Governing the Scientific Journals: What Big Data and Computational Modeling Tell Us about the Policies That Shape Editorial Boards

by

Fengyuan Liu

A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
Department of Computer Science
New York University
May, 2025

Professor Talal Rahwan

Professor Bedoor AlShebli

Dedication

To my wife Fay for your company, love, and support.

Acknowledgements

> *"But try and do what you love with people you love. And if you can manage that, it's the definition of heaven on earth."* — Conan O'Brien

I would like to express my deepest gratitude to my advisors, Professor Talal Rahwan and Professor Bedoor AlShebli. I still vividly remember the evening I first met both of you. Walking into the classroom of Capstone Seminar, I was desperate to find someone who could accommodate my burgeoning interest in computational social science. The moment I saw the first slides of Talal's research presentation, I knew immediately who I wanted to work with. Little did I know then how profoundly this decision would shape my academic journey.

You have been the best advisors I could have asked for—trusting me, giving me the freedom to think independently, while providing support for my research continuously. You never set deadlines or rushed me for results, allowing me to explore ideas at my own pace. Yet, whenever I needed your feedback, I could always count on prompt responses from both of you, always within the same day. This nurturing and intellectually liberating environment has been instrumental in my growth, and I deeply appreciate your trust in me. You taught me everything I know about research. I owe a special debt of gratitude to Talal, who spent countless hours refining my writing, sentence by sentence. Beyond research, you have created a sense of family within our research group—not just for me, but for everyone in the lab. I am proud to have you as my academic parents. If doing what I love with people I love is the definition of heaven on earth, then I have been in heaven for the past five years. Were I ever to become a professor myself (inshallah), I can only aspire to support my students as you have supported me.

I am also immensely grateful to my mentors, collaborators, colleagues, and friends: Josh, for admitting me to the SMaPP Lab as an undergraduate research assistant and kindling my passion for computational social science; Petter, for instilling in me a taste for good visualizations; Molly, Dashun, Greg, Fabian, and Xitong, for believing in me; Yasir, for valuable research ideas; Minsu, for constant encouragement and advice; Hazem, for always taking on the heavy lifting in our joint projects; Shahan and Bala, for many inspiring and fun conversations and for pointing me to exactly the papers and books I needed; Kareem, Maria, Alexander, and Minda, for making our office a fun place that I look forward to going to every morning; Xiaoyao, Keyu, Daniel, Ayush, Marcin, Sid, Nouar, Puti, Birol, Lier, Yutong, Hanbo, Guanghui, Ken, Le Hung, Anh, Samridha, Jia, and Calvin—each one of you has contributed to my journey in various ways. Thank you all for being part of my life.

Behind the scenes, numerous individuals have played crucial roles in ensuring the university functions smoothly and in supporting me along the way. I extend my sincere appreciation to Santiago and Emily (NYU GSAS), Lama (IRB), Ron (Library), Waqqas (HPC), Karl, Ross, and Aysha (GPPO), Rafi (CDC), and Abdul and Narida (Immigration). Your support has been instrumental.

To my parents: Thank you for always believing in that I would get a PhD one day, even when I could barely count to 100. You have motivated me to be a good person, to seek truth, and to lead a meaningful and thoughtful life. These are the most valuable things (besides money, of course) you have given me .

Finally, to Fay—my best friend and my greatest source of joy. I am so incredibly lucky to have married you. I can never thank you enough for spending your best years with me in Abu Dhabi. Your presence has made my life so much more enjoyable. We shared laughter and tears, spent time together in ten different countries, survived COVID and quarantine, food poisoning (multiple times), and everything in between. Even though we will be away from each other in most of the coming years, these memories will keep our hearts closer than ever. I will always remember this postcard that you wrote to me and now I want to say the same thing to you: Thank you for teaching me and experimenting with me what love is. You have always believed in me, offered me unconditional support, and motivated me when I lost direction. You have also been my most honest critic—never hesitating to give me merciless feedback on my research ideas when I needed it most. So many times, I would excitedly share a research design with you while strolling on the High Line, only for you to immediately and concisely point out its flaws. And every time, I would think, “Exactly! How did I not see that?” I will strive to match you intellectually. Despite our vastly different personalities, which make us complement each other so well in life, we share values and a vision for the future that is so aligned. We will live a happy life and do great things together. You are the best thing that has ever happened to me. I love you.

Abstract

Academic journal editors are the gatekeepers of science, collectively shaping the content of scientific publications and setting standards for their fields of research. Yet, most editors take on this role as a form of community service while maintaining their primary careers as research-active scientists. This dual role raises two key questions at the heart of this thesis: (1) To what extent are editors representative of scientists at large in terms of their demographic composition? (2) How prevalent are conflicts of interest among academic editors? To address these questions, I construct two large, novel longitudinal datasets of academic editors and provide quantitative evidence on both fronts. Furthermore, these datasets enable me to evaluate the impact of policy interventions designed to (1) increase editorial board diversity and (2) mitigate conflicts of interest. By leveraging natural experiments identified in historical archives of journal policy documents, I analyze cases where such policies have been implemented and evaluate their effectiveness. Finally, I discuss the broader implications of big data and computational modeling for quantitative policy research.

Contents

List of Figures

List of Tables

Appendices

Part I

Introduction

1 | Background and literature review

In 1992, when the then-Harvard Biologist Philip Auron obtained patents over his discovery of the genetic sequence for interleukin-1 (IL-1), a human immune system molecule, he was surprised to find out that he was not the only one who had done so. It turns out that a different group of researchers, supported by a biotechnology company Immunex, has obtained a patent over sequencing the same gene that encodes IL-1 (meanwhile, Auron's research is funded by a competing biotech company called Cistron). Curiously, not only were the two competing groups made the same discovery at around the same time, their patent fillings include seven identical errors in their reported nucleotide sequence of the molecule [Marshall 1995b]. When Auron and Cistron took the case to court, it was revealed that the mistakes were unlikely to be pure coincidence: the researchers at Immunex reviewed a manuscript authored by Auron and colleagues reporting the sequencing of IL-1, which was submitted to the prestigious journal *Nature*. In their lawsuit, Auron's group claimed that the peer reviewers from the competing company misappropriated the secret information contained in the *Nature* manuscript, but the defendants argued that since the genetic sequence was already revealed, there is no secrecy surrounding the particular discovery [Crimaldi 1996]. Immunex eventually settled the charges of misappropriation and paid Cistron 21 million USD before the case was trialed [Marshall 1996]. While this leaves the question of legality of confidentiality in peer review unanswered [Science News Staff 1996], this case illustrates two defining characteristics of academic publishing that are central to this thesis.

First, academic publishing is a self-governed enterprise, where scientists "take turns at disciplining each other into disciplines" [Biagioli 2002]. In other words, although some editors are full-time professionals (e.g., those handling journals such as *Cell*, *Nature*, and *Science*), the vast majority of editors are research-active academics, who are in charge of gate-keeping scientific knowledge while being scientific practitioners themselves. This duality of roles inevitably means that their private interests as scientists could interfere with their commitment to the scientific enterprise. But what are their private interests? Admittedly, not every scientific paper contains scientific breakthroughs that worth millions of dollars such as the genetic sequences for IL-1, but the personal interests of editors are not just financial. In order to understand this point, one needs to first understand the dual nature of scientific publishing. On the one hand, scientific publications document scientific findings and subsequently contribute to progress of science. Meanwhile on the other hand, it is the formal avenue for scientists to obtain recognition for their contribution as scientists. In fact, the referees (now more commonly known as peer reviewers) was initially conceptualized to be "conferrers of rewards" and "defenders of the reputations of the scientific societies", neither of them have anything to do with scientific knowledge [Csiszar 2019]. Even in the aforementioned lawsuit where millions of dollars are at stake, the scientists at Cistron were also concerned with improper assignment of recognition—scientists at Immunex called their sequencing "IL-1α" and the sequencing discovered by Cistron, "IL-1β"—so much so that they publicly announced their protest in a letter to *Nature*, citing chronology as one of the two reasons that their sequencing should be referred to as the "α" one [Wolff et al. 1986].

Scientists are rewarded for publishing papers in various ways. The first and foremost reward is job and promotion; as early as 1749, authorship was required to attain university positions [Csiszar 2019]. Despite the increasing popularity of pre-printing services in recent years, having research published in high-impact, or simply indexed journals [Tian et al. 2016], still plays an important role in scientists' evaluation and promotion [Duan et al. 2025; Heckman and Moktan 2020; Notman and Woolston 2020; De Rond and Miller 2005]. Being aware of this, scientists optimize their number of publications in response to external incentives [Brogaard et al. 2018; Groen-Xu et al. 2023]. Some other rewards that are associated with scientific publications include membership of prestigious academic societies (as early as 1825, The Royal Academy of Sciences in Paris select members based on their publication records [Csiszar

2019]) and even outright monetary rewards [Mallapaty 2020]. To be clear, people do not necessarily become scientists just for the recognition, but the institution of scientific publishing aligns the personal interests of scientists for recognition with the public interests in scientific advancement [Gaston 1973]. As a result, editors, being research active scientists, have an incentive to publish, while simultaneously having the responsibility to gate-keep scientific literature, creating a potential conflict of interests. In this thesis, when we refer to the personal interests of editors, we exclusively mean their interests in having a paper published in the journal that they edit (be it their own paper, or their friends').

The second defining characteristic of scientific publishing as revealed by the aforementioned lawsuit, is that rules governing scientific publishing are not always explicit. While giving depositions in the Cistron Biotech v. Immunex Corp. case, the then-editor-in-chief of *Nature*, John Maddox, states that "'we're in the process' of changing instructions to authors and reviewers to make than more explicit" [Marshall 1995a]. Although it has always been desirable to regulate the COI of editors and reviewers, both finacial and non-financial ones, one reason that rules governing such behavior have mostly remained informal until recent years is the lack of technical feasibility. Thanks to the emergence of large-scale bibliometrics databases, peer review systems can now automatically check for COIs when recommending potential editors and reviewers to handle a manuscript. Concurrently, in the years since Cistron Biotech v. Immunex Corp., the policies regulating editors' behavior is becoming increasingly concrete and detailed, but it remains uncertain whether these rules have achieved their goals. In fact, as we will see in Chapter 6, even in cases where there exists formal rules, these explicit rules can sometimes be superseded by implicit ones. When and how these policies work or not work are therefore central questions that will be central questions studied in this thesis.

This is when the increasing availability of "big data" becomes handy; such data enabled us to examine the effect of policy interventions and imagine counterfactual scenarios had different policies been adopted instead. Using such data, we can now systematically investigate three aspects of any research policies: First, prior to implementation of new policies, how big a problem there is with the status quo. Second, if we were to implement new policies, what would be the cost of implementation? And finally, third, after implementation, are those policies effective (and closely related to this question—would alternative policies be more effective?)

Situated against this background, in this thesis, I study two areas of policies governing editors of academic journals—(1) the demographic composition of editorial boards, which are discussed in Chapter 3 and Chapter 4, and (2) the competing interests of academic editors, discussed in Chapter 5 and Chapter 6. This thesis serves two purposes. First, these two lines of research provide case studies showcasing the potential of policy research in the era of big data and computational models. Second, due to the importance of editors, these two topics are also important in their own right. Before we dive into the studies, I will provide an overview of the two datasets curated as a result of this thesis, which are the bedrocks for the subsequent quantitative analyses.

2 | Data and methods

This chapter includes content previously published in Nature Human Behaviour *[Liu et al. 2023a] and* the Proceedings of the National Academy of Sciences *[Liu et al. 2023b]; the authors retain copyright to both published articles.*

Academic editors play a crucial role in the scientific community as gatekeepers of scientific publishing [Siler et al. 2015]. They have the final say about what gets published [Newton 2010; Burgess and Shaw 2010], thereby controlling not just what gets published, but also the channel through which scientists receive prestige and recognition [Campanario 1996]. This thesis curates and analyzes two novel datasets of academic editors. This chapter provides an overview of the data collection process of each of them.

2.1 Editorial boards of Elsevier journals

Elsevier publishes 4,289 different journals in 2019, all of which are listed on ScienceDirect—a website operated by the publisher [Elsevier 2020b]. Each journal curates some or all of its past issues, and all of the articles that appeared in every curated issue. In addition to research articles, many journals list their editors on the Editorial Board page, which can be found in the first volume of each issue. These pages, which constitute the primary source of our editor-related data, were retrieved using the Elsevier Article Retrieval API [Elsevier 2020a]. In total, we collected 173,434 editorial board pages from 1,893 different journals. From these pages, we were able to extract the following information about each journal: title, issue, volume, discipline, publication date, names of all , affiliations of all editorial board members (or country of affiliation, or both), and the role of each editor (e.g., editor-in-chief, associate editors, managing editors, etc.).

To retrieve the publication records of these editors, we paired them with scientists from the Microsoft Academic Graph (MAG) dataset. In particular, an editor in Elsevier and a scientist in MAG are considered to be the same person if, and only if, they uniquely share the same name and affiliation. For any editor-journal pair, (e, j), the first (last) year of editorship is assumed to be the publication year of the first (last) issue of j in which e is mentioned as an editor. Moreover, the editorial career of e (as an editor of j) is assumed to span the period between the first and last years of editorship (inclusive), implying that any gap years (if they exist) are included in our analysis. Similarly, the academic career of any scientist s is assumed to span the period between the publication years of their first and last papers. As a result, the academic age of s in any given year y is $y - year^s_{\text{first}} + 1$, where $\text{year}^s_{\text{first}}$ is the publication year of the first paper of s.

Editorials were then excluded from the publication record of each editor, to ensure that it consists of scientific papers. To this end, we queried ScienceDirect to identify the type of each publication in Elsevier, and excluded over 13,000 publications falling under the following types: Book review, Conference info, Editorial, Encyclopedia, Erratum, News, Practice guideline, and Product review. This left us with about 168,000 publications (co-)authored by the 20,000 editors identified in MAG. Out of those publications, we randomly sampled 200 and manually verified that only two were, in fact, editorial pieces.

2.1.1 Characteristics of Elsevier editors

Here, we provide a descriptive analysis of all editors in our dataset, by exploring the characteristics of editors-to-be (here, we refer to editors in any role as "editors") before the start of their editorship and compare them to an average scientist. This analysis provides a quantitative answer to the question: Who becomes editors? To this end, for every editor, we randomly select a scientist whose discipline and academic birth year—the year when their first paper was published—match that of the editor. Then, we compare the pair in terms of citation count, paper count, h-index, collaborator count, and affiliation rank. Note that the attributes of the editor are measured before their editorship starts, implying that the measurements are not influenced by the potential boost in visibility associated with being an editor. Moreover, the scientist being compared to the editor has their attributes measured in the same year, implying that the pair had the same career length when the measurements were taken. Finally, it should be noted that those scientists may themselves include editors of different publishing houses, as would be expected from the average scientist in MAG whom those scientists are meant to represent.

If editors are scientific elites, we would expect their bibliometric outcomes to be much higher than that of average scientists. Indeed, compared to an average scientist of the same academic age and in the same discipline, an editor tends to have seven times more papers (102 vs. 13), eight times more citations (1,786 vs. 193), and four times greater h-index (16 vs. 3); see Figures 2.1a to 2.1c. Note that these results disregard editorials, as previously explained. As for the number of collaborators, an editor has on average 163 at the start of the editorship, while the average scientist has about 29 (Figure 2.1d). Figure 2.2 shows the distribution of the data in Figures 2.1a to 2.1d on a log-log scale. In terms of affiliation, 35% of editors are affiliated with a top-ranked institution—one that is ranked amongst the top 100 according to the Academic Ranking of World Universities [ARWU 2019]—compared to just 20% for scientists (Figure 2.1e).

Next, we analyze how the characteristics of editors upon the start of their editorship have changed over the past four decades. Specifically, let (e, j) denote an editor-journal pair such that editor e served on journal j. Moreover, let $\text{year}_1^{(e,j)}$ be the first year of the editorship, and let $\text{year}_0^{(e,j)}$ be the year that precedes it. Then, for any given year $y \in [1980, 2017]$, we consider every editor-journal pair, (e, j), such that $\text{year}_0^{(e,j)} = y$, and measure the characteristics of e and their matched scientists at the year y. The results are depicted in Figures 2.1f to 2.1k, where the average values corresponding to editors and scientists are depicted as blue circles and green diamonds, respectively. As can be seen, the expected number of citations that an editor has accumulated by the start of their editorship has increased ninefold over the past decades (from 311 in 1980 to 3,014 in 2017), the number of accumulated papers has more than quadrupled (from 34 to 138), the h-index has tripled (from 7 to 21), the number of collaborators has increased fivefold (from 38 to 240), while the percentage of those affiliated with top-ranked institutions has decreased (from

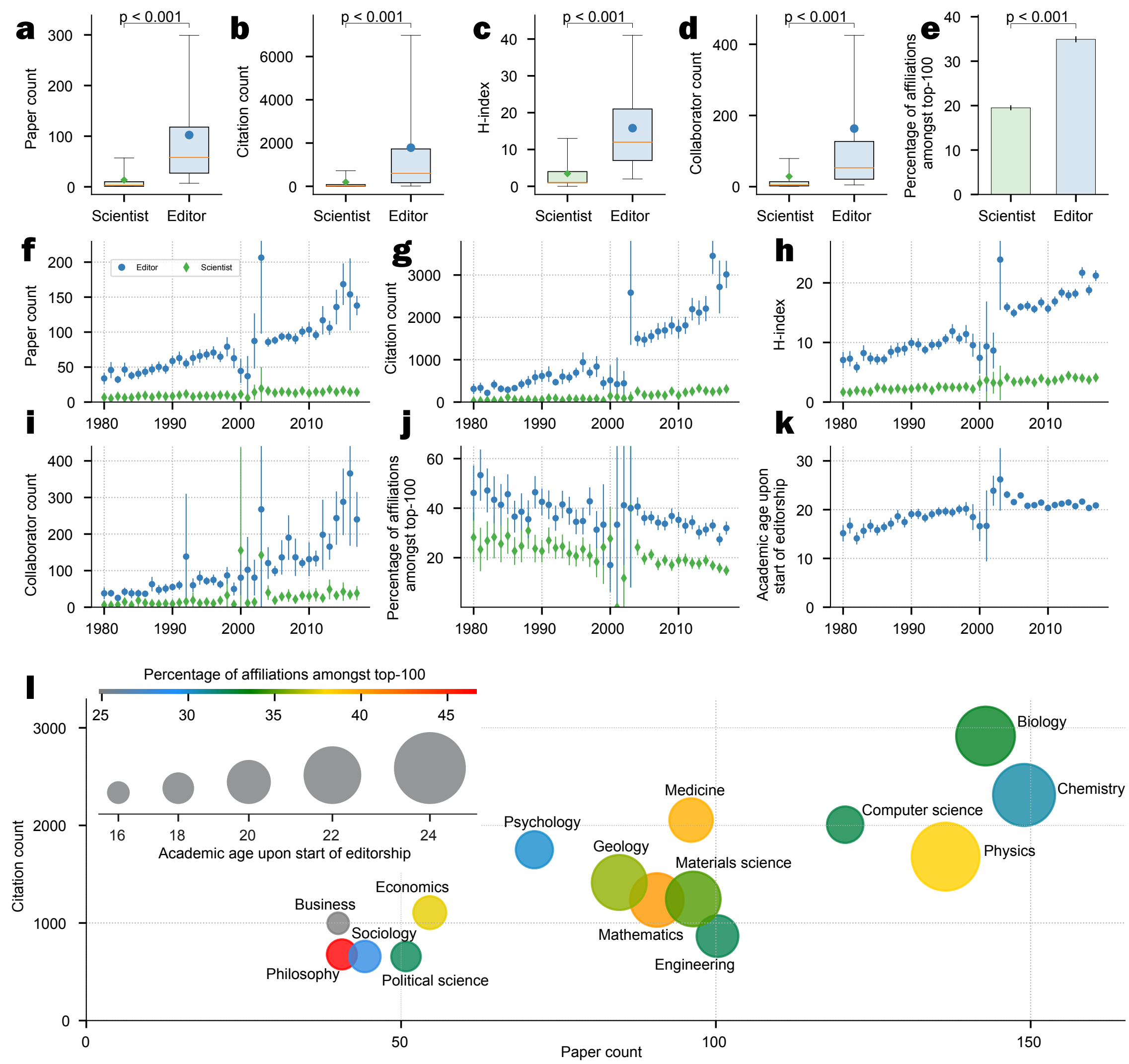

Figure 2.1: Editors' characteristics upon the start of editorship. Each editor ($n = 19,064$) is compared to a randomly selected scientist whose discipline and first year of publication matches that of the editor; descriptive statistics are measured at the year preceding the start of the editorship, with error bars representing the 95% confidence intervals. **a–e**, Comparing editors to scientists in terms of paper count, citation count, h-index, collaborator count, and percentage of those whose affiliation ranks among the top 100; circles and diamonds represent the sample mean of editors and scientists, respectively; the boxes extend from the lower to upper quartile values of the data, with a line at the median; whiskers extend until the 5-th and the 95-th percentile; p-values are calculated using two-sided Welch's T-tests (**a–d**) and two-sided Fisher's exact test (**e**); all p-values are less than 10^{-250}. **f–j**, Comparing editors to scientists over time in terms of paper count, citation count, h-index, collaborator count, and percentage of those whose affiliation ranks among the top 100. **k**, For each year, the mean academic age of editors upon the start of their editorship. **l**, Editors' paper count (x-axis), editors' citation count (y-axis), editors' academic age (circle size), and percentage of editors whose affiliation ranks among the top 100 (circle color) across disciplines; the differences in the circle sizes are exaggerated to improve visibility. Data are presented as mean values +/− 95% confidence intervals (**e–k**).

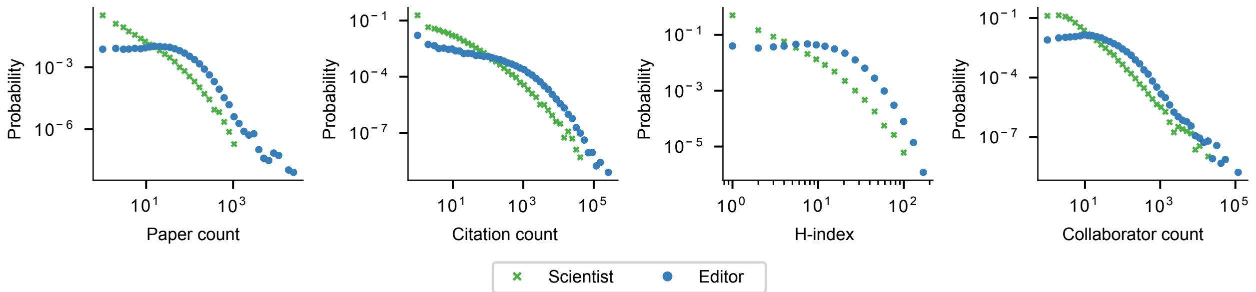

Figure 2.2: The distribution of the paper count, citation count, h-index, and collaborator count of editors and scientists. Only 2 editors never published a single paper before the start of their editorship.

46% to 32%). Next, we examine the gap between editors and scientists over the past decades. Comparing 1980 to 2017, we find that the gap in productivity has increased more than fourfold (from 27 in 1980 to 124 in 2017), the gap in impact has increased eightfold (from 289 to 2706), the gap in h-index has more than tripled (from 5 to 17), while the gap in collaborator count has increased more than fivefold (from 32 to 202). As for the percentage of those affiliated with a top-ranked institution, it has decreased over the years for both editors and scientists at about the same rate (from 46% to 32% for editors, and from 28% to 15% for scientists), suggesting that this trend is not related to changes in the way editors are recruited, but rather to changes in the global demographics in academia. Finally, looking at the academic age of the editors upon the start of their editorship, we find that it has increased from 15 years in 1980 to about 20 years in 2017 (Figure 2.1k). These findings suggest that, when it comes to assuming an editorial role, being impactful, productive, connected, and experienced seem to matter more than being affiliated with a top-ranked institution. Note that in Figures 2.1f to 2.1k an anomaly can be seen around the years 1998–2003. Upon inquiry, Elsevier representatives clarified that this anomaly is an artifact of an incomplete capture of all articles during the first years of their transition from print to online.

Having analyzed how different characteristics of editors change over time, we now compare those characteristics across disciplines. More specifically, Figure 2.1l compares editors from different disciplines in terms of the number of citations and papers that an editor has accumulated, as well as their affiliation rank and academic age, upon the start of the editorship. We find that Biology recruits the most highly cited editors, with 2,900 citations on average, while Chemistry recruits the most productive editors, with an average of 149 papers. In contrast, the impact seems to matter the least when recruiting editors in Philosophy, Sociology and Political Science, while productivity seems to matter the least when recruiting editors in Business and Philosophy. As for academic age, we find that Business recruits the youngest editors, with 16 years of experience on average, while Physics recruits the eldest, with 24 years of experience. We calculate the average academic age of editors across disciplines, and find it to be just over 20 years. Finally, in all disciplines, the percentage of editors affiliated with a top-ranked institution ranges from 25% to 47%, with Philosophy having the greatest percentage.

2.2 Editorial boards of PNAS and selected Open Access publishers

A notable limitation of the aforementioned dataset is that it lacks information about the handling editor of each paper. Therefore, we curate another dataset consisting of six different publishers which consistently specify the handling editor of all paper pubilshed therein. These six publishers are: the Public Library of Science (PLOS), Frontiers Media S.A. (Frontiers), the Multidisciplinary Digital Publishing Institute (MDPI), Hindawi Publishing Corporation (Hindawi), the Institute of Electrical and Electronics Engineers (IEEE), and the Proceedings of the National Academy of Sciences (PNAS). We refer to these as publishers, since they publish scientific papers, although it should be noted that these are actually four publishers, one academic society (IEEE), and one multidisciplinary journal (PNAS). For IEEE, this thesis only considers the ten open-access journals that publicize the editor's name and the dates of submission and acceptance. For PNAS, this thesis only considers the papers that are published since the year 2001, as none of the remaining five publishers existed before 2001. Notice that the publisher PNAS currenlty publishes two journals, namely PNAS and PNAS Nexus. Since the latter journal published its first issue in 2022, while our dataset does not extend beyond 2020, this journal is not included in our analysis. For a breakdown of the number of papers, authors, and editors from each publisher, see Table 2.1. Next, we describe the procedures of collecting information pertaining to the handling editors as well as the dates of submission and acceptance.

PLOS, Frontiers, MDPI, and Hindawi provide full-text corpora of all papers published therein, along with editorial process metadata, enabling us to extract the dates on which papers were received and accepted, as well as the names of the handling editors. As for PNAS, although it does not maintain such a corpus of its papers, it has granted us permission to scrape its website. As such, we scrape the webpage of each paper, and extract the dates on which the paper was received and accepted, as well as the name of its handling editor. We only considered papers submitted through the direct submission track, which makes up the vast majority of PNAS papers, and excluded from our analysis all communicated papers (a submission track that was discontinued in 2010) as well as all contributed papers (a submission track that only members of the National Academy of Sciences can use). As for IEEE, it neither maintains a full-text corpus of its papers, nor does it reply to our request to scrape its website. Therefore, we had to restrict our analysis to the subset of open access journals whose papers can be downloaded freely, and manually collect the information we need, i.e., the dates on which each paper was received and accepted, and the name of the handling editor. Similar to the dates and names of handling editors, the affiliation of editors were also extracted from the metadata of papers published by PLOS, Frontiers, PNAS, and IEEE. On the other hand, Hindawi and MDPI only specify this information for currently-active editors. As such, we downloaded past versions of the editorial board webpages using the Wayback Machine, and then recorded the affiliations of the editors listed in each version. For example, this page lists the current editorial board member of Disease Markers—a journal published by Hindawi—while this page tracks the historical snapshots taken of the same page.

Editor's name and affiliation allow us to identify the bibliometrics data of editors using the Microsoft Academic Graph (MAG)—a dataset that provides publication records of over 200 million scientists [Sinha et al. 2015; Wang et al. 2019], and it is widely used by the Science of Science researchers [Gomez et al. 2022; AlShebli et al. 2018; Huang et al. 2020; Benson et al. 2018; Frank et al. 2019; Murphy et al. 2020; Yang et al. 2020; Peng et al. 2021]. More specifically, an editor e affiliated with institute x in year t is considered the same person as a scientist s in MAG, if and only if s is the only one in MAG who has the exact same name as e, and is affiliated with institute x in year t.

Table 2.1: Number of papers, editorships, and authorships in each publisher.

Publisher	No. papers	No. authorships	No. editorships
PLOS	285502	1981433	177411
MDPI	249047	1310646	96729
Hindawi	208678	959212	97602
Frontiers	204582	1242286	138727
PNAS	45837	330699	37916
IEEE	40781	172022	12927

2.3 Methods

2.3.1 Discipline classification

MAG categorizes papers into 19 top-level disciplines, which are further categorized into lower-level sub-disciplines on five different levels. Let D be a high-level discipline, and let d be a lower-level sub-discipline. We write $d \in D$, if and only if d is a child of D. Each paper, p, is associated with a discipline, d, with a confidence score $conf(p, d) \in [0, 1]$. Using this information, we consider a paper p to be in a top-level discipline D with a certain confidence calculated as follows:

$$conf(p, D) = \max_{d \in D} conf(p, d)$$

Based on this, the primary discipline of a paper, p, is computed as follows:

$$\begin{aligned} \mathcal{D}(p) &= \arg\max_{D} conf(p, D) \\ &= \arg\max_{D} \max_{d \in D} conf(p, d) \end{aligned}$$

2.3.2 Race classification

To identify the race of each scientist, we followed the common practice of using computational methods designed specifically to infer an individual's race from their name [Le et al. 2021; AlShebli et al. 2018; Kozlowski et al. 2022]. More specifically, we use *NamePrism* to classify scientists into six different racial groups: Asian/Pacific Islander (API), American Indian/Alaskan Native (AIAN), Black, Hispanic, Two or more races (2PRACE), and White [Ye et al. 2017]. Note that NamePrism is widely used in the social sciences to infer the race or ethnicity of given names [AlShebli et al. 2018; Diamond et al. 2019; Kempf and Tsoutsoura 2021; Chen et al. 2020; Nadri et al. 2021; de Rassenfosse and Hosseini 2020; Ghosh et al. 2021; Zeina et al. 2020; O'Brochta 2022; Law and Zuo 2022]. Since an extremely small number of scientists were classified as either AIAN or 2PRACE, we excluded these two racial groups from this thesis. Using the classified race of scientists, we classify the papers into racial groups based on the race associated with more than 50% of the authors.

2.3.3 Gender Identification

Several gender classifiers have been proposed to date [Larivière et al. 2013; Wais 2016; West et al. 2013]. Following other studies in the literature [Topaz and Sen 2016; AlShebli et al. 2018; Jadidi et al. 2018; Holman et al. 2018; Huang et al. 2020], we use *Genderize.io*, which has been shown to outperform other alternatives [Wais 2016]. This classifier integrates publicly available census statistics to build a name database, mapping names to binary gender labels. In our gender-related analysis, we only considered scientists whose first names were classified with a confidence of 90% or above.

2.3.4 Calculating relative acceptance delay

The relative acceptance delay (RAD) is calculated for any paper p published in journal j in year y as the relative difference between the acceptance delay of p and the average acceptance delay of papers published in j in year y. Formally, for a paper p published in journal j in year y, the RAD of p equals (2.1)

$$\frac{(\text{acceptance delay of } p) - (\text{avg. acceptance delay of all papers published in } j \text{ in } y)}{(\text{avg. acceptance delay of all papers published in } j \text{ in } y)} \times 100 \tag{2.1}$$

2.3.5 Measuring citational distortion

In this section, I first show that, when studying citation, the content of papers provides additional information that cannot be inferred from the venue and discipline of a paper. Then, the second section provides details on how we applied citational lensing, a method recently proposed by Gomez et al. [2022] that accounts for the content of papers when studying citation disparity, to measure the racial gap of citation rates.

2.3.5.1 Textual similarity predicts citation

Gomez et al. [2022] improves over traditional methods of studying citation disparity (such as Nielsen and Andersen [2021]) by using an original measure that accounts for textual similarity between groups of papers when studying citation disparity. However, some may argue that bibliometric information such as venue and discipline of a paper roughly approximates its content, so there might be no need to consider textual information when studying citation.

To examine whether such is the case, we train two classifiers to predict whether a paper cites another given any pair of papers. Both classifiers are ensembles of fifty decision trees boosted using the AdaBoost algorithm [Freund and Schapire 1997]. The first classifier predicts whether one paper cites another using the discipline, journal, and year of publication of both papers, while the second one considers the content of both papers, and the textual similarity between the two, in addition to the aforementioned bibliometric features. Given a pair of papers, the content of either one of them is represented as a vector of topic distribution obtained using Latent Dirichlet Allocation (LDA), and the textual similarity between the pair is represented as the cosine similarity of those two vectors.

We found that, when the classifier only considers the papers' disciplines, journals, and years of publication, it achieves an accuracy of 68.61% on the test sets. However, if the textual features of a paper is included, the accuracy reaches 85.43%. This suggests that the content of a paper does provide insight that is not fully captured by a paper's venue and discipline, providing further evidence that textual information should be considered when studying citation disparity.

2.3.5.2 Studying citation disparity using citational lensing

Following Gomez et al. [Gomez et al. 2022], we construct multiplex networks consisting of three layers for each discipline t in each year y. The first layer, $\mathbf{L}_{\text{citation}}$, is a network such that each node represents a race, and the weight of an directed edge between node u and v is the number of citations that v receives from all papers that u publishes in discipline t and year y.

The second layer, $\mathbf{L}_{\text{text}}^{\mathrm{T}}$, is a network such that each node represents a race, and the weight of an directed edge between node u and v represents how similar the corpus of papers published by u is similar to that of v in discipline t in year y. Such similarity is calculated as the KL-divergence of the distribution of topics of all papers published by u and by v in the given year and discipline. To obtain the distribution of topics of a each race, we first label each paper by all unique races of authors on that paper, and apply the labelled LDA model [Ramage et al. 2009] to the collection of n-grams of those papers.

Lastly, we standardize the weight of edges within each network, and calculate the third layer as follows: $\mathbf{L}_{\text{distortion}} = \mathbf{L}_{\text{citation}} - \mathbf{L}_{\text{text}}^{\mathrm{T}}$. This layer represents how much more or less one race cites another relative to the textual similarity of research produced by both races.

Part II

Diversity

3 | Underrepresentation of non-White editors

Content of this chapter was previously published in the Proceedings of the National Academy of Sciences *[Liu et al. 2023b]; the authors retains copyright to the published articles.*

The underrepresentation of racial minorities in science is well-documented [Tilghman et al. 2021; National Center for Science and Engineering Statistics 2021, 2019; Jackson et al. 2019; Committee on Underrepresented Groups and the Expansion of the Science and Engineering Workforce Pipeline 2011; McGee Jr et al. 2012; Rushworth et al. 2021], but racial disparities in academia go beyond the problem of underrepresentation. Take citations for example. By analyzing the reference lists of papers published in top neuroscience journals, a recent study found that papers with White first and last authors are cited 5.4% more than expected, while those with non-White first and last authors are cited 9.3% less than expected [Bertolero et al. 2020]. Similarly, scientists of color receive less media coverage. More specifically, it has been shown that East-Asian scientists make up less than 7.7% of quotes in non-research articles published by the journal Nature, while they constitute 14.3% to 33.6% of all relevant last authorships [Davidson and Greene 2021]. Racial disparity is also observed in career opportunities. For example, among medical school faculty, underrepresented minorities (including Black, Mexican American, Native Alaskan, Native American, and Puerto Rican) are less likely to be promoted compared to their White counterparts at both assistant and associate professor level [Fang et al. 2000]. A follow-up study found that there is no longer a racial difference in the promotion rate of associate professors, but Black assistant professors still suffer from having the lowest promotion rates across all specialties, and take the longest time before getting promoted [Abelson et al. 2018]. Even after being appointed as faculty members, Black and Asian scientists are less likely to receive U.S. National Institutes of Health (NIH) grants compared with White scientists [Ginther et al. 2011]. Consequently, it is not surprising that names of Celtic/English origin are overrepresented while names of East Asian origin are underrepresented among honorees such as scientific society fellows or keynote speakers at conferences organized by those societies [Le et al. 2021].

This chapter contributes to this line of research by examining geographical and racial disparities in three aspects that are closely related to research-active scientists. The first is editorial board composition. Since editors can exert considerable control over scientific discourse, it is important to identify the underrepresented demographic groups among editors. Past studies on ethnic and racial diversity found that the majority of editorial board members are White in various disciplines [Salazar et al. 2021; Ford et al. 2017; Beath et al. 2021; Shim et al. 2021; Riano et al. 2022]. The unequal representation of nationalities on the editorial boards has also been considered in the literature. In particular, past studies found that editorial boards are dominated by scientists from North America and Europe [Murray et al. 2019; Braun et al. 2007; Harzing and Metz 2013; Polonsky et al. 2006; García-Carpintero et al. 2010; Espin et al. 2017; Svensson 2005].

The second aspect considered in this chapter is acceptance delay—the number of days between the submission and acceptance of a manuscript. While the peer review process is necessary for scientific rigor, prolonging this process may have a toll on the authors, especially if they are funded for a fixed period of time (as is typically the case with PhD students and postdoctoral researchers) or if they have a deadline after which their performance is evaluated (as is the case with tenure-track faculties) [Bilalli et al. 2021]. Various paper-related and scientist-related attributes have been found to correlate with the length of the peer review process. For example, papers whose authors are editorial board members, most frequent contributors of the journal, or from high-income countries experience shorter acceptance delays [Taşkın et al. 2022]. Papers with positive findings also spend significantly shorter time under review compared to those without [Stern and Simes 1997]. The personal relationship between an editor and a reviewer may also affect the timeline of the peer review process, with the reviewers known personally by the editor being more likely to respond to a review request [Mrowinski et al. 2016].

The third and final aspect is citation rates. Past studies have shown a racial gap in citation rates across disciplines [Bertolero et al. 2020; Kozlowski et al. 2022; Chakravartty et al. 2018]. However, all these studies quantify the citation gap while only taking into consideration bibliometric characteristics (e.g., publication year and publication venue, as well as the authors' disciplines, affiliations, and academic age), effectively disregarding what is arguably the most important factor that scientists consider when deciding whether to cite a paper or not—the content of that paper. To address this shortcoming, a recent study proposed a method called citational lensing [Gomez et al. 2022], which builds on the tradition of using textual analysis along with citation data to model the spread of knowledge [Dias et al. 2018; Altmann et al. 2017]. This method allows for quantifying citational distortions while controlling for textual similarities between papers. The authors applied their method to compare citation rates across countries, but not across races. One may argue that the citation gap between races can be inferred from the gap between countries, especially since the population in some countries is dominated by a certain race. However, such analysis would not be able to disentangle the effect of the author's race from the effect of the geographical location of their affiliation. To this end, there is a need for a study that examines the racial gap in citation rates based on textual similarity while holding the country constant.

Using the novel dataset curated as a result of this thesis (Chapter 2.2), we are able to chart the racial and geographical disparities in the aforementioned aspects—editorial board composition, acceptance delay, and citation rates—at an unprecedented scale. Taken together, this chapter offer a better understanding of the inequalities experienced by non-White scientists, showing that they appear on fewer editorial boards, spend more time under review, and receive fewer citations compared to White scientists doing similar research.

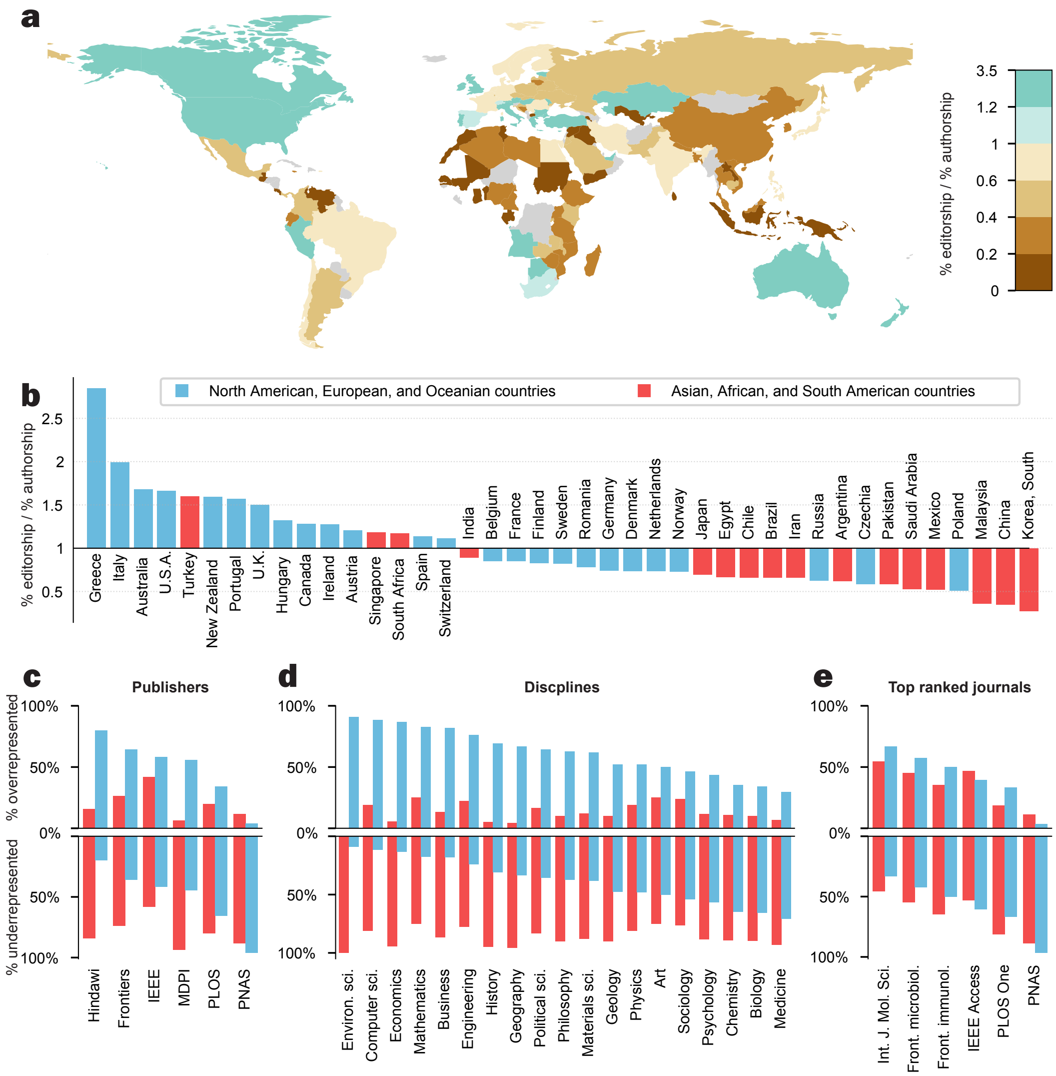

Figure 3.1: Representation of countries among editors. For any given country, the editor-to-author ratio is calculated as the percentage of editorship from that country, divided by the percentage of authorship from that country. A country is overrepresented among editors if the ratio is > 1, and underrepresented if the ratio is < 1. **a**, The editor-to-author ratio for countries around the globe. Here, a country is colored in (light or dark) green if it is significantly overrepresented, in (different shades of) brown if it is significantly underrepresented, and in gray otherwise (Fisher's exact test, $p < 0.001$). The editor-to-author ratios for all countries are divided into 5 quantile intervals. The interval containing 1 is further subdivided into two disjoint intervals, one consisting of values > 1 (assigned a shade of green) and another consisting of values < 1 (assigned a shade of brown). Countries for which the percentage of authorship or the percentage of editorship is zero are omitted from the map. **b**, Editor-to-author ratio of countries that have at least 1,000 editors and are significantly over- or under- represented in editorial boards; countries in Africa, Asia, and South America are colored in red while other countries are colored in blue. **c**, In each publisher, the percentage of countries that are significantly overrepresented (upper panel) and underrepresented (lower panel). **d**, The same as (**c**) but in each discipline. **e**, The same as (**c**) but in each top-ranked journal according to Google Scholar.

3.1 Editorial board representation

We start by examining the degree to which the scientists in any given country are represented on editorial boards. To this end, we divide the percentage of editorship by the percentage of authorship from each country, resulting in a national editor-to-author ratio. As such, the scientists in any given country are overrepresented if the ratio is > 1 and underrepresented if it is < 1. Figure 3.1a shows the editor-to-author ratio for all countries around the globe. As can be seen, the vast majority of countries in Asia, Africa, and South America (where most of the population is ethnically non-White) are underrepresented in editorial boards. Overall, scientists residing in these continents account for 35% of authorship, but only 19% of editorship. Note that there are countries in which the former percentage is extremely small, e.g., Botswana and Angola, the two main outliers in Africa, account for less than 0.02% of total editors combined. To exclude such countries, Figure 3.1b focuses on those that have at least 1,000 editors and are statistically significantly over- or under- represented on editorial boards. Indeed, out of the 16 countries in Africa, Asia, and South America, 13 are underrepresented, with Malaysia, China, and South Korea having less than half the editorships that one would expect based on their percentage of authorships.

So far, these findings reflect the average trend, taken over the six publishers and nineteen disciplines that we focus on in this Chapter. Figure 3.1c analyzes each publisher in isolation, showing that countries in Asia, Africa, and South America are more likely to be underrepresented on the editorial boards of each publisher, with the only exception being PNAS, whose editors are predominantly U.S.-based since they are all members of the National Academy of Sciences. The two publishers with the greatest disparities are MDPI and Hindawi, with 93% and 84% of Asian, African, and South American countries being underrepresented on their editorial boards, respectively, while 55% and 80% of North American, European, and Oceanian countries are overrepresented. Moreover, analyzing each discipline separately reveals that the geographical disparity is widespread across all disciplines (Figure 3.1d). Lastly, out of all journals in our dataset, we focus on those who happen to be among the top 20 journals in their respective discipline according to Google Scholar [Google 2022]. As can be seen in Figure 3.1e, these journals show little geographical disparities in terms of editorial board representation.

Having examined the representation of different countries in editorial boards, we now examine the representation of different races. Following other works in the literature [Le et al. 2021; Kozlowski et al. 2022; AlShebli et al. 2018] we infer the scientists' race from their names; see Methods for more details. To eliminate the above-established confounder—the country in which the scientists are affiliated—we restrict our analysis to those affiliated with U.S.-based institutions. Focusing on a single country may control for additional confounders, e.g., whether English is the authors' working language. Figure 3.2a shows that White scientists make up 57% of all editors, followed by Asian and Pacific Islanders (API) scientists who make up about 40% of all editors, while only 3% and 0.1% of editors are Hispanic and Black, respectively. One possible explanation could be the fact there are fewer non-White scientists compared to White ones in the U.S. To explore this possibility, we compared the racial distribution of editorship to that of authorship. As shown in Figures 3.2b to 3.2e, during the first years of the millennium, White scientists were markedly overrepresented, while Hispanic, API, and Black scientists were underrepresented on editorial boards. In the years that followed, the racial gap has been closed for Hispanic scientists, and appears to be closing for API scientists. Unfortunately, however, the gap grew even larger for Black scientists.

Next, to determine whether the underrepresentation of non-White scientists occurs in the editorial boards of certain publishers but not in others, we examined the editor-to-author ratio in each publisher separately during the past decade, i.e., from 2011 to 2020. As shown in Figures 3.2f to 3.2i, White scientists are underrepresented in only one out of the six publishers, API, and Hispanic scientists are underrepresented in four out of the six, while Black scientists are underrepresented across all publishers. When grouping editors into disciplines, we see broadly similar patterns. In particular, White editors are overrepresented in most disciplines (Figure 3.2j), while API and Hispanic editors are underrepresented in most disciplines, and Black editors are underrepresented in all disciplines (Figure 3.3).

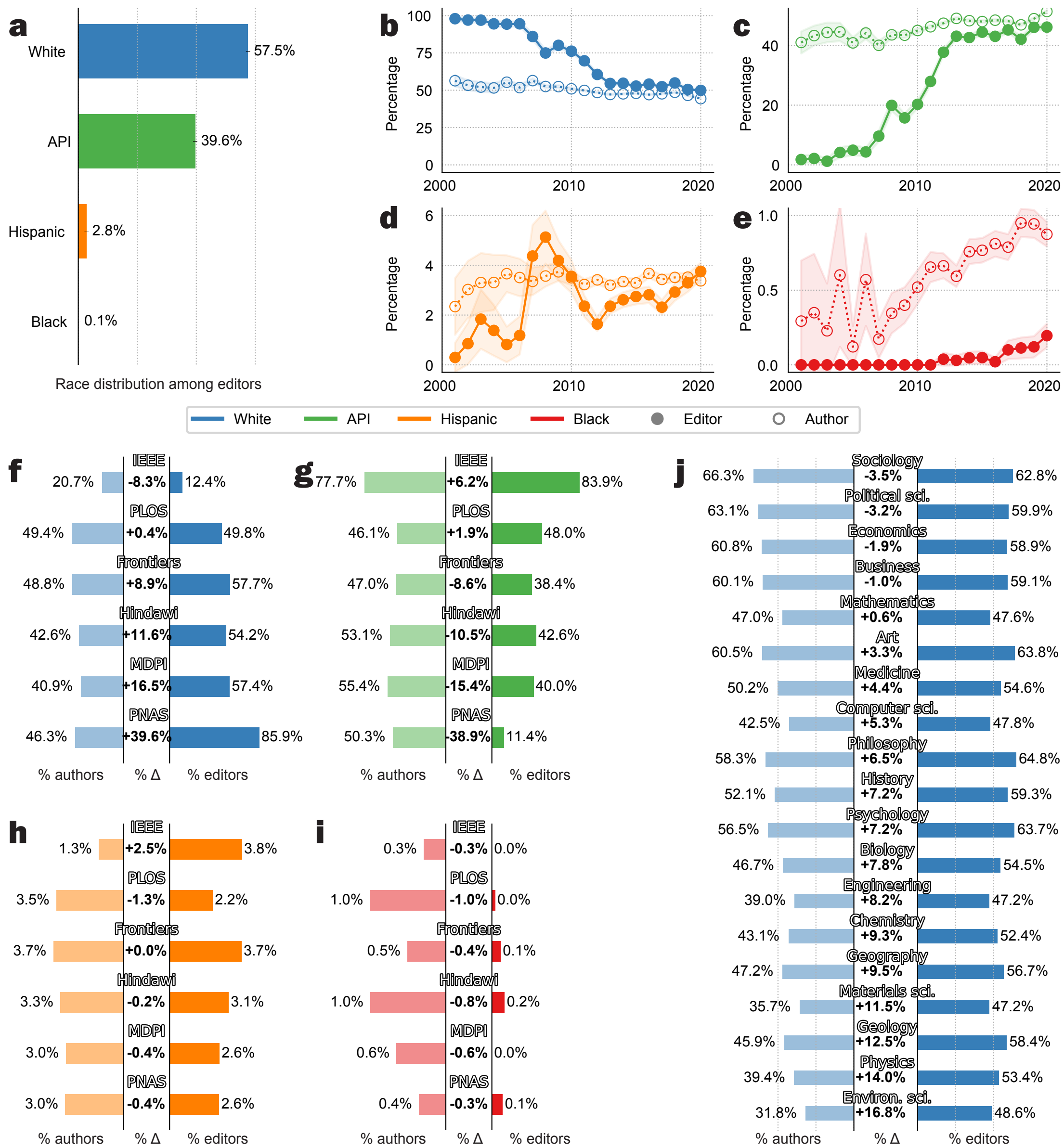

Figure 3.2: Representation of races among editors. This figure focuses on U.S.-based scientists. **a**, The percentage of White, API, Hispanic, and Black editorship. **b**, For each year between 2001 and 2020, the percentage of White editorship (solid circles) and White authorship (empty circles). **c**-**e**, The same as (**b**) but for API, Hispanic, and Black, respectively. Shaded areas and error bars represent 95% CIs. **f**, The percentage of White authorship (left panel) and the percentage of White editorship (right panel) in each publisher between the years 2011 and 2020 (inclusive). The number at the center represents the difference between the two panels; a positive number indicates that White editors are overrepresented. **g**-**i**, The same as (**f**) but for API, Hispanic, and Black, respectively. **j**, The same as (**f**) but in each discipline.

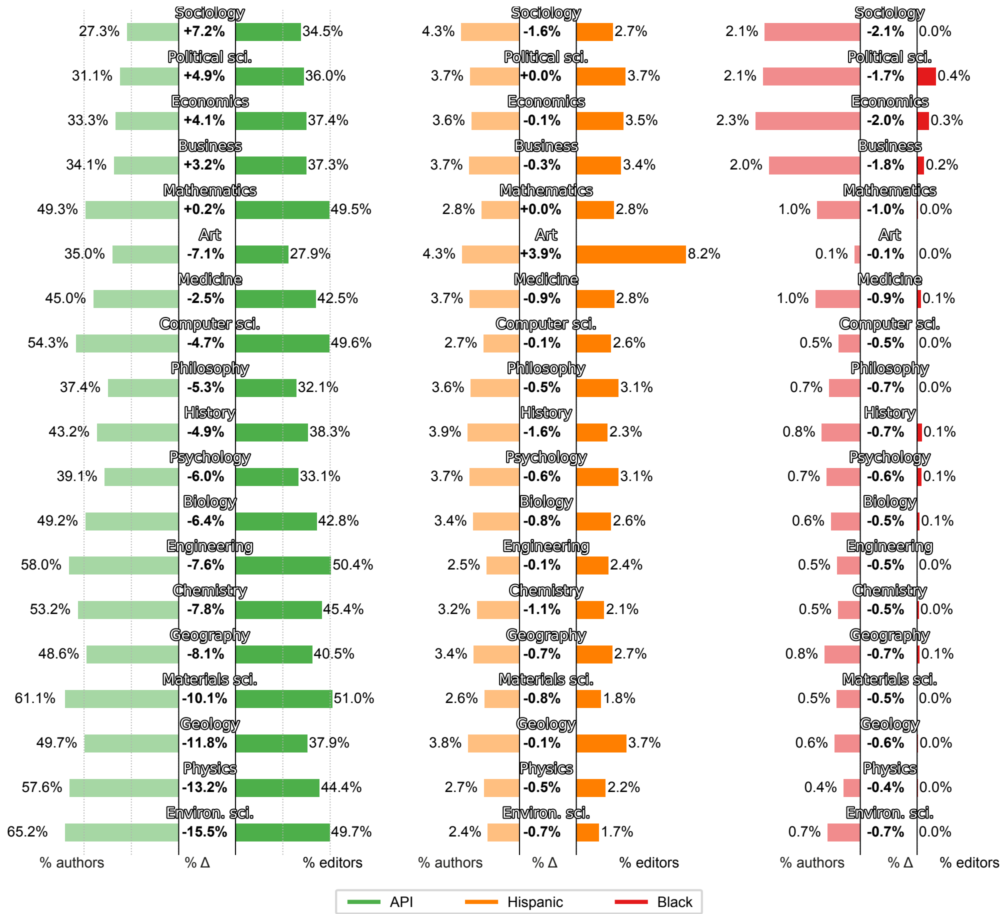

Figure 3.3: Representation of races among editors and authors in disciplines. The percentage of API, Hispanic, and Black authorship (left panel) and the percentage of API, Hispanic, and Black editorship (right panel) in each publisher between the years 2011 and 2020 (inclusive). The number at the center represents the difference between the two panels; a positive number indicates that editors of a specific race are overrepresented in the corresponding discipline.

3.2 Acceptance delay of papers

So far, we considered one outcome of interest: the representation of scientists on editorial boards. Let us now consider the second outcome of interest: the acceptance delay of papers. Specifically, acceptance delay is calculated as the number of days between the date on which a paper is received and the date on which it is accepted. Based on this, the relative acceptance delay (RAD) is calculated for any paper p published in journal j in year y as the relative difference between the acceptance delay of p and the average acceptance delay of papers published in j in year y; see Chapter 2.3 for a formal definition. Let us start by comparing the average RAD across countries. To this end, for any given country, we identify the papers of which the majority of authors are affiliated with an institution in that country, and then calculate the average RAD of all those papers.

Figure 3.5a depicts the average RAD for each country that has at least 500 papers published by the six publishers considered in this Chapter. We can see that countries in Asia, Africa, and South America have higher average RAD compared to other countries. More specifically, out of the 20 countries with the greatest average RAD, 19 are located in the above three continents. These countries are Uganda, Kenya, Bahrain, Nigeria, Bangladesh, Indonesia, Iran, Colombia, Ethiopia, Malaysia, Brazil, Chile, Ghana, Mexico, India, Tunisia, Vietnam, Pakistan, and South Africa, all of which have ethnically non-White majority populations. This geographical disparity in RAD has persisted over the past decade (Figure 3.5b). When restricting our attention to countries that have statistically significantly faster or slower RAD than average, we find that all countries experiencing longer delays are located in Asia, Africa, and South America, with Netherlands being the only exception (Figure 3.4).

Having examined the average RAD across countries, let us now examine it across races. Here, to eliminate the above-established confounder of countries, we restrict our analysis to papers of which all authors have an affiliation based in the U.S.—a racially heterogeneous country that contributes the largest number of papers in our dataset. This analysis reveals that papers with Black-majority authors experience significantly longer RAD compared to White-, API-, and Hispanic-majority papers (Figure 3.5c). Examining RAD over time reveals that, for each race, RAD remained stable over the past two decades (Figure 3.5d), suggesting that Black-majority papers have been consistently spending more time from submission to acceptance compared to other races.

So far in our analysis of RAD, we focused on the authors' race as well as the country in which they are affiliated. Next, we shift our attention to the editors, by examining their race and country of affiliation. To this end, for each country that was analyzed in Figure 3.5a, we divide all the papers produced by that country into two groups: (i) those whose handling editor is based in the same country as the majority

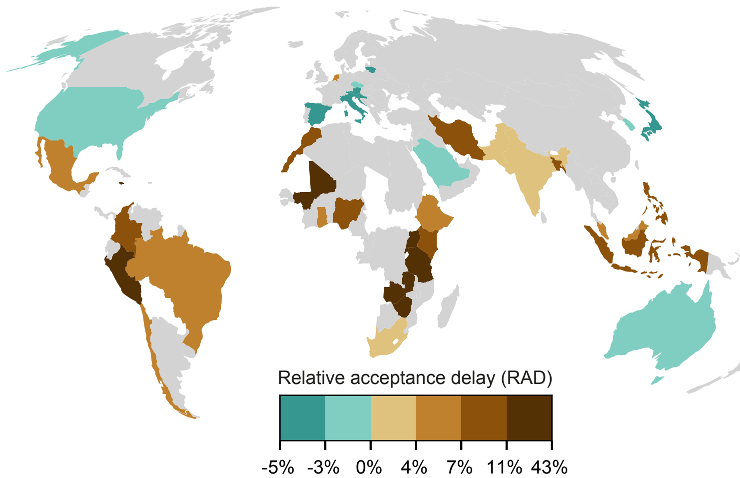

Figure 3.4: Average RAD of countries that have at least 10 papers published by the six publishers. The countries whose average RAD is not significantly different from 0 at the 0.01 level are colored in gray. The average RAD of all other countries is divided into 5 quantile intervals, with the interval containing 0 further subdivided into two disjoint intervals, one consisting of values > 0 (assigned a shade of brown) and another consisting of values < 0 (assigned a shade of green).

of authors, and (ii) those whose handling editor is based in a different country. We found that, for most countries, there are no statistically significant differences in RAD between the two groups. One possible explanation could be the lack of data, as suggested by the large error bars (Figure 3.5e), since most countries are not well represented on the editorial boards. However, among the countries that do show significant differences in RAD, apart from Ghana, papers experience significantly shorter delay when the handling editor and the majority of authors are based in the same country (Figure 3.5e). Next, we focus on the editors' race. As can be seen in Figure 3.5f, for papers with White-majority authors, we find no evidence that RAD is shorter when handled by a White editor. However, for papers of which the majority of authors are non-White, RAD is shorter by about 10% when the handling editor is non-White. Together, these results suggest that RAD is related to the demographic difference between editors and authors. Alternatively, if papers are classified according to the race of first authors, the result remains qualitatively unchanged, although racial disparity is more pronounced when we classify papers based on the majority race of a paper (Figure 3.6). Lastly, we incorporate various paper and author characteristics, including

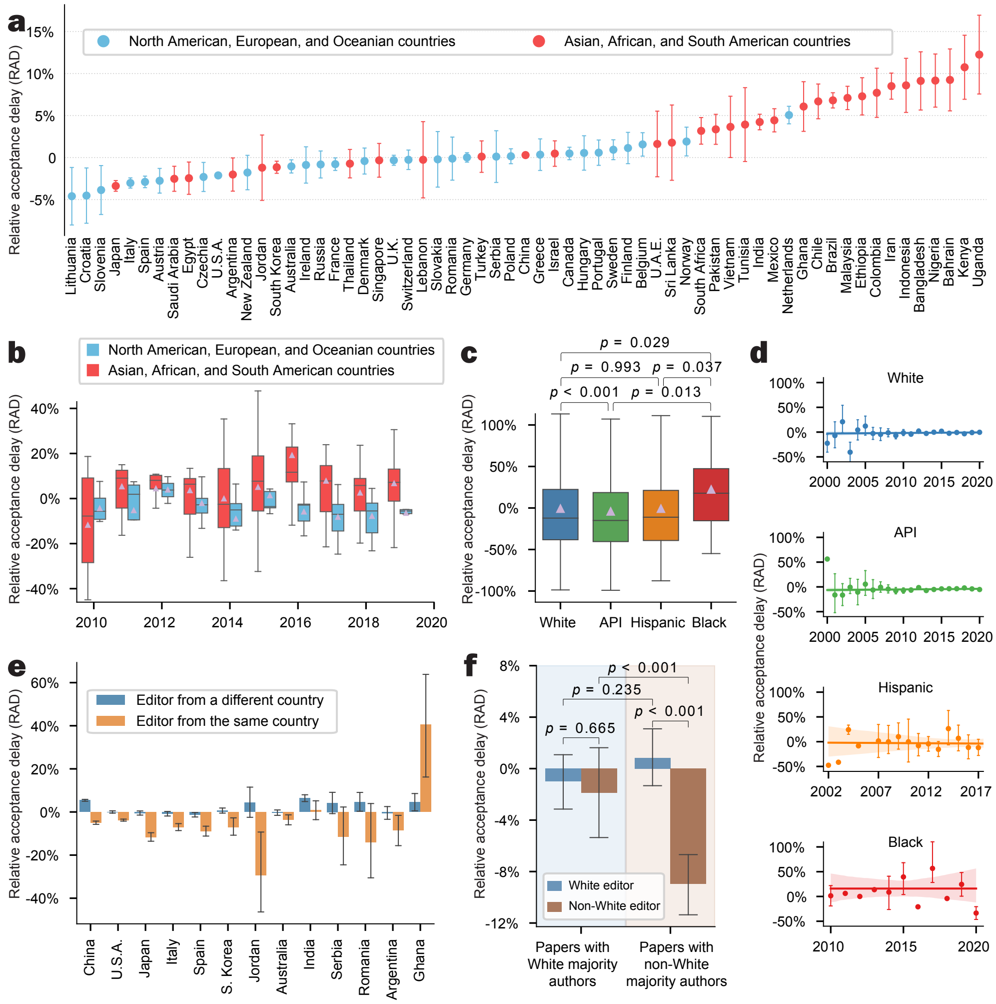

Figure 3.5: Relative acceptance delay (RAD). For any paper p published in journal j in year y, the relative acceptance delay (RAD) is calculated as the relative difference between the number of days p spent under review, and the number of days an average paper published in j in year y spent under review. **a**, RAD of each country that has at least 500 papers published by the publishers considered in this Chapter. Countries in Africa, Asia, and South America are colored in red while other countries are colored in blue. **b**, RAD distribution over time. **c**, RAD distribution of papers with White-, API-, Hispanic-, or Black-majority authors; mean values are depicted as triangles; p values are calculated using two-sided Welch's t-test. **d**, Average RAD over time for papers with White-, API-, Hispanic-, or Black-majority authors; lines are fitted using the OLS method, while the shaded region represents 95% confidence intervals of the regression estimate. **e**, RAD of papers handled by editors based in the same country as the authors or based in a different country; here, all countries show a statistically significant difference in RAD between the two groups of papers at the 0.05 level using two-sided Welch's t-test. **f**, RAD of papers handled by editors from the same or different racial group as the majority of authors; p values are calculated using two-sided Welch's t-test. In (**a**), (**d**), (**e**), and (**f**), data is presented as mean values ±95% confidence intervals. In (**b**) and (**c**), boxes extend from the lower to upper quartile values, with a horizontal line at the median; whiskers extend to the most extreme values no further than 1.5 times the interquartile range from the box.

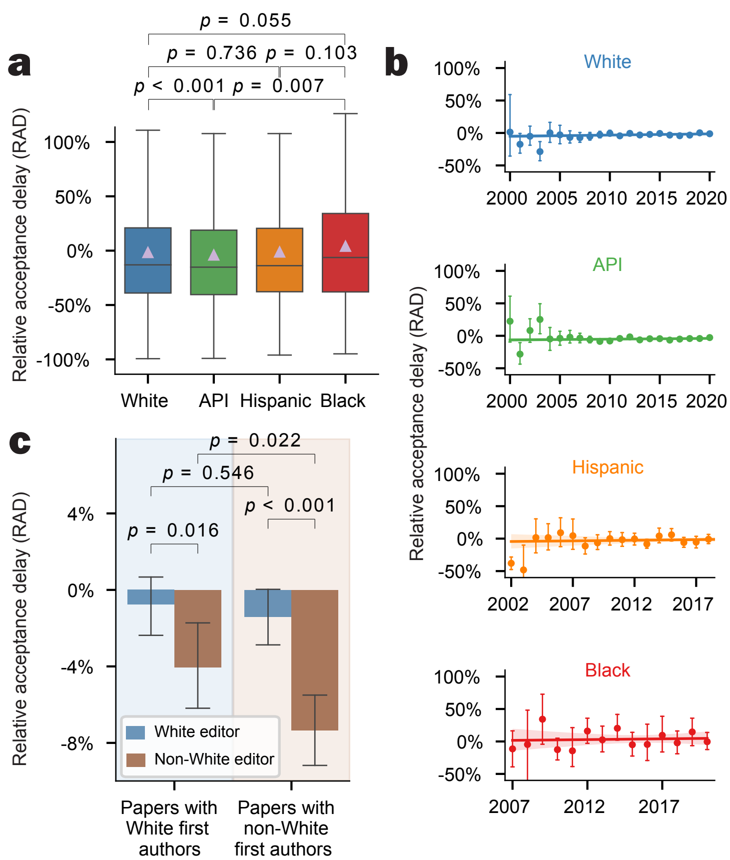

Figure 3.6: Racial disparity of relative acceptance delay (RAD). Papers are categorized based on the race of its first author. **a**, RAD distribution of papers with White, API, Hispanic, or Black first authors; mean values are depicted as triangles; boxes extend from the lower to upper quartile values, with a horizontal line at the median; whiskers extend to the most extreme values no further than 1.5 times the interquartile range from the box; p values are calculated using two-sided Welch's t-test. **b**, Average RAD over time for papers with White, API, Hispanic, or Black first authors; lines are fitted using the OLS method, while the shaded region represents 95% confidence intervals of the regression estimate. **c**, RAD of papers handled by editors from the same or different racial group as the first author; p values are calculated using two-sided Welch's t-test.

the ones examined so far, in an OLS regression where the outcome is the RAD of papers. As shown in Figure 3.7, the results provide further evidence that Black authors, as well as authors based in Asia, Africa, and South America, experience longer acceptance delays.

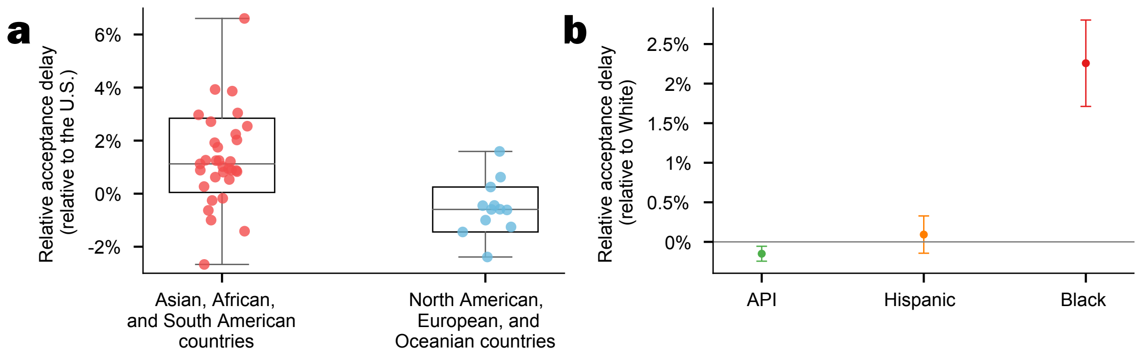

Figure 3.7: Regression results of RAD as a function of author and paper characteristics. The linear regression controls for: (i) number of authors from each country, (ii) number of authors from each race, (iii) total number of authors, (iv) maximum academic age of authors, (v) highest affiliation rank of authors, (vi) year of publication, (vii) discipline, (viii) whether the editor is from the same country as the author majority, and (ix) whether the editor is from the same race the author majority. $R^2 = 0.005$, and heteroskedasticity- and autocorrelation-consistent (HAC) standard errors are used. **a**, The distribution of OLS-estimated regression coefficients of country controls that are significant on the 0.05 level. Boxes extend from the lower to upper quartile values, with a horizontal line at the median; whiskers extend to the most extreme values no further than 1.5 times the interquartile range (IQR) from the box. Each data point corresponds to a country. Data outliers outside of the IQR are omitted. **b**, The OLS-estimated regression coefficient of race controls, represented as mean values ±95% confidence intervals.

3.3 Citational distortion

Lastly, we turn to the third outcome of interest—citational distortion. In particular, we used a recently proposed measure that quantifies how much more (or less) scientists of different cohorts cite one another relative to the pairwise textual similarity between research papers authored by scientists from each cohort; this measure was used in a recent study to analyze regional differences in citational distortion [Gomez et al. 2022]. Their study showed that Asia and Europe experience moderate citational distortion, Africa, the Middle East, Latin America, and the Caribbean are strongly under-cited, while North America, and Oceania are strongly over-cited across disciplines. We follow the same approach, except that we focus on the four racial groups considered in this Chapter, and restrict our attention to papers of which the majority of authors are affiliated with U.S.-based institutions, thereby eliminating the said confounding effects of countries. To broaden the scope of this analysis, we focus on all U.S.-majority papers in MAG rather than restricting our attention to the six publishers examined earlier. This, however, means that we cannot use editor-based information in this analysis, since such information is not provided by MAG. The result of this analysis is summarized in Figure 3.8. As can be seen in Figure 3.8a, Black and Hispanic scientists have been consistently under-cited over the past four decades, while API and White scientists have been consistently over-cited, relative to what is predicted by textual similarity. Figures 3.8b to 3.8e show that this phenomenon persists across four types of disciplines, namely, (i) biomedical, behavioral, and ecological sciences, (ii) engineering and computational sciences, (iii) physical and mathematical sciences, and (iv) social sciences.

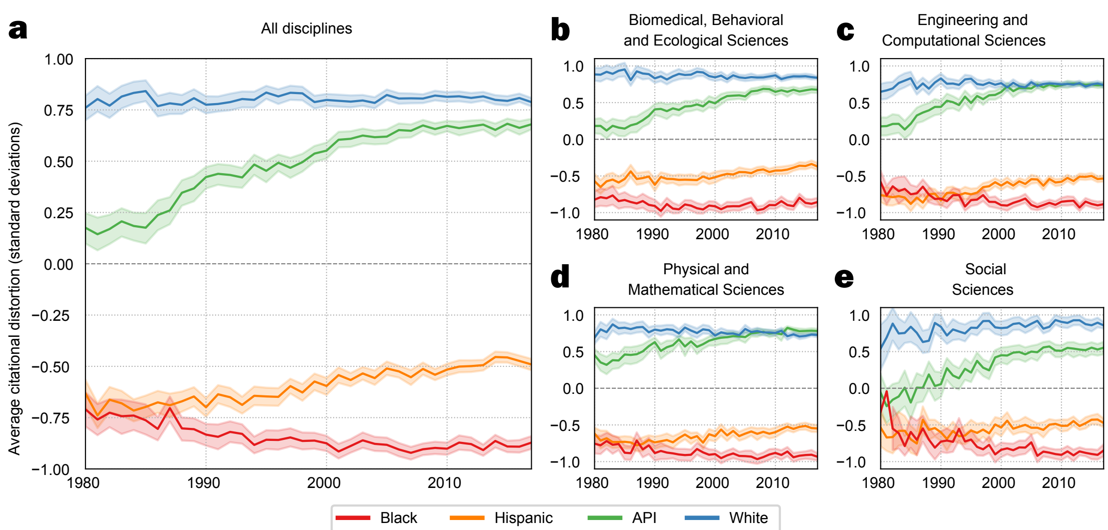

Figure 3.8: Racial gap in citation rates based on textual similarity. The average citational distortion experienced by U.S.-based White, API, Hispanic, and Black scientists, calculated across disciplines (**a**), in biomedical, behavioral, and ecological sciences (**b**), in engineering and computational sciences (**c**), in physical and mathematical sciences (**d**), and in social sciences (**e**). The citational distortion is measured by comparing the citation rates of textually similar papers. Shaded areas reflect 95% CIs.

3.4 Limitations and Discussions

The study presented in this Chapter is not without limitations. Firstly, it only considers six publishers, since these were the only ones we could find who specify the handling editor of each paper. Until other publishers make this information publicly available, the extent to which our findings generalize to other publishers remains unknown. Secondly, we demonstrate that non-White scientists experience disparity following two different approaches: (i) analyzing geographical disparity and comparing "White countries" to "non-White countries", i.e., comparing countries with ethnically White majority to those with ethnically non-White majority; (ii) by analyzing racial disparity while focusing on a single country, namely, the U.S. However, neither approach is perfect. The first shows that an average scientist based in a non-White country experiences disparity. Although it could be argued that scientists in non-White countries are themselves more likely to be non-White, there could still be White scientists in such countries. The second approach addresses this limitation, by focusing on a country with a racially heterogeneous population, and studying racial disparity within that country. Here, we use an algorithmic tool that classifies a scientist's race based on their name. Although this tool is widely used in the social sciences, it is not a perfect classifier. Still, despite their limitations, it is worth noting that two independent approaches reveal similar patterns, suggesting that non-White scientists indeed experience disparity.

More specifically, starting with the first outcome, we compared the editorship rate to the authorship rate from each country, and found that most countries in Asia, Africa, and South America (where the majority of the population are ethnically non-White) are underrepresented among editors. Note that the six top-ranked journals display a more balanced editorial board composition that does not systemically favor editors from North American, European, and Oceanian countries, suggesting that there could be a link between editor representation and the impact of a journal; exploring this link could a promising future direction. When comparing the racial composition of editors and authors who are based in the U.S., we found that Black scientists have been underrepresented on editorial boards across publishers over the past two decades.

Generally speaking, when studying the degree to which different races are over- or under- represented in any aspect of academia, a fundamental question is to determine the ideal racial composition to aspire to [Le et al. 2021]. One such composition could be that of members of a specific academic society [Ford et al. 2017; Beath et al. 2021] or that of the population of a specific country [Salazar et al. 2021]. In this Chapter, we quantified the racial gap in the editorial board of any given journal using two different benchmarks: (i) the composition of authorship in that journal, and (ii) the authorship composition in a journal's field. Having said that, closing the observed gap should not be taken as the ideal to aspire to, as the benchmark itself is likely to have a racial gap due to the documented entry barriers facing scientists of color across disciplines [Kozlowski et al. 2022]. While our work highlighted the racial gap in editorship, more research is needed to identify the policies required to close this gap.

Moving on to the second outcome of interest, we found that papers coming from Asian, African, and South American countries experience longer RAD (relative acceptance delay), i.e., more days between their submission and acceptance, compared to papers from other countries published in the same journal and the same year, indicating that ethnically non-White scientists spend on average more time waiting for their manuscripts to be accepted, and this disparity persisted over time. Moreover, we found evidence that papers handled by editors based in the same country as the majority of authors tend to experience shorter RAD. We then turned our attention to authorships coming from the U.S. and found that Black scientists experience significantly longer acceptance delays compared to White scientists in the U.S.; this persisted over the past decade.

The additional time Black scientists spend waiting for their submissions to be accepted is alarming, but unfortunately not surprising. Black people have already been shown to endure longer waiting times in many aspects of life. For example, during the 2016 U.S. presidential election, residents of entirely-Black neighborhoods spent more time waiting at voting stations compared to residents of entirely-White neighborhoods [Chen et al. 2022]; longer waiting times for Black voters have also been documented in the 2018 midterm elections [Klain 2020]. Unfortunately, similar observations were made in situations where longer waiting times could mean the difference between life and death. In emergency rooms, for example, Black patients are less likely to be placed into the "Most Urgent" category of the Emergency Severity Index (ESI) [Zhang et al. 2020]. Moreover, the time Black patients spend waiting to receive cancer diagnosis is significantly longer than that of White patients, both in the U.S. [Neal and Allgar 2005] and the U.K. [Martins et al. 2022]. This Chapter contributes to this line of this research by showing, for the first time, that Black scientists in the U.S. suffer from longer delays before their manuscript is accepted for publication. While this Chapter focused on acceptance delay, a future extension could focus on rejection delay, i.e., the number of days between the submission and rejection of a manuscript, to determine whether similar racial disparities can be observed. Unfortunately, however, such a study would require a rejection dataset which is hard to acquire.

As for the third outcome, we showed that Black and Hispanic scientists receive fewer citations than White and API scientists. Crucially, this result is obtained while accounting for the papers' textual similarity using the recently proposed method of citational lensing [Gomez et al. 2022]. The same trend is observed across four types of disciplines, namely, (i) biomedical, behavioral, and ecological sciences, (ii) engineering and computational sciences, (iii) physical and mathematical sciences, and (iv) social sciences. These findings persisted over the last four decades. The citational gap is particularly alarming for Black scientists, since the discrepancy between their actual citation rates, and those predicted by textual similarity, appear to be increasing over the past decades.

The racial gap in citations means that non-White scientists have lower visibility compared to White scientists doing similar research. This is especially alarming since those with low visibility are less likely to receive grants and awards [Desai et al. 2021], which, in turn, may lead to even greater disparities in visibility, thereby triggering a Matthew Effect [Bol et al. 2018]. More broadly, our three outcomes paint a grim picture in which non-White scientists suffer from inequalities that may hinder their academic careers. These disparities could be linked to non-White scientists receiving less professional respect [Cech 2022], though more research is needed to confirm this link. Addressing these disparities may require publishers to carry out internal audits to detect and eliminate any disparities in the publication process, from the selection of editorial board members, to the time spent reviewing submissions, to the promotion of published manuscripts. Having said that, the responsibility to take action falls not only on the shoulders of publishers, but also on the scientific community as a whole, to create an ecosystem without geographical and racial disparities.

4 | Underrepresentation of women editors

Content of this chapter was previously published in Nature Human Behaviour *[Liu et al. 2023a]; ownership of copyright in the original research articles remains with the Author.*

As we have seen in the previous chapter, not all scientists have an equal chance of becoming editors. In addition to non-White scientists, women, historically marginalized in academia, also face barriers in attaining scientific opportunities in general [Morgan et al. 2021; Witteman et al. 2019; Rotenstein and Jena 2018; Leslie et al. 2015], and scientific elites status in particular [Wold and Wennerås 1997; Widnall 1988; Lincoln et al. 2011; Nittrouer et al. 2018; Davidson and Greene 2022]. In this vein, there has been widespread, yet fragmented, evidence showing that women are underrepresented on editorial boards (see Dickersin et al. [1998]; Kennedy et al. [2001]; Amrein et al. [2011]; Ioannidou and Rosania [2015]; Topaz and Sen [2016]; Khan et al. [2019]; Salazar et al. [2021]; Palser et al. [2022]; Berenbaum [2019] for examples, and see Table C 1 for a comprehensive review). Gender diversity on editorial boards is not only important in its own right [Silver 2019], but also has broader implications. An inclusive editorial board signals that the journal is open to all authors [Beath et al. 2021], implying that the underrepresentation of female editors may create a vicious cycle that further deters women from participating in science [Silver 2019].

Although the underrepresentation of women have received widespread attention in different disciplines, key aspects remain missing due to the lack of a longitudinal dataset that spans multiple disciplines. In particular, none of the studies compare the gender gap across disciplines, as they only focus on one discipline each. The only exceptions are the work of Mauleon et al. [Mauleón et al. 2013] and Bošnjak et al. [Bošnjak et al. 2011], but their analyses are restricted to Spanish and Croatian journals, respectively. Another limitation in the literature is the lack of comparison between editors and other research-active scientists, with the exception of Mauleon et al. [Mauleón et al. 2013], whose analysis is restricted to Spanish journals only. Such a comparison is critical, as it provides a discipline-specific, and year-specific, benchmark against which gender disparity can be measured. Hence, our unique dataset described in Chapter 2.1 offers a unique opportunity to address the aforementioned shortcomings in the literature, and analyze editorial representation at an unprecedented scale.

4.1 Gender composition of editors

As can be seen in Figure 4.1a, although women are already underrepresented among scientists (26% of all unique scientists in MAG), they are even more underrepresented amongst editors and editors-in-chief (14% and 8%, respectively). Moreover, the gap remained stable over the past five decades; the proportion of female editors has consistently remained around half that of female scientists, although gender parity has been steadily increasing in science in general (Figure 4.1b). For example, in 2017, women represented 36% of scientists, but only 18% of editors; these proportions are extremely similar to those in 1970, when women represented 11.3% of scientists and 5.7% of editors. As for female editors-in-chief, their proportion has remained consistently smaller than that of female editors since 1970.

Let us now examine the gender disparity across disciplines. Figure 4.1c depicts the proportion of female editors against that of female scientists across disciplines during the 1970s (depicted as triangles), 1980s (squares), 1990s (crosses), 2000s (stars), and 2010s (circles). Apart from Sociology, the proportion of female scientists in any given discipline has remained greater than the proportion of female editors in that discipline; see how the vast majority of shapes fall under the diagonal. To obtain a better understanding of this phenomenon, we analyzed the length of editorial careers, i.e., the number of years during which editors assume their role. The box plot in Figure 4.1d compares the average editorial career length of women vs. men, while the scatter plot compares these quantities across disciplines. As can be seen, the editorial career length of men (mean, 5.03; 95%-CI, from 4.99 to 5.08) is greater than that of women (mean, 4.24; 95%-CI, from 4.17 to 4.32; $t_{80,774} = 15.02$, $p < 0.001$, $\beta = 0.15$, 95% CI = 0.13 to 0.16); this holds across all disciplines except Sociology.

As we have shown thus far, women have been consistently underrepresented on editorial boards across disciplines over the past decades. Let us now investigate whether this phenomenon can be explained by gender differences in productivity, impact, and career lengths, or whether additional hidden factors are at play. To this end, we use a randomized baseline model whereby each editor (or editor-in-chief) is replaced with a randomly chosen scientist who may have a different gender but is identical in terms of discipline and academic age (just like the matched scientists in Figure 2.1), and similar in terms of productivity and impact (both binned into deciles). In this model, the randomly selected scientist replaces the original editor for the entire duration of his/her editorial career. Such a null model simulates a world where the editors in each discipline are recruited solely based on their experience and research output while completely disregarding their gender. We generated 50 such worlds and computed the average percentage of female editors and editors-in-chief therein. It should be noted that such analysis cannot be done using any of the datasets previously considered in the literature, as it requires the publication records of not only the editors but also all research-active scientists in any given discipline. The results of this analysis are depicted in Figure 4.1e. As can be seen in the left panel, the representation of women among editors in a randomized world exhibits similar trends to those observed in the real world. This suggests that the gender gap among editors can be explained by the lack of women with sufficiently high productivity and impact, which, in turn, can be explained by attrition of women from academia [Huang et al. 2020]. In contrast, looking at the right panel of Figure 4.1e, we find a clear and persistent gap between the real and counterfactual worlds in terms of the proportion of female editors-in-chief. This suggests that factors other than career length, productivity, and impact may be at play, and these factors seem to persist over the past five decades.

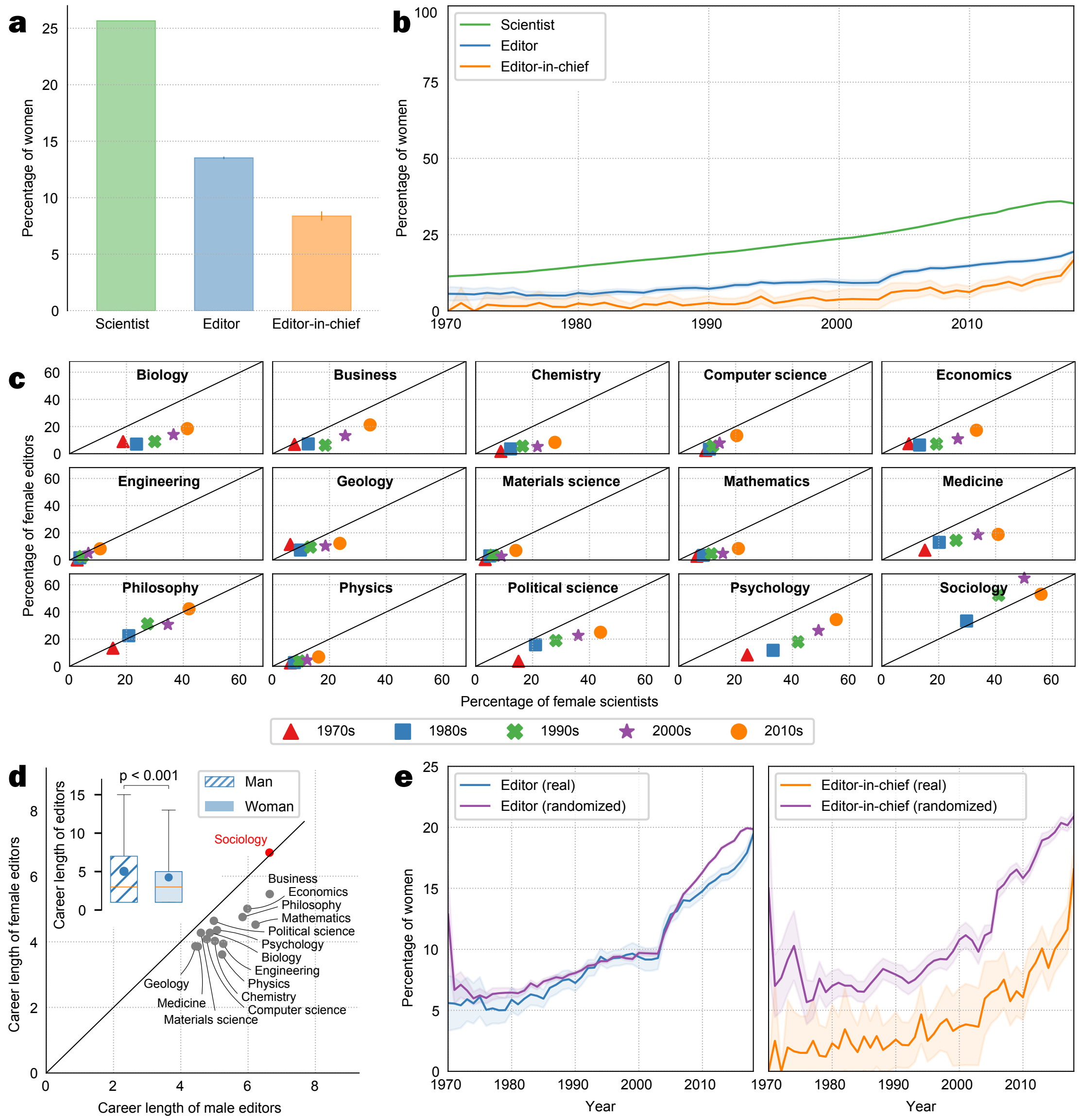

Figure 4.1: Gender disparity in editorship. **a**, Percentage of women among scientists (n = 42, 831, 834), editors (n = 80, 776), and editors-in-chief (n = 4, 692). **b**, Percentage of women among scientists, editors, and editors-in-chief over time. **c**, Percentage of female editors against percentage of female scientists across disciplines in the 1970s (triangle), 1980s (square), 1990s (cross), 2000s (star), and 2010s (circle). **d**, Average editorial career length of female (n = 12, 644) vs. male editors (n = 68, 132) overall (inset, with circles and diamonds represent the sample mean of man and woman, respectively; the boxes extend from the lower to upper quartile values of the data, with a line at the median; whiskers extend until the 5-th and the 95-th percentile) and across disciplines (scatter plot); red highlights the discipline in which the career length of female editors is greater than that of male editors; p-values are calculated using two-sided Welch's T-test (inset); the exact p-value is 1.46e-50. **e**, Percentage of women among editors and editors-in-chief in real vs. randomized data over time. Error bars and shaded regions represent 95% confidence intervals. Data are presented as mean values +/− 95% confidence intervals (**a**, **b**, and **e**).

4.2 Discussions and Limitations

Despite efforts to increase women's representation on editorial boards [Logan 2016], the present findings reveal a persistent gender gap. Using an unprecedented dataset, this chapter contributes to the literature in two ways. Firstly, we were able to examine the gender distribution among scientists and editors over the past five decades, revealing that the proportion of female editors persisted at about half that of female scientists, and that the proportion of female editors-in-chief has consistently been even smaller. Secondly, we were able to compare the gender gap across 15 disciplines, revealing that women have been consistently underrepresented among editors and editors-in-chief in every discipline other than Sociology. Furthermore, while gender disparity has often been measured in terms of impact [Larivière et al. 2013; Caplar et al. 2017], productivity [Larivière et al. 2013], and career length [Huang et al. 2020], we showed that, at least for editors-in-chief, gender disparity goes beyond what is predicted by these numbers, indicating a systematic role for non-meritocratic factors in the selection of editors-in-chief. This resonates with the past findings that women face a "glass ceiling" in their professional careers [Cotter et al. 2001], and suggests that women face additional obstacles in being recognized as elite scientists in their respective disciplines. Overall, this chapter contributes to the literature advocating a more inclusive editorial board in particular, and a more inclusive scientific community in general [Silver 2019; Stewart and Valian 2018].

Our analysis is not without limitations. Firstly, our work comes with the inherent restrictions of observational studies. In particular, although we use standard techniques such as matching and randomized baseline models to further our understanding of gender inequality and self-publication patterns, it is hard to pinpoint the underlying mechanisms behind these findings; this constitutes a potential direction for future research. Secondly, all analyses are done using editor data collected from Elsevier. Although this is the largest publisher in academia, other publishers could also be explored, which is left to future studies. Lastly, in order to infer gender at scale, the only practical solution was to use algorithmic tools. Despite their advantages, such tools do not provide 100% accurate. Although we restricted our analysis to names that are classified with at least 90% accuracy throughout the study, manual classification is likely to be more accurate.

There is more to the story of scientific publishing than statistics. Behind the numbers, some editors stand up for a more transparent selection of papers, and actively recruit board members from underrepresented groups, while others exploit their power to benefit their careers. After all, editors are humans. Our expectation of human behavior in imperfectly transparent institutions determines the narrative: Should we be satisfied with the increasing proportion of female editors over the past decades? Or should we be concerned that, despite all efforts to promote gender equality, women are still underrepresented among editors in nearly all disciplines? Either way, it might be reassuring to know that academic publishers such as Elsevier are actively promoting more diverse editorial boards using an array of measures. Either way, we hope our study, and the future work it may inspire, will contribute to a fairer, more transparent, and more inclusive culture of scientific editorship.

Part III

Conflict of Interests

5 | Self-publication of academic editors

Content of this chapter was previously published in Nature Human Behaviour *[Liu et al. 2023a]; ownership of copyright in the original research articles remains with the Author.*

Having analyzed the gender disparity on editorial boards in the previous two chapters, we now shift our attention to another interesting aspect of editorship—the fact that some editors publish original research in the journal they edit. Sometimes editors publish their findings in the journals they edit [Luty et al. 2009; Youk and Park 2019; Bošnjak et al. 2011; Mani et al. 2013; Rösing et al. 2014; Zdeněk and Lososová 2018; Walters 2015], occasionally resulting in controversies [Eiko 2008; Schiermeier 2008; Abdel-Baset et al. 2019a,b]. Such controversies are fueled by the possibility that the editors' submissions are treated favorably, which may be considered as "an abuse of the scientific publishing system" [Abdel-Baset et al. 2019a,b].

In this chapter, we first quantify the prevalence of the self-publishing behavior of editors before zooming in on the outliers to characterize the extent to which and editor could publish in his/her journal while keep serving on the editorial board.

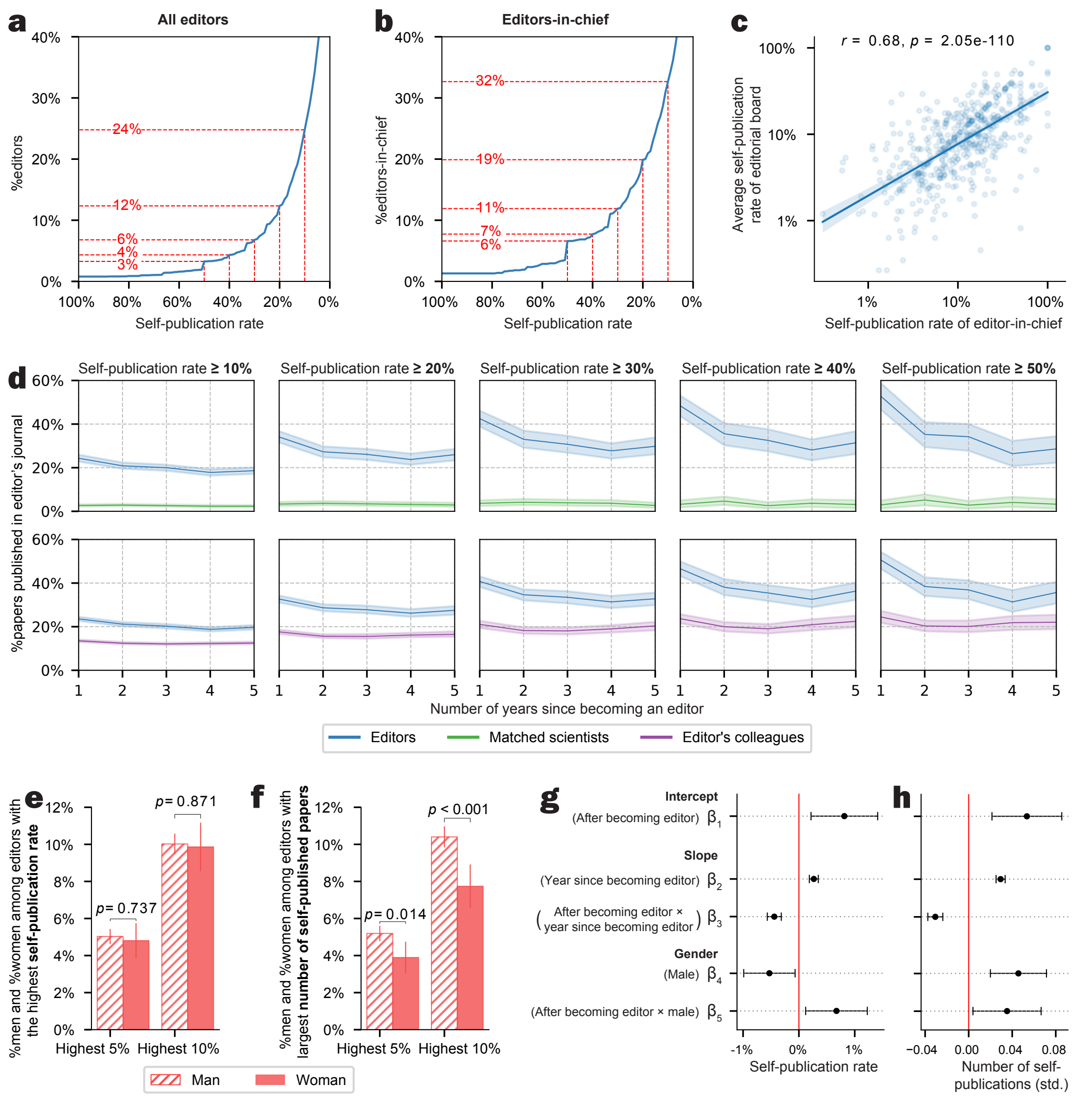

Figure 5.1: Self-publication rates. **a**, Cumulative distribution of editors' self-publication rate, highlighting the proportion of those whose rate is ≥10%, ≥20%, . . . , ≥50%. **b**, The same as (**a**) but for editors-in-chief. **c**, Correlation between the self-publication rates of editors-in-chief and their editorial boards; r represents the two-sided Pearson correlation coefficient, while the shaded region represents 95% confidence intervals of the regression estimate. **d**, Comparing editors whose self-publication rate is ≥10%, ≥20%, . . . , ≥50% to their matched scientists (upper row) and to their colleagues (lower row) in terms of the percentage of papers published in the editor's journal. **e**, Out of all men and women, the percentage of those who fall among the top 5% and 10% of editors with the highest self-publication rates; p-values are calculated using two-sided Fisher's exact tests, $n_{\text{male}} = 11,017$, $n_{\text{female}} = 1,978$. **f**, The same as (**e**), but for those who have the largest number of papers published in their own journal (the exact p-value for highest 10% is 2.08e-4). **g**, Regression-estimated temporal trend of the self-publication rate during the 5 years before, and the 5 years after, one becomes an editor. **h**, The same as (**g**), but the outcome is the number of self-published papers. Data are presented as mean values +/− 95% confidence intervals in (**d**) through (**h**).

5.1 Editors' self-publishing behavior

We start off by analyzing the editors' self-publication rate—the percentage of their papers published in their own journal—during the 5-year period following the start of their editorship. Based on this, as well as the fact that the publication records we extract from MAG do not go beyond 2018, we restrict this analysis to the 12,995 editors who start editing their respective journals no later than 2014. For editors who quit before completing 5 years, the self-publication rate is measured only over the years during which they serve as editors, rather than over the full 5-year period following the start of their editorship. Let us start by examining the cumulative distribution of self-publication rates. We find 24% of editors publish at least one tenth of their papers in the journal they edit (Figure 5.1a). There is also a considerable percentage of editors who publish at least one fifth of their papers (12% of editors) or even one third of their papers (6% of editors) in their own journal. Among editors-in-chief, these percentages are even higher (Figure 5.1b). More specifically, 32% of editors-chief publish at least one tenth of their papers in the journal they edit, 19% self-publish at least one fifth of their papers, and 11% self-publish one third of their papers. Next, we examine the correlation between the self-publication rate of the editors-in-chief and their editorial board (Figure 5.1c). To improve the visualization, the data points are plotted on a log-log scale while omitting zero values. As can be seen, there is a significant positive correlation between the self-publication rate of the editor-in-chief and that of the editorial board, suggesting that the two are linked.

To better understand these patterns, for every editor-journal pair, (e, j), we compare e to randomly selected scientists who are not editors of j but are similar to e in terms of gender, discipline, rank of first affiliation, and years during which they are research-active. Additionally, we ensure that e and their matched scientists are similar in terms of the rate at which they publish in j up to $\text{year}_0^{(e,j)}$. This is to rule out the possibility that the observed self-publication rate of an editor e in their own journal j can be explained by characteristics of e that are unrelated to e becoming an editor.

Formally, given an editor-journal pair (e, j), we match e to a scientist s who is not an editor of j based on a number of confounders, including the rate at which they publish in j. Ideally, the rate of e and

s should be similar up to $\text{year}_0^{(e,j)}$ (this way, if their rate starts to diverge after $\text{year}_0^{(e,j)}$, it suggests that the divergence is related to e becoming an editor of j). However, to increase the likelihood of finding a match for e, we do not require the rate of s to match that of e in $\text{year}_0^{(e,j)}$, but rather in a year y such that $|\text{year}_0^{(e,j)} - y| \leq 3$. More specifically, we say that e matches s in year y if all of the following conditions are met:

- e and s have the same discipline.
- e and s have the same gender; for details on how gender is identified, see the subsection titled Gender Identification.
- The rank of any first known affiliations of e and s fall in the same bin. Here, affiliations are ranked based on the 2019 Academic Ranking of World Universities (also known as the "Shanghai ranking" [ARWU 2019]), and are divided into the following bins: $[1, 20]$; $[21, 50]$; $[51, 100]$; $[101, 300]$; $[301, 600]$; $[601, 999]$; $[1000, \infty]$.
- The publication year of e's first paper does not differ from that of s by more than 3 years.
- There exists a year, $y \in [\text{year}_0^{(e,j)} - 3, \text{year}_0^{(e,j)} + 3]$ such that:
  - The academic age of e in $\text{year}_0^{(e,j)}$ does not differ from that of s in y by more than 10%.
  - The percentage of papers that e published in j in $\text{year}_0^{(e,j)}$ does not differ from that of s in y by more than 10%.
  - The percentage of papers that e published in j up to $\text{year}_0^{(e,j)}$ does not differ from that of s in y by more than 10%.

Note that the matched scientists may themselves be editors of other journals. As such, the outcome of this analysis reflects the difference between those who edit j and those who do not, rather than the difference between editors and non-editors. The results of this analysis are depicted in the upper row of Figure 5.1d. As shown in this figure, regardless of the rate at which e publishes in j, there is a marked gap between e and their matched scientists. This observation suggests that the difference in the rate at which e and their matched scientists publish in j is associated with e becoming an editor of j, bearing in mind that both of them published in j at comparable rates before $\text{year}_0^{(e,j)}$.

Another possible explanation for the observed increase in publication rate is the journal's culture, whereby editors are expected to contribute papers as part of their editorial duties. To determine whether this is the case, for every editor e whose self-publication rate is ≥10%, ≥20%, . . ., ≥50%, we compare the self-publication rate of e to that of the average editor serving at the same time on the same editorial board. This comparison considers the years after, but not before, e becomes an editor, since these are the years during which the publication rate of e in j could be influenced by the journal culture. As shown in the bottom row of Figure 5.1d, regardless of e's self-publication rate, they publish in j at a greater rate than their average colleague.

Finally, we check whether there exist gender differences in terms of self-publication rate, as well as the number of self-published papers. To this end, we first calculate the percentage of men, and the percentage of women, who fall among the top 1%, 2%, . . . , 10% of editors with the highest self-publication rates (Figure 5.1e). We find that men and women are equally likely to be found among those with the highest self-publication rates (top 5%: 5.03% male, 4.8% female, $p = 0.737$; top 10%: 10.02% male, 9.86% female, $p = 0.871$, Fisher's exact test). In other words, the gender composition of those with very high self-publication rates roughly reflects that of all editors. However, if we calculate the percentage of men, and the percentage of women, who fall among the top 1%, 2%, . . . , 10% of editors with the largest number of self-published papers (Figure 5.1f), we find more men among those with the highest numbers of self-published papers, and this difference is statistically significant (top 5%: 5.19% male, 3.89% female, $p = 0.014$; top 10%: 10.4% male, 7.74% female, $p < 0.001$, Fisher's exact test). In other words, while men account for 84.8% of all editors, they account for 88.2% of the top 10% editors with the highest number of self-published papers.

To further investigate the gender differences in self-publication behavior, we introduce a regression model to estimate the temporal trend of an editor's self-publication rate each year, while allowing a struc-

Table 5.1: Regression-estimated temporal trend of the number of papers e publishes in j during the 5 years before, and the 5 years after, e becomes an editor of j. The regression model controls for gender and journal fixed effects. More specifically, it is specified as follows: $Y_{it} = \beta_0 + \beta_1 * D_{it} + \beta_2 * (t - T_i) + \beta_3 * (t - T_i) * D_{it} + \beta_4 * G_i + \beta_5 * G_i * D_{it} + \beta_j + \epsilon_{it}$. In the model, the subscript i denotes an editor-journal pair, (e, j), while t denotes the year when an observation on (e, j) is made. Y_{it} is the number of papers e publishes in j in year t (standardized). T_i is $\text{year}_0^{(e,j)}$, implying that $t - T_i$ is the number of years between the year of observation and the year when e starts editing j. D_{it} is a binary indicator of whether t is greater than T_i, and G_i is a binary indicator of whether i is male. β_j is the journal fixed-effect control. p-values are calculated using the Student's t-test, with standard errors clustered at the editor level. The exact p-values of those less than 0.001 are 2.75e-43, 2.921876e-18, and 5.05e-04, respectively.

	b	95% CI	p
After editorship starts (β_1)	0.053	(0.021, 0.086)	0.001
Year since editorship starts (β_2)	0.029	(0.025, 0.034)	< 0.001
After editorship starts × Year since editorship starts (β_3)	-0.031	(-0.038, -0.024)	< 0.001
Male (β_4)	0.046	(0.02, 0.071)	< 0.001
After editorship starts × Male (β_5)	0.035	(0.004, 0.067)	0.027
Observations	119,553		
Adjusted R^2	0.160		

tural break of the trend to happen around the time that one becomes an editor. Additionally, the regression model controls for gender as well as journal fixed effects (Figure 5.1g and Table 5.1). The model indicates that the self-publication patterns of editors exhibit significant discontinuity around the time when the editorship starts, as both the intercept and the slope change significantly, providing further evidence of the link between becoming an editor of a journal and increasing the rate at which one publishes in that journal. The model also indicates that, around the start of the editorship, male editors show a higher increase in their self-publication rates compared to female editors. We repeat the same regression analysis but change the outcome to be the number of self-published papers per annum (Figure 5.1h and Table 5.2). Again, the model shows that the self-publication patterns of editors exhibit significant discontinuity around the time when the editorship starts, and male editors have a higher increase in the number of self-published papers after becoming editors.

Table 5.2: Regression-estimated temporal trend of the self-publication rate of e during the 5 years before, and the 5 years after, e becomes an editor of j. Model is specified in the same way as Table 5.1. The exact p-values of those less than 0.001 are 6.28e-11 and 5.17e-12, respectively.

	b	95% CI	p
After editorship starts (β_1)	0.008	(0.002, 0.014)	0.008
Year since editorship starts (β_2)	0.003	(0.002, 0.003)	< 0.001
After editorship starts × Year since editorship starts (β_3)	-0.004	(-0.006, -0.003)	< 0.001
Male (β_4)	-0.005	(-0.01, -0.001)	0.025
After editorship starts × Male (β_5)	0.007	(0.001, 0.012)	0.017
Observations	119553		
Adjusted R^2	0.087		

5.2 Extreme "self-publishers"

To understand the limits of the above phenomenon, i.e., the extent to which editors self-publish while continue to serve on the editorial board, we identified the 15 editors who publish the highest percentage of papers in their journals during editorship. For each of them, we plotted the number of papers published per year throughout their scientific careers aggregated over five-year periods, highlighting in different colors the proportion of the papers published in the journal(s) they were editing; see Figures 5.2a to 5.2c for the three most extreme editors, and Figure 18 for the remaining twelve. In these figures, random perturbations are added to the counts to preserve anonymity. Focusing on the most extreme editors, out of all the papers they published throughout their career, 72%, 66%, and 65% were in their own journal(s) while they were serving as editors. These cases demonstrate that even if an editor publishes three quarters of their entire career output in their own journal, they may continue to serve as editors for several decades. Similar trends were observed when considering the 15 (rather than the three) most extreme editors; see Figure 5.3. It is worth mentioning that 14 out of those editors are men, suggesting that women are less likely to engage in such extreme behavior. Also noteworthy is the fact that 6 out of the 15 extreme editors are, in fact, editors-in-chief.

Having analyzed extreme editors, let us now focus on the three extreme editorial boards corresponding to the journals with the highest percentage of papers authored by their editors. The results are depicted in Figures 5.2d to 5.2f, which follow a similar layout compared to our previous analysis of extreme editors. Starting with the most extreme journal (Figure 5.2d), one third (35%) of the papers published therein have an active editor among the authors. As for the second and third most extreme journals (Figures 5.2e and 5.2f), one fifth (about 20%) of the papers published therein include authors who happen to be active editors. These cases demonstrate that editorial board members can author a substantial share of the papers published in the journal, and continue to do so for several decades.

Note that editorials were then excluded from the publication record of each editor, to ensure that our analysis only considers original research articles. To provide additionally assurance of the accuracy of our method, we manually examined all publications (co-)authored by the three extreme editors considered in Figure 5.2, and found that only two were editorial pieces. This analysis suggests that our approach of identifying and excluding editorial pieces, while not perfect, is highly accurate.

5.3 Discussions

In this chapter, we showed that a substantial amount of editors publish in the journal they edit, and provided the first comparison of self-publication behavior across disciplines and genders. As such, the study contained in this chapter contributes to the line of research exploring gender differences in academia [Pezzoni et al. 2016; Nguyen et al. 2022; Lerman et al. 2022; King et al. 2017]. Moreover, our unique dataset allowed us to understand how far editors can reach with their self-publication practice. Naturally, these findings raise the question: How much self-publication should be considered too much? Of course, there are perfectly innocuous explanations of why editors self-publish. Some may conduct research in a niche field with only a few alternative journals to publish in; others may be established scientists who self-publish their best works in order to kickstart the reputation of a young journal. Still, if there is anything

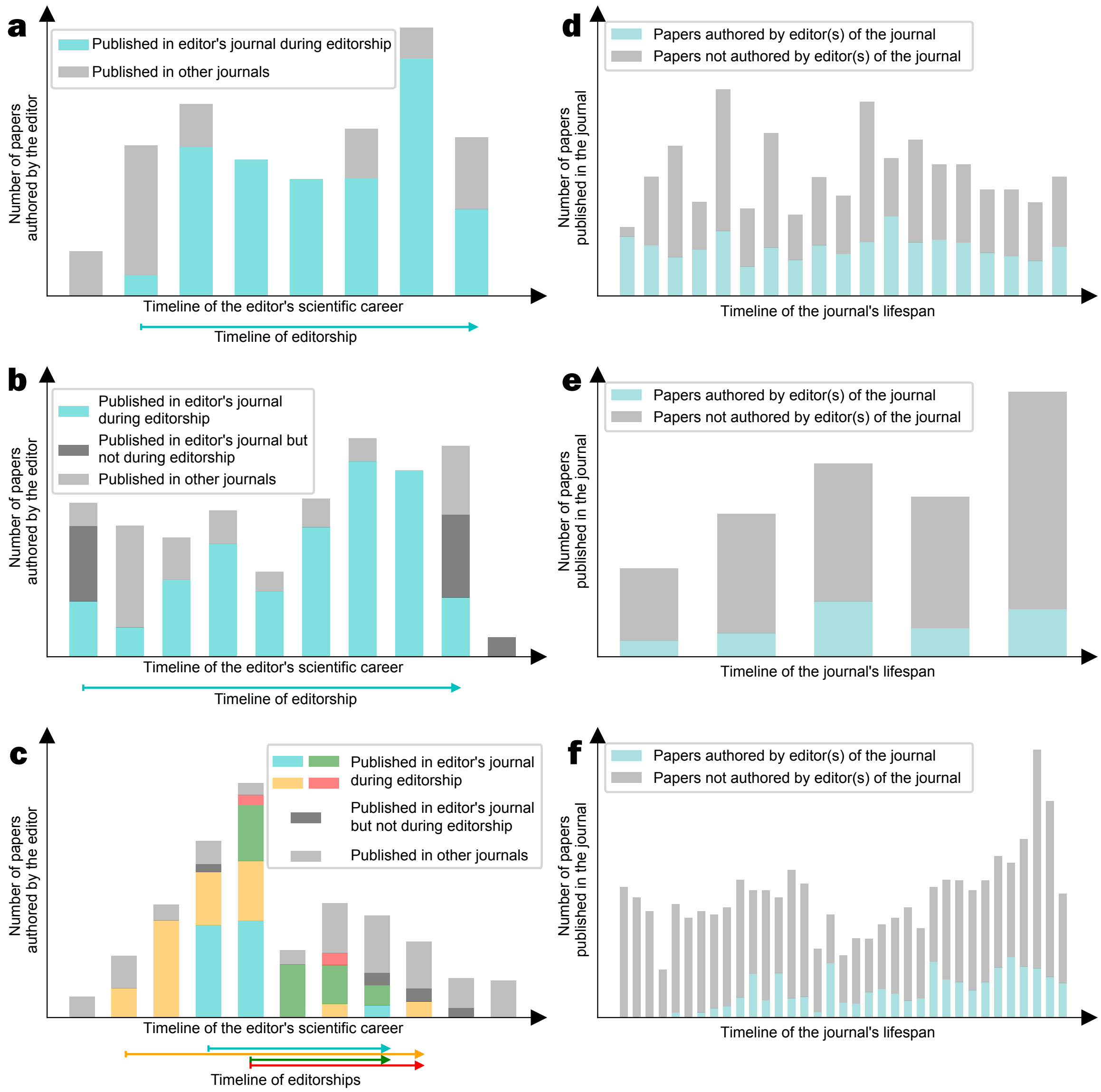

Figure 5.2: Extreme editors and extreme editorial boards. To preserve anonymity, ticks on the x-axis and y-axis are hidden and Gaussian noise is added to the bar heights. **a–c**, Out of all editors who publish at least 30 papers throughout their careers, the subfigures correspond to the three with the highest number of self-publications. For each of these editors, we show the total number of papers they publish as well as how many of those papers are published in the editor's journal(s); results are aggregated over five-year periods to preserve anonymity. The horizontal line(s) underneath the plot represent the span of the editorship(s). **d–f**, Out of all journals that have at least 30 papers, the subfigures depict the three with the highest proportion of papers whose authors include an editor of the journal.

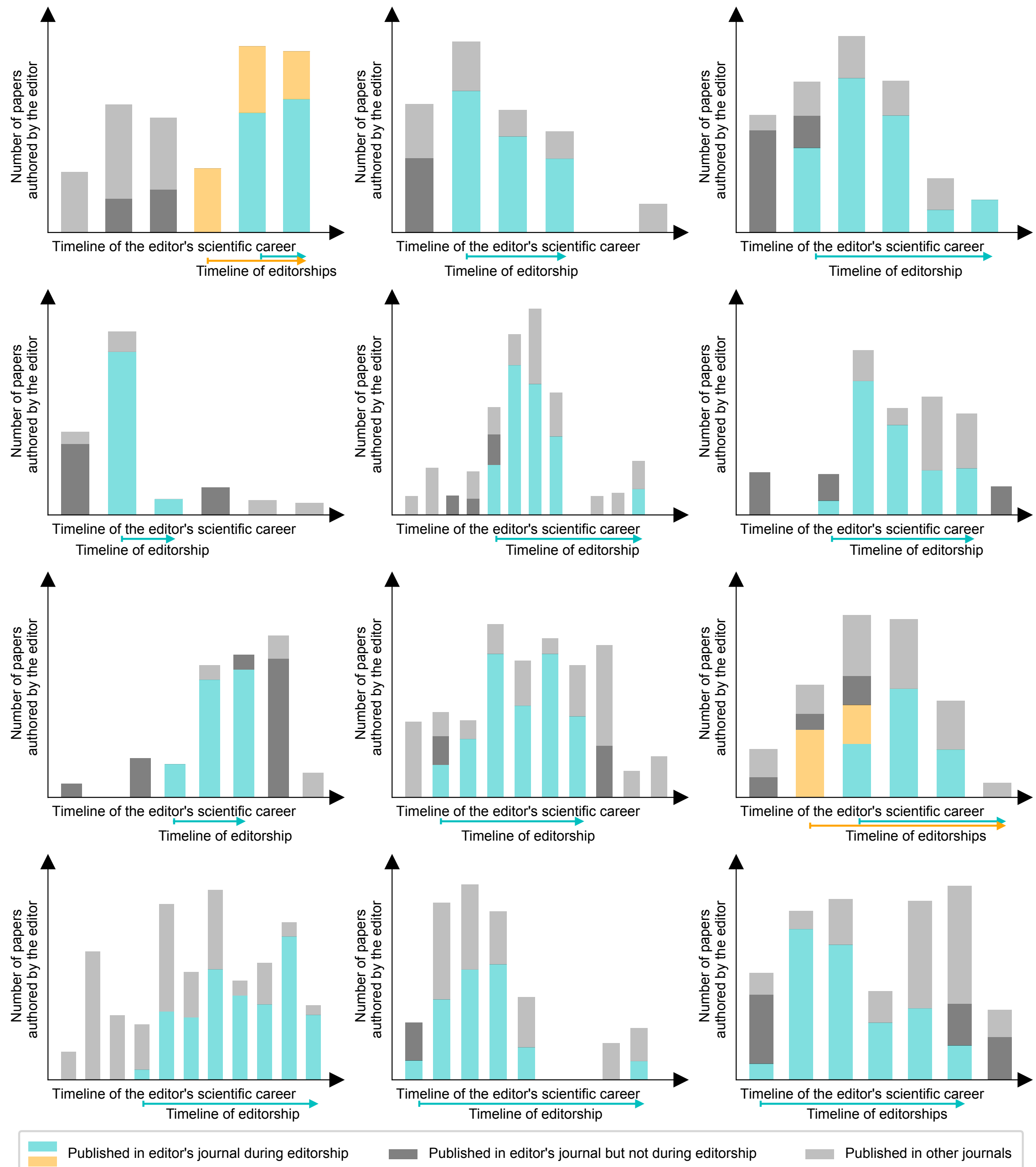

Figure 5.3: Extreme editors continued. Out of all editors who publish at least 30 papers throughout their careers, we analyze the 15 who have the highest proportion of their papers published in the journal(s) they are editing. Figures 4**a** to 4**c** in the main manuscript correspond to the top 3, while this figure corresponds to the remaining 12. To preserve anonymity, ticks on the x-axis and y-axis are hidden and Gaussian noise is added to the bar heights. For each of these editors, we show the total number of papers they publish as well as how many of those papers are published in the editor's journal(s); results are aggregated over five-year periods to preserve anonymity. The horizontal line(s) underneath the plot represent the span of the editorship(s).

that can be learned from recent scandals involving editors [Eiko 2008; Schiermeier 2008; Lockwood 2020; Van Noorden 2020], it is that the power enjoyed by editors can be exploited. For instance, consider those editors-in-chief who self-publish at high rates, despite being responsible for overseeing the review process of every submission, including their own. To an external observer, it may not be entirely clear how such articles are handled to circumvent the apparent conflict of interest. By providing an overview of the status quo of self-publishing practice, this chapter contributes to the discussion of whether self-publications should be governed with more transparency.

6 | Editor-author associations

In the previous chapter, we have seen one consequence of the dual role of editors as scientific gatekeepers and research-active scientists. In this chapter, we focus on a another type of COI that all research-active editors could face—non-financial COI due to personal connections. According to the Council of Science Editors, a COI arises when an editor handles a submission (co-)authored by a colleague (i.e., someone affiliated with the same institution) or by a person with whom they collaborated or co-authored recently [CSE 2012].

Despite the straightforward definition of COI, however, there are conflicting views regarding the governance of COI. Policies and proponents of regulating COI argue that COI may bias (consciously or subconsciously) editorial decisions [WAME 2009; CSE 2012]. Although biases may not necessarily lead to the publication of erroneous findings, they would mean that not all submissions are treated equally. This could be consequential to one's career, since scientists are often evaluated based on the venues in which they publish [Heckman and Moktan 2020; McKiernan et al. 2019; Shu et al. 2022]. Moreover, even in the absence of bias, simply the perceptions of COI may erode trust in science [WAME 2009; ICMJE 2023; Friedman 2002]. Naturally, a number of policies have been put in place to govern such COIs [WAME 2009; CSE 2012; ICMJE 2023; COPE 2021]. Despite the need for such policies, it remains unclear whether they fully reflect the complex situations in which scientific research takes place. On paper, such policies make sweeping statements that cover all editor-author associations. In practice, as we will show later on in our analysis, various factors complicate the implications of such policies. Moreover, having a COI does not necessarily imply wrongdoing [WAME 2009], e.g., some editors may rely on their personal social network to attract high-quality papers for the journal's benefit [Brogaard et al. 2014; Medoff 2003]. Hence, there is a need for a nuanced understanding of the various factors at play when governing editors' COI.

To date, there are very few quantitative studies on policies governing editors' COI, and these studies often focus on understanding the prevalence of such policies, rather than their impact, and are restricted to medical journals [Haivas et al. 2004; Bosch et al. 2013; Faggion Jr 2021; Smith et al. 2012]. Here, to understand the interplay between such policies and the way editors handle COIs, we rely on the dataset of half a million papers along with their handling editors from six different publishers, namely, Frontiers, Hindawi, IEEE, MDPI, PLOS, and PNAS (see Chapter 2.2). Using such data, we analyze the rate at which a published paper is handled by an editor who has recently collaborated with the author or by an editor who shares the same affiliation with the author. By doing so, we provide much needed evidence to inform the development of and implementation of COI policies [Editors et al. 2008].

6.1 An overview of policies governing editor-author associations

Before delving into quantitative analysis, we provide a qualitative overview of the policies governing editors' COI, gathered from four major organizations of academic editors, namely, the Committee on Publication Ethics (COPE), the Council of Science Editors (CSE), the International Committee of Medical Journal Editors (ICMJE), and the World Association of Medical Editors (WAME). Additionally, we examine the COI policies of the six academic publishers analyzed in this chapter; see Table 6.1 for a summary.

According to these policies, a conflict of interest, or a competing interest, arises when certain associations could influence, or could be perceived to influence, objective assessment of submissions. This broad definition encompasses actual, potential, and perceived conflicts of interest, recognizing that even the perception of COI can undermine trust in the editorial process. Consistent with this definition, we use the term "conflict of interest" throughout this chapter to refer to any situation involving actual, potential, or perceived interests that might compromise the impartiality of editorial decision-making, without making further distinctions.

Overall, there seems to be no consensus on the type of editor-author associations that would constitute a COI. However, several types of associations are commonly mentioned across policy documents. Among these, two of the most frequently mentioned ones are recent collaborations and shared institutional affiliations between the editor and author—both of which are the focus of this chapter. Additional relationships commonly identified as potential sources of COI include familial ties, direct competition, mentor-mentee relationships, and joint grant partnerships.

We start by reviewing policies governing editor-author associations arising from shared affiliations, which are summarized in Table 6.1. Editor-author associations are explicitly identified as a source of COI by three academic organizations (COPE, CSE, and WAME) as well as four academic publishers (Frontiers, Hindawi, MDPI, and PLOS). Among them, CSE adopts the most lenient policy, since it only considers being affiliated with the same department, not institution, as a source of COI. Similarly, WAME's policy is relatively relaxed because it considers being affiliated with the same institution as a source of COI only when the affiliation is small, although it does not provide any guidelines on what should be considered "small." On the contrary, Hindawi adopts the strictest policy, whereby COI exists not only when the editor and author share the same affiliation currently, but also in the recent past.

		Academic Associations				Publishers					
		COPE [COPE 2017]	**CSE** [CSE 2012]	**ICMJE** [ICMJE 2023]	**WAME** [WAME 2009]	**Frontiers** [“Policies and publication ethics” 2023]	**Hindawi** [“Publication ethics” 2023]	**IEEE** [“IEEE Policies” 2023]	**MDPI** [“Research and publication ethics” 2023]	**PLOS** [“Competing Interests” 2023]	**PNAS** [“Editorial and Journal Policies” 2023]
General policy regarding editor-author associations	Stringency of recusal policy	Medium	Medium	Medium	Medium	Low	Medium	Medium	Medium	Low	High
	Recommend or require disclosure of COI	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Other sources of non-financial COI	Mentor/mentee, joint grant holder	Competitors, or those addressing an issue in which they stand to gain financially	N.A.	Family members, friends, enemies, competitors	Family members	Have a close personal connection to any author; feel unable to be objective	N.A.	Personal friends, family members, or spouses, mentor/mentee	Joint grant holders, personal relationship	Family members, doctoral thesis advisor/advisee, postdoctoral mentor/mentee,
Editor-author associations due to recent collaboration	Mentioned in the policy	Yes	Yes	No	No	Yes	Yes	No	Yes	Yes	Yes
	Only recent collaboration	Yes	Yes	N.A.	N.A.		Yes	N.A.	Yes	Yes	Yes
	Clear definintion of "recent"	3 years	No	N.A.	N.A.	2 years	No	N.A.	3 years	5 years	48 months
	Additional contraints	close collaborator	No	N.A.	N.A.		No	N.A.	No	No	
Editor-author associations due to same affiliation	Mentioned in the policy	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	No
	Same department only	No	Yes	N.A.	Yes	No	No	N.A.	No	No	N.A.
	Small affiliation only	No	No	N.A.	Yes	No	No	N.A.	No	No	N.A.
	Sharing same affiliation in the past	No	No	N.A.	No	No	Yes	N.A.	No	No	N.A.
	Additional conditions	No	No	N.A.	No	Whether having the same affiliation resulted in interactions, collaborations, or mutual interests with the authors that would compromise your impartiality in conducting this review		N.A.	N.A.	N.A.	N.A.

Table 6.1: Overview of COI policies. Here, policy “stringency” refers to the degree of freedom that editors have when deciding their action, when they face a certain type of editor-author association that is specified in the policy; more details regarding how stringency level is coded can be found in Methods. Note that COPE does not formally adopt guidelines concerning editors’ COI. However, according to the COPE Council, COPE’s ethical guidelines for peer reviewers [COPE 2017] are also applicable to handling editors [COPE 2024].

Next, regarding editor-author association due to recent collaborations, two academic organizations (COPE and CSE) and five academic publishers (all except IEEE) explicitly address this type of editor-author association, but they disagree as to what constitutes a "recent collaboration." More specifically, according to PNAS, a collaboration is considered recent if the difference between the date on which it took place and the date of submission (Δ) does not exceed 48 months (i.e., if $\Delta \leq 48$m) ["Editorial and Journal Policies" 2023]. In contrast, Frontiers, MPDI, and PLOS consider the threshold to be 2 years, 3 years, and 5 years, respectively ["Policies and publication ethics" 2023; "Research and publication ethics" 2023; "Competing Interests" 2023]. As for the two remaining publishers in our dataset, Hindawi does not provide an explicit definition of what counts as a recent collaboration ["Publication ethics" 2023], while IEEE does not explicitly mention editor-author collaboration in its policies ["IEEE Policies" 2023; IEEE 2023].

Editors' COI is managed in two primary ways: disclosure and recusal. Most policy documents reviewed in this paper recommend or mandate the disclosure of editors' COI, but in practice such disclosures are never publicly released along with the paper in question. Most policies further recommend or mandate that editors recuse themselves from handling submissions with COI. The stringency of these recusal policies, however, varies across publishers. More specifically, different COI policies adopt different modal verbs (such as "may", "should", or "must") when it comes to expressing the recommendation, permission, or obligation regarding whether editors should recuse themselves when a COI is present. Depending on the modal verbs, we classify the publishers into three tiers. The first consists of PLOS and Frontiers, whereby both do not require nor recommend editors to recuse themselves when they have potential COIs, and simply offer recusal as an option. The second tier consists of IEEE, MDPI, and Hindawi, as well as all academic associations (i.e., WAME, CSE, ICMJE, and COPE), which recommend against editors' handling papers with COI, but do not prohibit such interaction. These publishers state that editors "should decline" to edit or "should not" edit such papers. The third tier, represented by PNAS, employs the strictest language, stating that editors "may not" handle papers with COI. The phrase "may not" typically expresses lack of permission or absolute prohibition ["May not definition"

2024], making it more stringent than "should not" ["Should not definition" 2024]. Notice, however, that PNAS does not consider editor-author sharing the same affiliation as a source of COI.

6.2 The percentage of papers with editor-author associations

In this section, we start our quantitative analysis by documenting the frequencies of editor-author associations observed in our dataset. As can be seen in Fig. 6.1a, 6.1b, and 6.1c, the percentage of papers with an editor-author association varies across publishers, with PNAS topping the chart with 10.5% of papers having recent editor-author collaboration, 6.9% of papers where the editor and an author share the same affiliation, and 15.3% of papers having either type of editor-author association; see Table 6.2 for detailed statistics. As for the journals, the ones with a high percentage of papers with editor-author association are PLOS Medicine (24%), Frontiers in Pediatrics (16%), PNAS (15%), Journal of Fungi (15%), PLOS Neglected Tropical Diseases (15%), and Frontiers in Neuroinformatics (14%); all these journals are ranked in the first quartile (Q1) in their respective disciplines. In fact, 16 out of the 20 journals with the highest percentage are ranked Q1, according to Scimago Journal & Country Rank (SJR) in 2022. Overall, nearly 6% of journals have a percentage ≥ 10%, and over half of them have a percentage ≥ 2%.

Journals that publish a huge number of special issues might have a higher percentage of papers with editor-author association for either nefarious reasons (having less stringent peer review process [Brainard 2023]) or benign reasons (being specialized with few alternative editors [Pfeffer 2018]). To explore this possibility, we calculate the percentage separately for papers published in special issues, and those published in "normal" issues. As can be seen in Table 6.3, the percentages of papers with editor-author association in special issues are indeed greater than those in normal editions. More specifically, the percentage in Hindawi drops from 6.68% in special issues to merely 1% in normal issues, the percentage drops from 9.95% to 4.35% in Frontiers, and from 2.77% to 2.01% in MDPI.

Next, we determine whether the percentages of papers with editor-author association varies with the

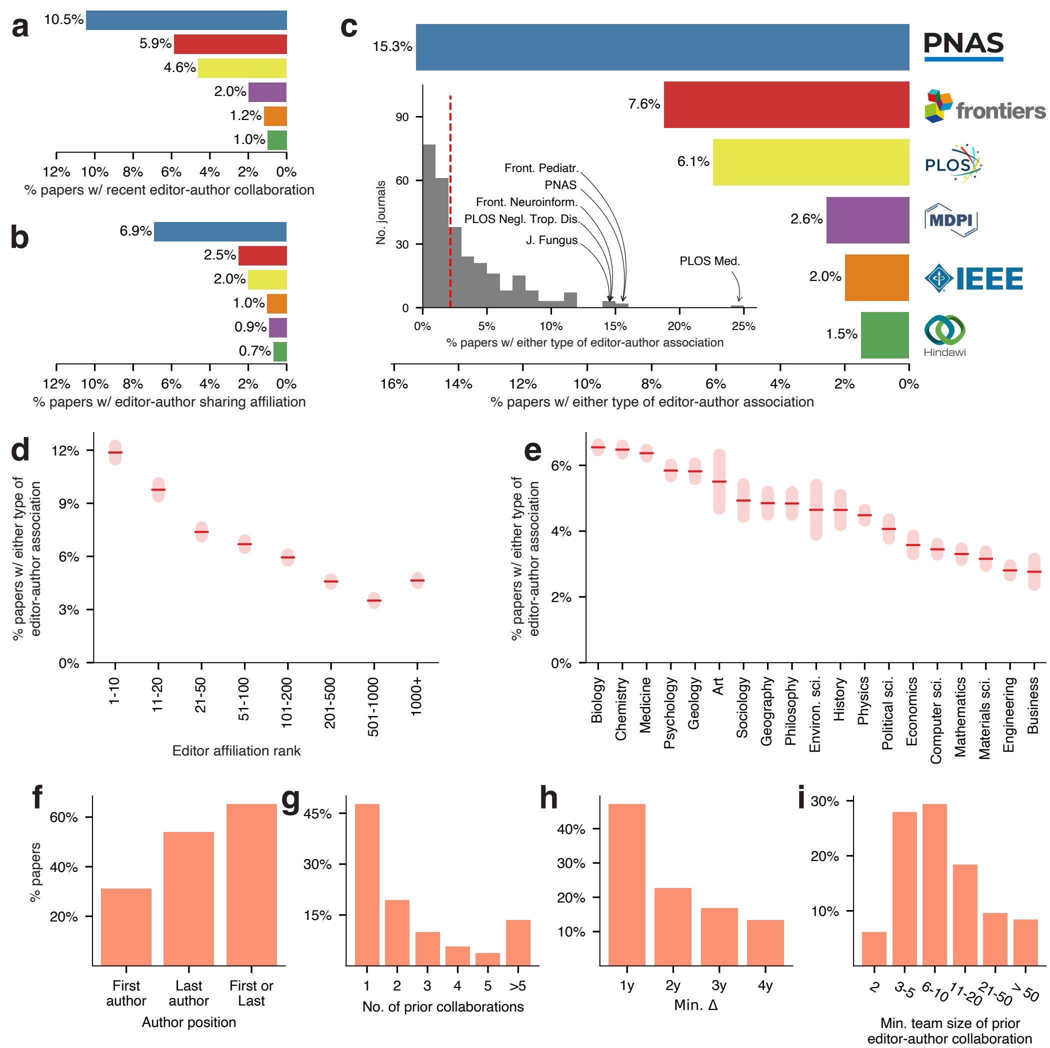

Figure 6.1: Quantifying the percentage of papers with editor-author associations. **a**, In each publisher, the percentage of papers with recent editor-author collaboration(s). **b**, In each publisher, the percentage of papers whose editor sharing the same affiliation with any author. **c**, In each publisher, the percentage of papers with either type of editor-author association. Inset shows the distribution of the percentage across all the journals in our dataset, highlighting the six journals with the highest percentage. The red dotted line highlights the median percentage. **d**, Percentage of papers with editor-author associations across editor's affiliation rank. **e**, Percentage of papers with editor-author associations across disciplines. **f**, Among papers with editor-author associations, the percentage of papers where the association was introduced by the first author only, the last author only, or either first or last author. **g**, Among papers with recent editor-author collaborations, the percentage of papers where the number of prior collaborations is between one and five, or greater than five. **h**, Among papers with recent editor-author collaborations, the percentage of papers where the most recent collaboration happened one year (0-12 months), two years (13-24 months), three years (25-36 months), and four years (37-48 months) ago. **i**, Among papers with recent editor-author collaborations, the percentage of papers where the minimum team size of prior collaboration falls in each of the six bins. In (**d**) and (**e**), lines represent the mean percentage and the shaded regions represent 95% confidence interval.

Publisher	Years	No. papers	No. editors	No. papers with recent editor-author collaboration	No. papers editor-author same affiliation	No. papers with either type of editor-author association
Frontiers	2002-2021	127050	25756	7468 (5.88%)	3193 (2.51%)	9679 (7.62%)
Hindawi	2007-2021	82856	10174	823 (0.99%)	574 (0.69%)	1232 (1.49%)
IEEE	2013-2021	12927	940	153 (1.18%)	132 (1.02%)	257 (1.99%)
MDPI	2014-2021	92803	13608	1837 (1.98%)	855 (0.92%)	2388 (2.57%)
PLOS	2001-2021	175240	13388	8077 (4.61%)	3517 (2.01%)	10674 (6.09%)
PNAS	2000-2021	32764	4188	3428 (10.46%)	2262 (6.90%)	5021 (15.32%)

Table 6.2: Descriptive statistics by publisher.

Publisher	% papers w/ editor-author sharing affiliation		% papers w/ recent editor-author collaboration		% papers w/ either type of editor-author association	
	Normal	Special Issue	Normal	Special Issue	Normal	Special Issue
Frontiers	1.42%	3.29%	3.22%	7.77%	4.35%	9.95%
Hindawi	0.45%	3.26%	0.65%	4.69%	1.00%	6.68%
MDPI	0.73%	0.99%	1.54%	2.13%	2.01%	2.77%

Table 6.3: Percentage of papers with either type of editor-author association among papers in Special Issues and those that are not.

editor's characteristics. We find that the percentage increases with the affiliation rank of handling editors, and varies across disciplines. Specifically, the percentages in Biology, Chemistry, and Medicine reach over 6%, while Business has the lowest rate of about 2.7% (Fig. 6.1e). In Figure 6.3, we find broadly similar patterns using a logistic regression model that controls for the affiliation, and discipline of the handling editor, in addition to journal age (number of years since the birth of the journal), editor age (number of years since the first time that the editor handles a paper in this journal), and the number of authors of the paper in question.

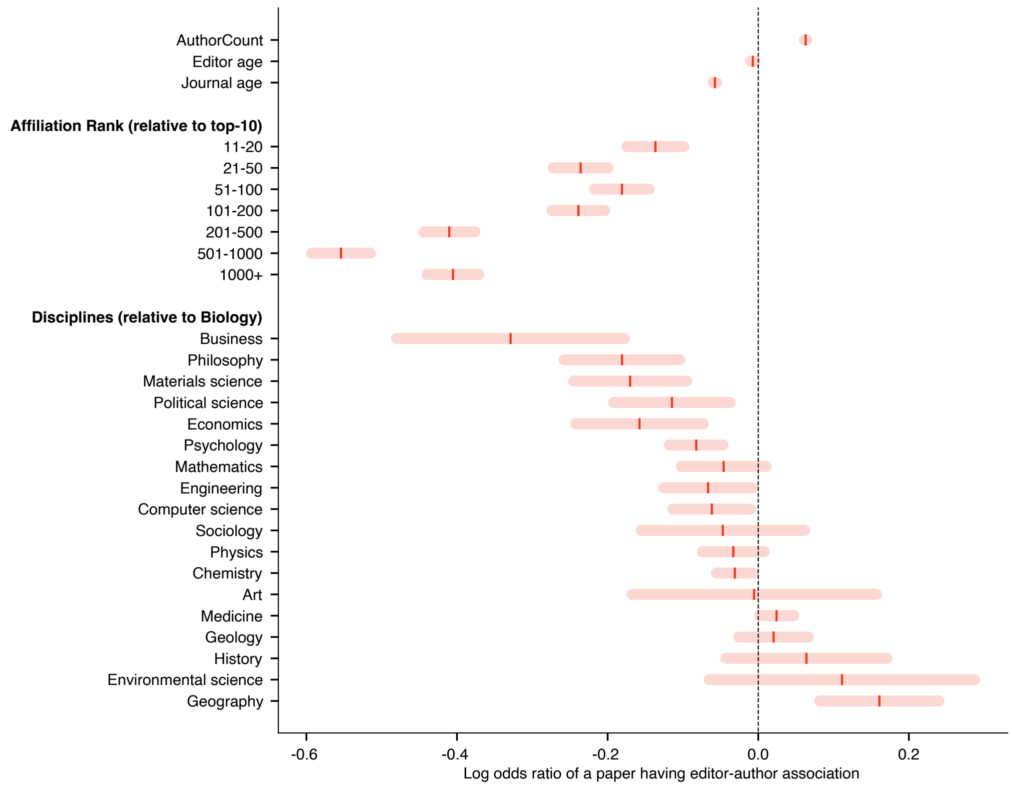

Figure 6.2: Features of papers and editors that correlate with the likelihood of a paper having editor-author association. Red lines denote the OLS-estimated coefficients of paper- and editor-related features predicting whether the handling editor of a paper has editor-author association. Shaded areas denote 95% confidence intervals.

Current COI policies make sweeping statements that cover all editor-author associations, regardless of the context in which the associations take place. For example, an editor-author collaboration that takes place in a team of three might have different implications than a collaboration in a team of thirty, but such a difference is not considered by current policies. Motivated by this observation, we examine some characteristics of the association between the editors and authors. Firstly, in over 65% of papers with editor-author association, the editor was associated with either the first or the last author (Fig. 6.1f). Secondly, in 53% of papers with recent editor-author collaborations, the editor and author have collaborated more than once during the 48 months prior to the submission of the paper in question (Fig. 6.1g). Thirdly, in over 47% of papers with recent editor-author collaborations, the most recent collaboration took place less than a year prior to the papers' submission (Fig. 6.1h).

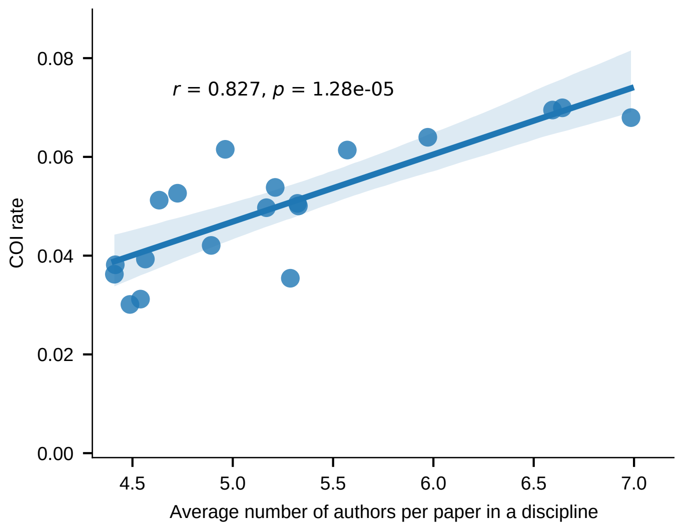

Figure 6.3: The relationship between the average team size and the percentage of papers with recent editor-author associations in each discipline. Each data point corresponds to a discipline. The Pearson correlation coefficient is reported in the figure.

Finally, we find that in over 81% of papers with recent editor-author collaborations, the prior collaborations happened in teams involving no more than 20 authors (Fig. 6.1i). Note that different disciplines have different distributions of team size. For example, the 75-th percentile value of team size is 4 in Philosophy and 7 in Medicine, and the 95-th percentile value of team size is 7 in Philosophy and 12 in Medicine. Disciplines with larger teams tend to have a higher percentage of papers featuring recent editor-author collaborations (Figure 6.2). Notably, Medicine and Chemistry exhibit the highest percentages, exceeding 4.5%, while Engineering and Business show the lowest, around 2%. Overall, 54% of papers with recent editor-author collaborations falls in either Biology, Medicine, or both. These two fields are also the most productive, accounting for 47% of the papers in our dataset. In each discipline, if we disregard all prior collaborations whose team size falls above the 95-th percentile in that discipline, between 56.41% to 78.46% of editor-author collaborations would still persist, suggesting that at least half of recent editor-author collaborations took place in small to medium-sized teams. If one were to further restrict their attention only to teams that fall under the 75th percentile value, between one-fifth (in Business) to half (in Engineering) of recent editor-author collaborations persist.

6.3 The acceptance delay of papers with recent editor-author collaborations

Having established that papers with recent editor-author collaborations are common, we now investigate whether they differ from other papers in terms of the time spent between submission and acceptance. We further account for the temporal and cross-sectional variation in acceptance delay by calculating relative acceptance delay (RAD); see Chapter 2.3 for more details. Scientists would clearly benefit from getting their manuscript accepted earlier. This is because the vast majority of them are funded for a fixed period of time or are constantly evaluated, implying that an earlier acceptance could allow the research carried out during the funded period to be published in time before their evaluation [Bilalli et al. 2021].

Past studies suggest that reviewing a paper takes an average of five hours, but authors could wait for months or even years before hearing back from editors [Ware and Mabe 2015]. This implies that any observed difference in the time spent under review is not primarily due to differences in the effort required from the reviewers. Rather, other factors play a significant role, such as whether the editors prioritize the paper, whether they reach out to responsive reviewers, and whether they constantly follow up with the reviewers. Additionally, editors have the liberty to reach out to reviewers who are likely to give favorable comments, or even override reviewers' requests to revise the manuscript [Gans and Shepherd 1994].

Against this background, we compare the papers with and without recent editor-author collaboration in terms of their acceptance delay, i.e., the number of days spent between submission and acceptance,

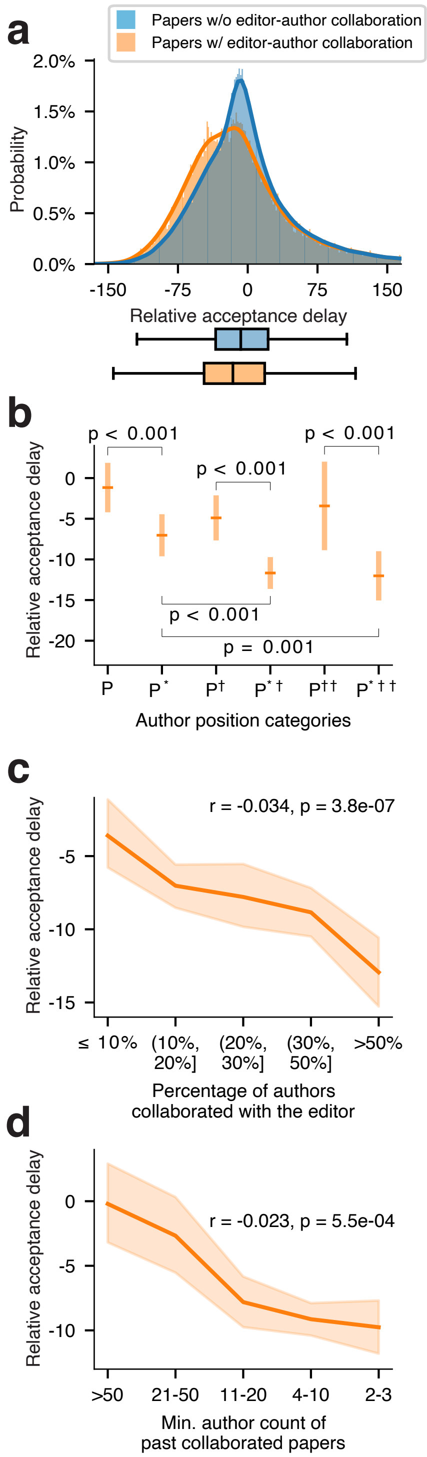

Figure 6.4: Comparing the acceptance delay of papers with or without editor-author associations. **a**, Distributions of relative acceptance delay (RAD) of papers with and without editor-author collaboration. These distributions are summarized as boxplots, where boxes extend from the lower to upper quartile values, and whiskers extend until the 5th and the 95th percentiles. The lines represent the median. **b**, Papers are grouped based on the author position of the editor's collaborator in the focal paper as well as their author positions in the prior collaboration. The asterisk superscript (p^*) indicates that the handling editor of p has collaborated with the first or last author of p, and the dagger superscript ($p^\dagger$) indicates that an author of p is the first or last author in a recent collaboration with the editor. The horizontal lines denote the mean RAD of each group of papers, and the vertical line denotes the 95% confidence interval (CI). p-values are calculated using the Welch's t-test. **c**, Correlation between RAD and the percentage of authors that have recently collaborated with the editor. **d**, Correlation between RAD and the minimum author count on any papers co-written by the editor and any authors of the focal paper in the past 48 months. In (**c**) and (**d**), lines represent the mean RAD and the shaded regions represent 95% CI; the Pearson correlation coefficients (r) and the associated p-values are calculated using the original data (not binned).

while accounting for the temporal and cross-sectional variation in acceptance delay.

As can be seen in Fig. 6.4a, papers with recent editor-author collaboration have a shorter RAD than those without. In particular, the RAD of papers without recent editor-author collaboration is normally distributed around 0 (mean: 1.56, standard deviation: 64.74), whereas the RAD of papers with recent editor-author collaboration has two modes, with one of them roughly around 0 and the other around -43. Such a bimodal distribution suggests that papers with recent editor-author collaboration consist of two distinct subpopulations, with one being handled at the usual pace (i.e., just like papers without recent editor-author collaboration), and the other being handled faster.

Next, we explore whether those who have a stronger relationship with the editor get their submissions accepted faster than those with a weaker relationship. We first look at how RAD is related to author positions. Here, when referring to a paper, p, we will add an asterisk superscript (p^*) to indicate that the handling editor has collaborated with the first or last author of p. Furthermore, we will add a dagger superscript ($p^\dagger$) to indicate that an author of p is the first or last author in a recent collaboration with the editor. Finally, two daggers ($p^{\dagger\dagger}$) would indicate that the editor and an author of p were the first and last authors in a recent collaboration. Note that these notations can be used simultaneously, e.g., we could write $p^{*\dagger}$, or $p^{*\dagger\dagger}$, depending on the paper type. Arguably, the link between the submission and the editor tends to be stronger in p^* than in p, and also tends to be stronger in $p^\dagger$ and $p^{\dagger\dagger}$ than in p. This argument is motivated the observation that, compared to middle authors, first and last authors are significantly more likely to be corresponding authors, as well as having broader involvement in research activities [Sauermann and Haeussler 2017], which means they play more important roles in a research paper as well as more likely to liaise with the handling editor. As can be seen in Fig. 6.4b, p^* is handled faster than p. Similarly, $p^{*\dagger}$ is handled faster than $p^\dagger$, and $p^{*\dagger\dagger}$ is handled faster than $p^{\dagger\dagger}$. Finally, both $p^{*\dagger}$ and $p^{*\dagger\dagger}$ are handled faster than p^*.

We then calculate the percentage of authors who have recently collaborated with the editor. As can be seen in Fig. 6.4c, the greater the percentage, the shorter the RAD. A third way to examine the strength of the relationship between an author and an editor is to consider the team size of their prior collaboration. Intuitively, if an author has collaborated with the editor as part of a smaller team (e.g., involving, say, three members), then the author-editor relationship is likely to be stronger than if they were part of a larger team (e.g., involving, say, 20 members). As can be seen in Fig. 6.4d, the smaller the team size, the shorter the RAD. These findings suggest that authors with a stronger connection to the editor experience shorter delays between the submission and acceptance of their manuscripts. More importantly, Fig. 6.4d suggests that the shorter RAD observed earlier (i.e., the one enjoyed by papers with recent editor-author collaborations) diminishes when the collaborations involve large teams. To identify the team size beyond which the effect disappears, we grouped papers based on the team size of recent editor-author collaborations, and then applied a one-sample t-test to examine whether the RAD of each group of papers are significantly different from zero, while ensuring similar statistical power in each group. As can be seen in Figure 6.5, when recent editor-author collaborations involve teams with fewer than 20 co-authors, the corresponding papers tend to be accepted faster than a typical paper published in the same journal in the same year. However, this difference in RAD disappears when recent editor-author collaboration involves teams of 20 or more co-authors.

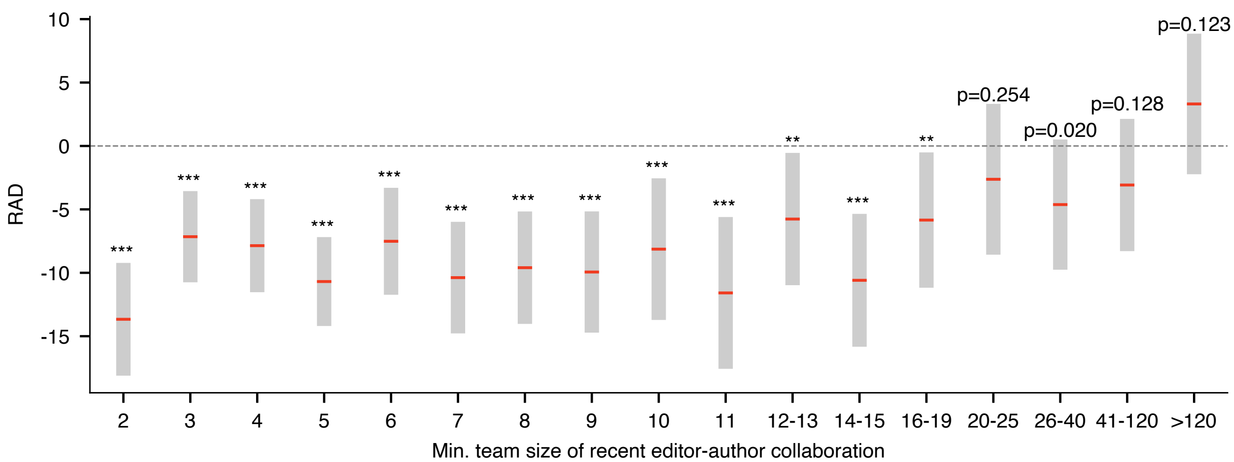

Figure 6.5: Average RAD of papers with recent editor-author collaboration, grouped according to the minimum author count on the past collaborated papers. Papers are grouped into the smallest integer-range bins such that each contains at least 5% of data. Red lines denote mean values, and the gray bars denote 99% confidence interval. Student's T-tests are applied to test whether the mean of each distribution is significantly different from zero; *** means $p < 0.001$ and ** means $p < 0.01$.

6.4 The effect of recusal policies

As we have seen in Table 6.1, many publishers have adopted recusal as a way to curb papers with editor-author associations, but it remains unclear whether these policies have any effect at all. In other words, what percentage of papers with editor-author associations do we expect to see in the absence of these policies?

Answering this counterfactual question based on observational data alone is challenging, since we cannot observe a parallel universe in which the COI policies were never introduced. Nevertheless, we are able to estimate the policies' effect by leveraging three quasi-experiments whereby certain changes were introduced to the COI policies of PNAS and PLOS at different points in time. Based on this, we set out to compare editors' behavior before vs. after the changes were introduced.

More specifically, the first policy change that we analyze (Case 1) took place in July 2011, when PNAS introduced a COI policy, prohibiting editors from handling submissions by authors with whom they collaborated during the past 24 months. Importantly, no such policy existed prior to that date. The second policy change that we analyze (Case 2) took place in January 2014, when PNAS updated its COI policy by modifying its definition of "recent collaboration" from the past 24 months to the past 48 months. The third and final policy change (Case 3) took place in May 2015, when PLOS introduced a COI policy, recommending against editors from handling submissions by authors with whom they collaborated during the past 60 months; no such policy existed in PLOS prior to that date. See Appendix A for more details regarding these policy changes.

In all three cases of policy change, the scope of editor-author collaborations considered as a source of COI was broadened. To put it differently, certain behavior that was considered acceptable by the publisher became prohibited as per the new policy. Despite this common attribute, three cases of policy change have some subtle distinctions. Unlike Case 1 and Case 2, where PNAS states that "recent collaborators ... must be excluded as editors", Case 3 (PLOS) adopts less strict policy by only suggesting that editors may recuse themselves if necessary (see Appendix A for policy text). Additionally, unlike Case 1 and Case 3, where COI policies were introduced for the first time in their respective publisher, Case 2 was an update of an existing policy in PNAS.

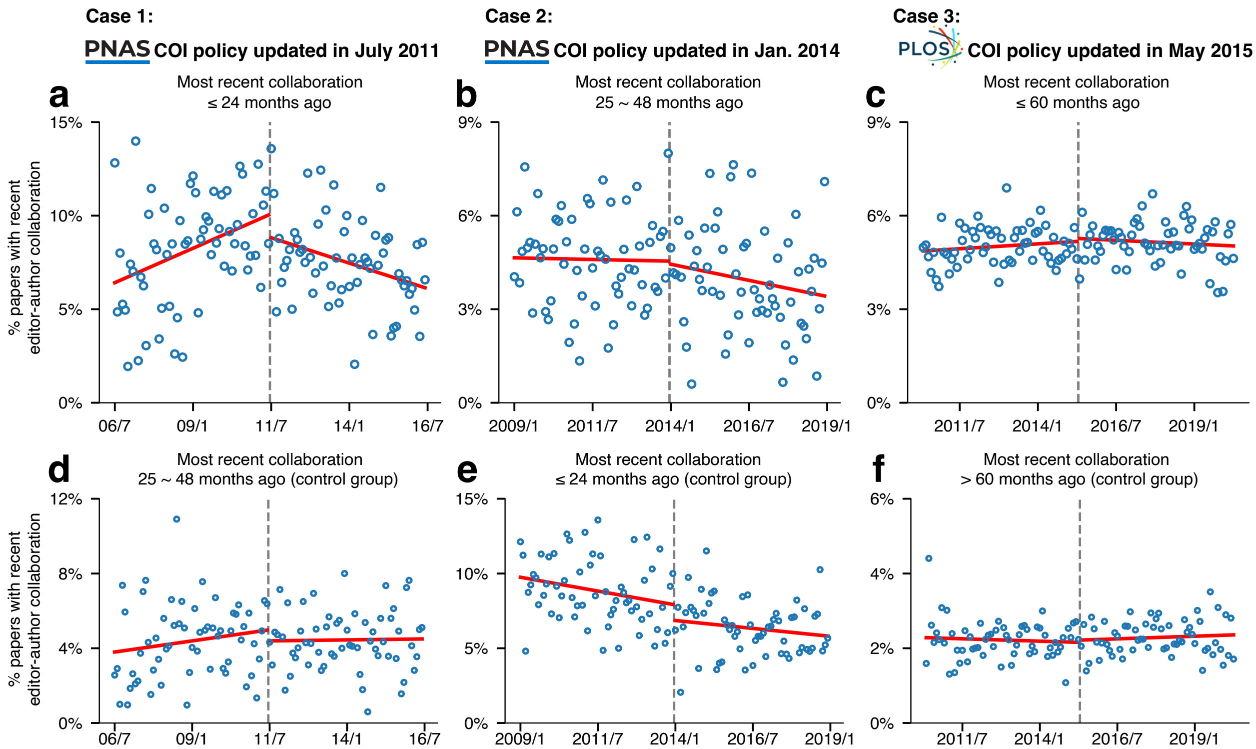

Figure 6.6: Policies fail to eliminate papers with recent editor-author collaboration. The x-axis represent the submission date (in month) of papers. For any given month, the corresponding circle represents the percentage of papers submitted that month whose authors had a recent collaboration with its handling editor. Recent collaboration is defined differently in each panel, as stated in their respective subtitles. Dashed lines denote the time when a policy was introduced that prohibits editors from handling submissions by recent collaborators. Red lines are fitted to the circles before and after the policy change using the OLS method. The top row corresponds to the treatment groups, i.e., the papers that are targeted by the policy change, while the bottom row corresponds to the control groups, i.e., papers that are not affected by the change.

We start by visualizing the percentage of papers with recent editor-author collaborations that were submitted around the month in which the policy change took place (Fig. 6.6a to 6.6c). To estimate the effect of the policy change, we use a regression discontinuity in time (RDiT) design, a method commonly used in the Social Sciences to study the treatment effect in quasi-experiments [Imbens and Lemieux 2008; Anderson 2014; Reny and Newman 2021]. Based on this, we estimate that in Case 1, after PNAS prohibited editors from handling submissions by any collaborators from the past 24 months, the number of papers with editor-author collaboration within that time span decreased from 10.32% to 8.49% ($p = 0.029$). Moreover, the percentage of papers with such editor-author collaboration continued to decrease by about 0.5% per year during the five-year period that followed the policy change ($p < 0.001$). In the other two cases, we found no evidence that the policies had any effect on the the percentage of papers with recent editor-author collaborations; see Table 6.4 for regression estimates. Together, our findings suggest that despite the stringent language employed in current COI policies on paper, they are rather serving as mere guidelines in practice.

As is the case with any observational study, an RDiT design, such as ours, comes with some intrinsic limitations that should be carefully considered. Firstly, there is often a need to expand the window (i.e., the period before and after the treatment) in order to obtain sufficient statistical power [Hausman and Rapson 2018]. However, by expanding the window, it becomes harder to attribute any observed change to the treatment in question. One way to alleviate this issue is to perform a sensitivity analysis while varying the window size. Accordingly, we adopt alternative specifications where the bandwidth around the cutoff date is varied; this yields similar results (Table 6.5). Here, we do not opt for thresholds smaller than 36 months to ensure sufficient statistical power. Consequently, our results rely on observations that may be considered relatively far from the threshold, even with the minimum bandwidth (i.e., 36 months).

Secondly, the observed change (or lack thereof) in the outcome around the treatment time could be attributed to other events that coincide with the treatment. To rule out this possibility, we use a negative control group for each of the three policy changes. These groups consist of papers whose author(s) collaborated with the handling editor, but the collaboration fell outside the range specified by the policy in question. Fig. 6.6d to 6.6f depicts the control groups of Cases 1 to 3, respectively. In Case 1, for example, the treatment group (Fig. 6.6a) involves collaborations within the past 24 months, while the control group (Fig. 6.6d) involves those within the past 25 to 48 months. Hence, the treatment and control groups are influenced by the same exogenous factors (if any) apart from the policy change, while the latter applies only to the treatment group. Now if the observed pattern around the cutoff date in the treatment group is attributed (at least partially) to the policy change, we would expect to see a different pattern in the control group. However, both groups differ only in Case 1 (see Table 6.4), suggesting that the decrease in the percentage of papers with editor-author collaboration in Case 1 is likely due to policy change, and that the policy likely did not have any effect on the percentage of papers with editor-author collaboration in Case 2 and 3. Together, these findings suggest that, at least in some cases, the policy has no detectable impact, and even when it does, the policy is insufficient to fully deter editors from handling the papers of their recent collaborators.

		Cases		
	Monthly Percentage	(1)	(2)	(3)
Treatment	Policy	-1.83%	-0.16%	0.26%
		(0.029)	(0.783)	(0.233)
	Month * Policy	-0.10%	-0.02%	-0.01%
		(<0.001)	(0.373)	(0.158)
	N	120	120	120
Control	Policy	-0.55%	-0.89%	0.08%
		(0.365)	(0.284)	(0.66)
	Month * Policy	-0.02%	0.01%	0.00%
		(0.376)	(0.515)	(0.503)
	N	120	120	120

Table 6.4: OLS-estimated regression coefficients of the RDiT design. The regression is specified as: percentage = Month + Policy + Month * Policy. Outcome is the percentage of papers with recent editor-author collaboration each month. "Month" represents the number of months before the cutoff date (if it is a negative value) or after the cutoff date (if it is a positive value). "Policy" is a binary variable, and is set to True if the current month is after the cutoff date of the policy change. The interaction term captures how the temporal trend changed after the policy change. The treatment groups correspond to the top row of Fig. 2 in the main manuscript, while the control groups correspond to the bottom row of that figure. Each column represents a separate regression. Parentheses contain P-values that are estimated using robust standard errors.

6.5 The suitability-integrity tradeoff of managing editor-author association

There could be many reasons why recusal policy is not working as intended. Here, we consider one of the biggest reason—suitability. Note that editors who are selected to handle a paper are often those whose

Window size	Monthly Percentage	Cases (1)	(2)	(3)
60 months	Policy	-1.83%	-0.16%	0.26%
		(0.029)	(0.783)	(0.233)
	Month * Policy	-0.10%	-0.02%	-0.01%
		(<0.001)	(0.373)	(0.158)
	N	120	120	120
54 months	Policy	-1.84%	-0.16%	0.27%
		(0.036)	(0.798)	(0.248)
	Month * Policy	-0.10%	-0.03%	-0.00%
		(0.001)	(0.107)	(0.751)
	N	108	108	108
48 months	Policy	-2.15%	-0.24%	0.29%
		(0.024)	(0.709)	(0.182)
	Month * Policy	-0.10%	-0.04%	0.01%
		(0.010)	(0.066)	(0.299)
	N	96	96	96
42 months	Policy	-2.27%	-0.55%	0.33%
		(0.023)	(0.412)	(0.169)
	Month * Policy	-0.11%	-0.02%	0.01%
		(0.011)	(0.451)	(0.189)
	N	84	84	84
36 months	Policy	-2.10%	-0.74%	0.34%
		(0.065)	(0.314)	(0.191)
	Month * Policy	-0.09%	-0.02%	0.01%
		(0.157)	(0.601)	(0.412)
	N	72	72	72

Table 6.5: Alternative RDiT specifications with different window size. Outcome is the percentage of papers with recent editor-author collaboration each month. The window size represents the number of months considered on either side of the cutoff date. Each column represents a separate regression. The table shows the OLS-estimated regression coefficients. Parentheses contain P-values that are estimated using robust standard errors.

field resembles that of the paper ["Editorial and Journal Policies" 2023; Resnik and Elmore 2016; "Editorial and peer review process" 2023; "Editors" 2023]. However, those are arguably the editors who are more likely to have a professional relationship with the authors. Based on this observation, some have argued that prohibiting all editor-author associations could compromise the quality of peer review, since the most suitable editors (in terms of expertise) may be prohibited from handling the paper in question [Resnik and Elmore 2018; Gottlieb and Bressler 2017]. However, this argument has not been put to the test to date. To this end, we use a graph embedding model to encode the fields of research of papers and scientists in a high dimensional space using MAG's citation network. We then apply a node2vec algorithm to calculate network embeddings using a scalable implementation of the algorithm [Cappelletti et al. 2023]. The expertise representation of a scientist is then calculated as the average embedding of all papers that they have (co-)authored. The similarity between an editor and a paper is calculated as the cosine similarity of their vector representations in the expertise space. This way, for any given paper p handled by editor e, we are able to determine whether there are editors on the same editorial board as e who could have handled p given their expertise.

To begin with, for any given paper p handled by editor e and published in journal j, let us examine the difference in expertise between e and a random editor e' serving on the same editorial board. Naturally, we would expect the expertise similarity between p and e to be greater than that between p and e', since the handling editor tends to be the most relevant to the paper in terms of expertise. Similarly, we would expect the similarity between p and e' to be greater than that between p and a random editor in our dataset, who may belong to an entirely different discipline. Fig. 6.7a shows that this is indeed the case, suggesting that our embeddings are able to capture the expertise of editors and papers.

Next, we examine the relationship between editor-author associations and expertise. Fig. 6.7b shows that the probability of having editor-author associations positively correlates with expertise similarity, i.e., the more similar the expertise of a paper is to that of its handling editor, the more likely it is for the handling editor to have an association with the authors. Importantly, when the expertise similarity between a paper and its handling editor is above 0.96 (the 95-th percentile value), we estimate that 17.12%

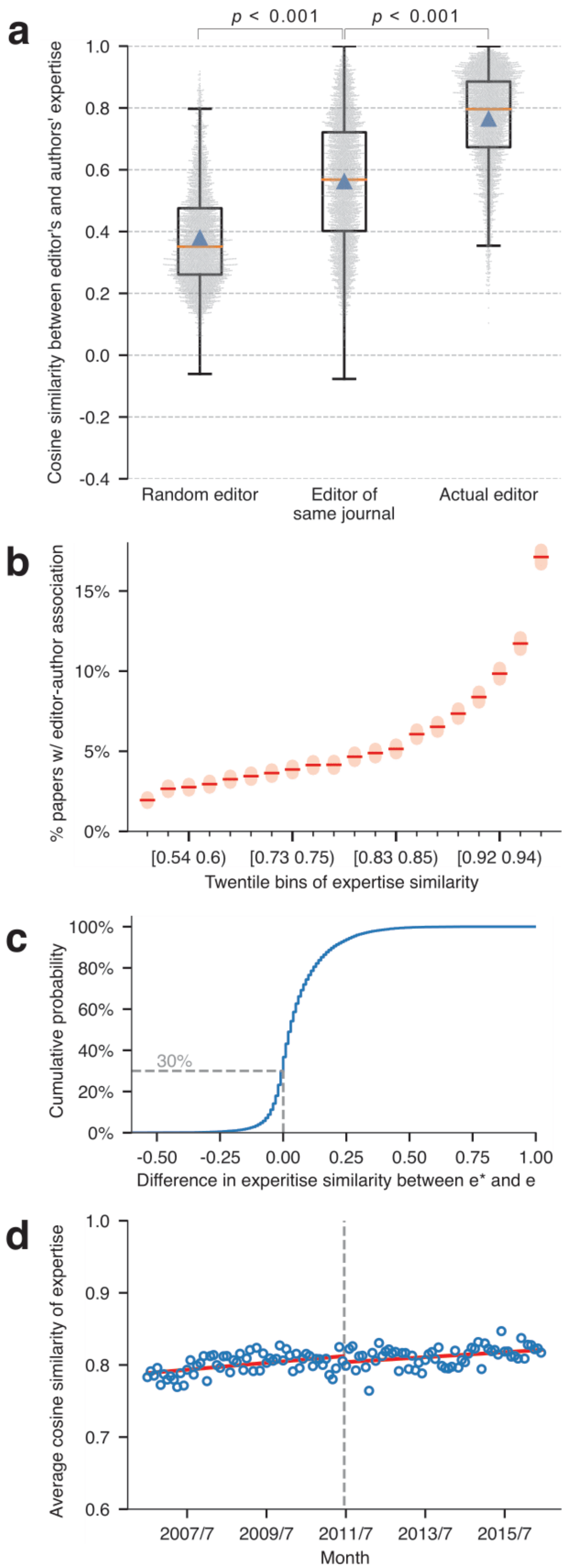

Figure 6.7: Expertise and editor-author association. **a**, Each data point correspond to a paper, and represents the cosine similarity between the paper and a given editor in terms of expertise. Here, the editor is either randomly sampled from our entire dataset (left), randomly sampled from the journal's editorial board (middle), or the actual editor who handled the paper (right). Boxes extend from the lower to upper quartile values, whiskers denote the interquartile range, lines denote the medians, and triangles denote the means. The swarmplots show the distribution of expertise similarity of 5000 randomly sampled papers. p-values are calculated using Mann–Whitney U test. **b**, The average percentage of papers with editor-author association as a function of the expertise similarity between a paper and its handling editor. Here, expertise similarity is binned into 20 twentile bins. Lines represent the mean percentage while the shaded regions represent 95%-CI. **c**, The cumulative distribution of the expertise similarity between e^* and p minus that between e and p, where p is a paper handled by editor e who has an association with an author, while e^* is most relevant editorial board member who does not have any association with any author. **d**, Temporal trend of the average expertise similarity between a paper and its handling editor in PNAS. For any given month, the corresponding circle represents the average expertise similarity between papers submitted in that month and their handling editors. Dashed line denotes July 2011 when PNAS updated its COI policy. Red lines are fitted to the circles before and after the policy change using the OLS method.

of editors have an association with the authors (95%-CI is [16.67%, 17.56%]). This suggests that, if journals were to enforce COI policies, then the editor who ends up handling the paper may not be the most relevant on the editorial board in terms of expertise. To determine whether this is the case, instead of comparing the handling editor e to a random member of the editorial board e', we need to compare e to the most relevant editorial board member (in terms of expertise) who does not have any association with the authors, denoted as e^*.

As can be seen in Fig. 6.7c, for the majority of papers (over 70%), the expertise similarity between e^* and p is higher than that between e and p. This analysis suggests that, in 70% of cases, the paper in question could have been handled by an alternative member of the editorial board who is not only more suitable (in terms of expertise), but also has no COI. Viewed from a different perspective, these findings suggest that 30% of COI cases can only be resolved by compromising the suitability of the handling editor.

Intrigued by the above findings, we further examine the trade-off between avoiding editor-author associations and assigning the most suitable editor. To this end, we adopt the same RDiT design used earlier in our examination of policy impact, and use it to estimate how PNAS's policy change affected the suitability of handling editors. Recall that this policy change reduced the percentage of papers with editor-author associations in PNAS soon after its introduction (Fig. 6.6a). Despite such reduction, however, we find no evidence that the policy change affected the average expertise similarity between papers and their handling editors (Fig. 6.7d).

6.6 Exploring public disclosure as an alternative approach to govern editors' COI

It has been argued that the existence, or even perception, of COI could decrease the public's trust in science [WAME 2009; ICMJE 2023; Friedman 2002], yet it is unclear how to best govern COIs stemming from editor-author associations. In particular, our previous analyses suggest that current COI policies have limited effect in regulating editor-author associations, but also suggest that a blanket restriction to prohibit all editor-author associations may compromise the suitability of a sizable portion of handling editors. These findings call for alternative approaches to manage such COIs, as opposed to the more common practice of recusal currently employed by most publishers. With this in mind, we consider adding to the paper a public disclosure that explicitly acknowledges the COI along with any measures taken to ensure impartiality, e.g., by appointing a secondary editor to oversee the handling the process. Although public disclosure has already been deployed widely to govern author-related COIs [Malički et al. 2021], it has not been adopted for editor-related COIs to date. While some publishers require editors to declare their competing interests, such declarations are never made public. Similarly, while some journals appoint a secondary editor (often editor-in-chief) to oversee editorial decision when a manuscript is submitted from an editorial board member (for example, ["Conflict of interest policy" 2024]), this policy is not applied in the case of editor-author associations.

To assess the viability of the proposed measure as an alternative governance of editors' COIs, we designed a preregistered survey experiment to measure the effect of the aforementioned disclosure on the general public's trust in science. In this survey, respondents are asked to first read descriptions of three hypothetical scientific articles, each consisting of a summary of the finding, followed by a short bio of the author. Then, they are asked to rate their level of trust in each finding and each author on a 7-point likert scale (Fig. 6.8a). The three articles are presented in random order. Importantly, when presenting the middle one, participants are informed that the study involves a COI due to an editor-author association. Depending on how the COI information is worded, respondents are randomly assigned to two conditions: (i) No-disclosure condition: Here, respondents are informed that the COI is not publicly disclosed; (ii) Disclosure condition: Here, respondents are presented with a statement openly disclosing the editor-author association along with measures taken to ensure impartiality; see Methods for more details regarding the survey design, and see Appendix B for survey vignettes corresponding to either condition.

Arguably, one would expect that reading about a COI would reduce the reader's trust in the findings. It is also plausible that reading the disclaimer would reduce the negative effect of the COI. However, what is not obvious is whether the disclaimer would entirely negate this effect. The primary purpose of our

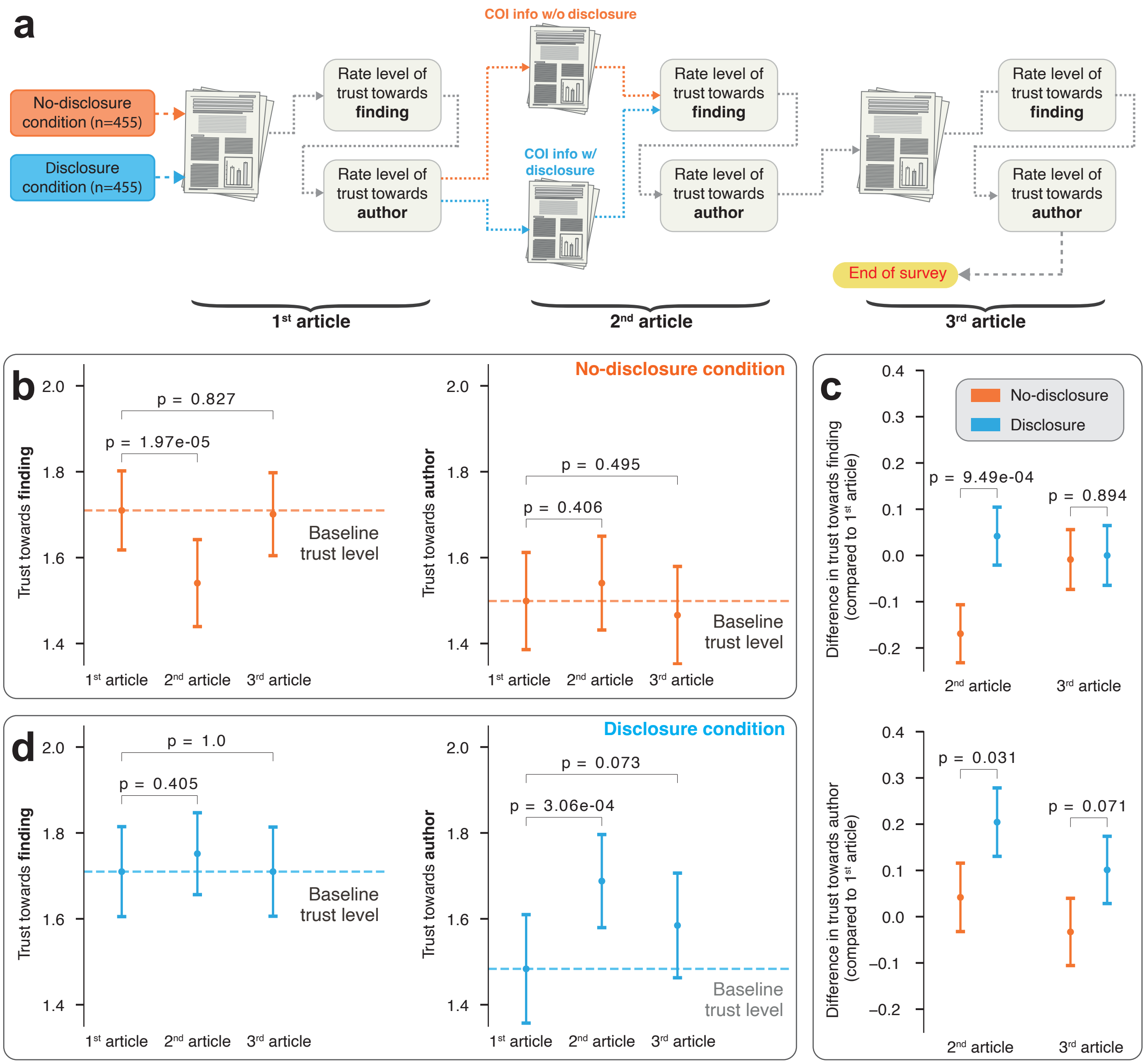

Figure 6.8: Assessing the impact of editor-author associations and their disclosure on trust in the paper and the author. **a**, Graphical representation of the experimental design and participant flow. **b**, For the no-disclosure condition, the participants' level of trust towards the findings reported in, and the authors of, each article. **c**, For both the disclosure condition (blue) and the no-disclosure condition (orange), the participants' level of trust towards the findings and authors of the second and third articles, relative to that of the first article. **d**, The same as (**b**), but for the disclosure, rather than no-disclosure, condition.

randomized controlled trial is to address this question. To this end, we first test whether knowledge about the COI decreases the respondents' trust in the finding and/or the author. In particular, we compare the level of trust reported towards the first article and the second article by respondents in the no-disclosure condition. As can be seen in Fig. 6.8b and 6.8c, knowing about the COI significantly reduced the respondent's trust in the scientific finding ($t_{454} = 4.313$, $P = 1.974e - 05$, Cohen's $d = 0.161$) but had no significant effect on the level of trust towards the author of that finding ($t_{454} = -0.832$, $P = 0.406$, Cohen's $d = 0.035$). Next, we investigate the extent to which public disclosure of COIs negates the aforementioned effect. To this end, we compare the difference in differences between the level of trust reported towards the second article and that of the first article among respondents of both conditions. As can be seen in Fig. 6.8d and 6.8e, we find that the public disclosure of editor's COI yields a significantly higher level of trust towards the finding ($t_{908} = -3.316$, $P = 9.486e - 4$, Cohen's $d = 0.220$) but not the author ($t_{908} = -2.159$, $P = 0.031$, Cohen's $d = 0.143$).

Now that we have shown that COI has a negative effect on trust, and disclosure has a positive effect, what remains to be answered is whether these effects cancel each other out. To address this question, we conduct an additional, non-preregistered analysis that focuses on the disclosure condition, comparing the trust levels between the first article (serving as the baseline) and the second article (which included the public disclosure). As can be seen in Fig. 6.8f and 6.8g, trust in the scientific finding with a disclosed COI is not significantly different to the baseline article ($t_{454} = -0.834$, $P = 0.404$, Cohen's $d = 0.038$), while trust in the author involved in the disclosed COI is significantly higher ($t_{454} = -3.638$, $P = 3.060e - 4$, Cohen's $d = 0.160$). These results provide evidence that public disclosure of editors' COIs could enhance trust in authors without compromising trust in scientific findings, suggesting that our proposed approach of governing editor-author associations comes with substantial benefits and no measurable drawbacks.

We already established that trust in a scientific finding decreases when respondents become aware of a COI due to an editor-author association. But does this effect extend beyond the scientific finding in question? In other words, if a particular paper involved such a COI, does it influence the reputation of other papers even if those papers did not involve any COI? To explore this possibility, we compared the respondents' trust towards the first and third articles. Notice that both articles do not involve any COI, with the only difference being that respondents went over the first article without reading about any COI, but went over the third one having read about a COI associated with the second article. Our results reveal that the levels of trust towards the third article are not statistically significantly different from those of the first article in all analyses (Fig. 6.8b through 6.8g). This suggests that both the effect of COIs and the effect of their disclosure are localized to the articles directly associated with the COI.

6.7 Discussions and limitations

In this chapter, we demonstrated that editors often handle papers (co-)authored by their recent collaborators or by their colleagues who share the same affiliation. Those who are affiliated with a higher ranked affiliation, or conduct research in the natural sciences are more likely to engage in such behavior. Additionally, we demonstrated that these papers are accepted faster only when the prior editor-author collaboration happens in relatively small teams, raising the possibility of favoritism in those cases. Leveraging three cases of policy change as quasi-experiments, we found that COI policies may have an effect on regulating papers with editor-author associations, even when they are not enforced in practice. However, enforcing such policies will compromise the suitability of the handling editors of some submissions. We estimated that while 70% of papers with editor-author associations can be handled by alternative suitable editors, enforcing such policies might result in 30% of such submissions being handled by less suitable editors, revealing a suitability-integrity trade-off when enforcing COI policies.

The study presented in this chapter, however, is not without limitations. One limitation stems from the fact that we focus on the publishers that openly share data on the handling editors of all papers, rather than analyzing a random sample of journals. Hence, each analyzed publisher has its own distinguished characteristics that may prevent the generalization of our findings. Specifically, Open Access publishers such as Frontiers, Hindawi, and MDPI attract scrutiny due to large volumes of Special Issues published therein [Nicholas et al. 2023], while PNAS has "inside tracks" that facilitate the publication of manuscripts submitted by members of the U.S. National Academy of Sciences [Kean 2009]. We accounted for these specific characteristics by comparing special issues to normal ones in Frontiers, Hindawi, and MDPI, and by excluding inside tracks from the analysis of PNAS. Having said that, a random sample of journals could be more informative. Unfortunately, this is not possible due to the lack of publicly available data specifying the handling editor of each paper. There are a few publishers, such as Elsevier, who selectively publicize such information in a small fraction of their journals, but these journals are not necessarily representative of all the journals handled by that publisher. Furthermore, upon reaching out to the top 30 publishers to request such data for analysis [Nishikawa-Pacher 2022], the few that responded denied our request. This highlights the need for greater transparency in sharing data related to editorial processes.

The second limitation is due to the fact that we infer collaborations using publication records. While co-authored papers necessarily indicate scientific collaboration, not all collaborations results in publications. Therefore, future studies should consider other types of editor-author association that are explicitly mentioned in the publishers' policies. Examples include situations where an author of the manuscript under consideration has previously written a grant proposal with the editor, or where an author has previously been a member of the editor's research lab, either as a PhD student or as a postdoc. While some traces of such relationships may already be captured by co-authorships in our dataset, additional datasets of grant proposals and mentor-mentee relationships would provide more insights into this form of editor-author association.

The third and final limitation is that, due to the quantitative nature of our study, we do not take into consideration the nuanced situations in which each manuscript is handled. Not all editors perform the same roles in the peer review process; some publishers allow the handling editors to decide the reviewers and overrule their recommendations, while others do not. Therefore, having the same type of editor-author association may carry different implications across publishers.

There is a wide spectrum of opinions regarding how non-financial COIs should be perceived. On one end of the spectrum, when commenting on the first ever case of retraction involving an editor's COI, the editor-in-chief of PNAS said that COI alone would have been enough to prompt a retraction, regardless of the correctness of the scientific findings [Oransky 2022]. On the other end of the spectrum, a perspective piece published by PLOS argued that having a non-financial COI is not a COI at all [Bero and Grundy 2016]. Our findings indicate that both opinions are limited by demonstrating that the reality of COI is far more complicated—collaborations that take place in different contexts may carry different implications, and policy-makers need to consider the integrity-suitability tradeoff that was quantified for the first time in this chapter. In light of these complexities, the study in this chapter identifies key limitations in current COI policies and raises two critical questions for better governance of COI.

The first question is whether it is possible to clearly define the types of editor-author associations that constitute COI. After all, numerous factors affect how COIs are perceived under different circumstances. For instance, an editor-author collaboration that took place a decade ago may not raise the same concern as another that took place only a year ago. Similarly, an editor-author collaboration involving 100 co-authors may not be perceived in the same way as one involving a smaller, close-knit team. While most current policies recognize the former factor, none of them recognize the latter. Indeed, our analysis of relative acceptance delay suggests that team size matters—our findings raise the possibility of favoritism only when the editor-author collaboration involves a team of fewer than 20 co-authors (Fig. 6.4d and Figure 6.2). Perhaps COI policies should be updated to take team size into consideration, especially as collaborations are increasingly involving larger teams [Wuchty et al. 2007]. Yet, many other factors could, in principle, be considered. For example, what was the role of the authors who previously collaborated with the editor? Were they the first or last author, or simply a middle author? Additionally, did the editor-author collaboration produce a conventional research paper, or a white paper published in a scientific journal? Moreover, personal associations take many forms; not all COIs arise from being a colleague, collaborator, mentor, and other roles defined by the current policies. Apart from these tangible influences, there are more subtle and elusive ones, such as intellectual COIs [Luborsky et al. 1999]. These examples demonstrate the intricacies involved when defining COIs, and suggest that producing a comprehensive list of COI sources—a prerequisite for enforceable recusal policies—is impractical.

This brings us to the second question: What is the goal of a COI policy? Drawing on our findings, we argue that any COI policy should balance three primary concerns: fairness, suitability, and public trust. First, fairness is critical because editors, being human, are susceptible to biases. For instance, our findings demonstrate that papers with COIs are, on average, accepted faster, suggesting that such biases may exist. This potential for bias underpins all COI policies, which universally advise against editors handling manuscripts whenever conflicts arise. As for the second concern, suitability must be balanced against fairness. If one were to eliminate all editor-author associations, the suitability of editors might be compromised, since those who are most suitable to handle a manuscript are arguably more likely to have some form of associations with its authors [Resnik and Elmore 2018]. As our analysis has demonstrated, this is indeed a legitimate concern, as it suggests that 30% of papers with editor-author association would have otherwise been handled by a less-suitable editor. One possible way around this tradeoff could be to invite guest editors when no other editorial board member is suitable to handle the paper in question, according to the editorial policy of many publishers ["Editorial and Journal Policies" 2023; "Editorial and peer review process" 2023; "Editors" 2023; "The MDPI Editorial Process" 2023], but this would increase the burdens of editorial board members, and risk further slowing down the peer review process. As for the third concern, public trust is at stake when governing editors' COI [WAME 2009; ICMJE 2023; Friedman 2002]. Indeed, our survey experiment demonstrates that informing a reader of the editor-author association can hurt readers' trust in the scientific findings. The broader implication of our experiment is that public trust can be restored when measures to ensure impartiality are taken and disclosed transparently.

Taken together, our results challenge whether recusal is a suitable approach for governing editor's COI and instead advocate for public disclosure as an alternative. In addition to safeguarding trust in science, such public disclosure could have a multitude of benefits. First, preparation of the disclosure requires editors to consciously examine their relationship with the authors and the manuscript in question, potentially improving the fairness of editor decisions. Second, disclosures allow readers to contextualize scientific findings within the broader social dynamics shaping their production. Last but not least, transparent disclosures enable quantitative studies of the epistemic impact of COIs on the production of science, which are currently limited due to the lack of data on the various forms of associations not captured in bibliographic databases. Such analyses could identify the ways in which social relationships advance or hinder scientific progress, providing crucial evidence to inform how policies should be designed to best manage such relationships.

Part IV

Conclusions

7 | How identity and relationships shape scientific gatekeeping

A central question that has been deliberately avoided so far, but should nevertheless not be ignored, is the quality of the papers in question. Upon reading the previous chapters, one would naturally ask whether papers that go through more diverse editorial boards are of higher average quality, or whether editors associated with the authors demonstrate better or poorer ability to distinguish papers of varying quality. These questions are challenging to answer, particularly due to the absence of universally agreed-upon measures for research quality. In this concluding chapter, I will unpack these questions and provide preliminary results that should help inform your thinking on this topic.

The most common measure of paper quality is the number of citations that a paper receives, which has been used as a measure of quality in a broad array of research articles [Li 2017; Brogaard et al. 2014]. However, this measure, like other indicators of research quality, fails to consider the social institution built around science [Sugimoto 2021]. In other words, quality measures like citation count are biased by many social factors, rooted in history, economics and politics [Sugimoto 2021], which determines how attention is distributed in science. The most well-studied of all is the Matthew Effect, which states that already well-known authors tend to receive a disproportionate amount of attention compared to lesser known scientists [Merton 1968]. Recent empirical work confirms this conception by demonstrating Matthew Effect in citation counts and research funding; one study shows that papers whose authors have more prior citations accumulate citations at a faster rate until it reaches a certain cutoff of citation count [Petersen et al. 2014], and another study shows that people who have received scientific funding are more likely to receive funding again by comparing those having near-identical review scores [Bol et al. 2018]. Additionally, evidence suggests that underrepresented scientists tend to receive less citations in science [Gomez et al. 2022; Teich et al. 2022]. In a similar vein, my own research has demonstrated that non-White scientists are undercited compared to White scientists doing similar research [Liu et al. 2023b]. As a result, many openly acknowledge that one cannot reliably infer the quality of publications using citation count alone [Petersen et al. 2014; Sugimoto 2021]. More often than not, citation count is used as a synonym for impact, recognition, or attention [Zeng et al. 2023; Wuchty et al. 2007; Sugimoto and Larivière 2018]. Still, the pursuit of a measure that can capture the inherent quality of papers or ability of scientists persists. Researchers often refer to these quantities of interests as "fitness", "ability", or "latent prominence" [Li et al. 2022; Sinatra et al. 2016; Wang and Barabási 2020]. However, these quantities are estimated a posteriori based on empirical observations, and represent residual citation counts that are not explained by other factors considered in those specific models. Therefore, to what extent do those residual citation counts reflect any inherent quality of a paper or scientist remain debatable.

If we view scientific papers as a cultural product, then we have to be aware that any measure of the inherent quality of scientific papers suffer from the unpredictability introduced by social influences [Salganik et al. 2006]. In fact, prior research has revealed evidence that the citation count of papers show the same patterns of unpredictability as the success of cultural products [Aksnes 2006]. More specifically, it was revealed that the citation counts of high and low quality papers more accurately reflect the quality of those papers compared to those of medium quality papers [Aksnes 2006]. This is consistent with the observation that "unpredictability varies with quality"—the success of intermediate cultural products are the most unpredictable compared to that of high or low quality products [Salganik et al. 2006].

7.1 Observing Goodhart's Law in action

Another reason why there lacks a reliable measure of quality is due to the social dynamics pithily summarize by the Goodhar's Law, which states that "when a measure becomes a target, it ceases to be a good measure [Sugimoto 2021]." One paper that I published during my PhD, which was not directly related to academic editors (therefore not included in this thesis), provides a nice example of how Goodhart's Law is affecting scientific evaluation [Ibrahim et al. 2025]. In that paper, we first made the observation that certain scientists experience abnormal increases in their citation counts before discovering that one such profile is linked to a website that purports to boost citations [Ibrahim et al. 2025]. Intrigued by this website, one of us posed as a fictional scientists, and were actually able to purchase 50 citations, thus verifying the possibility of artificially boost one's citation count through purchasing [Ibrahim et al. 2025]. Additionally, we revealed another, and even simpler way, to boost one's citation count, namely uploading AI-generated pre-prints to pre-print servers, which were then automatically indexed by Google Scholars [Ibrahim et al. 2025].

Notice that this trick only works on Google Scholar, which have the most comprehensive indexing of all databases surveyed by us, but it does not work on stricter databases. It may seem that such manipulations are futile, since one can easily verify the authors' publication records in other databases and discover that the citation count might be artificially inflated. Indeed, we showed that all studied Google Scholar profiles demonstrate sudden decrease in their citation count once we consult Scopus instead of Google Scholar [Ibrahim et al. 2025]. Interestingly, such verifications won't work, precisely due to the vast discrepancies in coverage between databases. Even for normal scientists, we observe huge gaps between their citation count recorded on Google Scholar and their citation count on Scopus [Ibrahim et al. 2025].

The question then arises: Why only optimize citation count on Google Scholar, given that there are many other databases that are supposingly more reliable? As revealed by a survey of academics from the top ranked universities in the world, most hiring committees consult Google Scholar when it comes to making hiring decisions [Ibrahim et al. 2025]. In other words, precisely because hiring committees rely on

Google Scholar when making hiring decisions, some researchers start to manipulate their citation count on Google Scholars, which renders citation count on Google Scholar ineffective in measuring the quality of a job candidate; exactly what the Goodhart's Law would predict.

Well, considering that some researchers already started manipulating their Google Scholar profiles to stand out among job candidates, does it mean that all of us should try to manipulate our citation count, in order to remain competitive on the job market? This may not necessarily be the case. As pointed by an anonymous reviewer:

> While citation metrics and Google Scholar play roles in evaluations, their primary function might be to *screen out* candidates rather than select them. It's a widespread practice to curate a shortlist from a larger pool of applicants. When the number of applicants is in the hundreds, it makes sense for recruiters to use heuristics. Yet, once shortlisted, a deeper evaluation ensues through interviews, presentations, or reading selected papers.

In those "deeper evaluations", different factors would be considered, but should those factors be?

7.2 Diversity as a defense against Goodhart's Law

In this section, I will touch upon a sensitive, yet unavoidable, topic when it comes to the discussion of diversity: quota. However, I want to shed a different light on the practice of setting quota in light of the previous discussion by highlighting a novel perspective of novelty, namely, that ensuring diversity using quota is a defense against Goodhart's Law.

To many, setting a quota might indicate "lowering the bar" so that candidates who would otherwise not be able to get a job can be hired [Schaede and Mankki 2022]. Intuitively, setting a quota indicates hiring "unqualified" candidates, which may likely lead to poor performance on the job and potentially waste of resources. However, this reasoning rests on a crucial assumption: that existing qualification metrics perfectly allocate resources. Empirical evidence consistently challenges this assumption. A compelling case study comes from Finland, where researchers examined the effects of revoking quotas for male primary school teachers. Contrary to common assumption, they found that primary schoolers taught by the male "quota teachers" have better educational and occupational outcomes in the long run [Schaede and Mankki 2022]. This findings challenge the perception that these male teachers hired to fill the quota are less qualified than their female counterparts. Upon closer look, the researchers further reveal that the reason for such performance premium of male teachers is unlikely due to skill complementarity but rather due to the imperfect standards normally employed to select primary school teachers [Schaede and Mankki 2022].

This study exemplifies how diversity can counteract Goodhart's Law. When institutions rely solely on easily measurable qualifications—such as standardized test scores—these metrics become targets that candidates optimize for, thereby failing to capture the full range of qualities that contribute to actual job performance. By introducing diversity through quotas, organizations inadvertently create alternative selection pathways that may identify valuable qualities overlooked by traditional metrics. In academia, it is possible that diversity can indeed have a similar effect. In the beginning of this chapter, I showed examples of how social factors bias citation counts. But in fact, many more factors contribute to the underpriviledge of underrepresented scholars: for example early collaboration with prominent authors lead to higher chance of publishing in prestigious journals (a phenomenon known as the "Chaperon effect") [Sekara et al. 2018], or the labor advantage enjoyed by those from prestigious affiliations [Zhang et al. 2022], or simply biases against relatively unknown early career researchers [Huber et al. 2022]. Together, these factors mean that those who are valued by current selection criteria in the academy may not necessarily have the highest "merit"—maybe they just happen to start their career in a prestigious university with experienced co-authors whose names are widely recognized within the field. Such resources are typically less accessible to underrepresented scholars. Meanwhile, such a selection criterion penalizes novelty [Hofstra et al. 2020] as prescient ideas usually originate from the periphery [Vicinanza et al. 2023]. In fact, it seems that we have created a system where the measurement tools themselves are biased against the very diversity that drives innovation.

7.3 Diversity pledge

Among academic journals, rarely do journals set quotas for editors of a certain background. In recent years, nevertheless, publishers started to adopt diversity initiatives aiming at increasing the representation of historically underrepresented groups on editorial boards, some involving setting explicit quotas when it comes to the composition of editorial boards. Naturally, one wonders whether such pledges result in observable changes on the editorial boards of journals that adopt such pledges. Thanks to the longitudinal datasets curated as a result of this thesis (see Chapter 2), we are able to track the composition of editorial boards throughout time and compare such composition after the adoption of the pledges to that from before. Using such a unique dataset, we are able to quantify the composition of editorial boards among journals that have adopted diversity pledges. Below, I will present the preliminary results from this analysis.

As can be seen in Figure 7.1a, 1375 Elsevier journals have adopted the diversity pledge between 2017 and 2024, with the first adoption happening on January 10, 2017. The vast majority of adoption happened between 2021 and 2023; 1326 out of 1375 (96%) adoptions happened during this period. Using a large language model (LLM), we are able to parse the content of those pledges and quantify the proportion of pledges that mention each aspect of diversity. Overall, four aspects received attention from at least 19% of journals, with gender diversity being the most frequent (889 or 65% of journals mentioned this aspect), followed by geographical diversity (415 or 30% of journals), racial and ethnic diversity (331 or 24%), and diversity of career stage (264 or 19% journals; see Figure 7.1b).

Since gender diversity is the most frequently mentioned aspect, we next quantify the extent to which the gender composition varies on editorial boards. To this end, we first extract the names, roles, and their affiliations (if available) from the editorial board pages, again assisted by an LLM, and then classify the gender of these editors using `genderize.io`. As can be seen in Figure 7.1c, the percentage of women increased from 32.2% in the year of pledge adoption to 35.4% three years after adopting the pledge on average across all journals. In relative terms, the percentage of women increased by 3.4 percentage points

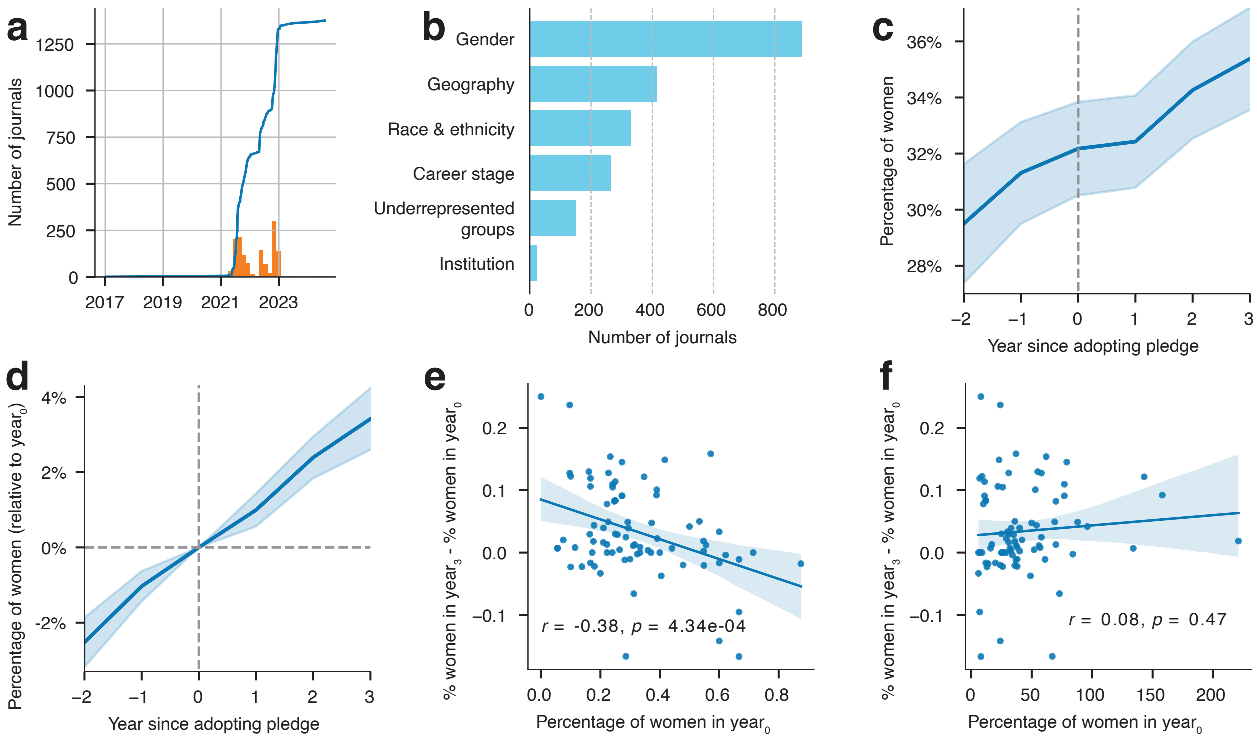

Figure 7.1: Quantifying the effect of diversity pledges. **a**, Number of journals (orange) and the cumulative number of journals (blue) that adopt diversity pledge over time. **b**, Six most frequently mentioned aspects of diversity and the number of journals mentioning each. **c**, The percentage of women on editorial boards in the three years upto and after the adoption of the pledges. **d**, The difference in the percentage of women on editorial boards compared to that in the year when pledge is adopted (year_0) over time. **e**, The correlation between the change in the percentage of women in the third year after pledge adoption (year_3) relative to that in year_0 and the percentage of women in year_0. **f**, The correlation between the change in the percentage of women in the third year after pledge adoption (year_3) relative to that in year_0 and the size of editorial boards in year_0.

on average compared to the baseline percentage of women on editorial boards (Figure 7.1d). Additionally, I find that the change in the percentage of women on editorial boards is negatively correlated with the percentage of women on an editorial board in the year when the pledge is adopted, but is not related to the size of the editorial board in the year when the pledge is adopted. Note that while it is tempting to attribute whatever difference observed before and after pledge adoption to the pledges, it is difficult to make causal claims of this nature.

7.4 How identities and social relationships affect the quality of scientific gatekeeping

When it comes to the effect of editors' identity on the quality of scientific gatekeeping, there are surprisingly little empirical evidence in this regard. Meanwhile, regarding editors' conflicts of interest (COI), two competing hypotheses have emerged: on the one hand, personal connections with authors could lead to better information about papers authored by their colleagues or collaborators [Brogaard et al. 2014], while on the other hand, editors could be favorable to their connected authors regardless of the quality of their papers. Empirical studies reveal conflicted findings when it comes to the effect of editors' conflict of interest [Brogaard et al. 2014; Si et al. 2023]. Interestingly, both studies focus on the effect of being within the same affiliation as the editor yet arrive at opposing findings. This suggests that the effect of COI is likely context-sensitive. Complicating matters further, in reality, the two opposing mechanisms—better information and favourtism—could co-exist and are difficult to disentangle. One study successfully separated these factors by analyzing National Institute of Health (NIH) grant applications, revealing that peer reviewers are both biased and better informed when evaluating submissions close to their own expertise [Li 2017]. Although this research did not directly examine editor-author associations, it effectively studied what could be considered a form of intellectual COI. In addition to studying the average citation count of papers, the variance of citation counts may also be informative. In a study of different publication tracks of the Proceedings of the National Academy of Sciences of the United States of America (PNAS), researchers find that papers published in the "inside tracks" of PNAS (where authors themselves select reviewers for their papers) tend to be average less impactful than papers published normally, while the most highly cited among these outperform the normal papers [Rand and Pfeiffer 2009].

Notice that all of these studies used citation count as the outcome of interest. While these studies provide valuable insights, how COI actually influence knowledge production, as well as the attention devoted to those knowledge, deserves more nuanced attention. Unlike in the funding phase, where securing certain funding may actually mean the life or death of a scientific idea [Li 2017], at the publication stage, the knowledge itself is created; the only remaining question is where it gets published. Academics typically have a list of target journals and will resubmit manuscripts down this hierarchy until achieving eventual acceptance [Chen et al. 2024]. Since papers will be published if any journal accepts them, editorial gatekeeping quality is effectively determined by its weakest link. With the rise of predatory journals, scientific literature faces significant challenges to the integrity of gatekeeping processes. Even when no journal accepts a paper, authors can still disseminate findings through preprint servers. This is not to say that papers undergo proper peer review and papers that are published in predatory journals or preprints receive equal amounts of academic attention, nor should they. Past studies demonstrate that journal reputation matters for the type of attention devoted to those papers [Teplitskiy et al. 2022]. Therefore, editorial gatekeeping should be conceptualized not as controlling knowledge itself, but as mediating attention to that knowledge. The attention certain papers receive inevitably shapes subsequent knowledge built upon them [Jo et al. 2022]. But the possibility that a rejected paper could always find a home in another journal makes it even more challenging to assess the impact that editors have on knowledge creation.

Appendix A: Historical COI policies

In Chapter 6, we analyze three cases of policy change during the lifespan of two publishers, namely PNAS and PLOS. Both PNAS and PLOS make their COI policy publicly available on their websites. To retrieve the historical version of those policies, we use Wayback Machine, a digital archive that records snapshots of hundreds of billions of webpages since 1996. Snapshots of a webpage, taken on different days, save the content of that webpage at that specific point of time, allowing us to "go back in time" and see how the same webpage has changed throughout history. Using those historical snapshots, we are able to track how the COI policies of PNAS and PLOS have changed over the past two decades.

PNAS

Up until 2008, the "PNAS Conflict of Interest Policy" is only concerned with financial COI in connection with the manuscript, and is not relevant to the type of COI considered in our study [PNAS 2008].

The earliest snapshot of PNAS's COI policy relevant to this study was saved on May 11, 2009 as part of its editorial policies on the "Information for Authors" page. Although the editorial policies mention that referees should not review papers by their recent collaborators, there is no clause governing the same COI for editors. Specifically, the relevant clause states the following

> Recent collaborators, defined as people who have coauthored a paper with the author or member within the past 48 months, should be excluded as referees [PNAS 2009].

In July 2011, the aforementioned clause was revised to include editors as well, as shown by the snapshot taken in September 2011. At this time, collaborations that took place during the 24 months preceding the submission were considered "recent collaborations" that constitute a conflict of interest.

> Recent collaborators, defined as people who have coauthored a paper or were a principal investigator on a grant with the author or member within the past 24 months, must be excluded as editors and reviewers [PNAS 2011]

Therefore, we take July 2011 to be the date at which the policy governing the editorial COI was introduced. To put it differently, July 2011 is the month after which editors are explicitly prohibited from handling submissions from their recent collaborators.

Several revisions to the above policy happened since July 2011, but the quoted clause remained the same until January 2014, when the criteria of recent collaboration was updated from 24 months to be 48 months.

> "Recent collaborators, defined as people who have coauthored a paper or were a principal investigator on a grant with the author or member within the past 48 months, must be excluded as editors and reviewers [PNAS 2014].

Since then, the exact wording has changed slightly (see, e.g., PNAS [2020]), but the policy itself remains unchanged to date.

Based on the above, we analyze two cases of policy change related to PNAS: the first case happened in July 2011, and the second case happened in January 2014.

PLOS

The COI policies governing non-financial COIs were significantly elaborated in July 2009 compared to the earlier versions [PLOS 2009a]. However, there were no explicit policies regulating the potential COI of editors handling submissions from collaborators [PLOS 2009b].

In May 2015, the policy was updated to prohibit editors from handling submissions by authors with whom they collaborated during the past five years.

> Editors (professional or academic, paid or unpaid) and reviewers must declare their own competing interests and if necessary disqualify themselves from involvement in the assessment of a manuscript.
>
> Common reasons for editors and reviewers to recuse themselves from the peer review process may include but are not limited to:
>
> (...) They have published with an author during the past 5 years [PLOS 2015]

The above policy remains unchanged to date. Hence, the policy change that took place on May 2015 constitutes the third case in our analysis.

Appendix B: Survey Vignette

Welcome to this survey conducted by Professors Talal Rahwan and Bedoor AlShebli from New York University Abu Dhabi.

Summary

You will receive information regarding 3 **scientific articles**, and you will complete 3 short questionnaires (one per article). Please note that you will have to pass **comprehension tests** after reading about each article. The estimated time for the survey is approximately **10 minutes**, half of which will be spent on the comprehension test. You will receive a fee of **$1.5** for completing the survey. If you fail any of the comprehension check questions, the survey will end automatically and you will only receive **$0.30**.

Consent to participate

Participation in this survey is voluntary, and you may leave the survey at any point. However, we can only pay you if you complete the survey. We will keep track of your MTurk ID for payment and tracking. We do not collect personally identifying information as part of the survey, such as your name or email. Please only participate in the survey once. Information not containing identifiers may be used in future research or shared with other researchers without your additional consent. We do not anticipate any risks to you directly resulting from your participation in this survey. There will also be no benefits to you beyond the money you earn from completing the survey.

For inquiries, please contact Professor Talal Rahwan and Professor Bedoor AlShebli (NYU Abu Dhabi) at: COI-survey@nyu.edu. For questions about your rights as a research participant, you may contact the IRB and refer to HRPP-2024-141, New York University Abu Dhabi, +971 2 628 4313 or IRB-nyuad@nyu.edu. If you would like to have a copy of this document, please make a screenshot and keep it.

Please click on "yes" if you agree to participate in the survey.

Once you click the button do not close this window, otherwise payment cannot be guaranteed.

Task

You will be presented with the description of **3 scientific articles**, and you will then be asked about your opinion regarding the each article and its implications.

Please read the description carefully, as **you will have to answer comprehension check questions** to test your understanding. You will only receive the full payment if you pass the test.

Article 1

[The actual sequence in which the articles are presented are randomized]

Title: Remote Work Is Associated with Higher Employee Productivity

Summary: The authors examine the effects of remote work on employee productivity by analyzing data from three different companies in the UK following the COVID-19 pandemic. Despite widespread concerns that remote work may cause distractions and reduce performance, the results suggest that remote work is linked to increased productivity. These findings have policy implications regarding the adoption of work-from-home jobs.

Bio: A professor of organizational psychology, the main author specializes in the dynamics of the workplace and employee performance. His research primarily explores the impact of different work environments on overall job satisfaction, with a specific emphasis on remote work settings.

Comprehension Test of Article 1

Please answer the following questions about the article you just read about:

According to the article, what is the relationship between remote working and employee productivity? [All Conditions; choices are shuffled]

- Remote working is associated with higher employee productivity
- Remote working is associated with lower employee productivity
- Remote working is not associated with employee productivity

What does the main author of the article specialize in? [All Conditions; choices are shuffled]

- Workplace dynamics
- Adolescent behavior
- Video games
- Political polarization

Rate the degree to which you agree with the following statement: [Shuffle the sequence of the following two questions]

I trust the **findings** reported in the article.

-3 (strongly disagree) -2 (disagree) -1 (somewhat disagree) 0 (neutral) 1 (somewhat agree) 2 (agree) 3 (strongly agree)

Rate the degree to which you agree with the following statement:

I trust the **main author** of this article as a scientist.

-3 (strongly disagree) -2 (disagree) -1 (somewhat disagree) 0 (neutral) 1 (somewhat agree) 2 (agree) 3 (strongly agree)

Article 2

[The actual sequence in which the articles are presented are randomized]

Title: Screen Time Is Not Associated with the Academic Performance of Teenagers

Summary: Using data from a large, representative sample of Australian adolescents in public high schools, the authors examine the potential impact of daily screen time on school grades. Their findings indicate that screen time does not affect school performance in various subjects, including physics, mathematics, and biology. This holds even when accounting for factors such as socioeconomic status, parental involvement, and extracurricular activities.

Bio: The main author is a professor of developmental psychology and an expert in adolescent behavior and media influence. She studies the effects of technology use on youth development, emphasizing its impact on both academic performance and mental health.

[COI information here]

Comprehension Test of Article 2

Please answer the following questions about the article you just read about:

According to the article, what is the relationship between screen time and school grades? [All Conditions; choices are shuffled]

- More screen time is associated with better school performance
- More screen time is associated with worse school performance
- Screen time is not associated with school performance

What does the main author of the article specialize in? [All Conditions; choices are shuffled]

- Workplace dynamics

- Adolescent behavior
- Video games
- Political polarization

What was the conflict of interest? [A1 A2 B1 B2 Condition; first four choices are shuffled]

- The editor has had a recent research collaboration with the main author of the article
- The editor was affiliated with the same institution as the main author of the article
- The editor had a financial incentive to get the article published in the journal
- The editor was a relative to the main author of the article
- None of the above

Was the conflict of interest disclosed in the article? [A1 B1 Condition; choices are shuffled]

- Yes
- No

How did the journal ensure that the article was handled impartially (select all that apply) [A2 B2 Condition; choices are shuffled]

- A disclaimer was added to the article to disclose and justify the conflict of interest
- A second member of the editorial board co-handled the article
- The article was forwarded to a different journal to avoid the conflict of interest
- The editor declined to handle the article due to the conflict of interest

According to the disclaimer, what was the justification for handling the article despite the conflict of interest? [A2 Condition; choices are shuffled]

- The previous research that the editor and the main author collaborated on involved more than 100 other collaborators
- The editor was the most suitable member of the editorial board to handle the article, given their expertise
- The editor did not recognize the main author is their research collaborator
- The editor did not provide any justification

According to the disclaimer, what was the justification for handling the article despite the conflict of interest? [B2 Condition; choices are shuffled]

- The editor and the main author are affiliated with a very large institution and have not met
- The editor was the most suitable member of the editorial board to handle the article, given their expertise
- The editor did not realize that they share the same affiliation as the main author, since the author has multiple affiliations
- The editor did not provide any justification

Rate the degree to which you agree with the following statement: [Shuffle the sequence of the following two questions]

I trust the **findings** reported in the article.

-3 (strongly disagree) -2 (disagree) -1 (somewhat disagree) 0 (neutral) 1 (somewhat agree) 2 (agree) 3 (strongly agree)

Rate the degree to which you agree with the following statement:

I trust the **main author** of this article as a scientist.

-3 (strongly disagree) -2 (disagree) -1 (somewhat disagree) 0 (neutral) 1 (somewhat agree) 2 (agree) 3 (strongly agree)

Article 3

[The actual sequence in which the articles are presented are randomized]

Title: Violent Video Game Play Is Associated with Less Aggressive Behavior in Adults

Summary: By analyzing longitudinal data spanning the years 2015-2023, the authors investigate the link between playing violent video games and behaving aggressively in real life. Contrary to common beliefs, the authors reveal that higher exposure to violent video games is actually associated with lower levels of aggressive behavior. This study contributes to a growing body of literature examining how interactive media affects social behavior.

Bio: The main author is a professor of psychology specializing in media effects and human behavior. Her research focuses on the nuances of how media consumption shapes perceptions and actions in real-life contexts, with a particular focus on video games.

Comprehension Test of Article 3

Please answer the following question about the article you just read about:

According to the article, what is the relationship between playing violent video games and aggressive behavior in real life? [All Conditions; choices are shuffled]

- Playing violent video games is associated with more aggressive behavior
- Playing violent video games is associated with less aggressive behavior
- Playing violent video games is not associated with aggressive behavior

What does the main author of the article specialize in? [All Conditions; choices are shuffled]

- Workplace dynamics
- Adolescent behavior
- Video games
- Political polarization

Rate the degree to which you agree with the following statement:

I trust the **findings** reported in the article.

-3 (strongly disagree) -2 (disagree) -1 (somewhat disagree) 0 (neutral) 1 (somewhat agree) 2 (agree) 3 (strongly agree)

Rate the degree to which you agree with the following statement:

I trust the **main author** of this article as a scientist.

-3 (strongly disagree) -2 (disagree) -1 (somewhat disagree) 0 (neutral) 1 (somewhat agree) 2 (agree) 3 (strongly agree)

[COI information]

Conflict of interest:

After the scientific article was published, it was revealed that there is a **conflict of interest** involving the journal editor, who decides which articles get accepted for publication. In particular, it turned out that **the editor**

CONDITION A: ... **has had a recent research collaboration with the main author** of the article just a few months before it was accepted.

CONDITION B: ... **is affiliated with the same institution as the main author** of the article.

CONDITION 1: Importantly, this conflict of interest was **not disclosed** in the article itself.

CONDITION 2: Importantly, this conflict of interest was **disclosed and justified** in the article with the following statement:

CONDITION A2: ***Disclaimer****: The editor acknowledges a recent collaboration with the main author. While this introduces a conflict of interest, the editor was chosen to handle the article since they were* ***the most suitable member of the editorial board*** *given their expertise. To ensure that the article was handled objectively and impartially,* ***a second member of the editorial board co-handled the article****.*

CONDITION B2: ***Disclaimer****: The editor acknowledges sharing the same affiliation with the main author. While this introduces a conflict of interest, the editor was chosen to handle the article since they were* ***the most suitable member of the editorial board*** *given their expertise. To ensure that the article was handled objectively and impartially,* ***a second member of the editorial board co-handled the article****.*

[IF FAILING THE COMPREHENSION TEST]

Thank you for your interest in our survey. Unfortunately, you have failed to answer all the comprehension questions correctly. Consequently, you are no longer eligible to complete the survey. As a token of our appreciation, we would like to compensate you $0.30 for the time you have spent so far on the survey. We will send a compensation HIT in the amount of $0.30. Please, return the HIT so that other MTurk workers may take it.

[DEMOGRAPHICS INFORMATION]

For tracking and payment purposes, please, give us your MTurk ID: [TEXT ENTRY]

How old are you, in years? [TEXT ENTRY]

What is your gender?

- Male
- Female
- Other

With which of the following groups do you identify? You may select more than one.

- White
- Black/African American
- Hispanic/Latinx
- Asian or Asian American
- American Indian or Alaska Native
- Middle Eastern or North African
- Other

What is the highest level of education you have completed?

- Less than high school
- High school or equivalent (e.g., GED)
- Some college (no degree)

- 2-year degree (Associate's)
- 4-year degree (Bachelor's)
- Graduate or professional degree (e.g., MSc, PhD, JD, MD)

Thank you for participating in this survey. Please note that the article, editor, and the author you just read about was entirely fictional and created solely for the purposes of this survey. It does not reflect any real scientific publications or findings. The goal of this survey was to explore attitudes and perceptions related to trust in science in the presence of conflicts of interest.

We will send a compensation HIT in the amount of $1.5. Please, return the HIT so that other MTurk workers may take it.

Thank you for your valuable contribution!

Appendix C: Summary of Literature

Table C 1: Comparing our study (red text) to other papers studying the gender gap in scientific editorship.

Reference	Publication year	Discipline(s) analyzed	No. journals analyzed	Year(s) analyzed
Teghtsoonian [Teghtsoonian 1974]	1974	Psychology	11	1970–1972
White [White 1985]	1985	Psychology	14	1972, 1977, 1982
Pion et al. [Pion et al. 1996]	1996	Psychology	5	1971, 1981, 1991
Dickersin et al. [Dickersin et al. 1998]	1998	Epidemiology	4	1982, 1987, 1992, 1994
Robinson et al. [Robinson et al. 1998]	1998	Educational Psychology	6	1976–1996
McSweeney et al. [McSweeney et al. 2000]	2000	Applied Behavior Analysis	5	1978–1997

Kennedy et al. [Kennedy et al. 2001]	2001	Medicine	12	1999
Addis and Villa [Addis and Villa 2003]	2003	Economics	36	1970–1996
Keiser [Keiser et al. 2003]	2003	Medicine	6	1993, 2003
Evans et al. [Evans et al. 2005]	2005	Psychology	6	2004
Morton & Sonnad [Morton and Sonnad 2007]	2007	Medicine	54	2004
Jagsi et al. [Jagsi et al. 2008]	2008	Medicine	5	1970, 1975, 1980, 1990, 1995, 2000, 2005
Fong et al. [Fong et al. 2009]	2009	Psychology	20	2003–2008
Metz and Harzing [Metz and Harzing 2009]	2009	Management	57	1989, 1994, 1999, 2004
Amrein et al. [Amrein et al. 2011]	2011	Medicine	60	2011
Stegmaier et al. [Stegmaier et al. 2011]	2011	Political Science	50	2010
Choi and Miller [Choi and Miller 2012]	2012	Otolaryngology	6	2010
Metz and Harzing [Metz and Harzing 2012]	2012	Management	57	1989–2009

Okike et al. [Okike et al. 2012]	2012	Orthopedics	2	1970, 1980, 1990, 2000, 2007
Mauleón et al. [Mauleón et al. 2013]	2013	All disciplines (Spanish journals)	131	1998-2009
Cho et al. [Cho et al. 2014]	2014	Environmental biology, natural resource management, and plant sciences	10	1985–2013
Erren et al. [Erren et al. 2014]	2014	Medicine	6	2010, 2011
Ioannidou et al. [Ioannidou and Rosania 2015]	2015	Dentistry	69	2014
Metz et al. [Metz et al. 2016]	2016	Management	52	1989, 1994, 1999, 2004, 2009
Topaz and Sen [Topaz and Sen 2016]	2016	Mathematical Sciences	435	2016
Dhanani and Jones [Dhanani and Jones 2017]	2017	Accounting	50	1999–2009
Gollins et al. [Gollins et al. 2017]	2017	Dermatology	25	1868–2017
Piper et al. [Piper et al. 2018]	2018	Radiology	4	1973–2017
Fox et al. [Fox et al. 2019]	2019	Ecology and Evolution	6	2003–2015

Hafeez et al. [Hafeez et al. 2019]	2019	Psychiatry	119	2018
Harris et al. [Harris et al. 2019]	2019	Surgery	10	1997, 2007, 2017
Jalilianhasanpour et al. [Jalilianhasanpour et al. 2019]	2019	Radiology	9	2002–2017
Kaji et al. [Kaji et al. 2019]	2019	Emergency Medicine	1	2018
Litvack et al. [Litvack et al. 2019]	2019	Otolaryngology	9	1997–2017
Lorello et al. [Lorello et al. 2019]	2019	Anesthesia	1	1954–2018
Pagel et al. [Pagel et al. 2019]	2019	Cardiothoracic and Vascular Anesthesia	1	1987–2019
Alonso-Arroyo et al. [Alonso-Arroyo et al. 2020]	2020	Pediatrics	125	2020
Balasubramanian et al. [Balasubramanian et al. 2020]	2020	Cardiology	22	1998, 2003, 2008, 2013, 2018
Rynecki et al. [Rynecki et al. 2020]	2020	Orthopedics	4	1997, 2007, 2017
Sarna et al. [Sarna et al. 2020]	2020	Medicine, Nursing, and Pharmacy	21	1995–2016
Schurr et al. [Schurr et al. 2020]	2020	Geography	22	1999, 2017

Alkhawtani et al. [Alkhawtani et al. 2021]	2021	Radiology	57	2020
Bennie and Koka [Bennie and Koka 2021]	2021	Prosthodontics	28	2020
Gottlieb et al. [Gottlieb et al. 2021]	2021	Emergency Medicine	37	2019
Hutchinson et al. [Hutchinson et al. 2021]	2021	Emergency Medicine	17	2019
Pflibsen et al. [Pflibsen et al. 2021]	2021	Plastic Surgery	3	2009–2018
Pinho-Gomes et al [Pinho-Gomes et al. 2021]	2021	Medicine	410	2019
Salazar et al. [Salazar et al. 2021]	2021	Medicine	25	2021
Sperotto et al. [Sperotto et al. 2021]	2021	Biotechnology	50	2021
Palser et al. [Palser et al. 2022]	2022	Psychology & Neuroscience	100	2020
Liu et al. [Liu et al. 2023a]	2022	Biology, Business, Chemistry, Computer Science, Economics, Engineering, Geology, Material Science, Mathematics, Medicine, Philosophy, Physics, Political Science, Psychology, Sociology	1,709	1970–2018

Bibliography

Abdel-Baset, M., Chang, V., and Gamal, A. (2019a). Evaluation of the green supply chain management practices: A novel neutrosophic approach. *Computers in Industry*, 108:210–220.

Abdel-Baset, M., Chang, V., Gamal, A., and Smarandache, F. (2019b). An integrated neutrosophic anp and vikor method for achieving sustainable supplier selection: A case study in importing field. *Computers in Industry*, 106:94–110.

Abelson, J. S., Wong, N. Z., Symer, M., Eckenrode, G., Watkins, A., and Yeo, H. L. (2018). Racial and ethnic disparities in promotion and retention of academic surgeons. *The American Journal of Surgery*, 216(4):678–682.

Addis, E. and Villa, P. (2003). The editorial boards of Italian economics journals: women, gender, and social networking. *Fem. Econ.*, 9(1):75–91.

Aksnes, D. W. (2006). Citation rates and perceptions of scientific contribution. *Journal of the American Society for Information Science and Technology*, 57(2):169–185.

Alkhawtani, R. H., Kwee, T. C., and Kwee, R. M. (2021). Gender diversity among editorial boards of radiology-related journals. *Clin. Imaging*, 75:30–33.

Alonso-Arroyo, A., de Dios, J. G., Aleixandre-Agulló, J., and Aleixandre-Benavent, R. (2020). Gender inequalities on editorial boards of indexed pediatrics journals. *Pediatr. Res.*, pages 1–15.

AlShebli, B. K., Rahwan, T., and Woon, W. L. (2018). The preeminence of ethnic diversity in scientific collaboration. *Nature communications*, 9(1):5163.

Altmann, E. G., Dias, L., and Gerlach, M. (2017). Generalized entropies and the similarity of texts. *Journal of Statistical Mechanics: Theory and Experiment*, 2017(1):014002.

Amrein, K., Langmann, A., Fahrleitner-Pammer, A., Pieber, T. R., and Zollner-Schwetz, I. (2011). Women underrepresented on editorial boards of 60 major medical journals. *Gend. Med.*, 8(6):378–387.

Anderson, M. L. (2014). Subways, strikes, and slowdowns: The impacts of public transit on traffic congestion. *American Economic Review*, 104(9):2763–2796.

ARWU (2019). Academic ranking of world universities 2019. https://web.archive.org/web/20210424072147/http://www.shanghairanking.com/ARWU2019.html. Accessed: 2021-04-24.

Balasubramanian, S., Saberi, S., Yu, S., Duvernoy, C. S., Day, S. M., and Agarwal, P. P. (2020). Women representation among cardiology journal editorial boards. *Circulation*, 141(7):603–605.

Beath, C., Chan, Y., Davison, R. M., Dennis, A. R., and Recker, J. C. (2021). Editorial board diversity at the basket of eight journals: A report to the college of senior scholars. *Communications of the Association for Information Systems: CAIS*, 48.

Bennie, K. R. and Koka, S. (2021). Leadership diversity in prosthodontics: number and percentage of women chief editors of journals publishing prosthodontic science. *J. Prosthet. Dent.*

Benson, A. R., Abebe, R., Schaub, M. T., Jadbabaie, A., and Kleinberg, J. (2018). Simplicial closure and higher-order link prediction. *Proc. Natl. Acad. Sci. USA*, 115(48):E11221–E11230.

Berenbaum, M. R. (2019). Speaking of gender bias. *Proc. Natl. Acad. Sci. USA*, 116(17):8086–8088.

Bero, L. A. and Grundy, Q. (2016). Why having a (nonfinancial) interest is not a conflict of interest. *PLOS Biol.*, 14(12):e2001221.

Bertolero, M. A., Dworkin, J. D., David, S. U., Lloreda, C. L., Srivastava, P., Stiso, J., Zhou, D., Dzirasa, K., Fair, D. A., Kaczkurkin, A. N., et al. (2020). Racial and ethnic imbalance in neuroscience reference lists and intersections with gender. *BioRxiv*.

Biagioli, M. (2002). From book censorship to academic peer review. *Emergences: Journal for the Study of Media & Composite Cultures*, 12(1):11–45.

Bilalli, B., Munir, R. F., and Abelló, A. (2021). A framework for assessing the peer review duration of journals: Case study in computer science. *Scientometrics*, 126(1):545–563.

Bol, T., de Vaan, M., and van de Rijt, A. (2018). The matthew effect in science funding. *Proceedings of the National Academy of Sciences*, 115(19):4887–4890.

Bosch, X., Pericas, J. M., Hernandez, C., and Doti, P. (2013). Financial, nonfinancial and editors' conflicts of interest in high-impact biomedical journals. *European journal of clinical investigation*, 43(7):660–667.

Bošnjak, L., Puljak, L., Vukojević, K., and Marušić, A. (2011). Analysis of a number and type of publications that editors publish in their own journals: case study of scholarly journals in Croatia. *Scientometrics*, 86(1):227–233.

Brainard, J. (2023). Fast-growing open-access journals stripped of coveted impact factors. https://www.science.org/content/article/fast-growing-open-access-journals-stripped-coveted-impact-factors. Accessed on October 09, 2023.

Braun, T., Zsindely, S., Diόspatonyi, I., and Zádor, E. (2007). Gatekeeping patterns in nano-titled journals. *Scientometrics*, 70(3):651–667.

Brogaard, J., Engelberg, J., and Parsons, C. A. (2014). Networks and productivity: Causal evidence from editor rotations. *Journal of Financial Economics*, 111(1):251–270.

Brogaard, J., Engelberg, J., and Van Wesep, E. (2018). Do economists swing for the fences after tenure? *Journal of Economic Perspectives*, 32(1):179–194.

Burgess, T. F. and Shaw, N. E. (2010). Editorial board membership of management and business journals: a social network analysis study of the Financial Times. *Br. J. Manag.*, 21(3):627–648.

Campanario, J. M. (1996). The competition for journal space among referees, editors, and other authors and its influence on journals' impact factors. *J. Am. Soc. Inf. Sci.*, 47(3):184–192.

Caplar, N., Tacchella, S., and Birrer, S. (2017). Quantitative evaluation of gender bias in astronomical publications from citation counts. *Nature astronomy*, 1(6):0141.

Cappelletti, L., Fontana, T., Casiraghi, E., Ravanmehr, V., Callahan, T. J., Cano, C., Joachimiak, M. P., Mungall, C. J., Robinson, P. N., Reese, J., et al. (2023). Grape for fast and scalable graph processing and random-walk-based embedding. *Nature Computational Science*, 3(6):552–568.

Cech, E. A. (2022). The intersectional privilege of white able-bodied heterosexual men in stem. *Science advances*, 8(24):eabo1558.

Chakravartty, P., Kuo, R., Grubbs, V., and McIlwain, C. (2018). #CommunicationSoWhite. *Journal of Communication*, 68(2):254–266.

Chen, G., Rolim, V., Mello, R. F., and Gašević, D. (2020). Let's shine together! a comparative study between learning analytics and educational data mining. In *Proceedings of the tenth international conference on learning analytics & knowledge*, pages 544–553.

Chen, H., Rider, C. I., Jurgens, D., and Teplitskiy, M. (2024). Geographical disparities in navigating rejection in science drive disparities in its file drawer. *Available at SSRN*.

Chen, M. K., Haggag, K., Pope, D. G., and Rohla, R. (2022). Racial disparities in voting wait times: Evidence from smartphone data. *Review of Economics and Statistics*, 104(6):1341–1350.

Cho, A. H., Johnson, S. A., Schuman, C. E., Adler, J. M., Gonzalez, O., Graves, S. J., Huebner, J. R., Marchant, D. B., Rifai, S. W., Skinner, I., et al. (2014). Women are underrepresented on the editorial boards of journals in environmental biology and natural resource management. *PeerJ*, 2:e542.

Choi, S. S. and Miller, R. H. (2012). Women otolaryngologist representation in specialty society membership and leadership positions. *Laryngoscope*, 122(11):2428–2433.

Committee on Underrepresented Groups and the Expansion of the Science and Engineering Workforce Pipeline (2011). *Expanding underrepresented minority participation*. National Academies Press Washington, DC.

"Competing Interests" (2023). PLOS One, https://journals.plos.org/plosone/s/competing-interests. Accessed on April 12, 2023.

"Conflict of interest policy" (2024). Public Health Nutrition, Cambridge Core. Accessed on December 17, 2024.

COPE (2017). Guidelines: Ethical guidelines for peer reviewers. COPE (Committee on Publication Ethics), https://publicationethics.org/sites/default/files/ethical-guidelines-peer-reviewers-cope.pdf. Accessed on August 11, 2024.

COPE (2021). Editorial board participation. COPE (Committee on Publication Ethics), https://publicationethics.org/resources/guidelines/editorial-board-participation. Accessed on May 8, 2023.

COPE (2024). Conflicts of interest between authors and editors. COPE (Committee on Publication Ethics), https://publicationethics.org/guidance/case/conflicts-interest-between-authors-and-editors. Accessed on August 11, 2024.

Cotter, D. A., Hermsen, J. M., Ovadia, S., and Vanneman, R. (2001). The glass ceiling effect. *Social forces*, 80(2):655–681.

Crimaldi, H. (1996). Trade secret law and confidentiality of peer review process for scientific papers: Trial date set for cistron biotech v immunex corp. *Biotechnology Law Report*, 15(2):229–232.

CSE (2012). CSE's White Paper on Promoting Integrity in Scientific Journal Publications. https://www.seaairweb.info/journal/3.CouncilofScientific-Editors-White-Paper.pdf, Council of Science Editors. Accessed on August 12, 2024.

Csiszar, A. (2019). *The scientific journal: Authorship and the politics of knowledge in the nineteenth century*. University of Chicago Press.

Davidson, N. R. and Greene, C. S. (2021). Analysis of science journalism reveals gender and regional disparities in coverage. Technical report, Manubot.

Davidson, N. R. and Greene, C. S. (2022). Analysis of science journalism reveals gender and regional disparities in coverage. *bioRxiv*, pages 2021–06.

de Rassenfosse, G. and Hosseini, R. (2020). Discrimination against foreigners in the us patent system. *Journal of International Business Policy*, 3(4):349–366.

De Rond, M. and Miller, A. N. (2005). Publish or perish: Bane or boon of academic life? *Journal of management inquiry*, 14(4):321–329.

Desai, T. A., Eniola-Adefeso, O., Stevens, K. R., Vazquez, M., and Imoukhuede, P. (2021). Perspectives on disparities in scientific visibility. *Nature Reviews Materials*, 6(7):556–559.

Dhanani, A. and Jones, M. J. (2017). Editorial boards of accounting journals: gender diversity and internationalisation. *Account. Audit. Account. J.*

Diamond, R., McQuade, T., and Qian, F. (2019). The effects of rent control expansion on tenants, landlords, and inequality: Evidence from san francisco. *American Economic Review*, 109(9):3365–94.

Dias, L., Gerlach, M., Scharloth, J., and Altmann, E. G. (2018). Using text analysis to quantify the similarity and evolution of scientific disciplines. *Royal Society open science*, 5(1):171545.

Dickersin, K., Fredman, L., Flegal, K. M., Scott, J. D., and Crawley, B. (1998). Is there a sex bias in choosing editors? Epidemiology journals as an example. *JAMA*, 280(3):260–264.

Duan, Y., Memon, S. A., AlShebli, B., Guan, Q., Holme, P., and Rahwan, T. (2025). Postdoc publications and citations link to academic retention and faculty success. *Proceedings of the National Academy of Sciences*, 122(4):e2402053122.

"Editorial and Journal Policies" (2023). PNAS Author Center, https://www.pnas.org/author-center/editorial-and-journal-policies. Accessed on April 26, 2023.

"Editorial and peer review process" (2023). https://journals.plos.org/plosone/s/editorial-and-peer-review-process. Accessed on December 4, 2023.

"Editors" (2023). Accessed on December 4, 2023.

Editors, P. M. et al. (2008). Making sense of non-financial competing interests. *PLOS med*, 5(9):e199.

Eiko (2008). 7 sternberg papers: 351 references, 161 self-citations.

Elsevier (2020a). Article (full text) retrieval api. https://dev.elsevier.com/documentation/ArticleRetrievalAPI.wadl. Accessed: 2020-09-07.

Elsevier (2020b). Journals and books. https://web.archive.org/web/20200907115741/https://www.sciencedirect.com/browse/journals-and-books. Accessed: 2020-09-07.

Erren, T. C., Groß, J. V., Shaw, D. M., and Selle, B. (2014). Representation of women as authors, reviewers, editors in chief, and editorial board members at 6 general medical journals in 2010 and 2011. *JAMA Intern. Med.*, 174(4):633–635.

Espin, J., Palmas, S., Carrasco-Rueda, F., Riemer, K., Allen, P. E., Berkebile, N., Hecht, K. A., Kastner-Wilcox, K., Núñez-Regueiro, M. M., Prince, C., et al. (2017). A persistent lack of international representation on editorial boards in environmental biology. *PLOS biology*, 15(12):e2002760.

Evans, J., Hsieh, P. P.-H., and Robinson, D. H. (2005). Women's involvement in educational psychology journals from 1976 to 2004. *Educ. Psychol. Rev*, 17(3):263–271.

Faggion Jr, C. M. (2021). Watching the watchers: A report on the disclosure of potential conflicts of interest by editors and editorial board members of dental journals. *European Journal of Oral Sciences*, 129(6):e12823.

Fang, D., Moy, E., Colburn, L., and Hurley, J. (2000). Racial and ethnic disparities in faculty promotion in academic medicine. *Jama*, 284(9):1085–1092.

Fong, C. J., Yoo, J. H., Jones, S. J., Torres, L. G., and Decker, M. L. (2009). Trends in female authorships, editorial board memberships, and editorships in educational psychology journals from 2003 to 2008. *Educ. Psychol. Rev*, 21(3):267–277.

Ford, E., Kaspar, W. A., and Seiden, P. (2017). Diversity of ACRL publications, editorial board demographics: A report from ACRL's Publications Coordinating Committee. *College & Research Libraries News*, 78(10):548.

Fox, C. W., Duffy, M. A., Fairbairn, D. J., and Meyer, J. A. (2019). Gender diversity of editorial boards and gender differences in the peer review process at six journals of ecology and evolution. *Ecol. Evol.*, 9(24):13636–13649.

Frank, M. R., Wang, D., Cebrian, M., and Rahwan, I. (2019). The evolution of citation graphs in artificial intelligence research. *Nat. Mach. Intell.*, 1(2):79–85.

Freund, Y. and Schapire, R. E. (1997). A decision-theoretic generalization of on-line learning and an application to boosting. *Journal of computer and system sciences*, 55(1):119–139.

Friedman, P. J. (2002). The impact of conflict of interest on trust in science. *Science and Engineering ethics*, 8:413–420.

Gans, J. S. and Shepherd, G. B. (1994). How are the mighty fallen: Rejected classic articles by leading economists. *Journal of Economic Perspectives*, 8(1):165–179.

García-Carpintero, E., Granadino, B., and Plaza, L. (2010). The representation of nationalities on the editorial boards of international journals and the promotion of the scientific output of the same countries. *Scientometrics*, 84(3):799–811.

Gaston, J. (1973). *Originality and competition in science: A study of the British high energy physics community*. The University of Chicago Press, Chicago 60637.

Ghosh, A., Dutt, R., and Wilson, C. (2021). When fair ranking meets uncertain inference. In *Proceedings of the 44th Int. ACM SIGIR Conf. on Research & Development in Information Retrieval*, pages 1033–1043.

Ginther, D. K., Schaffer, W. T., Schnell, J., Masimore, B., Liu, F., Haak, L. L., and Kington, R. (2011). Race, ethnicity, and nih research awards. *Science*, 333(6045):1015–1019.

Gollins, C., Shipman, A., and Murrell, D. (2017). A study of the number of female editors-in-chief of dermatology journals. *Int. J. Womens. Dermatol.*, 3(4):185–188.

Gomez, C. J., Herman, A. C., and Parigi, P. (2022). Leading countries in global science increasingly receive more citations than other countries doing similar research. *Nature Human Behaviour*, 6(7):919–929.

Google (2022). English - Google Scholar Metrics. Accessed on 2022-11-17.

Gottlieb, J. D. and Bressler, N. M. (2017). How should journals handle the conflict of interest of their editors? Who watches the "watchers"? *Jama*, 317(17):1757–1758.

Gottlieb, M., Krzyzaniak, S. M., Mannix, A., Parsons, M., Mody, S., Kalantari, A., Ashraf, H., and Chan, T. M. (2021). Sex distribution of editorial board members among emergency medicine journals. *Ann. Emerg. Med.*, 77(1):117–123.

Groen-Xu, M., Bös, G., Teixeira, P. A., Voigt, T., and Knapp, B. (2023). Short-term incentives of research evaluations: Evidence from the uk research excellence framework. *Research Policy*, 52(6):104729.

Hafeez, D. M., Waqas, A., Majeed, S., Naveed, S., Afzal, K. I., Aftab, Z., Zeshan, M., and Khosa, F. (2019). Gender distribution in psychiatry journals' editorial boards worldwide. *Compr. Psychiatry*, 94:152119.

Haivas, I., Schroter, S., Waechter, F., and Smith, R. (2004). Editors' declaration of their own conflicts of interest. *CMAJ*, 171(5):475–476.

Harris, C. A., Banerjee, T., Cramer, M., Manz, S., Ward, S., Dimick, J., and Telem, D. A. (2019). Editorial (spring) board? Gender composition in high-impact general surgery journals over 20 years. *Ann. Surg.*, 269(3):582.

Harzing, A.-W. and Metz, I. (2013). Practicing what we preach. *Management International Review*, 53(2):169–187.

Hausman, C. and Rapson, D. S. (2018). Regression discontinuity in time: Considerations for empirical applications. *Annual Review of Resource Economics*, 10:533–552.

Heckman, J. J. and Moktan, S. (2020). Publishing and promotion in economics: The tyranny of the top five. *Journal of Economic Literature*, 58(2):419–470.

Hofstra, B., Kulkarni, V. V., Munoz-Najar Galvez, S., He, B., Jurafsky, D., and McFarland, D. A. (2020). The diversity–innovation paradox in science. *Proc. Natl. Acad. Sci. USA*, 117(17):9284–9291.

Holman, L., Stuart-Fox, D., and Hauser, C. E. (2018). The gender gap in science: How long until women are equally represented? *PLoS biology*, 16(4):e2004956.

Huang, J., Gates, A. J., Sinatra, R., and Barabási, A.-L. (2020). Historical comparison of gender inequality in scientific careers across countries and disciplines. *Proc. Natl. Acad. Sci. USA*, 117(9):4609–4616.

Huber, J., Inoua, S., Kerschbamer, R., König-Kersting, C., Palan, S., and Smith, V. L. (2022). Nobel and novice: Author prominence affects peer review. *Proc. Natl. Acad. Sci. USA*, 119(41):e2205779119.

Hutchinson, D., Das, P., Lall, M. D., Hill, J., Fares, S., and Khosa, F. (2021). Emergency medicine journal editorial boards: analysis of gender, h-index, publications, academic rank, and leadership roles. *West. J. Emerg. Med.*, 22(2):353.

Ibrahim, H., Liu, F., Zaki, Y., and Rahwan, T. (2025). Citation manipulation through citation mills and pre-print servers. *Scientific Reports*, 15(1):5480.

ICMJE (2023). Disclosure of Financial and Non-Financial Relationships and Activities, and Conflicts of Interest. ICMJE, https://www.icmje.org/recommendations/browse/roles-and-responsibilities/author-responsibilities–conflicts-of-interest.html. Accessed on April 10, 2023.

IEEE (2023). IEEE publication services and products board operations manual 2023. IEEE Publications, Piscataway, NJ. Accessed on April 28, 2023.

"IEEE Policies" (2023). The Institute of Electrical and Electronics Engineers, Inc., New York, N.Y. Accessed on April 28, 2023.

Imbens, G. W. and Lemieux, T. (2008). Regression discontinuity designs: A guide to practice. *Journal of Econometrics*, 142(2):615–635.

Ioannidou, E. and Rosania, A. (2015). Under-representation of women on dental journal editorial boards. *PLoS One*, 10(1):e0116630.

Jackson, J. R., Holmes, A. M., Golembiewski, E., Brown-Podgorski, B. L., and Menachemi, N. (2019). Graduation and academic placement of underrepresented racial/ethnic minority doctoral recipients in public health disciplines, united states, 2003-2015. *Public Health Reports*, 134(1):63–71.

Jadidi, M., Karimi, F., Lietz, H., and Wagner, C. (2018). Gender disparities in science? Dropout, productivity, collaborations and success of male and female computer scientists. *Adv. Complex Sys.*, 21(03n04):1750011.

Jagsi, R., Tarbell, N. J., Henault, L. E., Chang, Y., and Hylek, E. M. (2008). The representation of women on the editorial boards of major medical journals: a 35-year perspective. *Archives of internal medicine*, 168(5):544–548.

Jalilianhasanpour, R., Charkhchi, P., Mirbolouk, M., and Yousem, D. M. (2019). Underrepresentation of women on radiology editorial boards. *J. Am. Coll. Radiol.*, 16(1):115–120.

Jo, W. S., Liu, L., and Wang, D. (2022). See further upon the giants: Quantifying intellectual lineage in science. *Quantitative Science Studies*, 3(2):319–330.

Kaji, A. H., Meurer, W. J., Napper, T., Nigrovic, L. E., Mower, W. R., Schriger, D. L., Cooper, R. J., Houry, D. E., Delbridge, T. R., DeLorenzo, R. A., et al. (2019). State of the journal: women first authors, peer reviewers, and editorial board members at annals of emergency medicine. *Ann. Emerg. Med.*, 74(6):731–735.

Kean, S. (2009). PNAS nixes special privileges for (most) papers.

Keiser, J., Utzinger, J., and Singer, B. H. (2003). Gender composition of editorial boards of general medical journals. *Lancet*, 362(9392):1336.

Kempf, E. and Tsoutsoura, M. (2021). Partisan professionals: Evidence from credit rating analysts. *The Journal of Finance*, 76(6):2805–2856.

Kennedy, B. L., Lin, Y., and Dickstein, L. J. (2001). Women on the editorial boards of major journals. *Acad. Med.*, 76(8):849–851.

Khan, M. S., Lakha, F., Tan, M. M. J., Singh, S. R., Quek, R. Y. C., Han, E., Tan, S. M., Haldane, V., Gea-Sánchez, M., and Legido-Quigley, H. (2019). More talk than action: gender and ethnic diversity in leading public health universities. *Lancet*, 393(10171):594–600.

King, M. M., Bergstrom, C. T., Correll, S. J., Jacquet, J., and West, J. D. (2017). Men set their own cites high: Gender and self-citation across fields and over time. *Socius*, 3:2378023117738903.

Klain, H. (2020). *Waiting to vote: Racial disparities in election day experiences*. Brennan Center for Justice at New York University School of Law.

Kozlowski, D., Larivière, V., Sugimoto, C. R., and Monroe-White, T. (2022). Intersectional inequalities in science. *Proceedings of the National Academy of Sciences*, 119(2):e2113067119.

Larivière, V., Ni, C., Gingras, Y., Cronin, B., and Sugimoto, C. R. (2013). Bibliometrics: global gender disparities in science. *Nature*, 504(7479):211.

Law, K. K. and Zuo, L. (2022). Public concern about immigration and customer complaints against minority financial advisors. *Management Science*.

Le, T. T., Himmelstein, D. S., Hippen, A. A., Gazzara, M. R., and Greene, C. S. (2021). Analysis of scientific society honors reveals disparities. *Cell Systems*, 12(9):900–906.

Lerman, K., Yu, Y., Morstatter, F., and Pujara, J. (2022). Gendered citation patterns among the scientific elite. *Proceedings of the National Academy of Sciences*, 119(40):e2206070119.

Leslie, S.-J., Cimpian, A., Meyer, M., and Freeland, E. (2015). Expectations of brilliance underlie gender distributions across academic disciplines. *Science*, 347(6219):262–265.

Li, D. (2017). Expertise versus bias in evaluation: Evidence from the nih. *American Economic Journal: Applied Economics*, 9(2):60–92.

Li, W., Zhang, S., Zheng, Z., Cranmer, S. J., and Clauset, A. (2022). Untangling the network effects of productivity and prominence among scientists. *Nature communications*, 13(1):4907.

Lincoln, A. E., Pincus, S. H., and Leboy, P. S. (2011). Scholars' awards go mainly to men. *Nature*, 469(7331):472–472.

Litvack, J. R., Wick, E. H., and Whipple, M. E. (2019). Trends in female leadership at high-profile otolaryngology journals, 1997–2017. *Laryngoscope*, 129(9):2031–2035.

Liu, F., Holme, P., Chiesa, M., AlShebli, B., and Rahwan, T. (2023a). Gender inequality and self-publication are common among academic editors. *Nature Human Behaviour*, 7(3):353–364.

Liu, F., Rahwan, T., and AlShebli, B. (2023b). Non-white scientists appear on fewer editorial boards, spend more time under review, and receive fewer citations. *Proceedings of the National Academy of Sciences*, 120(13):e2215324120.

Lockwood, M. (2020). Editorial: citation malpractice. *Proceedings of the Royal Society A*, 476(2242):20200746.

Logan, D. (2016). The importance of a gender-balanced editorial team: narrowing the gender gap begins with all of us.

Lorello, G. R., Parmar, A., and Flexman, A. M. (2019). Representation of women on the editorial board of the canadian journal of anesthesia: a retrospective analysis from 1954 to 2018. *Can. J. Anaesth.*, 66(8):989–990.

Luborsky, L., Diguer, L., Seligman, D. A., Rosenthal, R., Krause, E. D., Johnson, S., Halperin, G., Bishop, M., Berman, J. S., and Schweizer, E. (1999). The researcher's own therapy allegiances: A" wild card" in comparisons of treatment efficacy. *Clinical psychology: Science and practice*, 6(1):95.

Luty, J., Arokiadass, S. M. R., Easow, J. M., and Anapreddy, J. R. (2009). Preferential publication of editorial board members in medical specialty journals. *J. Med. Ethics*, 35(3):200–202.

Malički, M., Jerončić, A., Aalbersberg, I. J., Bouter, L., and Ter Riet, G. (2021). Systematic review and meta-analyses of studies analysing instructions to authors from 1987 to 2017. *Nature communications*, 12(1):5840.

Mallapaty, S. (2020). China bans cash rewards for publishing papers. *Nature*, 579(7797):18–19.

Mani, J., Makarević, J., Juengel, E., Ackermann, H., Nelson, K., Bartsch, G., Haferkamp, A., and Blaheta, R. A. (2013). I publish in I edit? Do editorial board members of urologic journals preferentially publish their own scientific work? *PLOS One*, 8(12):e83709.

Marshall, E. (1995a). Peer review: Written and unwritten rules. *Science*, 270(5244):1913–1913.

Marshall, E. (1995b). Suit alleges misuse of peer review. *Science*, 270(5244):1912–1914.

Marshall, E. (1996). Battle ends in $21 million settlement. *Science*, 274(5289):911.

Martins, T., Abel, G., Ukoumunne, O. C., Price, S., Lyratzopoulos, G., Chinegwundoh, F., and Hamilton, W. (2022). Assessing ethnic inequalities in diagnostic interval of common cancers: A population-based uk cohort study. *Cancers*, 14(13):3085.

Mauleón, E., Hillán, L., Moreno, L., Gómez, I., and Bordons, M. (2013). Assessing gender balance among journal authors and editorial board members. *Scientometrics*, 95(1):87–114.

"May not definition" (2024). Law Insider. Accessed on July 16, 2024.

McGee Jr, R., Saran, S., and Krulwich, T. A. (2012). Diversity in the biomedical research workforce: developing talent. *Mount Sinai Journal of Medicine: A Journal of Translational and Personalized Medicine*, 79(3):397–411.

McKiernan, E. C., Schimanski, L. A., Muñoz Nieves, C., Matthias, L., Niles, M. T., and Alperin, J. P. (2019). Use of the journal impact factor in academic review, promotion, and tenure evaluations. *elife*, 8:e47338.

McSweeney, F. K., Donahoe, P., and Swindell, S. (2000). Women in applied behavior analysis. *Behav. Anal.*, 23(1):267–277.

Medoff, M. H. (2003). Editorial favoritism in economics? *Southern Economic Journal*, 70(2):425–434.

Merton, R. K. (1968). The matthew effect in science: The reward and communication systems of science are considered. *Science*, 159(3810):56–63.

Metz, I. and Harzing, A.-W. (2009). Gender diversity in editorial boards of management journals. *Acad. Manag. Learn. Educ.*, 8(4):540–557.

Metz, I. and Harzing, A.-W. (2012). An update of gender diversity in editorial boards: a longitudinal study of management journals. *Pers.*

Metz, I., Harzing, A.-W., and Zyphur, M. J. (2016). Of journal editors and editorial boards: who are the trailblazers in increasing editorial board gender equality? *Br. J. Manag.*, 27(4):712–726.

Morgan, A. C., Way, S. F., Hoefer, M. J., Larremore, D. B., Galesic, M., and Clauset, A. (2021). The unequal impact of parenthood in academia. *Sci. Adv.*, 7(9):eabd1996.

Morton, M. J. and Sonnad, S. S. (2007). Women on professional society and journal editorial boards. *J. Natl. Med. Assoc.*, 99(7):764.

Mrowinski, M. J., Fronczak, A., Fronczak, P., Nedic, O., and Ausloos, M. (2016). Review time in peer review: Quantitative analysis and modelling of editorial workflows. *Scientometrics*, 107(1):271–286.

Murphy, M. C., Mejia, A. F., Mejia, J., Yan, X., Cheryan, S., Dasgupta, N., Destin, M., Fryberg, S. A., Garcia, J. A., Haines, E. L., et al. (2020). Open science, communal culture, and women's participation in the movement to improve science. *Proc. Natl. Acad. Sci. USA*, 117(39):24154–24164.

Murray, D., Siler, K., Larivière, V., Chan, W. M., Collings, A. M., Raymond, J., and Sugimoto, C. R. (2019). Author-reviewer homophily in peer review. *BioRxiv*, page 400515.

Nadri, R., Rodriguez-Perez, G., and Nagappan, M. (2021). Insights into nonmerged pull requests in github: Is there evidence of bias based on perceptible race? *IEEE Softw.*, 38(2):51–57.

National Center for Science and Engineering Statistics (2019). Women, minorities, and persons with disabilities in science and engineering. Accessed August 30, 2022, https://ncses.nsf.gov/pubs/nsf19304.

National Center for Science and Engineering Statistics (2021). Women, minorities, and persons with disabilities in science and engineering. Accessed August 30, 2022, https://ncses.nsf.gov/pubs/nsf21321.

Neal, R. and Allgar, V. (2005). Sociodemographic factors and delays in the diagnosis of six cancers: analysis of data from the 'national survey of nhs patients: Cancer'. *British journal of cancer*, 92(11):1971–1975.

Newton, D. P. (2010). Quality and peer review of research: an adjudicating role for editors. *Account. Res.*, 17(3):130–145.

Nguyen, M., Chaudhry, S. I., Asabor, E., Desai, M. M., Lett, E., Cavazos, J. E., Mason, H. R., and Boatright, D. (2022). Variation in research experiences and publications during medical school by sex and race and ethnicity. *JAMA Network Open*, 5(10):e2238520–e2238520.

Nicholas, D., Herman, E., Abrizah, A., Rodríguez-Bravo, B., Boukacem-Zeghmouri, C., Watkinson, A., Świgoń, M., Xu, J., Jamali, H. R., and Tenopir, C. (2023). Never mind predatory publishers… what about 'grey'publishers? *Profesional de la información*, 32(5).

Nielsen, M. W. and Andersen, J. P. (2021). Global citation inequality is on the rise. *Proceedings of the National Academy of Sciences*, 118(7):e2012208118.

Nishikawa-Pacher, A. (2022). Who are the 100 largest scientific publishers by journal count? a webscraping approach. *Journal of Documentation*, 78(7):450–463.

Nittrouer, C. L., Hebl, M. R., Ashburn-Nardo, L., Trump-Steele, R. C., Lane, D. M., and Valian, V. (2018). Gender disparities in colloquium speakers at top universities. *Proc. Natl. Acad. Sci. USA*, 115(1):104–108.

Notman, N. and Woolston, C. (2020). Fifteen to one: how many applications it can take to land a single academic job offer. *Nature*, 584(7820):315–316.

O'Brochta, W. (2022). Ethnic diversity in central government cabinets. *Politics, Groups, and Identities*, 10(2):189–208.

Okike, K., Liu, B., Lin, Y. B., Torpey, J. L., Kocher, M. S., Mehlman, C. T., Bhandari, M., and Biermann, J. S. (2012). The orthopedic gender gap: Trends in authorship and editorial board representation over the past 4 decades. *Am. J. Orthop. (Belle Mead NJ)*, 41(7):304–310.

Oransky, I. (2022). White house official banned from publishing in PNAS following retraction. Retraction Watch. Accessed on March 16, 2023.

Pagel, P. S., Freed, J. K., and Lien, C. A. (2019). Gender composition and trends of journal of cardiothoracic and vascular anesthesia editorial board membership: a 33-year analysis, 1987-2019. *J. Cardiothorac. Vasc. Anesth.*, 33(12):3229–3234.

Palser, E. R., Lazerwitz, M., and Fotopoulou, A. (2022). Gender and geographical disparity in editorial boards of journals in psychology and neuroscience. *Nature Neuroscience*, 25(3):272–279.

Peng, H., Ke, Q., Budak, C., Romero, D. M., and Ahn, Y.-Y. (2021). Neural embeddings of scholarly periodicals reveal complex disciplinary organizations. *Sci. Adv.*, 7(17):eabb9004.

Petersen, A. M., Fortunato, S., Pan, R. K., Kaski, K., Penner, O., Rungi, A., Riccaboni, M., Stanley, H. E., and Pammolli, F. (2014). Reputation and impact in academic careers. *Proc. Natl. Acad. Sci. USA*, 111(43):15316–15321.

Pezzoni, M., Mairesse, J., Stephan, P., and Lane, J. (2016). Gender and the publication output of graduate students: A case study. *PLoS One*, 11(1):e0145146.

Pfeffer, C. A. (2018). Queer accounting: Methodological investments and disinvestments. *Other, please specify: Queer methods in sociology*, pages 304–325.

Pflibsen, L. R., Foley, B. M., Bernard, R. W., Lee, G. K., Neville, M. R., Almader-Douglas, D., and Noland, S. S. (2021). Representation of women on plastic surgery journal editorial boards in the united states. *Aesthet. Surg. J.*

Pinho-Gomes, A.-C., Vassallo, A., Thompson, K., Womersley, K., Norton, R., and Woodward, M. (2021). Representation of women among editors in chief of leading medical journals. *JAMA network open*, 4(9):e2123026–e2123026.

Pion, G. M., Mednick, M. T., Astin, H. S., Hall, C. C. I., Kenkel, M. B., Keita, G. P., Kohout, J. L., and Kelleher, J. C. (1996). The shifting gender composition of psychology: trends and implications for the discipline. *Am. Psychol.*, 51(5):509.

Piper, C. L., Scheel, J. R., Lee, C. I., and Forman, H. P. (2018). Representation of women on radiology journal editorial boards: a 40-year analysis. *Acad. Radiol.*, 25(12):1640–1645.

PLOS (2009a). Competing Interests Policy, PLOS Biology. http://www.plosbiology.org/static/competing.action. Accessed on May 19, 2009 (WayBack Machine).

PLOS (2009b). PLOS Policy on Declaration and Evaluation of Competing Interests, PLOS Biology. http://www.plosbiology.org:80/static/competing.action. Accessed on September 20, 2009 (WayBack Machine).

PLOS (2015). Competing Interests, PLOS Biology. https://journals.plos.org/plosbiology/s/competing-interests. Accessed on May 11, 2015 (WayBack Machine).

PNAS (2008). PNAS Conflict of Interest Policy. http://www.pnas.org/misc/coi.shtml. Accessed on May 11, 2008 (WayBack Machine).

PNAS (2009). Information for Authors, PNAS. http://www.pnas.org/site/misc/iforc.shtml. Accessed on May 11, 2009 (WayBack Machine).

PNAS (2011). Information for Authors, PNAS. http://www.pnas.org/site/misc/iforc.shtml. Accessed on September 18, 2011 (WayBack Machine).

PNAS (2014). Editorial Policies, PNAS. http://www.pnas.org/site/authors/journal.xhtml. Accessed on April 19, 2014 (WayBack Machine).

PNAS (2020). Editorial and Journal Policies, PNAS Author Center. https://www.pnas.org/authors/editorial-and-journal-policies. Accessed on July 22, 2020 (WayBack Machine).

"Policies and publication ethics" (2023). Frontiers, https://www.frontiersin.org/guidelines/policies-and-publication-ethics. Accessed on March 15, 2023.

Polonsky, M. J., Garma, R., and Mittelstaedt, J. D. (2006). An examination of the globalisation of authorship in publishing in 20 leading marketing journals. *European Business Review*.

"Publication ethics" (2023). Hindawi, https://www.hindawi.com/publish-research/authors/publication-ethics/. Accessed on April 12, 2023.

Ramage, D., Hall, D., Nallapati, R., and Manning, C. D. (2009). Labeled lda: A supervised topic model for credit attribution in multi-labeled corpora. In *Proceedings of the 2009 conference on empirical methods in natural language processing*, pages 248–256.

Rand, D. G. and Pfeiffer, T. (2009). Systematic differences in impact across publication tracks at pnas. *PloS one*, 4(12):e8092.

Reny, T. T. and Newman, B. J. (2021). The opinion-mobilizing effect of social protest against police violence: Evidence from the 2020 george floyd protests. *American Political Science Review*, 115(4):1499–1507.

"Research and publication ethics" (2023). MDPI, https://www.mdpi.com/ethics. Accessed on April 25, 2023.

Resnik, D. B. and Elmore, S. A. (2016). Ensuring the quality, fairness, and integrity of journal peer review: A possible role of editors. *Science and Engineering Ethics*, 22:169–188.

Resnik, D. B. and Elmore, S. A. (2018). Conflict of interest in journal peer review. *Toxicologic Pathology*, 46(2):112–114.

Riano, I., Patel, S. R., Abuali, I., Ai, A., Geiger, G., Pimienta, J., Ramirez Roggio, A., Dhawan, N., Dizman, N., Salinas, A. L., et al. (2022). Self-identification of gender and race/ethnicity in hematology and oncology journal editorial boards: What is the state of diversity?

Robinson, D. H., McKay, D. W., Katayama, A. D., and Fan, A.-C. (1998). Are women underrepresented as authors and editors of educational psychology journals? *Contemp. Educ. Psychol.*, 23(3):331–343.

Rösing, C. K., Junges, R., and Haas, A. N. (2014). Publication rates of editorial board members in oral health journals. *Braz. Oral Res.*, 28(1):1–5.

Rotenstein, L. S. and Jena, A. B. (2018). Lost taussigs-the consequences of gender discrimination in medicine. *N. Engl. J. Med.*, 378(24):2255–2257.

Rushworth, C. A., Baucom, R. S., Blackman, B. K., Neiman, M., Orive, M. E., Sethuraman, A., Ware, J., and Matute, D. R. (2021). Who are we now? a demographic assessment of three evolution societies. *Evolution*, 75(2):208–218.

Rynecki, N. D., Krell, E. S., Potter, J. S., Ranpura, A., and Beebe, K. S. (2020). How well represented are women orthopaedic surgeons and residents on major orthopaedic editorial boards and publications? *Clin. Orthop. Relat. Res.*, 478(7):1563–1568.

Salazar, J. W., Claytor, J. D., Habib, A. R., Guduguntla, V., and Redberg, R. F. (2021). Gender, race, ethnicity, and sexual orientation of editors at leading medical and scientific journals: a cross-sectional survey. *JAMA Internal Medicine*, 181(9):1248–1251.

Salganik, M. J., Dodds, P. S., and Watts, D. J. (2006). Experimental study of inequality and unpredictability in an artificial cultural market. *science*, 311(5762):854–856.

Sarna, K. V., Griffin, T., Tarlov, E., Gerber, B. S., Gabay, M. P., and Suda, K. J. (2020). Trends in gender composition on editorial boards in leading medicine, nursing, and pharmacy journals. *J. Am. Pharm. Assoc.*, 60(4):565–570.

Sauermann, H. and Haeussler, C. (2017). Authorship and contribution disclosures. *Science advances*, 3(11):e1700404.

Schaede, U. and Mankki, V. (2022). Quota vs quality? long-term gains from an unusual gender quota. *Available at SSRN*.

Schiermeier, Q. (2008). Self-publishing editor set to retire. *Nature*.

Schurr, C., Müller, M., and Imhof, N. (2020). Who makes geographical knowledge? The gender of geography's gatekeepers. *Prof. Geogr.*, 72(3):317–331.

Science News Staff (1996). Peer review battle nets firm $21 million. *Science*.

Sekara, V., Deville, P., Ahnert, S. E., Barabási, A.-L., Sinatra, R., and Lehmann, S. (2018). The chaperone effect in scientific publishing. *Proc. Natl. Acad. Sci. USA*, 115(50):12603–12607.

Shim, R. S., Tully, L. M., Yu, G., Monterozza, E. C., and Blendermann, M. (2021). Race and ethnicity of editorial board members and editors as an indicator of structural racism in psychiatry and neuroscience journals. *JAMA psychiatry*, 78(10):1161–1163.

"Should not definition" (2024). Law Insider. Accessed on July 16, 2024.

Shu, F., Liu, S., and Larivière, V. (2022). China's research evaluation reform: What are the consequences for global science? *Minerva*, 60(3):329–347.

Si, K., Li, Y., Ma, C., and Guo, F. (2023). Affiliation bias in peer review and the gender gap. *Research Policy*, 52(7):104797.

Siler, K., Lee, K., and Bero, L. (2015). Measuring the effectiveness of scientific gatekeeping. *Proceedings of the National Academy of Sciences*, 112(2):360–365.

Silver, J. K. (2019). Gender equity on journal editorial boards. *The Lancet*, 393(10185):2037–2038.

Sinatra, R., Wang, D., Deville, P., Song, C., and Barabási, A.-L. (2016). Quantifying the evolution of individual scientific impact. *Science*, 354(6312):aaf5239.

Sinha, A., Shen, Z., Song, Y., Ma, H., Eide, D., Hsu, B.-J., and Wang, K. (2015). An overview of Microsoft Academic Service (MAS) and applications. In *Proceedings of the 24th international conference on World Wide Web*, pages 243–246.

Smith, E., Potvin, M.-J., and Williams-Jones, B. (2012). Accessibility and transparency of editor conflicts of interest policy instruments in medical journals. *Journal of Medical Ethics*, 38(11):679–684.

Sperotto, R. A., Granada, C. E., Henriques, J. A. P., Timmers, L. F. S., and Contini, V. (2021). Editorial decision is still a men's task. *An. Acad. Bras. Cienc.*, 93.

Stegmaier, M., Palmer, B., and Van Assendelft, L. (2011). Getting on the board: the presence of women in political science journal editorial positions. *PS - Political Sci. Politics*, 44(4):799–804.

Stern, J. M. and Simes, R. J. (1997). Publication bias: evidence of delayed publication in a cohort study of clinical research projects. *Bmj*, 315(7109):640–645.

Stewart, A. J. and Valian, V. (2018). *An Inclusive Academy: Achieving Diversity and Excellence*. MIT Press, Cambridge MA.

Sugimoto, C. R. (2021). Scientific success by numbers. *Nature*, 593(7857):30–31.

Sugimoto, C. R. and Larivière, V. (2018). *Measuring research: What everyone needs to know*. Oxford University Press.

Svensson, G. (2005). Ethnocentricity in top marketing journals. *Marketing Intelligence & Planning*.

Taşkın, Z., Taşkın, A., Doğan, G., and Kulczycki, E. (2022). Factors affecting time to publication in information science. *Scientometrics*, 127(12):7499–7515.

Teghtsoonian, M. (1974). Distribution by sex of authors and editors of psychological journals, 1970-1972: are there enough women editors? *Am. Psychol.*, 29(4):262.

Teich, E. G., Kim, J. Z., Lynn, C. W., Simon, S. C., Klishin, A. A., Szymula, K. P., Srivastava, P., Bassett, L. C., Zurn, P., Dworkin, J. D., et al. (2022). Citation inequity and gendered citation practices in contemporary physics. *Nature Physics*, 18(10):1161–1170.

Teplitskiy, M., Duede, E., Menietti, M., and Lakhani, K. R. (2022). How status of research papers affects the way they are read and cited. *Research policy*, 51(4):104484.

"The MDPI Editorial Process" (2023). Accessed on December 4, 2023.

Tian, M., Su, Y., and Ru, X. (2016). Perish or publish in china: Pressures on young chinese scholars to publish in internationally indexed journals. *Publications*, 4(2):9.

Tilghman, S., Alberts, B., Colón-Ramos, D., Dzirasa, K., Kimble, J., and Varmus, H. (2021). Concrete steps to diversify the scientific workforce. *Science*, 372(6538):133–135.

Topaz, C. M. and Sen, S. (2016). Gender representation on journal editorial boards in the mathematical sciences. *PLOS One*, 11(8):e0161357.

Van Noorden, R. (2020). Highly cited researcher banned from journal board for citation abuse. *Nature*, 578(7794):200–201.

Vicinanza, P., Goldberg, A., and Srivastava, S. B. (2023). A deep-learning model of prescient ideas demonstrates that they emerge from the periphery. *PNAS nexus*, 2(1):pgac275.

Wais, K. (2016). Gender prediction methods based on first names with genderizeR. *R Journal*, 8(1).

Walters, W. H. (2015). Do editorial board members in library and information science publish disproportionately in the journals for which they serve as board members? *J. Sch. Publ.*, 46(4):343–354.

WAME (2009). Conflict of interest in peer-reviewed medical journals. World Association of Mecial Editors. Accessed on March 16, 2023.

Wang, D. and Barabási, A.-L. (2020). *The Science of Science*. Cambridge University Press, Cambridge UK.

Wang, K., Shen, Z., Huang, C.-Y., Wu, C.-H., Eide, D., Dong, Y., Qian, J., Kanakia, A., Chen, A., and Rogahn, R. (2019). A review of Microsoft Academic Services for science of science studies. *Front. Big Data*, 2:45.

Ware, M. and Mabe, M. (2015). The STM report: An overview of scientific and scholarly journal publishing.

West, J. D., Jacquet, J., King, M. M., Correll, S. J., and Bergstrom, C. T. (2013). The role of gender in scholarly authorship. *PLOS One*, 8(7):e66212.

White, A. (1985). Women as authors and editors of psychological journals: a 10-year perspective. *Am. Psychol.*, 40(5):527.

Widnall, S. E. (1988). Aaas presidential lecture: Voices from the pipeline. *Science*, 241(4874):1740–1745.

Witteman, H. O., Hendricks, M., Straus, S., and Tannenbaum, C. (2019). Are gender gaps due to evaluations of the applicant or the science? a natural experiment at a national funding agency. *The Lancet*, 393(10171):531–540.

Wold, A. and Wennerås, C. (1997). Nepotism and sexism in peer review. *Nature*, 387(6631):341–343.

Wolff, S. M., Auron, P. E., Dinarello, C. A., Rosenwasser, L. J., WEBB, A. C., and RICH, A. (1986). Clone controversy at immunex. *Nature*, 319(6051):270–270.

Wuchty, S., Jones, B. F., and Uzzi, B. (2007). The increasing dominance of teams in production of knowledge. *Science*, 316(5827):1036–1039.

Yang, Y., Youyou, W., and Uzzi, B. (2020). Estimating the deep replicability of scientific findings using human and artificial intelligence. *Proc. Natl. Acad. Sci. USA*, 117(20):10762–10768.

Ye, J., Han, S., Hu, Y., Coskun, B., Liu, M., Qin, H., and Skiena, S. (2017). Nationality classification using name embeddings. In *Proceedings of the 2017 ACM on Conference on Information and Knowledge Management*, pages 1897–1906.

Youk, S. and Park, H. S. (2019). Where and what do they publish? Editors' and editorial board members' affiliated institutions and the citation counts of their endogenous publications in the field of communication. *Scientometrics*, 120(3):1237–1260.

Zdeněk, R. and Lososová, J. (2018). An analysis of editorial board members' publication output in agricultural economics and policy journals. *Scientometrics*, 117(1):563–578.

Zeina, M., Balston, A., Banerjee, A., and Woolf, K. (2020). Gender and ethnic differences in publication of bmj letters to the editor: an observational study using machine learning. *BMJ open*, 10(12):e037269.

Zeng, A., Fan, Y., Di, Z., Wang, Y., and Havlin, S. (2023). Disruptive papers in science are losing impact. *arXiv preprint arXiv:2305.03589*.

Zhang, S., Wapman, K. H., Larremore, D. B., and Clauset, A. (2022). Labor advantages drive the greater productivity of faculty at elite universities. *Science advances*, 8(46):eabq7056.

Zhang, X., Carabello, M., Hill, T., Bell, S. A., Stephenson, R., and Mahajan, P. (2020). Trends of racial/ethnic differences in emergency department care outcomes among adults in the united states from 2005 to 2016. *Frontiers in medicine*, 7:300.