Who does big team science?

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Abstract

This paper examined the nature of publications in Big Team Science (BTS) - large-scale collaborations between multiple researchers at multiple institutions. As interest in BTS increases, it is useful to explore who is currently involved in BTS projects to determine diversity in both research subject and researcher representation. The types of publication outlets, number of publications, and subject areas of publication are presented to summarize the publications in BTS. Information about authors included in BTS will be presented including career length, numbers of publications/impact variables, education, and affiliation. Last, we will explore the representation of geopolitical regions by examining affiliation location to explore the impact of BTS on the de-WEIRD movement to diversify researcher representation. REWRITE THIS

Keywords: big team, science, authorship, credit

Who does big team science?

According to the Oxford English dictionary, collaboration is two or more people working together to achieve a certain goal (OED, 2016). Collaboration in scientific endeavors involves multiple researchers at (potentially) multiple institutions to communicate and work together to advance knowledge in their chosen field. Collaboration can manifest uniquely in each project dependent on the skill sets, hypotheses, and perspectives of collaborators. While collaboration is not new in science, the current interest of "big team science" is increasing (Coles, Hamlin, Sullivan, Parker, & Altschul, 2022; Forscher et al., 2020; N. Stewart, Chandler, & Paolacci, 2017). Big team science projects and/or organizations utilize and run on large-scale collaboration to ensure that diverse populations and ideas are brought into research projects, which in turn allows for more reliability and generalizability in the results and method of the study. For this study, Big Team Science (BTS) will be defined as a collaboration of ten or more authors from at least ten different institutions.

BTS appears to be increasing as a result of two sources: 1) increasing globalization and technology that allows for real-time interdisciplinary research, and 2) increasing interest in reproducibility, replication, and generalizability (Maxwell, Lau, & Howard, 2015; Nelson, Simmons, & Simonsohn, 2018; Zwaan, Etz, Lucas, & Donnellan, 2018). Technological advances have provided easier ways to collaborate with people who are from other universities and countries through document sharing platforms (e.g., Google, GitHub, and the Open Science Framework), video chatting platforms (e.g., Zoom, Microsoft Teams), and messaging and project management platforms (e.g., Slack, Trello, when2meet, etc.). The credibility movement seems to suggest that by having both collaborations that span across the globe and subfields of research areas, age groups, and education levels should help to drive science in the path of better materials, reliability, generalizability and more robust sample sizes (when necessary) in a study (Auspurg & Brüderl, 2021; LeBel, McCarthy, Earp, Elson, & Vanpaemel, 2018; Brian A. Nosek & Lakens, 2014a).

The credibility movement was originally defined by a focus on large scale replications using in collaborative environments (Vazire, Schiavone, & Bottesini, 2022). Generally, the movement appears to have been driven by early career researchers (i.e., those who are within five years of their first appointment) (Maizey & Tzavella, 2019); however, there are no large meta-scientific investigations on this specific topic to date. Potentially, the lack of investigation is tied to the newness of the large-scale research in many fields, as it is only in recent years that publications like the Open Science Collaboration (Open Science Collaboration, 2015), Many Labs Collaborations (Buttrick et al., 2020; Ebersole et al., 2016, 2020; Richard A. Klein et al., 2022; for example, Richard A. Klein et al., 2018; Mathur et al., 2020; Skorb et al., 2020) or the first papers from the Psychological Science Accelerator (Bago et al., 2022; Dorison et al., 2022; Jones et al., 2021; Legate et al., 2022; Moshontz et al., 2018; Wang et al., 2021). Generally, the researcher incentive for replication was low: journals often prioritize "novel" or new results which led to rejection of replication manuscripts and publication bias (Franco, Malhotra, & Simonovits, 2014; Hubbard & Armstrong, 1997; Brian A. Nosek, Spies, & Motyl, 2012), the "failure" to replicate was often placed on the replication team as "bad science" rather than a careful consideration of publication biases and (potential) questionable research practices (Ioannidis, 2015; Richard A. Klein et al., 2022; Maxwell et al., 2015), and why should someone want to spend time and resources on an answer we already "know" (Isager et al., 2021a, 2021b)?

However, the success and interest in the large-scale reproducibility projects (Errington et al., 2021; Open Science Collaboration, 2015), paired with the meta-scientific publications focusing on researcher practices and incentive structures (John, Loewenstein, & Prelec, 2012; Silberzahn et al., 2018) led to a change in journal guidelines and incentives for researchers interested in participating in large-scale replication studies (Grahe, 2014; Kidwell et al., 2016; Mayo-Wilson et al., 2021; B. A. Nosek et al., 2015). For example, the support for Registered Reports, papers accepted before the data has been collected (Brian A. Nosek & Lakens, 2014b; S. Stewart et al., 2020), and entire sub-sections of journals devoted to only replication studies (e.g., *Nature, Royal Society Open Science, Advances in Methods and Practices in Psychological Science*) has allowed researchers to invest in projects that they know should be published when the project is complete. Further, the implementation of the Transparency and Openness Guidelines (B. A. Nosek et al., 2015) and the Contributor Role Taxonomy (CRediT) system (Allen, O'Connell, & Kiermer, 2019) have pushed journals and researchers to promote more open, inclusive publication practices.

The credibility movement has been mirrored by the calls for diversification or de-WEIRDing (e.g., Western, Educated, Industrialized, Rich, and Democratic) scientific research (Henrich, Heine, & Norenzayan, 2010; Newson, Buhrmester, Xygalatas, & Whitehouse, 2021; Rad, Martingano, & Ginges, 2018) by improving representation in research samples. Like the large-scale studies in Physics ("A Philosophical Case for Big Physics," 2021; Castelnovo, Florio, Forte, Rossi, & Sirtori, 2018) and Biology (Collins, Morgan, & Patrinos, 2003), the social sciences struggle to represent the breadth of humanity across both researcher and population characteristics. Now, grassroots organizations, such as the Psychological Science Accelerator (Moshontz et al., 2018), ManyBabies (https://manybabies.github.io/), NutNet (https://nutnet.org/), and DRAGNet (https://dragnetglobal.weebly.com/) can begin to tackle these issues by recruiting research labs from all over the globe to provide diversity in geographic, linguistic, and researcher representation. Publications have examined the global understanding of morality, face processing, COVID-19 information signaling, and more (Bago et al., 2022; Dorison et al., 2022; Jones et al., 2021; Legate et al., 2022; Van Bavel et al., 2022; Wang et al., 2021). While these organizations and one-time groups for BTS studies have provided an incredible wealth of data for the scientific community, we do not yet know exactly *who* is involved with, and benefits from, the BTS and credibility movement. Publications on BTS generally explore challenges, lessons learned, and the need for BTS (Coles et al., 2022; Forscher et al., 2020).

Therefore, the goal of this manuscript is to examine the *people* involved in BTS projects. We specifically examined the themes of inclusivity, research careers, and research globalization. We see an increasing interest and number of publications in BTS but we do not yet know if this uptick in large-scale projects has diversified the *people* involved in BTS. While a few publications have noted that BTS appears to be early career researchers (Maizey & Tzavella, 2019), no one has systematically investigated this perception. Further, it is unclear if the focus of de-WEIRDing science has only focused on the representation of the research participants or if it has also improved the representation of researchers outside of North America and Europe. Last, who runs these BTS projects? Do we see an increase in diversity for the authors who generally receive the most credit for these projects (i.e., first several author(s) and last author)? As hiring and promoting practices often place a heavy weight on publications and especially "influential" publications, it becomes necessary to critically examine the representation present in authorship in BTS projects.

Research Questions

- Research Question 1: What publication sources publish big team science papers?
- Research Question 2: What are the types of articles that are being published in big team science?
- Research Question 3: Who is involved in big team science?

This manuscript was preregistered with the same conceptual ideas using Google Scholar and ORC-ID databases (https://osf.io/f2dtr) but then was updated with access to the Scopus database for a broader picture of BTS projects (https://osf.io/fheun). All materials and code can be found on our OSF page: https://osf.io/cgx6u/ or corresponding GitHub archive: https://github.com/doomlab/big_team_who.

Method

Publications

We have defined BTS publications as publications with at least ten authors at ten different institutions that were published in peer-reviewed journals or had posted a full paper pre-print. We used data from 1970 and forward in the Scopus database, as it is noted online that this time period includes cited references for calculation of several of our variables described below. We will analyze our results based on four subject areas present in the Scopus database: Physical Sciences, Health Sciences, Social Sciences, and Life Sciences. We filtered the database to include articles, articles in press, business articles, conference papers, data papers, preprints, and surveys using Elsevier's classification system. This project was supported by access to the Scopus database through the International Center for the Study of Research.

Data Curation

RQ1: Publisher Information. We extracted the following information for publication sources: the name of the publication (source title), subject area (both the large four subject areas and the smaller four digit all science journal classification [ASJC] code), and the journal impact using the Source Normalized Impact per Paper (SNIP).

RQ2: Publication Information. For each publication of the identified BTS publications, we examined the full four digit ASJC subject areas codes for each of the larger four subject areas and the keywords present for these publications.

RQ3: Author Information. The author list was extracted from each publication. Next, we used the author and affiliation arrays to curate a list of all publications and author information included in BTS papers to calculate the variables described below.

Career Length. Career length for each author was defined as the year of the first publication minus the current year listed for each author.

Institution and Geopolitical Region. We used the affiliation ids and country to gather information about the places of education and/or employment for authors. Geopolitical region was created by binning these codes into United Nation Regions.

Education. We collected degree information from the author table. Information on this variable is in the appendix.

Types of Publications. We took information from the publication type variable for each author's publications to present information about the types of papers BTS authors publish. Information on this variable is in the appendix.

Publication Metrics. For each author, we calculated the total number of publications, and the h-index. The h-index represents the highest h number of publications that have at least h citations. h-count was only used for descriptive statistics.

Results

We used the 95% confidence interval to make decisions on predictor or effect size differences from zero. The confidence interval that does not include zero would be considered different from zero (to four decimal places). We made no directional predictions.

RQ1: Publisher Information.

Number of articles. The total number of articles included in this analysis was 510334 including 445301 Health Sciences articles, 228194 Physical Sciences articles, 26652 Social Sciences articles, and 307514 Life Sciences articles. Articles could be classified into multiple categories. Figure 1 shows the number of articles published across time for each of the four large subject areas.

Number of journals. The number of distinct journals big team science articles were published in was 14924 with 6559 journals in Health Sciences, 5787 journals in Physical

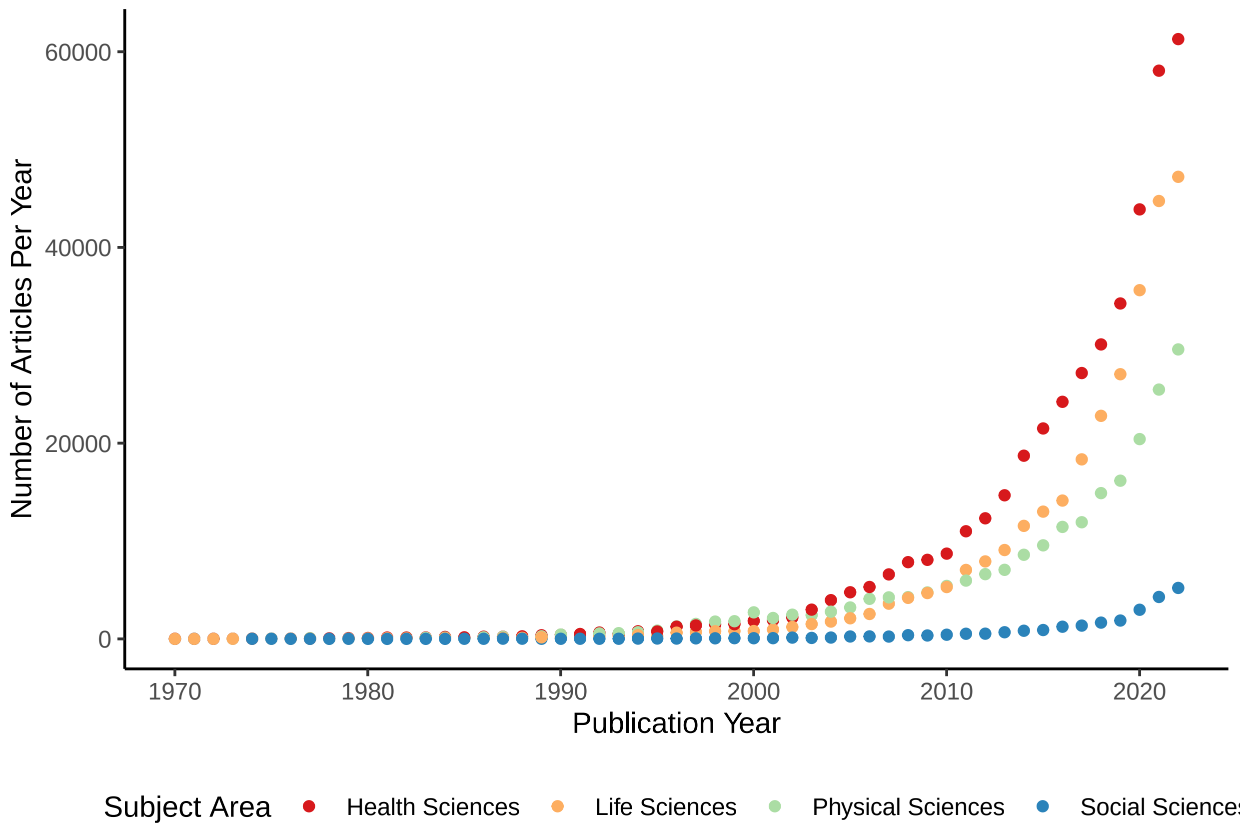

Figure 1. Number of big-team science publications separated by four large subject areas across years.

Sciences, 2500 journals in Social Sciences, and 4187 journals in Life Sciences. The descriptive statistics for the Source Normalized Impact per Paper is presented the supplemental materials with a comparison for all papers.

RQ2: Publication Information.

Publication interest area was summarized by the four large subject areas creating a word cloud plot of the total number of publications within the ASJCs. Figure 2 displays that the health sciences tends to publish within medicine and oncology, with a corresponding focus of cancer research and genetics for the life sciences. The physical sciences is mostly dominated by physics research, chemistry, and ecology. The BTS publications in the social sciences are mostly within psychology, education, and health.

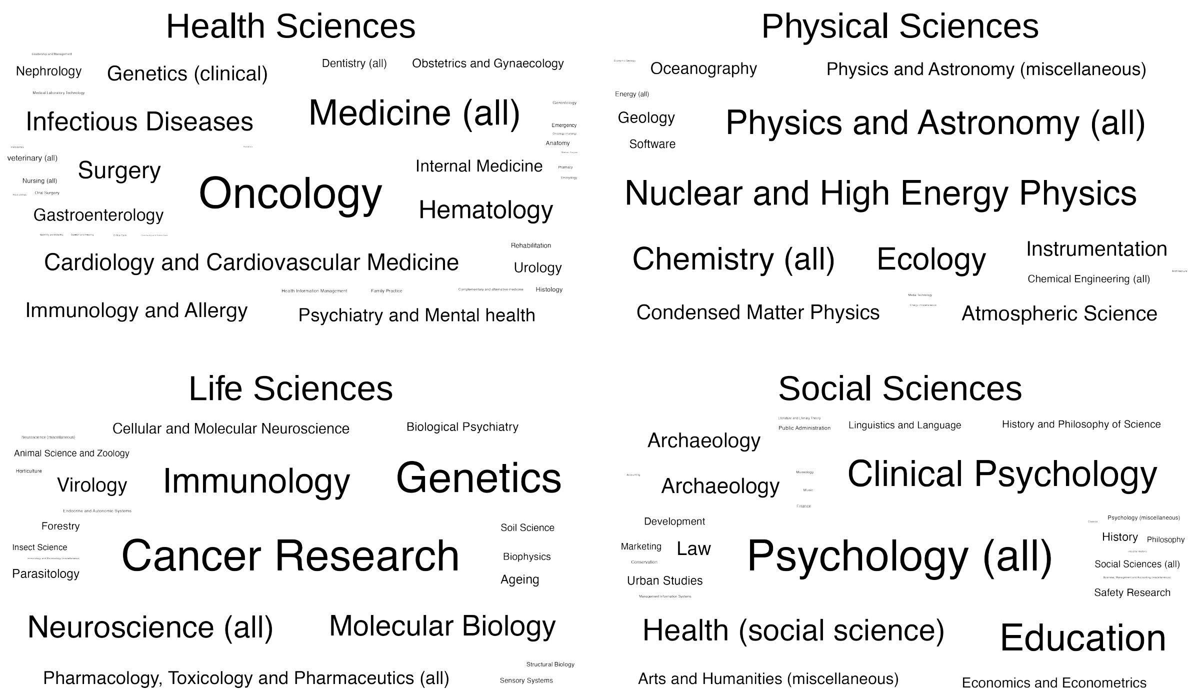

Figure 2. Journal Areas for Big-Team Science Publications by Subject Area

RQ3: Authors.

The total number of unique authors across all publications was 510334. The mean number of authors per publication was $M = 49.31$ ($SD = 212.98$, $Med = 18$) with a range of 10 to 5568. The median and average number of authors by subject area are displayed in Figure 3. In general, the average and median number of authors increased over time, with the exception of the skew in the physical sciences. Interestingly, the effect in the physical sciences appears to be declining toward the general trends seen in other areas in the last few decades.

Career Length.

Figure 4 portrays the average career length for authors involved in BTS publications

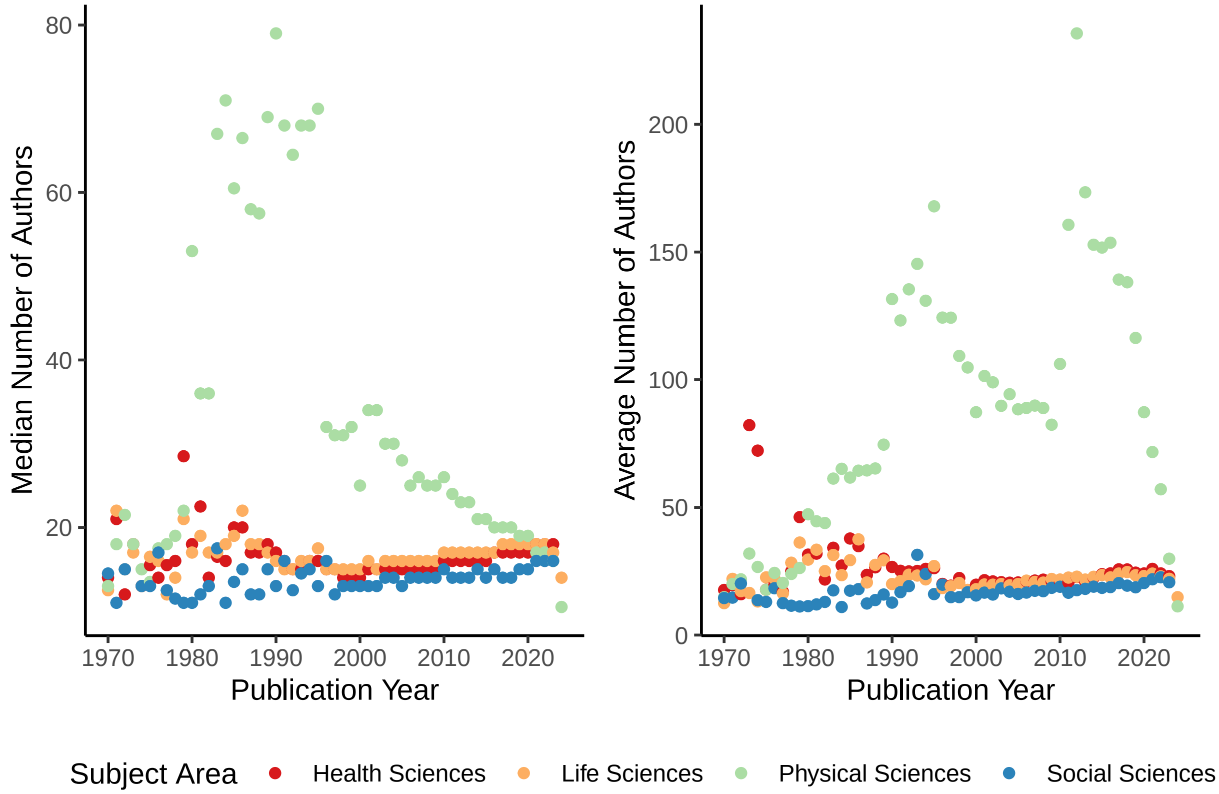

Figure 3. Number of authors included on big-team science papers per year by subject area. Given the large skew in the data, the left panel presents the median number of authors per manuscript, and the right panel presents the average number of authors per manuscript by year.

across years. Career length was defined as the year of first publication minus the current year, and higher numbers mean longer careers. To analyze trends over time, we calculated the average career length for each publication (i.e., average author career lengths to create one score for each paper) and analyzed a regression analysis using career length to predict year of publication. In order to show variance between individuals, we calculated the standard deviation of career length for each publication and used variance as an additional predictor.

Negative career length slopes would indicate more young scholars in later years (i.e., lower average career length as time increases). Positive career length slopes would indicate older scholars in later years (i.e., higher average career length as time increases). Negative career variance slopes imply that variability decreases over the years, so the average career length is more homogeneous. Positive career length slopes imply that variability increases over the years, so the average career length is varied across individuals (i.e., different stages of scholars). Figure 5 displays the results for all regression analyses to compare coefficient strength across and within hypothesis.

All values for this analyses were different from zero. The slopes for the average career length were negative for all four subject areas, indicating a trend toward younger scientist involvement over time for each area, with the strongest effect in the Physical sciences. The coefficient for variability in career length was also negative for each of the four subject areas with the highest in the Physical sciences and lowest in the Life Sciences. This result indicates a decrease in the variability of career lengths over time, likely from two sources: 1) more publications with more authors, thus, lowering variance estimations, and 2) more young scholars overall. The effect sizes for this analysis were surprisingly large ranging from R^2 to .25 to .47. All values and their confidence intervals can be found on our OSF page.

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Institution.

The total number of unique affiliation across all papers was 463876.

Publication Metrics.

The average number of publications by authors on big team sciences papers is $M =$

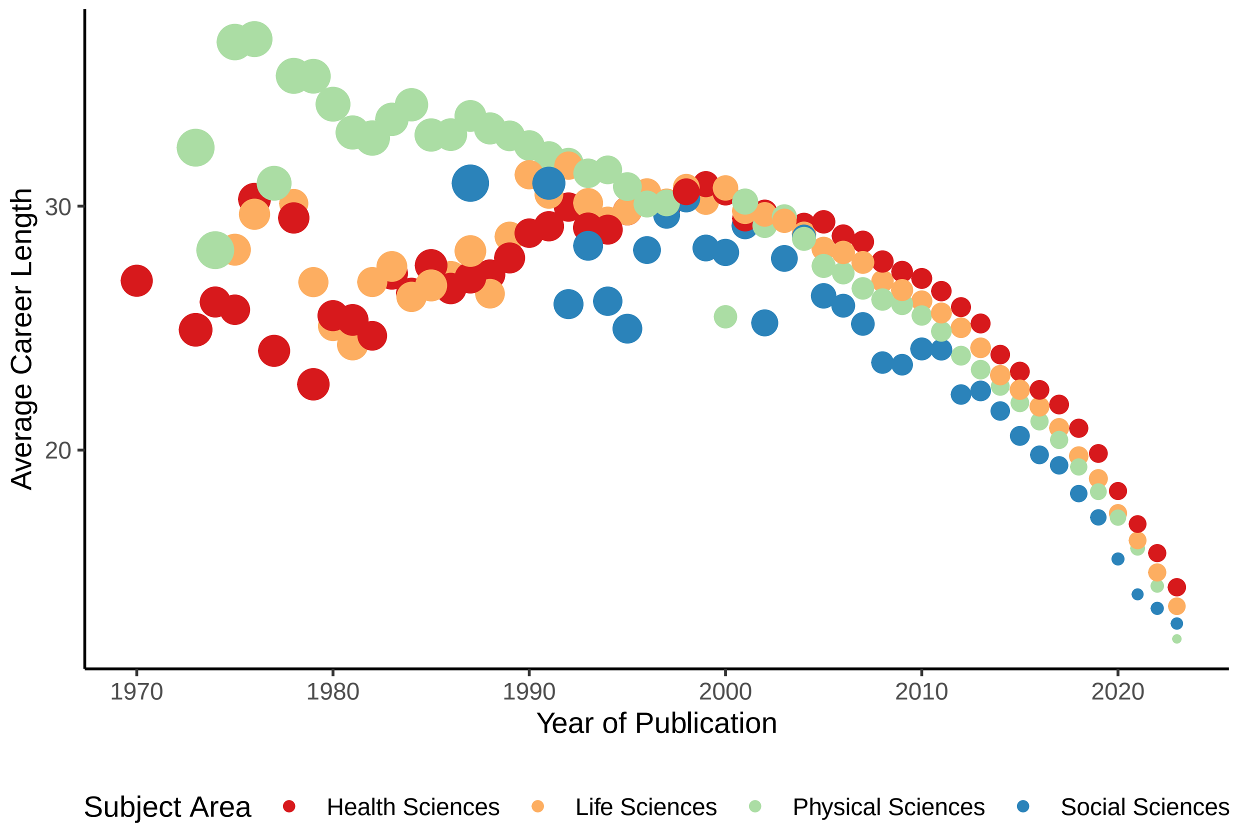

Figure 4. Average career length for big-team science authors. Larger dots indicate more variability in career length for authors by averaging the standard deviation in career length for each manuscript within a year. The data has been filtered to at least 10 publications in a year for this graph.

38.37 (SD = 102.54). The publication counts were averaged across authors for each publication, and then these average publication counts were averaged across publications M = 162.50 (SD = 155.17). The average variability (i.e., the average standard deviation with authors of a manuscript) with publication counts of a paper was M_{SD} = 164.27 (SD_{SD} = 127.21).

The same process was completed with h-index for each author and publication. The average h-index for authors overall was M = 33.65 (SD = 127.34, Med = 8.00). The average h-index for publications was M = 198.87 (SD = 248.78), and the variability of

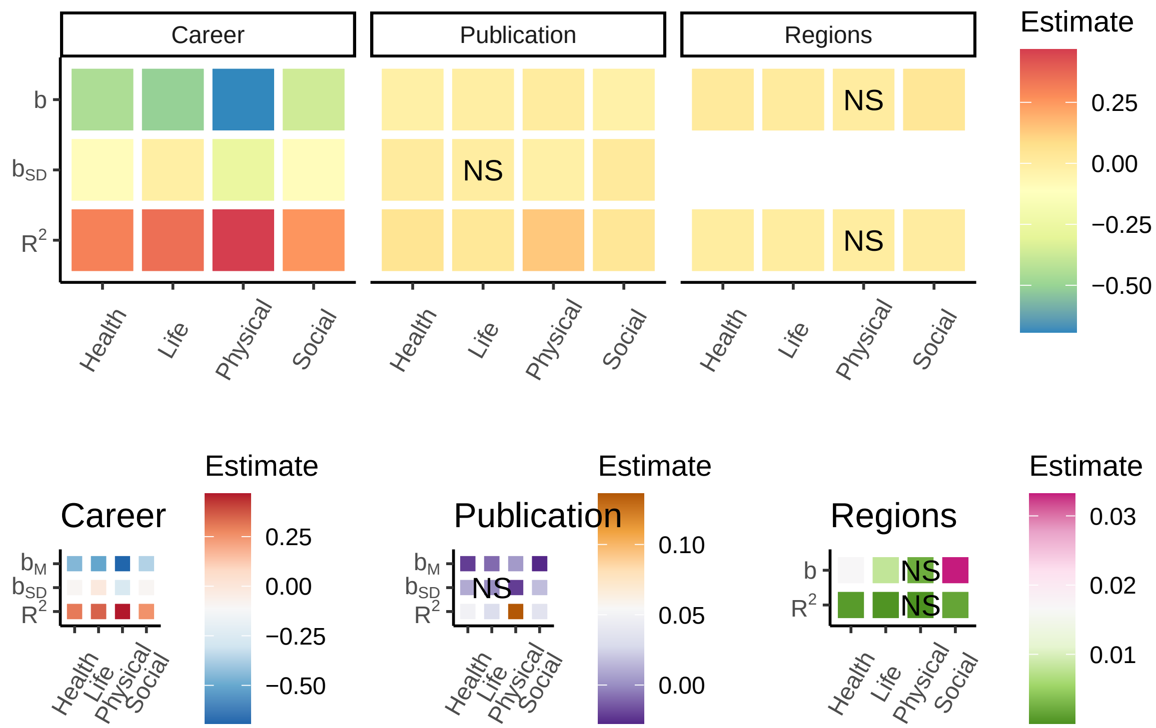

Figure 5. Heatmap results of regression analyses for career length, number of publications, and geopolitical diversity in region. The top figure represents all results together for comparison across analyses. The bottom row represents individual heatmaps for each hypothesis to distinguish small differences between subject areas for those research questions. Non-significant results are indicated with NS on the plot.

h-index across manuscripts was $M_{SD} = 211.80$ ($SD_{SD} = 238.53$, $Med_{Med} = 68.00$).

We used the same analyses described in the career length section to analyze trends over time. An increasing slope over time indicates that individuals who are publishing more are more represented in BTS over time (i.e., increasing numbers of scholars with higher publication rates), while a negative slope indicates more researchers with less publications. A positive slope for the standard deviation of publication metrics indicates increasing variance over time (i.e., more diversity in the individual publication rates), while a negative slope would indicate less diversity in researchers over time. While publication rates do not represent value as a researcher, they are often used in hiring and promotion decisions, and we used this variable as a proxy to gauge the diversity in scholars represented in big teams. As shown in Figure 5 publication metrics were generally negative for the average publication metrics, indicating more scholars over time with lower numbers of citations with the strongest effects in health and social sciences. The variability of publication counts was not significant for the life sciences but was negative for the physical sciences (less variability over time) and positive for social and health sciences (more variability and over time). This result indicates that the physical sciences are trending toward scholars with less publications but also less diverse in number of publications, while the health and social sciences see more diversity in publication counts and less published scholars overall.

Geopolitical Regions.

Author geopoligical region is displayed in Figure 6. Big team publications appear to be lead by North America and Western Europe, while all publications are lead by North America and East Asia. To understand the change in representation diversity, we examined if the number of regions in a publication is predicted by the year of publication. Increasing diversity would be represented by a positive slope, while decreasing diversity would be represented by a negative slope. As shown in Figure 5, the physical sciences do not show a trend of change in representation, while all other sciences showed a positive effect increasing in the number of geopolitical regions authors represent on publications.

Last, we examined the differences in representation for corresponding author sets versus all other authors. For papers with 10 to 49 authors, we used the three first authors and the last author to compare against other authors. For 50 to 99 authors, five first authors plus last were used, and for all papers with more than 100 authors, we used ten first authors and the last author as the corresponding author set. We then calculated the frequencies of each of the UN Sub-Regions for corresponding authors versus all other

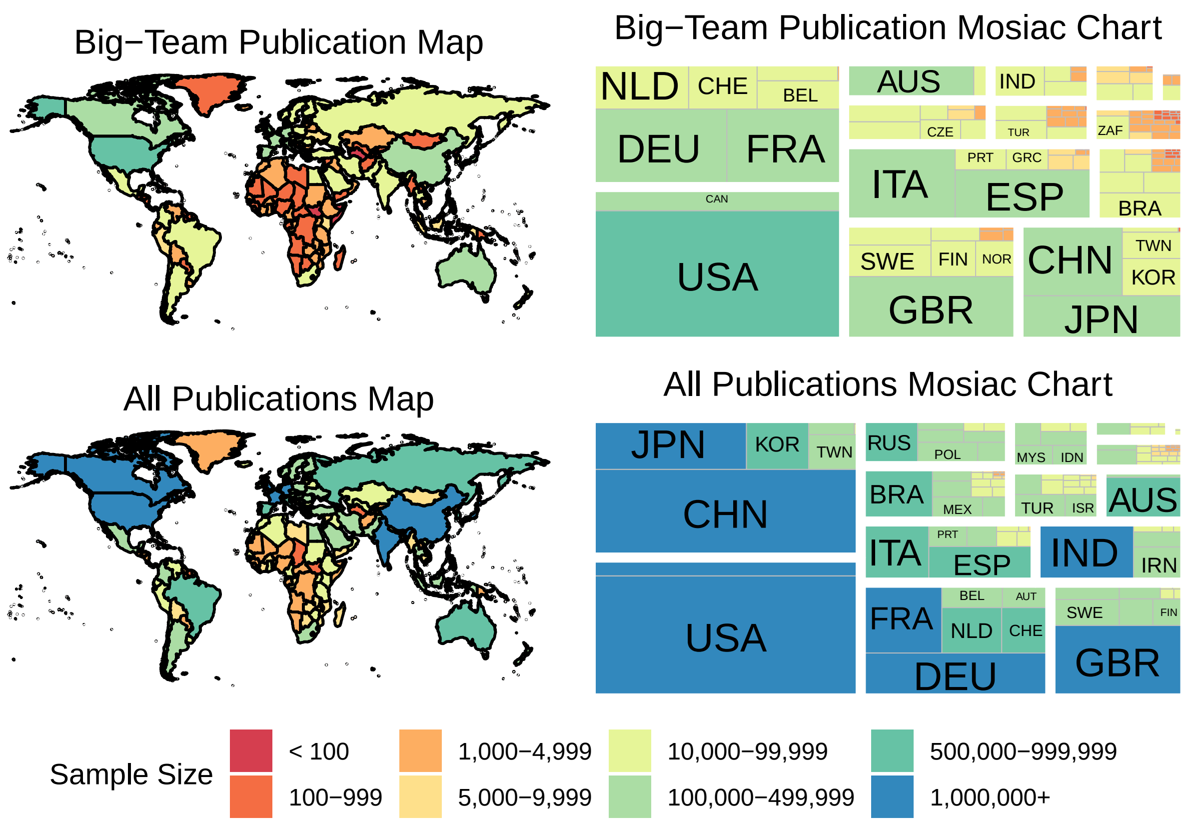

Figure 6. Geopolitical regions represented in big-team science publications versus all publications.

authors, converting these values to proportions. Given the expected small sample sizes of these contingency tables, we grouped together titles based on the year of publication. For each grouping, we then calculated the effect size of the differences in frequencies comparing corresponding authors to all other authors. Since this data is categorical, we used Cramer's V to represent the effect size. If the effect size includes zero in its confidence interval (to four decimal places), this result will imply that first and all other authors represent the same pattern of UN Sub-Region diversity. Any confidence interval that does include zero represents a difference in diversity.

Figure 7 indicates the percent of authors in regions. In general, we found the same pattern as the overall analysis wherein most authors are from Europe and North America.

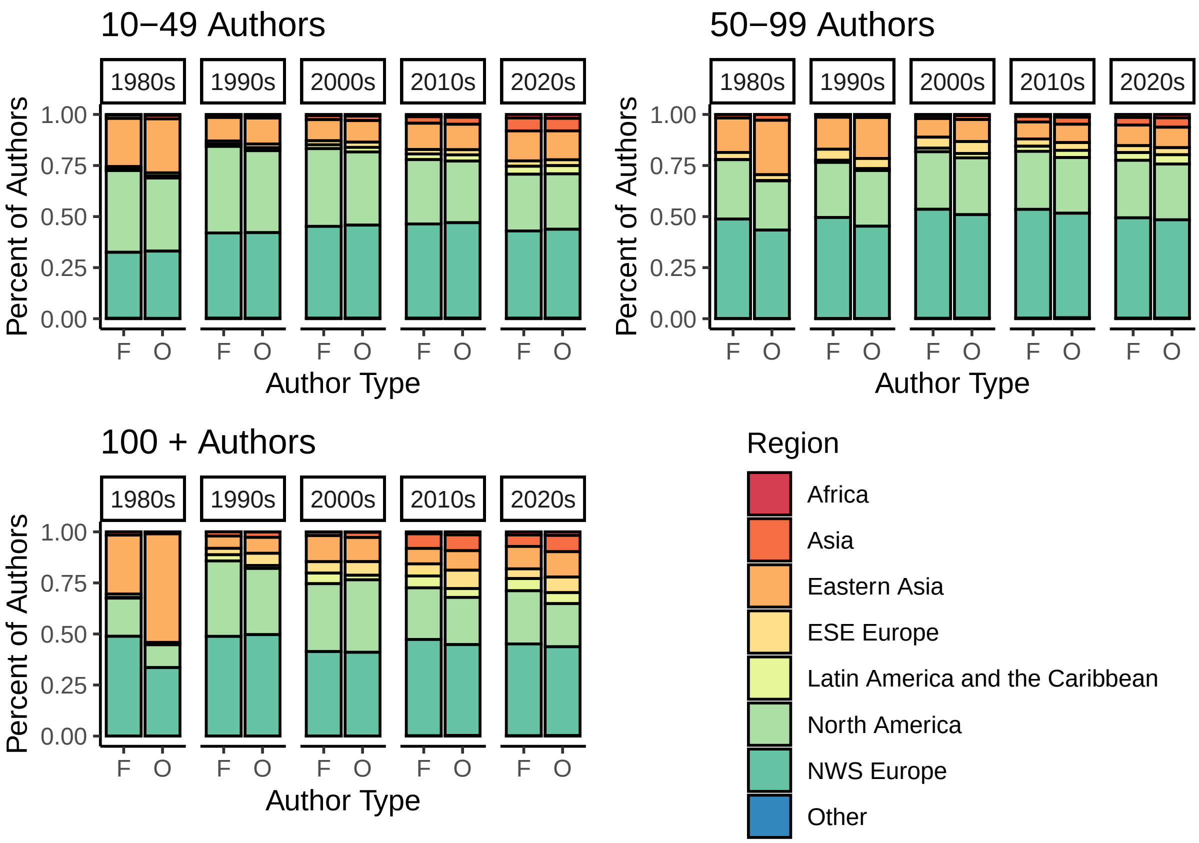

Figure 7. A comparison of author affiliation geopolitical region across decades. F stands for first authors and O stands for other authors.

The pattern of representation is roughly similar for the separation of small, medium, and large numbers of authors on papers. Across time, the representation does appear to diversify, with more representation in Asia, Latin American, and Africa. Figure 8 represents the size of the differences in first/corresponding authors and other authors across time and number of authors. The differences in representation are larger for papers with more authors; however, the effects are non-zero for many of the comparisons. Encouragingly, over time these effects appear to diminish in size. One limitation with the calculation of effect sizes for count data is the sensitivity of the data to sample size (i.e., χ^2 is upwardly biased by sample size, and V is calculated based on this value). While we used the inclusion of zero as our boundary for "significance", the interpretation of the effects is

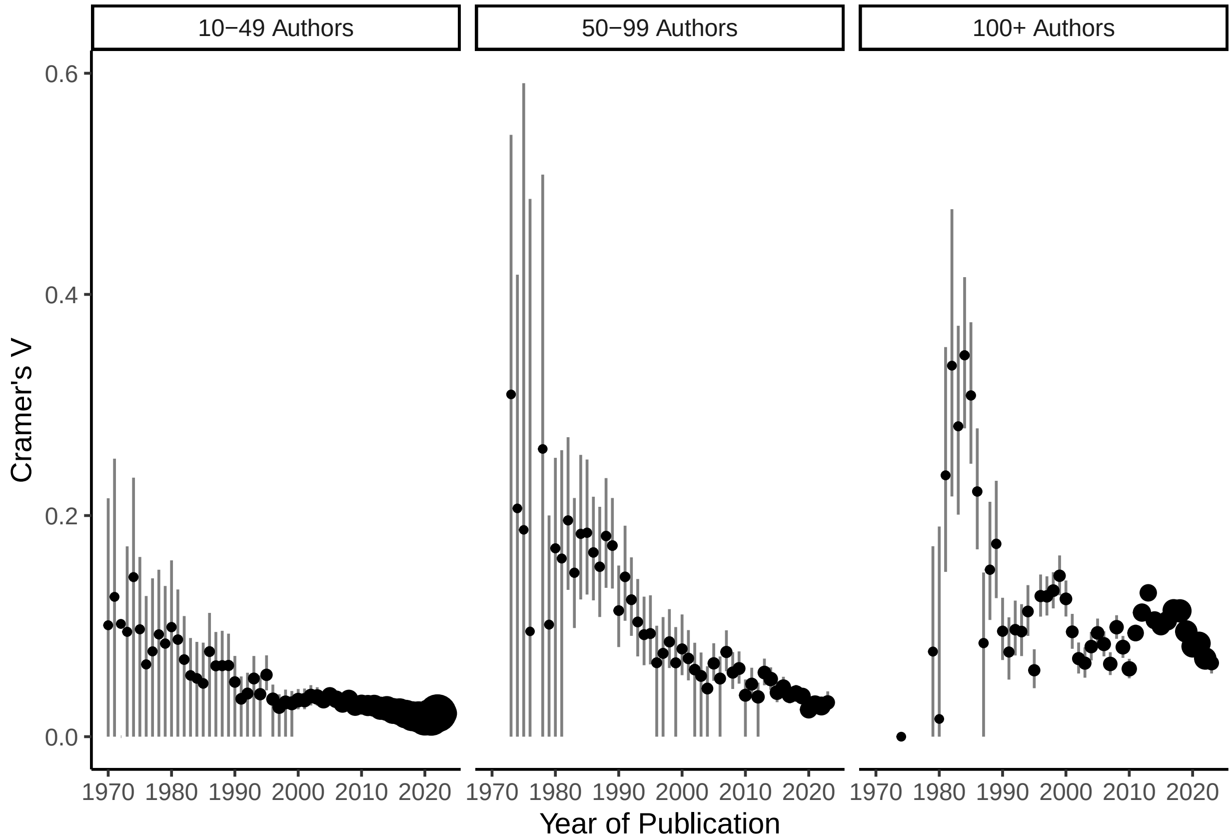

Figure 8. Effect size of the differences in representation for UN Regions for author affiliations in big-team science papers by year. Larger dots indicate more papers and authors represented in the calculation of effect size.

that most are likely small: $V < .05$: 31.79%, $< .10$: 70.20%, $< .20$: 94.04%.

Discussion

- number of publications increasing
- research areas appear to be cancer, physics, and psychology
- the number of authors is increasing as well
- career length is decreasing, number of publications necessary to be involved is decreasing
- number of gpe increasing
- appears to be slowly diversifying, yet still not equal in first and other authors in

diversity

limitations - based on the data we could get, we made up the definition of BTS, under-representation of articles in other languages/that they don't collect

future: incentives for bts and why people do it

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Table A1

Big-Team Science SNIP Values

Subject Area	M	SD	Minimum	Median	Maximum
Health Sciences	2.36	3.59	0.00	1.58	173.93
Physical Sciences	1.57	1.17	0.00	1.27	30.40
Social Sciences	1.94	1.72	0.00	1.52	30.40
Life Sciences	2.02	1.60	0.00	1.51	19.07

Appendix

Supplemental Materials

RQ1: Publisher Information.

Number of Journals.

Table A1 indicates the SNIP values for BTS publications, while Table A2. The results from these tables indicate that impact values are slightly higher for BTS publications, while the overall median, minimum, and maximum are the same for each grouping.

RQ2: Publication Information.

Keywords. Figure A1 indicates the most common keywords present for the BTS publications by subject area. The keywords were tokenized into single tokens. Keywords were then lowercased, and all stop words (for example, the, an, of, into, for) were removed. Finally, a frequency count of tokens was tabulated for each subject area, and this count is used to create the final word cloud presented.

RQ3: Authors

Institution.

Table A2

All Journal Articles SNIP Values

Subject Area	M	SD	Minimum	Median	Maximum
Health Sciences	1.45	2.87	0.00	1.15	173.93
Physical Sciences	1.08	0.77	0.00	0.97	30.40
Social Sciences	1.32	1.03	0.00	1.15	30.40
Life Sciences	1.19	0.86	0.00	1.06	19.07

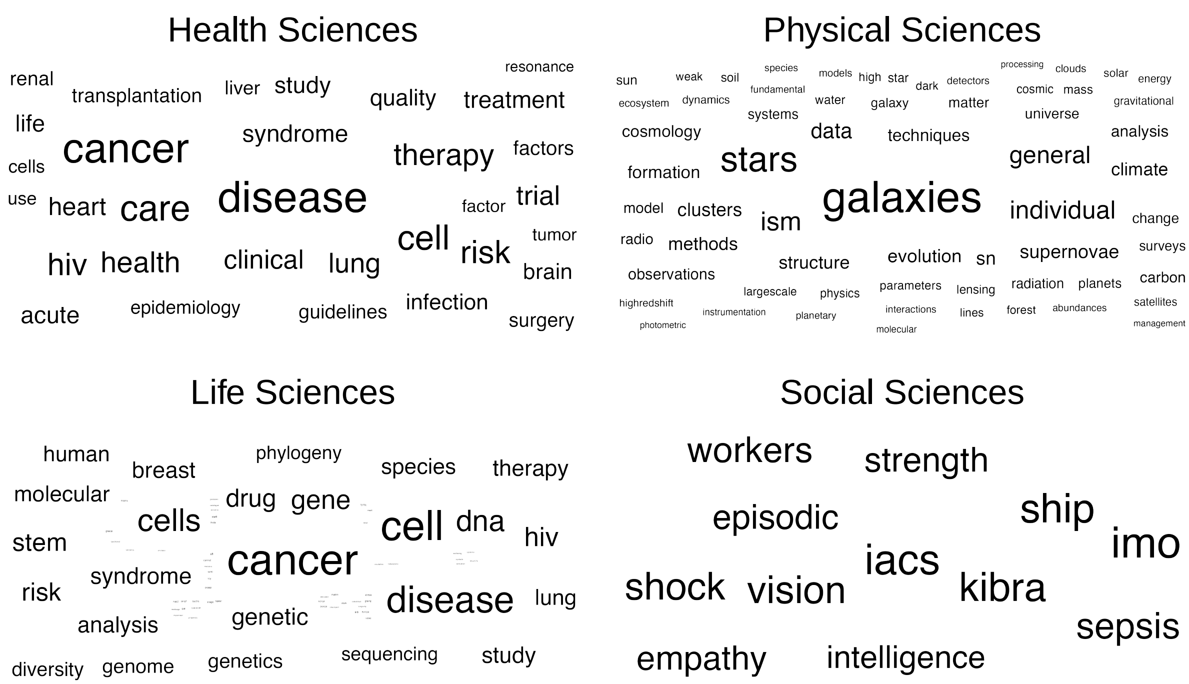

Figure A1. Keyword Analysis for Each of the Four Subject Areas.

Institution was normalized by taking the total number of unique institutions and dividing by the total number of institution listings. The patterns are similar for each decade in that papers are often either half unique institutions or mostly unique institutions overall as show in Figure A2.

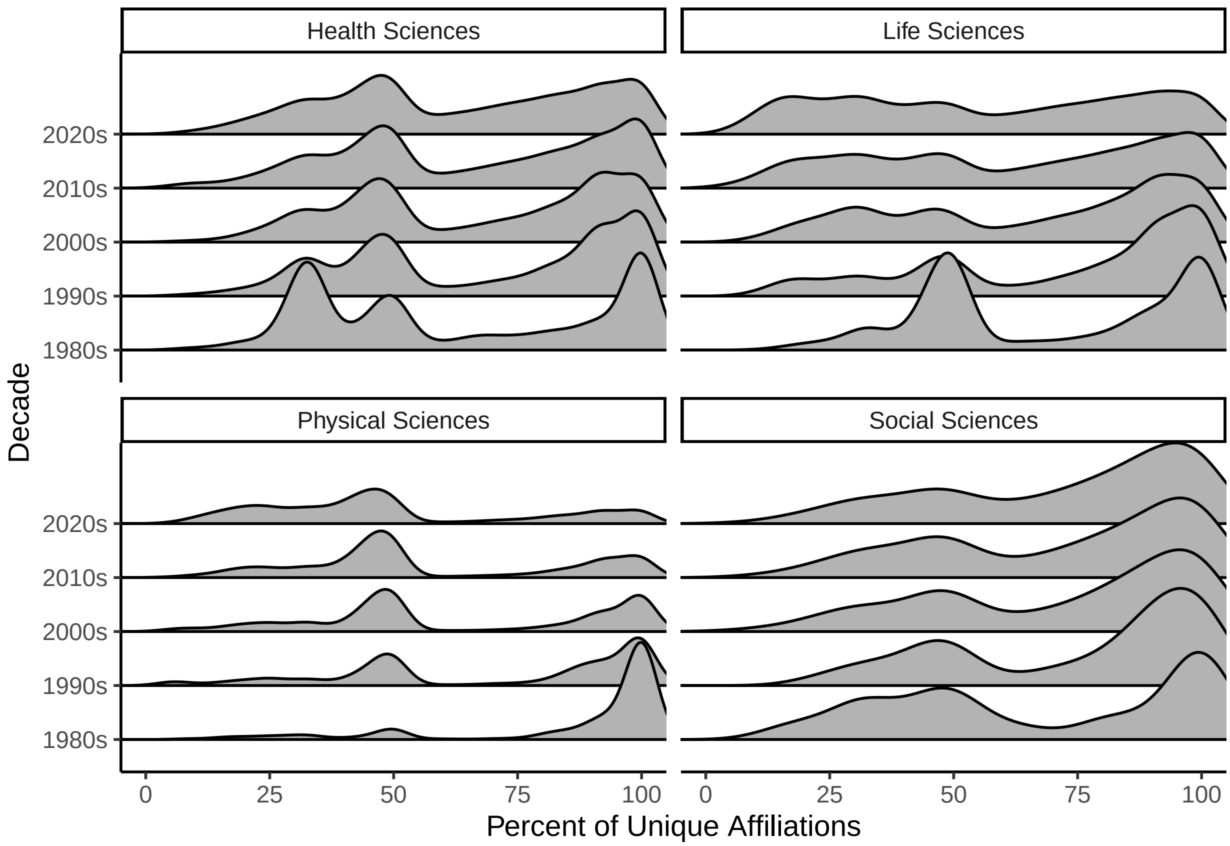

Figure A2. Number of unique institutions involved in big-team science papers across decades.

Education. As noted in our pre-registration, we would only present this variable if we could obtain at least 50% information on the authors who publish in big team science papers. 95.83% of the data was not available.

Types of Publications.

Types of publications are presented in Figure A3. The patterns of publications are roughly similar for big team science authors and all authors. It appears that porportionally, big team members are more likely to post preprints in comparison to all authors.

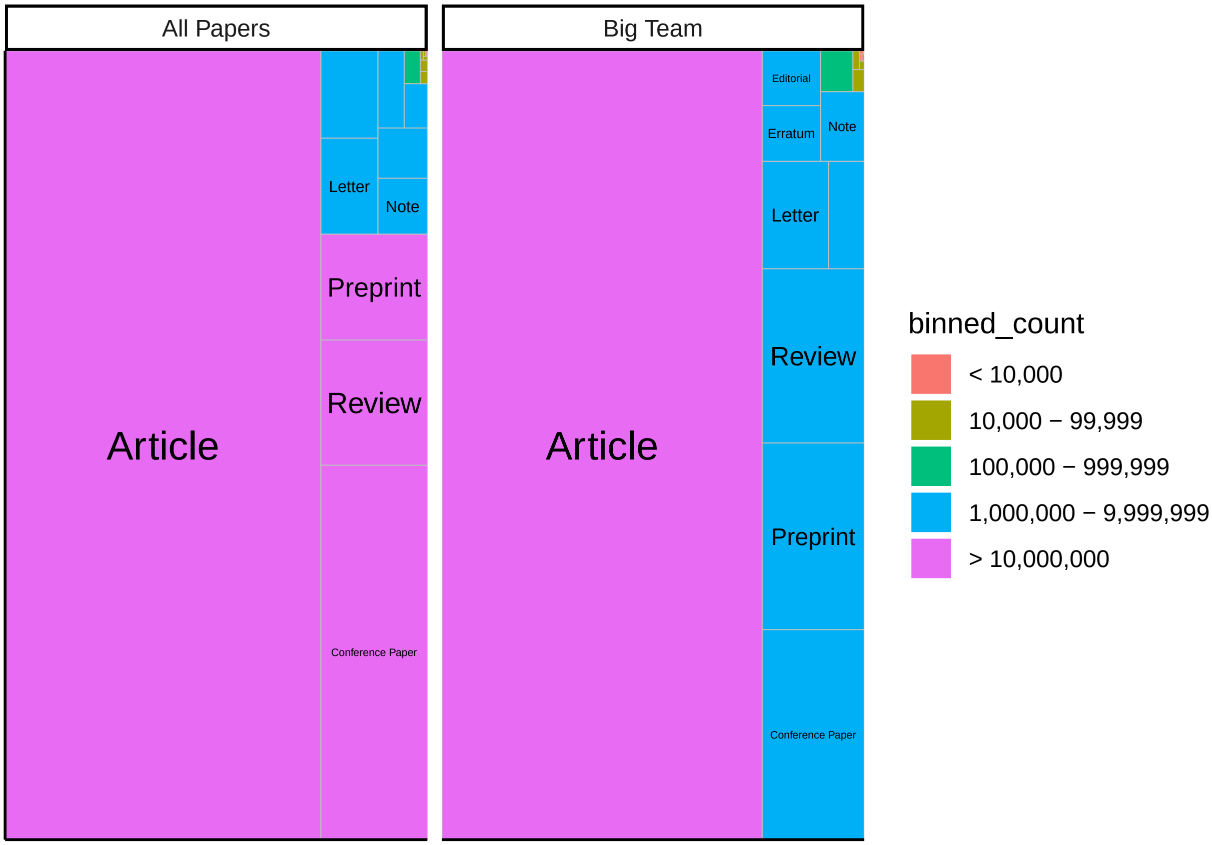

Figure A3. Types of publications for big-team science and all authors.