What defines big team science?

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Abstract

This study presents the first large-scale, data-driven analysis of authorship in Big Team Science (BTS) drawing on over half a million articles across four scientific domains. Using the top decile of the data, we defined BTS as collaborations with 11+ authors across six or more institutions. We compared BTS with traditional team science to investigate changes in publication rates, authorship characteristics, and global representation. Publication rates for traditional team science and BTS have both risen over time, but the growth trajectory varies depending on the subject area. We found that early-career researchers are increasingly represented in both BTS and smaller teams, suggesting greater accessibility over time. Leadership roles remain concentrated in high-income, WEIRD regions for smaller teams. This work contributes a replicable, empirical definition of BTS and highlights the need for more equitable recognition and inclusion in large-scale scientific collaboration.

General Disclosures

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Computational reproducibility: 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. Elsevier has agreed to provide access to determine reproducibility of the code for accessing and summarizing articles, and the reproducible manuscript has been provided for review.

Pre-registration: 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). After peer review, the preregisteration was updated to address the unclear definition of big team science to focus on a data-driven definition to explore the research questions.

Materials, Data, Analysis Scripts: 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.

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What defines big team science?

Scientific discovery has increasingly become a collaborative process, with the scale and scope of team science have dramatically expanded in recent years (Council et al., 2015). Collaboration in scientific endeavors involves multiple researchers (potentiality) at multiple institutions to communicate and work together to advance knowledge in their chosen field(s). This unique composition of a collaboration for each project is dependent on the skill sets, hypotheses, and perspectives of collaborators involved. A key strength of collaboration lies in its flexibility, allowing it to adapt to the needs of the project and the researchers themselves. While collaboration is not new in science, interest in "team science" is growing as individual researchers seek an interdisciplinary approach to research or bring on more students to their project. Team science is often defined as groups of researchers with various expertise working together to investigate complex problems (Fiore, 2008). Unlike general collaboration, team science involves structured roles, coordinated workflows, and shared resources to address challenges that would be difficult for individual researchers or one small team to solve independently.

The movement toward team science reflects demands of modern research to answer complex questions, meet funding agencies and universities desires for interdisciplinary research, and the desire to increase scientific representation (Council et al., 2015). Further, the evolution of team science reflects broader shifts in research practices, driven by two sources: 1) increasing globalization and technology that allows for real-time interdisciplinary research (B. F. Jones et al., 2008), and 2) expanding interest in reproducibility, replication, and generalizability (i.e., the credibility movement, Maxwell et al., 2015; Nelson et al., 2018; Vazire et al., 2022; Zwaan et al., 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 has been the main catalyst for the increased interest and broader shift of research practices. The movement emphasizes reproducibility and transparency in science, encouraging researchers to form new ways to increase the rigor in scientific endeavors. Throughout the last decade, the credibility movement has pushed for larger, more diverse teams and the involvement of participants from varied backgrounds. This shift in teams and participants focuses on increasing credibility, generalizability, and reliability of scientific findings. This form of collaboration has been coined "Big Team Science." Big Team Science (BTS) builds on team science by scaling efforts to include larger, often globally diverse teams, which requires significant coordination and infrastructure (Coles et al., 2022; Forscher et al., 2022; N. Stewart et al., 2017). BTS projects and organizations organize extensive collaborations, intentionally incorporating diverse populations and perspectives into research. This large-scale approach enhances the reliability and generalizability of findings by integrating varied methodologies and viewpoints, leading to more robust and inclusive scientific outcomes. BTS organizations often pool extensive networks of researchers and resources, aiming to tackle grand scientific challenges that would be difficult to address within smaller or less coordinated collaborations. 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 in a study (Auspurg & Brüderl, 2021; LeBel et al., 2018; Nosek & Lakens, 2014a).

For example, psychology has seen an increase in BTS publications like the Open Science Collaboration (Open Science Collaboration, 2015), Many Labs Collaborations (Buttrick et al., 2020; Ebersole et al., 2016, 2020; Klein et al., 2018; Klein et al., 2022; Mathur et al., 2020; Skorb et al., 2020) or the first papers from the Psychological Science Accelerator (Bago et al., 2022; Buchanan et al., 2023; Dorison et al., 2022; B. C. Jones et al., 2021; Moshontz et al., 2018; Psychological Science Accelerator Self-Determination Theory Collaboration, 2022; Wang et al., 2021). 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 et al., 2012; Silberzahn et al., 2018) led to a change in journal guidelines and incentives for researchers interested in participating in large-scale studies overall (Grahe, 2014; Kidwell et al., 2016; Mayo-Wilson et al., 2021; Nosek et al., 2015). In some fields, the BTS movement demonstrated that large-scale teams were a practical (and publishable) solution to answering research questions in generalizable way. The support for Registered Reports, papers accepted before the data has been collected (Nosek & Lakens, 2014b; S. Stewart et al., 2020), 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 (Nosek et al., 2015) and the Contributor Role Taxonomy (CRediT) system (Allen et al., 2019) have pushed journals and researchers to promote more open, inclusive publication practices.

Beyond replication concerns, the credibility movement has mirrored calls for diversification or de-WEIRDing (e.g., Western, Educated, Industrialized, Rich, and Democratic) scientific research (Henrich et al., 2010; Newson et al., 2021; Rad et al., 2018) by improving representation in research samples. Like the large-scale studies in Physics ("A Philosophical Case for Big Physics," 2021; Castelnovo et al., 2018) and Biology (Collins et al., 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 (https://psysciacc.org), ManyBabies (https://manybabies.github.io/), NutNet (https://nutnet.org/), DRAGNet (https://dragnetglobal.weebly.com/), and IceCube (https://icecube.wisc.edu/) 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; B. C. Jones et al., 2021; Psychological Science Accelerator Self-Determination Theory Collaboration, 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 how to define BTS: which is generally termed “an unusually large number of collaborators” (Coles et al., 2022; Forscher et al., 2022).

The lack of formal definition raises questions about whether it represents a distinct phenomenon or simply a natural extension of team science. These big teams pose unique challenges, including coordinating work across diverse time zones, managing conflicts in decision-making, and ensuring fair distribution of credit for contributions (Cummings & Kiesler, 2007; Wuchty et al., 2007), but also could provide big rewards by pooling expertise and increased interdisciplinary funding (Fiore, 2008). This paper seeks to clarify the concept of BTS by first establishing a data-driven definition based on publication patterns. With this quantitative distinction in place, we analyze publication trends over time to assess the trajectories of both traditional team science and BTS. Furthermore, we investigate the diversity of authors involved in these collaborations to explore whether shifts in the scientific landscape, such as efforts to de-WEIRD science and the expansion of collaborative opportunities, have influenced who participates in team science and BTS. By synthesizing insights from the growth and diversification of team science, this paper seeks to critically examine the emergence of big teams. Specifically, it aims to explore whether big teams are quantitatively different from traditional collaboration models with the following research questions.

Research Questions

- Research Question 1: Exploring historical and current publication values, what should define big team science versus traditional team science?

  - Question 1A: What number of authors and institutional affiliations should designate the differences between traditional team science and big team science?
  - Question 1B: Using the definition from 1A, are there changes in the number of publications over time?
- Research Question 2: How has the diversity of those involved in traditional team science and big team science changed over time?

Method

Publications

We used data from 1970-2024 in the Scopus database, as it is noted online that 1970 and forward includes cited references for calculation of several of our variables described below. We analyzed our results based on four subject areas present in the Scopus database: Physical Sciences, Health Sciences, Social Sciences, and Life Sciences. We used the subject area split to ensure one field did not dominate BTS definitions and determine differences in trends across sub-areas of science. 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: Defining BTS

For each of the publications in Scopus, we calculated the number of distinct authors and institutions. If an author had multiple affiliations, we used the first affiliation listed. Each publication was classified into the four subject areas based on the All Journal Subject Codes present in the database. Publications can be included in multiple subject codes. For example, a medical paper may be listed in both life sciences and health sciences.

RQ2: Seniority

Career length for each author was defined as the year of the first publication minus the current year listed for each author. Number of publications included the number of unique entries an author was included in the database. Career length and number of publications was used as a proxy for the "age" or "seniority" of a scholar.

RQ2: Geopolitical Region

Geopolitical region was created by binning country code identifiers into the 17 identified United Nation subregions.

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.

RQ1A: Defining BTS

The total number of papers included in the Scopus database at the time of this analysis was 97,532,104. 62,966,549 articles were included past 1970 in the defined article types, which included 53,622,443 distinct authors. We then filtered the data to include only teams, which was defined as two authors from at least two institutions. The total number of papers for team projects was 32,454,393 and 28,353,445 distinct authors. The data was then classified into subject areas by paper, which lead to missing data. The final number of papers included was 32,448,373 with 28,350,468 distinct authors. The dataset was curated to include one row per author, paper, and subject area (i.e., long format (Wickham, 2007)) which included 241,269,297 total rows of data.

Figure 1 displays the number of authors and affiliations by subject area. The figure demonstrates that the median number of authors is largest for health sciences, followed by life science, physical sciences, and then social sciences. The general pattern of team authorship includes about 2-8 authors, from about 2-4 institutions. We used the maximum

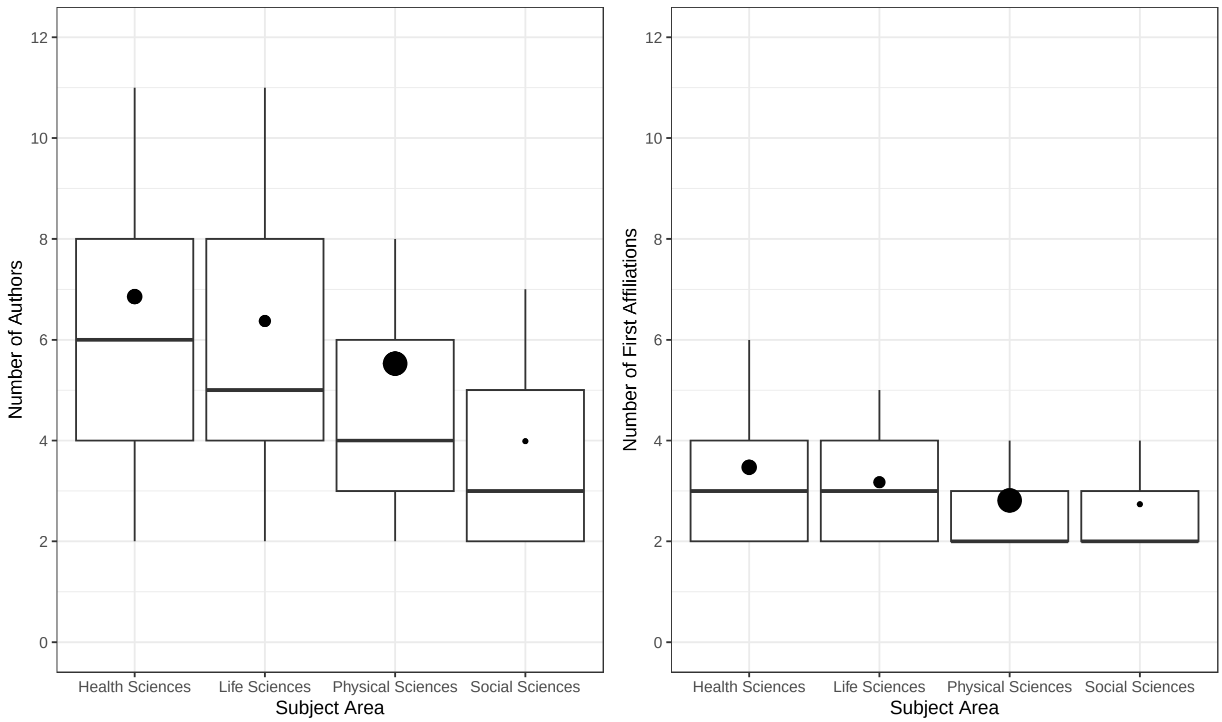

Figure 1

The left panel depicts the number of authors included on a paper by subject area, and the right panel demonstrates the number of affiliations by subject area. The boxplot shows the median (bold line), the interquartile range (the box), and the minimum to the 90th percentile of the number of authors/affiliations as the range line. Normally these plots include the entire range of the data, but these extreme range made the boxplot information unreadable. The dots indicate the average number of authors/affiliations for each area with the size of the dot indicating the standard deviation of the statistic. Therefore, larger dots indicate more variability in the number of authors and affiliations.

value (i.e., across all subject areas) for the 90th percentile as our exploratory definition for big team papers after examining the results from this analysis. We selected this percentile to have the high of the distribution, but also to be able to include enough papers for analysis across time. Therefore, big teams were defined as 11 authors from at least 6 different institutions.[1]

We applied a consistent definition of Big Team Science (BTS) across all four research domains in our analysis. As shown in Figure 1, the 90th percentile of team size is consistent across subject areas, varying by only four authors (e.g., from 7 to 11), which supports the use of a unified threshold. Over time (Figure 2), we observe increasing publication counts in all fields. While social sciences currently lag behind in both volume and growth rate, we anticipate continued growth as more infrastructure and funding are directed toward collaborative efforts in this area. Unlike fields such as health sciences, which often benefit from greater financial resources and institutional support (e.g., through IRBs and clinical networks), social science collaborations face unique structural barriers that may slow their expansion. Additionally, defining BTS consistently across fields is methodologically important because many publications are interdisciplinary and assigned to multiple subject categories. A unified operationalization allows for clearer comparisons and avoids arbitrary distinctions between overlapping research areas.

Supplemental Table A1 includes the number of distinct authors and papers for each subject area by overall teams and big teams using our 90th percentile definition. The total number of distinct authors for big team papers was 968,765 with 4,541,369 distinct authors. In RQ2, we split the big team data into bins using 11-49 authors, 50-99 authors, and 100+ authors groupings for convenience to display/analyze geopolitical regions. The table shows

[1] In a previous version of this manuscript, we defined big teams as 10 authors from at least 10 institutions based on our own experiences working within a research consortium. All definitions are likely subjective, but the definition in this manuscript represents the top 10% of author and affiliations in a large body of papers.

the number of authors and papers for those analyses.

RQ1B: Changes over Time

For analyzing changes across time, we split the data into traditional team science projects (2-10 authors, 2-5 affiliations) and BTS projects (as defined above, 11+ authors, 6+ affiliations). The number of papers found in Scopus across time for each subject area are displayed in Figure 2. The visual results indicated that the number of traditional team science papers was increasing the most in physical sciences for all manuscripts, followed by life and health sciences, and the last is social sciences. Examining only BTS projects shows that the rate is also increasing across time. All teams appear to start increasing in the 1990s, while BTS projects do not start increasing off floor effects until past 2000. The health and life sciences show the largest increases across time in big teams with the smallest trend in the social sciences.

Using the `minpack.lm` library (Elzhov et al., 2023), we calculated the exponential rate of growth for traditional team science and BTS projects, and these results are shown in Supplemental Figure A1. All growth rate confidence intervals excluded zero, indicating an exponential increase in the number of team papers over time. BTS growth rates were always higher than their traditional team science counterparts, but the 95% confidence intervals for the growth estimate overlapped for all statistics. Therefore, the growth trends, while visually appearing to be different, were likely similar for each subject area and team size when examined by estimating exponential growth statistics.

RQ2: Seniority

Figure 3 portrays the average career length for authors involved in traditional team science and BTS projects over time. Career length was defined as the year of first publication minus the current year, and higher numbers mean longer careers. The general pattern for traditional team science and BTS projects is a decrease in average career length over time. However, it appears that, in at least the last two decades, BTS projects average a

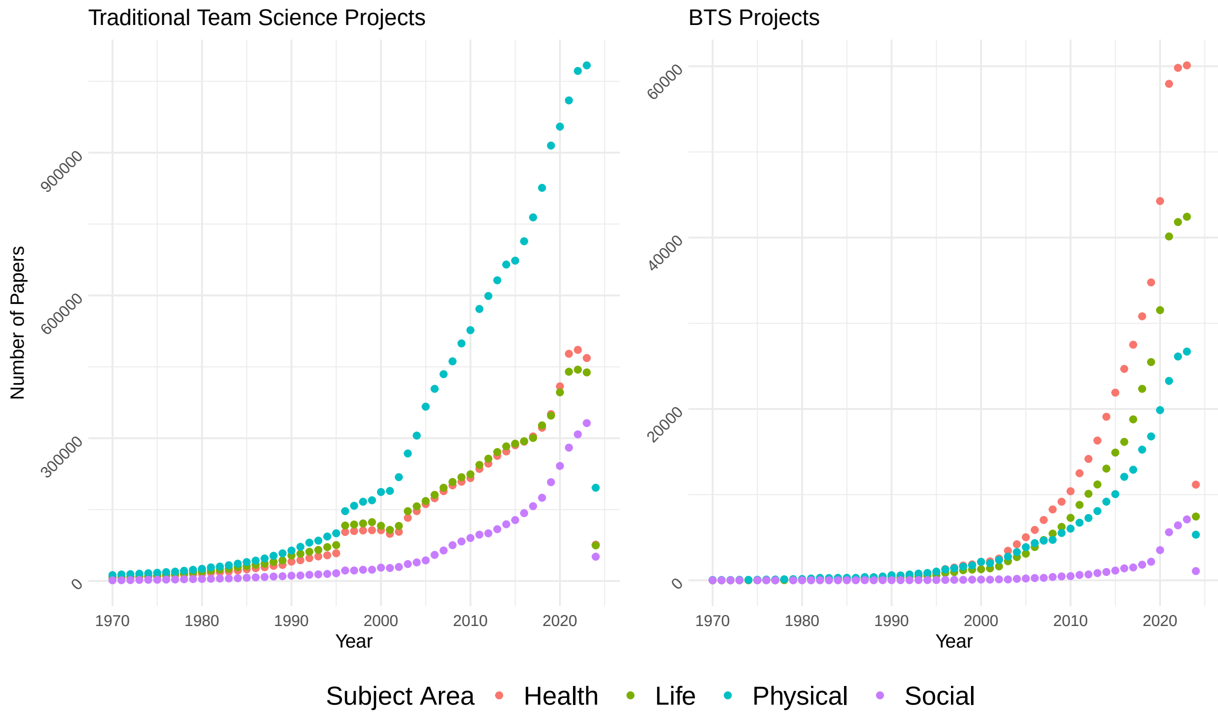

Figure 2

The number of manuscripts across time for all traditional team science papers (left) and big team science papers (right).

longer career length than traditional team science projects. This trend is visually consistent across all four subject areas examined.

Career Length

To analyze these trends over time, we calculated the average career length for each publication (i.e., averaging 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 this 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

Figure 3

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.

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 4 displays the results for all regression analyses.

As shown in Figure 4, all estimated slopes were negative, indicating that author teams are, on average, composed of younger scholars over time. The slope of the mean career length (b_M) and variability in career length (b_{SD}) was consistently negative across disciplines and team sizes, with all estimates falling outside the defined null threshold (i.e., $|b| > 0.00001$). Most subject areas showed significantly different slopes within their

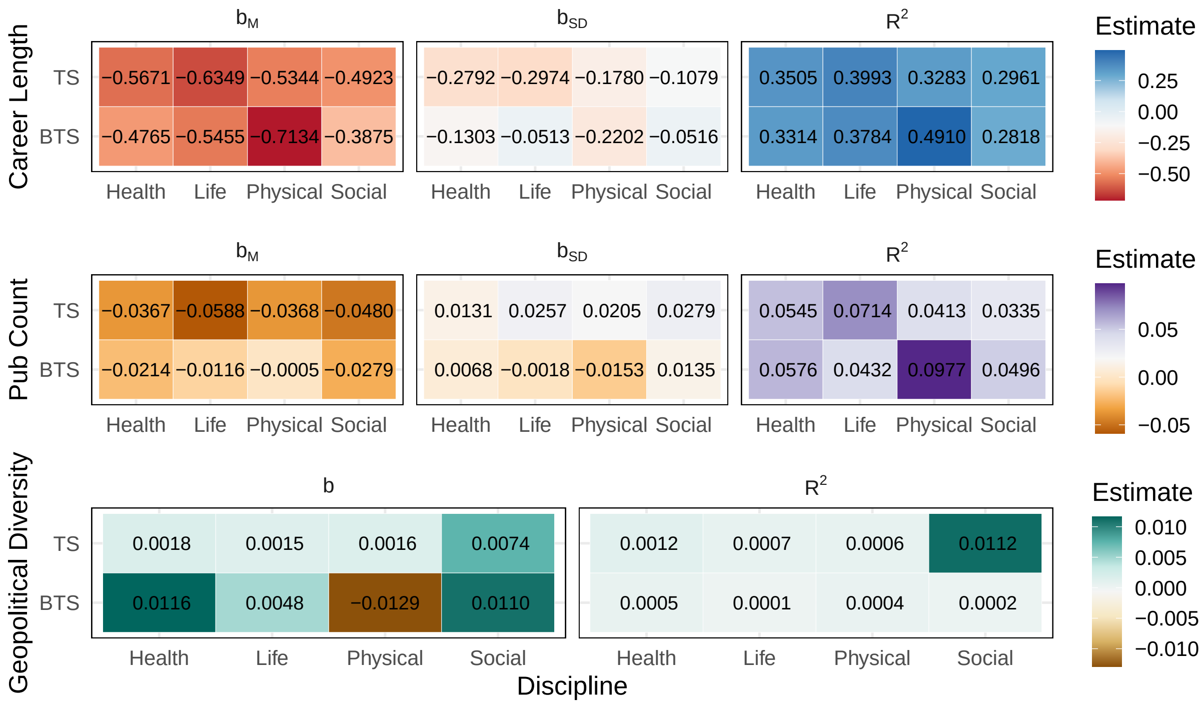

Figure 4

Heatmap results of regression analyses for career length, number of publications, and geopoliticalwithin the region. Each square represents a b *value or the slope of the predictor (x-axis) onto the dependent variable (each panel), with the exception of the bottom row which is the effect size of each regression analysis R^2. Slopes included both the overall value of the predictor (b, b_M) and the standard deviation of the predictor over time (b_{SD}). The color of the square represents the strength of the predictor. 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.*

respective team size, as evidenced by non-overlapping 95% confidence intervals for both b_M and b_{SD}. The Physical Sciences exhibited the steepest declines in both average career length and its variability (e.g., b_M = -0.7134, b_{SD} = -0.2202 for big teams), suggesting a sharp shift toward younger and more uniformly early-career author teams. In comparison, life sciences showed a slightly smaller shift toward earlier career scholars with less variability, followed by health and social sciences. The only non-significant difference was found between life and social sciences in big teams for author career variability.

These findings suggest a widespread trend toward younger, less-senior authorship over time. However, this trend was more pronounced in team science-sized teams than in BTS teams. In all four subject areas, team science teams showed steeper declines in both the average and variability of author career length, as reflected by significantly different slopes with no overlapping confidence intervals. This finding indicates that regular teams are more strongly influenced by the increasing participation of earlier-career researchers, whereas big teams exhibit the same general trend but to a lesser extent. Effect sizes were substantial across all models, with R^2 values ranging from .2818 to .4910. The largest effect was observed in the Physical Sciences for big teams (R^2 = .4910), reflecting the strongest association between author career stage and publication timing. Together, these results indicate that the shift toward younger, more early-career author teams is widespread but not uniform across disciplines, and that team size plays a meaningful role in moderating the strength of these temporal trends. Full model estimates and confidence intervals are available on the OSF repository.

Publication Count

We used the same analyses using number of publications to represent diversity instead of career length. 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 BTS teams.

All slopes for both the average (b_M) and standard deviation (b_{SD}) of publication count were significantly different from zero, indicating meaningful change over time in the types of researchers contributing to publications across subject areas and team sizes (see Figure 4). Most subject areas differed significantly from one another within their team size, with the exception of Health Sciences and Physical Sciences for traditional team science, whose b_M values overlapped in their confidence intervals. Across the remaining comparisons, Life Sciences showed the steepest decline in average publication count over time for regular teams (b_M = -0.0588), suggesting a shift toward including authors with fewer publications. In contrast, the smallest change in publication count was observed in Physical Sciences for big teams (b_M = -0.0005), indicating some stability scholar publication count when examining diversity. Standard deviation slopes (b_{SD}) were generally low in magnitude, with both positive and negative values depending on subject area. This suggests some variation in the diversity of publication rates across disciplines, with no uniform pattern of increasing or decreasing diversity.

All subject areas showed significant differences between BTS and team science teams in both b_M and b_{SD}, as indicated by non-overlapping confidence intervals. Traditional team science consistently exhibited stronger negative slopes for average publication count than BTS teams, reflecting a more pronounced trend toward authors with fewer publications appearing over time. This result suggests that smaller teams are increasingly composed of researchers with lower overall publication counts, whereas BTS teams show a more muted shift. Effect sizes for these models were smaller than those observed for career length, with

R^2 values ranging from .0335 to .0977. The strongest association was observed in the Physical Sciences for big teams ($R^2 = .0977$), though all models showed low-to-moderate predictive ability.

Geopolitical Regions

Geographic patterns in authorship differed notably between BTS and team science publications, as shown in the publication maps and mosaic charts (Supplemental Figure A2). BTS publications were overwhelmingly concentrated in high-income countries, particularly the United States, Western European nations (e.g., Germany, the United Kingdom, France, and the Netherlands), and East Asian countries (e.g., China, Japan, and South Korea). In contrast, traditional team science publications showed broader geographic distribution, with relatively higher representation from Latin America (e.g., Brazil, Mexico), South and Southeast Asia (e.g., India, Pakistan, Indonesia), and parts of Africa and the Middle East. While both team types were led by traditionally defined Global North institutions, the mosaic charts revealed that traditional team science included a more diverse range of countries contributing at moderate levels. These patterns suggest that although BTS involves international collaborations, it remains more centralized in historically dominant research regions, whereas traditional team science may offer relatively greater global inclusivity at a smaller scale.

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. All slopes predicting geopolitical diversity over time were significantly different from zero, indicating small but non-zero changes in the number of regions represented on publications across disciplines and team types. Additionally, all slopes differed significantly between BTS and traditional team science publications, suggesting distinct patterns in the evolution of international collaboration. Within BTS publications, Life Sciences and Social Sciences showed statistically indistinguishable trends in regional diversity over time, as did Social Sciences and Health Sciences. In contrast, all other within-BTS comparisons differed significantly. For traditional team science publications, all four disciplines showed significantly different slopes, although the magnitudes of these differences were relatively small. Overall, the results suggest modest increases in geopolitical diversity in most disciplines, with a small decline observed only in Physical Sciences within BTS publications (b = -0.0129). Despite small effect sizes (all $R^2 < .012$), the consistent differences between BTS and traditional team science point to structural differences in how global participation is evolving across large-scale versus more traditional collaborations.

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 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.

Across all decades and team sizes, North America and Northwestern Europe consistently made up the majority of corresponding authors, as shown in Figure 5. This pattern held even as total team size increased, though the proportion of corresponding

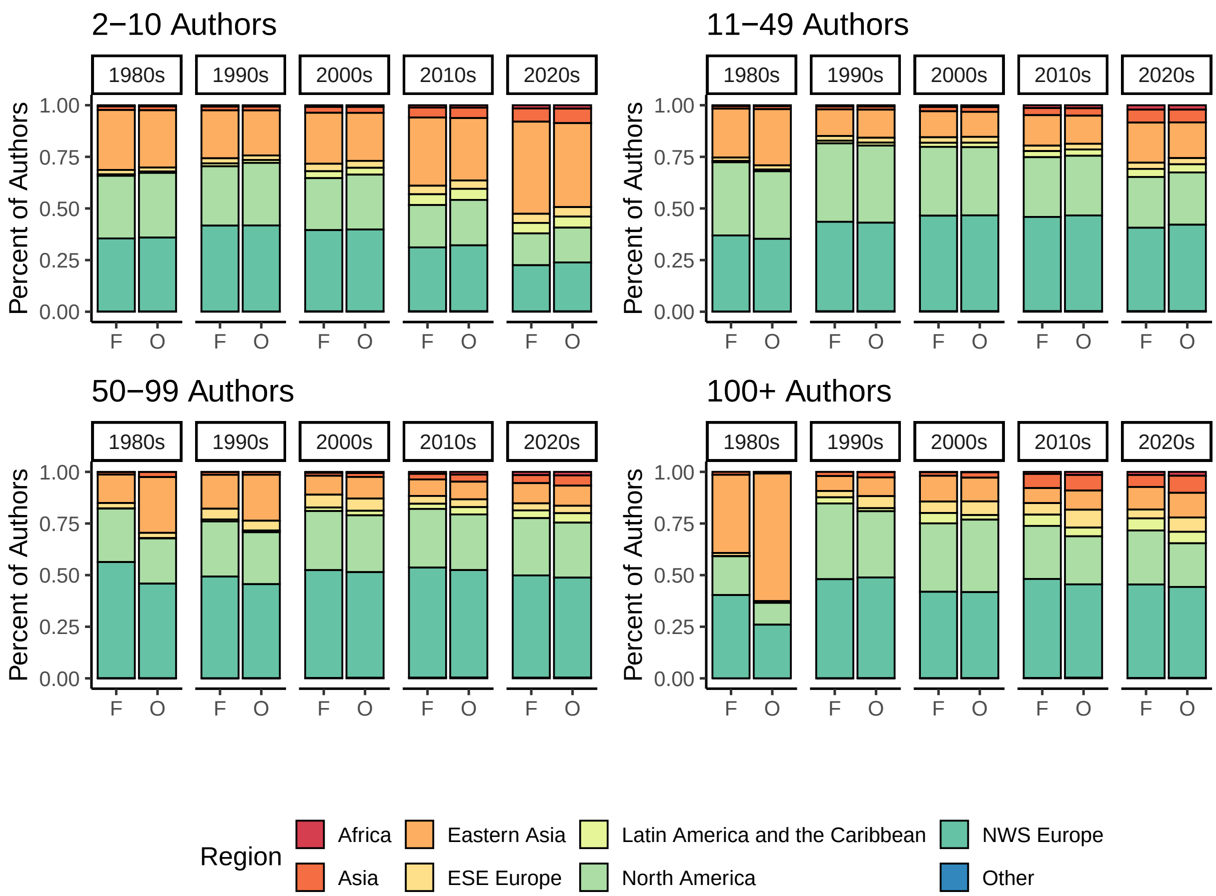

Figure 5

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

authors from other regions (e.g., Asia, Latin America and the Caribbean, and Africa) showed gradual increases over time. For traditional team science (2–10 authors), the dominance of North America and Western Europe in corresponding author roles was particularly pronounced. In contrast, for very large teams (100+ authors), regional diversity appeared somewhat more balanced, with more visible contributions from Asia and other regions among both corresponding and non-corresponding authors. However, visual inspection suggests that corresponding author sets remained less regionally diverse than the rest of the author team, particularly in earlier decades. While representation from regions like Africa and Latin America grew slightly among non-corresponding authors, they remained minimally represented in lead authorship positions. Notably, Eastern Asia's representation increased more substantially over time, especially in teams with 50 or more authors. These visual trends suggest persistent regional disparities in leadership roles within scientific publications, despite increasing global collaboration. Quantitative effect sizes (Cramer's V) and confidence intervals are reported in the following section to determine the importance of these observed differences.

Supplemental Figure A3 shows the magnitude of the difference in regional representation between corresponding authors and all other authors over time. A value of zero would indicate perfectly balanced regional diversity between the two groups, whereas larger values reflect increasing skew toward certain regions being more prominent in lead authorship positions. Effect sizes were often non-zero across much of the time span, particularly in publications with larger team sizes. Papers with 50–99 authors and 100+ authors showed the highest effect sizes in the 1970s through the 1990s, with V values frequently exceeding .20. This suggests that early large-team collaborations were especially likely to concentrate lead authorship within a narrow set of regions. However, across all team sizes, there was a clear downward trend in effect sizes over time, indicating that the regional composition of corresponding authors has become more similar to the rest of the author team. In recent decades, effect sizes for team science and mid-sized BTS teams (11–49 authors) have generally remained below 0.05, suggesting relatively balanced representation. For larger teams, effect sizes have also decreased, although they remain slightly elevated in more recent years compared to smaller teams. As a reference for interpretation, the vast majority of observed effects were small: 49.52% of comparisons had $V < .05$, 78.57% had $V < .10$, and 92.38% had $V < .20$. These results suggest that while regional imbalances in leadership authorship persist, they have gradually diminished in magnitude over time.

Discussion

This study expands on prior efforts to characterize Big Team Science (BTS) by providing a systematic, field-wide analysis of authorship composition across time, team size, and geography. While BTS efforts have been increasingly promoted as vehicles for collaboration, scale, and rigor (Adams, 2012; Uhlmann et al., 2019), questions remain about who gets included, who leads, and how equitably credit is distributed. A key contribution of our study is that it is the first to propose a data-driven operationalization of "big" teams: defined here as publications with 11 or more authors and contributions from at least 6 institutions, grounded in the empirical distribution of team sizes and affiliations across millions of papers. By comparing BTS publications with traditional team science publications across four major scientific domains, we clarify how BTS compares with traditional team science and how it is evolving. All areas of research show growth in the number of publications and authors included on manuscripts, replicating previous investigations (Hunter & Leahey, 2008; Sinatra et al., 2015; Wuchty et al., 2007).

Next, we find that early-career researchers are increasingly represented in both BTS and smaller teams. Across all disciplines, the average career length of authors decreased significantly over time. Traditional team science exhibited even steeper declines in both average and variability of career length than big teams, suggesting that smaller teams may be an especially important entry point for early-career researchers. These trends echo broader shifts in academia's incentive structures, where publishing early and often is increasingly required for career advancement (Larivière et al., 2015; Milojević, 2014). Publication counts showed similar but smaller effects. The average number of publications per author declined over time in both big and small teams, with smaller teams again showing more pronounced shifts. These findings support claims that collaborative science is no longer dominated exclusively by elite or high-output researchers (Milojević, 2014), but may instead be expanding to include contributors with more varied publication histories.

Our findings build on previous research by also examining diversity in author seniority and geopolitical affiliation. The growing participation of early-career scholars over time suggests that big team science may be increasingly accessible to a broader range of researchers, not just senior or established scientists. This trend is interesting given the challenges BTS projects can pose for non-permanent researchers: slow publication timelines, uncertain publication outcomes, and fewer incentives for non-corresponding authors. Yet, large teams may allow for more distributed workloads and reduced individual time investment, which could make them appealing even for early-career researchers. Moreover, prior work has shown that publications from larger teams tend to receive more citations and have broader impact (Larivière et al., 2015), which may further incentivize early-career involvement despite the structural risks. Globalization, the internet, and the focus on interdisciplinary research are potentially driving forces behind our results, but, hopefully, the results also point to a decline in scientific gate keeping (Lu, 2007; Siler et al., 2015).

Our results confirm and extend prior observations that both traditional team science and BTS are disproportionately concentrated in high-resource, highly networked regions, namely, North America and Western Europe (Adams, 2012; Singh et al., 2023; Sugimoto et al., 2017). However, this study offers a more nuanced picture. We observed modest increases in the geographic diversity of authorship. Yet, lead authorship remained concentrated in a relatively narrow set of regions. These findings parallel previous critiques of global equity in scientific collaboration, where authors from the Global South are often included in co-authorship lists but remain underrepresented in leadership roles (Chan et al., 2011; Sumathipala et al., 2004). Though Cramer's V values reflecting geographic imbalance decreased over time, especially for small and mid-sized teams, some asymmetries persist in large teams, reinforcing concerns about exclusion even within globally scoped research efforts (Abimbola, 2019).

Diverse teams are more likely to produce research with stronger impact, as reflected in higher citation metrics and broader dissemination, particularly when author lists include individuals from varied backgrounds and institutions (Freeman & Huang, 2014; B. F. Jones et al., 2008; Yang et al., 2022). These patterns underscore a broader shift in how scholarly contributions are valued and attributed. As scientific teams become larger and more interdisciplinary, traditional authorship conventions, especially the emphasis on first and last author positions, become less informative indicators of individual contribution (Allen et al., 2019; Brand et al., 2015). In response, initiatives like the CRediT taxonomy have emerged to increase transparency around contributor roles (Allen et al., 2014). Our findings reinforce the importance of such systems: as early-career and less-published researchers increasingly participate in both BTS and regular teams, formal recognition of diverse contributions becomes essential for equitable credit and career advancement.

The limitations for this research are tied to the curation of the Scopus dataset: the correct author affiliations, the correct author publication information, and the correctly marked geopolitical entity. Scopus is a carefully curated and large dataset, but these limitations must be kept in mind when interpreting the results. Publication language diversity was not investigated, and a previous study indicates that most publications in big databases are in English (Albarillo, 2014). Certainly, publications in non-English languages would improve the statistics on diversity in scientific publishing - but the English language barrier likely exists regardless of inclusion in databases (Meneghini & Packer, 2007; Ramírez-Castañeda, 2020). Another limitation is the process of indexing across time has significantly changed with the availability of the internet. For example, in Figure 2, traditional team science papers show a bump in the number of publications around approximately 1995, and the Web of Science came online in 1997, which included back indexing of journals not previous indexed.

Taken together, our findings suggest that BTS is evolving to include a broader and more diverse range of contributors, but also that smaller teams may remain more flexible or inclusive in incorporating early-career and globally distributed researchers. This result carries important implications for funders and institutions encouraging large-scale collaboration. Without structural support for equitable leadership, credit, and inclusion, particularly for authors from underrepresented regions, BTS risks reinforcing the very hierarchies it seeks to eliminate (Forscher et al., 2022).

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Appendix

Supplemental Material

We have included several supplemental tables and figures for visualization of results discussed in the manuscript.

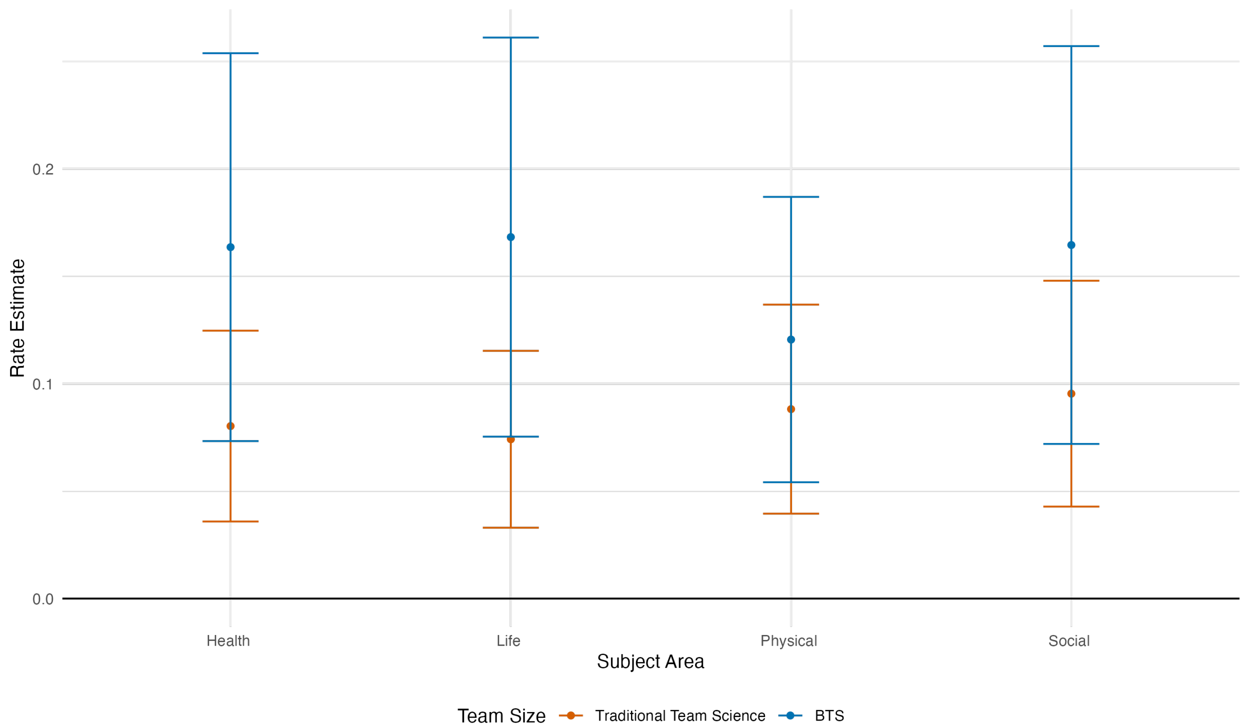

Figure A1

Exponential growth rate estimates with 95% confidence intervals.

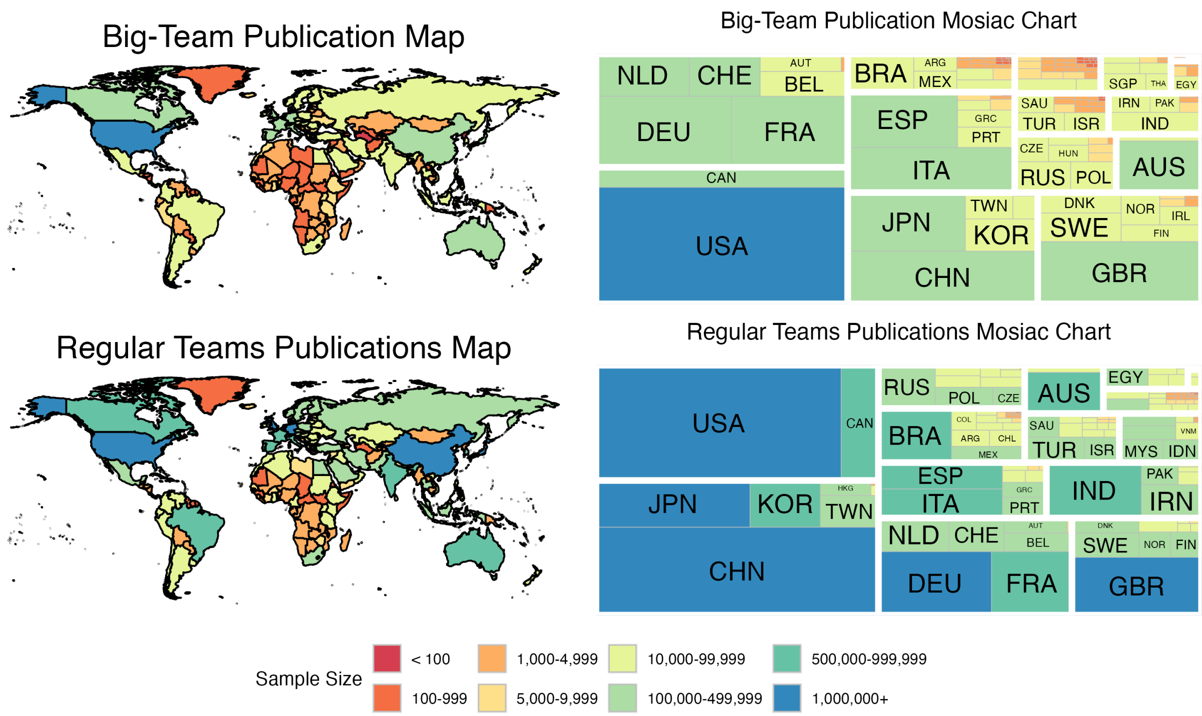

Figure A2

Geopolitical regions represented in big-team science publications versus all publications. The mosaic plot is grouped by UN subregion with the largest number of publications starting on the bottom left and smallest on the top right. Therefore, North America represents the largest number of authors within BTS (i.e., bottom right, then separated into the geopolitical areas within that subregion), followed by Eastern Europe (top left), and so on.

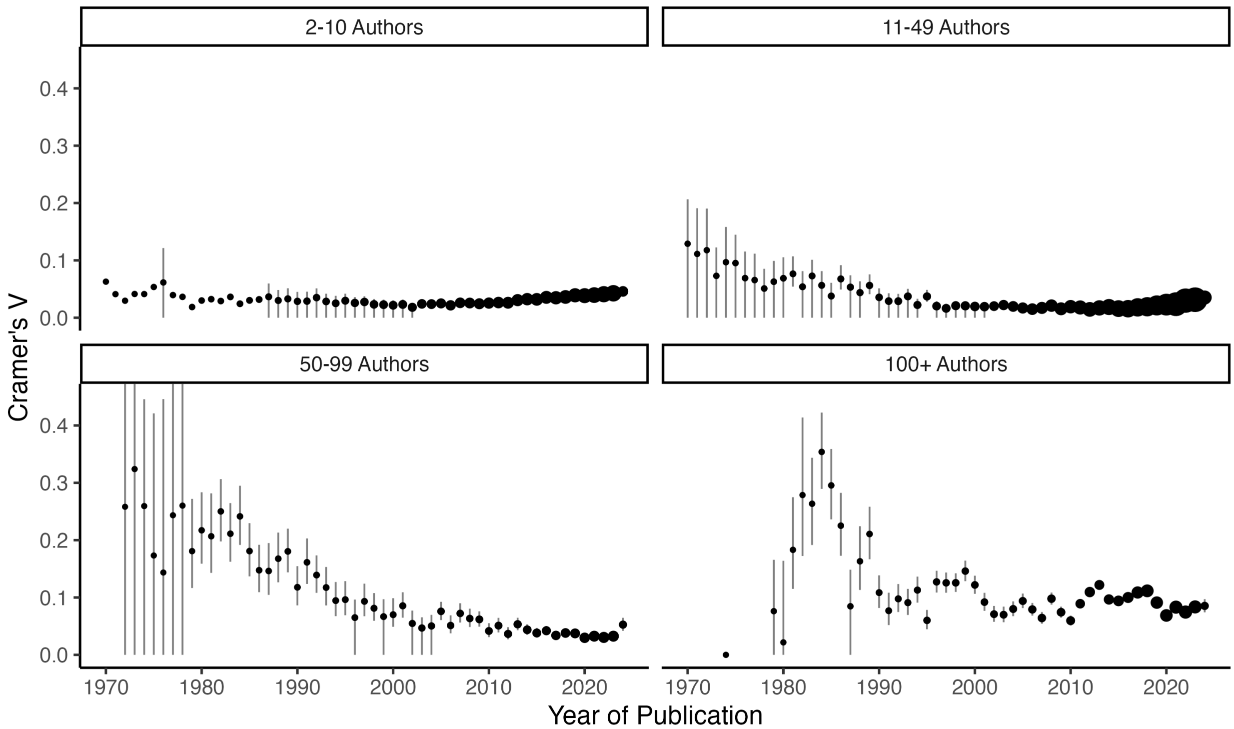

Figure A3

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.

Table A1

Number of Authors and Papers by Subject Area

Number of Authors	Statistic	Health Sciences	Physical Sciences	Social Sciences	Life Sciences
2+	Authors	12,096,908	15,366,570	5,182,626	11,557,780
11+	Authors	2,726,450	1,513,520	445,271	2,208,278
50+	Authors	767,322	319,453	65,409	378,522
100+	Authors	502,493	217,863	34,708	214,346
2+	Papers	8,758,846	17,195,880	3,441,064	8,705,266
11+	Papers	507,871	255,587	38,011	352,012
50+	Papers	17,184	26,010	894	8,690
100+	Papers	5,429	15,009	242	2,622

Note. Papers can be classified into multiple categories.