Author Mentions in Science News Reveal Wide-Spread Ethnic Bias

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Abstract

Media outlets play a key role in spreading scientific knowledge to the general public and raising the profile of researchers among their peers. Yet, given time and space constraints, not all scholars can receive equal media attention, and journalists’ choices of whom to mention are poorly understood. In this study, we use a comprehensive dataset of 232,524 news stories from 288 U.S.-based outlets covering 100,208 research papers across all sciences to investigate the rates at which scientists of different ethnicities are mentioned by name. We find strong evidence of ethnic biases in author mentions, even after controlling for a wide range of possible confounds. Specifically, authors with non-British-origin names are significantly less likely to be mentioned or quoted than comparable British-origin named authors, even within the stories of a particular news outlet covering a particular scientific venue on a particular research topic. Instead, minority scholars are more likely to have their names substituted with their role at their institution. This ethnic bias is consistent across all types of media outlets, with even larger disparities in General-Interest outlets that tend to publish longer stories and have dedicated editorial teams for accurately reporting science. Our findings reveal that the perceived ethnicity can substantially shape scientists’ media attention, and, by our estimation, this bias has affected thousands of scholars unfairly.

Scientific breakthroughs often attract media attention, which serves as a key mechanism for public dissemination of new knowledge (Scheufele, 2013; Brossard and Scheufele, 2013). Science reporting not only distills research insights but also puts a face on who was responsible for the research. The media coverage can then feed back into researchers’ careers (Cronin and
Besides well-established gender and ethnic disparities in conventional scientific outcomes including funding allocation (Ley and Hamilton, 2008; Ginther et al., 2011; Oliveira et al., 2019; Hoppe et al., 2019), hiring decisions (Xie et al., 2003; Turner et al., 2008; Moss-Racusin et al., 2012; Way et al., 2016), publishing (Ding et al., 2006; West et al., 2013), citations (Larivière et al., 2013; Huang et al., 2020), and monetary or non-monetary rewards (Holden, 2001; Shen, 2013; Xie, 2014), emerging evidence has pointed to demographic disparities in general media coverage (Behm-Morawitz and Ortiz, 2013; Jia et al., 2016; Merullo et al., 2019; Smith, 1997; Devitt, 2002), raising the possibility that some scientists are not receiving their due attribution (Jia et al., 2015; Amberg and Saunders, 2018).

Going unnamed as an author in science reporting not only removes the reputational benefits associated with the report, signalling a person is not worthy of public mention, but also potentially shifts the public’s perception of who is a scientist (Miller et al., 2018). Under-representing certain demographics groups can perpetuate the stereotype that scientists are white males (Turner et al., 2008; Banchefsky et al., 2016), which in turn weakens the pipeline of recruiting and training diverse students into new scientists, exacerbating the current representation issues (Cole, 1979; Reuben et al., 2014; Hill et al., 2018).

Academic careers are characterized by cumulative advantage, where successes compound, amplifying each other and become easier to sustain (Merton, 1968). As a result, the inhibitory biases against minority groups have a cumulative penalty that reduce representation and visibility, and can result in a loss of symbolic capital for advancing one’s career (Leahey, 2007).

Given known institutional and cultural barriers faced by minority scholars during the early stages of research (e.g., gathering resources) and middle stages (e.g., publishing), a sizable gap still remains in our understanding of the latter stages as research disseminates to the public. While it is possible that, once published in the academic literature and covered by the news media, similar contributions receive similar attention regardless of the authors’ perceived identities, a number of mechanisms may produce divergence between contribution and attention in science coverage.

Here, we present the first large-scale and science-wide effort to measure demographic biases
in science news through a computational analysis of 232,524 news stories mentioning 100,208 published scholarly work (Section S1). Specifically, we investigate whether the first author of a scientific paper is mentioned by name in news stories that reference their paper. In multi-author papers, first authors are commonly junior scholars who are directly responsible for the work and stand the most to gain in recognition from being mentioned.

We use mixed-effects regression models to examine and quantify demographic differences in author mentions, while controlling for a broad range of plausible confounding factors. The complexity of our models and the scale of the data enable unusually strict controls, such as measuring differential mentions within a particular news outlet covering a particular academic journal on a particular research topic. These controls help ensure that we are comparing media mentions of researchers doing comparable work.

Furthermore, the richness of the data enables us to delve into the mechanisms causing the disparities, and to refer to them using the stronger language of “bias.” Ethnic and gender biases in mentions may be plausibly caused by a number of mechanisms, involving different actors. First, journalists may not be the relevant actors at all. Some news coverage originates from press releases created by in-house public relation staff at universities to disseminate their researchers’ work. News outlets often reprint these press releases in part or in full, and any biases therein may thus be passed on to the outlets’ audiences. We test this hypothesis by comparing mentions in journalist-written pieces versus press releases, and by whether journalists differentially mention additional information about particular researchers, such as their institutions.

Second, biases may be driven by pragmatic difficulties of interviewing researchers in distant time-zones and possibly with limited English proficiency. Journalists (and/or their editors) may use researchers’ names and institutions to “statistically discriminate” and infer from them scheduling or other difficulties. We test this hypothesis by focusing on a subset of the data where journalists and researchers are located in relatively close geographic proximity (within the U.S.), and by comparing simple mentions of names vs. direct quotes.

Lastly, journalists may have personal animus towards particular ethnic or gender groups or expectations of animus from their audience members to whom they cater. We use “animus”
to refer to direct negative attitudes towards particular demographic groups and/or incorrect or unfounded negative inferences about their English proficiency and other factors that can affect article quality. We test for the possible role of audience by comparing mentions across outlet (and presumably audience) types, and statistically control for English proficiency using ease-of-reading measures on the abstracts of the research papers.

## Results

### Who Gets Named?

We find strong ethnic bias in mentioning first authors by name in science news reporting scientific papers. This bias is robust to the inclusion of increasingly stringent controls (Model 5 in Table S5). Specifically, compared to British-origin named authors, all minority-ethnicity authors are significantly less likely to receive name attributions in science reporting. Indeed, this bias appears to increase with English-centric assessments of cultural distance, with other European ethnicities penalized the least while Asian and African authors penalized the most.

Surprisingly, we find no gender bias in author mentions. However, when random effects for news outlets and publication venues are not considered, the first author gender variable appears to have a significant effect. As gender representation varies widely across academic disciplines (Xie et al. 2003; Handelsman et al. 2005), this result suggests that gender differences in mention rates are likely to be explained by relative attention rates to publication venues in different fields. This phenomenon is reminiscent of the Simpson’s paradox observed for gender bias in graduate school admissions (Wagner 1982), which, when academic department was controlled for, revealed no gender bias.

To quantify the exact effect of having a name with a perceived demographic on the probability of being mentioned by name in media coverage, we calculated the average marginal effects for the first author ethnicity and gender variable respectively using our finest model.

As shown in Fig. 1, the estimated probability of being mentioned decreases by an absolute 1.0%–6.4% for authors with minority-ethnicity names, compared to their British-origin named counterparts. As the average mention rate is only 36.6% (Section S1), these absolute drops
represent significant disparities: the 6.3% and 6.4% marginal decreases for Chinese and African authors represent a 17.5% relative decrease in media representation. This result reveals that the mainstream U.S. media outlets have profound bias against authors from all minority ethnicities in mentioning them by name in science news: Given the current disparities, we estimate that more than four thousand minority scholars have gone unmentioned in our data alone.

**Does Location Matter?**

In reporting on research, journalists often directly seek out the authors by phone or email to contextualize and explain their results. If an author is at a non-U.S. institution, a journalist from a U.S.-based outlet could be less likely to reach out due to perceived challenges in time-zone differences or lower expectations of fluency, potentially resulting in a lower rate of being mentioned or quoted. Since non-U.S. institutions typically have more Asian and African authors due to their locations, this mechanism could potentially explain the disparity in being mentioned.

To examine the effect of geographical factors, we measured the bias separately for (i) the
subset of our data where the first author is from U.S.-based institutions, and (ii) that for non-U.S. authors. Compared to U.S.-based authors, international scientists have far lower rates of being mentioned, with coefficients (negatively) decreased by a factor of 2-4 for each ethnicity compared with their domestic counterparts (Table S6). This considerable gap reveals that geographic location is one major issue influencing mention biases in science news. However, international location alone does not explain all disparities in who is mentioned: The average marginal effects shown in Fig. 2 indicate that similar magnitude of mention biases still exist among U.S.-based authors. This comparative result indicates that other factors besides location play a substantial effect in which authors are named.

### How Authors Are Referred To?

![Figure 2: U.S.-based authors with minority-ethnicity names are less likely to be mentioned by name (left) or quoted (middle), and are more likely to be substituted by their institution (right). The average marginal effects are estimated based on 169,984 observations where the first author is from U.S.-based institutions. A negative (positive) marginal effect indicates a decrease (increase) in probability compared to authors with Male (for gender) or British-origin (for ethnicity) names. The colors are proportional to the absolute probability changes. Female is colored as blue to reflect its difference from ethnicity identities. The error bars indicate 95% bootstrapped confidence intervals.](image)

Journalists have multiple options in how they incorporate the scientists performing the research. They may go beyond simply naming the scientist and incorporate quotes from them...
about the research; alternatively, they may have the scientist play a minimal agentive role by using references like “researchers from University.” These discourse mechanisms serve to further integrate or distance the scientist from their role in the described research—giving them a name and a voice or removing their individuality.

Our prior result demonstrates that, even within the U.S., African and Asian authors experience substantial under-reporting in being named. As U.S.-based authors may still differ in their perceived fluency in oral English, and also journalists may simply be less willing to contact certain ethnic authors even if they speak fluent English, we hypothesize that authors from privileged demographics will be more likely to receive a quote, whereas those from disadvantaged demographics will be more likely to indirectly mentioned as a role associated with their institutions, rather than explicitly named.

To test these hypotheses we further identified (i) authors who are named as part of quotations (a subset of name mentions), and (ii) authors who get unnamed but their institution is named instead (Section S1). Since fluency is correlated with location, we focused on the U.S. subset and applied the same mixed-effects regression framework to model two dependent variables: (1) whether the first author is quoted, and (2) whether the first author is indirectly mentioned by their institution instead being named or quoted.

The average marginal effects in Fig. 2 reveal that U.S.-based African and Asian authors are less likely to be quoted, and instead are more likely to be substituted by their role within their institutions (See Fig. S3 for results based on our full data). The significant differences in being quoted in U.S. subset indicate that the perceived English fluency may play a major role in name mentions. However, language proficiency is not the only driving mechanism, as a strong bias appears for authors with Indian names, despite English being an official language in India. This, along with the “positive” effect in being substituted by institutions when name is not mentioned for Asian and African authors, suggests that journalist animus also plays a role in author mentions. This is the case especially given that journalists can always contact authors perceived to be less fluent via email to get a quote as a way to bypass potential challenges in oral communications, and that overall journalists are dealing with authors of research papers
written in English, which would potentially signal some English proficiency for all authors.

Note that the result on institution substitution also demonstrates that the mention bias does not result from a potential mechanism where Asian and African authors working on research that is more likely to be used in news stories where there is no need for agency at all (e.g., survey-like stories summarizing lots of recent results that briefly mention research papers on their topic without any form of attribution).

**Does It Matter Who Is Reporting?**

Understanding whether this ethnic bias is related to journalists’ own demographics is another crucial step towards uncovering its mechanisms, as they are the actors who are directly responsible for writing the stories. First, journalists may differ in their overall tendencies to mention first authors when covering science. Second, there might exist interaction effects between authors and journalists. One intuitive hypothesis, which we call “cultural hierarchy,” is that all journalists, regardless of their gender and ethnicity, prefer to mention Male and British-origin named scholars over minority others. At the same time, journalist may also prefer to mention authors from demographic categories that match their own, which we call “cultural homophily.” (McPherson et al., 2001)

Our model controls for journalists’ demographics and their interactions with that of first authors (Section S1). Due to insufficient instances of identified journalists (Table S3), we report the result based on our finest model trained with the full data. No meaningful ethnic preferences are seen for author-journalist interactions to suggest either cultural hierarchy or cultural homophily hypothesis. However, when dropping controls for outlets (Table S5, Models 3-4), journalists’ ethnicities become significant, suggesting that journalists’ behavior might be explained by variations at the outlet level, i.e., certain news outlets mention authors more or less often and certain groups of journalists are under- or over-represented in those outlets.
Differences Across Outlet Types

Outlets vary in the depth and breadth of their reporting, e.g., Science & Technology outlets write about 650 words per story on average, while General News outlets write about 850 words (Section S1, Fig. S2). These differences suggest potentially important variability in the nature of journalists’ day-to-day work and backgrounds. To explore the discrepancy of bias across different types of outlets in author mentions, we fitted the specification of Model 5 separately for three outlet types in our data and quantified the average marginal effects.

![Figure 3: Probability of being mentioned compared to Male/British-origin named authors](image)

Surprisingly, the ethnic bias remains consistent across all outlet types, as shown in Fig. 3, with authors having non-British-origin names being mentioned less frequently across all three outlet types. Larger disparities are found for ethnic categories that are more distant from British-origin (e.g., Asian and African). However, outlet types vary substantially in the magnitude of their bias: Science & Technology outlets and General News outlets are, on average, three times more biased against non-British-origin named scholars than outlets in Press Releases (6% vs. 2% marginal decrease).
The bias in stories from Press Releases outlets is particularly notable, as stories in these outlets typically reuse content from university press-releases, suggesting that universities’ press offices themselves, while less biased than other outlet types, still prefer to mention scholars with British-origin names. This result is surprising because local press offices are expected to have greater direct familiarity with their researchers, reducing the misuse of stereotypes, and to be more responsible for representing minority researchers equitably.

The largest disparities are seen in General News outlets, e.g., The New York Times and The Washington Post, where again African and Chinese scholars have nearly a 10% absolute drop in representation. General News outlets mention first authors with a 22.1% chance on average (Table S4), so this drop in author coverage nearly halves the perceived role of a large community of scientists. As General News outlets have well trained editorial staff and science journalists dedicated to accurately reporting science and tend to publish longer stories that have room to mention and engage with authors, this result is alarming. Historically, these ethnic minorities have been underrepresented, stereotyped, or even completely avoided in U.S. media (Behm-Morawitz and Ortiz, 2013), which has continued in objective science reporting across all outlet types. The mechanisms behind variations by outlet type deserve further investigation.

**Is the Situation Getting More Equitable?**

The longitudinally-rich nature of our dataset allows us to examine how author mentions in science news have changed over the last decade. Mention rates are on average decreasing over time, as shown by the coefficient for the mention year scalar variable in Model 5 (Table S5).

To examine the time trends across demographic categories, separate models (Model 5) were trained to quantify the marginal change per year increase for each gender and ethnicity in our data. Note that demographic attributes not under study are still included in each model, e.g., when examining the temporal changes in mention rates for male and female authors, ethnicity is still included as a factor, and vice versa.

As shown in Fig. 4, the mention year has a negative association with author mentions for Male and most ethnicity groups, indicating that most authors are less likely to be mentioned
Figure 4: Average marginal effects on mention probability for a one-unit increase in mention year for authors in each gender (blue) and ethnicity (red) group, revealing that the benefits of prestiged demographics (Male, British-origin) are decreasing over time. However, only small improvements are seen for Chinese and Indian first authors. African is not shown due to insufficient data for fitting a Model 5. Error bars show 95% bootstrapped confidence intervals.

in later years. When compared with the average marginal effects of minority ethnicities on the likelihood of being mentioned (Fig. 1), the larger decreases for ethnic groups such as British-origin and Scandinavian & Germanic indicate that their overall advantages are shrinking.

Indeed, Chinese and Indian authors, two of the most disadvantaged groups in this study, have mention rates that are increasing over time, although more data is needed for precise estimation. However, their estimated rates of increase are relative small, suggesting that ethnic biases for these authors are unlikely to disappear soon without purposeful behavior change. Based on the absolute mention rate disparities between minority and British-origin named authors shown in Fig. 1 and assuming a constant change rate per year for each ethnicity shown in Fig. 4, we estimate that only authors with Romance Language, Chinese, or Indian names will reach parity with their British-origin named colleagues within 5-12 years in their rates of being mentioned; all other ethnicities see their overall mention rates drop similarly to that for British-origin names, indicating the current gap will persist.
Discussion

Our analyses reveal that the attention researchers get in news coverage is strongly associated with their ethnicities. The associations are robust to a variety of plausible confounds, and even appear when controlling for the (1) particular news outlet, (2) particular scientific venue, and (3) particular research topic. Although we cannot claim the reported associations as causal, this unusually strong observational evidence is a “smoking gun” of bias in coverage and deserves attention.

Ethnicity and Gender

Authors with non-British-origin names are mentioned substantially less when their research is discussed. The disparity appears for all non-British-origin names. However, mention rates are especially low for Asian and African names, less pronounced for Indian, Middle Eastern, and Romance Language names, are even less pronounced for Scandinavian & Germanic and Eastern European names. The pattern is suggestive of stronger biases against non-Western ethnicities, but more evidence is needed to explain it. As science becomes more global and is increasingly driven by non-Western ethnicities, the way English-language media responds to non-British-named scholars will only grow in importance.

In contrast to ethnicity, we do not find bias in mentions of female scholars, once research fields are controlled for. One possible reason is that fields vary in their overall level of coverage and in their gender representation (Handelsman et al., 2005). Looking within fields may thus mask or sidestep gender bias that is manifested between them.

Ruling in and out different mechanisms

Our analyses above point to a multi-causal generation of ethnic biases, in which both pragmatic difficulties of interviewing distant researchers and journalists’ personal biases play key roles. In support of the pragmatic difficulties mechanism, we find that biases are substantially smaller when both the journalists and researchers are U.S.-based. Additionally, the largest biases appear in direct quotations, which may be more difficult to acquire from researchers in different time-
zones and who are likely to have non-British-origin names. In these cases, journalists appear to “substitute” the researcher’s institution for a direct quote.

Nevertheless, biases remain even among geographically proximate actors, and journalists’ choices are key. Supportive evidence comes from outlet types: when journalists’ role in the news articles is minimal—when the outlet simply republishes a university press release—the biases are also minimal (however, the disparities for many groups are still statistically distinguishable from 0); when the news stories were written by journalists themselves, the biases are the largest. The data does not allow us to rule out that journalists’ choices reflect personal animus-based biases or the expected biases of their audiences. For example, the biases remain even when controlling for readability of the research abstract, a potential signal of English proficiency that might influence journalists’ decisions (Table SS). Furthermore, the fact that Science & Technology and General News outlets have biases of similar magnitude yet likely differ in their audiences, suggests again the important role played by journalists’ personal biases.

Lastly, we cannot rule out that the biases stem from the academic literature itself, and in particular which author is designated as “corresponding” (our data did not include this designation). Further disentangling these mechanisms is an important avenue for future work.

Limitations

Although the scale and the breadth of our dataset enable the use of unusually fine-grained controls, the analysis is not without limitations. First, the observational nature of the data precludes strong causal statements. Second, some plausible explanatory covariates are unavailable for inclusion, such as which author is designated as corresponding or the number of citations a paper received at the time of being mentioned. However, we anticipate the effect of such covariates to be small given current controls. Fig. SI shows that the majority of papers were mentioned within one year after publication, which limits the citations a paper can accrue in such a short academic time period. Third, the Ethnea classifier is unable to identify African American scholars by name due its definition of ethnicity at the country level. A manual analysis shows that authors with stereotypical African American names are classified as English (British-origin) if
they have common English surnames. However, as a robustness test, we repeated our experiments using an additional ethnicity classification based on coarser-grained U.S. census data (Fig. S3), which is able to identify such authors as Black; the result therein does not show any significant under-representation of Black scholars. Note that African-named authors (based on Ethnea) are not necessarily classified as Black based on the Census data (Table S7-S8). Finally, we note that our data contains too few examples of some ethnicities (e.g., Polynesian and Caribbean) to accurately estimate biases; such ethnicities are regrettably omitted, though we recognize that these groups likely experience bias from their minority status as well.

Conclusions and Implications

Our work shows that science journalism is rife with biases in who receives favorable coverage, with certain ethnic groups receiving much more name mentions and quotations than their peers conducting comparable research. These ethnic biases likely have direct negative consequences for the careers of unmentioned scientists, and skew the public perception of who a scientist is—a key factor in recruiting and training new scientists.

Our findings have two important implications for science policy and science journalism. First, simply identifying large-scale ethnic disparities in science news, of which journalists may themselves have been unaware, can be an agent of change. Second, decision-makers at U.S. research institutions may take ethnic disparities of media attention into account when making hiring or promotion decisions. More importantly, addressing this problem requires more research to investigate the mechanisms leading to it, which we hope this paper helps stimulate.

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Supplemental Material

S1 Materials and Methods

To test for and quantify gender and ethnic bias across media outlets, we constructed a massive dataset by combining news media reports with metadata for the scientific papers they cover, and then inferring demographics of the papers’ authors.

We focused on mentions of the first authors for two reasons: (i) the first author position is more likely to be occupied by early career researchers, and as a result, media coverage may be more consequential for their careers; (ii) science journalism guidelines highlight the first author as the one who has likely contributed most to the work (Blum and et al., 2006) and therefore is a natural person to mention. Papers in a few research fields that commonly use the alphabetic-based authorship contributions are also included since journalists may be unfamiliar with this norm.

S1.1 News Stories Mentioning Research Papers

The dataset of news stories mentioning scientific papers was collected from Altmetric.com (accessed on Oct 8, 2019), which tracks a variety of sources for mentions of research papers, including coverage from over 2,000 news outlets around the world. To control for differences in the frequency of scientific reporting and potential confounds from variations in journalistic practices across different countries, the list of news outlets was curated to 423 U.S.-based news media outlets, with each having at least 1,000 mentions in the Altmetric database. Location data for each outlet is provided by Altmetric. This exclusion criterion ensures that the dataset has sufficient volume to estimate outlet-level biases, while still retaining sufficient diversity in outlet types, stories, and the scientific articles they cover. This initial dataset consists of 2.4M mentions of 521K papers by 1.7M news articles before 2019-10-06. Each mention in the Altmetric data has associated metadata that allows us to retrieve the original citing news story as well as the DOI for the paper itself.
S1.2 Scraping News Content and Identifying Journalists

Due to access and permission limitations when retrieving news stories, 135 outlets were excluded due to insufficient volume (27 outlets denied our access entirely; 65 outlets had less than 100 urls crawled; 43 outlets had at least 100 urls crawled, but only with non-news content such as subscription ads). For the remaining 288 outlets, 48.6% of the stories were successfully retrieved. The stories were then cleaned to remove all html tags and unrelated content such as advertisements. Stories with less than 100 words were removed (0.7%) as a manual inspected showed the vast majority of these do not contain the complete content of the story. This process results in 568,785 downloaded stories mentioning 290,469 papers from the 288 outlets.

In order to control for the effects of journalists’ ethnicity and gender (cf. Section S1.3), we used the newspaper Python package (https://github.com/codelucas/newspaper) to extract the journalists’ names from the retrieved html news content. Since not all stories in each outlet contain the journalist information and the newspaper package does not work perfectly for every story that has journalist information, we focused on the top 100 outlets (ranked by the story count). With manual inspection, we verified that this package can consistently and reliably identify journalist names for 41 of the top 100 outlets. We excluded extracted names with words signaling institutions and organizations (such as “University”, “Hospital”, “World”, “Arxiv”, “Team”, “Staff”, and “Editors”). We also cleaned names by removing prefix words, such as “PhD.”, “M.D.”, and “Dr.”. We eventually obtained the journalist names in 100,163 news stories for 41 outlets (17.5%).

S1.3 Retrieving Paper Metadata

The Altmetric database does not contain author information and therefore an additional dataset is needed to identify the authors for mentioned papers. We used the Microsoft Academic Graph (MAG) snapshot data (accessed on June 01, 2019) to retrieve information for each paper based on its DOI [Sinha et al., 2015]. Not all papers with a DOI in the Altmetric database are indexed in the MAG. We were ultimately able to retrieve 269,509 papers from MAG based on DOIs (matching based on lower-cased strings). MAG also provides rich metadata for papers, includ-
ing author names, author rank, author affiliation rank, publication year, publication venue, the paper abstract, and paper topical keywords. As all of this information will be used in our regression models (cf. Section S1.8), we excluded papers with missing metadata and two papers that list organizations as first authors, leaving us with 100,208 papers.

S1.4 Inferring Author and Journalist Gender and Ethnicity

We used Ethnea to infer the gender and ethnicity for authors. The library makes its prediction based on the nearest-neighbor matches on authors’ first and last names using a ground-truth database of scholars’ country of origin, which offers superior performance over alternative approaches (Ambekar et al., 2009; Treeratpituk and Giles, 2012).

Author names in the MAG have varying amounts of completeness. While most have the first name and surname, special care is taken for three cases: (1) If the name has a single word (e.g., Curie), the ethnicity and the gender are both set to Unknown, as Ethnea requires at least an initial. Single-word name cases occurred for seven authors total. (2) If the name has an initial and surname (e.g., M. Curie), we directly feed it into the API, which provides an ethnicity inference but returns Unknown for gender due to the inherent ambiguity. (3) If the name has at three or more words, we take the first word as the given name and the last word as the surname. However, if the first word is an initial and the second word is not an initial, we take the second word as the given name (e.g., M. Salomea Curie would be Salomea Curie) to improve prediction accuracy and retrieve a gender inference.

While Ethnea is trained with scholar names, we also applied it to predict the gender and ethnicity for journalists (cf. Section S3 for robustness check).

Ethnea assigns fine-grained ethnic categories based on nationality. Here, we follow their same term of ethnicity, recognizing that while ethnicity and nationality are closely related, the two are not synonymous (discussed in the main text). To test for macro-level trends around larger ethnic categories and to ensure sufficient samples to estimate the effects, we group the 24 observed ethnicities into 9 higher-level categories based on linguistic families and cultural distance (Table S1).
Table S1: 24 individual ethnicities are grouped into the 9 broad ethnic categories.

Note that due to sample size and our hypotheses, African, Chinese, Indian, and English (renamed as “British-origin”) are kept as separate high-level categories. Caribbean and Polynesian are excluded due to less than 50 mentions in total. Examples of names classified into each ethnicity are provided in Table S9. Ethnea returns binary gender categories: Female and Male, though we recognize that researchers may identify with genders outside of these two categories. For both gender and ethnicity separately, some names are classified as “Unknown” if no discernable signal is found for the respective attribute by Ethnea.

### S1.5 Final Dataset and Statistics

The final dataset consists of 232,524 news stories referencing 100,208 research papers. As some stories mentioned more than one paper and some papers were mentioned in more than one story, we have 285,708 total observations to test whether a paper’s first author is mentioned in a story.

Figs. S1a-b show the distribution of papers and news stories over time and attention per paper. News story data is left censored and primarily includes stories written after 2010. Censoring can be explained by the fact that Altmetric.com was only launched in 2012, limiting the collection of earlier news. As shown in Fig. S1c, news stories can mention papers that were published several decades before, highlighting the potential lasting value of scientific work. However, the majority of papers are mentioned within the same year or just a few years after publication. Table S2 shows the mention counts for authors in each broad ethnicity group, and
Figure S1: 

**a**, The number of news stories and research papers in our mention date over time. 
**b**, The distribution of the number of news mentions per paper. 
**c**, The distribution of the *year gap* between paper publication date and news story mention date for all 285,708 story-paper mention pairs in the final dataset.

Table S3 shows the mention counts by journalist ethnicity.

| Authors Broad Ethnic Category | # Papers | # Mentions | # Mentions Per Paper |
|-------------------------------|----------|------------|----------------------|
| British-origin                | 41,446   | 12,189     | 2.94                 |
| Scandinavian & Germanic       | 14,982   | 41,982     | 2.80                 |
| Romance Language              | 14,982   | 41,156     | 2.75                 |
| Chinese                       | 9,262    | 25,968     | 2.80                 |
| Middle Eastern                | 5,291    | 15,267     | 2.89                 |
| Eastern European              | 4,313    | 12,222     | 2.83                 |
| Indian                        | 4327     | 12,576     | 2.91                 |
| non-Chinese East Asian        | 4,408    | 11,254     | 2.55                 |
| African                       | 682      | 1902       | 2.79                 |
| Unknown Ethnicity             | 515      | 1,490      | 2.89                 |
| Total                         | 100,208  | 285,708    | 2.85                 |

Table S2: The number of mentioned papers (unique ones), the total number of story-paper mention pairs, and the average number of mentions per paper for authors in each of the 9 high-level ethnicity groups.

### S1.6 News Outlets Categorization

To estimate differences across outlets, we grouped 288 news outlets into three categories according to their news report publishing mechanisms. The three categories are: (1) Press Releases,
Table S3: The number of story-paper mention pairs by journalists in each of the 9 high-level ethnicity groups.

(2) Science & Technology, and (3) General News. The categorization is based on manual inspections of three random stories for each outlet (Appendix Table S10 shows the full list).

The Press Releases category is unique since many outlets in this category commonly—if not exclusively—republish university press-releases as stories, making them reasonable proxies for estimating bias from a university’s own press office. The Science & Technology category consists of magazines that primarily focus on reporting science, such as “MIT Technology Review” and “Scientific American.” These outlets typically construct a large scientific narrative referencing several papers in their stories. The General News category includes mainstream news media such as “The New York Times” and “CNN.com” that publish stories in a wide variety of topics. They also have well-trained editorial staff and science journalists who are focused on accurately reporting science.

Table S4 shows the paper-story mention pairs for three types of outlets. The average number of words per story for each outlet type is shown in Fig. S2.
### Table S4: The number of outlets for three outlet types, their number of story-paper mentions, and the percentage of mentions that have named the first authors. The full list of 288 outlets are available in Appendix Table S10.

| Outlet Type            | # Outlets | Example Outlet      | # Mentions | Perc. Aut. Ment. |
|------------------------|-----------|---------------------|------------|------------------|
| Press Releases         | 18        | EurekAlert!         | 81,486     | 44.9%            |
| Science & Technology   | 79        | MIT Technology Rev. | 69,966     | 51.8%            |
| General News           | 171       | The New York Times  | 125,241    | 22.1%            |

Figure S2: The average story length for three types of outlets. Error bars show 95% confidence intervals.

### S1.7 Check Author Attributions in Science News

#### S1.7.1 Author Name Mentions

We normalized both the news content and the author names to ensure that this computational approach works for names with diacritics. For each story-paper mention pair, each author’s last name is searched for using a regular expression with word boundaries around the name, requiring that the name’s initial letter be capitalized. While the chance exists that this process may introduce false positives for authors with common words as last names (e.g., “White”), such cases are rare because (i) few authors in our dataset have common English words as their last names, and (ii) these words rarely appear at the beginning of a sentence in the story when they would be capitalized. However, a particular exception is for two common Chinese last names “He” and “She,” which can appear as third person pronouns at the start of sentences. We thus imposed additional constraints for these two names such that they must be immediately preceded with one of the following titles to be considered as a name mention: “Professor”,

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“Prof.”, “Doctor”, “Dr.”, “Mr.”, “Miss”, “Ms.”, ‘Mrs.”. Ultimately, first authors were found in 104,569 of the 285,708 story-paper mention pairs (36.6%).

**S1.7.2 Author-Quote Detection**

Authors can be mentioned by name in different forms, including quotation (e.g., “‘We are getting close to the truth.’ said Dr. Xu”), paraphrasing (e.g., “Timnit says she is confident, however, that the process will soon be perfected.”), and simple passing (e.g., “A recent research conducted by Dr. Jha found that drinking coffee has no harmful effects on mental health.”).

We used a rule based matching method to detect explicit quotes for each story-paper pair. We first parsed our news corpus using spacy ([https://spacy.io/](https://spacy.io/)). We identified 18 verbs that were commonly used to integrate quoted materials in news stories, from the most 50 frequently used verbs in our news corpus, including “describe”, “explain”, “say”, “tell”, “note”, “add”, “acknowledge”, “offer”, “point”, “caution”, “advise”, “emphasize”, “see”, “suggest”, “comment”, “continue”, “confirm”, “accord”. A sentence is determined to contain a quote from the first author if the following two conditions are met: (i) both the quotation mark and the author’s last name appear in the sentence, and (ii) any of the 18 quote-signaling verbs (or their verb tenses) appear with five tokens before or after the author’s last name. A manual inspection of 100 extracted quotes revealed no false quote attributes. This conservative method only gives an underestimate of the quote rate, as it may not be able to detect every quote due to unusual writing styles or article formatting. So the benefit of English-named scholars in getting a quote (Fig. 2 in the main text) may be even higher.

**S1.7.3 Institution Mentions**

We checked institution mentions based on exact string matching with the reported institution name for the first author in the MAG, i.e., for each story-paper pair, we examined whether the first author’s full institution name appeared in the news story. Similar to quote detection, this method may not be able to identify every instance of institution mentions due noise in the MAG or the story using slightly different nomenclature such as institutions’ abbreviation. However, a full list of alternate names for each institution is not available to us, we thus used
this conservative method. For this reason, minority scholars’ the trend in being substituted by
institutions (Fig. 2 in the main text) is likely an underestimation.

S1.8 Regression Models

We adopted a logistic regression framework to examine the demographic bias in author men-
tions in science reporting. Many factors are known to influence name mentions that could
confound the analysis of ethnicity and gender, such as author reputation, institutional prestige
and location, publication topics and venues, or outlets and journalist demographics.

Here, we provide details of these factors and present a series of five regression models
that build upon one another by adding more rigorous control variables at each step. In our
regression framework, each story-paper mention pair is an observation, with the dependent
variable indicating whether the first author of the paper is mentioned or not in the story. We
designed a mixed-effects model with five groups of variables: (1) first author demographics
(gender and ethnicity); (2) paper author controls, including prestige factors, last name factors,
and other authors; (3) paper and story content, including temporal factors, paper readability,
story length, number of papers mentioned per story, and journalist demographics; (4) fixed-
effects for paper domains and topics; (5) random effects for outlets, publication venues, and
popular last authors. The increasing level of model complexity allows us to test the robustness
of the effects of ethnicity and gender, and also to examine potential factors at play in science
coverage. Table S5 shows the step-wise regression results.

Model 1: Naive Bias

The first model directly encodes our two variables of focus, gender and ethnicity, as the sole
categorical factors of the regression model. Here and throughout the study, we treat the ref-
ence coding for ethnicity as British-origin and for gender as Male. While overly simplistic
in its modeling assumptions, Model 1 nevertheless tests for systematic differences for whether
authors of a particular demographic are mentioned less frequently and serves as a baseline for
layering on controls to explain such bias.
Model 2: Paper Author Controls

Many author-level attributes other than demographics could influence journalistic perceptions on authors and the coverage of them. Model 2 introduces 20 additional factors for controlling for features of the paper’s authors.

Prestige Factors. The reputation of the first author may also influence the chance of being named. High-status actors and institutions tend to receive preferential treatment within science (Merton, 1968; Azoulay et al., 2013; Tomkins et al., 2017), and we hypothesize that these prestige-based disparities may carry over to media coverage as well. To account for prestige effects, we include the author rank and institution rank provided by the MAG (Wang et al., 2019). This ranking estimates the relative importance of authors and institutions using paper-level features derived from a heterogeneous citation network; while similar to h-index, the method has been shown to produce more fine-grained and robust measurements of impact and prestige. Institution and author ranks are not necessarily directly related, as institutions may be home to authors of varying ranks (e.g., early- or late-career faculty) and the same author may appear with different affiliations on separate papers due to a career move. Note that for rank values, negative-valued coefficients in the regression models would indicate that higher-ranked individuals and those from higher-ranked institutions are more likely to be mentioned.

We also add a variable indicating the location of the first author’s institution with three categories: (1) domestic, (2) international, (3) unknown. This variable controls for the geographical factor that may influence journalists’ willingness to contact by phone or video chat service and therefore influence whether they mention the author. We infer the country of origin for institutions based on their latitude and longitude provided in the MAG.

Last Name Factors. People are known to have a preference for both familiar and more easily-pronounceable names (Song and Schwarz, 2009; Laham et al., 2012), and this preference could potentially bias which author a journalist mentions. Therefore, we introduce two factors as proxies: (1) the number of characters in the last name as a proxy for pronounceability, and (2) the log-normalized count of the last name per 100K Americans from the 2018 census data. As journalists are drawn from U.S.-based news sources, the latter reflects potential familiarity.
**Other Authors.** Scientific knowledge is increasingly discovered by large teams, as tackling complex problems often require the collaboration between experts with diverse sets of specialization (Guimera et al., 2005; Greene 2007; Milojević 2014). On these multi-author projects, the last author is typically the senior author responsible for directing the project—a trend that is known in science journalism guidelines when determining whom to interview (Blum and et al., 2006). The last author could be more likely to be mentioned in press coverage, which could potentially reduce the chance for the first author. Therefore, we control for whether the last author is mentioned in the news article using a binary factor. As the demographics of the last author may influence whom a journalist decides to mention, we control for the ethnicity and gender of the last author, using *British-origin* and *Male* as the reference category respectively. Note that some papers are monographs with no last author. To control for these cases, we include a binary factor *Solo* which is set to 1 for monographs, at which point all factors related to the last author (gender, ethnicity, and is-mentioned) are set to 0.

When journalists examine a paper’s author list, the team size may influence their understanding of the distribution of credits among authors, potentially reducing the chance of any author being mentioned for papers with many authors. We thus include a factor for the number of authors.

**Model 3: Paper and Story Content**

Besides author-level attributes, the content of the paper and story, and journalist demographics also can play a role in affecting author mentions. We thus control for the following factors in Model 3.

*Year of News Story (Mention Year).* Bias in science coverage may have temporal variations due to unpredictable factors that are directly or indirectly related to research. For instance, the available funding resources can affect the number of research outputs in a year, which would in turn influence the amount of time and space journalists devote to scientists in news articles. We thus control for the year of the news story, i.e., the mention year of the paper. We treat it as a scalar variable (zero-centered).

*Year Gap between Story and Paper.* News stories often reference older scientific papers in
the narrative, as shown in Fig. S1c. For older papers, at the time of a recent story publication, the original authors may be unable to be reached or the story may be framed differently from recent science that is considered “fresh.” Indeed, citing timely scientific evidence in a news report can increase credibility perceptions of a story (Sundar 1998; Rieh and Belkin 1998). Therefore we include a factor that quantifies the year difference between the mention year and the publication year of the mentioned paper.

**Number of papers mentioned in a story.** A story can mention several papers to help frame and construct its scientific narrative, and potentially increase its news credibility perception. However, the more papers being referenced in a story may reduce the amount of space and attention allocated to each paper by journalists, and therefore may decrease the chance of its authors being mentioned. We thus control for the number of mentioned papers in a story.

**News Story Length.** Longer articles provide more space in depicting stories about the science being covered, we thus control for the length of each story, measured as the total number of words.

**Paper Readability.** Given the tight timelines under which journalists work, quickly identifying and understanding insights is likely critical to what is said about a paper. A paper’s readability may thus influence whether a journalist feels the need to reach out to the author, with more readable papers requiring less contact. Readability, in turn, may also be tied to author’s demographics like gender (Hengel 2017), making it important to take readability into account. Due to licensing restrictions, the full text of the majority of papers is unavailable freely; therefore we compute readability over the paper abstract using three factors: (1) the Flesch-Kincaid readability score, which estimates the grade-level needed to understand the passage; (2) the number of sentences per paragraph, which is a proxy for information content and density; and (3) the type-token ratio, which is a measure of lexical variety. Another reason we focus particularly on the abstract is that journalists may not read the entire paper but very likely read the abstract.

**Journalist Demographics.** It is ultimately the journalist’s decision to mention authors when writing science reports. Motivated by the commonly observed homophily principle in social
networks (McPherson et al., 2001), we hypothesize that the mentioning behavior in science reporting is associated with homophilous effects by ethnicity and gender. To model such effects, we include the journalists’ demographics and their interactions with first authors’ gender and ethnicity.

Due to insufficient instances of journalists identified in news stories (cf. Section S1.2: Table S3), we further coarsen the 9 broad ethnicity categories into 4 groups: (1) Asian (Chinese, Indian, and non-Chinese East Asian), (2) British-origin, (3) European (Eastern European, Romance Language, and Scandinavian & Germanic), and (4) Other Unknown (Middle Eastern, African, and Unknown).

**Model 4: Paper Domains and Topics**

Some scientific domains and topics may be inherently more news-worthy than others. Furthermore, journalists’ academic backgrounds may be unequally distributed across scientific fields, resulting in different propensities to reach out to authors. Therefore, in Model 4, we include factors to capture the domain of a paper using metadata from the MAG, which includes a large volume of keywords (665K) at different levels of specificity. A paper can have multiple keywords, with each having an associated confidence score between 0 and 1. To capture high-level topical and methodological differences, we restrict our focus to the most-common 533 keywords that occur in at least 500 papers in our dataset. Each keyword is used as an independent variable in the regression, whose value is the keyword’s confidence score for the paper.

**Model 5: Outlets, Venues, and Famous Research Labs**

News outlets and publication venues both reflect extra sources of variability in the regression models. Individual news outlets may follow different standards of practice in how they describe science, creating a separate source of variability in who is mentioned. Publication venues each come with different levels of impact and topical focus that potentially affect the depth of journalistic focus on papers published in them. Additionally, famous research labs managed by senior researchers may be more likely to receive media attention and name attribution as a benefit of their visibility gained by previous research outputs. Such popularity can be approximated
by famous last authors based on their number of mentioned papers in our data. To accurately model these sources of variations, we treat outlets, venues, and top 100 last authors as *random effects* in regression Model 5. This mixed-effect regression model implicitly captures a robust set of factors involved in science reporting such as the tendency of specific journals to be mentioned more frequently (e.g., *Nature*, *Science*, or *JAMA*), the focus of news outlets on specific topics covered by different journals, and the attention benefits for authors working with famous research labs.

### S2 Regression Results

#### S2.1 Coefficients for Five Models in Author Mentions

The coefficients for five regression models are shown in Table S5. For space, all variables in Model 5, including the paper keywords and author-journalist interaction terms, are shown in Appendix Table S11.

#### S2.2 Influence of Control Variables

Although our focus is on ethnicity and gender, we find that many controls are also strongly associated with author mention rates. Examining the influence of these factors can lead to a better understanding of the mechanisms at play in science reporting. Below we interpret their effects based on Model 5 (Table S5) along three themes: (1) prestige related inequality, (2) impact of co-authorship, and (3) story content effects.

Scholars who have a high professional rank or are affiliated with prestigious institutions receive outsized attention in science news. This result suggests that the benefits of status, the so-called “Matthew Effect” ([Merton, 1968](#)), persist even after publication.

Although having more authors has a weak negative effect on the first author being mentioned, if the last author is mentioned, the first author is substantially more likely to be mentioned as well, suggesting that many stories tend to only engage with a few authors per referenced paper. Surprisingly, the demographics of last authors also play a weak role in first author
mentions, with slightly negative effects for last authors with Eastern European, Middle Eastern, and Chinese names.

Solo-authored papers have been decreasing over time and are associated with lower impact on average (Greene 2007; Milojević 2014). However, our results highlight an underappreciated benefit—conditional on a paper being referenced in the news, a solo author is significantly more likely to be mentioned compared to the first author of a multi-author paper. Although seemingly counter to previous studies, this result has a natural explanation—there is only one author to mention if need be.

The coefficients for story features point to the multifaceted nature of science reporting. Although the volume of science reporting is increasing over time (Fig. S1a), journalists tend to mention authors less frequently in later years. At the same time, while older papers are still discussed in the media (Fig. S1c), journalists are less likely to mention authors of these studies as often. When more papers are referenced in a story, their first authors are less likely to be mentioned. We hypothesize that such stories are often citing multiple scientific papers to construct a large narrative and thus those papers are only mentioned in passing.

S2.3 U.S. vs. non-U.S. Institutions in Author Mentions

When fitting a model for the U.S. subset (or non-U.S. subset), we omitted the location variable introduced in Section S1.8 (Model 2). The coefficients for gender and ethnicity in two models are shown in Table S6, which reveal that scholars from non-U.S. institutions are much less likely to be mentioned by U.S. media than their counterparts from U.S.-based institutions, with four categories reaching statistical significance, including Romance Language, Scandinavian & Germanic, Chinese, and Middle Eastern.

S2.4 Who is Quoted or Institutionally Substituted?

The three subplots in Fig. S3 show the average marginal effects for minority gender and ethnicity authors in being mentioned by name, quoted, or substituted by institution when author name is not mentioned, respectively. Note that each model is fitted with our full data.
Figure S3: Authors with minority-ethnicity names are less likely to be mentioned by name (left) or quoted (middle), and are more likely to be substituted by their institution (right). The average marginal effects are estimated based on 285,708 observations in our data. A negative (positive) marginal effect indicates a decrease (increase) in probability compared to authors with Male (for gender) or British-origin (for ethnicity) names. The colors are proportional to the absolute probability changes. *Female* is colored as blue to reflect its difference from ethnicity identities. The error bars indicate 95% bootstrapped confidence intervals.

**S3 Additional Ethnicity Coding**

While *Ethnea* provides a large set of nationality-based ethnicity codings specifically tailored to scientists, the library could potentially introduce artifacts in its labeling. As a robustness check, we re-coded the ethnicities of all authors and journalists using two separate sources to test whether the observed bias persists. Specifically, we used the *ethnicolr* library ([https://pypi.org/project/ethnicolr/](https://pypi.org/project/ethnicolr/)) to code ethnicity using either data derived from (i) the nationalities listed in Wikipedia infoboxes to infer nationality-based ethnicity, or (ii) self-reported ethnicity data associated with last names from the 2010 U.S. census. While these two new sources of data use different definitions and granularities of ethnicity from *Ethnea*, they nonetheless provide approximately-similar categories to *Ethnea* that enable us to validate our results.

**Ethnicity based on Wikipedia Data.** We used the Wikipedia infobox data to code author and journalist ethnicity based on the first name and the last name ([Ambekar et al., 2009; Sood and Laohaprapanon, 2018](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5844167/)). To make the results comparable to that based on *Ethnea* (Section S1.4), we placed 13 individual ethnicities defined in the Wikipedia data into 8 broad
categories:

- (1) African (*Africans*),
- (2) British-origin (*British*),
- (3) East Asian (*EastAsian, Japanese*),
- (4) Eastern European (*EastEuropean*),
- (5) Indian (*IndianSubContinent*),
- (6) Middle Eastern (*Muslim, Jewish*)
- (7) Roman Language (*French, Hispanic, Italian*),
- (8) Scandinavian & Germanic (*Germanic, Nordic*).

Note that Chinese ethnicity (defined in *Ethnea*) is by default incorporated into the *EastAsian* ethnicity in the Wikipedia data. We further placed the 8 categories into 4 groups for journalist ethnicity due to insufficient data size: (1) Asian (East Asian, Indian), (2) British-origin, (3) European (Eastern European, Roman Language, Scandinavian & Germanic), (4) Other Unknown (African, Middle Eastern, Unknown). We fitted the specification of Model 5 using this coding scheme (British-origin and Male are still used as the reference categories).

**Race in U.S. Census Data.** Similarly, we coded the race for authors and journalists using the 2010 U.S. Census data based on the last name ([Ambekar et al., 2009](#) [Sood and Laohaprapanon, 2018](#)). The four race categories: (1) Asian (*api*; [note that *api* denotes Asian and Pacific Islander]), (2) Black (*black*), (3) Hispanic (*hispanic*), (4) White (*white*), are directly used to fit the specification of Model 5 with White and Male used as the reference categories.

Fig. S4 shows the average marginal effects in mention rates for scholars of minority ethnicity (or race) compared to British-origin (or White) named authors. As neither tool infers gender, we thus report the result for gender here using *Ethnea’s* labels. Like the case of *Ethnea*, we find
Figure S4: The average marginal effects in mention probability for first authors’ demographic variables, using (Left) Wikipedia data for coding ethnicity or (Right) U.S. Census data for coding race based on author (or journalist) names. Note that the gender is still inferred using Ethnea.

strong anti-Asian biases in author mentions in science news, highlighting the robustness of our findings in the main text.
Table S5: Coefficients of five increasing-complexity regression models in predicting if the first author is mentioned using 285,708 observations. For author-journalist interactions (AUT-JRN.), only significant terms are shown. All variables in Model 5, including 533 keywords, are provided in Appendix Table S11. *** p<0.001, ** p<0.01, and * p<0.05.
Table S6: The gender and ethnicity coefficients of regression Model 5 in predicting author mentions. A separate model is trained for the U.S.-based institutions subset, and the non-U.S. institutions subset, respectively. Stars indicate the significance level for each coefficient (Sig. levels: *** p<0.001, ** p<0.01, and * p<0.05). The p-values are based on the statistical test of differences in coefficients between two models using the equation provided in (Clogg et al., 1995).

| Gender/Ethnicity          | U.S.-based | non-U.S. | p-value |
|---------------------------|------------|----------|---------|
| Female                    | 0.08       | 0.06     | 0.851   |
| Romance Language          | −0.14*     | −0.52*** | 0.000   |
| Scandinavian & Germanic   | −0.14*     | −0.48*** | 0.001   |
| Eastern European          | −0.09      | −0.50*** | 0.013   |
| non-Chinese East Asian    | −0.70***   | −0.53*** | 0.388   |
| Chinese                   | −0.67***   | −1.07*** | 0.005   |
| Middle Eastern            | −0.16      | −0.62*** | 0.004   |
| Indian                    | −0.26**    | −0.42*   | 0.462   |
| African                   | −0.27      | −0.87*   | 0.206   |

Table S7: A random sample of 10 African authors predicted by Ethnea (out of 613 in total in our data) and their ethnicity or race categories based on the U.S. census or the Wikipedia data.
Table S8: A random sample of 10 Black authors predicted based on the U.S. census data (out of 560 in total in our data) and their ethnicity categories based on *Ethnea* or the Wikipedia data.

| First Author Name          | U.S. Census | Ethnea         | Wikipedia     |
|----------------------------|-------------|----------------|---------------|
| E. Robinson                | Black       | British-origin | British-origin|
| Momar Ndao                 | Black       | Romance Language| African      |
| Angela F Harris            | Black       | British-origin | British-origin|
| Daddy Mata-Mbemba          | Black       | Romance Language| African      |
| A Bolu Ajiboye             | Black       | African        | African      |
| Lasana T. Harris           | Black       | British-origin | British-origin|
| John M. Harris             | Black       | British-origin | British-origin|
| Edwin S Robinson           | Black       | British-origin | British-origin|
| Eric A. Coleman            | Black       | British-origin | British-origin|
| Mp Coleman                 | Black       | British-origin | British-origin|


A Tables

Table S9: A random sample of 10 names for each of the 24 individual ethnicities and the “Unknown” category. All 6 MONGOLIAN names in our data are shown here.

| Ethnicity  | Name Example                  | Gender |
|------------|-------------------------------|--------|
| AFRICAN    | Dora Wynchank                  | F      |
|            | Benjamin D. Charlton           | M      |
|            | J. Nwando Olayiwola            | unknown|
|            | Ayodeji Olayemi                | M      |
|            | Elizabeth Gathoni Kibaru       | F      |
|            | Christopher Changwe Nshimbi    | M      |
|            | Naganna Chetty                 | unknown|
|            | Benjamin Y. Ofori              | M      |
|            | Khadijah Essackjee             | F      |
|            | Jeanine L. Marnewick           | F      |
|            | Habtamu Fekadu Gemed            | M      |
| ARAB       | Zaid M. Abdelsattar            | M      |
|            | Alireza Dirafzoon              | M      |
|            | Ahmad Nasiri                   | M      |
|            | Saleh Aldasouqi                | M      |
|            | Ibrahim A. Arif                | M      |
|            | Sameer Ahmed                   | M      |
|            | A Elgalib                      | unknown|
|            | Taha Adnan Jan                 | M      |
|            | Mohsen Taghizadeh              | M      |
|            | Behnam Nabet                   | M      |
| BALTIC     | Skirmantas Kriaucionis         | M      |
|            | Airidas Korolkovas             | M      |
|            | Egle Cekanaviciute             | F      |
|            | Arunas L. Radzvilavicius       | M      |
|            | Ieva Tolmane                   | F      |
|            | Alberts B                     | M      |
|            | Gediminas Gaigalas             | M      |
|            | Armandas Balcytis              | unknown|
|            | Ruta Ganceviciene              | F      |
|            | Andrius Paukonis               | M      |
| CHINESE    | Chin Hong Tan                  | unknown|
|            | Li Yuan                        | unknown|
|            | Yalin Li                       | unknown|
| Name               | Gender | Affiliation     |
|--------------------|--------|-----------------|
| Xian Adiconis      | unknown|                 |
| Philip Sung-En Wang| M      |                 |
| Xiaohui Ni         | unknown|                 |
| Minghua Li         | unknown|                 |
| Fang Fang Zhang    | F      |                 |
| Li-Qiang Qin       | M      |                 |
| Jian Tan           | unknown|                 |
| Pieter A. Cohen    | M      |                 |
| I. Vandersmissen   | unknown|                 |
| Marleen Temmerman  | F      |                 |
| Gerard 't Hooft    | M      |                 |
| A. Yool            | unknown|                 |
| G. A W Rook        | unknown|                 |
| Fatima Foflonker   | F      |                 |
| Mirjam Lukasse     | F      |                 |
| Sander Kooijman    | M      |                 |
| Izaak D. Neveln    | M      |                 |
| Isabel Hilton      | F      |                 |
| Gavin J. D. Smith  | M      |                 |
| Katherine A. Morse | F      |                 |
| Andrew S. Bowman   | M      |                 |
| T. M. L. Wigley    | unknown|                 |
| Francis Markham    | M      |                 |
| Neil T. Roach      | M      |                 |
| Brooke Catherine Aldrich | F | | |
| Vaughn I. Rickert  | M      |                 |
| Kellie Morrissey   | F      |                 |
| Lucas V. Joel      | M      |                 |
| Daniel Clery       | M      |                 |
| Pierre Jacquemot   | M      |                 |
| Scott Le Vine      | M      |                 |
| Nathalie Dereuadde-Bosquet | F | | |
| Stphane Colliac    | unknown|                 |
| Adelaide Haas      | F      |                 |
| Julie M. D. Paye   | F      |                 |
| Justine Lebeau     | F      |                 |
| Arnaud Chiolero    | M      |                 |
| Laure Schnabel     | F      |                 |
| Jeff M. Kretschmar | M      |                 |
| E. Homeyer         | unknown|                 |
| Maren N. Vitousek  | F      |                 |
| Name                        | Gender | Country |
|-----------------------------|--------|---------|
| D. Wild                     | unknown|         |
| Hany K. M. Dweck            | M      |         |
| E. M. Fischer               | unknown|         |
| Paul Marek                  | M      |         |
| Hans-Jrg Rheinberger        | M      |         |
| Daniel James Cziczo         | M      |         |
| Mary J. Scourboutakos       | F      | GREEK   |
| Anita P Courcoulas          | F      |         |
| Elgidius B. Ichumbaki       | unknown|         |
| Stavros G. Drakos           | M      |         |
| Nikolaos Konstantinides     | M      |         |
| Constantine Sedikides       | M      |         |
| Maria A. Spyrou             | F      |         |
| Panos Athanasopoulos        | M      |         |
| Aristeidis Theotokis        | M      |         |
| Amy H. Mezulis              | F      |         |
| Mirela Donato Gianeti       | F      | HISPANIC|
| Julio Cesar de Souza        | M      |         |
| Paulina Gomez-Rubio         | F      |         |
| Jos A. Pons                 | M      |         |
| Arnau Domenech              | M      |         |
| Nicole Martinez-Martin      | F      |         |
| Mauricio Arcos-Burgos       | M      |         |
| Raquel Muoz-Miralles        | F      |         |
| Annmarie Cano               | F      |         |
| Merika Treants Koday        | F      |         |
| Andrea Tabi                 | F      | HUNGARIAN|
| Robert Erdlyi               | M      |         |
| Gabor G. Kovacs             | M      |         |
| Xenia Gonda                 | F      |         |
| Erzsbet Bukodi              | unknown|         |
| Julianna M. Nemeth          | F      |         |
| Ian K. Toth                 | M      |         |
| Zoltan Arany                | M      |         |
| Cory A. Toth                | M      |         |
| Ashley N. Bucsek            | unknown|         |
| Sachin M. Shinde            | M      | INDIAN  |
| Govindsamy Vediyappan       | M      |         |
| Ashish K. Jha               | M      |         |
| Tamir Chandra               | M      |         |
| Hariharan K. Iyer           | M      |         |

Row 43
| Name                          | Gender | Language  |
|-------------------------------|--------|-----------|
| Chanpreet Singh               | unknown|
| Ravi Chinta                   | M      |
| Madhukar Pai                  | M      |
| Lalitha Nayak                 | F      |
| Ravi Dhingra                  | M      |
| **INDONESIAN**                |        |
| Dewi Candraningrum            | unknown|
| Richard Tjahjono              | M      |
| T. A. Hartanto                | unknown|
| Johny Setiawan                | M      |
| Truly Santika                 | unknown|
| Chairul A. Nidom              | unknown|
| Christine Tedijanto           | F      |
| Alberto Purwada               | M      |
| Ardian S. Wibowo              | M      |
| Anna I Corwin                 | F      |
| **ISRAELI**                   |        |
| Ron Lifshitz                  | M      |
| Martin H. Teicher             | M      |
| Ruth H Zadik                  | F      |
| Gil Yosipovitch               | M      |
| Mor N. Lurie-Weinberger       | unknown|
| J. Tarchitzky                 | unknown|
| Ilana N. Ackerman             | F      |
| B. Trakhtenbrot               | unknown|
| Yoram Barak                   | M      |
| Mendel Friedman               | M      |
| **ITALIAN**                   |        |
| Tiziana Moriconi             | F      |
| Marco Gobbi                   | M      |
| Marco De Cecco                | M      |
| F. Govoni                     | unknown|
| Theodore L. Caputi            | M      |
| Mark A Bellis                 | M      |
| Fernando Migliaccio           | M      |
| Julien Granata                | M      |
| Jennifer M. Poti              | F      |
| Brendan Curti                 | M      |
| **JAPANESE**                  |        |
| Takuji Yoshimura              | M      |
| Maki Inoue-Choi               | F      |
| Masaaki Sadakiyo              | M      |
| Moeko Noguchi-Shinohara       | F      |
| Naoto Muraoka                 | M      |
| Shigeki Kawai                 | M      |
| Country     | Name                      | Gender | Status     |
|-------------|---------------------------|--------|------------|
| KOREAN      | Jih-Un Kim                | M      | unknown    |
|             | Hanson Cho                | unknown|            |
|             | Hyung-Soo Kim             | M      |            |
|             | Yun-Hee Youm              | F      |            |
|             | Yoon-Mi Lee               | unknown|            |
|             | Soo Bin Park              | F      |            |
|             | Yungi Kim                 | unknown|            |
|             | Woo Jae Myung             | unknown|            |
|             | Kunwoo Lee                | unknown|            |
|             | Sandra Soo-Jin Lee        | F      |            |
| MONGOLIAN   | C. Jamsranjav             | unknown|            |
|             | Jigjidsurengiin Batbaatar | unknown|            |
|             | Khishigjav Tsogbaatar     | unknown|            |
|             | Migeddoj Batchimeg        | unknown|            |
|             | Tsolmon Baatarzorig       | unknown|            |
| NORDIC      | Steven G. Rogelberg       | M      |            |
|             | Kirsten K. Hanson         | F      |            |
|             | Jan L. Lyche              | M      |            |
|             | Morten Hesse              | M      |            |
|             | Karolina A. Aberg         | F      |            |
|             | Britt Reuter Morthorst    | F      |            |
|             | Kirsten F. Thompson       | F      |            |
|             | Shelly J. Lundberg        | F      |            |
|             | G Marckmann               | unknown|            |
|             | David Hgg                 | M      |            |
| ROMANIAN    | Afrodita Marcu            | F      |            |
|             | Iulia T. Simion           | F      |            |
|             | Liviu Giosan              | M      |            |
|             | Alina Sorescu             | F      |            |
|             | Liviu Giosan              | M      |            |
|             | Mircea Ivan               | M      |            |
|             | Dana Dabelea              | F      |            |
|             | Constantin Rezlescu       | M      |            |
|             | Christine A. Conelea      | F      |            |
|             | R. A. Popescu             | unknown|            |
| SLAV        | Nomi Koczka               | F      |            |
|             | Mikhail G Kolonin         | M      |            |
| Name                          | Gender | Country       |
|-------------------------------|--------|---------------|
| Richard Karban                | M      |               |
| Branislav Dragovi             | M      |               |
| H Illnerov                    | unknown|               |
| Marte Bjrk                    | F      |               |
| Jacek Niesterowicz           | M      |               |
| Justin R. Grubich            | M      |               |
| Mikhail Salama Hend          | M      |               |
| Snejana Grozeva               | F      |               |
| THAI                          |        |               |
| Piyamas Kanokwongnuwut        | unknown|               |
| Clifton Makate               | M      |               |
| Noppol Kobmoo                | unknown|               |
| Kabkaew L. Sukontason        | unknown|               |
| Aroonsiri Sangarlangkarn     | unknown|               |
| Yossawan Boriboonthana       | unknown|               |
| Ekalak Sitthipornvorakul     | unknown|               |
| Tony Rianprakaisang          | M      |               |
| Apiradee Honglawan           | F      |               |
| Wonngarm Kittanamongkolchai  | unknown|               |
| TURKISH                       |        |               |
| Iris Z. Uras                 | F      |               |
| Metin Gurcan                 | unknown|               |
| Mustafa Sahmaran             | M      |               |
| Pinar Akman                  | F      |               |
| Joshua Aslan                 | M      |               |
| Selin Kesebir                | F      |               |
| Tan Yigitcanlar              | unknown|               |
| Thembela Kepe                | unknown|               |
| Ulrich Rosar                 | M      |               |
| Selvi C. Ersoy               | F      |               |
| VIETNAMESE                    |        |               |
| Huong T. T. Ha               | unknown|               |
| Vu Van Dung                  | M      |               |
| H ChuongKim                  | unknown|               |
| Daniel W. Giang              | M      |               |
| Nhung Thi Nguyen             | unknown|               |
| V. Phan                      | unknown|               |
| Oanh Kieu Nguyen             | F      |               |
| Phuc T. Ha                   | M      |               |
| Bich Tran                    | unknown|               |
| Oanh Kieu Nguyen             | F      |               |
| Unknown                      |        |               |
| Gene Y. Fridman              | M      |               |
| Judith Glick                 | F      |               |
| Noor Edi Widya Sukoco        | unknown|               |
| Name                | Gender |
|---------------------|--------|
| Charlene Laino      | F      |
| Benot Brard         | unknown|
| David Znd           | M      |
| Katarzyna Adamala   | F      |
| K.A. Godfrin        | unknown|
| Shadd Maruna        | M      |
| Mariette DiChristina| F      |
Table S10: The 288 U.S.-based outlets are grouped into 3 categories based on their topics of reports. Note that other 135 U.S.-based outlets, which are not shown in this table, are excluded in our analyses due to technical limitations in accessing sufficient volumes of their content (e.g., view-limited paywalls or anti-crawling mechanisms).

| Outlet                      | Type            |
|-----------------------------|-----------------|
| OnMedica Sci. & Tech.       |                 |
| Huffington Post General News|                 |
| KiiiTV 3 General News       |                 |
| Carbon Brief Sci. & Tech.   |                 |
| PR Newswire Press Releases  |                 |
| Nutra Ingredients USA Sci. & Tech. |         |
| The Bellingham Herald General News |           |
| CNN News General News       |                 |
| Health Medicinet Press Releases |             |
| Herald Sun General News     |                 |
| EurekAlert! Press Releases  |                 |
| AJMC Press Releases         |                 |
| The University Herald General News |          |
| Lincoln Journal Star General News |          |
| Cardiovascular Business Sci. & Tech. |        |
| MinnPost General News       |                 |
| CNET Sci. & Tech.           |                 |
| Infection Control Today Sci. & Tech. |         |
| Science 2.0 Sci. & Tech.    |                 |
| Lexington Herald Leader General News |        |
| Statesman.com General News  |                 |
| Nanowerk Press Releases     |                 |
| The San Diego Union-Tribune General News |         |
| The Daily Beast General News |                 |
| Lab Manager Press Releases  |                 |
| SDPB Radio General News     |                 |
| New Hampshire Public Radio  General News |         |
| Health Day Press Releases   |                 |
| Rocket News General News    |                 |
| KPBS General News           |                 |
| Technology.org Press Releases |             |
| UPI.com General News        |                 |
| WUWM General News           |                 |
| Source                                      | Category          |
|---------------------------------------------|-------------------|
| Central Coast Public Radio                  | General News      |
| The Hill                                    | General News      |
| The Epoch Times                             | General News      |
| Biospace                                    | Sci. & Tech.      |
| Minyanville: Finance                        | General News      |
| Nature World News                           | Sci. & Tech.      |
| New York Post                               | General News      |
| Action News Now                             | General News      |
| WUNC                                        | General News      |
| Futurity                                    | Press Releases    |
| Reason                                      | General News      |
| azfamily.com                                | General News      |
| Idaho Statements                            | General News      |
| Google News                                 | General News      |
| Tri States Public Radio                     | General News      |
| American Physical Society - Physics         | Press Releases    |
| KTEP El Paso                                | General News      |
| LiveScience                                 | Sci. & Tech.      |
| KUNC                                        | General News      |
| The Daily Meal                              | Sci. & Tech.      |
| AOL                                         | General News      |
| Women’s Health                              | Sci. & Tech.      |
| Prevention                                  | Sci. & Tech.      |
| ECN                                         | Sci. & Tech.      |
| Iowa Public Radio                           | General News      |
| Becker’s Hospital Review                    | Sci. & Tech.      |
| 7th Space Family Portal                     | Press Releases    |
| Springfield News Sun                        | General News      |
| Environmental News Network                  | Press Releases    |
| Sky Nightly                                 | Sci. & Tech.      |
| Quartz                                     | Sci. & Tech.      |
| Benzinga                                    | General News      |
| Headlines & Global News                     | General News      |
| The Denver Post                             | General News      |
| Science Daily                               | Press Releases    |
| The Advocate                                | General News      |
| ABC News                                    | General News      |
| Newswise                                    | Press Releases    |
| hellogiggles.com                            | General News      |
| WLRN                                        | General News      |
| EarthSky                                    | Sci. & Tech.      |
| Source                                      | Category          |
|---------------------------------------------|-------------------|
| Becker’s Spine Review                       | Sci. & Tech.      |
| MIT News                                    | Press Releases    |
| MarketWatch                                 | General News      |
| Arstechnica                                 | Sci. & Tech.      |
| Journalist’s Resource                       | Sci. & Tech.      |
| Northern Public Radio                       | General News      |
| Everyday Health                             | Sci. & Tech.      |
| Star Tribune                                | General News      |
| TCTMD                                       | Sci. & Tech.      |
| The Verge                                   | General News      |
| She Knows                                   | General News      |
| SeedQuest                                   | Sci. & Tech.      |
| Tech Times                                  | Sci. & Tech.      |
| Wichita’s Public Radio                      | General News      |
| Oncology Nurse Advisor                      | Sci. & Tech.      |
| Delmarva Public Radio                       | General News      |
| Medical Daily                               | Sci. & Tech.      |
| Homeland Security News Wire                 | General News      |
| Discover Magazine                           | Sci. & Tech.      |
| Washington Post                             | General News      |
| MSN                                         | General News      |
| Hawaii News Now                             | General News      |
| The Daily Caller                            | General News      |
| News Tribune                                | General News      |
| The Fresno Bee                              | General News      |
| King 5                                      | General News      |
| Star-Telegram                               | General News      |
| CNBC                                        | General News      |
| Salon                                       | General News      |
| WJCT                                        | General News      |
| WVPE                                        | General News      |
| KTEN                                        | General News      |
| Wired.com                                   | General News      |
| Daily Kos                                   | General News      |
| USA Today                                   | General News      |
| Men’s Health                                | Sci. & Tech.      |
| Boise State Public Radio                    | General News      |
| Voice of America                            | General News      |
| PR Web                                      | Press Releases    |
| Georgia Public Radio                        | General News      |
| FiveThirtyEight                             | General News      |
| Website                          | Category          |
|---------------------------------|-------------------|
| ABC News WMUR 9                 | General News      |
| Healthline                      | Sci. & Tech.      |
| Mongabay                        | Sci. & Tech.      |
| Vox.com                         | General News      |
| WPTV 5 West Palm Beach          | General News      |
| Popular Mechanics               | Sci. & Tech.      |
| PM 360                          | Sci. & Tech.      |
| SFGate                          | General News      |
| Seed Daily                      | Sci. & Tech.      |
Table S11: The coefficients of all independent variables (including 533 keywords) in Model 5 in predicting whether the first author is mentioned or not by name in a news story referencing their research papers. Random effects for 100 top last authors, 288 outlets, and 8,268 publication venues are also included in the model. Note that “FA” denotes the first author and “J” denotes the journalist.

| Dependent variable: | First author mentioned |
|---------------------|------------------------|
| FA_African          | \(-0.468 (-0.883, -0.052)\) p = 0.028 |
| FA_Chinese          | \(-0.800 (-0.927, -0.674)\) p = 0.000 |
| FA_EastAsian        | \(-0.570 (-0.748, -0.392)\) p = 0.000 |
| FA_EasternEuropean  | \(-0.190 (-0.347, -0.033)\) p = 0.018 |
| FA_Indian           | \(-0.328 (-0.498, -0.158)\) p = 0.0002 |
| FA_MiddleEastern    | \(-0.307 (-0.456, -0.159)\) p = 0.0001 |
| FA_RomanceLanguage  | \(-0.244 (-0.338, -0.150)\) p = 0.00000 |
| FA_ScandinavianGermanic | \(-0.203 (-0.296, -0.110)\) p = 0.00002 |
| FA_unknown          | \(-0.131 (-0.577, 0.315)\) p = 0.565 |
| J_Asian             | \(-0.152 (-0.331, 0.026)\) p = 0.095 |
| J_European          | \(-0.050 (-0.135, 0.035)\) p = 0.248 |
| J_OtherUnknown      | \(-0.030 (-0.117, 0.058)\) p = 0.505 |
| FA_gender_F         | \(0.045 (-0.043, 0.133)\) p = 0.315 |
| FA_gender_unknown   | \(-0.096 (-0.207, 0.016)\) p = 0.093 |
| J_gender_F          | \(-0.051 (-0.124, 0.022)\) p = 0.169 |
| J_gender_unknown    | \(-0.020 (-0.109, 0.068)\) p = 0.653 |
| FA_African:J_Asian  | \(0.050 (-1.682, 1.782)\) p = 0.956 |
| FA_Chinese:J_Asian  | \(0.191 (-0.234, 0.615)\) p = 0.379 |
| FA_EastAsian:J_Asian | \(0.405 (-0.282, 1.093)\) p = 0.248 |
| FA_EasternEuropean:J_Asian | \(0.547 (-0.047, 1.141)\) p = 0.072 |
| FA_Indian:J_Asian   | \(0.255 (-0.264, 0.774)\) p = 0.336 |
| FA_MiddleEastern:J_Asian | \(0.445 (-0.125, 1.016)\) p = 0.127 |
| FA_RomanceLanguage:J_Asian | \(0.183 (-0.198, 0.565)\) p = 0.347 |
| FA_ScandinavianGermanic:J_Asian | \(0.374 (0.034, 0.714)\) p = 0.032 |
| FA_unknown:J_Asian  | \(-1.314 (-3.553, 0.924)\) p = 0.250 |
| FA_African:J_European | \(0.045 (-0.714, 0.805)\) p = 0.907 |
| FA_Chinese:J_European | \(0.278 (0.057, 0.499)\) p = 0.014 |
| FA_EastAsian:J_European | \(0.144 (-0.187, 0.476)\) p = 0.393 |
| FA_EasternEuropean:J_European | \(0.112 (-0.184, 0.409)\) p = 0.458 |
| FA_Indian:J_European | \(0.150 (-0.165, 0.466)\) p = 0.351 |
| FA_MiddleEastern:J_European | \(0.245 (-0.024, 0.514)\) p = 0.074 |
| FA_RomanceLanguage:J_European | \(0.185 (0.012, 0.357)\) p = 0.037 |
| FA_ScandinavianGermanic:J_European | \(0.150 (-0.019, 0.318)\) p = 0.082 |
| FA_unknown:J_European | \(0.578 (-0.236, 1.393)\) p = 0.164 |
| FA_African:J_OtherUnknown | \(-0.035 (-0.473, 0.404)\) p = 0.877 |
| FA_Chinese:J_OtherUnknown | \(0.362 (0.230, 0.494)\) p = 0.00000 |
| FA_EastAsian:J_OtherUnknown | \(0.135 (-0.051, 0.321)\) p = 0.155 |
| FA_EasternEuropean:J_OtherUnknown | \(0.116 (-0.050, 0.281)\) p = 0.172 |
| Category                                      | Mean (Lower, Upper) | p-value |
|-----------------------------------------------|--------------------|---------|
| FA_Indian:J_OtherUnknown                      | 0.093 (-0.085, 0.271) | 0.308   |
| FA_MiddleEastern:J_OtherUnknown               | 0.144 (-0.012, 0.300) | 0.071   |
| FA_RomanceLanguage:J_OtherUnknown             | 0.028 (-0.071, 0.127) | 0.576   |
| FA_ScandinavianGermanic:J_OtherUnknown       | 0.131 (0.033, 0.229)  | 0.009   |
| FA_unknown:J_OtherUnknown                     | -0.131 (-0.603, 0.341) | 0.587   |
| FA_gender_F:J_gender_F                        | -0.082 (-0.200, 0.036) | 0.172   |
| FA_gender_unknown:J_gender_unknown            | 0.125 (-0.021, 0.271)  | 0.095   |
| FA_gender_F:J_gender_unknown                  | -0.049 (-0.141, 0.042) | 0.289   |
| FA_gender_unknown:J_gender_unknown            | 0.002 (-0.114, 0.117)  | 0.975   |
| eth_last_authorAfrican                        | 0.106 (-0.065, 0.277)  | 0.225   |
| eth_last_authorChinese                        | -0.081 (-0.136, -0.025) | 0.005   |
| eth_last_authorEastAsian                      | 0.043 (-0.029, 0.115)  | 0.240   |
| eth_last_authorEasternEuropean                | -0.153 (-0.212, -0.095) | 0.00000 |
| eth_last_authorIndian                         | -0.015 (-0.077, 0.047) | 0.631   |
| eth_last_authorMiddleEastern                  | -0.117 (-0.172, -0.061) | 0.00004 |
| eth_last_authorRomanceLanguage                | -0.026 (-0.061, 0.009) | 0.144   |
| eth_last_authorScandinavianGermanic           | 0.002 (-0.032, 0.035)  | 0.928   |
| eth_last_authorsolo                           | 0.672 (0.616, 0.727)   | 0.000   |
| eth_last_authorunknown                        | -0.640 (-0.806, -0.473) | 0.000   |
| gender_last_authorF                           | 0.042 (0.014, 0.070)   | 0.004   |
| gender_last_authorunknown                     | -0.032 (-0.070, 0.006) | 0.102   |
| last_author_mentionedeyes                    | 0.669 (0.643, 0.696)   | 0.000   |
| first_fname_length                           | -0.007 (-0.012, -0.002) | 0.004   |
| first_fname_prob                              | 0.005 (-0.0002, 0.011)  | 0.061   |
| first_author_name                             | -0.0001 (-0.0001, -0.0001) | 0.000   |
| affi_rank                                     | -0.00002 (-0.00002, -0.00001) | 0.00001 |
| affi_cateinternational                        | -0.267 (-0.292, -0.242) | 0.000   |
| affi_cateunknown                              | 0.212 (-0.037, 0.461)   | 0.095   |
| gap_in_years                                  | -0.125 (-0.129, -0.121) | 0.000   |
| mention_year_center                           | -0.021 (-0.029, -0.014) | 0.000   |
| num_authors                                   | -0.003 (-0.003, -0.002) | 0.000   |
| num_words                                     | 0.0002 (0.0002, 0.0002)  | 0.000   |
| num_mentioned_papers                          | -0.101 (-0.105, -0.096) | 0.000   |
| FleschReadingEase                             | -0.001 (-0.001, -0.0004) | 0.000   |
| sentences_per_paragraph                       | 0.008 (0.002, 0.013)    | 0.005   |
| type_token_ratio                              | 0.176 (0.018, 0.333)    | 0.029   |
| Composite_material                             | -0.526 (-0.905, -0.147) | 0.007   |
| Chemistry                                     | 0.149 (-0.170, 0.468)   | 0.361   |
| Chromatography                                | 0.331 (-0.283, 0.944)   | 0.291   |
| Botany                                        | -0.364 (-0.729, 0.0004) | 0.051   |
| Surgery                                       | -0.062 (-0.253, 0.129)  | 0.526   |
| Medicine                                      | 0.005 (-0.254, 0.263)   | 0.973   |
| Cognitive_psychology                          | 0.060 (-0.180, 0.300)   | 0.626   |
| Affect_psychotherapy                          | -0.518 (-0.811, -0.225) | 0.001   |
| Aggression                                    | 0.368 (0.044, 0.693)    | 0.027   |
| Psychology                                    | 0.761 (0.484, 1.038)     | 0.00000 |
| Psychiatry                                    | 0.067 (-0.111, 0.245)    | 0.461   |
| Cell_biology                                  | -0.502 (-0.679, -0.325) | 0.00000 |
| Transcriptome                                 | -0.381 (-0.697, -0.066) | 0.018   |
| Term                                | Coefficient (95% CI) | p-value |
|-------------------------------------|----------------------|---------|
| Molecular biology                   | -0.732 (-0.930, -0.534) | 0.000  |
| Carcinogenesis                      | 0.527 (0.140, 0.913)  | 0.008  |
| Biology                             | 0.136 (-0.139, 0.410) | 0.333  |
| Human sexuality                     | -0.518 (-1.019, -0.017) | 0.043  |
| Physical therapy                    | 0.200 (0.036, 0.364)  | 0.017  |
| Testosterone                        | -0.375 (-0.845, 0.094) | 0.018  |
| Psychotherapist                     | -0.334 (-0.724, 0.055) | 0.093  |
| Prostate cancer                     | -0.559 (-0.863, -0.256) | 0.0004 |
| Mood                                | -0.612 (-0.871, -0.352) | 0.0001 |
| Disease                             | 0.070 (-0.062, 0.201)  | 0.300  |
| Genetics                            | -0.596 (-0.777, -0.414) | 0.000  |
| Genome                              | -0.058 (-0.286, 0.170) | 0.620  |
| Randomized controlled trial         | 0.156 (0.008, 0.304)  | 0.039  |
| Quality of life                     | 0.055 (-0.210, 0.321)  | 0.683  |
| Comorbidity                         | 0.203 (-0.117, 0.522)  | 0.214  |
| Severity of illness                 | -0.475 (-0.978, 0.027) | 0.064  |
| Diabetes mellitus                   | -0.107 (-0.237, 0.023) | 0.107  |
| Prospective cohort study            | -0.299 (-0.472, -0.127) | 0.001  |
| Ideology                            | -0.788 (-1.214, -0.362) | 0.0003 |
| China                               | -0.138 (-0.497, 0.220) | 0.450  |
| Law                                 | -0.644 (-1.057, -0.231) | 0.003  |
| Sociology                           | 1.368 (0.983, 1.753)   | 0.000  |
| Environmental engineering           | 0.283 (-0.187, 0.754)  | 0.238  |
| Environmental resource management   | 0.264 (-0.038, 0.566)  | 0.087  |
| Economics                           | 0.857 (0.510, 1.204)   | 0.0001 |
| Climate change                      | -0.143 (-0.313, 0.027) | 0.100  |
| Population                          | -0.177 (-0.250, -0.104) | 0.0001 |
| Evolutionary biology                | 0.268 (-0.011, 0.547)  | 0.061  |
| Cell                                | 0.067 (-0.186, 0.319)  | 0.605  |
| Phylogenetics                       | -0.164 (-0.551, 0.223) | 0.407  |
| Ecology                             | 0.544 (0.370, 0.717)   | 0.000  |
| Taxon                               | 0.503 (0.032, 0.974)   | 0.037  |
| Biodiversity                        | 0.213 (-0.027, 0.453)  | 0.083  |
| Atmospheric sciences                | 0.745 (0.444, 1.046)   | 0.0001 |
| Environmental science               | 0.614 (0.300, 0.928)   | 0.0002 |
| Global warming                      | -0.322 (-0.539, -0.105) | 0.004 |
| Meteorology                         | -0.059 (-0.496, 0.378) | 0.792 |
| Pedagogy                            | -0.227 (-0.664, 0.210) | 0.309 |
| Social science                      | 0.075 (-0.342, 0.492)  | 0.725  |
| Social psychology                   | -0.050 (-0.208, 0.107) | 0.530  |
| Confidence interval                 | -0.214 (-0.402, -0.026) | 0.026 |
| Referral                            | 0.259 (-0.230, 0.749)  | 0.299  |
| Young adult                         | -0.131 (-0.309, 0.047) | 0.149  |
| Medical prescription                | 0.485 (0.215, 0.756)   | 0.0005 |
| Molecule                            | -0.331 (-0.714, 0.052) | 0.091  |
| Organic chemistry                   | -0.652 (-1.126, -0.178) | 0.007 |
| Materials science                   | 0.290 (-0.050, 0.630)  | 0.096  |
| Environmental health                | -0.172 (-0.361, 0.017) | 0.076  |
| Obesity                             | -0.276 (-0.479, -0.074) | 0.008 |

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| Entity                          | Coefficient | 95% Confidence Interval | p-value |
|--------------------------------|-------------|-------------------------|---------|
| Body_mass_index                | -0.161      | (-0.366, 0.044)         | 0.125   |
| Public_health                  | -0.291      | (-0.456, -0.127)        | 0.001   |
| Biochemistry                   | -0.853      | (-1.087, -0.620)        | 0.000   |
| Endocrinology                  | -0.471      | (-0.645, -0.297)        | 0.00000 |
| Internal_medicine              | 0.557       | (0.376, 0.737)          | 0.000   |
| Mitochondrion                  | -0.452      | (-0.859, -0.045)        | 0.030   |
| Democracy                      | -0.751      | (-1.304, -0.198)        | 0.008   |
| Political_economy              | 1.491       | (0.862, 2.119)          | 0.00001 |
| Public_administration           | 0.766       | (0.266, 1.266)          | 0.003   |
| Politics                       | 0.251       | (-0.008, 0.511)         | 0.058   |
| Public_opinion                 | -0.449      | (-0.991, 0.092)         | 0.104   |
| Gerontology                    | -0.548      | (-0.758, -0.339)        | 0.00000 |
| Cohort_study                   | -0.142      | (-0.299, 0.016)         | 0.078   |
| Lower_risk                     | -0.067      | (-0.421, 0.287)         | 0.709   |
| Developmental_psychology       | -0.022      | (-0.203, 0.159)         | 0.810   |
| Paleontology                   | 0.876       | (0.613, 1.140)          | 0.000   |
| Geology                        | 1.215       | (0.893, 1.537)          | 0.000   |
| Neuroscience                   | -0.511      | (-0.725, -0.297)        | 0.00001 |
| Biophysics                     | -0.243      | (-0.643, 0.156)         | 0.233   |
| RNA                            | 0.425       | (0.104, 0.745)          | 0.010   |
| Atomic_physics                 | 0.015       | (-0.489, 0.518)         | 0.955   |
| Physics                        | 0.757       | (0.406, 1.107)          | 0.00003 |
| Ion                            | -0.102      | (-0.554, 0.349)         | 0.657   |
| Photon                         | -0.210      | (-0.699, 0.279)         | 0.400   |
| Optics                         | 0.148       | (-0.206, 0.502)         | 0.412   |
| Climatology                    | 0.028       | (-0.244, 0.300)         | 0.840   |
| Geography                      | 0.901       | (0.560, 1.241)          | 0.00000 |
| Precipitation                  | -0.181      | (-0.487, 0.125)         | 0.248   |
| Chemical_engineering           | 0.142       | (-0.381, 0.665)         | 0.595   |
| Membrane                       | -0.093      | (-0.521, 0.336)         | 0.672   |
| Inorganic_chemistry            | -0.632      | (-0.962, -0.301)        | 0.00002 |
| Environmental_chemistry        | -0.943      | (-1.408, -0.478)        | 0.00001 |
| Psychological_resilience       | 0.383       | (-0.051, 0.816)         | 0.084   |
| Risk_assessment                | 0.433       | (0.125, 0.741)          | 0.006   |
| Cardiology                     | -0.189      | (-0.488, 0.109)         | 0.215   |
| Cause_of_death                 | -0.516      | (-0.826, -0.206)        | 0.002   |
| Atrial_fibrillation            | 0.270       | (-0.192, 0.732)         | 0.252   |
| Stimulus Physiology            | -0.047      | (-0.369, 0.274)         | 0.774   |
| Schizophrenia                  | -0.449      | (-0.814, -0.084)        | 0.016   |
| Neuroimaging                   | -0.151      | (-0.596, 0.293)         | 0.505   |
| Perception                     | 0.074       | (-0.162, 0.311)         | 0.539   |
| Intensive_care_medicine        | 0.286       | (0.039, 0.533)          | 0.024   |
| Nursing                        | 0.137       | (-0.123, 0.398)         | 0.301   |
| Developing_country             | 0.045       | (-0.362, 0.451)         | 0.830   |
| Health_care                    | -0.259      | (-0.412, -0.107)        | 0.001   |
| Drug                           | 0.313       | (0.018, 0.607)          | 0.038   |
| Distress                       | 0.260       | (-0.050, 0.569)         | 0.100   |
| Political_science              | 0.779       | (0.360, 1.197)          | 0.0003  |
| Prefrontal_cortex              | -0.467      | (-0.810, -0.124)        | 0.008   |
| Term                                      | Correlation | p Value |
|-------------------------------------------|-------------|---------|
| Social relation                          | 0.469       | 0.010   |
| Chromatin                                | -0.126      | 0.506   |
| Microbiology                             | -0.228      | 0.179   |
| Antimicrobial                            | -0.177      | 0.508   |
| Antibiotics                              | -0.373      | 0.059   |
| Pregnancy                                | -0.342      | 0.003   |
| Pathology                                | -0.295      | 0.173   |
| Applied psychology                       | 0.224       | 0.007   |
| Anxiety                                  | -0.572      | 0.000   |
| Radiology                                | -0.640      | 0.004   |
| Radiation therapy                        | 0.364       | 0.091   |
| Biopsy                                   | -0.552      | 0.017   |
| Chemotherapy                             | -0.361      | 0.051   |
| Multimedia                               | 1.214       | 0.0001  |
| Autism                                   | 0.100       | 0.538   |
| Socioeconomics                           | 0.721       | 0.00004 |
| Agriculture                              | 0.110       | 0.471   |
| Gynecology                               | -0.228      | 0.208   |
| Breast_cancer                            | 0.329       | 0.001   |
| Obstetrics                               | 0.667       | 0.0001  |
| Gestation                                | 0.329       | 0.162   |
| Pharmacology                             | -1.027      | 0.000   |
| Clinical_trial                           | -0.401      | 0.001   |
| Food_science                             | -0.936      | 0.00002 |
| Escherichia_coli                         | 0.177       | 0.496   |
| Agriculture                              | -0.411      | 0.021   |
| Photochemistry                           | -0.797      | 0.003   |
| Injury_prevention                        | 0.263       | 0.086   |
| Human_factors_and_ergonomics            | -0.345      | 0.042   |
| Suicide_prevention                       | -0.026      | 0.851   |
| Social_environment                       | -0.249      | 0.278   |
| Occupational_safety_and_health           | -0.413      | 0.009   |
| Heart_failure                            | -1.016      | 0.000   |
| Predation                                | 0.026       | 0.851   |
| In_vivo                                  | -0.703      | 0.00001 |
| CRISPR                                   | -0.010      | 0.958   |
| Crop                                     | 0.159       | 0.499   |
| Carbon                                   | -0.310      | 0.086   |
| Public_relations                         | -0.109      | 0.454   |
| Demography                               | 0.452       | 0.00000 |
| Dentistry                                | 1.135       | 0.012   |
| Logistic_regression                      | 0.852       | 0.000   |
| Health_equity                            | -0.299      | 0.135   |
| Medicaid                                 | 0.227       | 0.136   |
| Epidemiology                             | -0.195      | 0.046   |
| Threatened_species                       | 0.033       | 0.872   |
| Species richness                         | 0.109       | 0.619   |
| Harm                                     | 0.200       | 0.333   |
| Term                                      | Estimate (95% CI)       | p-value |
|-------------------------------------------|-------------------------|---------|
| Classical mechanics                       | -0.055 (-0.637, 0.528)  | 0.855   |
| Quantum mechanics                         | 0.290 (-0.238, 0.817)   | 0.282   |
| Odds_ratio                                | -0.160 (-0.327, 0.008)  | 0.062   |
| Homeostasis                               | -0.084 (-0.508, 0.341)  | 0.699   |
| Type_2_diabetes                           | 0.033 (-0.231, 0.297)   | 0.808   |
| Cohort                                    | -0.069 (-0.215, 0.077)  | 0.352   |
| Anatomy                                   | 0.047 (-0.247, 0.342)   | 0.754   |
| Interpersonal relationship                | -0.498 (-0.904, -0.092) | 0.017   |
| Norm_social                               | 0.065 (-0.408, 0.538)   | 0.788   |
| Crystallography                           | -0.368 (-0.993, 0.257)  | 0.249   |
| Physiology                                | 0.171 (-0.207, 0.549)   | 0.377   |
| Placebo                                   | 0.369 (0.169, 0.570)    | 0.0004  |
| MEDLINE                                   | -0.978 (-1.458, -0.498) | 0.0001  |
| Pediatrics                                | -0.158 (-0.355, 0.038)  | 0.115   |
| Adverse_effect                            | 0.139 (-0.076, 0.354)   | 0.207   |
| Transplantation                           | 0.136 (-0.126, 0.398)   | 0.309   |
| Dopamine                                  | -0.600 (-1.038, -0.161) | 0.008   |
| Embryonic_stem_cell                       | -0.478 (-0.871, -0.084) | 0.018   |
| Criminology                               | -0.033 (-0.620, 0.554)  | 0.913   |
| Astrophysics                              | -0.240 (-0.610, 0.130)  | 0.205   |
| Astronomy                                 | 0.933 (0.613, 1.253)    | 0.000   |
| Condensed_matter_physics                  | -0.892 (-1.207, -0.576) | 0.00000 |
| Optoelectronics                           | -0.614 (-0.939, -0.289) | 0.0003  |
| Molecular_physics                         | -0.015 (-0.517, 0.488)  | 0.955   |
| Nanotechnology                            | -0.646 (-0.940, -0.353) | 0.0002  |
| Crystal                                   | 0.112 (-0.359, 0.582)   | 0.642   |
| Animal_science                            | 0.497 (-0.014, 1.009)   | 0.057   |
| Sediment                                  | 0.170 (-0.264, 0.604)   | 0.443   |
| Melanoma                                  | -0.258 (-0.663, 0.146)  | 0.211   |
| Cell_culture                              | -0.011 (-0.443, 0.421)  | 0.961   |
| Electronic_engineering                    | -0.178 (-0.663, 0.307)  | 0.472   |
| Odds                                      | 0.511 (0.208, 0.813)    | 0.001   |
| Overweight                                | 0.039 (-0.210, 0.288)   | 0.759   |
| Confounding                               | 0.870 (0.521, 1.220)    | 0.00001 |
| Communication                             | 0.117 (-0.211, 0.444)   | 0.486   |
| Child_development                         | -0.062 (-0.465, 0.340)  | 0.762   |
| Psychological_intervention                | 0.081 (-0.087, 0.249)   | 0.343   |
| Gene                                      | -0.721 (-0.917, -0.525) | 0.000   |
| Management_science                        | 0.092 (-0.559, 0.743)   | 0.782   |
| Offspring                                 | 0.135 (-0.147, 0.418)   | 0.348   |
| Epigenetics                               | -0.669 (-1.030, -0.308) | 0.0003  |
| Mental_health                             | 0.473 (0.286, 0.659)    | 0.00000 |
| Well_being                                | -0.193 (-0.574, 0.188)  | 0.321   |
| Immigration                               | 0.539 (0.084, 0.993)    | 0.021   |
| Coping_psychology                          | -0.076 (-0.583, 0.431)  | 0.769   |
| Physical_exercise                         | 0.606 (0.042, 1.170)    | 0.036   |
| Personality                               | -0.199 (-0.509, 0.110)  | 0.207   |
| Particle_physics                          | -0.846 (-1.670, -0.021) | 0.045   |
| Alternative_medicine                      | -0.459 (-0.799, -0.119) | 0.009   |
| Category                             | Correlation Coefficient | p-value   |
|-------------------------------------|-------------------------|-----------|
| Immunology                          | -0.499 (-0.684, -0.313) | 0.00000   |
| Big_Five_personality_traits        | -0.217 (-0.640, 0.205)  | 0.313     |
| PsyCNINFO                           | -0.294 (-0.946, 0.357)  | 0.376     |
| Happiness                           | -0.104 (-0.422, 0.214)  | 0.522     |
| Extinction                          | -0.358 (-0.622, -0.093) | 0.009     |
| Environmental_protection            | -0.728 (-1.107, -0.349) | 0.00002   |
| Land_use                            | 0.323 (-0.128, 0.774)   | 0.161     |
| Agroforestry                        | -0.180 (-0.613, 0.252)  | 0.414     |
| Vegetation                          | 1.243 (0.831, 1.654)    | 0.000     |
| Habitat                             | 0.110 (-0.165, 0.386)   | 0.433     |
| Ecosystem                           | 0.190 (-0.053, 0.433)   | 0.125     |
| Mineralogy                          | -0.607 (-1.118, -0.096) | 0.020     |
| Geochemistry                        | 1.164 (0.726, 1.603)    | 0.00000   |
| Economic_growth                     | 0.219 (-0.137, 0.576)   | 0.229     |
| Vaccination                         | 0.305 (0.046, 0.563)    | 0.022     |
| Recall                              | 0.035 (-0.399, 0.470)   | 0.873     |
| Working_memory                      | 0.620 (0.217, 1.023)    | 0.003     |
| Radiation                           | -0.353 (-0.645, -0.062) | 0.018     |
| Atmosphere                          | 0.294 (-0.021, 0.608)   | 0.068     |
| Vulnerability                       | -0.656 (-1.083, -0.229) | 0.003     |
| Catalysis                           | -0.315 (-0.723, 0.092)  | 0.130     |
| Anesthesia                          | -0.522 (-0.791, -0.253) | 0.00002   |
| Toxicology                          | -1.432 (-1.933, -0.932) | 0.00000   |
| Cannabis                            | -0.118 (-0.433, 0.198)  | 0.465     |
| Government                          | 0.042 (-0.250, 0.333)   | 0.781     |
| European_union                      | -0.291 (-0.688, 0.107)  | 0.152     |
| Risk_factor                         | 0.120 (-0.080, 0.319)   | 0.239     |
| Systematic_review                   | -0.870 (-1.310, -0.430) | 0.00002   |
| General_surgery                     | 0.524 (0.076, 0.971)    | 0.022     |
| Clinical_endpoint                   | -0.738 (-1.043, -0.433) | 0.00001   |
| Lung_cancer                         | -0.223 (-0.563, 0.116)  | 0.198     |
| Polymer                             | -0.024 (-0.396, 0.347)  | 0.898     |
| Geophysics                          | 1.045 (0.691, 1.398)    | 0.000     |
| Geomorphology                       | 0.798 (0.472, 1.124)    | 0.00001   |
| Advertising                         | -0.035 (-0.499, 0.430)  | 0.885     |
| Cross_sectional_study               | -0.194 (-0.460, 0.071)  | 0.152     |
| Interquartile_range                 | -0.156 (-0.470, 0.158)  | 0.330     |
| Weight_loss                         | -0.356 (-0.610, -0.102) | 0.006     |
| Health_promotion                    | 0.141 (-0.325, 0.608)   | 0.553     |
| Academic_achievement                | 0.273 (-0.182, 0.728)   | 0.240     |
| Finance                             | 0.283 (-0.261, 0.827)   | 0.309     |
| Chronic_pain                        | -0.132 (-0.508, 0.244)  | 0.493     |
| Immune_system                       | -0.235 (-0.452, -0.018) | 0.034     |
| T_cell                              | 0.056 (-0.292, 0.403)   | 0.754     |
| Immunity                            | 0.191 (-0.201, 0.583)   | 0.341     |
| Virology                            | -1.108 (-1.365, -0.851) | 0.000     |
| Dementia                            | -0.459 (-0.730, -0.187) | 0.001     |
| Alzheimer_s_disease                 | 0.052 (-0.369, 0.474)   | 0.809     |
| Socioeconomic_status                | -0.053 (-0.296, 0.189)  | 0.668     |
| Term                              | Value                          | p_value |
|----------------------------------|-------------------------------|--------|
| Allele                           | 0.071 (−0.299, 0.441)         | 0.706  |
| Insulin                          | −0.192 (−0.491, 0.106)        | 0.207  |
| Hormone                          | −0.251 (−0.689, 0.188)        | 0.263  |
| Evidence_based_medicine          | 1.052 (0.502, 1.602)          | 0.002  |
| Meta_analysis                    | −0.676 (−0.913, −0.438)       | 0.0000 |
| Medical_emergency               | −0.561 (−0.851, −0.272)       | 0.002  |
| Zoology                          | 0.113 (−0.165, 0.391)         | 0.427  |
| Actuarial_science                | −1.394 (−1.893, −0.895)       | 0.0000 |
| Hydrology                        | 0.192 (−0.601, 0.984)         | 0.636  |
| Functional_magnetic_resonance_imaging | 0.870 (0.434, 1.305)     | 0.001  |
| Electroencephalography           | −0.017 (−0.502, 0.469)        | 0.947  |
| Machine_learning                 | −0.758 (−1.268, −0.249)       | 0.004  |
| Artificial_intelligence          | 0.666 (−0.077, 1.409)         | 0.079  |
| Clinical_psychology              | −0.245 (−0.452, −0.038)       | 0.021  |
| Nanoparticle                     | −0.285 (−0.655, 0.085)        | 0.131  |
| Laser                            | −0.138 (−0.517, 0.241)        | 0.476  |
| Ethnic_group                     | 0.552 (0.285, 0.819)          | 0.0001 |
| Cancer                           | −0.254 (−0.404, −0.105)       | 0.001  |
| Magnetic_field                   | 0.353 (−0.074, 0.780)         | 0.106  |
| Antigen                          | 0.125 (−0.234, 0.485)         | 0.495  |
| Antibody                         | 0.054 (−0.264, 0.372)         | 0.739  |
| Seismology                       | −0.344 (−0.893, 0.205)        | 0.219  |
| Addiction                        | 0.054 (−0.290, 0.398)         | 0.758  |
| Vitamin_D_and_neurology          | −0.016 (−0.447, 0.416)        | 0.943  |
| Athletes                         | 0.797 (0.335, 1.259)          | 0.001  |
| Marketing                        | 0.414 (−0.033, 0.860)         | 0.070  |
| Receptor                         | −0.365 (−0.626, −0.105)       | 0.007  |
| Social_support                   | −0.886 (−1.227, −0.546)       | 0.0000 |
| Sleep_deprivation                | −0.302 (−0.644, 0.039)        | 0.084  |
| Microeconomics                   | 0.258 (−0.230, 0.746)         | 0.300  |
| Legislation                      | −0.489 (−1.018, 0.039)        | 0.070  |
| Transcription_factor             | 0.104 (−0.207, 0.414)         | 0.512  |
| Fertility                        | −0.675 (−1.062, −0.289)       | 0.001  |
| Dermatology                      | −0.237 (−0.882, 0.409)        | 0.473  |
| Pathogenesis                     | −0.614 (−1.040, −0.189)       | 0.005  |
| Apoptosis                        | −0.845 (−1.302, −0.388)       | 0.0003 |
| Proinflammatory_cytokine         | 0.205 (−0.193, 0.604)         | 0.313  |
| Ovarian_cancer                   | −0.150 (−0.663, 0.364)        | 0.568  |
| Stem_cell                        | −0.236 (−0.502, 0.031)        | 0.083  |
| Multivariate_analysis            | −0.424 (−0.930, 0.083)        | 0.102  |
| Fishery                          | 1.242 (0.877, 1.608)          | 0.000  |
| Mortality_rate                   | −0.482 (−0.707, −0.257)       | 0.00003|
| Virulence                        | −0.808 (−1.313, −0.303)       | 0.002  |
| Malaria                          | −1.124 (−1.628, −0.619)       | 0.00002|
| Knowledge_management             | −0.169 (−0.819, 0.481)        | 0.611  |
| Analytical_chemistry             | −0.851 (−1.248, −0.455)       | 0.00003|
| Graphene                         | −0.396 (−0.742, −0.051)       | 0.025  |
| Semiconductor                    | −0.422 (−0.932, 0.088)        | 0.106  |
| Coronary_artery_disease          | 0.056 (−0.356, 0.468)         | 0.791  |
Heart disease  $-0.135 (-0.429, 0.158)$  $p = 0.366$
Cholesterol  $-0.212 (-0.607, 0.182)$  $p = 0.292$
Veterinary medicine  $-0.432 (-1.216, 0.352)$  $p = 0.281$
Engineering  $0.074 (-0.418, 0.566)$  $p = 0.768$
Biomarker medicine  $0.185 (-0.100, 0.470)$  $p = 0.204$
Electron  $-0.182 (-0.602, 0.238)$  $p = 0.397$
Microbiome  $-0.630 (-0.903, -0.358)$  $p = 0.00001$
Gut flora  $-0.317 (-0.657, 0.024)$  $p = 0.069$
Physical medicine, and rehabilitation  $-0.165 (-0.615, 0.286)$  $p = 0.474$
Stroke  $-0.079 (-0.312, 0.154)$  $p = 0.509$
Bioinformatics  $-0.910 (-1.238, -0.582)$  $p = 0.00000$
Arctic  $-0.060 (-0.377, 0.258)$  $p = 0.714$
Poverty  $-0.235 (-0.587, 0.117)$  $p = 0.191$
Exoplanet  $-0.065 (-0.518, 0.388)$  $p = 0.780$
Planet  $0.669 (0.333, 1.005)$  $p = 0.0001$
Stars  $0.173 (-0.219, 0.565)$  $p = 0.388$
Foraging  $0.330 (-0.010, 0.670)$  $p = 0.058$
National Health Nutrition Examination  $0.154 (-0.171, 0.479)$  $p = 0.354$
Urine  $0.126 (-0.416, 0.667)$  $p = 0.649$
Hazard ratio  $0.501 (0.322, 0.680)$  $p = 0.00000$
Observational study  $-0.178 (-0.455, 0.099)$  $p = 0.207$
Proportional hazards model  $-0.031 (-0.287, 0.225)$  $p = 0.813$
Inflammation  $-0.253 (-0.522, 0.016)$  $p = 0.065$
Kidney disease  $-0.307 (-0.765, 0.152)$  $p = 0.190$
Gastroenterology  $0.372 (-0.015, 0.759)$  $p = 0.060$
Text mining  $0.261 (-0.500, 1.021)$  $p = 0.502$
Locus genetics  $0.311 (-0.070, 0.693)$  $p = 0.110$
Genome wide association study  $-0.789 (-1.160, -0.418)$  $p = 0.00004$
Urology  $0.591 (-0.042, 1.223)$  $p = 0.068$
Ranging  $-0.206 (-0.481, 0.069)$  $p = 0.142$
Survival rate  $0.142 (-0.336, 0.621)$  $p = 0.560$
Incentive  $0.212 (-0.021, 0.633)$  $p = 0.325$
Phenomenon  $-0.135 (-0.410, 0.140)$  $p = 0.338$
Statistics  $-0.503 (-1.148, 0.142)$  $p = 0.127$
Longitudinal study  $0.157 (-0.096, 0.409)$  $p = 0.225$
Brain mapping  $0.194 (-0.668, 0.281)$  $p = 0.424$
Metabolic syndrome  $-0.816 (-1.221, -0.411)$  $p = 0.0001$
Agronomy  $-0.921 (-1.407, -0.434)$  $p = 0.0003$
Asthma  $0.495 (0.160, 0.830)$  $p = 0.004$
Relative risk  $0.378 (0.157, 0.599)$  $p = 0.001$
Breastfeeding  $-0.168 (-0.593, 0.257)$  $p = 0.439$
Endangered species  $0.199 (-0.234, 0.633)$  $p = 0.368$
Climate model  $0.095 (-0.211, 0.400)$  $p = 0.544$
Social perception  $-0.063 (-0.516, 0.390)$  $p = 0.785$
Social media  $0.429 (0.121, 0.736)$  $p = 0.007$
Social network  $-0.129 (-0.437, 0.179)$  $p = 0.413$
Business  $0.973 (0.550, 1.396)$  $p = 0.00001$
Etiology  $-0.224 (-0.834, 0.386)$  $p = 0.472$
Mesenchymal stem cell  $-0.275 (-0.736, 0.185)$  $p = 0.241$
| Category                          | Estimate (95% CI)         | p-value |
|----------------------------------|---------------------------|---------|
| Weight gain                      | -0.057 (-0.384, 0.270)    | 0.733   |
| Mathematics                      | 1.821 (1.257, 2.385)      | 0.000   |
| Nicotine                         | -0.762 (-1.206, -0.318)  | 0.001   |
| Emergency_department             | -0.630 (-0.915, -0.345)  | 0.00002 |
| Myocardial_infarction            | -0.114 (-0.392, 0.163)   | 0.420   |
| Emergency_medicine               | 0.311 (0.018, 0.604)      | 0.038   |
| Labour_economics                 | -0.161 (-0.574, 0.252)   | 0.445   |
| Health_policy                    | -0.405 (-0.767, -0.043)  | 0.029   |
| Qualitative_research             | -0.133 (-0.612, 0.346)   | 0.586   |
| Guideline                        | -0.746 (-1.102, -0.389)  | 0.00005 |
| Wildlife                         | 0.725 (0.352, 1.098)      | 0.000   |
| Family_medicine                  | -0.481 (-0.683, -0.280)  | 0.00001 |
| Regulation_of_gene_expression    | -0.545 (-0.927, -0.163)  | 0.006   |
| Cellular_differentiation         | -0.100 (-0.455, 0.255)   | 0.581   |
| microRNA                         | -0.400 (-0.909, 0.110)   | 0.125   |
| Downregulation_and_upregulation  | -0.266 (-0.675, 0.143)   | 0.204   |
| Computer_science                 | 0.519 (0.161, 0.877)      | 0.005   |
| Developed_country                | -0.223 (-0.742, 0.297)   | 0.402   |
| Demographic_economics            | -0.176 (-0.580, 0.228)   | 0.393   |
| Colorectal_cancer                | 0.057 (-0.265, 0.379)    | 0.728   |
| Nutrient                         | -0.441 (-0.962, 0.079)   | 0.097   |
| Mutant                           | -0.266 (-0.647, 0.115)   | 0.171   |
| Cancer_research                  | -0.723 (-0.943, -0.503)  | 0.000   |
| Allergy                          | 0.086 (-0.419, 0.590)    | 0.740   |
| Biological_dispersal             | 0.182 (-0.179, 0.542)    | 0.324   |
| Magnetic_resonance_imaging       | -0.330 (-0.751, 0.091)   | 0.125   |
| Transmission_mechanics_          | 0.095 (-0.413, 0.603)    | 0.714   |
| Retrospective_cohort_study       | 0.319 (0.095, 0.542)     | 0.006   |
| Metastasis                       | -0.376 (-0.726, -0.025)  | 0.036   |
| Feeling                          | 0.058 (-0.252, 0.369)    | 0.712   |
| Metabolism                       | -0.834 (-1.386, -0.282)  | 0.004   |
| Signal_transduction              | -0.505 (-0.802, -0.208)  | 0.001   |
| Traumatic_brain_injury           | -0.619 (-1.136, -0.101)  | 0.020   |
| Genomics                         | -0.667 (-1.063, -0.272)  | 0.001   |
| DNA_methylation                  | 0.027 (-0.374, 0.429)    | 0.895   |
| Oncology                         | -0.364 (-0.634, -0.094)  | 0.009   |
| Mutation                         | -0.096 (-0.357, 0.165)   | 0.472   |
| Phenotype                        | -0.031 (-0.347, 0.285)   | 0.846   |
| Smoking_cessation                | 0.410 (0.050, 0.770)     | 0.026   |
| Black_hole                       | 1.086 (0.673, 1.500)     | 0.00000 |
| Air_pollution                    | -0.420 (-0.798, -0.042)  | 0.030   |
| Hippocampus                      | -0.569 (-0.970, -0.167)  | 0.006   |
| Biotechnology                    | -1.509 (-2.080, -0.937)  | 0.00000 |
| Biomass                          | -0.874 (-1.326, -0.421)  | 0.0002  |
| Volcano                          | -0.189 (-0.630, 0.251)   | 0.400   |
| Longevity                        | -0.587 (-1.000, -0.174)  | 0.006   |
| Empathy                          | -0.445 (-0.863, -0.028)  | 0.037   |
| Psychosocial                     | 0.089 (-0.195, 0.374)    | 0.539   |
| Greenhouse_gas                   | -0.115 (-0.378, 0.149)   | 0.394   |
| Term                                   | Coefficient | 95% CI       | P       |
|----------------------------------------|-------------|--------------|---------|
| Focus_group                            | 0.716       | (0.140, 1.291) | 0.015   |
| Regimen                                | 0.461       | (−0.011, 0.932) | 0.056   |
| Fetus                                  | −0.374      | (−0.788, 0.040) | 0.077   |
| Computer_vision                        | −0.255      | (−0.742, 0.231) | 0.304   |
| Computational_biology                  | −0.407      | (−0.803, −0.011) | 0.044   |
| Gene_expression                        | 0.597       | (0.272, 0.921) | 0.0004  |
| DNA                                    | −0.202      | (−0.520, 0.117) | 0.215   |
| Nuclear_magnetic_resonance             | −0.836      | (−1.355, −0.318) | 0.002   |
| Solar_System                           | 0.572       | (0.225, 0.918) | 0.002   |
| Astrobiology                           | 0.001       | (−0.334, 0.336) | 0.995   |
| Audiology                              | 0.088       | (−0.290, 0.466) | 0.648   |
| Circadian_rhythm                       | −0.312      | (−0.604, −0.019) | 0.037   |
| Rehabilitation                         | −1.482      | (−2.004, −0.960) | 0.0000  |
| Toxicity                               | −0.385      | (−0.895, 0.124) | 0.139   |
| Global_health                           | −0.045      | (−0.397, 0.307) | 0.802   |
| Reproductive_health                    | −0.443      | (−0.904, 0.019) | 0.061   |
| Neurodegeneration                      | −0.506      | (−0.909, −0.102) | 0.015   |
| Galaxy                                 | 0.195       | (−0.101, 0.492) | 0.198   |
| Virus                                  | 0.079       | (−0.214, 0.372) | 0.596   |
| InnateImmune_system                    | −0.585      | (−0.976, −0.195) | 0.004   |
| Early_childhood                        | −0.168      | (−0.604, 0.268) | 0.450   |
| Amygdala                               | −0.040      | (−0.446, 0.366) | 0.847   |
| Vitamin                                | −0.765      | (−1.299, −0.232) | 0.005   |
| Adipose_tissue                         | −0.591      | (−0.962, −0.219) | 0.002   |
| Architecture                           | −0.146      | (−0.520, 0.228) | 0.445   |
| Data_mining                            | −0.758      | (−1.352, −0.164) | 0.013   |
| Quantum                                | −0.685      | (−1.169, −0.202) | 0.006   |
| Blood_pressure                         | −0.104      | (−0.380, 0.172) | 0.460   |
| Waste_management                       | −0.122      | (−0.577, 0.334) | 0.601   |
| Sustainability                         | −0.121      | (−0.502, 0.261) | 0.535   |
| Incidence_epidemiology                 | 0.617       | (0.307, 0.928) | 0.0001  |
| Substance_abuse                        | −0.326      | (−0.666, 0.014) | 0.061   |
| In_vitro                               | −0.290      | (−0.786, 0.206) | 0.252   |
| The_Internet                           | −0.581      | (−0.923, −0.239) | 0.001   |
| Attention_deficit_hyperactivity_disorder| −0.709     | (−1.117, −0.301) | 0.001   |
| Opioid                                 | −0.497      | (−0.821, −0.174) | 0.003   |
| DNA_damage                             | 0.421       | (−0.048, 0.889) | 0.079   |
| Visual_perception                      | −0.011      | (−0.465, 0.444) | 0.964   |
| Sensory_system                         | −0.391      | (−0.722, −0.061) | 0.021   |
| Genotype                               | 0.055       | (−0.425, 0.535) | 0.824   |
| Antibiotic_resistance                  | −0.190      | (−0.665, 0.285) | 0.434   |
| Multiple_sclerosis                     | 0.170       | (−0.389, 0.728) | 0.552   |
| Case_control_study                     | −0.046      | (−0.431, 0.338) | 0.814   |
| Single_nucleotide_pseudopolymorphism   | −0.305      | (−0.798, 0.189) | 0.227   |
| Cancer_cell                            | −0.120      | (−0.455, 0.214) | 0.481   |
| Trait                                  | 0.799       | (0.280, 1.317) | 0.003   |
| Empirical_research                     | −0.006      | (−0.454, 0.441) | 0.978   |
| Simulation                             | 0.851       | (0.267, 1.436) | 0.005   |
| Oxidative_stress                       | 0.237       | (−0.199, 0.673) | 0.287   |
Antioxidant $-0.877 (-1.576, -0.177)$ $p = 0.015$
Progenitor_cell $-0.495 (-0.847, -0.142)$ $p = 0.006$
Lung $-0.218 (-0.623, 0.187)$ $p = 0.293$
Oceanography 0.444 (0.118, 0.769) $p = 0.008$
Immunotherapy 0.307 (-0.077, 0.691) $p = 0.117$
Cytokine $-0.442 (-0.857, -0.026)$ $p = 0.038$
Kinase $-0.423 (-0.903, 0.058)$ $p = 0.085$
Development_economics 0.081 (-0.411, 0.573) $p = 0.748$
Cell_type $-0.070 (-0.488, 0.348)$ $p = 0.742$
Social_cognition $-0.457 (-0.803, -0.111)$ $p = 0.010$
Major_depressive_disorder $-0.812 (-1.183, -0.440)$ $p = 0.00002$
Hippocampal_formation 0.186 (-0.281, 0.653) $p = 0.435$
Central_nervous_system $-0.802 (-1.295, -0.310)$ $p = 0.002$
Medical_record 0.497 (0.054, 0.939) $p = 0.029$
Psychopathology 0.504 (0.092, 0.915) $p = 0.017$
Skeletal_muscle $-0.508 (-0.931, -0.086)$ $p = 0.019$
Transcription_biology_1.776 (1.309, 2.243) $p = 0.000$
Ecosystem_services $-0.801 (-1.155, -0.447)$ $p = 0.00001$
Heart_rate $-0.074 (-0.651, 0.503)$ $p = 0.803$
Outbreak $-0.378 (-0.692, -0.064)$ $p = 0.019$
Phylogenetic_tree 0.504 (0.092, 0.915) $p = 0.017$
Enzyme $-0.309 (-0.775, 0.158)$ $p = 0.195$
Genetic_variation 0.049 (-0.328, 0.425) $p = 0.801$
Psychosis 0.625 (0.085, 1.166) $p = 0.024$
Pathogen 0.924 (0.450, 1.398) $p = 0.0002$
History 1.167 (0.284, 2.050) $p = 0.010$
Atom $-0.863 (-1.312, -0.414)$ $p = 0.0002$
Arousal 0.004 (-0.467, 0.474) $p = 0.987$
Remote_sensing $-0.800 (-1.629, 0.029)$ $p = 0.059$
Crossover_study 0.180 (-0.347, 0.706) $p = 0.504$
Programmed_cell_death 1.163 (0.707, 1.619) $p = 0.00000$
Human_brain 0.596 (0.191, 1.001) $p = 0.004$
Stimulation $-0.573 (-0.930, -0.216)$ $p = 0.002$
Scattering $-0.072 (-0.548, 0.403)$ $p = 0.766$
Antidepressant $-0.437 (-0.993, 0.120)$ $p = 0.124$
Population_study 0.015 (-0.411, 0.442) $p = 0.944$
Corporate_governance $-0.264 (-0.889, 0.362)$ $p = 0.409$
Interpersonal_communication 1.040 (0.596, 1.484) $p = 0.00001$
Osteoporosis $-0.206 (-0.828, 0.415)$ $p = 0.516$
Alcohol $-0.232 (-0.756, 0.293)$ $p = 0.387$
Biomedical_engineering $-1.278 (-1.815, -0.742)$ $p = 0.00001$
Induced_pluripotent_stem_cell $-0.118 (-0.463, 0.227)$ $p = 0.504$
Insulin_resistance $-0.456 (-0.812, -0.100)$ $p = 0.012$
Autism_spectrum_disorder $-0.707 (-1.068, -0.346)$ $p = 0.0002$
Mindfulness $-0.487 (-0.988, 0.014)$ $p = 0.057$
Cretaceous 1.414 (0.997, 1.830) $p = 0.000$
Spectroscopy 0.301 (-0.197, 0.800) $p = 0.237$
Prosocial_behavior $-0.183 (-0.564, 0.198)$ $p = 0.346$
Computer_security 0.470 (-0.176, 1.116) $p = 0.154$

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| Variable              | Coefficient | 95% Confidence Interval | p-value |
|-----------------------|-------------|-------------------------|---------|
| Gestational age       | -0.108      | (-0.522, 0.305)         | 0.607   |
| Archaeology           | 1.034       | (0.628, 1.440)          | 0.0000  |
| Welfare               | -0.234      | (-0.747, 0.279)         | 0.372   |
| Mental illness        | -0.267      | (-0.680, 0.146)         | 0.205   |
| Phosphorylation       | -0.401      | (-0.871, 0.068)         | 0.094   |
| Life expectancy       | -0.080      | (-0.428, 0.268)         | 0.654   |
| Spin half             | -0.153      | (-0.541, 0.235)         | 0.440   |
| Thin film             | -0.398      | (-0.902, 0.105)         | 0.122   |
| Narrative             | 0.103       | (-0.394, 0.600)         | 0.685   |
| Gender studies        | 0.123       | (-0.418, 0.663)         | 0.657   |
| Public policy         | -0.142      | (-0.560, 0.276)         | 0.506   |
| Epilepsy              | -0.140      | (-0.605, 0.325)         | 0.555   |
| Metal                 | -0.135      | (-0.666, 0.397)         | 0.620   |
| Instability           | -0.341      | (-0.759, 0.076)         | 0.109   |
| Particle              | -0.424      | (-0.935, 0.087)         | 0.104   |
| Spectral line         | 0.236       | (-0.300, 0.773)         | 0.388   |
| Cell growth           | -0.568      | (-0.984, -0.153)        | 0.008   |
| Cytotoxic T cell      | -0.098      | (-0.518, 0.322)         | 0.648   |
| Cycling               | 0.037       | (-0.457, 0.531)         | 0.884   |
| Intracellular         | 0.453       | (-0.048, 0.955)         | 0.077   |
| Ageing                | -0.001      | (-0.474, 0.472)         | 0.998   |
| Bipolar disorder      | -0.672      | (-1.113, -0.230)        | 0.003   |
| Meal                  | -0.583      | (-1.132, -0.034)        | 0.038   |
| Ingestion             | 0.931       | (0.443, 1.419)          | 0.0002  |
| DNA sequencing        | -0.542      | (-1.055, -0.029)        | 0.039   |
| Amino acid            | -0.373      | (-0.854, 0.108)         | 0.129   |
| Constant              | 1.525       | (1.177, 1.873)          | 0.000   |

Observations: 285,708
Log Likelihood: -114,476.700
Akaike Inf. Crit.: 230,167.500
Bayesian Inf. Crit.: 236,579.100