For each consumer type $c \in \{\text{news, patents, policy}\}$, each party group g, and each field f, the RCI is the share of papers in cell (g, f) consumed by c, divided by a single corpus-wide baseline—the share of all partisan papers consumed by c:

$$\mathrm{RCI}_{c,g,f} = \frac{\Pr(\text{consumed by } c \mid g, f)}{\Pr(\text{consumed by } c)}$$

The baseline denominator was computed over the deduplicated partisan universe (6,199,026 papers with an assigned field, mixed teams counted once), yielding overall consumption rates of 0.018 (news), 0.135 (patents), and 0.118 (policy); cell numerators were computed over the duplicated universe (6,526,495 paper-group rows). Because RCI is dimensionless, all three axes in Fig. 4A share one radial scale, with the dashed reference ring at RCI = 1 marking the literature-wide average: values outside the ring indicate over-consumption relative to all partisan-authored work, values inside indicate under-consumption.

Supplementary Text

Partisan Distribution Across Scientific Fields Over Time

The main text notes that Democratic dominance among contributing scientists holds across all major scientific fields. In Fig. S2, we show the field-by-field time series of partisan shares, demonstrating that the share of contributors supporting Democratic candidates has widened over time in every field. For this analysis, we use the Field of Research Division level categorization from the Australian and New Zealand Standard Research Classification, 2020, provided by Dimensions. The partisan skew is most pronounced in the social sciences and humanities and somewhat less extreme in engineering, agricultural and veterinary sciences, and commerce, management, and tourism.

ANES Benchmark: Partisan Composition of Educated Donors

According to the American National Election Study (ANES), the share of Americans contributing to campaigns grew from 6.7 percent in 1990 to a peak of 18.9 percent in 2020. Among those with at least a college education, the share rose from 17.7 percent in 1990 to 29.7 percent in 2020 (see Fig. S3) (68). Note, however, that ANES estimates apply to eligible voters, whereas our estimates cover all tenure-line faculty. A substantial portion of faculty in the United States are not U.S. citizens, and while green card holders are technically permitted to contribute to campaigns, they very rarely do. The ratio of Democrats to Republicans among those who contribute to campaigns and have at least a college education was roughly 80:20 in 2024. Using the ANES Cumulative Data File with full sample weights, we compute weighted partisan shares among donors across four subgroups: (i) the overall public, (ii) respondents with a college degree or higher, (iii) respondents in the top two income groups (68th percentile and above), and (iv) college-educated professionals. Among college-educated donors, the weighted share identifying as Democratic has grown from approximately 50 percent in 1990 to roughly 80 percent by 2024, while the Republican share has declined correspondingly (Fig. S4).

Contribution Rates Among Tenure-Line Faculty (AARC)

Using the AARC faculty roster matched to FEC records, we compute contribution rates by academic rank and election cycle. Across all ranks, approximately 10 percent of tenure-line faculty contribute in a typical cycle, with a pronounced spike in 2020. Full professors consistently contribute at the highest rates—peaking at 25.9 percent in 2020—approximately three times the rate of assistant professors. Across the full 2012–2022 window, 23.5 percent of tenure-line faculty contributed to either Democratic or Republican candidates at least once. Results shown in Figure S5.

Party of Voter Registration Among Scientists

The main text notes that voter-registration records corroborate the survey finding that, although Democrats outnumber Republicans among scientists, a large share are registered as Independent or nonpartisan. Figure S6 shows the distribution of party of registration for scientists linked to the L2 voter file. Among all matched scientists in states with partisan registration (n = 1,534,363), roughly half are registered as Democrats, about 30 percent as Independent or nonpartisan (Ind/NP), roughly 17 percent as Republican, and the remainder with a third party ("Other"). Restricting to our highest-confidence type 0 matches (n = 638,549; see Methods) yields a nearly identical pattern (approximately 50 percent Democratic, 31 percent Ind/NP, and 16 percent Republican), indicating that the prominence of Independents is not an artifact of lower-confidence linkages. Figure S7 disaggregates registration by Field of Research: the Democratic share is highest in the humanities and social science fields (for example, history and archaeology, language and communication, human society, creative arts, and law) and lowest in engineering, chemical sciences, agricultural and veterinary sciences, and commerce and management, while Independent or nonpartisan registrants constitute a substantial share and Republican registration remains a minority in every field. These administrative data reinforce the survey evidence that the scientific workforce is politically asymmetric without being ideologically monolithic.

Supplementary Figures

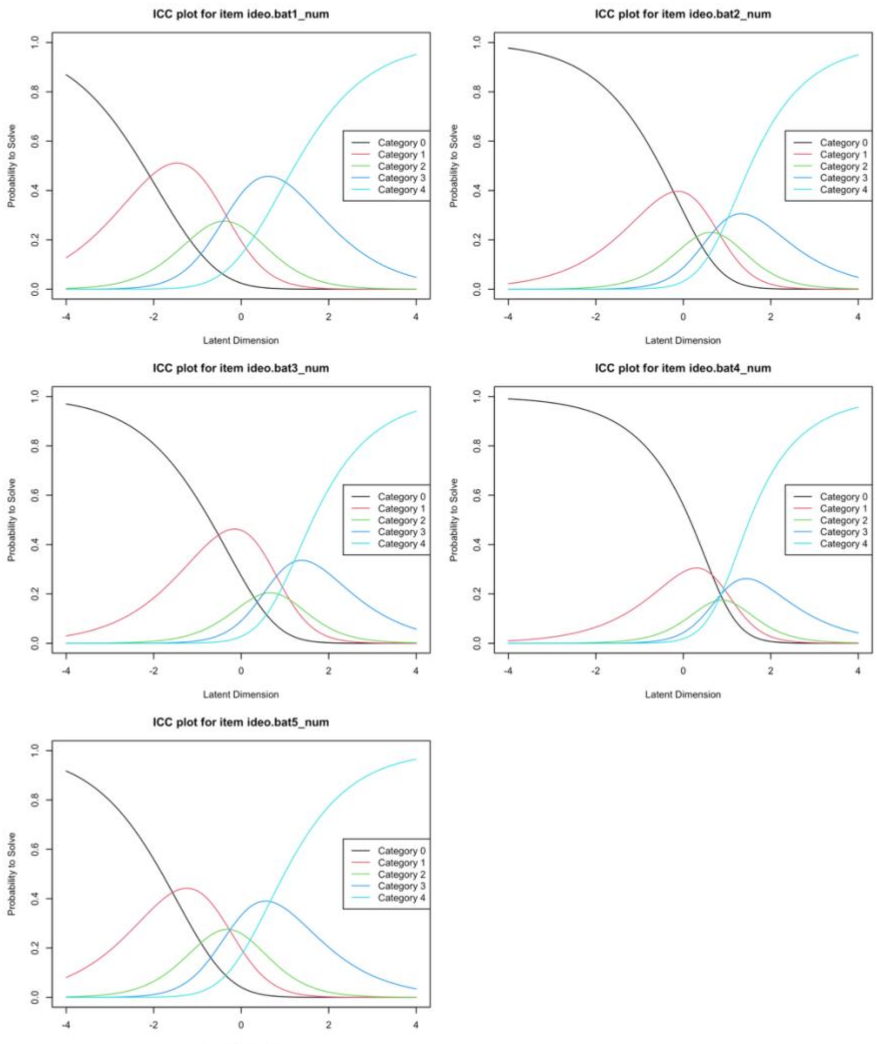

Fig. S1.
Item Characteristic curves from the PCM for estimating scientist ideology.

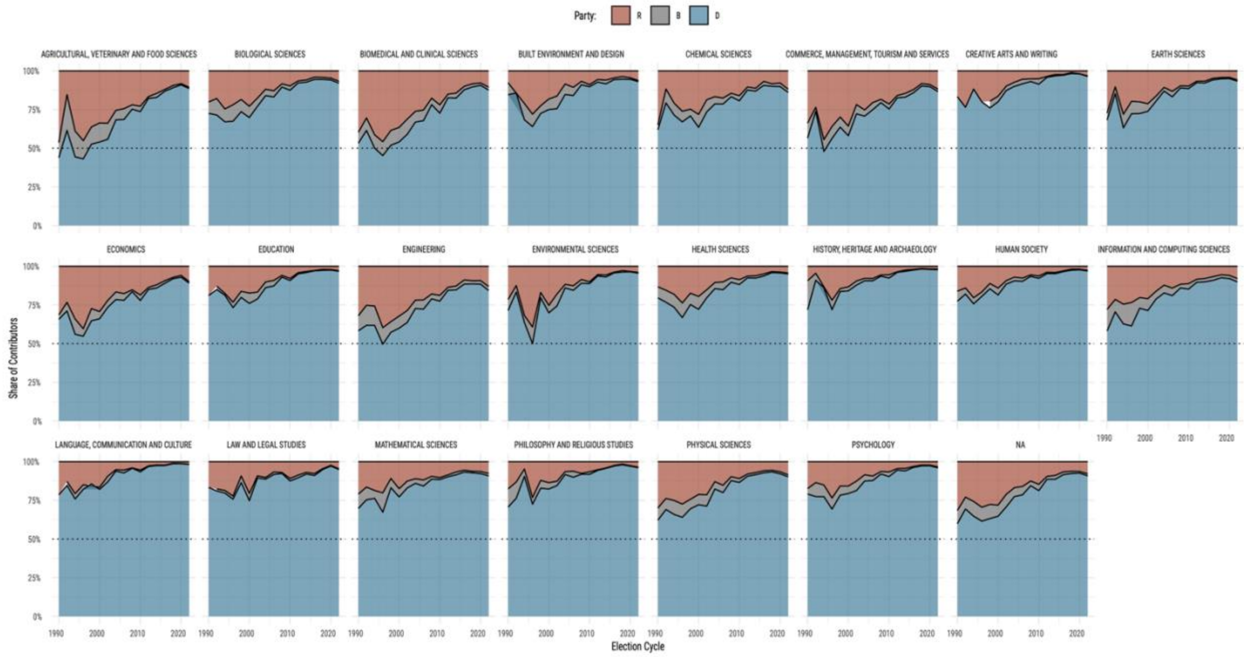

Fig. S2.
Share of contributing scientists by party affiliation over time, by scientific field. Each panel shows one ANZSRC field. This is the field-level version of Fig. 1C.

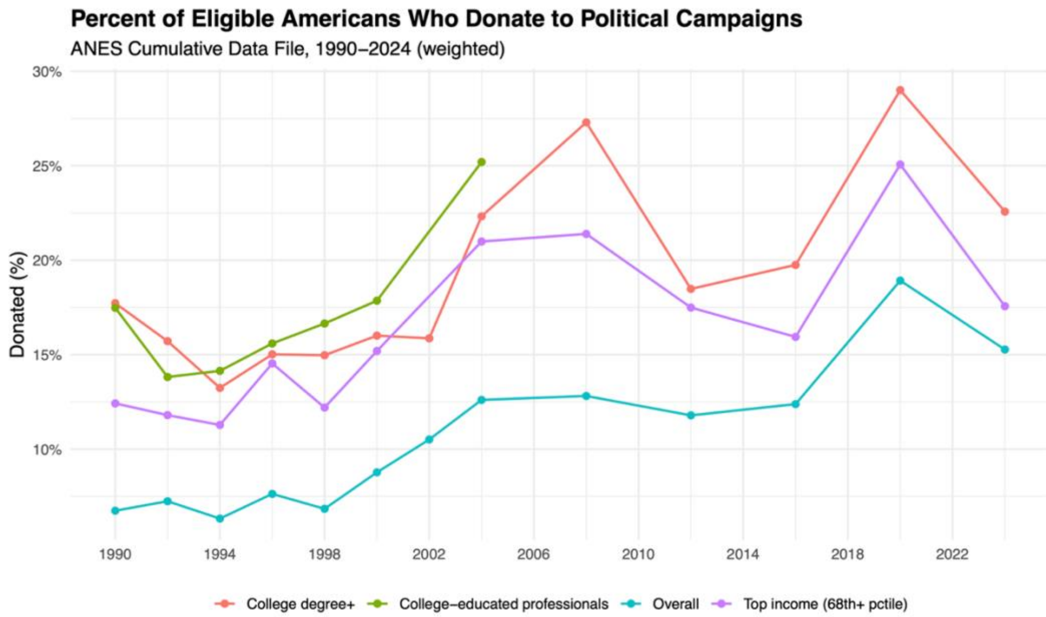

Fig. S3.

ANES benchmark: weighted donation rates over time for the overall public, college-educated, high-income, and college-educated professional subgroups. The ANES no longer had a "college-educated professional" categorization for respondents after 2002.

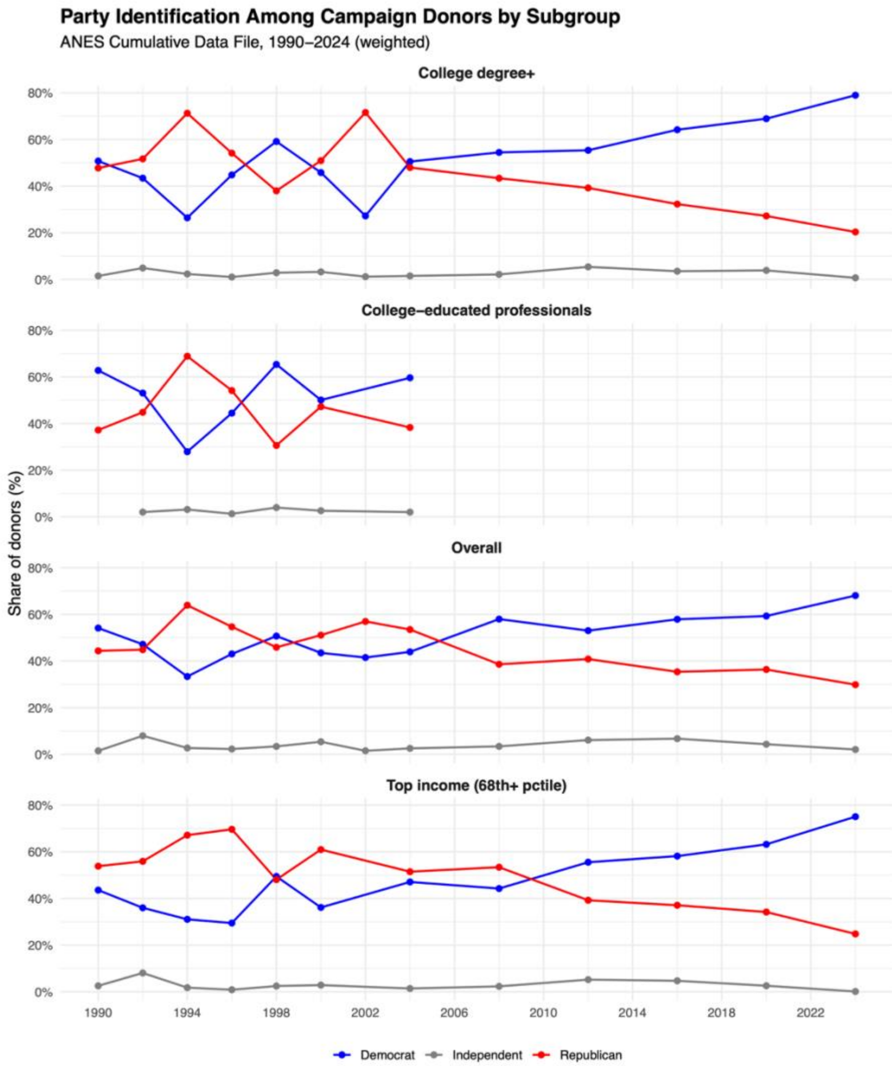

Fig. S4.

ANES benchmark: partisan composition (Democrat, Independent, Republican) among donors over time, by subgroup. The ANES no longer had a “college-educated professional” categorization for respondents after 2002.

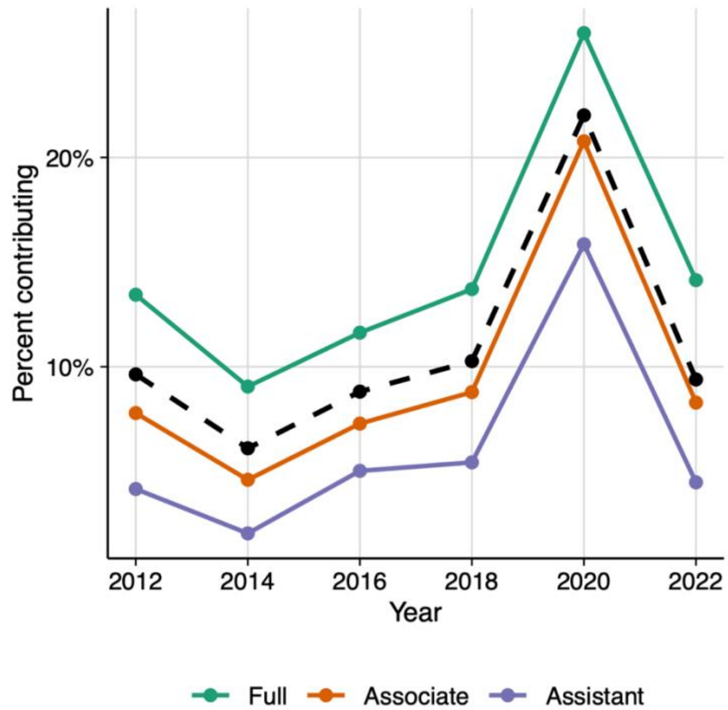

Fig. S5.
AARC benchmark: Rates of contribution by rank for faculty in AARC faculty rosters 2012-2022.

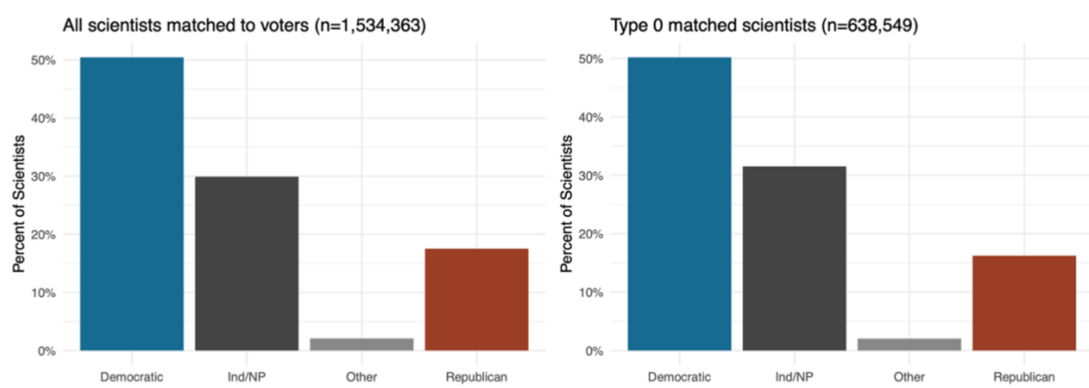

Fig. S6.
Party of registration for all scientists matched to the L2 voter file (left) and all type 0 matched scientists (right). Type 0 matched scientists are our highest confidence matches, as outlined in the Methods.

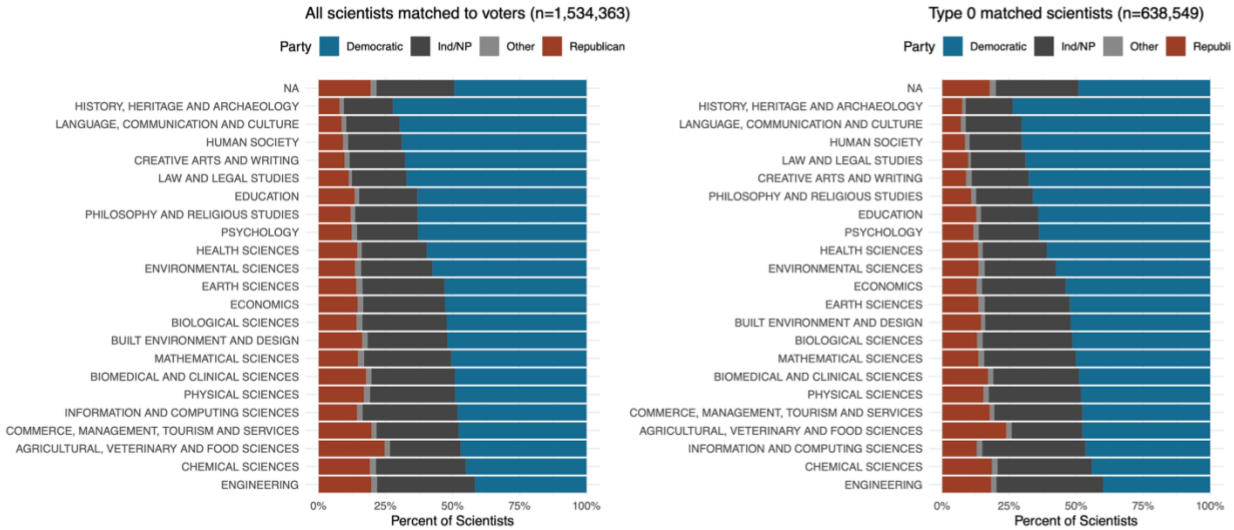

Fig. S7.

Party of registration for all scientists matched to the L2 voter file (left) and all type 0 matched scientists (right), by Field of Research. Type 0 matched scientists are our highest confidence matches, as outlined in the Methods.

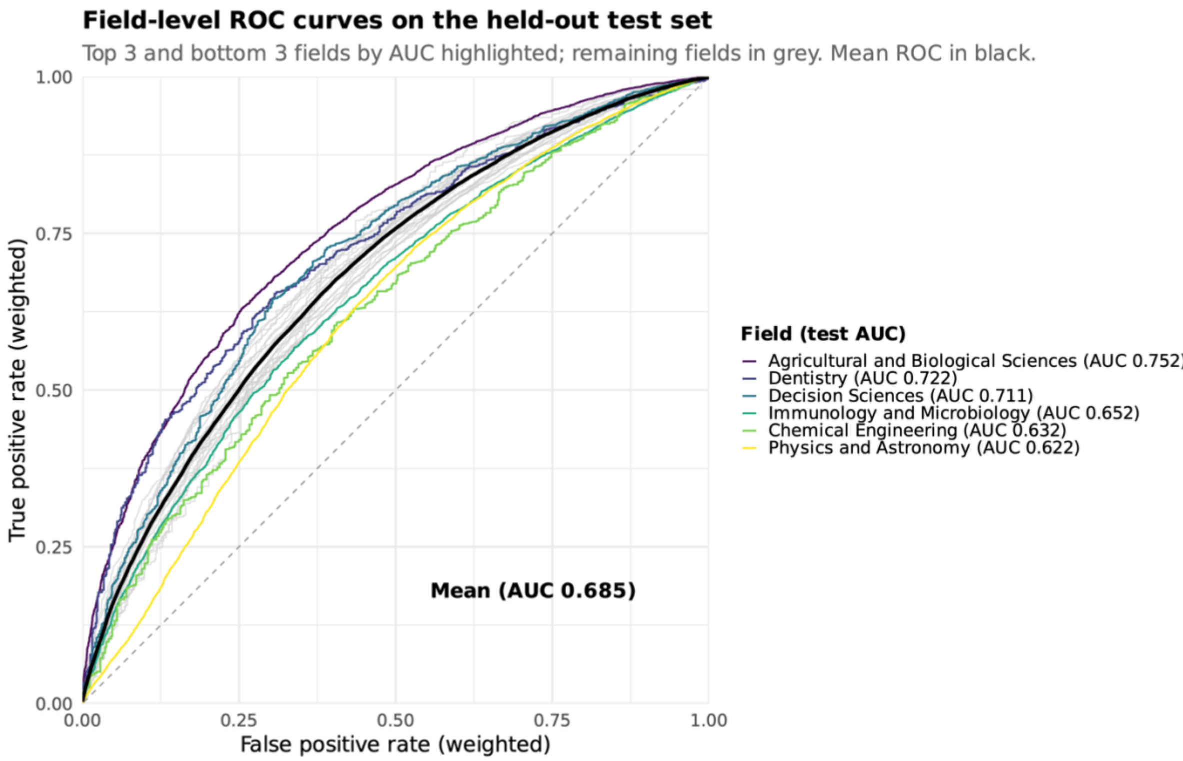

Fig. S8.

Receiver Operator Characteristic (ROC) curves for all fields, with top 3 and bottom 3 by area under the curve highlighted.

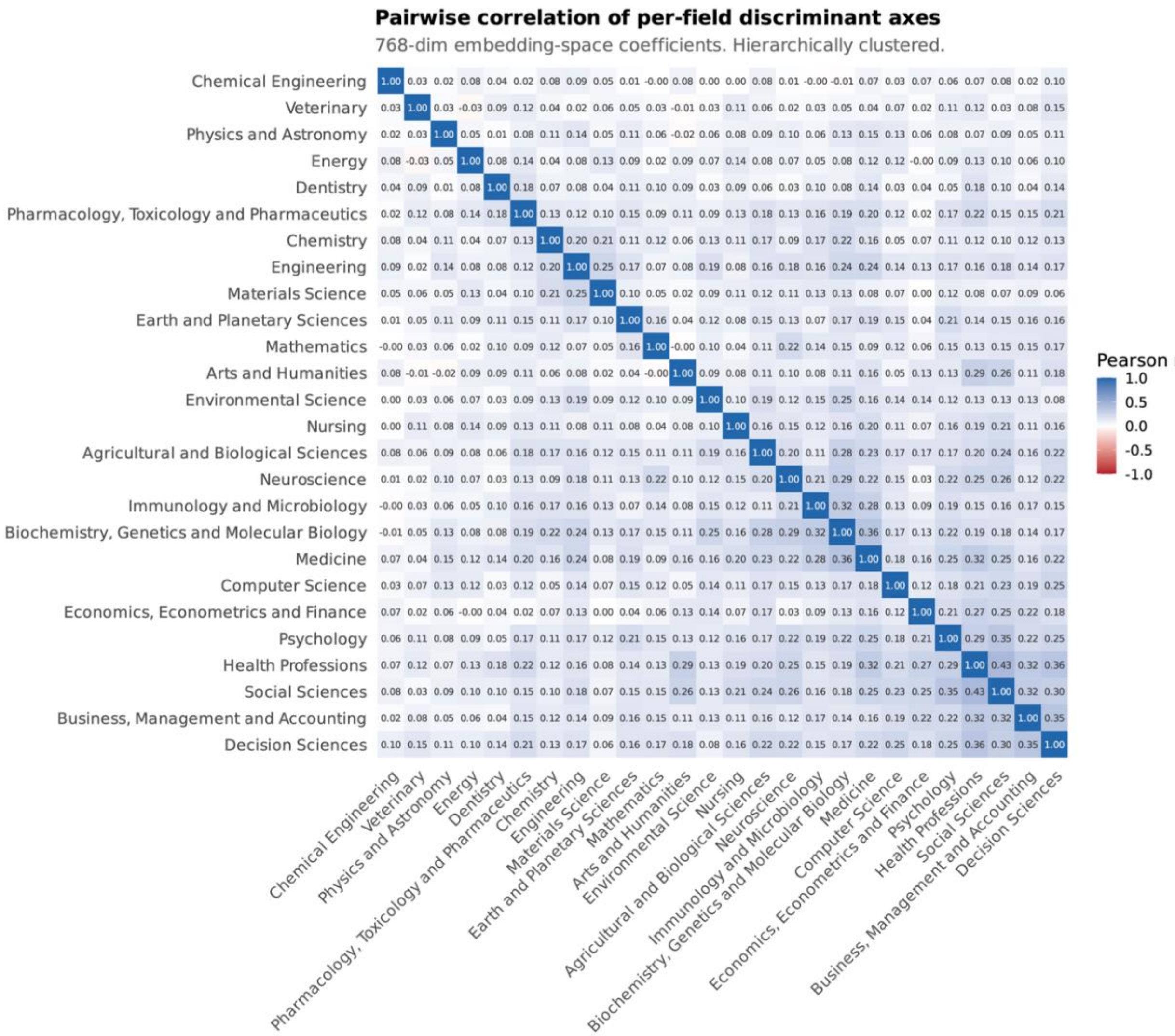

Fig. S9.
Heatmap of the correlations between partisan discriminant axes for each Open Alex Field.

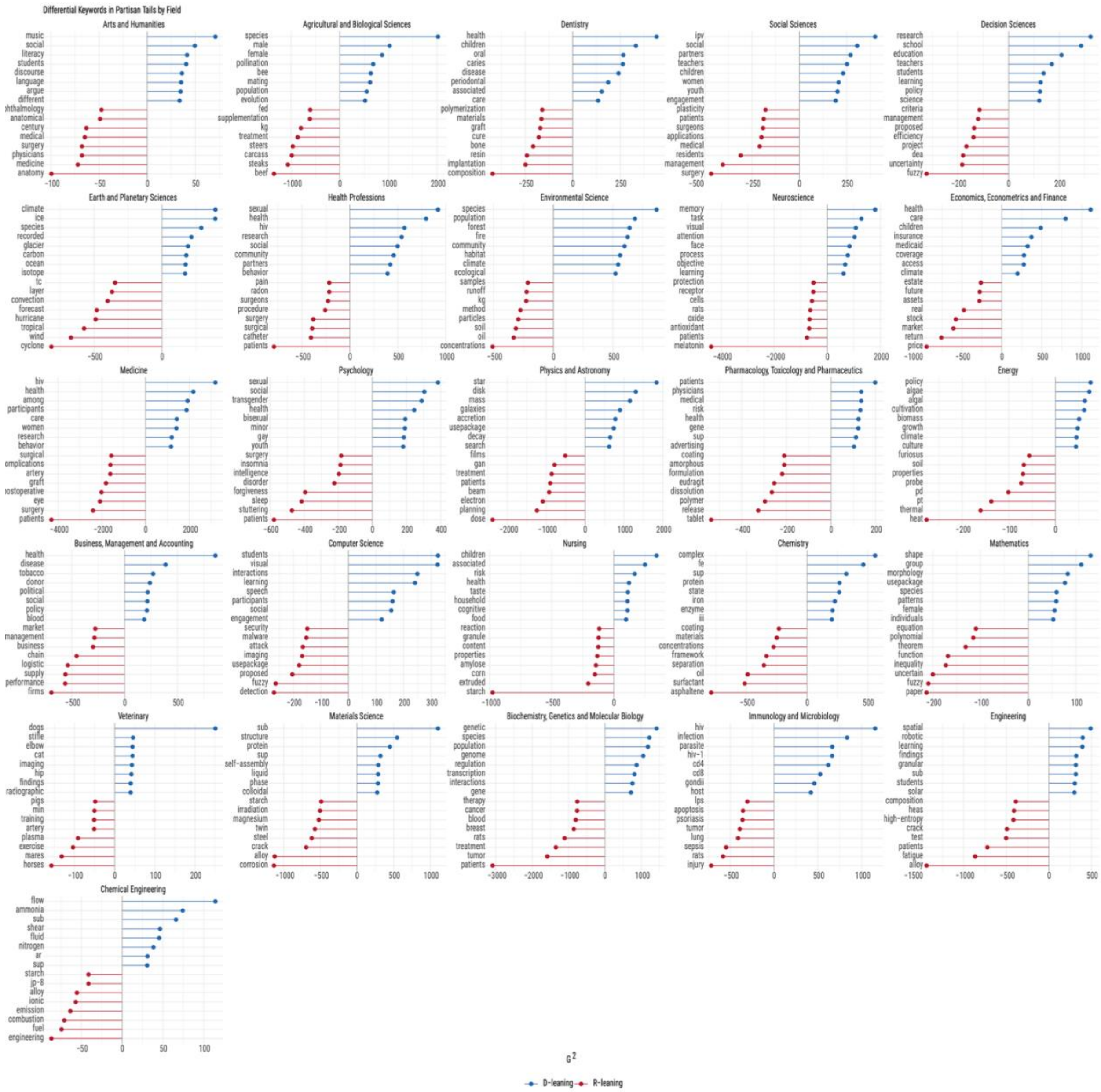

Fig. S10.

Top 8 keywords by (G^2) for papers in the <5% and >95% tails of the latent partisan discriminant axis for each field.

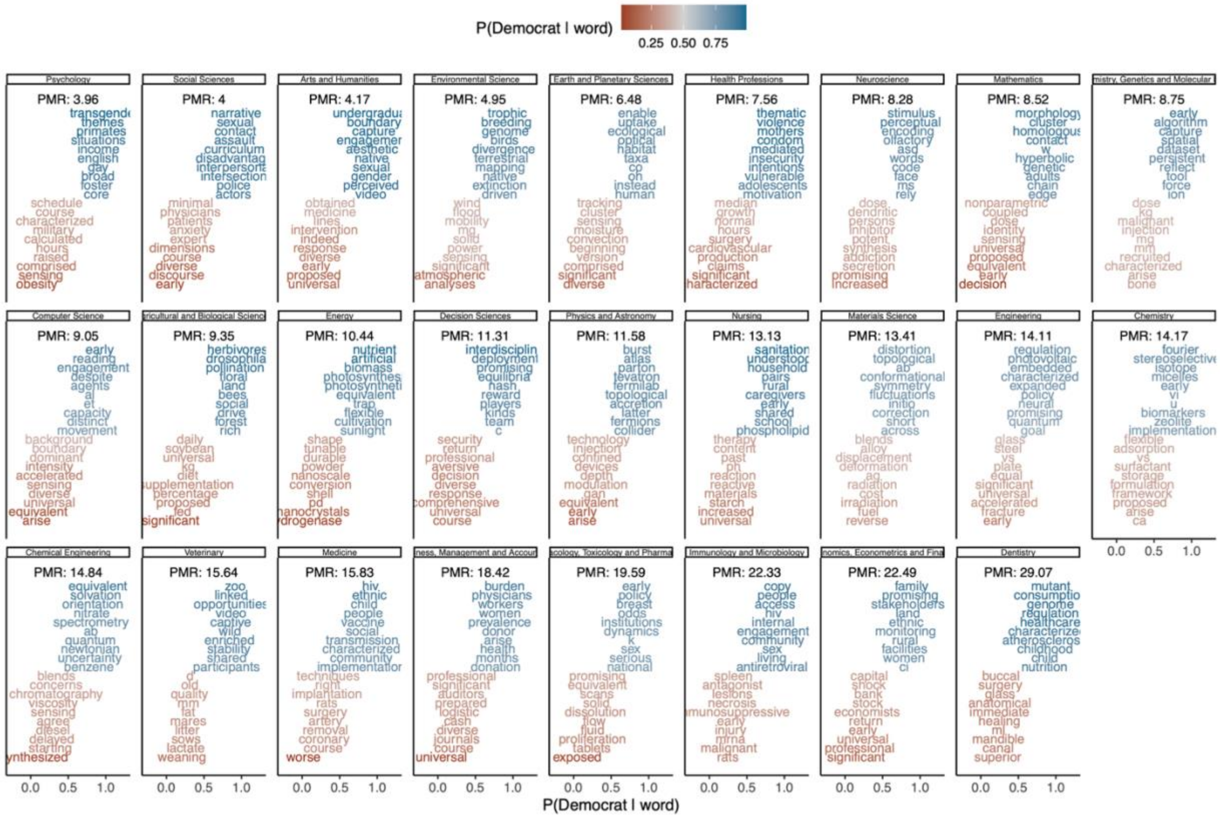

Fig. S11.

Top 10 and bottom 10 abstract words by predicted probability of Democratic authorship from field specific stylometric models, per field ordered by percent misclassification rate (PMR).

Supplementary Tables

field	n_train_per_label	n_train	n_test	n_test_d_only	n_test_r_only	n_test_mixed	W_pos	W_neg	pct_mixed_test	n_topics	test_auc	lambda_min
Medicine	25000	50000	323243	249936	22771	25268	262570	35405	8.480	684	0.6908	0.0079
Health Professions	3087	6174	23453	20960	771	861	21390.5	1201.5	3.811	100	0.6969	0.1731
Economics, Econometrics and Finance	3844	7688	12636	10818	960	429	11032.5	1174.5	3.514	88	0.7056	0.0450
Environmental Science	5530	11060	46421	42295	1382	1372	42981	2068	3.046	184	0.7092	0.0077
Biochemistry, Genetics and Molecular Biology	24619	49238	131986	111148	6154	7342	114819	9825	5.890	247	0.6625	0.0058
Psychology	3536	7072	43397	40387	884	1063	40918.5	1415.5	2.511	137	0.6744	0.0718
Pharmacology, Toxicology and Pharmaceutics	1326	2652	3456	2665	331	230	2780	446	7.130	23	0.6783	0.2402
Neuroscience	6419	12838	46229	40351	1604	2137	41419.5	2672.5	4.847	61	0.6957	0.0427
Social Sciences	4710	9420	47660	44795	1177	844	45217	1599	1.803	574	0.7057	0.0596
Agricultural and Biological Sciences	5527	11054	27173	24212	1381	790	24607	1776	2.994	218	0.7523	0.0303
Computer Science	5020	10040	19316	16953	1255	554	17230	1532	2.953	274	0.6769	0.0298
Immunology and Microbiology	5114	10228	27275	22847	1278	1575	23634.5	2065.5	6.128	44	0.6520	0.0422
Business, Management and Accounting	4338	8676	9135	7471	1084	290	7616	1229	3.279	121	0.6870	0.1499
Decision Sciences	1572	3144	5397	4707	392	149	4781.5	466.5	2.839	54	0.7114	0.3857
Arts and Humanities	556	1112	5239	4978	139	61	5008.5	169.5	1.178	221	0.7107	0.5194
Engineering	21046	42092	58866	48339	5261	2633	49655.5	6577.5	4.682	537	0.6642	0.0047
Dentistry	1159	2318	2416	1875	289	126	1938	352	5.502	12	0.7224	0.4193
Veterinary	436	872	1514	1292	108	57	1320.5	136.5	3.912	11	0.6782	0.9131
Nursing	1285	2570	5780	4833	321	313	4989.5	477.5	5.725	21	0.6611	0.0805
Materials Science	9340	18680	28930	24028	2334	1284	24670	2976	4.644	123	0.6801	0.0160
Chemistry	5592	11184	18437	15471	1398	784	15863	1790	4.441	101	0.6869	0.0263
Mathematics	2218	4436	9136	8204	554	189	8298.5	648.5	2.112	80	0.6754	0.1751
Chemical Engineering	887	1774	2381	1994	221	83	2035.5	262.5	3.612	13	0.6322	0.0196
Earth and Planetary Sciences	3317	6634	24026	21597	829	800	21997	1229	3.444	57	0.6899	0.0525
Physics and Astronomy	9739	19478	60249	50633	2434	3591	52428.5	4229.5	6.338	104	0.6223	0.0156
Energy	772	1544	3009	2613	192	102	2664	243	3.509	26	0.6797	0.6631

Table S1.

Sample sizes and weighted sample sizes of the train and test sets for papers by each partisan authorship group, number of topics (after collapsing topics with fewer than 20 papers), test set AUC and the lambda that minimizes cross validation error that was used in the L2 regressions for the partisan discriminant content analysis for each field.

Field	Estimated Difference	p-value	CI Lower	CI Upper
Agricultural and Biological Sciences	9.21819726	4.65652828546825e-50	8.33534074	10.1010538
Arts and Humanities	10.1316275	2.60305165972844e-38	8.93025914	11.3329959
Biochemistry, Genetics and Molecular Biology	4.17284977	1.20754822557121e-46	3.75201171	4.59368783
Business, Management and Accounting	3.89564663	5.68850334107818e-27	3.2952701	4.49602317
Chemical Engineering	2.33667495	1.51308772700812e-21	1.91107278	2.76227711
Chemistry	2.3371608	5.43717161523621e-25	1.95500359	2.71931801
Computer Science	2.53733635	1.23607367019288e-32	2.19736129	2.8773114
Decision Sciences	6.78909721	1.64497282642865e-46	6.10983435	7.46836006
Dentistry	9.41810531	2.34933205658228e-34	8.20246457	10.6337461
Earth and Planetary Sciences	2.54737135	7.13744985413305e-10	1.7724281	3.3223146
Economics, Econometrics and Finance	5.07899901	3.27449663915233e-23	4.19368568	5.96431235
Energy	3.71374479	3.59758986957134e-34	3.22376072	4.20372887
Engineering	1.43092627	7.45379127284141e-20	1.15424433	1.70760821
Environmental Science	4.00880656	7.98587202442682e-23	3.30209947	4.71551365
Health Professions	8.36370014	1.18002523690871e-38	7.37614155	9.35125873
Immunology and Microbiology	3.02250557	3.54144645012718e-40	2.67794653	3.36706461
Materials Science	3.30562845	1.38392172559544e-39	2.92335341	3.68790349
Mathematics	1.92847217	1.81859475070351e-19	1.55054648	2.30639786
Medicine	3.82945644	3.23797343506283e-21	3.12189646	4.53701643
Neuroscience	7.23233919	9.26387255834723e-38	6.35642323	8.10825515
Nursing	3.66866808	2.80077936307952e-18	2.91919305	4.4181431
Pharmacology, Toxicology and Pharmaceutics	3.56803577	1.85621736619186e-23	2.95528915	4.18078239
Physics and Astronomy	3.02380368	3.09078970194118e-24	2.51645961	3.53114775
Psychology	4.4024772	1.96845388630864e-46	3.9614766	4.84347781
Social Sciences	6.73530673	2.39292376218276e-58	6.18384126	7.28677219
Veterinary	4.2079329	1.22876925264686e-47	3.7901941	4.62567169

Table S2.

T-tests of the difference of means between the bootstrapped observed Cramér statistics and permuted null distribution of Cramér statistics for each field.

field	observed	perm_mean	perm_sd	perm_ci_lo	perm_ci_hi	excess	z_score	p_two_sided	n_perm	vcount	ecount
Medicine	0.9209	0.8743	0.0005	0.8733	0.8752	0.0467	97.08	0.001	1000	1888230	16455457
Biochemistry, Genetics and Molecular Biology	0.9536	0.9180	0.0007	0.9166	0.9193	0.0356	53.45	0.001	1000	804269	8901783
Engineering	0.9263	0.8445	0.0011	0.8424	0.8467	0.0818	76.00	0.001	1000	465846	1682158
Physics and Astronomy	0.9649	0.9343	0.0008	0.9327	0.9359	0.0306	37.25	0.001	1000	427930	4332265
Social Sciences	0.9755	0.9560	0.0009	0.9541	0.9576	0.0194	22.48	0.001	1000	325017	1804221
Neuroscience	0.9642	0.9331	0.0009	0.9314	0.9348	0.0311	36.08	0.001	1000	298276	3494495
Environmental Science	0.9754	0.9465	0.0008	0.9448	0.9482	0.0289	34.28	0.001	1000	292039	2345615
Psychology	0.9774	0.9589	0.0009	0.9569	0.9605	0.0185	19.91	0.001	1000	283556	2461671
Computer Science	0.9446	0.8901	0.0014	0.8874	0.8925	0.0545	40.33	0.001	1000	247645	928179
Materials Science	0.9219	0.8613	0.0015	0.8583	0.8642	0.0606	39.76	0.001	1000	181085	890603
Agricultural and Biological Sciences	0.9650	0.9255	0.0010	0.9236	0.9275	0.0395	38.55	0.001	1000	176842	997762
Earth and Planetary Sciences	0.9666	0.9375	0.0011	0.9353	0.9396	0.0291	26.86	0.001	1000	158295	1531523
Immunology and Microbiology	0.9529	0.9143	0.0013	0.9116	0.9171	0.0386	28.78	0.001	1000	156599	1598579
Chemistry	0.9396	0.8650	0.0016	0.8617	0.8681	0.0745	46.05	0.001	1000	152561	628968
Health Professions	0.9651	0.9394	0.0014	0.9367	0.9421	0.0257	18.36	0.001	1000	142055	620295
Economics, Econometrics and Finance	0.8892	0.8377	0.0027	0.8322	0.8429	0.0515	18.96	0.001	1000	98380	337264
Mathematics	0.9490	0.8999	0.0025	0.8948	0.9043	0.0491	19.95	0.001	1000	72001	206432
Business, Management and Accounting	0.8241	0.7737	0.0035	0.7666	0.7804	0.0503	14.44	0.001	1000	68679	303571
Decision Sciences	0.9349	0.8773	0.0063	0.8654	0.8886	0.0576	9.12	0.001	1000	45387	108703
Arts and Humanities	0.9775	0.9593	0.0027	0.9535	0.9641	0.0182	6.81	0.001	1000	34991	41696
Nursing	0.9496	0.9005	0.0031	0.8942	0.9062	0.0491	15.74	0.001	1000	34623	156537
Pharmacology, Toxicology and Pharmaceutics	0.9162	0.8399	0.0043	0.8315	0.8482	0.0763	17.70	0.001	1000	24425	73302
Energy	0.9400	0.8863	0.0047	0.8770	0.8952	0.0537	11.45	0.001	1000	18745	78631
Chemical Engineering	0.9196	0.8286	0.0048	0.8195	0.8381	0.0910	18.90	0.001	1000	17377	48381
Dentistry	0.9009	0.8227	0.0046	0.8128	0.8316	0.0782	16.86	0.001	1000	14016	55084
Veterinary	0.9250	0.8656	0.0054	0.8544	0.8763	0.0594	11.07	0.001	1000	9469	20101

Table S3.

Full results of the citation homophily analysis comparing observed share of citations whose endpoints share at least one party to a null distribution derived from permutation tests.

Weighted Poisson QMLE Models of Policy Document Citations (inclusive-set, topic FE)

	Republican Committee Citations	Democratic Committee Citations	Right Think Tank Citations	Left Think Tank Citations
author_partyR	0.077	-0.045	0.450***	-0.291***
	(0.050)	(0.039)	(0.051)	(0.036)
log(num_DR_auth)	0.372***	0.382***	0.277***	0.361***
	(0.031)	(0.026)	(0.040)	(0.022)
log(times_cited + 1)	0.955***	1.007***	1.011***	1.048***
	(0.013)	(0.010)	(0.012)	(0.007)
log(num_funds + 1)	-0.119***	-0.087***	-0.178***	-0.117***
	(0.025)	(0.018)	(0.030)	(0.016)
log(num_authors)	-0.025	-0.067**	-0.244***	-0.239***
	(0.025)	(0.021)	(0.024)	(0.017)
log(num_references + 1)	-0.188***	-0.174***	-0.149***	-0.174***
	(0.011)	(0.009)	(0.010)	(0.007)
Num.Obs.	3748717	4224653	3825440	4553792
R2	0.288	0.319	0.379	0.471
R2 Adj.	0.272	0.306	0.369	0.466
R2 Within	0.151	0.174	0.199	0.265
R2 Within Adj.	0.151	0.174	0.199	0.265
AIC	105514.6	138747.2	156828.7	409253.1
BIC	120346.2	156921.8	172893.7	432676.5
RMSE	0.07	0.08	0.14	0.25
Std.Errors	by: doi & topic ^year	by: doi & topic ^year	by: doi & topic ^year	by: doi & topic ^year
FE: topic	X	X	X	X
FE: year	X	X	X	X

- p < 0.05, ** p < 0.01, *** p < 0.001

Table S4.

Full regression results: Weighted Poisson QMLE of policy citation counts from Republican-controlled congressional committees, Democratic-controlled congressional committees, right-leaning think tanks, and left-leaning think tanks with year and topic fixed effects.

G-computation: standardized citation difference, ≥1 R vs ≥1 D authorship (topic FE)

Model	Contrast	Estimate	SE	z	p	conf.low	conf.high
Republican Committee Citations	R - D	0.0002	0.0002	1.4768	0.1397	-0.0001	0.0005
Democratic Committee Citations	R - D	-0.0002	0.0001	-1.1664	0.2435	-0.0004	0.0001
Right Think Tank Citations	R - D	0.0029	0.0004	6.6705	0.0000	0.0021	0.0038
Left Think Tank Citations	R - D	-0.0041	0.0004	-9.4089	0.0000	-0.0049	-0.0032

Table S5.

G-computation predicted contrasts for the difference between D- and R-authored papers in policy citations from Republican-controlled congressional committees, Democratic-controlled congressional committees, right-leaning think tanks, and left-leaning think tanks from the Weighted Poisson QMLE models with year and topic fixed effects.

Weighted Poisson QMLE Models of Policy Document Citations (inclusive-set, journal FE, appendix)

	Republican Committee Citations	Democratic Committee Citations	Right Think Tank Citations	Left Think Tank Citations
author_partyR	0.006	-0.140***	0.360***	-0.346***
	(0.051)	(0.039)	(0.051)	(0.034)
log(num_DR_auth)	0.369***	0.399***	0.287***	0.397***
	(0.034)	(0.028)	(0.040)	(0.023)
log(times_cited + 1)	0.824***	0.923***	0.874***	0.945***
	(0.014)	(0.011)	(0.013)	(0.009)
log(num_funds + 1)	-0.219***	-0.199***	-0.232***	-0.208***
	(0.027)	(0.022)	(0.029)	(0.019)
log(num_authors)	-0.168***	-0.195***	-0.310***	-0.271***
	(0.032)	(0.021)	(0.030)	(0.018)
log(num_references + 1)	-0.158***	-0.174***	-0.160***	-0.170***
	(0.015)	(0.013)	(0.014)	(0.011)
Num.Obs.	2894632	3365238	3210668	3966466
R2	0.259	0.277	0.357	0.445
R2 Adj.	0.234	0.252	0.338	0.434
R2 Within	0.092	0.113	0.120	0.170
R2 Within Adj.	0.092	0.113	0.119	0.170
AIC	107069.5	144709.0	160513.0	424579.4
BIC	129606.7	176408.6	190073.0	481614.4
RMSE	0.09	0.09	0.15	0.27
Std.Errors	by: doi & journal.id^year	by: doi & journal.id^year	by: doi & journal.id^year	by: doi & journal.id^year
FE: journal.id	X	X	X	X
FE: year	X	X	X	X

- p < 0.05, ** p < 0.01, *** p < 0.001

Table S6.

Full regression results: Weighted Poisson QMLE of policy citation counts from Republican-controlled congressional committees, Democratic-controlled congressional committees, right-leaning think tanks, and left-leaning think tanks with year and journal fixed effects.

Fixed effect specification	model	contrast	estimate	std.error	statistic	p.value	conf.low	conf.high
journal (appendix)	Democratic Committee Citations	R - D	-0.0006	0.0002	-3.7949	0.0001	-0.0010	-0.0003
subfield (robustness)	Democratic Committee Citations	R - D	-0.0004	0.0001	-4.9132	0.0000	-0.0005	-0.0002
topic (main)	Democratic Committee Citations	R - D	-0.0002	0.0001	-1.1664	0.2435	-0.0004	0.0001
journal (appendix)	Left Think Tank Citations	R - D	-0.0054	0.0005	-10.3153	0.0000	-0.0064	-0.0044
subfield (robustness)	Left Think Tank Citations	R - D	-0.0034	0.0003	-13.7035	0.0000	-0.0039	-0.0029
topic (main)	Left Think Tank Citations	R - D	-0.0041	0.0004	-9.4089	0.0000	-0.0049	-0.0032
journal (appendix)	Republican Committee Citations	R - D	0.0000	0.0002	0.1166	0.9072	-0.0004	0.0004
subfield (robustness)	Republican Committee Citations	R - D	0.0000	0.0001	-0.5677	0.5702	-0.0002	0.0001
topic (main)	Republican Committee Citations	R - D	0.0002	0.0002	1.4768	0.1397	-0.0001	0.0005
journal (appendix)	Right Think Tank Citations	R - D	0.0027	0.0005	5.4875	0.0000	0.0018	0.0037
subfield (robustness)	Right Think Tank Citations	R - D	0.0010	0.0002	5.3471	0.0000	0.0007	0.0014
topic (main)	Right Think Tank Citations	R - D	0.0029	0.0004	6.6705	0.0000	0.0021	0.0038

Table S7.

G-computation predicted contrasts for the difference between D- and R-authored papers in policy citations from Republican-controlled congressional committees, Democratic-controlled congressional committees, right-leaning think tanks, and left-leaning think tanks from the Weighted Poisson QMLE models with different fixed effects specifications.

Weighted Poisson QMLE Model of Scientific Citations (inclusive-set, topic FE)

author_partyR	-0.086***
	(0.008)
log(num_DR_auth)	0.183***
	(0.005)
log(num_funds + 1)	0.298***
	(0.003)
log(num_authors)	0.286***
	(0.005)
log(num_references + 1)	0.423***
	(0.002)
Num.Obs.	8189257
R2	0.444
R2 Adj.	0.444
R2 Within	0.168
R2 Within Adj.	0.168
AIC	609533055.4
BIC	609596564.8
RMSE	187.79
Std.Errors	by: doi & display_name^year
FE: display_name	X
FE: year	X

- p < 0.05, ** p < 0.01, *** p < 0.001

Table S8.

Full regression results: Weighted Poisson QMLE models of scientific citation counts with year and topic fixed effects.

spec	contrast	estimate	std.error	statistic	p.value	conf.low	conf.high
topic (main)	R - D	-3.3481	0.2933	-11.4143	0.0000	-3.9230	-2.7732
journal (appendix)	R - D	-0.6137	0.3082	-1.9909	0.0465	-1.2178	-0.0095
subfield (robustness)	R - D	-3.4411	0.2979	-11.5530	0.0000	-4.0248	-2.8573

Table S9.

G-computation predicted contrasts for the difference between D- and R-authored papers in scientific citations from Weighted Poisson QMLE models with different fixed effects specifications.