Gender and Ethnic Disparities in Science Production and Dissemination

by

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DEDICATION

To Beilei Zeng, Hobert Peng, and my parents.

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ABSTRACT

There is constant under-representation of women and racial minorities in the research workforce. Past research has demonstrated considerable gender and ethnic disparities in conventional scientific outcomes including careers, funding, publications, and citations. However, addressing the issue of under-representation requires examining the disparities throughout the scientific pipeline from the process of knowledge production to their dissemination in online media. Furthermore, a sizable gap still remains in our understanding of the mechanisms behind these disparities, which can involve different actors and institutions. For instance, the gap in publication counts at leading journals may be caused by the submission volume or the acceptance rate, which in turn may be caused by meritorious factors or bias in review. Disentangling different mechanisms is thus essential for designing effective policy interventions to restore equality in science.

In this dissertation, we utilize large-scale bibliometric data, including publicly available datasets and private peer-review data from leading academic journals, to examine the demographic disparities and explore their potential mechanisms in three key activities in science production and dissemination, including (1) ethnic disparity in acceptance rate at top biology journals, (2) ethnic disparity in author mentions in science news, and (3) gender differences in scholarly self-promotion on social media. We leverage novel computational techniques and statistical models to precisely measure the magnitude of the disparities. The fine-grained nature of these data also enables us to pinpoint the actors (e.g., journal editors or peer reviewers) and processes (e.g., publishing stage or dissemination stage) where the disparity is produced, and dig into the mechanisms leading to it. We demonstrate how this computational social science approach can provide insights into practical policy interventions to reduce disparity in science.

CHAPTER 1

Introduction

Scientific breakthroughs can advance human society in numerous ways. Promoting innovation and scientific advancement is thus important for the development of modern society. One of the core ingredients in science are working scientists who collectively solve challenging problems facing our society. Here we define scientists as producers of public knowledge. This definition excludes researchers working in private industry if their work is not indexed in public bibliometric databases and therefore inaccessible by the public. Understanding scientists' day-to-day work experience and their achievements is the first step towards building an efficient production system in science.

In the past century, science has undergone drastic shift in the way it produces knowledge [Adams, 2013]. First, scientific work is increasingly conducted by teams across disciplines and institutions [Wuchty et al., 2007, Jones et al., 2008]. The second change is the globalization of the scientific workforce due to advances in communication technologies. This trend is also facilitated by the fact that science has a common language—English [Ammon, 2001]. The change in scientific collaboration and globalization has greatly contributed to scientific progress in the past century [Adams, 2013, Sugimoto et al., 2017a].

As science continues to globalize, scientists are moving across countries more freely than ever before [OECD, 2008]. Today's academic institutions in most countries are hiring international candidates globally [Altbach and Yudkevich, 2017]. Major English-speaking countries with many international researchers such as the United States, Canada, and Australia have been driving the scientific progress. The United States in particular has served for decades as a hub for foreign-born scientists [Stephan and Levin, 2001]. Immigrants in the U.S. have played a remarkable role in its scientific achievements [Anderson, 2017]. Research shows that immigrants have won 38% of the Nobel Prizes awarded to Americans in chemistry, medicine, and physics since 2000 [NFAP, 2021].

However, many of these international scientists are from economically less developed countries and often experience cultural and institutional barriers in the work environment in the U.S. [Kerr, 2018, Kahn and MacGarvie, 2020]. It is thus important to understand and explain minority scientists' experience in the context of western society. If they do not have equal access to career opportunities and other outcomes directly and indirectly related to careers, it will undermine scientific progress in the long run as talented individuals from these groups will be less motivated to pursue academic careers in the global market.

Past research in this space has mainly focused on gender inequalities [Ley and Hamilton, 2008, Way et al., 2016, Oliveira et al., 2019] and racial disparities faced by African Americans [Erosheva et al., 2020, Turner et al., 2008, Hoppe et al., 2019, Ginther et al., 2011]. Less attention has been paid to other ethnic minorities with foreign background such as scientists of Asian ethnicities. This community of scientists is large, complex, and important because they and their domestic counterparts are contributing greatly to science in recent years [Xie et al., 2014, Van Noorden, 2018, Stuen et al., 2012, Hunt and Gauthier-Loiselle, 2010, Kahn and MacGarvie, 2020]. A better understanding of their work experience in science production that used to be driven by western countries can contribute to a better science by harnessing their unique perspectives and potentials.

This dissertation aims to reveal disparities faced by gender and ethnic minority scholars throughout the scientific pipeline including science production and its dissemination to the public. We conduct three studies of different scholarly activities primarily through the lens of the U.S. context, including manuscript acceptance at top journals by a U.S.-based publisher, author mentions in science news in U.S.-based media outlets, and scholars' self-promotion behavior on a U.S.-based social media platform. We also test different mechanisms and actors behind these disparities to properly inform policy interventions. By revealing inequalities in science production and dissemination, we contribute to a broader agenda that aims to equalize scholars' careers and ultimately promote scientific innovation at a global scale.

1.1 Literature Review

1.1.1 Processes of scientific production

Humans have always been curious about the physical world surrounding us. Our ancestors spent thousands of years wondering about why the sun rises in the east and sets in the west. In the 21st century, scientists are debating about the theory of relativity and quantum mechanics. Although we have made great advancements in science throughout human history, our curiosity in understanding and explaining the natural world has not changed a bit. Such curiosity has been and is going to be the driving force in the production of scientific knowledge.

Before the 19th century, science was mainly pursued by leisure-class amateurs out of personal interest, partly due to a scarcity of knowledge and limited access to resources required to participate in scientific activities [Price, 1963]. This constrain has made it possible that the development of science is predominantly pushed forward by a few elite individuals including Nicolaus Copernicus, Galileo Galilei, and Isaac Newton [Levinson, 2012].

The paradigm of doing science has shifted dramatically in the modern society, especially in the 21st century, where knowledge is increasingly produced through team work by millions of researchers from different disciplines at a global scale [King, 2004, Jones et al., 2008, Xie et al., 2014, Dong et al., 2017]. Such a drastic change is made possible due to the growing public interest in science and the increasing investment in funding resources [Krapp and Prenzel, 2011, Katsnelson, 2016]. This change from meritocracy to collaborative science is beneficial because it enables us to tackle challenging problems that require the collaboration between experts with diverse sets of specialization [Guimera et al., 2005, Greene, 2007, Milojević, 2014, Wu et al., 2019].

However, as science grows much bigger than it was a few decades ago, its production has become more complex than ever before. Science can be both for-profit and non-profit. While the advancement of some fields such as biomedical research can greatly benefit from industries labs that are profit-driven, many disciplines still have their knowledge produced primarily in the academy that is not for profit. In this dissertation, we focus on the knowledge production in academia. Modern academic science involves many different scientific enterprises and can be characterized by a few distinctive features [Xie, 2014]. First, as a non-profit business, science in the academia is primarily supported by large-scale government and industry funding. Second, the work is collaboratively conducted by a professional workforce with well-paid financial incentives. Third, scientists are often organized around academic institutions such as universities which also function as the educational unit for training its workforce. Fourth, there is a peer-review system serving as quality control for the knowledge it intends to produce. These actors and their interplay have made science a complex and evolving system. To improve the production of this system, we need to develop a principled understanding of the different processes involved in its production, including obtaining funding resources, seeking interdisciplinary collaborations, and undergoing peer evaluations.

1.1.1.1 Resources

Today's scientific knowledge is often produced in research labs within a department or school. These research labs function like small-sized companies, with the principle investigator serving as the manager and junior scholars working as employees. Like the manufacturing of goods in a company, the production of science needs resource and capital.

One essential capital is called *material resource* such as monetary funds that can be used to purchase laboratory equipment and hire qualified human labor. For example, a cell biologist who wants to start a virology lab may need to purchase sophisticated laboratory instruments to perform gene editing and hire experienced data scientists to analyze data. An experimental physicist may need access to complex particle accelerators to perform experiments and use supercomputers to process the massive data. Even in disciplines that do not require extensive laboratory experiments, such as many fields in social sciences, scholars still need funding to travel to conferences and attend specialized seminars. Money can also be used to pay for subscriptions to paywalled scientific journals and for the article processing fee charged by publishers [Boudry et al., 2019, Jain et al., 2021]. Scientists who have access to more monetary funding can be more productive and be able to generate more high-impact research, which in turn makes them more influential on the future direction of scientific development [Merton, 1968, Wagner and Jonkers, 2017, Chinchilla-Rodríguez et al., 2019].

Science in the academy is not for-profit, thus its funding needs to come from external sources. Many professional scientists have to compete for funding resources from government agencies and private organizations in order to continuously produce knowledge. However, the funding resource is not evenly distributed among scientists. Many scholars from underrepresented demographic groups and those from developing countries have less funding than peers from socially privileged groups in developed countries [Brahmakulam et al., 2001, Ginther et al., 2011, Hoppe et al., 2019].

Social capital is another type of resource available to scientists, which includes one's professional network and social status. As science is now predominantly produced by teams [Dong et al., 2017], the ability to collaborate with others and leverage one's social connections has become more important than ever before. Throughout a scientist's career, their social capital is constantly growing, often derived from the relationships with their mentors, peers, and colleagues in numerous occasions [Teplitskiy et al., 2018].

Though invisible and non-quantifiable, scholars' network resources often play a vital role in how successful a scientist is able to publish the research. For instance, junior scholars who interact with prestigious mentors have a greater chance of achieving success similar to their mentors, such as publishing in elite journals [Sekara et al., 2018] and winning the Nobel prize [Zuckerman, 1967]. Research also shows that manuscripts tend to be rated more favorably when being reviewed by referees from one's professional networks [Wennerås and Wold, 1997, Sandström and Hällsten, 2008, Teplitskiy et al., 2018]. Thus scientists' position in their social networks can greatly influence their success, careers, and their impact on the production of science.

Another important social capital is scientists' *prestige*, which can manifest in various factors, such as one's nationality, affiliation, collaboration network, citation impact, etc. Research shows that scholars from prestige institutions are advantaged in peer reviews [Ross et al., 2006, Tomkins et al., 2017], job opportunities [Burris, 2004, Clauset et al., 2015], and are more likely to have their research ideas diffused through the scientific community [Morgan et al., 2018].

1.1.1.2 Collaboration

Obtaining resources is typically the first step in initiating research projects. The actual process of knowledge production is falling on the shoulders of working scientists. Great science was used to be developed by a few talented individuals. For instance, well-known scientific elites such as Newton, Einstein, and Darwin all attained their greatest achievements mostly on their own. This phenomenon may once have been true, but great science now is no longer produced by any individual. Teams, often consist of a group of scientists with diverse skills, are becoming the dominant force in science production [Wuchty et al., 2007, Wu et al., 2019]. Solo authored papers are constantly decreasing over time [Greene, 2007, Leahey, 2016]. This change has been attributed to the specialization of academic research, improvements in communication technology [Xie, 2014], and the growing complexity of scientific problems [Wu et al., 2019]. Research finds that science has benefited from the shift from individual work to collaborative effort, with over 90% of the world-leading innovations generated by collaborations in this century, nearly four times higher than they were in the 1900s [Dong et al., 2017].

The magnitude of scientific collaboration has been intensified across both disciplines and institutions [Jones et al., 2008]. The discovery of the first gravitational wave by the LIGO Scientific Collaboration is a good example demonstrating the advantage of conducting collaborative research [Abbott et al., 2016]. The LIGO project team announced the discovery of gravitational waves in the United States, but in fact, the LIGO Scientific Collaboration is a massive flagship organization built at a global scale, with research teams coming from the U.S., Germany, the United Kingdom, and Australia, etc. Furthermore, these scientists come from many different disciplines. Some of them are specialized in theoretical physics, and some are excelled at computing technologies, each with their own different professional backgrounds and strengths.

Besides this example of a massive scientific collaboration and their Nobel prize winning work [Abbott et al., 2016], a systematic analysis of the entire academic literature indexed in the Microsoft Academic Graph shows that the international scientific collaborations have experienced a 25-fold increase from 1900 to 2015 [Dong et al., 2017]. As the emerging problems we experience in modern society are becoming more complex and intriguing than ever before, a shift to collaborative teams may be the only way to solve those challenging problems by exploring interdisciplinary solutions [Falk-Krzesinski et al., 2011].

1.1.1.3 Evaluation

Science relies on a formal process called "peer review" to legitimize the produced knowledge. Manuscripts that have passed the critical reviews by peers in the scientific community are deemed trustworthy and sound for the claimed findings. As an established scientific component, peer review is intended to evaluate the novelty and quality of the submitted work produced by others in the field [Lee et al., 2013]. Peers often hold shared norms to ensure that this system works as expected. It is commonly conceived that these norms are being universally applied to all scientific members, and that the implementation of these norms should be pertain to only the work's content (argument and evidence) independent of other external attributes such as the authors' identify or reviewers' personal preference [Merton, 1973, 1996].

To fulfill the desired impartiality, the peer review process typically involves the use of "third party" individuals, who are neither affiliated with the reviewing party nor associated with the authors being reviewed [Smith, 2006]. The reviewer identity is typically hidden to authors, which can encourage objective critics by offering reviewers protection against possible resentment from authors. In some cases, the author identity is also masked from reviewers (double-blind review), but in other cases, it is available to reviewers (single-blind review).

Reviewers in the single-blind model may infer from author identities a number of factors that can affect how they evaluate a paper, thus permitting a possibility of bias in the review process [Wennerås and Wold, 1997, Lee et al., 2013]. As a potential solution, some disciplines such as computer science has adopted the double-blind review model to reduce reviewing bias [Snodgrass, 2006, Sun et al., 2021]. However, the double-blind review model may not be able to address all limitations occurred in the review process. For example, research finds that the inter-reviewer disagreement increased significantly in the double-blind format [Sun et al., 2021].

The peer-review system, regardless of the review model, mostly operates on a voluntary and uncompensated basis, which has increased the workload of the scientific community. First, manuscript evaluation is a process that involves assessing the validity of complex ideas. Evaluating the merit of complex ideas is difficult [Jones, 2009], because the expertise needed is increasingly beyond the grasp of any specific individual [Wuchty et al., 2007, Jones et al., 2008]. Second, scientific research has become so highly sophisticated that many manuscripts are now accompanied by large amounts of supplementary materials that require careful scrutiny, placing an even greater burden on conscientious reviewers [Lee et al., 2013]. Third, the growing competition in academia has increased instances of scientific misconduct to the extent that reviewers now need to be alert to possible research fraud and reproducibility crisis [Fang et al., 2012].

However, this is only part of the story. The number of publications across all subjects has been tripled every 12 years for the past 116 years [Dong et al., 2017]. Nowadays, scientists are publishing millions of papers each year. Each of these published article has been reviewed by several independent reviewers, and has possibly gone through multiple rounds of reviews before publication. In addition to these published literature, there are also a considerable number of manuscripts rejected in the review process, as reflected in their typically low acceptance rates. Many of these rejected papers will be submitted to other journals for review. This laborious process has placed an enormous burden on members of the scientific community [Vines et al., 2010]. To curb this trend and reduce the burden on reviewers, some communities have started encouraging authors to declare the previous submission history of their papers and even considering reusing previous review comments [Stelmakh et al., 2021].

1.1.2 Demographic disparity in science production

Science has become a global enterprise, with English being used as the primary language in knowledge production. This unification and advances in communication technologies have greatly facilitated international collaboration, and offered scientists increased mobility in the global scientific workforce [Sugimoto et al., 2017a, Kerr, 2018, Kahn and MacGarvie, 2020]. The United States, in particular, has benefited considerably from the flow of global talents [Stephan and Levin, 2001]. Immigrants have made up one-third of U.S. recipients of Nobel prizes since 1900. Among all enrollees at U.S. universities, over 5% (more than 1 million) are foreign students. The majority of STEM doctoral students at U.S. institutions are of foreign origin, and most of them are from China and India [Kahn and MacGarvie, 2020].

The globalization of science has allowed more people from different backgrounds and cultures to enter the academic world. The gender and ethnic composition of the scientific workforce has become more and more diverse in recent years. For instance, faculty of color at U.S. institutions has increased from 20% in 2005 to 25% in 2018 [Taylor et al., 2010, Kozlowski et al., 2022]. However, many scientists still endure marginalization and discrimination in many scientific activities, ranging from obtaining research resources to the publication at top journals, despite evidence showing the benefit of diversity in scientific collaboration [AlShebli et al., 2018].

Historically, women faced barrier in participating in science. At the global level, only a third of scientists are women [Kozlowski et al., 2022]. In the U.S., women only account for 28.4% of the academic workforce [Rivers, 2017]. A similar trend has been observed in Europe, where only 7.4% female scholars hold the highest research positions as opposed to 16.7% for males [Sato et al., 2021]. The under-representation of women is even more severe in science, technology, engineering, and mathematics (STEM) than in other disciplines [Kahn and Ginther, 2017].

A line of research has established consistent gender inequities in science. Prior studies show that female scholars have received less funding and rewards [Ley and Hamilton, 2008, Bedi et al., 2012, Van der Lee and Ellemers, 2015, Oliveira et al., 2019, Ma et al., 2019], which likely has negative impact on their productivity [Way et al., 2016]. They also receive less credit or authorship in scientific collaborations [West et al., 2013, Sarsons, 2017, Macaluso et al., 2016]. Female authors need to meet higher standards to get their papers published [Hengel and Moon, 2020], possibly due to more unprofessional peer reviews [Card et al., 2020, Silbiger and Stubler, 2019] and less referee opportunities [Lerback and Hanson, 2017]. Not only have women published less papers and patents [Huang et al., 2020, Ding et al., 2006], but once published, women's papers are cited less [Larivière et al., 2013, Dworkin et al., 2020], and have received less online attention [Vasarhelyi et al., 2021]. Women have fewer career opportunities in science [Reuben et al., 2014, Clauset et al., 2015, Moss-Racusin et al., 2012], are paid less salary [Barbezat and Hughes, 2005, Shen, 2013], and are less likely to secure tenure at academic institutions [Perna, 2001, Weisshaar, 2017].

Besides gender, the literature has also revealed considerable disparities for racial and ethnic minorities in science, including securing funding opportunities and producing high-impact publications [Hoppe et al., 2019]. For instance, African-American applicants are 13 percentage points less likely to receive the U.S. NIH investigator-initiated research funding compared with whites, and Asian applicants experience a 4 percentage points lower funding rate [Ginther et al., 2011]. Individuals from minority ethnic groups also have less publication counts [Ginther et al., 2018, Willis, 2021] and job placements [Turner et al., 2008].

The established demographic disparity is detrimental to scientific progress, as research shows that groups composed of cognitively diverse individuals develop more effective approaches to solving complex problems relative to groups that are not cognitively diverse [Hong and Page, 2004]. The benefit of diversity in team performance has been empirically observed in many settings, including management [Dwyer et al., 2003], business [Herring, 2009], technology [Shachaf et al., 2008], health care [Cohen et al., 2002], education [Denson and Chang, 2009], and science [Campbell et al., 2013, Freeman and Huang, 2015, AlShebli et al., 2018]. In science in particular, studies have shown that both gender heterogeneity and ethnic diversity have a positive association with the quality and impact of science produced by collaborative scientists [Campbell et al., 2013, Freeman and Huang, 2015, AlShebli et al., 2018]. It is thus important to enhance the diversity of research workforce by identifying and eliminating individual and institutional barriers faced by minority scholars. Fulfilling such an endeavour requires first revealing the disparities systematically with both large scale data and rigorous scientific approaches.

1.2 Motivation

Scientific breakthroughs play a key role in the development of human society. For example, knowledge about human cell biology can help to create vaccines; technological innovations can help to stimulate economic growth; research on social inequality can help to improve modern democracy. Nowadays, nearly every country has established funding programs to support science. It is thus important to ensure that this system is working efficiently and unbiased in its production. If talented researchers are unable to publish papers effectively due to bias, it will result in less quality research being produced. Yet, the scientific workforce is hardly representative of the general population both at the global level or in a regional context (such as in the U.S) [Larivière et al., 2013, Kozlowski et al., 2022, Ginther et al., 2011, Hoppe et al., 2019]. Addressing the issue of underrepresentation requires examining inequalities in the whole scientific process.

Previous research revealed constant underrepresentation of women and ethnic minorities in conventional scientific outcomes such as publications [King, 2004, Way et al., 2016], citations [Larivière et al., 2013, Huang et al., 2020], and rewards [Holden, 2001, Ma et al., 2019]. However, this line of literature has mainly focused on examining disparities in science production such as gathering funding, publishing new findings, and getting the work cited in the scientific community. Fewer studies have investigated the dissemination stage as scientific knowledge reaches the general public through different online channels. Underrepresenting certain demographic groups and their science in online media could potentially have several negative consequences: (1) it undermines its ability to publicly disseminate new knowledge effectively, (2) it can affect the careers of minority scholars, (3) it can discourage minorities from pursuing academic careers and thus weaken the effort in recruiting diverse scientific workforces, (4) it can also lead to less research in areas that specifically affect these underrepresented groups, creating even more societal disparities downstream.

Besides a lack of systematic investigation of disparities in science dissemination, we also have limited understanding of the mechanisms behind these disparities in the whole scientific pipeline. Here, *we define mechanism as the causal process through which disparities are occurring*. One important causal factor of demographic disparities in science and other domains is simply bias that reflects demographic preferences conditioning on different groups having the same performance, which is often referred to as "taste-based" discrimination in the literature [Becker, 2010, Neumark, 2018]. However, disparities may or may not directly imply bias, as they can be due to "statistical discrimination" [Becker, 2010], which arises when decision-makers have imperfect information about individuals they interact with, and it can produce inequality even when decision-makers are rational and non-prejudiced because they may use demographic signals (e.g., ethnicity or gender) or other factors (e.g., institutional prestige) to make an inference of individual quality and/or performance [Tversky and Kahneman, 1974]. For instance, scientists of certain ethnicities may be quoted less often in science news because journalists may infer from scholars' ethnicity that their English speaking fluency is less fluent than others. Disparities can also be produced by non-discriminatory factors. For example, scientists of certain ethnicities may be quoted less often in science news because they and journalists are located in different time zones that presents difficulties in scheduling interviews. Disentangling different mechanisms is thus essential for designing effective policy interventions to restore equality in science as they involve different processes.

Science is becoming more complex than ever before, with millions of researchers from a variety of disciplines collaboratively producing an enormous amount of knowledge each year. Improving the equity of this system thus requires systematically examining different processes and actors involved in the scientific pipeline, including the publication of new findings in prestigious journals and their dissemination in online media.

The goal of this dissertation is to examine systemic ethnic and gender disparities in the production and dissemination of science and innovation and enrich our understandings of the mechanisms that lead to the disparities. We focus on three key activities in science production and dissemination: (1) publishing success at top academic journals, (2) author mentions in major science news, and (3) scholarly self-promotion behaviors on social media platforms. Revealing demographics disparities in these scientific activities and digging into their underlying mechanisms can inform appropriate policy interventions to address the current representation issues in science and ultimately promote innovations to further advance society. In this dissertation, we try to examine as many potential mechanisms as we can in each study. In some cases, we can find direct evidence to rule out certain mechanisms. In other cases, we are only able to find suggestive evidence to rule them in. We also demonstrate how computational methods can derive actionable insights through large-scale observational studies to influence policy interventions and improve equality in science.

Our goal has been made possible with the help of novel computational techniques and large-scale bibliometric data, including both publicly available datasets (e.g., the Microsoft Academic Graph [Sinha et al., 2015] and the Altmetric attention database [Altmetric, 2021a]) and private peer review data from leading academic journals. By linking the complete historical submission data to their post-publication records in the bibliometric database, we can conduct large-scale observational studies to examine demographic disparities with increasingly stringent controls such as author prestige and paper novelty that has been inaccessible in previous work. We then leverage state-of-the-art statistical models to precisely measure the magnitude of the disparities and forecast its change over time. The fine-grained nature of these data also enables us to pinpoint the actors (e.g., journal editors or peer reviewers) and processes (e.g., publishing stage or dissemination stage) where the disparity is produced, and dig into the potential mechanisms leading to it.

Leveraging large-scale observational data to study disparities in science production and dissemination presents many challenges. First, the data often do not contain scholars' self-reported identities (ethnicity and gender). To address this challenge, we use the perceived identity as the construct when appropriate in the studied evaluation context (e.g., when decision-makers also do not have access to scholars' self-identity) and infer it from authors' names with existing state-of-the-art algorithms with extensive validation. Second, large-scale bibliometric datasets are massive, but typically do not provide measures of important manuscript factors related to papers' quality. We address this challenge by leveraging quantitative measures developed in the literature such as paper novelty [Uzzi et al., 2013] and citation disruption [Wu et al., 2019]. Third, the publishing and dissemination process involves many steps with different decision-makers. Uncovering the causes behind demographic disparities in key scientific outcomes requires careful study designs to rule in/our different mechanisms, to which this dissertation aims to contribute.

This dissertation addresses these challenges through a combination of data-driven and computational techniques in data mining, statistical modeling, and natural language processing. We will leverage billion-scale academic graphs that index millions of research papers with comprehensive records of their authors, institutions, and citation metadata, coupled with the complete review data from top journals, and data about the media attention to these papers, to conduct massive observational studies of what drives publishing success and its dissemination in news media and social media. We will demonstrate how this computational social science approach can provide insights into unequal behaviors in science production and offer policy implications to reduce disparity.

1.3 Overview and Summary of Contributions

The overall structure of this thesis is as follows. In Chapter 2, we utilize the peer review data of tens of thousands of submissions to two major life sciences journals to examine the association between author ethnicity and acceptance rates. In Chapter 3, we leverage the media coverage of millions of research papers from hundreds of U.S. news outlets to study the ethnic disparity in author mentions. In Chapter 4, we perform a systematic analysis of self-promotion behaviours by millions of scholars to investigate gender differences in how often scientists self-advertise their research on Twitter. We summarize the main contributions below.

1.3.1 Acceptance in two major life sciences journals shows large disparities across name-inferred ethnicities

Research consistently finds that individuals from minority social groups are underrepresented throughout the scientific career pipeline [Valantine and Collins, 2015, Boekhout et al., 2021, Ley and Hamilton, 2008, Shen, 2013, Huang et al., 2020]. A key, if not the most important, scientific activity contributing to persistence in the pipeline is publishing papers, especially in prestigious academic journals [Xie, 2014, Allison and Long, 1987, Long et al., 1993, Niles et al., 2020].

In this chapter, we investigate the ethnic disparity in acceptance rates using the peer review data of 16.5K manuscripts submitted between 2013-2018 to a field-leading life sciences journal (called "Top Journal") and a middle-tier journal of similar scope (called "Middle Journal"). The editorial data are supplemented with the authors' name-inferred ethnicities and extensive controls including submissions' research topic, author prestige, novelty, and citation impact, even for rejected-and-published-elsewhere submissions.

We find that, relative to authors with British-origin names, authors with non-British-origin ethnicity names had significantly lower acceptance rates at both journals. For most groups, these disparities are mainly accounted for by author prestige, novelty, and future citation impact.

Nevertheless, holding constant future citations, novelty, and all other considered factors, *Top Journal* editors were about 7.1-8.1 percentage points less likely to send East Asian-authored (Chinese and non-Chinese) papers out for peer review and, holding constant reviewer enthusiasm and all other factors, 7.2 percentage points less likely to ultimately accept them post peer review (non-Chinese only). In contrast, *Top Journal* peer reviewers gave recommendations that were similar across all name-inferred ethnicities.

The findings suggest that understanding disparities in acceptance is key for understanding ethnic disparities in publishing. Our results reveal the important role played by the journal editorial process in producing considerable ethnic disparities in publication counts at top journals, and thus have implications for science policy at the journal level.

1.3.2 Author mentions in science news reveal widespread disparities across name-inferred ethnicities

Past studies on gender and ethnic bias in science have mainly focused on conventional outcomes such as faculty hiring, funding, publishing, and citations [Turner et al., 2008, Ginther et al., 2011, Ding et al., 2006, Huang et al., 2020]. Limited attention has been paid to the dissemination stage of science after the research has been published [Vasarhelyi et al., 2021]. Media outlets play a key role in spreading scientific knowledge to the general public and raising the profile of researchers among their peers. Yet journalists' choices of which researchers to credit and mention when reporting a research paper are poorly understood.

In this chapter, we use a comprehensive dataset of 223,587 news stories from 288 U.S.-based outlets covering 100,486 research papers across all areas of science to investigate the rates at which scientists of these covered papers are mentioned or quoted in the stories about their work as a function of the perception of their ethnicity. Featuring less often scientists from certain groups can affect public perception about who is a scientist and ultimately weaken the pipeline of recruiting and training new scientists.

We find substantial disparities in mention rates across names associated with particular ethnicities, despite accounting for a wide range of possible confounding factors. Authors with non-British-origin names, especially those with East Asian and African names, are significantly less likely to be mentioned in stories of their own research than those with British-origin names, even when controlling for stories of a particular news outlet covering a particular scientific venue on a particular research topic. The disparities are explained in part by authors' locations, suggesting that pragmatic factors like difficulties in scheduling interviews play a role. Furthermore, among U.S.-based authors, journalists more often use authors' institutions instead of names when referring to non-British-named authors, suggesting that journalists' rhetorical choices are key.

Overall, multiple causes generate substantial disparities across ethnicity-associated names in researchers' media attention, and these disparities have likely affected thousands of scholars. These ethnic disparities likely have negative consequences for the careers of unmentioned scientists, and skew the public perception of who a scientist is—a key factor in recruiting and training new scientists. Our findings have practical implications for science policy and science journalism.

1.3.3 The gender gap in scholarly self-promotion on social media

Inequality in science dissemination can happen on platforms besides news media (such as social media) and in other types of propagation (such as self-promotion by scientists themselves). Highlighting personal achievements is important for professional success in science and innovation. Yet, there are limited studies of gender differences in scholarly self-promotion on social media and the returns scientists get from it.

In this chapter, we leverage 45M Tweet mentions of 539K research papers published in 2018 by 1.3M authors to examine gender differences in scholarly self-promotion. Our analysis shows that female authors are significantly less likely than male authors to promote their own papers, even after controlling for a number of important factors including journal impact, affiliation prestige and location, author productivity, authorship position, and research topics. The magnitude of the gender gap is largely explained by papers' journal impact, rather than by authors' affiliation prestige, their previous productivity, or academic discipline. In relative terms, the gender gap is the largest among junior researchers from lower-ranking institutions who publish papers in higher impact journals. Although women self-promote less often overall, when they do, their papers receive slightly more mentions. Our findings offer the first large-scale evidence for the gender gap in scholarly self-promotion and ultimately they inform science policy aimed at closing the gender gap in visibility and recognition.

CHAPTER 2

Acceptance in Two Major Life Sciences Journals Shows Large Disparities Across Name-Inferred Ethnicities

2.1 Introduction

Research consistently finds that individuals from minority social groups are underrepresented throughout the scientific career pipeline [Valantine and Collins, 2015, Boekhout et al., 2021, Ley and Hamilton, 2008, Shen, 2013, Huang et al., 2020]. The ubiquitous phrase "publish or perish" vividly summarizes that a key, if not most important, scientific activity contributing to persistence in the pipeline is publishing papers, especially in prestigious academic journals [Xie, 2014, Allison and Long, 1987, Long et al., 1993, Niles et al., 2020]. Understanding disparities in publishing is thus important for understanding broader social inequalities in science.

Across fields, different ethnic groups publish at different rates [Ginther et al., 2018, Willis, 2021, King, 2004]. These disparities in publication counts may be related to disparities in the production of manuscripts or getting them accepted. Distinguishing between the mechanisms is important because they entail different institutions and actors and, consequently, different policy interventions, but is difficult to do with publicly available data. Here, we examine the latter mechanism, the manuscript review process, using large-scale data from two top journals in life sciences.

Disparities across social groups in review may arise through a variety of merit-based and other mechanisms. Manuscript review and selection typically involves several individuals, specifically editors and peer reviewers. The fundamental premise, or aspiration, of this system is that these individuals assess research based on its intellectual merit, regardless of authors' social identities [Merton, 1996, Lee et al., 2013]. If journals' evaluation processes live up to this aspiration, then ethnic disparities in publishing outcomes may be the result of disparities in merit. However, these disparities in merit may be caused by a variety of factors upstream in the research process [Long and Fox, 1995]. One important factor is the institution, which is likely to be associated with ethnicity globally. Research shows that scientists' academic environments affect their productivity, above and beyond their individual capabilities [Way et al., 2019, Allison and Long, 1990, Deville et al., 2014, Fox and Mohapatra, 2007]. Ethnic sorting into institutions may thus affect the merit of manuscripts sent for review. In addition, prior work has identified disparities, particularly by gender, in obtaining resources such as funding and mentorship that are also likely to affect manuscript merit [Moss-Racusin et al., 2012, Ginther et al., 2011, Oliveira et al., 2019]. These literature shows that upstream factors, including institutions and funding, may contribute to ethnic disparities in merit, without implying ethnic bias on the part of editors and reviewers downstream.

Disparities in publishing may also arise through non-merit mechanisms. First, evaluators may be directly biased, perhaps implicitly, against particular social groups. Second, they may be biased indirectly, through bias in favor of prestigious institutions [Tomkins et al., 2017], which may be associated with ethnicity. Third, evaluators may rely on stereotypes. Evaluating the merit of complex ideas is difficult, and has arguably become only more so over time [Jones, 2009]. The expertise needed to evaluate scientific papers is increasingly beyond the grasp of any specific individual [Wuchty et al., 2007, Jones et al., 2008]. Consequently, decision-makers may try to facilitate evaluations by substituting costly-to-acquire but direct knowledge of manuscript content with "cheap" inferences made via stereotypes [Tversky and Kahneman, 1974, Gigerenzer and Todd, 1999, Bingham and Eisenhardt, 2011], such as inferring from authors' names and locations their expertise, resource availability, or other factors related to manuscript quality [Knobloch-Westerwick et al., 2013]. In principle, such inferences may be valid on average. For example, recent research finds associations between innovators' demographic characteristics and the types of innovation they pursue [Nielsen et al., 2017, Hoppe et al., 2019, Koning et al., 2021]. If the inferences are valid, they may not result in acceptance disparities across demographic groups, but may lock-in existing inequalities [Correll and Ridgeway, 2006], normalize discrimination [Tilcsik, 2020], and penalize (or reward) individuals who do not fit their group's average tendency.

However, stereotypes may be faulty. For example, they may indicate the past but fail to properly reflect the present in a quickly changing environment. In this case, disparities in acceptance conditional on merit may appear across demographic groups with negative stereotypes. In practice, evaluations using faulty stereotypes can create double standards across groups [Foschi, 2000]. Specifically, if a disfavored group of submitting authors faces lower expectations of quality, their actual quality will need to be unusually high to overcome the expectations. Double standards may thus manifest empirically in lower acceptance rates for disfavored groups conditional on merit, but higher merit conditional on acceptance [Card et al., 2020].

Additionally, editors may also use criteria loosely related to merit, for example, discriminating on research topics in order to achieve a particular portfolio of publications. If demographic characteristics are associated with topics, disparities may appear without bias *per se*. Overall, disparities in acceptance may or may not indicate bias on the part of editors and reviewers, and it is important to consider a variety of mechanisms when interpreting disparities.

There is a lack of systematic evidence on ethnic disparities in review and the mechanisms driving them. Much of the related research investigates disparities related to gender, location, social connections, and prestige [Helmer et al., 2017, Card et al., 2020, Day et al., 2020, Link, 1998, Ross et al., 2006, Okike et al., 2016, Tomkins et al., 2017, Teplitskiy et al., 2018, Lee et al., 2013]. Some studies suggest that women and underrepresented minorities face discrimination in perceptions of quality, obtaining research grants, and recognition for novel contributions [Ginther et al., 2011, Hoppe et al., 2019, Hofstra et al., 2020, Witteman et al., 2019, Knobloch-Westerwick et al., 2013]. However, these findings of discrimination are far from unequivocal, as some recent audit experiments find little evidence of gender or race discrimination [Williams and Ceci, 2015, Forscher et al., 2019, Carlsson et al., 2021].

The applicability of extant research to ethnic disparities in publishing has three limitations. First, many existing studies examine relatively quick and low-stakes evaluations, such as in responding to emails. In contrast, publishing involves time-consuming evaluations conducted by experienced and well-incentivized evaluators. Second, past research typically focuses on science in the U.S. and other Western countries. Yet scientific research is increasingly global [Witze, 2016], with China now producing the most papers of any nation [Tollefson, 2018], while the reviewers and editors of major journals, are often based in the West [Elsevier]. It is thus important to study publishing inequalities among ethnic groups from a global perspective. Third, many prior studies focus on the early part of research—obtaining funding. Evaluating applicants is generally a formal part of funding competitions [Witteman et al., 2019], so it is possible, and maybe even likely, that applicants' ethnic or other social identities affect evaluations. In contrast, authors' identities should in principle play no role once the research is complete and submitted for publication. To our knowledge, there have been no studies of global ethnic disparities in acceptance in prestigious journals. This is the gap our study aims to fill.

We partnered with the editors of two major journals in the life sciences (see Data and Methods for details), which we call *Top Journal* and *Middle Journal* to ensure anonymity. The journals provided us the review files of all submissions between 2013-2018. *Top Journal* is field-leading while *Middle Journal* is middle-tier. Some descriptive statistics of these data, such as impact factors, may be identifying and are therefore omitted (both journals are in the top quartile of life sciences journals by impact factor). Both journals use nearly identical review procedures, and particularly single-blind review—authors' identities are visible to editors and reviewers.

We measured authors' *perceived* ethnicity and gender algorithmically, using their first and last names with the classifier *Ethnea* [Torvik and Agarwal, 2016](Data and Methods). We call this name-inferred ethnicity "perceived" to distinguish it from authors' self-identifications, which are at the present rarely collected by publishers [Wu, 2020]. We adopt the term "ethnicity" instead of "nationality" because decision-makers in our data can directly observe the national location of authors' institutions, so "ethnicity" reflects the richer set of characteristics decision-makers can infer from names above and beyond location. Using ethnicities determined via algorithms has several important limitations [Kozlowski et al., 2021] (discussed in Data and Methods). However, lacking detailed data on authors' self-identities, reviewers and editors may themselves make inferences similar to those of the algorithm. Overall, the findings should be interpreted as only suggestive of associations between ethnic self-identities and publishing success, a point we return to in the discussion.

Although most submissions were authored by several individuals, we assigned the perceived ethnicity and gender to each manuscript based on the name of its last author, given the tendency in biology for the last author to be seen as inspiring, funding, and managing the research [Wren et al., 2007, Ginther et al., 2011, Sekara et al., 2018]. We placed authors into 9 broad ethnic categories based on geographic regions (Data and Methods and *Appendix* Table A.1) and the submission volume the journals receive from those groups.

Submissions rejected and published elsewhere were identified via literature searches by a third-party contractor. We used the Microsoft Academic Graph (MAG) bibliometric database to supplement the editorial data with key covariates, including author prestige, manuscript topics, and other important factors (Data and Methods).

To better understand the mechanisms driving acceptance, it is crucial to account for submissions' underlying quality [Long and Fox, 1995]. Scholars typically quantify quality using peer reviewer recommendations and/or citations [Card et al., 2020], both of which present challenges. On the one hand, both journals desk reject a large fraction of submissions, leading to missing reviewer recommendations. On the other hand, a sizeable fraction of papers are rejected and never published or published in a much altered form[1], leading to missing citations for the original submission. Even when citations are available, there are long-standing concerns that they are confounded by a number of factors unrelated or only marginally related to quality [Waltman, 2016]. Some of the most important confounders, such as papers' language and topic, should play relatively small roles in our setting: we study English-language submissions in the life sciences, and control for topic with an extensive set of keywords.

We use both citation impact and reviewer recommendations, where possible, and supplement them with a measure of novelty. We measure two aspects of citation impact: impact *amount* is quantified as citation counts, and impact *disruption* is quantified by how much a paper replaces its predecessors in the eyes of future citers [Wu et al., 2019]. We measure the novelty of manuscripts

[1]This issue can occur for both desk-rejected submissions and submissions that are rejected after peer review, with the latter case being less likely as submissions sent out for review tend to be of higher quality.

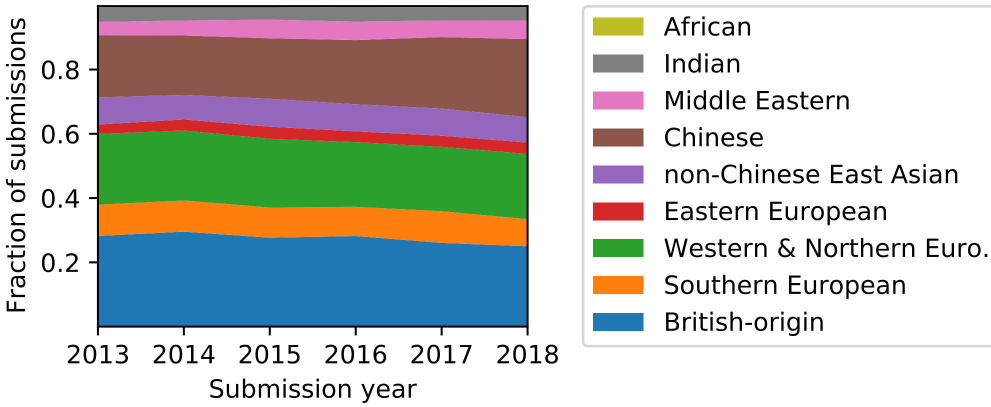

Figure 2.1: **Statistics of *Top Journal* submission data.** The yearly percentage of submissions from each ethnicity between 2013 and 2018. Note that African-named percentages are invisible due to a relatively small number of submissions. Raw submission counts per year and final acceptance rates per ethnic group are not shown to protect journal anonymity.

using atypical combinations of cited journals in a paper's reference list [Uzzi et al., 2013].

Despite these measures, the research design introduces a selection bias due to unpublished papers. To mitigate this bias, we separately examine disparities in the final-review stage, referred to as "post review", in which editors make decisions on the set of papers receiving reviews. Having gone through desk and peer review, this stage is less representative of the full submission pool, but it suffers less from selection bias as most submissions of this quality are eventually published in the literature. Crucially, this stage enables us to tightly control for paper quality using reviewer recommendations, citation impact, and novelty.

2.2 Disparities in Publishing Success

2.2.1 Submissions over time

We focused on *Top Journal* for this analysis due to its more complete submissions data relative to *Middle Journal*. Among all 17,433 submissions to *Top Journal*, 27.3% were from British-origin authors; 20.9% were Western & Northern European; 20.7% were Chinese; 9.4% were Southern European; 8.3% were non-Chinese East Asian; the remaining 13.1% were from Middle Eastern, Indian, Eastern European, and African authors. 0.4% submissions were labeled as "Unknown Ethnicity". The relatively small number of observations for African authors (N $<$ 50) prevented us from reaching robust conclusions, and these observations were excluded in the subsequent analysis.

Fig. 2.1 shows the perceived-ethnicity composition of submitting authors and its change over time. The raw submission count (not shown here) from Chinese authors, the third largest group, increased by about half from 2013 to 2018. By the year 2018, the number of Chinese submissions was comparable to British-origin submissions. The number of submissions from other ethnicities, including the British-origin, remained relatively stable over time.

2.2.2 Disparities in acceptance

We examined the association between author ethnicity and acceptance rates through five increasingly parameterized logistic regression models, with an indicator variable (1=Accepted, 0=Rejected) as the outcome (see *Appendix* Table A.2 and *Appendix* Table A.3 for model coefficients). For each model, we calculated the average marginal effects (AMEs) of perceived ethnicities on the probability of being accepted, with British-origin ethnicity as the reference category. The AME for a particular ethnicity reflects the difference (averaged over all observations) in the acceptance probability compared to British-origin names, holding other variables constant.

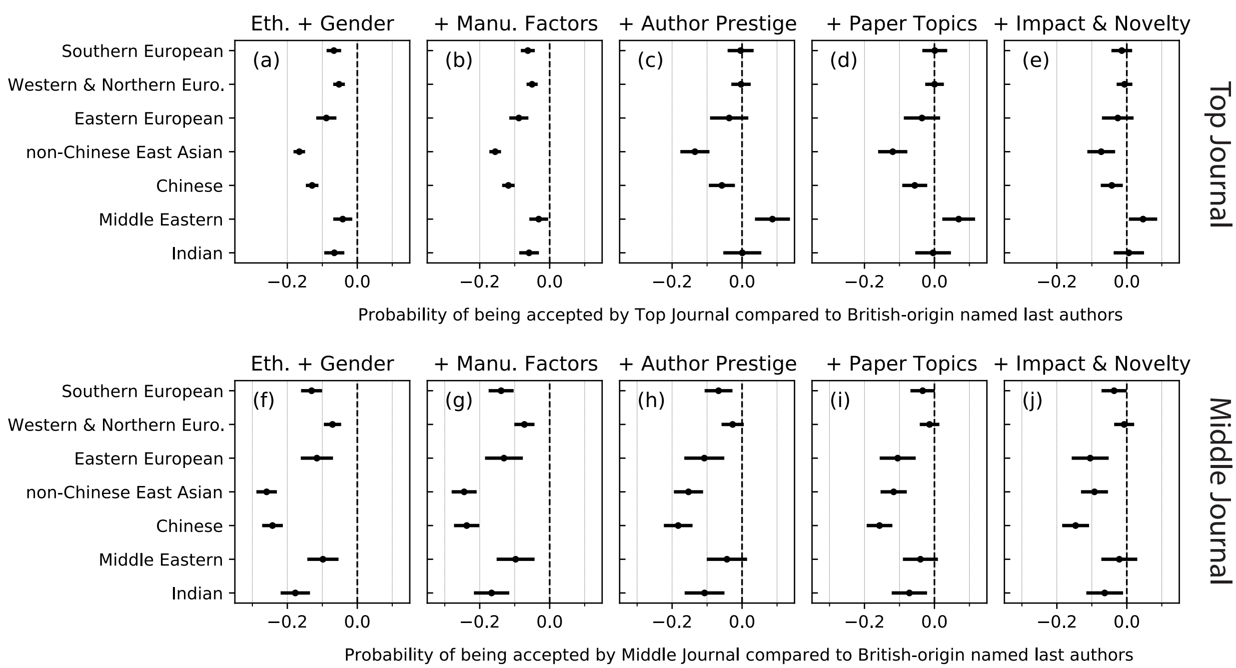

Figure 2.2: **The average marginal effects of last author's ethnicity on the final acceptance rate. a-e**, For submissions at *Top Journal*. **a**, Model 1 includes only authors' perceived ethnicity and gender (16,956 observations due to missing final acceptance for 477 submissions). **b**, Model 2 adds manuscript factors (16,954 observations). **c**, Model 3 adds author prestige (7,062 observations). **d**, Model 4 adds paper topics (7,062 observations). **e**, Model 5 adds log citations, citation disruption, and novelty (6,947 observations). **f-j**, For submissions at *Middle Journal*, there are 14269, 8874, 7195, 7195, and 6365 observations in Models 1-5, respectively. Error bars indicate 95% bootstrapped confidence intervals.

Focusing first on *Top Journal*, Model 1 reflects raw differences in success rates by last authors' perceived ethnicity and gender. The rates reveal that submissions from all non-British-origin ethnicity authors were significantly less likely to be accepted compared to British-origin-named authors. The magnitude of the disparities (Fig. 2.2a) varies across groups: European- and Asian-named authors experience 5 and 15 percentage points lower acceptance, respectively. Model 2 shows that the magnitude of disparities is substantively similar after controlling for manuscript factors including submission year, the number of authors, title and abstract length, and abstract readability (Data and Methods). While all these factors are associated with acceptance (*Appendix* Table A.2 and *Appendix* Table A.3), they had limited influence on the magnitude of ethnic disparities. For example, compared to Model 1, there is only 1 percentage point drop in the acceptance gap for three Asian ethnicities (Fig. 2.2b).

Model 3 adds factors related to author prestige and productivity, including last author's rank, number of previous publications, and affiliation rank and location (U.S.-based or International; see Data and Methods). Adding author prestige factors makes the acceptance rates for European and Indian authors no longer significantly different from British-origin authors. The disparities for the two East Asian groups decrease by about 4.5 percentage points (Fig. 2.2c). The acceptance probability for Middle Eastern-named authors was even higher than that for British-origin after controlling for prestige. In other words, at similar prestige levels, Middle Eastern authors were accepted even more often than British-origin authors.

Adding controls for paper topics in Model 4, we find that the marginal effects change little, although the disparity for non-Chinese East Asian authors drops an additional 1.6 percentage points (Fig. 2.2d). This suggests that the topics that authors work on either did not vary systematically by ethnicity or did not vary in how much they were favored by editors and reviewers.

Finally, Model 5 controls for paper novelty and citation impact. The disparities for East Asian authors further decrease by 1.3-4.7 percentage points. Nevertheless, even in this extensively controlled model, compared to British-origin-named authors, the acceptance rates for the two East Asian-named authors were 4.3 and 7.3 percentage points lower (Fig. 2.2e).

In summary, observable characteristics of the submissions account for many, but not all, of the disparities across perceived ethnicities. For European and Indian authors, disparities are not statistically different from 0 when accounting for factors related to author and affiliation prestige. Middle Eastern authors' disparity is accounted for by the combination of author prestige and paper quality. However, while accounting for these characteristics substantially decreases the magnitude of acceptance disparities for East Asian authors, measurable disparities nevertheless remain.

Repeating this analysis for *Middle Journal* (Fig. 2.2f-j) shows even larger disparities for East Asian-named authors compared to *Top Journal* (4.3 vs. 14.6 for Chinese and 7.3 vs. 9.2 for non-Chinese East Asian). Additionally, the disparities for Indian- and Eastern European-named authors are now larger and statistically significant. These results raise the possibility that ethnic disparities increases as one moves down the journal status hierarchy, although we cannot rule out differences in unmeasured manuscript and reviewer characteristics. For example, it is possible that editors appear to "require" above-average reviewer enthusiasm for non-Chinese East Asian submissions because of a desire to achieve a particular portfolio of fine-grained topics, which our coarse-grained measures control for imperfectly.

We also controlled for author gender in the five regression models. Although our focus is ethnicity, we briefly discuss the association between gender and acceptance. Submissions from female authors had 1.6 percentage point lower acceptance rate compared to those from male authors based on Model 1. However, this gap disappears after controlling for manuscript factors such as the submission year, number of authors, and title and abstract characteristics (*Appendix* Table A.2 and *Appendix* Table A.3). The observed raw gender disparity is likely to be driven by non-East Asian ethnicities since their names usually do not clearly signal gender and are mostly classified as "Unknown" in our data.

2.2.3 The role of location and writing fluency

The full model (Model 5) shown in Fig. 2.2 controls for the location of last author's affiliation (U.S.-based or International), and indicates that international submissions were significantly less likely than U.S. ones to be accepted (*Appendix* Table A.2 and *Appendix* Table A.3). This association corroborates other studies which find that manuscripts from relatively wealthy countries such as the United States are evaluated more favorably than those from poorer countries [Link, 1998, Ross et al., 2006, Harris et al., 2015, 2017]. However, the fact that disparities for East Asian-named authors appear despite controlling for location suggests that location drives only part of the disparities.

We thus further examine whether location impacts the magnitude of disparities between British-origin and non-British-origin authors. In particular, editors and reviewers of the two journals we study may be more familiar with U.S.-based authors and their affiliations. Greater direct knowledge of authors and institutions may reduce reliance on indirect but easily-observable cues like ethnicities. Moreover, submissions from different ethnic groups may vary in the quality of writing, *i.e.*, papers written by non-native English speakers may be more difficult for editors and reviewers to assess and cause lower evaluations [Politzer-Ahles et al., 2020]. We expect differences in writing quality to be relatively small among U.S.-based authors[2], and consequently, hypothesized that perceived ethnicity would be associated with acceptance less strongly among these authors. To test this hypothesis, we fitted a Model 5 separately to submissions from U.S.-based and international authors.

[2]While U.S.-based authors may differ greatly in oral communication, we expect differences in academic *writing* among last authors, who tend to be the more senior and published researchers, to be smaller.

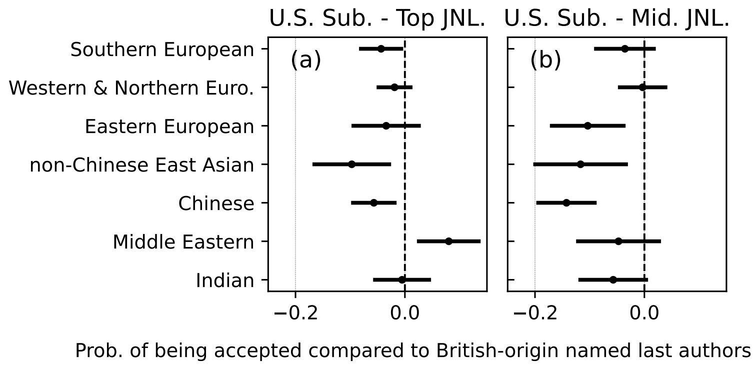

Figure 2.3: **The average marginal effects of ethnicity on the acceptance for U.S. submissions.** The specifications of Model 5 was fitted to U.S. submissions for each journal. **a**, Based on 4,075 U.S. submissions at *Top Journal*. **b**, Based on 2,812 U.S. submissions at *Middle Journal*. Note that these submissions were all *published* in the literature as Model 5 includes variables such as citation-based impact that are only available for published papers. Error bars indicate 95% bootstrapped confidence intervals.

The average marginal effects in Fig. 2.3 indicate that submissions from U.S.-based East Asian authors had 5.7-9.7 percentage points lower acceptance rates than their British-origin counterparts at *Top Journal*, and about 11.7-14.2 percentage points lower at *Middle Journal*.

For *Top Journal*, the ethnic disparity coefficients are significant for East Asian authors in the U.S. subset (*Appendix* Table A.4), and are negative but imprecisely estimated and not statistically significant in the international subset. However, the coefficients of East Asian disparities in the two separate regressions are not statistically different from each other, suggesting that international East Asian authors likely had lower acceptance rates than international British-origin named authors. This is also confirmed by including interactions between ethnicity and location in Model 5 in the full data, as no interaction terms have a statistically significant negative effect. We observed a more clear pattern at *Middle Journal*, as the ethnicity coefficients for the U.S. subset and the international subset are both significantly different from 0, and are not statistically different from each other for East Asian-named authors (*Appendix* Table A.4).

Overall, the subgroup analyses show that the disparities among U.S.-based submitters are similar to that among international submitters, suggesting that, although being affiliated with a U.S. institution increases the overall acceptance rate for all ethnicities, it is unlikely to mitigate much of the disparities between non-British-origin and British-origin authors. Furthermore, the disparities among U.S.-based last authors indicate that factors beyond writing fluency is driving the observed disparities in acceptance, especially given that our full model controls for writing fluency through abstract readability and authors' previous publishing success at both journals, which to some extent reflects authors' writing skills in English.

2.3 Locating Disparities in the Evaluation Pipeline

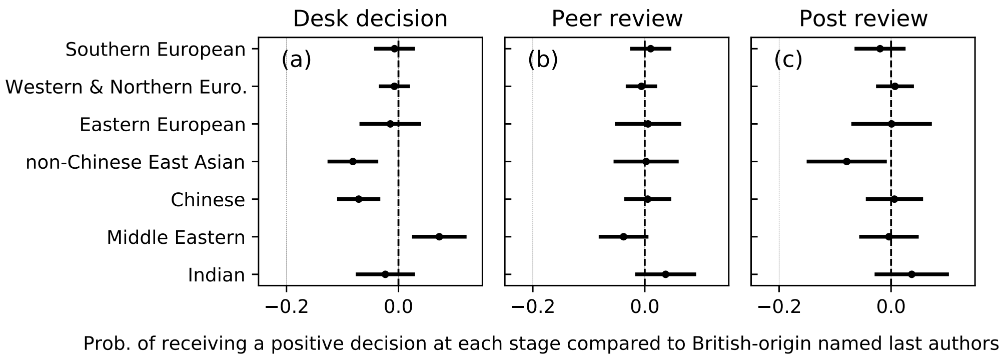

Figure 2.4: **The average marginal effects of ethnicity for three review stages at *Top Journal*.** The marginal estimations are based on a Model 5 estimated on ultimately-published submissions. **a**, Each submission is an observation for the desk-decision stage. 3,331 out of 6,972 observations (47.8%) were not desk-rejected. **b**, For the peer-review stage, we focused on the first round of review for each manuscript. Each (submission, reviewer) pair is an observation in the regression. 5,399 out of 9,077 observations (59.5%) received a positive recommendation (Revision or Accept) at this stage. Reviewer random effects are included in the model. **c**, We used the first round of each submission as an observation in the post-review stage. 2,217 out of 3,294 observations (67.3%) received a positive editorial decision (not being rejected) after the first round of peer review. The model for this stage also controls for the average reviewer recommendation score. Error bars indicate 95% bootstrapped confidence intervals.

Manuscript evaluation usually involves a number of steps and decision-makers, so it is not clear from the overall acceptance patterns where in the pipeline the disparities arise. Here, we take advantage of fine-grained data from each step of the evaluation pipeline at *Top Journal* to better locate the source of the disparities.

At both journals, manuscripts proceed through (1) desk decision and, if sent out for review, (2) external peer review and (3) post-peer review decision. Whereas the first and the third steps involve editors, the second step entails external peer reviewers. Each stage may contribute differently to ethnic disparities in the final acceptance rates. To examine the contributions, we relied on the more complete submission data from *Top Journal* and fitted a separate regression Model 5 using data from each stage. Since our full model controls for paper citation impact, which is only available for published papers, we focused on submissions that were eventually published *somewhere* and successfully located in the literature.

2.3.1 Desk-decision stage

Top Journal desk-rejects a substantial fraction of the submissions. To model desk rejection as a function of last author perceived ethnicity and other submission characteristics, we fitted a logistic regression model (Model 5) with an indicator variable desk-rejected (coded as 0) or not (coded as 1) as the outcome.

Fig. 2.4a shows that manuscripts from East Asian-named authors (Chinese and non-Chinese) had 7.1-8.1 percentage points lower probability to be sent out for review than those from British-origin-named authors, keeping all other variables constant. The model reveals no statistically significant disparities for European and Indian authors. However, Middle Eastern-named authors were favored by 7.3 percentage points at this stage.

2.3.2 Peer-review stage

For the peer-review stage, we considered only submissions that were sent out for external review. A manuscript can have several rounds of reviews. To ensure the independence of reviewer recommendations, we used only the first round of reviews for each submission, as reviewers are typically informed of other referees' comments after the first round.

We defined the indicator variable "Accept or R&R" as 1 if the reviewer gave a positive recommendation, including "Minor revision", "Major revision", and "Accept" ("Accept" constitutes only 3.1% of the recommendations). Negative recommendations such as "Reject" were coded as 0. To account for differences in reviewers' overall tendency to make positive recommendations, we included in Model 5 random effects for each reviewer (while our data do not include reviewers' identities, they include anonymized reviewer IDs).

Fig. 2.4b shows that peer reviewers do not appear to have any systematic preference for or against authors of any perceived ethnicity. A plausible interpretation is that reviewers did not use ethnicity as a heuristic, perhaps due to likely longer and more intensive evaluation compared to that of editors at the desk-review stage. Alternately, peer reviewers may have evaluated manuscripts on criteria orthogonal to that of editors.

2.3.3 Post-review stage

After each round of peer review, the editor selects a decision ("Accept", "Minor Revison", "Major Revision", or "Reject") based on reviewers' recommendations. We focused on the first round of review, due to decisions in subsequent rounds (where those exist) being likely highly correlated with the first decision. The dependent variable is the editorial decision for the first round, coded as 0 if it ended with a "Reject" decision and 1 if it led to another round of review or "Accept." We included in the regression a variable that we call "reviewer enthusiasm," defined as the reviewer recommendation (0 or 1, defined above) averaged across all reviewers.

Fig. 2.4c shows that, similar to the desk-review stage, manuscripts from non-Chinese East Asian authors had 7.2 percentage points lower positive rate in the post-review decisions, despite conditioning on reviewer enthusiasm, novelty, citation impact, and other observable characteristics. Given that the overall positive rate is 67.3% in the data sample at this stage, the observed disparity is *relatively* small, compared to the desk-decision stage (Fig. 2.4a). The disparities observed at this final or near-final stage indicate that editors exercised additional filtering after peer review, and this filtering resulted in the additional ethnic disparity for non-Chinese East Asian authors.

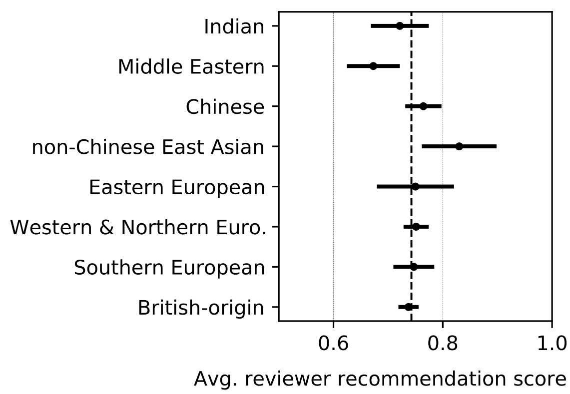

Figure 2.5: **The average reviewer recommendation score for *accepted papers* at *Top Journal*.** The calculation is based on the first round of review for each submission. Reviewers' recommendations were coded as "Accept or R&R"=1, and otherwise=0. The dashed vertical line is the mean score of all accepted papers. Non-Chinese East Asian papers have a statistically higher average score than that of British-origin ones (0.83 vs. 0.74, $p = 0.008$). Error bars indicate 95% confidence intervals.

If these disparities reflect editors' bias, it is likely manifested in holding non-British-named authors to a higher standard. The key empirical signature of such double standards is that the discriminated groups that are able to meet the higher bar are, on average, of higher quality than favored groups. To test for the double standards hypothesis, we again used the reviewer enthusiasm as a measure of paper quality. We compared the average reviewer enthusiasm for papers *accepted* at *Top Journal* (using only the first round of review). As predicted, Fig. 2.5 shows that non-Chinese East Asian accepted papers have on average higher reviewer enthusiasm than British-origin accepted ones (0.83 vs. 0.74, $p = 0.008$). Published Chinese-named papers have higher reviewer enthusiasm than British-origin ones (0.764 vs. 0.737, $p = 0.089$), but the difference is imprecisely estimated and not statistically significant at the conventional level.

2.4 Discussion

2.4.1 Disparities in publishing success across perceived ethnicities

Understanding disparities in publishing in top journals is crucial for understanding broader inequality in science, yet the evaluation processes leading to publication, particularly by the most prestigious journals, are very often opaque. Here, we leveraged large-scale review data from a field-leading and a middle-tier life sciences journal with similar scope and near-identical evaluation process, to examine disparities in acceptance by last author ethnicity, inferred from the author's name.

The findings show that the large disparities in publishing in these journals is not simply the result of disparities in the volume of manuscripts different ethnic groups produce. Instead, the review process is a major contributor to these disparities. In raw terms, acceptance rates for all non-British-origin ethnicity names are lower than that of British-origin ones, who have an acceptance rate that is nearly 20 percentage points higher than that of the lowest-accepted group (Fig. 2.2). These raw differences may be caused by a number of factors other than bias, such as paper quality and topic. Indeed, manuscript factors (submission year, number of authors, title and abstract length, and abstract readability), author prestige (such as author rank, affiliation rank and location, prior publications at two journals), paper topics, and paper novelty and impact all had strong associations with acceptance (*Appendix* Table A.2 and *Appendix* Table A.3).

Adding these various factors to increasingly parameterized regressions showed that disparities for European-, Indian-, and Middle Eastern-named authors are accounted for by author prestige. Whether this pattern reflects a prestige bias [Tomkins et al., 2017, Lee et al., 2013] is unclear, because author prestige may be correlated with papers' merit or journal fit.

However, all these measured factors, including paper topic, novelty, and impact, do not fully account for the lower acceptance rates of East Asian authors: net of these factors, their submissions had 6 and 12 percentage points lower acceptance rates than those from British-origin authors at *Top Journal* and *Middle Journal*, respectively (Fig. 2.2). These disparities appear even among U.S.-based authors after controlling for their previous publishing success, making it unlikely that differences in English writing are the key driver of acceptance gaps. Indeed, the disparities among U.S.-based authors were of similar magnitude to that among international authors, especially at *Middle Journal* (Fig. 2.3 and *Appendix* Table A.5).

The practical significance of these disparities is very substantial. Across fields, top journals have acceptance rates as low as single digits percentage-wise. Consequently, a 6 percentage points acceptance reduction from an already small rate implies that publication is extremely improbable for all but a few submitters.

2.4.2 Mechanisms

The detailed data from *Top Journal* enabled us to locate the source of these disparities in the evaluation pipeline. Disparities for East Asian-named authors occurred mainly at the desk-review and final review stages. Crucially, we find no systematic ethnic disparities in peer reviewers' recommendations. This finding makes less likely that the analysis is afflicted by measurement error and omitted variable bias. Specifically, a classic concern with our research design is that an important confound differs across name-inferred ethnic groups, but is unmeasured or measured with error. Such errors, if present, should affect both editors' and reviewers' decisions, but this is not observed. This finding also shifts focus to editors as the key decision-makers in understanding the disparities, especially given that disparities are seen in the post-review stage, but not in the peer-review stage where editors and reviewers evaluate the same set of submissions.

The analysis does not, however, imply bias by editors of both journals, as the results are consistent with other mechanisms as well. First, editors' decisions at the desk may have filtered out the weakest submissions, leaving reviewers to assess a relatively homogeneous pool. Second, disparities in editors' decisions at the post-review stage do not provide an unequivocal interpretation. The magnitude of the disparities was smaller and statistically significant only for one group. However, post review involves manuscripts pre-selected to be relatively homogeneous, so the disparities in acceptance among them may understate disparities in the more heterogeneous original submission pool. More data are needed to increase certainty. Third, editors at *Top Journal* may assess manuscripts on different dimensions than peer reviewers, *e.g.*, on topical fit to the journal, and these editor-valued characteristics may be associated with perceived ethnicities *but* not captured by our topical variables. Another candidate mechanism is that some ethnic groups submit their papers when they are less polished than the submissions of others, resulting in lower acceptance. However, since our analysis relies on the *published* versions of the papers, potential differences in polish are unmeasured. Lastly, research in decision-making consistently shows that biases can arise when cognitively challenging evaluation are hurried, resulting in evaluators leaning on heuristics [Bodenhausen and Wyer, 1985, Bohnet et al., 2016]. If this mechanism was indeed operative, a natural intervention is to enable editors to evaluate slower. This mechanism may also explain why the disparities appear at the desk-reject stage (faster decision) but not the peer-review stage (slower decision).

2.4.3 Limitations and directions for future research

Our study has a number of limitations, which we believe are fruitful directions for future research. First, our data do not include self-reported author ethnicity. This limitation is especially problematic in cases where the author-identified ethnicity is known to evaluators and is different from that perceived from author names, i.e., as inferred by the algorithm or naive observer. Furthermore, we did not address multi-ethnic identities or key racial/ethnic groups, such as African American. Second, some ethnicities, such as Caribbean, Polynesian, and African had too few submissions to enable robust statistical comparison, and thus were excluded in the analysis and interpretation. Third, the research design we employed is not suitable for gold-standard causal claims. Consequently, we cannot rule out that the observed disparities were driven by some unmeasured differences between the submissions. We hope our research stimulates experimental studies that are better suited for establishing causality. Fourth, we focused on submissions that were eventually published in order to control for key confounding factors, such as papers' novelty and impact. This choice excluded a large fraction of rejected submissions that were never published. However, these missing data may under-estimate the actual disparities as non-British groups have more of these missing rejections (cf. Fig. 2.2a vs. Fig. 2.2e), and it should not affect conclusions on the set of submissions with valid citations data. Furthermore, our analyses of the peer-review stage and post-review stage suffer less from this selection bias as submissions went this far are most likely published eventually and therefore included in the analysis. In addition, we have several analyses that have no selection bias, such as the average reviewer recommendation score for accepted papers at *Top Journal* (Fig. 2.5).

Fifth, many controls such as paper topics and novelty scores were based on the published version of a manuscript, which might be different from its submitted version [Goodman et al., 1994]. Nonetheless, a related study using the same data shows that there is a high correlation between the submitted novelty and the published novelty [Teplitskiy et al., 2021]. Sixth, the analyses revealed that the ethnic disparities were larger at *Middle Journal* than at *Top Journal*, despite similar topical scope and nearly identical reviewing procedures. This difference deserves further investigation, ideally across journals using very different review processes and in different domains, which would also aid in generalizability. One possibility relates to the different article processing charges assessed by the two journals: the larger charge by *Top Journal* may attract a more homogeneous set of submitters. Seventh, we focused on the ethnicity of the last author, but team composition and acceptance patterns deserve direct analysis. Eighth, we used citation impact to measure one dimension of quality. Yet citations may be biased across demographic groups [Hengel, 2017]. As a preliminary check of this possibility, we investigated whether papers by different perceived ethnicities receive similar citations conditional on acceptance and controlling for reviewer recommendations (*Appendix* Section A.1.1). The analysis suggests that if there is citation bias, it likely makes our results conservative.

Despite these limitations, our study sheds light on the selection process at major journals and reveals substantial disparities across name-inferred ethnicities. These findings complement studies of publishing *amount*, showing that some differences in amount may be due not to lack of trying, but lack of success in those attempts. We hope these results can stimulate more fine-grained analyses and, crucially, the collection of relevant data such as self-reported identities [Wu, 2020]. If supported by further research, the ethnic disparities in acceptance could call for policy interventions. For instance, journals may switch to double-blind review or solicit additional opinions on manuscripts from rarely accepted ethnic groups.

2.5 Data and Methods

2.5.1 *Top Journal* submissions

We had access to the full set of 17,509 submissions to *Top Journal* between 2013 and 2018. Each submission includes rich metadata, including all intermediate decisions and their dates. We removed from further analysis 72 submissions with missing first decision, 3 submissions with an organization as the last author, and 1 submission from a last author coded as Caribbean (Section 2.5.4), leaving us with 17,433 submissions.

The data include the document object identifier (DOI) for manuscripts that were ultimately published in the literature and successfully located, including those published by *Top Journal* and those published by other journals. Based on the DOI, we were able to locate 9,814 published papers (both accepted and rejected) in the Microsoft Academic Graph (MAG) database (accessed in June 2019), which is the largest public bibliometric dataset to date [Wang et al., 2019, Visser et al., 2020]. This literature lookup enables us to obtain additional control variables for each paper using MAG, including author prestige, paper topics, and paper impact (Section 2.5.6).

The data include peer review reports and recommendations for manuscripts that were sent out for external review. A manuscript can be reviewed by several referees and over several rounds of review, although we focused on the first review round. The data included an anonymous Reviewer ID, which enables us to control for the reviewers' overall tendencies to recommend acceptance or rejection in cases where reviewers reviewed multiple manuscripts.

2.5.2 *Middle Journal* data

The data for *Middle Journal* were less complete. It was missing peer review reports and the year of submission. For the latter, we use the year of publication as an approximation. However, the data identify submissions that were rejected between 2013 and 2018, published elsewhere, and successfully located (with DOI). We were able to retrieve 14,270 published papers (by *Middle Journal* or other journals) from MAG based on DOI, and obtained many control variables for these papers (Section 2.5.6). The final analytic sample consists of 14,269 observations, after excluding

1 paper from an author coded as Caribbean.

2.5.3 Submitted vs. published versions

Many of the key variables in our analysis come from MAG, which contains data on *published* rather than submitted papers. A limitation of using papers' published versions is that some of these covariates may change during the review process. However, existing work shows that the core content of manuscripts tends to change little from submission to publication, with most changes occurring in framing and tone [Goodman et al., 1994, Ellison, 2002, Siler et al., 2015, Strang and Siler, 2015, Teplitskiy, 2016]. Furthermore, some important covariates, such as the number of authors or their prominence, is unlikely to change substantially from submission to publication.

2.5.4 Ethnicity and gender coding

We used *Ethnea* to infer author gender and ethnicity using author names [Torvik and Agarwal, 2016]. *Ethnea* is trained using the PubMed database, with the location of the authors' affiliations as the ground truth. For a specific name, *Ethnea* assigns the ethnicity probabilities among matched authors. In the case of two or more predicted ethnicities, we took the one with the highest probability. It also provides ethnicity-specific gender predictions, such as Italian vs. English "Andrea." *Ethnea* has been shown to perform better than other machine learning approaches that rely on model training and feature selection of names [Torvik and Agarwal, 2016, Ambekar et al., 2009, Treeratpituk and Giles, 2012].

Author names were cleaned of suffixes, such as PhD, MD, and their variations. We placed 26 individual ethnicities defined by *Ethnea* into 11 high-level categories (*Appendix* Table A.1). We dropped manuscripts from organizations and ethnicities with less than 5 observations (including Caribbean and Polynesian). The largest group, *British-origin*, is used as the reference category for ethnicity in the regression analysis. *Ethnea* offers binary gender predictions including *Female* and *Male* (used as the reference category in the regression). Names that are not recognized by *Ethnea* were assigned "Unknown" for both gender and ethnicity.

We categorized manuscripts into different perceived gender and ethnic groups based on their last authors. In case of solo-authored papers, we treated the single author as the last author.

2.5.5 Perceived vs. self-identified ethnicity

Relying on perceived (name-inferred) ethnicities comes with several limitations. First, perceived ethnic identities may differ from authors' self-identifies. In some cases, reviewers and editors may have personal knowledge of the authors and know how they self-identify. Second, authors may change last names, for example after marriage, further weakening the inferences based on current last names. However, evaluators most likely are unaware of such personal events. Third, authors may identify as multi-ethnic, whereas we assign each author to just one group. Overall, these limitations of inferring ethnicity from names also likely apply to the perceptions editors and reviewers form, in most cases.

2.5.6 Control variables in regression models

Many factors can influence manuscript evaluation, which could potentially confound the effect of ethnicity. We thus included many control variables. For *Top Journal*, only the manuscript factors were based on the submitted manuscript; all other controls were based on its published version (including author prestige, paper topics, novelty, and impact). For *Middle Journal*, the author names (therefor ethnicity and gender prediction) and all controls were based on the published version of a manuscript. Due to different variables having different degree of missing values, the number of observations used in the regression varies across models.

2.5.6.1 Manuscript factors

Many manuscript characteristics can be associated with quality or influence the perception of quality. We thus considered the following characteristics:

- *The year of submission*: Acceptance rates can vary by year. We treated submission year as a categorical variable ("2013" was used as the reference category). For *Middle Journal*, for which we lacked data on year of submission, we used year of publication.
- *The number of authors*: Team size may be related to both the quality and type of submission [AlShebli et al., 2018, Wu et al., 2019]. We thus controlled for the number of authors for each submission.
- *The title length*: number of words in the title of a manuscript.
- *The abstract length*: number of words in the abstract of a manuscript.
- *The abstract readability*: We used two measures of abstract readability: (1) the Flesch-Kincaid reading ease score, which estimates the grade-level needed to understand the passage, (2) the type-token ratio, which is a measure of lexical variety and complexity.

2.5.6.2 Last author prestige

Many author-level attributes can influence the perception of manuscript quality and acceptance decisions. For example, studies of the effects of blinding show that high status authors benefit when their identity is visible [Tomkins et al., 2017, Sun et al., 2021]. We thus controlled for several factors related to author prestige.

- *Author rank*: this metric is provided by MAG, which estimates the relative importance of an author in the heterogeneous citation network including papers, authors, and affiliations [Wang et al., 2019]. Note that the author's total number of citations was collinear with the author's rank in a multicollinearity test, thus is excluded in the model.

- *Author's previous publications*: we approximated author's research experience as the total number of publications by the time of submission (the publication year was used for Middle Journal). We used all papers indexed in MAG to count authors' prior publications.

- *Author's previous publications at Top/Middle Journal*: we counted the number of Top/Middle publications up to the submission year (the publication year was used for Middle Journal). This variable captures the last author's degree of recognition at a specific Top Journal and their familiarity of the journal's style and mission.

- *Author's affiliation rank*: similar to the author rank, we also considered the rank of their affiliations provided by MAG. In case of multiple affiliations for the last author, we used the one with the highest rank (a smaller value indicates a higher rank).

- *Author's affiliation location*: We inferred the country of the last author's institution using the latitude and longitude information provided in MAG, with three categories: (1) Domestic (in the U.S.), (2) International, (3) Unknown. When an author had multiple affiliations with at least one in the U.S., we classified them as "U.S." We used "U.S." as the reference category in the regressions.

2.5.6.3 Paper topics

Manuscripts in trending areas may be more likely to be accepted than others. We thus controlled for research topics and domains. MAG provides a list of keywords for each paper with associated confidence score between 0 and 1. For each journal, we focused on the most common keywords used by at least 500 published papers (accepted and rejected). There are 13 and 26 keywords for *Top Journal* and *Middle Journal*, respectively. Each keyword was used as a variable in the regression, whose value is the keyword's confidence score for the paper.

2.5.6.4 Paper impact and novelty

Manuscript quality is one of the most important factors in determining acceptance. However, quality is a subjective evaluation criterion that cannot be quantified with a single metric. We therefore measure three dimensions of paper quality: (1) Novelty, (2) Disruption, (3) Citations.

(1) Novelty. Most journals aim to publish novel research in their stated missions. We adopted the widely used novelty measure proposed by Uzzi et al. [Uzzi et al., 2013], which defines paper novelty as the "atypical combinations" of existing knowledge. This measure has been shown to correlate with subjective perceptions of novelty [Bornmann et al., 2019].

This measure considers pairwise combinations of cited journals in the reference of each paper. Journal pairs that have been rarely combined by the literature in a year are considered to be novel in that year. The novelty score of each journal pair in a given year is calculated by comparing its observed co-citation frequency across all published papers in that year to those expected by pure chance. This method then gives each paper a distribution of novelty scores for all journal pairs in its reference. It provides two summary statistics for each paper: (1) the median novelty and (2) the tail novelty (10th percentile).

Uzzi et al. used all research articles published over the 1950-2000 period by 15,613 journals indexed in the Thomson Reuters Web of Science (WoS) database [Uzzi et al., 2013]. Here, we used the MAG database to quantify the novelty of published papers submitted to *Top Journal* and *Middle Journal*. MAG indexes 48,757 journals which cover Top Journalrticles, working papers, book chapters, and other article types. The scope of coverage by MAG clearly surpasses the WoS database [Visser et al., 2020].

To make the literature size comparable to that of Uzzi et al., we focused on all 21,357 journals in MAG that are also indexed in the Scopus database (matched based on ISSN). We thus limited the analysis to all papers published in 21K journals, and only consider, for each paper, its references to those journals in MAG. The literature pool for the novelty calculation consists of 10,144,021 citing papers published in the 2013-2019 period, and their 311,074,438 reference pairs (note that the cited papers were published between 1950 and 2019, which is the same as Uzzi et al.). Our novelty-related factors are:

- *Tail novelty*: the 10th percentile novelty score of a paper;
- *Median novelty*: the 50th percentile novelty score of a paper;
- *Number of references*: this variable is by definition related to the Uzzi novelty measure as it affects the number of journal combinations. We thus controlled for the total number of cited papers in a paper's reference.
- *Number of unique journals cited*: similarly, we also controlled for the number of unique journals cited by a paper. This variable captures the breadth of existing knowledge that a paper builds on. It also approximates the interdisciplinarity of a paper.

- *Number of Top Journal/Middle Journal papers cited*: a manuscript that cites many papers from a journal to which it is submitted is probably very relevant to that journal's topic of interest. It also reflects whether the editor is familiar with the research topic. We thus controlled for the number of cited papers from the focal journal.

(2) Disruption. While the Uzzi novelty defines innovation as combinations of existing knowledge in the space of literature, this concept does not capture other types of innovation and creativity. Disruption is another notion that has been introduced for the evaluation of novel contributions. The disruption measure was initially designed in the study of patented inventions [Funk and Owen-Smith, 2017], and has been recently introduced in the analysis of scientific papers [Wu et al., 2019]. It measures innovation across time by assessing the degree to which a paper destabilizes existing knowledge it builds upon. A paper is considered disruptive if it introduces something new that shadows the attention (citations) to its cited papers ("parents") after publication. It has been validated through evaluation tasks, such as consulting domain experts and examining Nobel-prize-winning papers.

Specifically, for a given paper and its cited papers (references), the measure examines three groups of papers (G_i, G_j, G_k) published after the focal paper. Papers in G_i only cited the focal paper; papers in G_j cited both the focal paper and its references; papers in G_k only cited the focal paper's references. The disruption is calculated as: $\frac{|G_i|-|G_j|}{|G_i|+|G_j|+|G_k|}$, where $|G_n|$ is the number of papers in group G_n.

(3) Citations. Innovation alone cannot capture many different aspects of scholarly contributions. Another important dimension of paper quality is its scientific impact, which is often measured as the observed citation count—the number of times that the research community has credited a paper for its inspiration of new ideas. High impact papers are often considered to be of high quality. We thus considered the total number of citations up to June 2019 (the MAG access date) in log scale for each published paper. The results presented in the main paper are similar when using the raw number of citations. Since citations are heavily influenced by the time of publication, we also controlled for the publication year of a paper (treated as a categorical variable with "2013" used as the reference category).

CHAPTER 3

Author Mentions in Science News Reveal Widespread Disparities Across Name-Inferred Ethnicities

3.1 Introduction

Scientific breakthroughs often attract media attention, which serves as a key channel for public dissemination of new knowledge [Scheufele, 2013, Brossard and Scheufele, 2013]. Science news not only distills research insights but also puts a face on who was responsible for the research. The media coverage can then feed back into researchers' careers [Fanelli, 2013]. Furthermore, science reporting may over time shift the public's perception of *who* a scientist is [Miller et al., 2018]. Under-representing particular demographic groups can perpetuate the view that scientists are white males [Turner et al., 2008, Banchefsky et al., 2016], and potentially weaken the pipeline of recruiting diverse students into academia [Cole, 1979, Reuben et al., 2014, Hill et al., 2018].

In writing about specific scientific developments, journalists face choices over how much attention to devote to each relevant researcher, and whom to ignore altogether. Empirical and theoretical literature motivates the possibility that ethnic disparities exist in journalists' choices of whom to feature and the nature of the resulting coverage [Callison and Young, 2019, Robinson and Culver, 2019, Sui et al., 2018].

Empirically, a number of studies have established gender and ethnic disparities in conventional scientific outcomes, such as funding [Ley and Hamilton, 2008, Ginther et al., 2011, Oliveira et al., 2019, Hoppe et al., 2019], hiring [Xie et al., 2003, Turner et al., 2008, Moss-Racusin et al., 2012, Way et al., 2016], publishing [Ding et al., 2006, West et al., 2013], citations [Larivière et al., 2013, Huang et al., 2020], and other rewards [Holden, 2001, Shen, 2013, Xie, 2014]. Furthermore, research points to demographic disparities in traditional media coverage [Behm-Morawitz and Ortiz, 2013, Jia et al., 2015, 2016, Merullo et al., 2019, Smith, 1997, Devitt, 2002]. The presence of abundant ethnic disparities in science and media suggests that the disparities may appear at the very latter stage as research disseminates to the public.

Theoretically, we hypothesize a number of mechanisms that may produce ethnic disparities in media mentions, and test them where possible. First, U.S.-based journalists may face pragmatic difficulties in interviewing researchers in distant time-zones and possibly with limited English proficiency. Furthermore, journalists may rely on their professional networks to contact sources. Analyses of the media landscape in the U.S. [Grieco, 2018, Clark, 2018] and other markets [Nielsen et al., 2020] show that the demographics of journalists and editors are highly unrepresentative of the broader populations. The demographics of journalists are likely to correlate with that of individuals in their professional networks [McPherson et al., 2001], suggesting that the researchers journalists can reach most readily are also unrepresentative. To the extent that these pragmatic factors—interviewing difficulties and professional networks—correlate with the perceived ethnicities of names, certain researchers may be more or less mentioned.

Second, while science journalists aim to write stories that appear credible to their audiences [Sundar, 1998], they may lack direct information on the credibility of authors of the relevant research papers and may not have the time to acquire such information. Facing unfamiliar names and time constraints, journalists may rely on stereotypes, inferring for example that some researchers are less competent or authoritative on some topics than others, or expecting their audiences to harbor such perceptions. Prior research has found such stereotyping in the context of researcher gender and gender-typical research topics [Knobloch-Westerwick et al., 2013]. Inferences of competence and authoritativeness can lead journalists to choose some names over others, which we refer to as taste-based [Lang and Lehmann, 2012] or "rhetorical" discrimination.

Third, reporters may not be the relevant actors at all. Some news coverage originates from press releases created by in-house public relation staff at universities. News outlets often reprint these press releases in part or in full, and any disparities therein may thus be passed on directly to the outlets and their audiences.

Here, we present the first large-scale and science-wide analysis of ethnic disparities in author mentions in science news and the mechanisms producing them. We use a computational analysis of 223,587 news stories mentioning 100,486 published papers to test for disparity in the type of media coverage by examining whether the paper's authors are mentioned by name (see Data and Methods). For each paper, we focus on authors at the highest "risk" of mention: first author, last author, and any authors designated as "corresponding."

By focusing on papers that already were deemed newsworthy, our research design side-steps the question of whose research is covered in the news in the first place, choices which may themselves be associated with ethnicity. Thus our analysis focuses on *how* rather than *whether* reporters chose to cover a scientific paper. We use mixed-effects regression models to control for a broad range of plausible confounding factors, including affiliation location, author prestige, authorship position, and corresponding author designation. The models also enable us to measure differential mentions within a particular news outlet covering a particular academic journal on a particular research topic, which helps ensure that we are comparing media mentions of researchers doing comparable work. Nevertheless, these models cannot provide conclusive causal evidence of ethnic discrimination by journalists or other actors.

The ethnicity of authors is algorithmically inferred from their names, which mirror how a reader might perceive ethnicity based on regularities in where the name originates. We refer to these inferences as "perceived identities" and "ethnicity-associated names" to distinguish them from authors' true self-identities. This research choice entails substantial trade-offs. In fact, authors' self-identities may differ from algorithmically inferred ones, and some authors may self-identify with more than one ethnicity. In some cases, journalists know authors' self-identified ethnicity. Nevertheless, in many cases, journalists will not know authors' self-identities and rather infer them from names, just as the algorithm does. In these cases, using authors' self-identities would be problematic, as it would misrepresent the actual perceptions journalists form and possibly use when they write their stories. Furthermore, in *Appendix* Figure B.4, we provide some evidence of consistent results with self-identities using the U.S. census data. Overall, we base our study on the *perceived* identities, and our conclusions should be interpreted as reflecting disparities among scientists with name-inferred ethnicities rather than self-identified ethnicities directly.

3.2 Results

3.2.1 Who gets mentioned?

We find substantial and wide-spread disparities in author mentions across ethnicity association with their names. These disparities are robust to the inclusion of increasingly stringent controls (Model 5 in *Appendix* Table B.5). Specifically, compared to British-origin named authors, most authors with minority-ethnicity[1] names are significantly less likely to be mentioned, with European-associated names disadvantaged the least while East Asian and African names disadvantaged the most.

In contrast to ethnicity, we find no disparity in author mentions across gender-associated names. However, when fixed effects for paper keywords are not considered, the author gender variable appears to have a significant effect (*Appendix* Table B.5). As gender representation varies widely across academic disciplines [Xie et al., 2003, Handelsman et al., 2005], this result suggests that

[1]Here we refer to non-British-origin ethnicities as minorities based on the number of scientists whose papers received media coverage. *Appendix* Table B.2 shows that British-origin named authors have their research covered more than twice as much as that of Western & Northern European authors, the second largest group in our data.

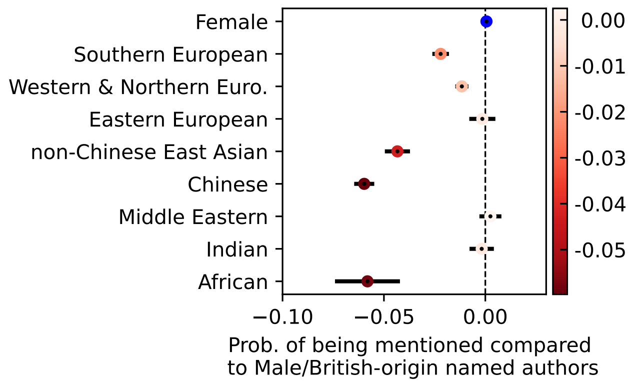

Figure 3.1: The marginal effects for authors' gender and ethnicity, averaged over all 524,052 observations in the dataset using Model 5. A negative average marginal effect indicates a decrease in mention probability compared to authors with Male (for gender-association) or British-origin (for ethnicity-association) names. The colors are proportional to the absolute probability changes. *Female* is colored as blue to reflect its difference from ethnicity-associated identities. The error bars indicate 95% bootstrapped confidence intervals.

gender differences in mention rates are likely to be explained by relative author mention rates to research papers in different fields.

To quantify ethnic disparities in mentions, we calculated the average marginal effects for the author ethnicity and gender variables using the fullest model (Model 5). As shown in Fig. 3.1, the estimated probability of being mentioned is 1.2-6.0 percentage points lower for most ethnicities compared to the British origins. As the average mention rate is only 41.2% (see Data and Methods), these absolute drops represent significant disparities: the 4.3-6.0 percentage points marginal decrease for East Asian and African names represents a 10.4%-14.6% relative decrease in media representation for authors with those names. This result reveals that the U.S. mainstream media outlets exhibit profound disparity against authors from many non-British-origin ethnicities in mentioning them by name in science news: Given the current disparities, *we estimate that about six thousand minority scholars should have been mentioned in our data alone if they had names of British origin.*

3.2.2 Disparities among U.S.- and non-U.S.-based authors

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

Indeed, our previous result shown in Fig. 3.1 (based on Model 5) already controls for author's affiliation location, which shows that international scientists are significantly less likely to be mentioned compared with their U.S. domestic counterparts of the same ethnicity (see the affiliation location coefficient in *Appendix* Table B.5), suggesting that affiliation location is one major factor influencing the *mention probability*. However, the same result also suggests that location drives only part of the *mention disparities*, as disparities between minority and British-origin still exist conditioning on authors being in the same geographical location (see ethnicity coefficients in *Appendix* Table B.5 and the average marginal effects in Fig. 3.1). In other words, the chance of being mentioned is not entirely determined by whether the author is in the U.S. or not; if it is, we would see no ethnic disparity after controlling for location.

To further demonstrate this claim and quantify the mention disparities between minority ethnicities and British-origin in different locations, we measured the disparities separately for (i) the subset of our data where the authors are from U.S.-based institutions (comparing U.S.-based minority authors to U.S.-based British-origin named authors), and (ii) that for non-U.S. authors (comparing international minority authors to international British-origin named authors).

The disparity coefficients (*Appendix* Table B.6) show that *international authors with names associated with each minority ethnicity are significantly less likely to be mentioned than international scholars with British-origin names, despite that they are all distant to U.S.-based journalists*. Compared to international scientists, the mention disparities are much smaller for U.S.-based authors, suggesting that being affiliated with a U.S. institution does decrease the disparity between names associated with each minority ethnicity and British-origin, and for some groups including Eastern European, Middle Eastern, and Indian, the mention rate is even higher than that of British-origin.

This gap between disparities among U.S.-based and that among international authors reveals that, unlike its negative effect on the likelihood of being mentioned, distant geographic distance to U.S.-based journalists actually increases mention disparities between authors with minority and British-origin names. Nevertheless, close proximity between journalists and authors does not eliminate all disparities in who is mentioned: The average marginal effects shown in Fig. 3.2a using Model 5 with the U.S. subset indicate that similar magnitudes of mention disparities for Chinese, non-Chinese East Asian, and African-named authors (4.8, 3.8, and 4.6 percentage points drop, respectively) still exist among U.S.-based scholars, suggesting that other factors besides location play a substantial effect in which authors are named.

3.2.3 English fluency and journalists' rhetorical choices

Our prior result shows that ethnic disparities in mentions are observed even among authors based in the U.S. (Fig. 3.2a), where scheduling difficulties should be minimized or, at least, not associated with ethnicity. Focusing on the U.S.-based subset of authors, we further disaggregate mentions into different types to better understand the mechanisms driving ethnic disparities.

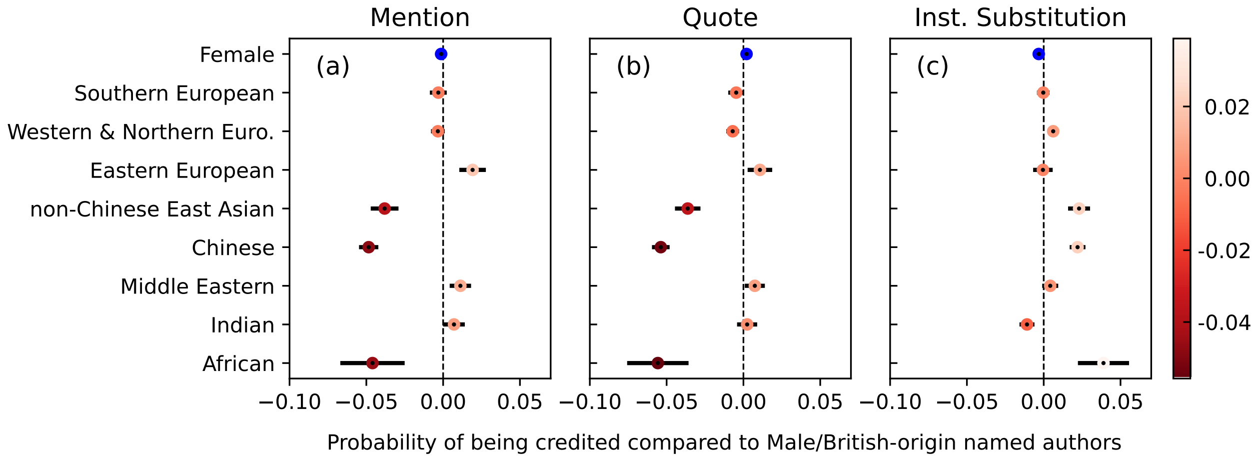

Figure 3.2: U.S.-based authors with minority-ethnicity names are less likely to be mentioned by name (**a**) or quoted (**b**), and are more likely to be substituted by their institution (**c**). The average marginal effects are estimated based on 317,626 observations where the author is from U.S.-based institutions (Model 5). A negative (positive) marginal effect indicates a decrease (increase) in probability compared to authors with Male (for gender) or British-origin (for ethnicity) names. The colors are proportional to the absolute probability changes. *Female* is colored as blue to reflect its difference from ethnicity identities. The error bars indicate 95% bootstrapped confidence intervals.

One plausible mechanism generating disparities for U.S.-based authors is journalists' perceptions of, or actual differences in, authors' English fluency, which should manifest in how often authors are directly quoted. To measure disparities in quotation rates, we identified authors who are named as part of quotations (a subset of name mentions) and applied the same regression framework to only the U.S.-based subset of authors. Fig 3.2b shows that there are substantial disparities in quotation rates for authors with East Asian-associated and African-associated names. We note that this result suggests, but does not prove, that fluency is a driving mechanism, as other mechanisms such as the rhetorical value of names, may also explain this result.

To more directly test the rhetorical ("taste-based") mechanism, we consider "institution-substitution," in which the author is mentioned by their institution but not by name (see Data and Methods), e.g., being named as "researchers at the University of Michigan." Among U.S.-based authors, this mention type should not depend on pragmatic factors such as scheduling difficulties or English fluency. Thus, this substitution effect likely reveals the rhetorical value journalists place on authors' names vs. institutions. Fig. 3.2c shows the probability of institution-substitution relative to authors whose names are of British-origin, revealing that U.S.-based authors with African and East Asian names are more likely to have their names substituted for their institutions (*Appendix* Figure B.3 shows results of this analysis using the full data). Different mention types thus reveal that while some mention disparities may be explained by English fluency or other pragmatic factors, journalists' rhetorical choices are also key.

3.2.4 Differences across outlet types

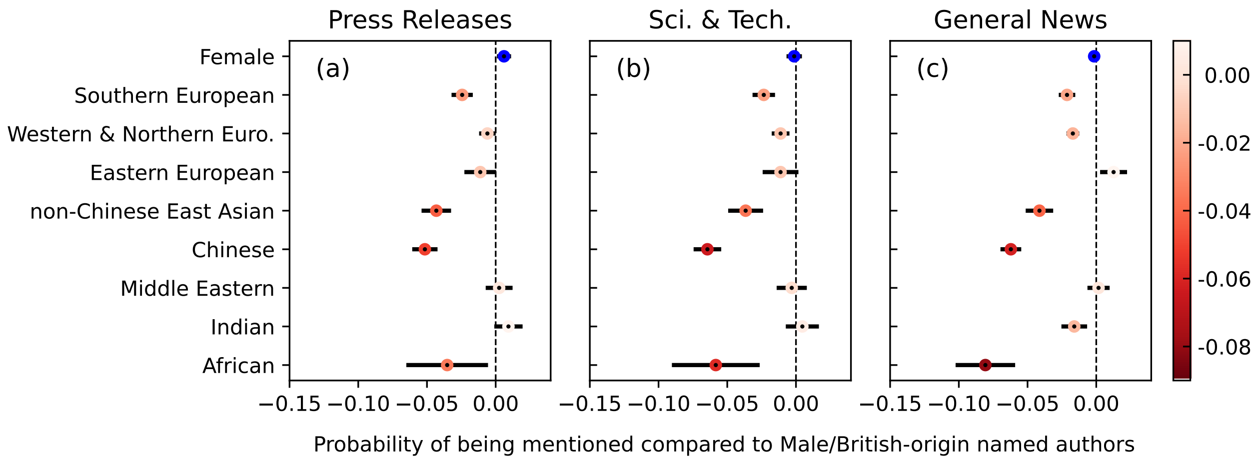

Figure 3.3: The relative decrease in the probability of being mentioned for author names associated with the female gender and each minority ethnicity reveals a consistent disparity across three types of outlet. The average mention rates in Press Releases, Science & Technology, and General News outlets are 63.5%, 41.9%, and 24.2%, respectively. The similar sizes of absolute disparities in three outlet types thus reflect starkly different relative magnitude of effects. The colors are proportional to the absolute probability changes. Error bars represent 95% bootstrapped confidence intervals.

Outlets vary in the depth and breath of their reporting, e.g., Science & Technology outlets write about 650 words per story on average, while General News outlets write about 900 words (*Appendix* Figure B.2). These differences suggest potentially important variability in the nature of journalists' day-to-day work and backgrounds. To explore the discrepancy of disparities in author mentions across different types of outlets, we fit the specification of Model 5 separately for three outlet types in our full data and quantified the average marginal effects.

Surprisingly, the ethnic disparities remain consistent across all outlet types, as shown in Fig. 3.3, with authors of non-British-origin names being mentioned less frequently. Larger disparities are found for ethnic categories that are more culturally distant from British-origin (e.g., East Asian and African). Although the three outlet types have similar sizes of absolute disparities, they vary substantially in the relative scale, as the average mention rates of Science & Technology outlets and General News outlets are 34.0%-61.9% less than Press Releases outlets (*Appendix* Table B.4).

The disparity in Press Releases outlets is particularly notable, as stories in these outlets typically reuse content from university press-releases, suggesting that universities' press offices themselves, while less biased than other outlet types, still prefer to mention scholars with British-origin names. This result is unexpected because local press offices are expected to have greater direct familiarity with their researchers, reduce the misuse of stereotypes, and to be more responsible for representing minority researchers equitably.

The largest disparities are seen in General News outlets, e.g., The New York Times and The Washington Post, where again scholars with African- and Chinese-associated names have 6.0-8.0 percentage points drop in representation. General News outlets mention authors with a 24.2% chance on average (*Appendix* Table B.4), so this drop nearly reduces to two thirds the perceived role of a large community of scientists. As General News outlets have well trained editorial staff and science journalists dedicated to accurately reporting science and tend to publish longer stories that have room to mention and engage with authors, this result is alarming. Historically, these ethnic minorities have been underrepresented, stereotyped, or even completely avoided in U.S. media [Behm-Morawitz and Ortiz, 2013], which has continued in objective science reporting across all outlet types. The mechanisms of this variation deserve further investigation.

3.2.5 Is the situation getting more equitable?

The longitudinally-rich nature of our dataset allows us to examine how author mentions in science news have changed over the last decade. Mention rates are on average decreasing over time, as shown by the coefficient of the *mention year* scale variable in Model 5 (*Appendix* Table B.5). To examine the time trends across demographic categories, a separate Model 5 was trained to quantify the marginal change per year increase for each gender and ethnicity in our full data. Note that demographic attributes not under study are still included in each model, e.g., when examining the temporal changes in mention rates for male and female authors, ethnicity is still included as a factor, and vice versa.

As shown in *Appendix* Figure B.5, the mention year has a negative association with author mention rates for all gender and ethnic groups, and the larger decrease for the British-origin indicates that their overall advantages are shrinking. Indeed, authors with non-Chinese East Asian names, one of the most disadvantaged group in this study, have the lowest decreasing rate compared to others.

However, the estimated rates of change are relative small for most ethnic groups, suggesting that the existing disparities are unlikely to disappear in the short term without intentional behavior change. Since the relationship between the mention year and author's mention probability is nonlinear in the model's assumption, we are unable to make broader predictions as to when the mention equality will be reached eventually. We also refrain from adopting other more sophisticated time series analysis models to forecast the trajectory of mention rates in the long run, because such extrapolation will be of little practical use, especially given that the long-term changes in the academia and media practices remain unforeseeable.

3.3 Discussion

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

3.3.1 Ethnicity and gender

Authors with most non-British-origin names are mentioned substantially less when their research is discussed. Mention rates are especially low for East Asian and African names, less pronounced for European names, are even less pronounced for Indian and Middle Eastern names. As science becomes more global and is increasingly driven by authors of non-Western ethnicities, the way English-language media responds to non-British-named scholars will only grow in importance.

In contrast to ethnicity, we do not find disparities in mentions of scholars with gender-associated names once research fields are controlled for. One possible reason is that fields vary in their overall level of mention rates and in their gender representation [Handelsman et al., 2005]. Looking within fields masks gender disparity that may exist between them. We would like to note that this result may not apply to Asian authors, as their gender is often classified as "Unknown" based on names.

3.3.2 Ruling in and out different mechanisms

Our analyses point to a multi-causal generation of ethnic disparities, in which both pragmatic difficulties of interviewing researchers (location and fluency) and journalists' tastes play key roles.

In support of pragmatic difficulties, we find that international locations (which tend to have scholars with more non-British-origin names) have a negative effect on mention rates (*Appendix* Table B.5). However, location is not the only driving mechanism as disparities still occur when controlling for location (Fig. 3.1). Additional evidence is that disparities persist among both international authors and U.S.-based authors, which would disappear if location was the decisive factor (*Appendix* Table B.6). In support of the language fluency mechanism, we find that ethnic disparities appear in direct quotations among U.S.-based authors. These authors are unlikely to suffer from time-zone difficulties in scheduling interviews, but may differ in their perceived English fluency based on their name (Fig. 3.2b).

In addition to these pragmatic factors, journalists' rhetorical choices are key. In support of the role of choice, journalists are more likely to "substitute" a direct name mention with the researcher's institution for authors with East Asian and African names (Fig. 3.2c), suggesting that the context of discovery is important, but the institution serves the journalists' rhetorical goals better than the name. Additional evidence comes from outlet types: when journalists' role in the news articles is minimal—when the outlet simply republishes a university press release—the (relative) disparities are also minimal; when the news stories are written by journalists themselves, the (relative) disparities are the largest. However, we note that the disparities in Press Releases outlets also suggest that journalists are not the only actor behind the inequality.

The data do not allow us to fully explain journalists' rhetorical preferences or tastes. For example, we hypothesize that these tastes may be driven by journalists' perceptions of author authoritativeness or by expected tastes of their audiences. However, we observe that ethnic disparities in mentions do not vary substantially across Science & Technology and General News outlets, although the two likely differ in their audiences. This observation suggests again that journalists' *personal* tastes and choices play an important role. Furthermore, in *Appendix* Section B.1.2, we consider whether the interaction between author and journalist name-inferred identities are associated with mentions, but do not find clear evidence. Disentangling the source of journalists' tastes is an important avenue for future work.

3.3.3 Limitations

Although the scale and the breath of our dataset enable the use of unusually fine-grained controls, the analysis is not without limitations. First, the observational nature of the data precludes strong causal statements. Second, the analysis was conducted with ethnicities inferred by using a name-based classifier, *Ethnea*. Although journalists, like the classifier, may have no information about authors except their names, the inferences will undoubtedly not match all authors' self-identities accurately, nor account for multi-ethnic identities. We hope our work stimulates the collection of such data where possible, to enable more accurate and fine-grained conclusions [Wu, 2020]. Furthermore, the classifier is unable to identify key demographic groups, such as African American scholars. Nevertheless, as an exploratory test, we repeated our analysis using an additional classification of races defined in the U.S. census data (*Appendix* Figure B.4), which includes "Black" as one of the labels. The result does not show any statistically significant under-representation of Black scholars relative to "White." Note that African-named authors (based on *Ethnea*) are not necessarily classified as "Black" based on the Census data (*Appendix* Table B.7 and *Appendix* Table B.8).

Third, some plausible covariates are unavailable for inclusion, such as the number of citations a paper received at the time of being mentioned. However, we anticipate the effect of such covariates to be small given current controls. *Appendix* Figure B.1 shows that the majority of papers were mentioned within one year after publication, which limits the citations a paper can accrue in such a short academic time period. Fourth, we did not test other potential mechanisms. For instance, reporters often choose whom to interview based on who is listed as the corresponding author. Although our model controls for the corresponding author status (*Appendix* Table B.5), however, which author of a paper is designated as corresponding—and whose contribution is seen as deserving of formal authorship at all—may itself be a product of structural discrimination with respect to authors' demographics. Thus disparities seen in the press may be partly driven by decades or centuries of decisions that are ingrained in publishing practices and institutions [Small and Pager, 2020]. Fifth, we note that our data contains too few examples of some ethnicities (e.g., Polynesian and Caribbean) to accurately estimate disparities; such ethnicities are regrettably omitted, though we recognize that these groups likely experience disparity from their minority status as well.

Sixth, our study has focused solely on the disparity in the publication behaviors of U.S.-based news outlets. Many of these outlets are often global in reach and mentions in them often serve as markers of prestige for scholars. However, the outlets' behavior may not be representative of broader publication practices. At present, the Almetrics data only provides sufficient quantity for U.S.-based outlets to control for potential confounds and explanations (62% of mentions are solely from U.S.-based outlets), which is critical for our study's approach. Nevertheless, bias is likely not unique to one country and additional global data is necessary to move beyond a U.S. focus and study country-specific and global journalistic practices.

Lastly, this research relies on large-scale datasets and algorithms that may themselves encode systemic social inequalities. For instance, which venues are considered "mainstream" and therefore worthy of tracking by Altmetric may be the outcome of racial inequities [Alamo-Pastrana and Hoynes, 2020]. Which groups the algorithms choose to identify as distinct groups are choices that may reflect long histories of racialization seen through a "white racial frame" [Tatum, 2017, Feagin, 2020]. The availability of data also drove our focus on English-language science and media, thereby accumulating more activity around certain settings over others. We believe these limitations place substantial scope conditions on the findings.

3.3.4 Conclusions and implications

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

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

3.4 Data and Methods

To test for and quantify gender and ethnic disparity in author mentions, we constructed a massive dataset by combining news stories with metadata for the scientific papers they cover, and then inferring demographic attributes of the papers' authors based on their names.

3.4.1 Summary of dataset

Our dataset is sourced from *Altmetric.com*, which consists of 223,587 news stories from 288 U.S.-based outlets referencing 100,486 scientific papers, with a total of 276,202 story-paper mention pairs. For all new stories, we have the textual content, the mention date, and the outlet information. All mentioned papers have rich metadata including author information (such as author name, rank, affiliation, corresponding author status, etc.), paper publication year and venue, and paper abstract and keywords.

Journalists can mention several authors when covering a paper in a news story. Since the first and the last authors often contribute most to the work and are recognized as such in science journalism guidelines [Blum and et al., 2006], we include them in our analysis by default. We also include any additional corresponding author of a paper. We use each (story, paper, author) triplet as an observation in the regression, with 524,052 observations in total.

3.4.2 Detailed dataset description

3.4.2.1 News stories mentioning research papers

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

3.4.2.2 Scraping news content and identifying journalists

Due to access and permission limitations when retrieving news stories, 135 outlets were excluded due to insufficient volume (27 outlets denied our access entirely; 65 outlets had less than 100 urls crawled; 43 outlets had at least 100 urls crawled, but only with non-news content such as subscription ads). For the remaining 288 outlets, 44.1% of the stories were successfully retrieved after cleaning, including dropping duplicated htmls and removing all html tags and unrelated content such as advertisements. Stories with less than 100 words were removed (less than 1%) as a manual inspection showed that the vast majority of these do not contain the complete content of the story. This process resulted in 520,061 downloaded news stories mentioning 275,403 papers from the 288 outlets.

In order to control for the effects of journalists' ethnicity and gender, we first used the *newspaper* Python package (`https://github.com/codelucas/newspaper`) to extract the journalists' names from the retrieved html news content. Since not all stories in each outlet contain the journalist information and the *newspaper* package does not work perfectly for every story that has journalist information, we focused on the top 100 outlets (ranked by the story count). With manual inspection, we verified that this package can consistently and reliably identify journalists' names for 41 of the top 100 outlets. We excluded extracted names with words signaling institutions and organizations (such as "University", "Hospital", "World", "Arxiv", "Team", "Staff", and "Editors"). We also cleaned names by removing prefix words, such as "PhD.", "M.D.", and "Dr.". We eventually obtained the journalist's name in 100,163 news stories (18.1% of all cleaned stories) for 41 outlets. Note that we did not drop any data where the journalist's name is missing. When coding journalists' gender and ethnicity, we assigned "Unknown" to those missing names.

3.4.2.3 Retrieving paper metadata

The Altmetric database does not contain detailed author information and therefore an additional dataset is needed to identify the authors of mentioned papers. We used the Microsoft Academic Graph (MAG) data [Sinha et al., 2015] (accessed on June 01, 2019) to retrieve information for each paper based on its Document Object Identifier (DOI). Not all papers with a DOI in the Altmetric database are indexed in the MAG. We were ultimately able to retrieve 251,630 papers (all have author names) from MAG based on DOIs (matching based on lower-cased strings), which were mentioned by 472,762 stories from 288 outlets. MAG also provides rich metadata for papers, including author names, author rank, author affiliations, affiliation rank, publication year, publication venue, the paper abstract, and paper topical keywords. As all of this information will be used in our regression models, we excluded papers with missing metadata and story-paper-author triplets from rare ethnicity groups, leaving us with 100,486 papers in the final dataset.

3.4.2.4 Story-Paper-Author triplets and corresponding authors

We further used the Web of Science database (2019 version) to retrieve the corresponding authors for 86.0% papers in the final dataset based on the DOI. The remaining papers are mainly from disciplines such as computer science that do not have the norm to specify corresponding authors.

We focused on several authors whom journalists are likely to mention by name when covering a paper in a news story, including the first author, the last author, and any middle author who is designated as the corresponding author (note that the first author and the last author can be corresponding as well). It is possible that some papers could have equal-contributing first authors, however, our data does not have this information. We estimate that such cases are rare. For solo-author papers, we included the single author in the analyses. Papers in a few research fields that commonly use the alphabetic-based authorship ordering are also included as journalists may be unfamiliar with this norm. To examine whether a specific author is mentioned, we use each (*story, paper, author*) triplet as an observation in the regression.

3.4.2.5 Inferring author and journalist gender and ethnicity

As authors' gender and ethnicity are not directly available, we relied on the inferred demographic associations of their name. While such inferences could be inaccurate relative to how authors self-identify, self-identities are generally not available to journalists. Instead, classifier-based predictions on gender and ethnicity reflect stereotypical norms of the *expected* demographics given a name—norms that journalists are likely to share and unconsciously use when first examining the author names of a paper and deciding whom to mention. Therefore, while imperfect, we based our study on these inferred attributes.

Gender and ethnicity were inferred using the *Ethnea* API [Torvik and Agarwal, 2016], which is specifically designed for use in bibliometric settings like ours. We grouped the 24 observed individual ethnicites from *Ethnea* into 9 higher-level categories based on geographical proximity and cultural distances, including (1) African, (2) British-origin, (3) Chinese, (4) non-Chinese East Asian, (5) Eastern European, (6) Indian, (7) Middle Eastern, (8) Southern European, (9) Western & Northern European.

The library makes its prediction based on the nearest-neighbor matches on authors' first and last names using the PubMed database of scholars' country of origin, which offers superior performance over alternative approaches [Ambekar et al., 2009, Treeratpituk and Giles, 2012].

Author names in the MAG have varying amounts of completeness. While most have the first name and surname, special care was taken for three cases: (1) If the name has a single word (e.g., Curie), the ethnicity and the gender were both set to *Unknown*, as *Ethnea* requires at least an initial. Single-word name cases occurred for 208 authorships in the final dataset. (2) If the name has an initial and surname (e.g., M. Curie), we directly fed it into the API, which provides an ethnicity inference but returns *Unknown* for gender due to the inherent ambiguity. (3) If the name has three or more words, we took the first word as the given name and the last word as the surname. However, if the first word is an initial and the second word is not an initial, we took the second word as the given name (e.g., M. Salomea Curie would be Salomea Curie) to improve prediction accuracy and retrieve a gender inference.

While *Ethnea* is trained with scholar names, we also applied it to infer the gender and ethnicity of journalists. *Ethnea* assigns fine-grained ethnic categories that are leaning towards country of origin. Here, we recognize that ethnicity, race, and nationality are three related concepts. Ethnicity categorizes people based on origin and cultural background, which is often reflected in names, whereas race is a social construct. In contrast, nationality reflects country of affiliation and is a bit more fluid due to immigration or migration. We thus decided to use the term "ethnicity" because it is the most accurate and relevant concept in the study of names.

To test for macro-level trends around larger ethnic categories and to ensure sufficient samples to estimate the effects, we grouped individual ethnicities into higher-level categories based on geographical proximity and cultural distance (*Appendix* Table B.1).

Note that due to the sample size and our hypotheses, *African*, *Chinese*, *Indian*, and *English* (renamed as "British-origin") were kept as separate high-level categories. *Caribbean* and *Polynesian* authors were excluded due to less than 100 observations (triplets) in total. A few authors with organization names were also excluded. Examples of names classified into each ethnicity are provided in *Appendix* Table B.9. *Ethnea* returns binary gender categories: *Female* and *Male*, though we recognize that researchers may identify with gender identities outside of these two categories. For both gender and ethnicity separately, some names are classified as "Unknown" if no discernible signal is found for the respective attribute by *Ethnea*.

3.4.2.6 Final dataset and statistics

The final dataset consists of 223,587 news stories referencing 100,486 research papers. As some stories mentioned more than one paper and some papers were mentioned in more than one story, we have 276,202 (story, paper) mention pairs. Since multiple authors are likely to be mentioned per paper, we have 524,052 (story, paper, author) triplets in total to test whether an author is mentioned in a story.

The distribution of the number of papers and news stories over time and attention per paper are shown in *Appendix* Figure B.1. News story data is left censored and primarily includes stories written after 2010, as *Altmetric.com* was only launched in 2012, which limits the collection of earlier news. As shown in *Appendix* Figure B.1, news stories can mention papers that were published several decades before, highlighting the potential lasting value of scientific work. However, the majority of papers are mentioned within the same year or just a few years after publication. *Appendix* Table B.2 shows the the number of authorships and triplets for authors in each broad ethnicity group, and *Appendix* Table B.3 shows the number of triplets by journalists' inferred ethnicities.

3.4.2.7 News outlets categorization

To estimate differences across outlets, we grouped 288 news outlets into three categories according to their news report publishing mechanisms (*Appendix* Table B.10). The three categories are (1) Press Releases, (2) Science & Technology, (3) General News. The categorization is based on manual inspections of three random stories per outlet.

The Press Releases category is unique since many outlets in this category commonly—if not exclusively—republish university press-releases as stories, making them reasonable proxies for estimating disparity from a university's own press office. The Science & Technology category consists of magazines that primarily focus on reporting science, such as "MIT Technology Review" and "Scientific American." These outlets typically construct a large scientific narrative referencing several papers in their stories. The General News category includes mainstream news media such as "The New York Times" and "CNN.com" that publish stories in a wide variety of topics. They also have well-trained editorial staff and science journalists who are focused on accurately reporting science. *Appendix* Table B.4 shows the number of (story, paper, author) triplets by outlet types. The average number of words per story for each outlet type is shown in *Appendix* Figure B.2.

3.4.3 Check author attributions in science news

Our dataset does not come with information on author mentions. We thus developed a computational approach to identifying author mentions and quotes (based on their last names) and institution mentions for each (story, paper, author) triplet.

3.4.3.1 Detecting Author Name Mentions

We normalized both the news content and the author names to ensure that this approach works for names with diacritics. For each story-paper-author triplet, the author's last name was searched for using a regular expression with word boundaries around the name, requiring that the name's initial letter be capitalized. While the chance exists that this process may introduce false positives for authors with common words as last names (e.g., "White"), such cases are rare because (i) few authors in our dataset have common English words as their last names, and (ii) these words rarely appear at the beginning of a sentence in the story when they would be capitalized. However, a particular exception is for two common Chinese last names "He" and "She," which can appear as third person pronouns at the start of sentences. We thus imposed additional constraints for these two names such that they must be immediately preceded with one of the following titles to be considered as a name mention: "Professor", "Prof.", "Doctor", "Dr.", "Mr.", "Miss", "Ms.", 'Mrs.". Occasionally, the author name can occur within a reference to the paper at the end of the story, which should not be counted as a name mention. As authors are typically mentioned at the beginning or in the middle of the news story, we removed the last 10% of the story content when checking name mentions (note that we obtained similar results without this filtering). Ultimately, author names were found in 41.2% of all (story, paper, author) triplets.

3.4.3.2 Author-Quote Detection

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

We used a rule based matching method to detect explicit quotes for each (story, paper, author) triplet. We first parsed our news corpus using *spacy* (`https://spacy.io/`). We identified 18 verbs that were commonly used to integrate quoted materials in news stories, from the most 50 frequently used verbs in our news corpus, including "describe", "explain", "say", "tell", "note", "add", "acknowledge", "offer", "point", "caution", "advise", "emphasize", "see", "suggest", "comment", "continue", "confirm", "accord". A sentence is determined to contain a quote from the author if the following two conditions are met: (i) both the quotation mark and the author's last name appear in the sentence, and (ii) any of the 18 quote-signaling verbs (or their verb tenses) appears within five tokens before or after the author's last name. A manual inspection of 100 extracted quotes revealed no false quote attributes. This conservative method only gives an underestimation of the quote rate, as it may not be able to detect every quote due to unusual writing styles or article formatting. So the benefit of British-origin named scholars in getting a quote (Fig. 3.2) may be even higher.

3.4.3.3 Detecting Institution Mentions

We checked institution mentions based on exact string matching with authors' listed institution names in the MAG, i.e., for each (story, paper, author) triplet, we examined whether any of the author's full institution name appears in the news story. Similar to quote detection, this method may not be able to identify every instance of institution mentions due to noise in the MAG or the story using slightly different nomenclature such as an institution's abbreviation. However, a full list of alternative names for each institution is not available to us, we thus used this conservative method. For this reason, minority scholars' trend in being substituted by institutions (Fig. 3.2) is likely underestimated.

3.4.4 Mixed-effects regression models

We adopted a mixed-effects logistic regression framework to examine the demographic disparity in author mentions in science reporting. In our regression framework, each (story, paper, author) triplet is an observation, with the dependent variable indicating whether the author is mentioned or not in the story. Many factors are known to influence name mentions that could confound the analysis of ethnicity and gender, such as author reputation, institutional prestige and location, publication topics and venues, outlets, and journalist demographics. Here, we provide details of these factors and present a series of five regression models that build upon one another by adding more rigorous control variables at each step. The increasing level of model complexity allows us to test the robustness of the effects of ethnicity and gender association, and also to examine potential factors at play in science coverage.

3.4.4.1 Model 1: Naive Disparity

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

3.4.4.2 Model 2: Paper Author Controls

Many author-level attributes other than demographics could influence journalists' perceptions on authors and the coverage of them. Model 2 introduces 13 additional factors to control for features of papers' authors.

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

We also add a variable indicating the author's institution location with three categories: (1) domestic, (2) international, (3) unknown. For authors with multiple affiliations, we assign "domestic" if there is at least one U.S. institution. This variable controls for geographical factors that may influence journalists' willingness to contact by phone or video chat service and therefore influence whether they mention the author. We infer the country for institutions based on their latitude and longitude provided in the MAG.

Popular authors who have lots of press coverage may be more likely to be mentioned. We add a factor indicating whether the author is among the top 100 most popular scholars based on their number of papers mentioned in the news in our final dataset.

In multi-author papers, the team often designates one or more corresponding authors, who are presumably more likely to be contacted and therefore mentioned by journalists. Our data includes the corresponding author information for most papers. We thus include a variable indicating whether the author is corresponding or not on the covered paper.

Last Name Factors. People are known to have a preference for both familiar and more easily-pronounceable names [Song and Schwarz, 2009, Laham et al., 2012], and this preference could potentially affect which author a journalist mentions. Therefore, we introduce two factors as proxies: (1) the number of characters in the last name as a proxy for pronounceability, and (2) the log-normalized count of the last name per 100K Americans from the 2018 census data. As journalists are drawn from U.S.-based news sources, the latter reflects potential familiarity.

Other Authors. Scientific knowledge is increasingly discovered by teams, as tackling complex problems often require the collaboration between experts with diverse sets of specialization [Guimera et al., 2005, Greene, 2007, Milojević, 2014]. On these multi-author projects, the first authors are commonly junior scholars who are directly responsible for the work; the last authors are typically the senior author responsible for directing the project; these two author positions are suggested in science journalism guidelines when determining whom to interview [Blum and et al., 2006]. We thus control for the position of an author with four categories: (1) first position, (2) middle position, (3) last position, (4) solo author. The last author position is used as the reference category in the regression.

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

3.4.4.3 Model 3: Paper and Story Content

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

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

Year Gap between Story and Paper. News stories often reference older scientific papers in the narrative, as shown in *Appendix* Figure B.1c. For older papers, at the time of a recent story publication, the original authors may be unable to be reached or the story may be framed differently from recent science that is considered "fresh." Indeed, citing timely scientific evidence in a news report can increase credibility perceptions of a story [Sundar, 1998, Rieh and Belkin, 1998]. Therefore we include a variable that quantifies the year difference between the mention year and the publication year of the mentioned paper.

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

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

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

Journalist Demographics. It is ultimately the journalist's decision to mention authors when writing science reports. Motivated by the commonly observed homophily principle in social networks [McPherson et al., 2001], we hypothesize that the mentioning behavior in science reporting is associated with homophilous effects by ethnicity and gender. To model such effects, we include the journalists' demographics in the regressions. Due to insufficient instances of journalists identified in news stories (*Appendix* Table B.3), we further coarsen the 9 broad ethnicity categories into four groups: (1) Asian (Chinese, Indian, and non-Chinese East Asian), (2) British-origin, (3) European (Eastern European, Southern European, Western & Northern European), and (4) Other/Unknown (Middle Eastern, African, and Unknown).

3.4.4.4 Model 4: Paper Domains and Topics

Some scientific domains and topics may be inherently more attention-getting than others. Some may be harder to understand without seeking additional explanation from authors. Furthermore, journalists' academic backgrounds may be unequally distributed across scientific fields, resulting in different propensities to reach out to authors.

We thus include factors to capture the domain of a paper using metadata from the MAG, which includes a large volume of keywords (665K) at different levels of specificity. A paper can have multiple keywords, with each having an associated confidence score between 0 and 1. To capture high-level topical and methodological differences, we focus on the most common 199 keywords that occur in at least 500 papers in our final dataset. Each keyword is used as an independent variable in the regression, whose value is the keyword's confidence score for the paper.

3.4.4.5 Model 5: News Outlets and Publication Venues

Individual news outlets may follow different standards of practice in how they describe science, creating a separate source of variability in who is mentioned. Publication venues each come with different levels of impact and topical focus that potentially affect the depth of journalistic focus on papers published in them. To accurately model these sources of variations, we treat outlets and venues as *random effects* in regression Model 5. This mixed-effect regression model implicitly captures a robust set of factors involved in science reporting such as the tendency of specific journals to be mentioned more frequently (e.g., *Nature*, *Science*, or *JAMA*) and the focus of news outlets on specific topics covered by different journals.

3.4.5 Additional ethnicity coding

Although *Ethnea* is specifically designed for inferring scholars' ethnicity in bibliographic records, it is not expected to be entirely error-free. As a robustness check, we replicated our analyses by inferring the ethnicity for the names of authors and journalists using two separate data sources to test whether the observed disparity persists.

Specifically, we used the *ethnicolr* (`https://pypi.org/project/ethnicolr/`) library to code ethnicity using either data derived from (i) the nationalities listed in Wikipedia infoboxes to infer nationality-based ethnicity, or (ii) self-reported ethnicity data associated with last names from the 2010 U.S. census. While these two sources of data use different definitions and granularities of ethnicity from *Ethnea*, they nonetheless provide approximately-similar categories to *Ethnea* that enable us to validate our results.

3.4.5.1 Ethnicity based on Wikipedia

We used the Wikipedia infobox data to code ethnicity based on the first name and the last name [Ambekar et al., 2009, Sood and Laohaprapanon, 2018]. To make the results comparable to that based on *Ethnea*, we placed 13 individual ethnicities defined in the Wikipedia into 8 broad categories:

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

Note that Chinese ethnicity (defined in *Ethnea*) is by default incorporated into the *EastAsian* ethnicity in the Wikipedia data. We further placed the 8 categories into 4 groups for journalists' ethnicity due to insufficient instances of identified journalists in news stories: (1) Asian (East Asian, Indian), (2) British-origin, (3) European (Eastern European, Southern European, Western

& Northern European), (4) Other Unknown (African, Middle Eastern, Unknown). We fit the specification of Model 5 with British-origin and Male used as the reference categories.

3.4.5.2 Race in U.S. census data

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

Appendix Figure B.4 shows the average marginal effects in mention rates for scholars with names having minority ethnicity (or race) compared to British-origin (or White) named authors. As neither tool infers gender, we thus report the result for gender here using *Ethnea*'s labels. Like the case of *Ethnea*, we find strong evidence of disparities for Asian-associated names in author mentions in science news, highlighting the robustness of our findings in the main text.

CHAPTER 4

The Gender Gap in Scholarly Self-Promotion on Social Media

4.1 Introduction

Traditional and social media have long played an important part in the dissemination of research and researchers' careers [Rowlands et al., 2011, Van Eperen and Marincola, 2011, Peters, 2013, Editorial, 2018a]. Emerging research suggests that online visibility of scholarly papers amplifies their impact within and beyond the traditional academic audiences [Eagleman, 2013, Cronin and Sugimoto, 2014, Sugimoto et al., 2017b]. A sign of this recognition is the increasing ubiquity and importance of "altmetrics", which are metrics largely focused on capturing the online attention to academic research that have been adopted for scholarly evaluation by prestigious journals and research institutions [Kwok, 2013, Hicks et al., 2015].

One common and intuitive way to increase public attention to one's scholarly work is self-promotion. Given the proliferation of diverse online platforms and their high adoption rate among the public, it has become more important than ever for scholars to take advantage of the highly spreadable nature of online media to disseminate their research [Eagleman, 2013]. In fact, research shows that social media platforms such as Twitter have been widely adopted by scholars as a communication channel to discuss ideas and disseminate their research [Priem and Costello, 2010, Darling et al., 2013, Hadgu and Jäschke, 2014, Morello, 2015, Ke et al., 2017, Gero et al., 2021].

Past research has revealed considerable gender disparities in conventional scientific outcomes such as publications, citations, funding and awards [Larivière et al., 2013, Way et al., 2016, Oliveira et al., 2019, Ma et al., 2019] as well in the online dissemination of scholarly work [Vasarhelyi et al., 2021]. While many sources of these disparities are widely discussed and studied, it is unclear what role, if any, is played by self-promotion. Specifically, do authors of different genders self-promote their research equally on social media and do they get similar returns out of these efforts? Answering these question can help us better understand gender disparities in scholars' online success and motivate the design of relevant policy interventions to close the gender gap [Dehdarirad, 2020, Klar et al., 2020, Fortin et al., 2021, Vasarhelyi et al., 2021]. We hypothesized that female scholars self-promote less often than males based on a number of theoretical and empirical studies on the role of gender in science and other domains.

Self-promotion is a social behavior publicizing one's own strengths and achievements [Schlenker, 1980]. Self-promoting is often necessary for professional success in numerous settings including job interviews, salary negotiations, and career promotions [Laschever and Babcock, 2003, Moss-Racusin and Rudman, 2010]. Research finds that individuals who do not engage in self-promotion are likely to be rated as less competitive or qualified than their self-promoting peers [Janoff-Bulman and Wade, 1996, Wade, 2001]. Such research also finds that women face a double bind when it comes to self-promotion [Phelan and Rudman, 2010]. On the one hand, women need to self-promote in order to demonstrate leadership skills [Yang et al., 2019]. On the other hand, self-promoting women risk penalties for violating negative gender stereotypes that women are modest and less competent than men [Eagly and Kite, 1987, Heatherington et al., 1993].

Women's self-promotion may cause "backlash effects" for demonstrating counter-stereotypical behaviors [Rudman and Phelan, 2008, Moss-Racusin and Rudman, 2010]. Indeed, studies find that women who self-promote are seen as more arrogant and less likable than self-promoting men [Hagen and Kahn, 1975, Rudman and Glick, 2001, Moss-Racusin et al., 2010], and are judged to be unfeminine and dominant [Janoff-Bulman and Wade, 1996, Rudman, 1998]. This double standard may discourage female scientists from self-advertising their research on social media. In addition to concerns about backlash, women may also self-promote less in science due to self-stereotyping in areas that are typically male-dominated. Self-stereotyping may reduce self-promotion even when without clear evidence of negative consequences like backlash [Coffman, 2014, Josephs et al., 1992, Kling et al., 1999, Orenstein, 2013, Bleidorn et al., 2016]. Furthermore, women may be more conservative in self-promotion due to a "role model" type mechanism where women are under-represented in many occasions. For instance, studies find that daughters are mentioned less frequently than sons on social media by their parents [Sivak and Smirnov, 2019]. Business ideas pitched by women entrepreneurs are favored less by investors [Brooks et al., 2014]. In science dissemination, female scholars are mentioned by name less often when their research is covered in news media [Peng et al., 2020], and male scholars are twice as likely to be referred to by surname than female peers in scientific domains, which in turn causes males scientists to be more confident and perceived as higher status than female counterparts [Atir and Ferguson, 2018]. Gender differences in media representation may thus create gaps in self-promotion on part of scientists themselves.

A number of empirical studies in various self-promotion contexts also motivate the possibility that female scientists are less likely to self-promote than males. Research shows that women professionals are less likely than men to self-promote themselves on online hiring platforms [Altenburger et al., 2017]. In science production, men are more likely to cite their own papers [King et al., 2017, Andersen et al., 2019, Azoulay and Lynn, 2020], and present their research as novel and important than women [Lerchenmueller et al., 2019]. These gender inequalities in different scholarly settings suggest the possibility that female scientists may be more conservative in online self-promotion.

Gender differences in self-promotion may be particularly consequential in the early stages of research dissemination, where small initial differences may accumulate into more substantial differences in coverage over time [Lieberman and Montgomery, 1988, Merton, 1968, Bol et al., 2018]. Furthermore, observational and experimental studies reveal a positive correlation between online mentions and citations [Phillips et al., 1991, Eysenbach, 2011, Costas et al., 2015, Dehdarirad, 2020, Klar et al., 2020, Luc et al., 2021]. This line of research suggests that differences in coverage and attention in social and other media may spill over into other, more traditional measures of recognition, such as citations.

Here, we leverage a multi-disciplinary dataset of 539,345 research papers published in 2018 to examine the rate at which scientists of different genders self-promote their research on social media. We focus on Twitter, which is the ubiquitous platform of online science dissemination that accounts for 92% of all mentions across social media platforms tracked by the Altmetric database [Peng et al., 2021] (see Data and Methods). Our data contain the complete tweet mentions for each paper provided by Altmetric. As each author of a paper has the option of self-promoting their research, we treated each (paper, author) pair as an observation (2,375,419 observations for 1,335,603 authors in total).

To link authors of papers to their Twitter accounts, if available, we designed and validated a heuristic to match author names to Twitter usernames and identify instances when an author mentioned their own paper (self-promoted) on Twitter with high accuracy (see Data and Methods). Here, our definition of self-promoted authors are those on Twitter and have self-promoted the paper, whereas "no self-promotion" means authors who are either not on Twitter or are on Twitter but have not self-promoted. This is a reasonable operationalization of self-promotion as existing research finds no evidence of a gender gap in scholars' presence on Twitter [Bowman, 2015].

We inferred the gender of each author based on their first names using the algorithm developed by Ford et al. [Ford et al., 2017], which categorized 59% of the authors as males and 41% as females (Unisex and Unknown were excluded in the analysis). While inferred gender may differ from how authors self-identify, self-identity is not available in our data. However, our gender inference achieved a high level of agreement with gender labels generated through a manual verification process and also with self-reported gender labels from another dataset (see Data and Methods). We collected metadata for all papers and their authors from the Microsoft Academic Graph database, which enabled us to control for important factors such as journal impact, affiliation prestige, author productivity, research topics, which can affect self-promotion (see Data and Methods).

Our large-scale analysis shows considerable and universal gender differences in academic self-promotion on Twitter. This gender disparity is persistent in different types of self-promotion and across attributes such as academic disciplines, journal impact, affiliation prestige, and author productivity. We further find that, although women self-promote less often, when they do, they actually receive slightly higher "return" in attention than their male counterparts. These findings improve our understanding of gender disparities in scholarly self-promotion and suggest that academic institutions could invest in efforts to promote recognition of female scholars' research and encourage their self-promotion.

4.2 Results

4.2.1 Universal gender gap in self-promotion

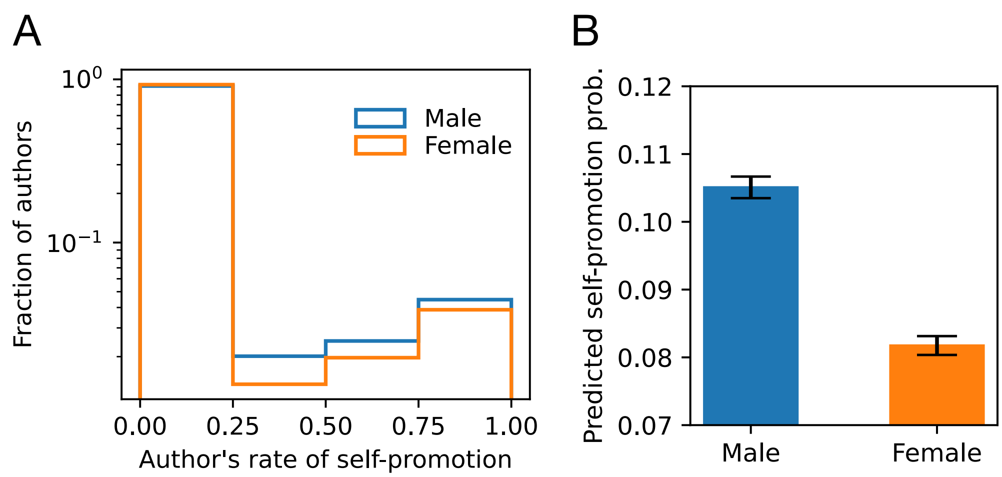

Figure 4.1: **Self-promotion by author gender.** **A**, Histogram (normalized) of the self-promotion rate per author, which is calculated as the fraction of an author's papers they have self-promoted. **B**, Predicted probability of self-promotion after controlling for confounding factors. The estimation is based on a mixed effects regression model fitted to all 2.38M observations. The model also includes random effects for each paper. The predicted probability for each gender is calculated by setting all non-gender variables at their median values.

We find that, on average, 5.9% of a paper's tweet mentions are from authors of the paper, and this fraction is similar regardless of a paper's popularity (*Appendix* Figure C.1B). People who engaged in excessive self-promotion are often at risk of being judged negatively [Godfrey et al., 1986]. Therefore, most people promote their own paper at most once, and it is not surprising that self-promotional tweets typically account for a small percentage of all tweet mentions of a paper.

The average fraction of self-promotion out of a paper's total number of mentions on Twitter is similar to the average fraction of self-citations out of a paper's total number of citations in the academic literature [King et al., 2017].

Raw gender differences in self-promotion. To examine whether there is a gender difference in how often authors self-promote their papers, we calculated the self-promotion rate of each author. Fig. 4.1A shows that men tend to self-promote their papers more often than women. This finding is robust when focusing on authors with at least five publications in the data (*Appendix* Figure C.2).

However, how much the authors self-promote their papers on average does not take into account the differences in individual papers. To examine more nuanced factors related to self-promotion behaviors, we examine whether an author promotes each of their own papers, by treating each (paper, author) pair as an observation. For each observation, the author may or may not have self-promoted the paper. We coded the dependent variable, author's self-promotion status, based on a method that matches the author name to tweet user names (Data and Methods).

In this analysis, men account for a much larger fraction of all 2.38M observations than women (63.8% vs. 36.2%), which reflects the gender imbalance in publications and authorship [West et al., 2013, Larivière et al., 2013]. We find that male scholars have an average self-promotion rate that is 21.9% higher than that of females (7.8% vs. 6.4%). This gender gap is universal across different authorship positions and academic disciplines (*Appendix* Figure C.3). First and last authors are more likely than middle-position authors to self-promote (*Appendix* Figure C.3A), which might be explained by the different roles played by authors at different positions [Vasilevsky et al., 2021]. Across various research fields, self-promotion is much more common among social scientists than that among physical, health, and life scientists (*Appendix* Figure C.3B). However, regardless of author roles and research fields, there is a universal gender gap in self-promotion practices, with men self-advertising from 12% to 35% more often than women.

Besides these factors, self-promotion behaviors may also be impacted by other institutional and organizational factors, such as the journal impact, author productivity, and affiliation prestige (*Appendix* Figure C.4). As there is typical gender imbalance among these correlated factors [Larivière et al., 2013, Jena et al., 2015, Way et al., 2016], the raw gender difference in self-promotion rate may be explained by these factors rather than by gender. It is thus important to isolate the effects of potential confounding factors in order to assess the role played by author gender in generating the observed disparity.

Gender disparities in self-promotion after adjusting for confounds. We examined the correlation between author gender and self-promotion using a mixed effects logistic regression model [Bates et al., 2015] that controlled for the random effects of each paper and a number of important confounding factors including paper's journal impact, affiliation prestige and location, author's productivity, number of authors, authorship position, and research topics (Data and Methods).

Since there was a quadratic relationship between author productivity and self-promotion rate in the data (*Appendix* Figure C.4), we included a second order polynomial term for author productivity in the model. We treated all other variables as linear terms in the regression. The dependent variable is author's self-promotion status (a binary variable). Based on the fitted model (see regression coefficients in *Appendix* Table C.2), we estimated the adjusted probability of self-promotion for both genders, by setting all other variables at their median values across all observations.

Fig. 4.1B shows that, a typical female author has a 8.2% chance of self-promoting her research, while a comparable male author has a 10.5% probability of self-promoting, which is 28% higher than for females. This disparity also exists among female vs. male authors of the same paper, as our model accounts for the random effect of each paper. The results are consistent when coding the self-promotion variable based on either *original tweets* or *retweets* (*Appendix* Figure C.5; see details of two types of self-promotion tweets in Data and Methods).

Our model does not control for authors' presence on Twitter. Thus, a lack of self-promotion could be due to an author who has a Twitter account but chooses not to tweet about their paper, or an author who is not on Twitter at all. While these are two different situations, they are both cases where the authors does not engage in self-promotion on the platform.

As a robustness check, we obtained consistent results (*Appendix* Table C.3) when restricting the analysis to the subset of authors who have ever self-promoted their papers in our data (therefore have a Twitter account). Note that this subset of the data also contains (author, paper) pairs that did not self-promote since not all authors self-promote all their papers.

The observed gender gap in self-promotion is unlikely to be explained by women's under-representation on Twitter. In fact, past research shows that women academics are at least as likely as men to be on the platform [Bowman, 2015].

4.2.2 Heterogeneity in gender disparities in self-promotion

Academic disciplines. Research fields vary substantially in gender representation in publishing and scholars' presence on Twitter [Bowman, 2015, Ke et al., 2017, Costas et al., 2020], which can create an additional variability in self-promotion with regard to gender. To examine the disparities across research fields, we fitted a separate model for each of the four broad disciplines, including social, life, health, and physical sciences (Data and Methods). When fitting a model for each discipline, we still controlled for the 26 fine-grained Scopus Subject Areas. Papers belong to multiple disciplines are assigned to each discipline.

Fig. 4.2A shows the predicted probability of self-promotion for men and women by setting all non-gender variables at their median values. The female coefficient in each regression model is significantly negative, and the predicted mean self-promotion rate is always higher for men

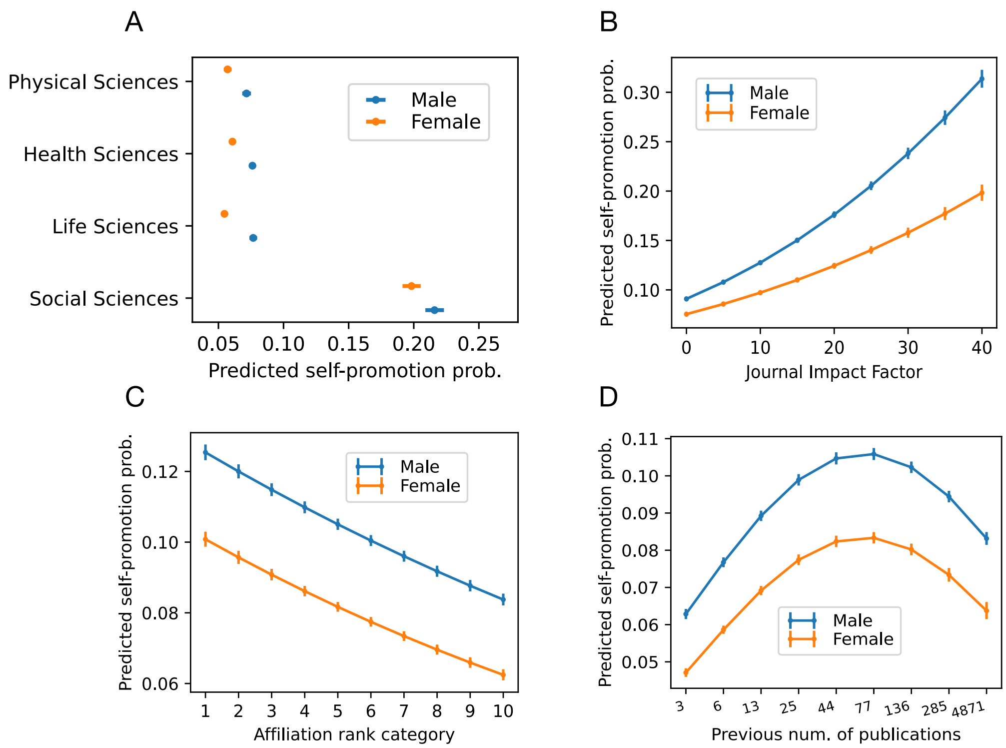

Figure 4.2: **A**, Predicted self-promotion probability across four broad disciplines. We fitted a mixed effects logistic regression for the data in discipline. Across all four broad disciplines, the predicted self-promotion rate for men is always higher than that for women. Social scientists have the highest self-promotion probability, but the smallest gender gap in the relative scale. **B-D**, Predicted probability of self-promotion as a function of journal impact, affiliation prestige, and author productivity. For each variable, we fitted a separate mixed effects logistic regression to the full data by including an interaction term between that variable and author gender. The journal impact factor (**A**) is provided by The Web of Science (2018 version). We categorized (deciled) author's affiliation rank (**B**, a smaller bin indicates a higher rank category) and authors' previous number of publications (**C**, a smaller bin indicates a less productive category) in the regression. Error bars indicate 95% bootstrapped confidence intervals.

than for women in each discipline. Furthermore, there are much variations in gender disparities across disciplines. The absolute gender disparity is universally similar across four disciplines, suggesting that men are self-promoting more often than women in science in general. However, social scientists are about four times as likely to self-promote their research as scientists in the other three disciplines. This makes the relative gender gap in Social Sciences the smallest, indicating that both male and female scholars in this field are similarly active in promoting their research.

Scholarly self-promotion is influenced by a number of factors besides gender (*Appendix* Table C.2), including the impact of the journal where the paper is published, the prestige of author's affiliation, and the productivity of the author. Previous research found that these three status-related factors are themselves associated with gender. For instance, women published fewer papers in leading journals [Larivière et al., 2013, Editorial, 2018b], were placed at lower-ranked institutions [Smart, 1991], and were less likely to achieve tenure status [Jena et al., 2015, Way et al., 2016]. To explore how different factors affect gender disparities in self-promotion, we included in the model a separate interaction term between gender and journal impact, affiliation prestige, and author productivity, and calculated the predicted probability of self-promotion for both genders.

Journal impact. Publishing in top-tier journals can boost authors' confidence and therefore may reduce the gender disparity in self-promotion as authors of both genders may be more active in sharing the research. In contrast, past research shows that high-achieving women can elicit more pushback for their success as this violates gender expectations [Cooper, 2013, Djupe et al., 2019]. This may cause female scholars to self-promote less for their high-impact papers out of the fear of backlash. The two competing hypotheses raise the question: does the journal impact decrease or increase the gender disparity in self-promotion rate?

Fig. 4.2B shows that authors of both genders are more likely to share their research published in higher impact journals, and they don't self-promote their subordinate papers as often, suggesting that authors are sensitive to associating their names with lower-tier publications on Twitter. However, this effect is less pronounced for females, resulting in an even larger disparity for papers published in top-tier venues: for papers of an impact factor 40, male scholars are 55% more likely to self-promote than female scholars (0.31 vs. 0.20), whereas for low-tier publications, the same probability is only 12.5% higher for men than for women (0.09 vs. 0.08).

Affiliation prestige. Fig. 4.2C shows that authors affiliated with prestigious institutions self-promote much more often than those with lower-ranked affiliations. Specifically, authors from top-tier affiliations are 50% more likely to self-promote their research than those from bottom-tier affiliations. However, this effect applies nearly equally to both genders, resulting in a similar magnitude of absolute gender gap in self-promotion probabilities across the institution hierarchy. That is, men's self-promotion probability is, on average, 2.5 percentage points higher than that of women across all affiliation ranks.

Author productivity. As shown in Fig. 4.2D, there is a quadratic relationship between author's research experience and self-promotion. Throughout a scholar's career, their self-promotion probability first increases, but only up to the mid-career stage, after which the probability starts to decrease. Mid-career scholars are much more likely to self-promote than early- and late-career scholars. This pattern is similar for both genders.

One possible reason is that junior researchers spend most of the time conducting the research, while the marketing job is often taken by senior scholars once the research is finished [Wren et al., 2007, Sekara et al., 2018], thus early-career scholars have less energy and opportunity to advertise their own research. However, as senior authors further make progress in their careers and achieve tenure or full professor status, they have less time, motivation, and incentive to self-promote.

The gender gap is consistent as men are always more likely to self-promote than women across career stages. But the largest absolute gender disparity occurs among authors at their mid-career, where both male and female scholars are at their peak of self-promotion probabilities (0.106 vs. 0.083). However, the relative gender difference is the largest among junior scholars (33.4%).

These results suggest that self-promotion on Twitter is very strategic, with men and women adopting slightly different tactics in sharing their own research. Relatively speaking, men are much more active in self-promotion than women when they are junior scholars from lower-ranked affiliations publishing higher-impact papers. The findings illustrate the subtle nature of gender differences in scholarly self-advertising on social media and provide new insights into the gender inequities in scientists' online visibility and success [Vasarhelyi et al., 2021].

4.2.3 Gender differences in the sentiment of self-promotion content

To compare the self-promotion content posted by men and women, we first directed our attention to analyze the sentiment carried in tweets that involve self-promotion. We used a software called "Vader" [Hutto and Gilbert, 2014] to predict the sentiment of each tweet. This tool is specifically developed and attuned to detect sentiment expressed in social media posts and is widely used in past studies [Davidson et al., 2017, Cheng et al., 2017]. It outputs a composite score between -1 and 1, which can be used as a single unidimensional measure of sentiment for a given text. As recommended by [Hutto and Gilbert, 2014], we classify each tweet as either positive, neutral, or negative by setting two thresholds: -0.05 and 0.05.

Fig. 4.3 shows that scholars of both genders tend to share non-negative sentiment during self-promotion, which is not unexpected. However, women are more positively sharing their research than men (49.1% vs. 45.7%), whereas men have being more neutral than women (40.0% vs. 36.8%). A Chi-squared test of independence indicates that the difference between the sentiment distributions for men and women are statistically significant ($p < 10^{-5}$).

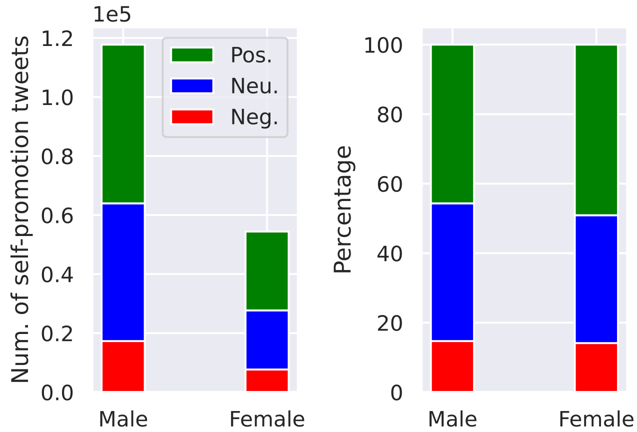

Figure 4.3: Female scholars are more likely to share positive sentiment than males in self-promotion on Twitter. *Left*: the number of positive, neutral, and negative tweets that involve self-promotion by males and females. *Right*: the percentage of three types of tweets by gender.

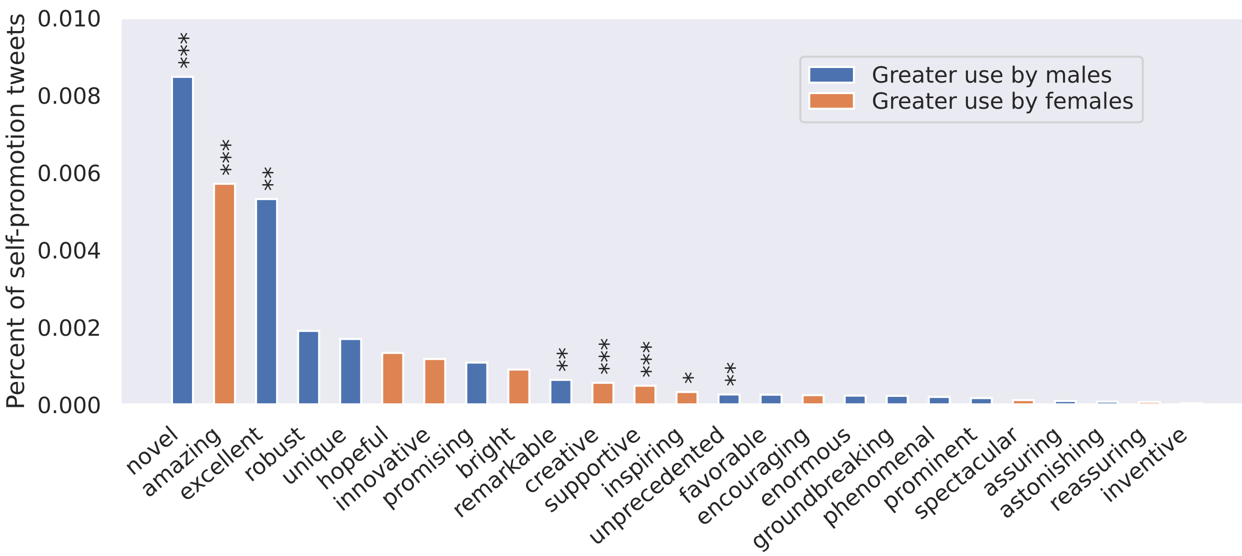

Figure 4.4: Gender differences in the usage of specific positive words in self-promotion, estimated based on a Mann–Whitney U test of the distribution of word usage by both genders. For each positive word, the variable for each self-promotion observation is set to one if the tweet contains that word and zero otherwise. The y-axis shows the percentage of self-promotion tweets that have used each positive word. Significance levels: *** $p<0.001$, ** $p<0.01$, and * $p<0.05$.

Male and females have different language styles [Bamman et al., 2014]. However, the overall sentiment distribution does not indicate how men and women are using different words to convey the positive sentiment when sharing their research. We thus analyzed each of the 25 positive words adopted in [Lerchenmueller et al., 2019] and compared their usage by both genders in self-promotion tweets. Fig. 4.4 shows that men use "novel", "excellent", "remarkable", and "unprecedented" more often than women, whereas women more often use "amazing", "creative",

Table 4.1: Coefficients of all variables in a negative binomial regression model that predicts the total number of tweets for each (author, paper) observation. The 26 Scopus Subject Areas controls are omitted here due to space constraint (but are available in *Appendix* Table C.4). Significance levels: *** p<0.001, ** p<0.01, and * p<0.05.

Female	0.018^{***}	p = 0.000
Self promotion = True	1.566^{***}	p = 0.000
Female x (Self promotion = True)	0.033^{***}	p = 0.000
First position	-0.004	p = 0.182
Middle position	0.268^{***}	p = 0.000
Solo author	-0.204^{***}	p = 0.000
Author pub. count category	0.014^{***}	p = 0.000
Affiliation rank category	-0.025^{***}	p = 0.000
Affiliation location = International	-0.115^{***}	p = 0.000
Number of authors	0.0001^{***}	p = 0.000
Journal impact	0.095^{***}	p = 0.000
Constant	1.729^{***}	p = 0.000

"supportive", and "inspiring" when promoting their research. Other positive words often used by both genders in self-promotion include "robust", "unique", "hopeful", "innovative", and "promising". The gender differences in the use of positive words suggest that not only do men and women self-promote at different rates, they also frame the language and sentiment of promotion differently.

4.2.4 Are there disparities in the return on self-promotion?

Self-promotional tweets are often expected to attract attention to one's papers. However, we know little about the effect of self-promotion on a paper's overall popularity and whether there is a gender difference in the return associated with self-promotion. We set out to measure these effects.

The distribution of a paper's total number of tweets is over-dispersed (the variance exceeds the mean), we thus fitted a negative binomial regression model to this dependent variable. In our data, female scholars' papers received less attention than that of males (the average total number of tweets: 16.8 vs. 18.2; p = 0), which is consistent with a previous study [Vasarhelyi et al., 2021]. To examine how self-promotion impacts the dependent variable differently for men and women, we included in the model an interaction term between author gender and self-promotion (a binary variable). The controls include journal impact, author's affiliation prestige and location, author's prior number of publications, number of authors, authorship position, and research areas (Data and Methods).

As shown in Table 4.1, self-promotion can indeed significantly increase a paper's total number of tweet mentions. Surprisingly, women are slightly advantaged in receiving online attention for their papers (the Female coefficient), after controlling for important confounding factors that are associated with attention. What's more, although women self-promote less often than men, but when they do, they on average get more return on the overall attention to their papers (the coefficient for the interaction term). The model's adjusted prediction of a paper's total number of tweets reveals that, without self-promotion, females' advantage over males is very limited on average (the predicted total number of tweets: 7.50 vs. 7.64). However, with self-promotion, women have a 5.3% advantage over men (the predicted total number of tweets: 37.8 vs. 35.9).

Furthermore, these results also hold true for different types of audiences on Twitter, including scientists and non-scientists (see *Appendix* Table C.8-*Appendix* Table C.9). This suggests that female scholars' research attracts more audiences in the scientific community and also more audiences among the public than comparable male scholars' research.

The result is consistent when fitting the same model to the subset of our data that involve self-promotion (that is all (paper, author) pairs with self-promotion) and dropping the interaction term between author gender and self-promotion, and additionally controlling for the author's follower count on Twitter (*Appendix* Table C.5). As our design treats each (paper, author) pair as the unit of analysis, a paper's total number of tweets might be affected by the self-promotion benefit from coauthors. To rule out this possibility, we fitted a separate model to solo-authored papers (dropping controls for the number of authors and authorship position) and obtained similar results (*Appendix* Table C.6). This finding is also robust when defining self-promotion tweets as those posted within one day after paper publication (*Appendix* Table C.7).

In summary, our analysis points to the surprising finding that women have a slight advantage over men in the return of self-promotion, of which scholars themselves may be previously unaware. This result suggests that the gender disparity in scholars' online success may be partly driven by the disparity in self-promotion rate. However, establishing this causal relationship requires further experimental investigations. More importantly, this finding suggests that encouraging and enabling female scholars to be more active in self-promotion may be one solution to reduce gender disparities in scholars' online success.

4.3 Discussion

Our analysis based on 1.3M authors and 45M tweet mentions of their published research papers shows that scholarly self-promotion is highly dependent on gender. Female scholars are significantly less likely to advertise their own papers on Twitter than their male colleagues. This association persists even after controlling for a number of important factors, including journal impact, affiliation prestige and location, author productivity, authorship position, and research areas. The disparity also occurs in different types of self-promotion, including original tweets and retweets.

The absolute gender disparity is the largest for papers published in top-tier journals, suggesting that while publishing in high-impact journals increases the willingness to self-promote for both genders, this effect is stronger for male authors. This also indicates that men are more sensitive to associating their names with papers published in lower-tier journals, and women are more held back in promoting their top-tie papers. However, the absolute gender gap is rather stable across disciplines, affiliation ranks, and author productivity, but the relative difference varies. The relative gender gap is the smallest among social scientists across fields, and is the largest among junior researchers from lower-ranked institutions who publish papers in higher-impact journals.

Besides gender, we also find that self-promotion behavior varies substantially across disciplines, affiliations, journal impact, and author productivity. Social scientists self-promote the most often than scientists in the other three disciplines. Scholars are much more likely to self-promote when they are affiliated with prestigious institutions, are at their mid-career stages, and have published papers in top-tier journals. Men and women also use slightly different languages in self-promotion, and women are more likely to share positive sentiment than men.

We further find that, while all authors receive higher social media attention when they self-promote their papers, this increase in attention is higher for female authors than for their male counterparts. This finding suggests that self-promotion could play an important role in reducing the gender inequities in online attention to scientific work [Vasarhelyi et al., 2021].

The self-promotion gender difference is consistent with gender gaps observed in traditional activities such as self-citation [King et al., 2017] and research presentation [Lerchenmueller et al., 2019]. It is thus critical to close the gender gap in self-promotion early on because small differences in the initial stage of research dissemination may grow into large disparities in scholars' ultimate recognition across different online platforms and other types of outcomes such as citations.

Although our study does not uncover the causes in generating the observed gender differences in self-promotion due to its observational nature, several of our analyses point to a process that likely involves multiple mechanisms. Female scientists may be more conservative in self-promotion due to fear of backlash [Rudman and Phelan, 2008, Moss-Racusin and Rudman, 2010] and self-stereotyping [Coffman, 2014]. In support of this, we find that female scholars self-promote less even in the form of retweeting others' tweets promoting their work, which likely reduces the burden associated with self-promotion. Furthermore, women are not self-promoting their high-impact research as much as men do (Fig. 4.2B), possibly out of fear of getting more backlash for advertising their higher achievements [Phelan and Rudman, 2010, Cooper, 2013]. Examining these mechanisms is a fruitful avenue for future research.

Our study is not without limitations. First, our analysis was focused on papers published in 2018. The finding might not generalize to other time periods as the gender trend can be changing over time. Second, we limited our study to a single social media platform, Twitter. Although it is the largest platform, it would be interesting to extend the investigation to other platforms such as Facebook in future work. Besides, we focused on self-promotion of research papers. Future work can examine gender differences in self-promotion of other scholarly achievements such as career promotion and winning awards. Third, we used the inferred gender as a proxy of authors' true gender. Although our manual verification shows that there is a high degree of agreement between the two attributes, the perceived identity and the true (or self-reported) identity may mismatch in some cases. What's more, people may identify themselves as non-binary [Tannenbaum et al., 2019, Brooke, 2021], which were regrettably omitted in our study since it is challenging to identify non-binary gender scientists based on their names. Future work can extend the investigation to non-binary genders.

Fourth, our study requires matching of authors to Twitter users. We addressed and validated this problem using a name matching algorithm. Although the matching is not without any error, our manual verification shows that it achieves a F1 score above 0.9. Finally, we did not distinguish between cases when an author did not self-promote despite having a Twitter account and cases when the author is not on Twitter. This raises the concern that the lower self-promotion rate by female authors may be due to a lower female representation on Twitter. However, past literature suggests that this is unlikely to be the case since studies have shown that female researchers are not less represented on Twitter than male researchers [Bowman, 2015]. Furthermore, we obtained consistent results (*Appendix* Table C.3) on the subset of the data where the authors have ever self-promoted any paper in the dataset (therefore are on Twitter).

Despite these limitations, our study offers novel insights into scholars' self-promotion behaviors on social media overall and based on their gender, and enrich our understanding of the broader gender inequity in scientists' online visibility. Our findings have policy implications for online science dissemination. For instance, to restore gender parity in scholars' online visibility, institutions could support efforts and allocate resources that aim to encourage more self-promotion by female scholars, especially given their slightly advantage associated with self-promotion. Additionally, such policies could let females focus on advertising more of their high-impact research.

4.4 Data and Methods

4.4.1 Altmetric database

Our data are based on the most complete record of research papers' online mentions, maintained by Altmetric.com [Altmetric, 2021a]. This service has been tracking the online mentions of research outputs since 2011 in different platforms including news media and social media such as Twitter and Facebook. We accessed the database (referred to as "Altmetric" hereafter) on Oct 8,

2019. Altmetric matches the online attention to papers based on their unique identifiers, such as the Digital Object Identifier (DOI), PubMed ID, and arXiv ID. Utilizing these identifiers, it also collapses the attention for different versions of each paper into a single unique record [Altmetric, 2021b]. This ensures that the data contains the complete mentions of each paper.

We focused on all 1,218,710 research papers (before dropping observations with missing values for all control variables) published in 2018 in the database. We obtained all their mentions in the largest platform, Twitter, which consists of about 74% of all mentions (posts) and 92% of all social media mentions in the entire database [Peng et al., 2021].

Due to Altmetric's data license agreement with Twitter, the dataset contains only the tweet ID for each tweet. We thus collected all tweets using the Twitter API. Due to privacy issues and account deletion for some Twitter users, we successfully retrieved about 90% of all tweets. The Altmetric data also provides metadata for each paper, such as the DOI, publication year, publication venue, research topics. There are 26 Scopus Subject Areas, which belong to 4 broad disciplines including Social Sciences, Life Sciences, Physical Sciences, and Health Sciences [Elsevier, 2021]. The classification was performed by in-house experts based on the aim and scope of the content a journal publishes [Elsevier, 2021].

4.4.2 Microsoft Academic Graph

We used the Microsoft Academic Graph (MAG) database [Sinha et al., 2015, Wang et al., 2019] (accessed on June 01, 2019) to retrieve other metadata for each paper based on the DOI. We obtained essential author information for each paper including author name, author affiliation, affiliation location, affiliation rank. We also counted author's previous number of publications up to the publication year of each paper, which reflects author's previous productivity at the time of deciding whether to self-promote or not, assuming authors tend to self-promote soon after the publication of a paper. MAG leverages data mining and artificial intelligence techniques to address author conflation and disambiguation, which ensures that the author's number of publications is counted accurately [Wang et al., 2019]. A paper can have multiple authors and we track whether each of then posted about the paper on Twitter. We therefore used each (paper, author) pair as an observation in the analysis. In our final dataset after dropping missing values for all control variables, there were 2,380,098 observations for 539,848 papers, which were mentioned in about 45 million tweets.

4.4.3 Gender prediction

We used Ford's algorithm [Ford et al., 2017] to infer the gender of a author based on their first name. The algorithm returns, for a given name, one of 4 categories: Female, Male, Unisex, Unknown. A name is predicted as “Female” (“male”) if it is at least twice as frequently used for women (men) as for men (women), based on data from national statistics institutes [gen]. Otherwise, the name is labeled as “Unisex” (gender-neutral). If the name is not found in the database, it is labeled as “Unknown”. The percentage of observations for Male, Female, Unknown, and Unisex is 49%, 28%, 17%, 6%, respectively. In the final dataset, we excluded “Unknown” and “Unisex” categories (we obtained consistent results when including the two categories). We used “Male” as the reference category in the regression.

4.4.3.1 Validation with manually verified gender

We evaluated the performance of this algorithm based on a random sample of 100 authors in our data, for which we manually labelled their gender. In the labeling process, the author gender was determined by their pronouns and profile pictures displayed on their personal websites, institutional directories, and Wikipedia pages found via a Google search of author names. We used the author’s affiliated institution to disambiguate multiple authors with the same name. If the gender could not be verified, it was labeled as “Unknown”. There were 19 females, 57 males, and 24 authors with unknown gender in the labelled sample. Based on the set of 76 authors with confirmed gender, the algorithm achieved an accuracy of $F1_m = 0.91$ and $F1_f = 0.88$. Using the Genderize API [gen, 2021, Lerchenmueller et al., 2019, cod, 2015, Karimi et al., 2016] produced a similar result.

4.4.3.2 Validation with author self-reported gender

We also validated the accuracy of the gender prediction using author self-identified gender labels in the data provided by IOP Publishing (https://ioppublishing.org/), which is an academic publishing company specialized in the field of physics.

Each author has reported their gender and country of residence such as China, India, U.S., Canada, Australia, etc. In our evaluation, we focused on authors with reported gender as either male or female, and whose names were predicted as either male or female, as our actual analysis was focused on authors with distinctly predicted gender labels. There are 432,888 authors submitting to 62 journals in this data. Here we list authors from China as a separate group because Chinese names typically do not encode clear gender signal when written in English characters [Jia and Zhao, 2019]. For instance, we found that the vast majority of names (475 such names in total) with both male and female as self-reported gender are from China. As shown in *Appendix* Table C.1, the prediction accuracy for Chinese names is lower than non-Chinese names, and the overall F1 score is close to 0.9. However, this is likely an underestimation because China is better represented in the IOP data (where China has the most number of submissions) than in the Altmetric data.

4.4.3.3 Robustness check on non-East Asian names

Since the gender prediction is less accurate for East Asian names including Chinese names, we repeated our analysis by excluding author names predicted to be East Asian ethnicities using the Ethnea API [Torvik and Agarwal, 2016]. The result is consistent on authors with non-East Asian names (*Appendix* Table C.10). *Ethnea* is trained using the PubMed database, with the location of the authors' affiliations as the ground truth. For a specific name, *Ethnea* assigns the ethnicity probabilities among matched authors. In the case of two or more predicted ethnicities, we took the one with the highest probability. There are 26 individual ethnicities and we categorized 7 of them as East Asian, including *Chinese*, *Indonesian*, *Japanese*, *Korean*, *Mongolian*, *Thai*, *Vietnamese*.

4.4.4 Detecting self-promotion among a paper's tweet mentions

Each paper has a list of tweets that mention the paper, with each tweet containing the twitter handle and the screen name of the user (referred to as "tweet names" hereafter). We defined self-promotion as the author posting a tweet sharing the unique identifier of their paper [Altmetric, 2021b], such as the DOI, PubMedID, arXiv ID, etc. Self-promotion on Twitter comes in different forms, which can manifest in the type of the tweet that shares the research, including (i) an original tweet, or (ii) a retweet. The two types of self-promotion differ in how direct the promotion is: the original-tweet-based promotion comes from the authors themselves whereas the retweet-based promotion originates from others (e.g., an author A retweets a tweet from others sharing A's paper). Self-promotion in the form of posting an original tweet potentially indicates a stronger intention to advertise one's paper than that based on a retweet, which is more indirect in the nature of promotion.

We constructed a binary dependent variable indicating whether the author self-promoted the paper or not, based on both retweets and original tweets. We determined if an author was among the users who tweeted the paper using string matching between names.

There is no perfect method to match author names with tweet names because scholars can use whatever strings they like as the handle or screen name on Twitter. We thus adopted a simple "containment-matching" approach that searched the author name in tweet names—if either the first name or the last name string was contained in the user handle or screen name (lowercased), we considered the user to be the author of the paper. In case of multiple matches, we used the one with the highest fuzzy matching score [fuz].

We validated this method using a random sample of 100 papers (each has at least one tweet) with manual verification. Due to having multiple authors per paper, there were 521 (paper, author) pairs in the manual labelling process. For each observation, we verified the author against all tweets of the paper to check if the author was among the tweet users. This method achieved an initial F1 score of 0.85 (precision: 0.77 and recall: 0.95).

We refined this method through an iterative process by experimenting with various new heuristics to address false predictions and evaluating its performance based on an independent manual verification process at each iteration. In the final version, we used "containment-matching" only if the tweet names are single-token string and the author's first name (or last name) had at least 4 characters; otherwise, we used "token-matching', i.e., the first name or the last name should be matched to the tokens of tweet names (split by space or underscore). This final heuristic achieved a precision of 0.95 and a recall of 1.00 (F1 score: 0.97).

4.4.5 Control variables in regression models

We used a mixed effects logistic regression to estimate the probability that an author of a paper self-promoted the paper on Twitter as a function of their gender, while controlling for a variety of important confounding factors.

Many factors besides author gender can have an effect on author's tendency to self-promote. For instance, papers published in high impact journals may be more likely to be shared by their authors. Research topics may also affect the shareability of the paper since different fields vary in their norms of promotion on social media. The audiences on Twitter may be field-specific, which might in turn influence authors' self-promotion behaviors. We thus controlled for the following fixed and random effects variables:

- *Journal impact factor*: We obtained the impact factor for journals indexed in The Web of Science (2018 version), which can be used as a measure of paper impact. Journals with missing impact factor were dropped in the analysis.

- *Author's affiliation rank*: Authors from prestigious institutions may be more likely to self-promote. We thus considered the rank of their affiliations provided in the MAG. When an author has multiple affiliations in a paper, we used the one with the highest rank. The rank value is log-transformed in the MAG raw data and is thus non-linear. We therefore categorized the rank values into ten equally-sized bins (a smaller bin indicates a higher rank category).

- *Author's previous publications*: Authors' career stage and previous research experience can influence their likelihood of self-promoting. To measure this factor, we counted each author's total number of publications before the publication year of the current paper, using all papers indexed in MAG. We also categorized this numerical variable into ten equally-sized bins due to non-linearity of this variable and also to reduce noise and outliers. Note that the first two bins were combined into one group as they had the same intervals.

- *Number of authors*: We also counted the number of authors in each paper. We hypothesized that having more coauthors in a paper would be negatively correlated with an author's likelihood of self-promoting, as some authors may find it unnecessary to post about the paper if a coauthor already did.

- *Authorship position*: Different authors often play different roles in multi-author projects. The first authors are commonly early-career scholars who may be more likely to self-promote the research than senior authors. In contrast, authors who play a supportive role in the project may self-promote less frequently. This variation is often captured by the authorship position in the paper. We thus controlled for the position of an author with four categories: (1) first position, (2) middle position, (3) last position, (4) solo author. The last position was used as the reference category in the regression.

- *Affiliation location*: We inferred the country of the author's institution using the latitude and longitude information in the MAG. There were two categories: (1) U.S., (2) international. We used "U.S." affiliation as the baseline to control for the fact that Twitter is a U.S. social media platform that is more likely to be adopted by authors based in the U.S. Observations with unknown affiliation location information were excluded in the analysis. When an author had multiple affiliations with at least one located in the U.S., we classified them as "U.S." In the regression, we treated "U.S." as the reference category.

- *Research fields*: Not all scholars employ Twitter as a channel to share their research, and scientists' representation on Twitter varies across disciplines [Ke et al., 2017]. To control for field-specific effects, we used the 26 Scopus Subject Areas. Each subject area was treated as a fixed variable in the regression, whose value was coded as 1 if the paper was assigned that subject (0 otherwise). Note that a paper can belong to multiple subject areas.

- *Paper random effects*: Individual papers have different degrees of newsworthiness (e.g., biomedical papers have much more online coverage than papers from other disciplines [Banshal et al., 2019]). Different papers may vary in the likelihood of being shared on social media by their authors. Gender representation also varies across disciplines [Vasarhelyi et al., 2021]. To capture such paper-level variations, we added random effects for each paper in the model.

CHAPTER 5

Conclusion

5.1 Summary of Contributions

The purpose of this dissertation is to systematically examine ethnic and gender disparities in the production and dissemination of science, and enrich our understandings of the mechanisms leading to such disparities. Addressing these disparities not only impacts individuals' careers, but also affects the overall progress in science and innovation. Our goal has been made possible with novel computational techniques and large scale observational data. We have investigated three important scholarly activities in the scientific pipeline, including manuscript review at prestigious journals, author mentions in U.S. science news, and scientists' self-promotion behavior on social media.

First, by leveraging private journal peer-review data and comprehensive bibliometric databases, we showed that the acceptance rate at two biological journals is significantly associated with author's ethnicity inferred from their names (Chapter 2). The acceptance rate is especially lower for East Asian-named authors, relative to their British-origin-named counterparts. This association is robust to the inclusion of important confounding factors. This ethnic disparity is likely driven by editorial decisions but not peer reviewers.

We then investigated whether the disparity continues to arise after the research has been published and already received coverage in science news in major U.S. media outlets (Chapter 3). We found that authors with most non-British-origin names are mentioned substantially less when their research is discussed, even after controlling for a number of plausible factors that could impact mention rates. Mention rates are especially low for East Asian and African-named authors. These disparities are likely driven by both pragmatic difficulties associated with interviewing researchers (such as location and English speaking fluency) and journalists' personal choices.

Finally, beyond disparities produced by external forces, we studied the disparity in scholar's self-promotion on social media with respect to their name-inferred gender (Chapter 4). We revealed a universal gender gap in self-promotion, with women consistently advertising their own papers less often than men even after adjusting for confounds. We further found that, although women self-promote less often, they receive slightly more mentions in return for their advertised papers.

Our findings contribute to addressing the under-representation issue in the scientific workforce by improving our understanding of disparities experienced by under-represented groups throughout the pipeline of science production and dissemination. Disparities in publishing success, media recognition, and self-promotion likely have unfavorable consequences on scholars' careers and can potentially undermine their motivation to produce more creative and innovative work.

5.1.1 Discussion

We find large disparities for scholars with East Asian and African names. Some of these disparities are unexplained by observable factors. Disparities remain even among U.S.-affiliated scholars with whom the decision-makers (e.g., U.S.-based journalists and the U.S. publisher) should be able to have more direct knowledge. Disparities in major activities such as publishing success in top journals can affect scholars' overall reputation in the scientific community, which in turn could undermine their career progress and future productivity. This is even worse for international scholars who experience additional cultural and institutional barriers in a foreign workplace. The exact consequence of these disparities is difficult to measure due to a lack of longitudinal data and the complex nature of scholarly evaluation in various outcomes. However, it can be detrimental for leading countries that have long welcomed international researchers in their scientific development (e.g., the U.S.) as it eventually leads to less recruitment and retention in their innovation ecosystem [Kahn and MacGarvie, 2020, Kania and Gorman, 2020].

Besides ethnicity, we also find gender differences in scholarly self-promotion on social media. Self-promotion of one's work may influence their online recognition and citations by other scientists, eventually affecting scholars' prestige, reputation, and careers in the long run. The gender disparity in research dissemination enriches past literature in understanding women's under-representation in science. Although we focused on self-promotion of research papers, this gender disparity may also exist for other scholarly achievements such as career promotion.

Our studies also shed light on the possible mechanisms producing these disparities, which have practical implications for designing policy interventions to restore equality in science. For example, knowing that editors not peer reviewers are the key in producing ethnic disparities in manuscript acceptance, leading journals should consider masking author identities not only for reviewers but also for editors ("triple-blind" review) when considering changing their review model. In science reporting, guidelines in science journalism may consider discouraging journalists from replacing author names with their institutions. Similarly, in light of less self-promotion from women and their slight advantage in receiving attention conditioning on self-promotion, institutions could support and invest in efforts that aim to encourage self-promotion by their female colleagues to reduce gender inequity in scholar's online success.

Although this dissertation does not examine whether disparities in the studied scientific processes actually impact individuals' careers and whether they collectively have negative consequences on institutions' intellectual outputs, being able to reveal such disparities can stimulate future efforts to directly investigate potential consequences for scholars, institutions, and science as a whole.

5.2 Future Directions

5.2.1 Establishing demographic bias in science

We have revealed gender and ethnic disparities in several important scientific activities, and tested many potential mechanisms whenever possible. However, due to the observational nature of our study design, we lacked strong evidence for causal claims. For instance, although we showed that the ethnic disparity in acceptance rate is likely driven by journal editors not peer reviewers (Chapter 2), it does not necessarily imply ethnic bias on the part of editors, because they may be selecting manuscripts to achieve a portfolio of research topics, which might be correlated with ethnicities in a way that our keyword-based topics are unable to control for perfectly.

The gold-standard method to establish causality is through field experiments, where the investigator can randomly assign subjects to either the treatment or the control group. For example, if one wants to test ethnic bias in the review process of a particular journal, they can design an experiment to randomly assign either African-American or White-sounding names to each submitted manuscript, and compare the acceptance rates across two groups of papers. This type of design has been widely used in studies of racial discrimination in the labor market that rely on racial or ethnic perceptions from names of hypothetical subjects [Bertrand and Mullainathan, 2004, Butler and Broockman, 2011, Einstein and Glick, 2017, Gaddis, 2015, Hanson et al., 2016, Hogan and Berry, 2011, Sharma et al., 2015].

However, such randomized controlled trials are often costly and sometimes infeasible to implement in practice. Furthermore, their results may lack generalizability if the study is conducted at a small scale. They can also suffer from ethical concerns. For example, in the hypothetical experiment described above, it is difficult to acquire the authors' consent to randomly assign a name to their papers submitted to a journal. It also puts journals and reviewers at an unethical situation because the review process is based on altered information.

In some cases, these limitations can be reduced by designing appropriate experiments. For example, one can test for reviewer bias through an experiment without altering the manuscript information and wasting reviewer resources. We can randomly place all reviewers of a journal into two groups—one group of reviewers participate in the single-blind review and the other group in the double-blind review. For each submitted paper, we can randomly assign two reviewers in single-blind review and the other two reviewers in double-blind review. This design allows us to measure differential acceptance rates (or reviewer recommendation) by different ethnic groups both within and between review models, without affecting the fairness of the review outcome and changing the paper's information.

5.2.2 Examining the effectiveness of science policies

Based on past studies of disparities and biases in science production, many institutions, journals, and funding agencies have implemented relevant policies to address those issues. For instance, many scientific publishers are experimenting or have already adopted the double-blind review model to reduce bias (demographic or institutional) in the review process [Cressey, 2014]. However, it is unclear whether those interventions are effective in practice.

Although it looks like double-blind makes the review process a bit more scientific by removing the opportunity for subconscious bias, many critics have expressed concerns over its effectiveness in removing potential biases against women and minorities from scientific publishing. Many scientists worry that, even with double-blind reviewing, reviewers can often guess authors' identities, due to the highly specialized nature of academic research. It would be interesting to examine if the double-blind review model has an effect on what is published by whom.

Many journals are currently experimenting with changes in their review model. These changes can be considered as natural experiment that is suitable for studying the effect of such policy changes. We can partner with them to study questions such as: Are authors of different groups (ethnicity, gender, country, seniority) equally complying to the change? Does it change the submission volume or the acceptance rates? How often can reviewers correctly guess authors' identities? Understanding these questions can help journals and the scientific community to avoid spending extra efforts on the submission process, and devise more appropriate methods to improve fairness.

We can also study the impact of educational policies in other areas. For example, U.S. universities have recently dropped the GRE requirement for applications to graduate programs. Does this change affect who gets admitted? Are the admitted students becoming more diverse than previous cohorts? Are students more successful post-graduation than past students? The United States Citizenship and Immigration Services implemented a policy called the "STEM OPT Extension" for international students in 2016. This policy allows a two-year extension of the post-completion OPT employment authorization for students pursuing a degree in STEM-related fields at U.S. universities. However, for students in non-STEM fields, the post-graduation OPT work authorization is still valid only for one year. This policy is aimed to provide international students more flexibility in seeking jobs in the U.S. However, many critics worry that it may actually narrow students' degree choices because non-STEM students may be more actively considering switching to STEM degrees for better employment opportunities. It would be interesting to study the effects of such policy on students' degree and career choices. If many students are changing their majors for practical career considerations, not only can it be harmful for the students in terms of achieving their dreams and fulfilling their true potential, but it can also be detrimental for non-STEM departments in U.S. universities. as they are losing passionate students.

5.2.3 Demographic disparities in the education system

This dissertation and the line of past literature have focused on uncovering disparities among scientists, with a goal to address the under-representation of women and minorities in the scientific workforce. However, beyond the academic circle, there are considerable disparities in the labor market faced by general populations [Altonji and Blank, 1999], who are often trained by the education system supported by us working scientists.

Historically, women and racial minorities have been disadvantaged in seeking jobs in many economic sectors, and are often paid less for the same position than socially privileged groups [England, 2005, Manning and Swaffield, 2008, Fryer et al., 2013]. Furthermore, women and people of color continue to face barriers moving up the career ladder, especially when moving into leadership positions [Sandberg, 2013, Cooper, 2013, Djupe et al., 2019]. For example, in 2020, only 37 CEOs of Fortune 500 companies are women [Hinchlifee, 2020]. Many companies and organizations have tried to create a working environment that is open and inclusive to all their employees. However, cultivating a workplace culture that embraces diversity is not enough to address gender and racial disparities in the labor market. We also need to address the disparities occurred early on in obtaining educational and training opportunities needed to develop leadership skills.

Research shows that managerial skills are often acquired through academic training and postgraduate education [Beaman et al., 2009]. Some leading MBA programs at prestigious graduate schools can even directly place their students into leadership positions [Yang et al., 2019]. If such scarce educational resources are not distributed equally among the general population [Moss-Racusin et al., 2012], it can contribute to the gender and racial imbalance in leadership roles. Future studies can collaborate with the admission offices at elite universities to examine disparities in the admission to graduate programs by analyzing their student applications and acceptance rates.

APPENDIX A

Supplemental Materials for Chapter 2

A.1 Supplementary Text

A.1.1 Are citations a biased measure of impact across perceived ethnicities?

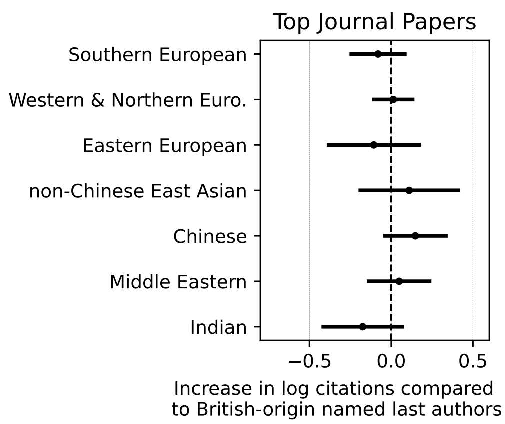

Figure A.1: **The average marginal effects of ethnicity on the log number of citations.** The specifications of Model 5 (excluding paper's log citations) was fitted to 1,976 submissions accepted by *Top Journal*. Note that accepted manuscripts with missing values on any variables were excluded in the regression. The reviewer enthusiasm is included in the regression. Error bars indicate 95% bootstrapped confidence intervals.

Existing research has argued against using citations as a measure of impact, and in particular that citations are biased against particular demographic groups [Hengel and Moon, 2019]. If citations do not accrue similarly across ethnic groups for similar contributions, then using them as a control for impact may understate (or overstate) the true ethnic disparities in acceptance. To test for ethnic citation bias in the present data, we focus on a subset of the submissions which are likeliest to be of similar quality—submissions *accepted* at *Top Journal* after receiving similar reviewer enthusiasm. We fitted a linear regression model with the log-citations as the outcome variable (raw citation counts produced similar results). The control variables include "reviewer enthusiasm" (mean reviewer recommendation) and all covariates from Model 5 except the log citations.

The average marginal effects in Fig. A.1 show that papers published in *Top Journal* by different ethnic groups received statistically indistinguishable numbers of citations conditional on covariates. This result suggests that, in this subset of papers, citations are not substantially biased by perceived ethnicity.

However, it does not rule out ethnic citation bias in the full set of submissions. Specifically, if the field-leading *Top Journal* is less likely to accept papers from non-British-named groups, these papers will later receive fewer citations once published in lower-tier journals. In other words, citations would be downward-biased relative to the papers' true impact. In sum, if citations are ethnically biased, it is likely that the true disparities in acceptance at *Top Journal* are even larger than those observed in Figure 2 in the main text.

A.2 Supplementary Tables

Broad Ethnic Category	**Individual Ethnicity**
African	*African*
British-origin	*English*
Chinese	*Chinese*
non-Chinese East Asian	*Indonesian*, *Japanese*, *Korean*, *Mongolian*, *Thai*, *Vietnamese*
Western & Northern European	*German*, *French*, *Dutch*, *Nordic*, *Baltic*
Southern European	*Greek*, *Hispanic*, *Italian*
Eastern European	*Romanian*, *Hungarian*, *Slav*
Indian	*Indian*
Middle Eastern	*Arab*, *Israeli*, *Turkish*
Caribbean	*Caribbean*
Polynesian	*Polynesian*
Unknown	Note: names are unrecognized by *Ethnea*.

Table A.1: 26 individual ethnicities were grouped into 11 broad ethnic categories. Two ethnicity groups, Caribbean and Polynesian, were excluded in the analysis due to less than 5 observations.

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
African	−0547	−0542	0.320	0.265	0.310
Chinese	−1109***	−1057***	−0351**	−0374**	−0390**
non-Chinese East Asian	−1758***	−1701***	−0922***	−0863***	−0686***
Eastern European	−0656***	−0710***	−0219	−0232	−0231
Indian	−0457***	−0437***	0.004	−0025	0.050
Middle Eastern	−0273**	−0218*	0.466***	0.414**	0.392*
Southern European	−0467***	−0468***	−0024	0.006	−0127
Western & Northern European	−0351***	−0365***	−0017	0.002	−0058
Unknown Ethnicity	0.124	0.029	0.122	0.307	−0383
Female	−0131*	−0119	0.038	0.040	0.051
Unknown Gender	−0166*	−0171*	−0164	−0157	−0251
Submission year 2014		−0050	−1273***	−1292***	−0300
Submission year 2015		−0262***	−1459***	−1401***	0.280
Submission year 2016		−0398***	−1584***	−1485***	1.262***
Submission year 2017		−0233**	−1296***	−1079***	2.557***
Submission year 2018		−0806***	−0855***	−0581***	4.015***
Number of authors		0.012***	0.012**	0.010*	−0020***
Title length		−0131***	−0140***	−0146***	−0115***
Abstract length		−0018***	−0025***	−0030***	−0034***
Flesch-Kincaid score		−0006***	−0004**	−0008***	−0008***
Type-Token ratio		3.522***	4.554***	3.686***	2.960***
Last author rank			−00002***	−00002***	−000000
Last author affiliation rank			−000003	−000002	0.00000
Last author affiliation intl. (location)			−0406***	−0466***	−0444***
Last author affiliation unknown (location)			0.715	0.288	−0086
Last author prior publications.			−0002***	−0001***	−00005
Last author prior *Top Journal* publications			0.042***	0.041***	0.031***
Tail novelty					−0005***
Median novelty					−0001
Disruption					0.118
Number of references					0.018***
Number of unique journals cited					−0042***
Number of *Top Journal* papers cited					0.043**
Total citations (log)					1.124***
Publication year 2014					−0520*
Publication year 2015					−0987***
Publication year 2016					−1211***
Publication year 2017					−1818***
Publication year 2018					−1132**
Publication year 2019					0.056
Intercept	−1274***	−0164	5.680***	4.923***	−2938*
Keywords included	N	N	N	Y	Y
Observations	16,956	16,954	7,062	7,062	6,947

Table A.2: Coefficients of five increasing-complexity regression models in predicting if a manuscript was finally accepted by *Top Journal*. Coefficients for 13 keywords are omitted to ensure journal anonymity. Significance levels: *** p<0.001, ** p<0.01, and * p<0.05.

	Model 1	Model 2	Model 3	Model 4	Model 5
African	−0.418	−0.185	−0.051	−0.069	0.216
Chinese	−1.025***	−1.100***	−0.887***	−0.970***	−0.960***
non-Chinese East Asian	−1.107***	−1.136***	−0.743***	−0.724***	−0.612***
Eastern European	−0.470***	−0.599***	−0.526***	−0.653***	−0.691***
Indian	−0.730***	−0.761***	−0.522***	−0.449**	−0.423*
Middle Eastern	−0.399***	−0.448***	−0.214	−0.254	−0.146
Southern European	−0.533***	−0.636***	−0.330***	−0.213	−0.246*
Western & Northern European	−0.288***	−0.333***	−0.133	−0.089	−0.052
Ethnicity Unknown	−2.009***	−1.545***	−0.616	−0.619	0.118
Female	−0.076	−0.052	0.002	0.090	0.144
Gender Unknown	−0.527***	−0.486***	−0.326***	−0.228*	−0.149
Number of authors		0.026***	0.023***	0.035***	0.034***
Title length		−0.056***	−0.038***	−0.040***	−0.038***
Abstract length		−0.025***	−0.027***	−0.030***	−0.029***
Flesch-Kincaid score		−0.007***	−0.006***	−0.009***	−0.011***
Type-Token ratio		−7.513***	−4.420***	−4.244***	−3.346***
Last author rank			−0.0002***	−0.0001***	−0.0001**
Last author affiliation rank			−0.0001***	−0.0001***	−0.0001**
Last author affiliation intl. (location)			−0.448***	−0.441***	−0.459***
Last author affiliation unknown (location)			0.342	−0.044	−0.184
Last author prior publications.			−0.002***	−0.001***	−0.001*
Last author prior *Middle Journal* publications			0.278***	0.252***	0.198***
Tail novelty					−0.001
Median novelty					0.002***
Disruption					−0.168
Number of references					−0.011*
Number of unique journals cited					−0.014
Number of *Middle Journal* papers cited					0.089*
Total citations (log)					0.464***
Publication year 2014					−1.191***
Publication year 2015					−1.120***
Publication year 2016					−0.536**
Publication year 2017					−0.368*
Publication year 2018					0.510*
Publication year 2019					1.437***
Intercept	0.347***	9.193***	10.628***	7.788***	5.242***
Keywords included	N	N	N	Y	Y
Observations	14,269	8,874	7,195	7,195	6,365

Table A.3: Coefficients of five increasing-complexity regression models in predicting if a manuscript was finally accepted by *Middle Journal*. Coefficients for 26 keywords are omitted to ensure journal anonymity. Significance levels: *** p<0.001, ** p<0.01, and * p<0.05.

Ethnicity	U.S.-based	International	p-value
Southern European	-0.35^{*}	0.26	0.035
Western & Northern European	-0.15	0.08	0.306
Eastern European	-0.28	-0.08	0.660
non-Chinese East Asian	-0.82^{*}	-0.52	0.485
Chinese	-0.47^{**}	-0.13	0.334
Middle Eastern	0.62^{**}	0.24	0.303
Indian	-0.04	0.44	0.314
African	-0.59	1.12	0.361

Table A.4: The ethnicity coefficients of Model 5 in predicting the final acceptance at *Top Journal*. A separate model is trained for the submissions from U.S.-based authors (4,075 observations), and the international authors subset (2,942 observations), respectively. Stars indicate the significance level for each coefficient (*** p<0.001, ** p<0.01, and * p<0.05). The p-values are based on the statistical test of differences in coefficients between two models [Clogg et al., 1995].

Ethnicity	U.S.-based	International	p-value
Southern European	-0.24	-0.34^{*}	0.719
Western & Northern European	-0.02	-0.16	0.511
Eastern European	-0.68^{**}	-0.74^{*}	0.864
non-Chinese East Asian	-0.76^{**}	-0.70^{***}	0.855
Chinese	-0.91^{***}	-1.19^{***}	0.294
Middle Eastern	-0.32	-0.05	0.452
Indian	-0.38	-0.65^{*}	0.481
African	-1.44	1.31	0.116

Table A.5: The ethnicity coefficients of Model 5 in predicting the final acceptance at *Middle Journal*. A separate model is trained for submissions from U.S.-based authors (2,812 observations), and the international authors subset (3,549 observations), respectively. Stars indicate the significance level for each coefficient (*** p<0.001, ** p<0.01, and * p<0.05). The p-values are based on the statistical test of differences in coefficients between two models [Clogg et al., 1995].

APPENDIX B

Supplemental Materials for Chapter 3

B.1 Supplementary Text

B.1.1 Associations of control variables with author mentions

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

Not surprisingly, being designated as the corresponding author is positively associated with name mentions. Scholars who have a high professional rank or are affiliated with prestigious institutions receive outsized attention in science news when their research is covered. Popular authors whose research received many press coverage are more likely to be mentioned by name. This result suggests that the benefits of status, the so-called "Matthew Effect" [Merton, 1968], persist even after publication.

Having more co-authors on a paper has a negative effect on the author being mentioned. Compared to the last author position, the first author is more likely to be mentioned by name, whereas the middle author is less likely to be named. The observed first position effect might due to the fact that, among papers (excluding solo-author papers) that have the corresponding author information, 59.9% have the first author as corresponding and only 36.1% have the last author as corresponding. Solo-authored papers have been decreasing over time and are associated with lower impact on average [Greene, 2007, Milojević, 2014]. However, our results highlight an underappreciated benefit—conditional on a paper being referenced in the news, a solo author is significantly more likely to be mentioned compared to authors of a multi-author paper. Although seemingly counter to previous studies, it has a natural explanation—there is only one person to mention if need be.

The coefficients for story features point to the multifaceted nature of science reporting. Although the volume of science reporting is increasing over time (Fig. B.1a), journalists tend to mention authors less frequently in later years. At the same time, while older papers are still discussed in the media (Fig. B.1c), journalists are less likely to mention authors of these studies as often. When more papers are referenced in a story, their authors are less likely to be mentioned. We hypothesize that such stories are often citing multiple scientific papers to construct a large narrative and thus those papers are only mentioned in passing. Longer stories are more likely to mention author names as they have more space to engage the authors.

B.1.2 Does it matter who is reporting?

Understanding whether disparities across ethnic names are related to journalists' own identities may help uncover the mechanisms producing them. First, journalists of different ethnicities may differ in their overall tendencies to mention authors. If so, disparities may be driven by the composition of journalists doing the mentioning. Our fullest model controls for journalists' ethnicity-associated names, and shows that journalists with minority-identity associated names are not more or less likely to mention authors compared with journalists with Male or British-origin names (Table B.5, Model 5). We also note that, when dropping controls for outlets (Models 3-4), journalists' ethnicities become significant, suggesting that journalists' differential behavior might be explained by variations at the outlet level, *i.e.* certain news outlets mention authors more or less often and certain groups of journalists are under- or over-represented in those outlets.

Second, there might exist interactive relationships between authors' and journalists' ethnic identities. One intuitive hypothesis, which we call "ethnic hierarchy," is that all journalists, regardless of their perceived ethnicity, prefer to mention British-origin named scholars over others. On the other hand, journalists may prefer to mention authors of same ethnicity, which we call "ethnic homophily". Evidence for demographic homophily is pervasive [McPherson et al., 2001]. For example, concordance of gender identities between actors has been found to predict outcomes in domains such as healthcare [Greenwood et al., 2018]. However, the relatively small number of cases of journalists with inferred ethnicities (Table B.3) prevents us from including the full interactions between author's and journalist's ethnicities in the model. The present study thus lacks the evidence to suggest either ethnic hierarchy or homophily hypotheses. However, this is an important avenue for future research.

B.2 Supplementary Figures

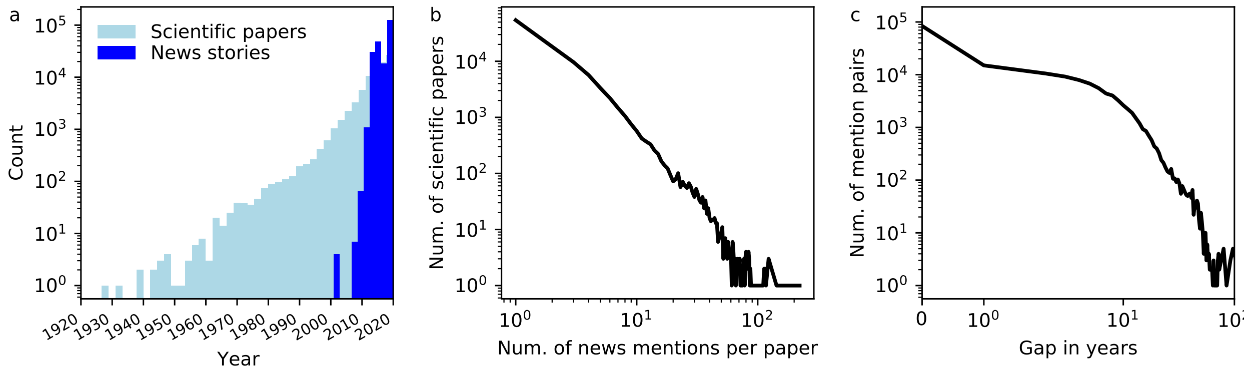

Figure B.1: **a,** The number of news stories and research papers in our mention date over time. **b,** The distribution of the number of news mentions per paper. **c,** The distribution of the *year gap* between paper publication date and news story mention date for all 276,202 story-paper mention pairs in the final dataset.

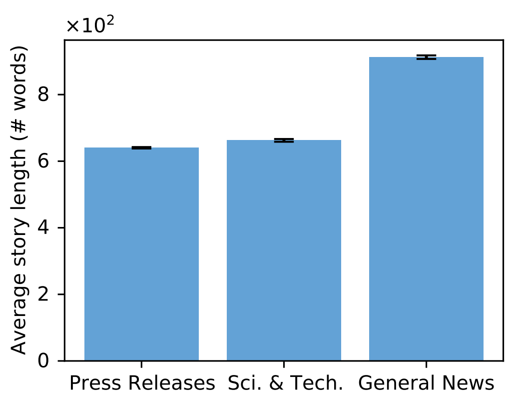

Figure B.2: The average story length for three types of outlets. Error bars show 95% confidence intervals.

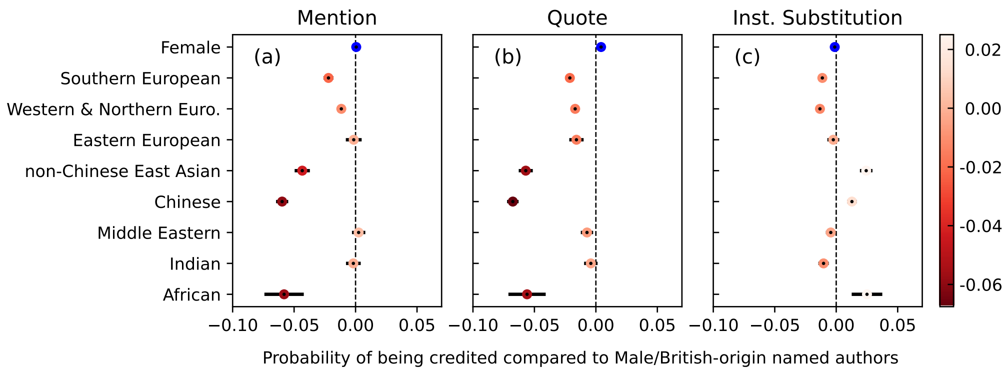

Figure B.3: The average marginal effects of ethnicity estimated based on 524,052 observations in the full data. Authors with minority-ethnicity names are less likely to be mentioned by name (**left**) or quoted (**middle**), and are more likely to be substituted by their institution (**right**). A negative (positive) marginal effect indicates a decrease (increase) in probability compared to authors with Male (for gender) or British-origin (for ethnicity) names. The colors are proportional to the absolute probability changes. *Female* is colored as blue to reflect its difference from ethnicity identities. The error bars indicate 95% bootstrapped confidence intervals.

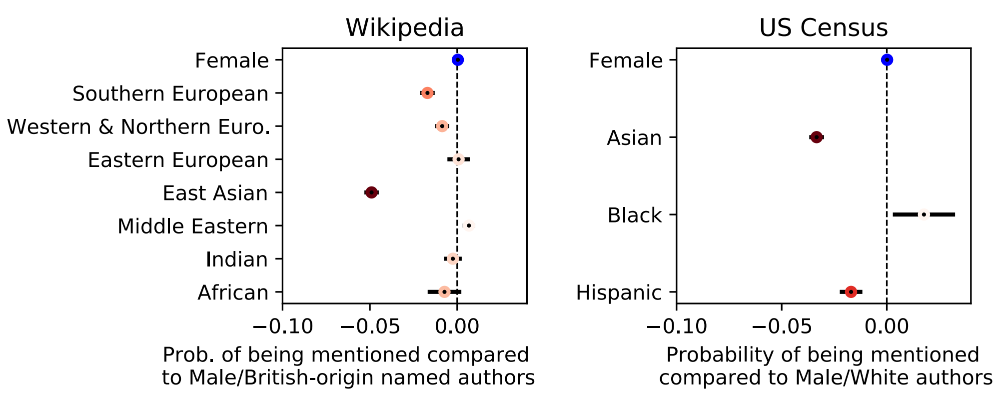

Figure B.4: The average marginal effects in mention probability for author names' demographic associations, using Wikipedia data for coding ethnicity (**Left**) or U.S. Census data for coding race (**Right**) based on author (or journalist) names. Note that gender is still inferred using *Ethnea*.

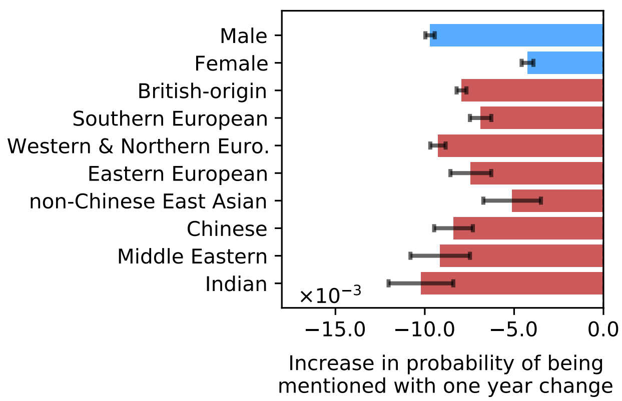

Figure B.5: Estimated average marginal effects on mention probability for a one-unit increase in mention year for names associated with each gender (blue) and ethnicity (red) group. The African ethnicity is not shown due to insufficient data for fitting a model 5. Error bars show 95% bootstrapped confidence intervals.

B.3 Supplementary Tables

Broad Ethnic Category	**Individual Ethnicity**
African	*African*
British-origin	*English*
Chinese	*Chinese*
non-Chinese East Asian	*Indonesian*, *Japanese*, *Korean*, *Mongolian*, *Thai*, *Vietnamese*
Eastern European	*Hungarian*, *Romanian*, *Slav*
Indian	*Indian*
Middle Eastern	*Arab*, *Israeli*, *Turkish*
Southern European	*Hispanic*, *Italian*, *Greek*
Western & Northern European	*Baltic*, *Dutch*, *French*, *German*, *Nordic*
Caribbean	*Caribbean*
Polynesian	*Polynesian*
Unknown	Note: names are unrecognized by *Ethnea*.

Table B.1: 26 individual ethnicities were grouped into 11 broad ethnic categories. The last two groups, Caribbean and Polynesian, were excluded due to less than 100 observations.

Authors Broad Ethnic Category	**# Paper Authorships**	**# Triplets**
British-origin	81,226	234,510
Western & Northern European	39,007	106,331
Southern European	19,109	51,134
Chinese	16,054	43,039
Middle Eastern	9,185	26,082
Indian	7,505	21,314
non-Chinese East Asian	7,816	19,068
Eastern European	6,315	17,251
African	1,079	2,774
Unknown Ethnicity	898	2,549
Total	188,194	524,052

Table B.2: The number of paper authorships and the total number of (story, paper, author) triplets for the 9 high-level ethnic groups. Note that there are 100,486 unique papers, with some counted twice or more for authorships. For example, if a paper has 3 authors and gets covered by 2 news stories, it contributes 3 (paper, author) pairs, and 6 (story, paper, author) triplets.

Journalists Broad Ethnic Category	# Triplets
British-origin	68,652
Western & Northern European	13,790
Southern European	10,594
Middle Eastern	3,494
Eastern European	2,924
Chinese	2,449
Indian	2,409
non-Chinese East Asian	910
African	643
Unknown Ethnicity	418,187
Total	524,052

Table B.3: The number of (story, paper, author) triplets in our regression data by journalists' ethnicity.

Outlet Type	# Outlets	Example Outlet	# Triplets	Perc. Aut. Ment.
Press Releases	21	EurekAlert!	165,343	63.5%
Science & Technology	86	MIT Technology Rev.	137,851	41.9%
General News	181	The New York Times	220,858	24.2%

Table B.4: The number of outlets, the number of (story, paper, author) triplets, and the percentage of triplets that have mentioned the author, for three outlet types. The full list of 288 outlets are available in Table B.10.

		Model 1	Model 2	Model 3	Model 4	Model 5
Author Demog.	African	−0457***	−0394***	−0388***	−0371***	−0366***
	Chinese	0.132***	0.099***	−0054***	−0254***	−0376***
	non-Chinese East Asian	0.015	0.123***	0.037*	−0179***	−0272***
	Eastern European	0.211***	0.253***	0.149***	−0021	−0009
	Indian	0.138***	0.154***	0.048**	−0020	−0011
	Middle Eastern	0.100***	0.134***	0.083***	0.014	0.016
	Southern European	−0003	0.041***	−0017	−0114***	−0138***
	Western & Northern European	−0002	0.070***	0.027**	−0047***	−0072***
	Unknown Ethnicity	−0210***	−0275***	−0354***	−0380***	−0227***
	Female	−0150***	−0188***	−0128***	−0012	0.003
	Unknown Gender	−0188***	−0158***	−0128***	−0117***	−0113***
	Author rank		0.00002***	−000003***	−000005***	−00001***
	Affiliation rank		−00001***	−00001***	−00001***	−000004***
	Affiliation international (location)		−0271***	−0263***	−0300***	−0307***
	Affiliation unknown (location)		0.072	0.046	0.026	0.056
	Not a top author		0.176***	0.168***	0.031	−0090**
	Not a corresponding author		−1116***	−1230***	−1255***	−1448***
	Corresponding status unknown		−1250***	−0519***	−0445***	−0506***
	Last name length		−0005***	−0007***	−0007***	−0010***
	Last name frequency		0.004**	0.003	0.002	0.004*
	Is the paper solo authored?		−0152***	0.508***	0.561***	0.683***
	First author position		0.142***	0.295***	0.340***	0.397***
	Middle author position		−0329***	−0451***	−0623***	−0814***
	Number of authors in the paper		−0001***	−0004***	−0005***	−0007***
Jrn. Demog.	Asian			−0255***	−0250***	−0051
	European			−0057**	−0010	−0033
	Other Unknown Ethnicity			0.342***	0.327***	0.054*
	Female			−0185***	−0126***	−0015
	Unknown Gender			0.094***	0.118***	0.015
	Year of news story (mention year)			−0089***	−0088***	−0051***
	Year gap between story and paper			−0228***	−0216***	−0145***
	Num. of papers mentioned in a story			−0159***	−0153***	−0120***
	News story length			0.0001***	0.0001***	0.0002***
	Flesch-Kincaid score			−00002***	−0001***	−0001***
	Sentences per paragraph			−0006***	0.011***	0.008***
	Type-Token ratio			0.864***	0.347***	0.300***
	Intercept	−0308***	0.448***	0.463***	1.319***	0.968***
	Fixed effects for paper keywords	No	No	No	*Yes*	*Yes*
	Random effects for outlets and venues	No	No	No	No	*Yes*
	Akaike Inf. Crit.	709,086.7	664,229.8	580,589.5	565,155.4	511,537.0

Table B.5: Coefficients of five increasing-complexity regression models in predicting if the author is mentioned by name using 524,052 (story, paper, author) observations. All variables in Model 5, including 199 keywords, are provided in Table B.11. Significance levels: *** p<0.001, ** p<0.01, and * p<0.05.

Gender/Ethnicity	U.S.-based	non-U.S.	p-value
Female	-0.01	0.01	0.254
Southern European	-0.02	-0.33^{***}	0.000
Western & Northern European	-0.02	-0.19^{***}	0.000
Eastern European	0.12^{***}	-0.24^{***}	0.000
non-Chinese East Asian	-0.24^{***}	-0.36^{***}	0.003
Chinese	-0.31^{***}	-0.57^{***}	0.000
Middle Eastern	0.07^{**}	-0.11^{***}	0.000
Indian	0.04^{*}	-0.16^{***}	0.000
African	-0.29^{***}	-0.52^{***}	0.034

Table B.6: The gender and ethnicity coefficients of regression Model 5 in predicting author mentions. A separate model is trained for the U.S.-based institutions subset, and the non-U.S. institutions subset, respectively. When fitting a model for the U.S. subset (or non-U.S. subset), we omitted the *affiliation location* variable introduced in Model 2. The coefficients for ethnicity reveal that disparities between non-British-origin and British-origin scholars are significant when they are all affiliated with international institutions, with each minority reaching statistical significance. The disparities are largely reduced when scholars are all affiliated with U.S.-based institutions. However, even within the U.S., there are significant disparities for East Asian and African named authors; in contrast, Eastern European, Indian, and Middle Eastern named authors are slightly more likely to be mentioned than British-origin named authors in the U.S. subset. Stars indicate the significance level for each coefficient (Sig. levels: *** $p<0.001$, ** $p<0.01$, and * $p<0.05$). The p-values are based on the statistical test of differences in coefficients between two models using the equation provided in [Clogg et al., 1995].

Author Name	*Ethnea*	U.S. Census	Wikipedia
Alana Lelo	African	White	Romance Language
Samuel Lawn	African	White	British-origin
Saka S Ajibola	African	Black	East Asian
Mosi Adesina Ifatunji	African	Black	African
Sebastian Giwa	African	White	African
Olabisi Oduwole	African	White	African
Chidi N. Obasi	African	White	African
Habauka M. Kwaambwa	African	Asian	African
Esther E Omaiye	African	White	African
Aurel T. Tankeu	African	White	British-origin

Table B.7: A random sample of 10 African-named authors predicted by *Ethnea* (out of 908 in total in our data) and their ethnicity or race categories based on the U.S. census data or the Wikipedia data.

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

Table B.8: A random sample of 10 Black authors predicted based on the U.S. census data (out of 892 in total in our data) and their ethnicity categories based on *Ethnea* or the Wikipedia data.

Table B.9: A random sample of 10 names for each of the 24 individual ethnicities and the "Unknown" category. All 6 MONGOLIAN names in our data are shown here.

Ethnicity	Name Example	Gender
AFRICAN	Dora Wynchank	F
	Benjamin D. Charlton	M
	J. Nwando Olayiwola	unknown
	Ayodeji Olayemi	M
	Elizabeth Gathoni Kibaru	F
	Christopher Changwe Nshimbi	M
	Naganna Chetty	unknown
	Benjamin Y. Ofori	M
	Khadijah Essackjee	F
	Jeanine L. Marnewick	F
	Habtamu Fekadu Gemede	M
ARAB	Zaid M. Abdelsattar	M
	Alireza Dirafzoon	M
	Ahmad Nasiri	M
	Saleh Aldasouqi	M
	Ibrahim A. Arif	M
	Sameer Ahmed	M
	A Elgalib	unknown
	Taha Adnan Jan	M
	Mohsen Taghizadeh	M
	Behnam Nabet	M
BALTIC	Skirmantas Kriaucionis	M
	Airidas Korolkovas	M
	Egle Cekanaviciute	F
	Arunas L. Radzvilavicius	M
	Ieva Tolmane	F
	Alberts B	M
	Gediminas Gaigalas	M
	Armandas Balcytis	unknown
	Ruta Ganceviciene	F
	Andrius Pašukonis	M
CHINESE	Chin Hong Tan	unknown
	Li Yuan	unknown
	Yalin Li	unknown
	Xian Adiconis	unknown
	Philip Sung-En Wang	M
	Xiaohui Ni	unknown
	Minghua Li	unknown
	Fang Fang Zhang	F
	Li-Qiang Qin	M

	Jian Tan	unknown
DUTCH	Pieter A. Cohen	M
	I. Vandersmissen	unknown
	Marleen Temmerman	F
	Gerard ’t Hooft	M
	A. Yool	unknown
	G. A W Rook	unknown
	Fatima Foflonker	F
	Mirjam Lukasse	F
	Sander Kooijman	M
	Izaak D. Neveln	M
ENGLISH	Isabel Hilton	F
	Gavin J. D. Smith	M
	Katherine A. Morse	F
	Andrew S. Bowman	M
	T. M. L. Wigley	unknown
	Francis Markham	M
	Neil T. Roach	M
	Brooke Catherine Aldrich	F
	Vaughn I. Rickert	M
	Kellie Morrissey	F
FRENCH	Lucas V. Joel	M
	Daniel Clery	M
	Pierre Jacquemot	M
	Scott Le Vine	M
	Nathalie Dereuddre-Bosquet	F
	Stéphane Colliac	unknown
	Adelaide Haas	F
	Julie M. D. Paye	F
	Justine Lebeau	F
	Arnaud Chiolero	M
GERMAN	Laure Schnabel	F
	Jeff M. Kretschmar	M
	E. Homeyer	unknown
	Maren N. Vitousek	F
	D. Wild	unknown
	Hany K. M. Dweck	M
	E. M. Fischer	unknown
	Paul Marek	M
	Hans-Jörg Rheinberger	M
	Daniel James Cziczo	M
GREEK	Mary J. Scourboutakos	F
	Anita P Courcoulas	F
	Elgidius B. Ichumbaki	unknown

	Stavros G. Drakos	M
	Nikolaos Konstantinides	M
	Constantine Sedikides	M
	Maria A. Spyrou	F
	Panos Athanasopoulos	M
	Aristeidis Theotokis	M
	Amy H. Mezulis	F
HISPANIC	Mirela Donato Gianeti	F
	Julio Cesar de Souza	M
	Paulina Gomez-Rubio	F
	José A. Pons	M
	Arnau Domenech	M
	Nicole Martinez-Martin	F
	Mauricio Arcos-Burgos	M
	Raquel Muñoz-Miralles	F
	Annmarie Cano	F
	Merika Treants Koday	F
HUNGARIAN	Andrea Tabi	F
	Róbert Erdélyi	M
	Gabor G. Kovacs	M
	Xenia Gonda	F
	Erzsébet Bukodi	unknown
	Julianna M. Nemeth	F
	Ian K. Toth	M
	Zoltan Arany	M
	Cory A. Toth	M
	Ashley N. Bucsek	unknown
INDIAN	Sachin M. Shinde	M
	Govindsamy Vediyappan	M
	Ashish K. Jha	M
	Tamir Chandra	M
	Hariharan K. Iyer	M
	Chanpreet Singh	unknown
	Ravi Chinta	M
	Madhukar Pai	M
	Lalitha Nayak	F
	Ravi Dhingra	M
INDONESIAN	Dewi Candraningrum	unknown
	Richard Tjahjono	M
	T. A. Hartanto	unknown
	Johny Setiawan	M
	Truly Santika	unknown
	Chairul A. Nidom	unknown
	Christine Tedijanto	F

	Alberto Purwada	M
	Ardian S. Wibowo	M
	Anna I Corwin	F
ISRAELI	Ron Lifshitz	M
	Martin H. Teicher	M
	Ruth H Zadik	F
	Gil Yosipovitch	M
	Mor N. Lurie-Weinberger	unknown
	J. Tarchitzky	unknown
	Ilana N. Ackerman	F
	B. Trakhtenbrot	unknown
	Yoram Barak	M
	Mendel Friedman	M
ITALIAN	Tiziana Moriconi	F
	Marco Gobbi	M
	Marco De Cecco	M
	F. Govoni	unknown
	Theodore L. Caputi	M
	Mark A Bellis	M
	Fernando Migliaccio	M
	Julien Granata	M
	Jennifer M. Poti	F
	Brendan Curti	M
JAPANESE	Takuji Yoshimura	M
	Maki Inoue-Choi	F
	Masaaki Sadakiyo	M
	Moeko Noguchi-Shinohara	F
	Naoto Muraoka	M
	Shigeki Kawai	M
	Koji Mikami	M
	Masayoshi Tokita	M
	Naohiko Kuno	M
	Saba W. Masho	F
KOREAN	Jih-Un Kim	M
	Hanseon Cho	unknown
	Hyung-Soo Kim	M
	Yun-Hee Youm	F
	Yoon-Mi Lee	unknown
	Soo Bin Park	F
	Yungi Kim	unknown
	Woo Jae Myung	unknown
	Kunwoo Lee	unknown
	Sandra Soo-Jin Lee	F
MONGOLIAN	C. Jamsranjav	unknown

	Jigjidsurengiin Batbaatar	unknown
	Khishigjav Tsogtbaatar	unknown
	Migeddorj Batchimeg	unknown
	Tsolmon Baatarzorig	unknown
NORDIC	Steven G. Rogelberg	M
	Kirsten K. Hanson	F
	Jan L. Lyche	M
	Morten Hesse	M
	Karolina A. Aberg	F
	Britt Reuter Morthorst	F
	Kirsten F. Thompson	F
	Shelly J. Lundberg	F
	G Marckmann	unknown
	David Hägg	M
ROMANIAN	Afrodita Marcu	F
	Iulia T. Simion	F
	Liviu Giosan	M
	Alina Sorescu	F
	Liviu Giosan	M
	Mircea Ivan	M
	Dana Dabelea	F
	Constantin Rezlescu	M
	Christine A. Conelea	F
	R. A. Popescu	unknown
SLAV	Noémi Koczka	F
	Mikhail G Kolonin	M
	Richard Karban	M
	Branislav Dragović	M
	H Illnerová	unknown
	Marte Bjørk	F
	Jacek Niesterowicz	M
	Justin R. Grubich	M
	Mikhail Salama Hend	M
	Snejana Grozeva	F
THAI	Piyamas Kanokwongnuwut	unknown
	Clifton Makate	M
	Noppol Kobmoo	unknown
	Kabkaew L. Sukontason	unknown
	Aroonsiri Sangarlangkarn	unknown
	Yossawan Boriboonthana	unknown
	Ekalak Sitthipornvorakul	unknown
	Tony Rianprakaisang	M
	Apiradee Honglawan	F
	Wonngarm Kittanamongkolchai	unknown

TURKISH	Iris Z. Uras	F
	Metin Gurcan	unknown
	Mustafa Sahmaran	M
	Pinar Akman	F
	Joshua Aslan	M
	Selin Kesebir	F
	Tan Yigitcanlar	unknown
	Thembela Kepe	unknown
	Ulrich Rosar	M
	Selvi C. Ersoy	F
VIETNAMESE	Huong T. T. Ha	unknown
	Vu Van Dung	M
	H ChuongKim	unknown
	Daniel W. Giang	M
	Nhung Thi Nguyen	unknown
	V. Phan	unknown
	Oanh Kieu Nguyen	F
	Phuc T. Ha	M
	Bich Tran	unknown
	Oanh Kieu Nguyen	F
Unknown	Gene Y. Fridman	M
	Judith Glück	F
	Noor Edi Widya Sukoco	unknown
	Charlene Laino	F
	Benoît Bérard	unknown
	David Zünd	M
	Katarzyna Adamala	F
	K.A. Godfrin	unknown
	Shadd Maruna	M
	Mariette DiChristina	F

Table B.10: The 288 U.S.-based outlets are grouped into 3 categories based on their topics of reports. Note that other 135 U.S.-based outlets, which are not shown in this table, are excluded in our analyses due to technical limitations in accessing sufficient volumes of their content (e.g., view-limited paywalls or anti-crawling mechanisms).

Outlet	**Type**
OnMedica	Sci. & Tech.
Huffington Post	General News
KiiiTV 3	General News
Carbon Brief	Sci. & Tech.
PR Newswire	Press Releases
Nutra Ingredients USA	Sci. & Tech.
The Bellingham Herald	General News
CNN News	General News
Health Medicinet	Press Releases
Herald Sun	General News
EurekAlert!	Press Releases
AJMC	Press Releases
The University Herald	General News
Lincoln Journal Star	General News
Cardiovascular Business	Sci. & Tech.
MinnPost	General News
CNET	Sci. & Tech.
Infection Control Today	Sci. & Tech.
Science 2.0	Sci. & Tech.
Lexington Herald Leader	General News
Statesman.com	General News
Nanowerk	Press Releases
The San Diego Union-Tribune	General News
The Daily Beast	General News
Lab Manager	Press Releases
SDPB Radio	General News
New Hampshire Public Radio	General News
Health Day	Press Releases
Rocket News	General News
KPBS	General News
Technology.org	Press Releases
UPI.com	General News
WUWM	General News
Central Coast Public Radio	General News
The Hill	General News
The Epoch Times	General News
Biospace	Sci. & Tech.
Minyanville: Finance	General News

Nature World News	Sci. & Tech.
New York Post	General News
Action News Now	General News
WUNC	General News
Futurity	Press Releases
Reason	General News
azfamily.com	General News
Idaho Statements	General News
Google News	General News
Tri States Public Radio	General News
American Physical Society - Physics	Press Releases
KTEP El Paso	General News
LiveScience	Sci. & Tech.
KUNC	General News
The Daily Meal	Sci. & Tech.
AOL	General News
Women's Health	Sci. & Tech.
Prevention	Sci. & Tech.
ECN	Sci. & Tech.
Iowa Public Radio	General News
Becker's Hospital Review	Sci. & Tech.
7th Space Family Portal	Press Releases
Springfield News Sun	General News
Environmental News Network	Press Releases
Sky Nightly	Sci. & Tech.
Quartz	Sci. & Tech.
Benzinga	General News
Headlines & Global News	General News
The Denver Post	General News
Science Daily	Press Releases
The Advocate	General News
ABC News	General News
Newswise	Press Releases
hellogiggles.com	General News
WLRN	General News
EarthSky	Sci. & Tech.
Becker's Spine Review	Sci. & Tech.
MIT News	Press Releases
MarketWatch	General News
Arstechnica	Sci. & Tech.
Journalist's Resource	Sci. & Tech.
Northern Public Radio	General News
Everyday Health	Sci. & Tech.
Star Tribune	General News
TCTMD	Sci. & Tech.

The Verge	General News
She Knows	General News
SeedQuest	Sci. & Tech.
Tech Times	Sci. & Tech.
Witchita's Public Radio	General News
Oncology Nurse Advisor	Sci. & Tech.
Delmarva Public Radio	General News
Medical Daily	Sci. & Tech.
Homeland Security News Wire	General News
Discover Magazine	Sci. & Tech.
Washington Post	General News
MSN	General News
Hawaii News Now	General News
The Daily Caller	General News
News Tribune	General News
The Fresno Bee	General News
King 5	General News
Star-Telegram	General News
CNBC	General News
Salon	General News
WJCT	General News
WVPE	General News
KTEN	General News
Wired.com	General News
Daily Kos	General News
USA Today	General News
Men's Health	Sci. & Tech.
Boise State Public Radio	General News
Voice of America	General News
PR Web	Press Releases
Georgia Public Radio	General News
FiveThirtyEight	General News
Public Radio International	General News
Harvard Business Review	General News
Inverse	General News
Doctors Lounge	Sci. & Tech.
North East Public Radio	General News
The Charlotte Observer	General News
National Geographic	Sci. & Tech.
Pharmacy Times	Sci. & Tech.
Popular Science	Sci. & Tech.
ABC Action News WFTS Tampa Bay	General News
News Channel	General News
The University of New Orleans Public Radio	General News
Mic	General News

Health Canal	Sci. & Tech.
KOSU	General News
Raleigh News and Observer	General News
The Atlantic	General News
newsmax.com	General News
Yahoo! Finance USA	General News
Government Executive	General News
International Business Times	General News
Emaxhealth.com	Press Releases
Newsweek	General News
FOX News	General News
The New York Observer	General News
Sign of the Times	General News
The Inquisitr	General News
ABC News 15 Arizona	General News
Parent Herald	General News
The ASCO Post	Sci. & Tech.
Clinical Advisor	Sci. & Tech.
Slate Magazine	General News
NPR	General News
Health	Sci. & Tech.
Dayton Daily News	General News
Guardian Liberty Voice	General News
Belleville News-Democrat	General News
Yahoo! News	General News
WCBE	General News
Buzzfeed	General News
Sci-News	Sci. & Tech.
The Seattle Times	General News
Philly.com	General News
Renal & Urology News	Sci. & Tech.
Arizona Public Radio	General News
Interlochen Public Radio	General News
12 News KBMT	General News
New York Magazine	General News
Medium US	General News
KPCC : Southern California Public Radio	General News
2 Minute Medicine	Sci. & Tech.
Pediatric News	Sci. & Tech.
redOrbit	Sci. & Tech.
Insurance News Net	General News
Drug Discovery and Development	Sci. & Tech.
USNews.com	General News
Yahoo!	General News
The Body	Sci. & Tech.

GEN	Sci. & Tech.
Pacific Standard	General News
Northwest Indiana Times	General News
Psychology Today	Sci. & Tech.
Oregon Public Broadcasting	General News
Mother Nature Network	Sci. & Tech.
Pressfrom	General News
Physician's Weekly	Sci. & Tech.
Pettinga: Stock Market	General News
Winona Daily News	General News
Runner's World	Sci. & Tech.
Bio-Medicine.org	Press Releases
Alternet	General News
Mother Jones	General News
The Wichita Eagle	General News
Cornell Chronicle	Press Releases
Politico Magazine	General News
Equities.com	General News
WBUR	General News
ABC 7 WKBW Buffalo	General News
Billings Gazette	General News
My Science	Sci. & Tech.
The Week	General News
BioTech Gate	Sci. & Tech.
Kansas City Star	General News
The Deseret News	General News
PBS	General News
Space.com	Sci. & Tech.
Astrobiology Magazine	Sci. & Tech.
Outside	General News
Value Walk	General News
WYPR	General News
Bustle	General News
Science World Report	Sci. & Tech.
Inside Science	Sci. & Tech.
Science Alert	Sci. & Tech.
Breitbart News Network	General News
St. Louis Post-Dispatch	General News
HowStuffWorks	General News
Wyoming Public Radio	General News
UBM Medica	Sci. & Tech.
Fight Aging!	Sci. & Tech.
MIT Technology Review	Sci. & Tech.
WVXU	General News
The Ecologist	Sci. & Tech.

Alaska Despatch News	General News
Health Imaging	Sci. & Tech.
Kansas City University Radio	General News
Christian Science Monitor	General News
Medicinenet	Sci. & Tech.
WTOP	General News
Business Insider	General News
Real Clear Science	Sci. & Tech.
Counsel & Heal	Sci. & Tech.
The Raw Story	General News
Medcity News	Sci. & Tech.
Drugs.com	Sci. & Tech.
Relief Web	Press Releases
SPIE Newsroom	Sci. & Tech.
New York Daily News	General News
Newser	General News
The Sacramento Bee	General News
Vice	General News
R&D	Sci. & Tech.
KCENG12	Sci. & Tech.
Inc.	General News
Science/AAAS	Sci. & Tech.
The Atlanta Journal Constitution	General News
Brookings	General News
Common Dreams	General News
Physician's Briefing	Press Releases
KERA News	General News
Space Daily	Sci. & Tech.
Tech Xplore	Sci. & Tech.
US News Health	Sci. & Tech.
KUOW	General News
WRKF	General News
TIME Magazine	General News
Smithsonian Magazine	Sci. & Tech.
Herald Tribune	General News
Lifehacker	General News
Fast Company	General News
Kansas Public Radio	General News
Omaha Public Radio	General News
New York Times	General News
Technology Networks	Sci. & Tech.
Elite Daily	General News
Centre for Disease Research and Policy	Sci. & Tech.
Business Wire	General News
KUNM	General News

CBS News	General News
Scientific American	Sci. & Tech.
NBC News	General News
Sun Herald	General News
KRWG TV/FM	General News
TODAY	General News
Radio Acadie	General News
The Columbian	General News
Houston Chronicle	General News
WABE	General News
The Modesto Bee	General News
American Council on Science and Health	Sci. & Tech.
WKAR	General News
Psych Central	Sci. & Tech.
WebMD News	Sci. & Tech.
Green Car Congress	Sci. & Tech.
ABC News WMUR 9	General News
Healthline	Sci. & Tech.
Mongabay	Sci. & Tech.
Vox.com	General News
WPTV 5 West Palm Beach	General News
Popular Mechanics	Sci. & Tech.
PM 360	Sci. & Tech.
SFGate	General News
Seed Daily	Sci. & Tech.

Table B.11: The coefficients of all variables (including 199 keywords) in Model 5 in predicting whether the author is mentioned by name in a news story referencing a research paper. Random effects for 288 outlets and 8,261 publication venues are also included in the model.

	Dependent variable:	
	Is author mentioned	
Author ethnicity African	−0.366	p = 0.000
Author ethnicity Chinese	−0.376	p = 0.000
Author ethnicity non-Chinese East Asian	−0.272	p = 0.000
Author ethnicity Eastern European	−0.009	p = 0.653
Author ethnicity Indian	−0.011	p = 0.560
Author ethnicity Middle Eastern	0.016	p = 0.366
Author ethnicity Southern European	−0.138	p = 0.000
Author ethnicity Western & Northern Euro.	−0.072	p = 0.000
Author ethnicity Unknown	−0.227	p = 0.00002
Author gender Female	0.003	p = 0.695
Author gender Unknown	−0.113	p = 0.000
Reporter ethnicity Asian	−0.051	p = 0.176
Reporter ethnicity European	−0.033	p = 0.095
Reporter ethnicity Other Unknown	0.054	p = 0.047
Reporter gender Female	−0.015	p = 0.405
Reporter gender Unknown	0.015	p = 0.560
Last name length	−0.010	p = 0.000
Last name frequency	0.004	p = 0.028
First author position	0.397	p = 0.000
Middle author position	−0.814	p = 0.000
Is the paper solo authored	0.683	p = 0.000
Author rank	−0.0001	p = 0.000
Not a top author	−0.090	p = 0.004
Not a corresponding author	−1.448	p = 0.000
Corresponding status unknown	−0.506	p = 0.000
Affiliation rank	−0.00004	p = 0.000
Affiliation international (location)	−0.307	p = 0.000
Affiliation unknown (location)	0.056	p = 0.571
Number of authors in the paper	−0.007	p = 0.000
Year of news story (mention year)	−0.051	p = 0.000
Year gap between story and paper	−0.145	p = 0.000
News story length	0.0002	p = 0.000
Num. of papers mentioned in a story	−0.120	p = 0.000
Flesch-Kincaid score	−0.001	p = 0.000
Sentences per paragraph	0.008	p = 0.00002
Type-Token ratio	0.300	p = 0.00000

Cell biology	0.301	p = 0.00000
Genetics	0.001	p = 0.980
Biology	0.032	p = 0.701
Body mass index	−0.329	p = 0.00001
Health care	−0.183	p = 0.0005
Disease	−0.103	p = 0.018
Gerontology	−0.607	p = 0.000
Population	−0.103	p = 0.00003
Public health	−0.165	p = 0.004
Medicine	−0.361	p = 0.00001
Materials science	0.352	p = 0.001
Composite material	0.162	p = 0.188
Nanotechnology	0.255	p = 0.007
Cohort study	−0.009	p = 0.861
Social psychology	−0.154	p = 0.006
Cohort	0.069	p = 0.155
Psychological intervention	0.009	p = 0.879
Young adult	−0.309	p = 0.00000
Family medicine	−0.306	p = 0.00001
Cancer	−0.097	p = 0.038
Surgery	−0.019	p = 0.779
Randomized controlled trial	−0.095	p = 0.062
Placebo	0.019	p = 0.790
Clinical trial	−0.105	p = 0.190
Nursing	−0.288	p = 0.002
Applied psychology	−0.425	p = 0.011
Human factors and ergonomics	−0.220	p = 0.061
Injury prevention	0.335	p = 0.002
Suicide prevention	0.003	p = 0.978
Psychiatry	−0.362	p = 0.000
Occupational safety and health	−0.471	p = 0.00002
Intensive care medicine	−0.286	p = 0.001
Pediatrics	−0.241	p = 0.0003
Hazard ratio	0.266	p = 0.00001
Confidence interval	−0.147	p = 0.020
Retrospective cohort study	0.148	p = 0.039
Vaccination	0.059	p = 0.493
Psychology	0.078	p = 0.384
Perception	0.185	p = 0.021
Cognition	−0.117	p = 0.034
Environmental health	−0.347	p = 0.00000
Obesity	−0.203	p = 0.003
Risk factor	0.236	p = 0.001
Quality of life	−0.035	p = 0.702
Physical therapy	−0.094	p = 0.095

Weight loss	−0.357	p = 0.0001
Anatomy	0.625	p = 0.000
Mental health	0.140	p = 0.030
Psychosocial	0.271	p = 0.011
Anxiety	−0.334	p = 0.00000
Distress	0.269	p = 0.012
Business	−0.660	p = 0.00001
Public relations	−0.244	p = 0.023
Marketing	0.168	p = 0.295
Immunology	−0.164	p = 0.007
Global warming	−0.100	p = 0.178
Economics	−0.040	p = 0.741
Climatology	−0.254	p = 0.003
Climate change	−0.461	p = 0.000
General surgery	0.008	p = 0.960
Endocrinology	−0.154	p = 0.007
Internal medicine	0.341	p = 0.000
Receptor	−0.160	p = 0.055
Inflammation	0.199	p = 0.019
Stimulus physiology	0.091	p = 0.390
Immune system	0.132	p = 0.050
Meta analysis	−0.696	p = 0.000
Sociology	0.371	p = 0.008
Gene	−0.131	p = 0.031
Cancer research	−0.025	p = 0.705
Breast cancer	0.075	p = 0.230
Cell	0.385	p = 0.00001
Diabetes mellitus	−0.062	p = 0.159
Blood pressure	−0.127	p = 0.177
Oncology	−0.172	p = 0.049
Gynecology	−0.338	p = 0.006
Communication	0.319	p = 0.006
Cognitive psychology	0.002	p = 0.983
Adverse effect	−0.092	p = 0.208
Clinical endpoint	−0.626	p = 0.000
Pharmacology	−0.392	p = 0.0001
Virology	−0.330	p = 0.0001
Risk assessment	0.250	p = 0.021
Transcription factor	0.383	p = 0.0001
Political science	−0.280	p = 0.054
Ecology	0.062	p = 0.270
Geography	0.018	p = 0.864
Cross sectional study	−0.024	p = 0.792
Odds ratio	−0.114	p = 0.040
Comorbidity	−0.136	p = 0.209

Environmental engineering	−0.452	p = 0.005
Chemistry	0.097	p = 0.320
Medical emergency	−0.711	p = 0.000
Physics	0.131	p = 0.214
Social science	0.448	p = 0.008
Ethnic group	0.018	p = 0.848
Labour economics	0.380	p = 0.015
Antibody	0.274	p = 0.008
Geomorphology	−0.160	p = 0.102
Geophysics	0.081	p = 0.461
Geology	−0.312	p = 0.002
Ranging	−0.113	p = 0.215
Stroke	−0.003	p = 0.974
Environmental resource management	−0.132	p = 0.203
Type 2 diabetes	0.169	p = 0.053
Cardiology	0.066	p = 0.502
Molecular biology	0.169	p = 0.007
Developmental psychology	−0.043	p = 0.499
Agriculture	−0.393	p = 0.00002
Signal transduction	−0.188	p = 0.053
Optoelectronics	−0.047	p = 0.651
Psychotherapist	−0.413	p = 0.004
Affect psychology	−0.319	p = 0.003
Clinical psychology	−0.036	p = 0.622
Anesthesia	−0.311	p = 0.001
Atmospheric sciences	−0.029	p = 0.774
In vivo	−0.117	p = 0.192
Biochemistry	0.0001	p = 0.999
Analytical chemistry	−0.078	p = 0.553
Neuroscience	0.310	p = 0.00001
Botany	−0.292	p = 0.015
Gene expression	0.242	p = 0.017
Politics	0.170	p = 0.070
Demography	0.339	p = 0.000
Socioeconomic status	−0.345	p = 0.00004
Mortality rate	−0.225	p = 0.002
Virus	0.066	p = 0.494
Optics	0.411	p = 0.0004
Condensed matter physics	−0.591	p = 0.000
Bioinformatics	−0.510	p = 0.00001
Law	−0.111	p = 0.494
Physical medicine and rehabilitation	−0.086	p = 0.583
Stem cell	−0.056	p = 0.496
Biodiversity	−0.167	p = 0.022
Astrophysics	−1.033	p = 0.000

Astronomy	−0.203	p = 0.041
Radiology	−0.400	p = 0.007
Pathology	−0.014	p = 0.858
Proportional hazards model	−0.137	p = 0.108
Chemotherapy	−0.662	p = 0.00000
Predation	−0.196	p = 0.029
Food science	−0.300	p = 0.034
Artificial intelligence	1.100	p = 0.00002
Overweight	−0.049	p = 0.571
Antibiotics	−0.043	p = 0.710
Microbiology	0.143	p = 0.173
Zoology	0.280	p = 0.002
Paleontology	0.200	p = 0.016
Habitat	0.546	p = 0.000
Public administration	0.924	p = 0.00001
Ecosystem	−0.062	p = 0.424
Economic growth	0.095	p = 0.450
Organic chemistry	0.254	p = 0.100
Government	−0.135	p = 0.199
Autism	−0.140	p = 0.133
Transplantation	0.250	p = 0.003
Gastroenterology	−0.297	p = 0.022
Insulin	0.018	p = 0.849
Engineering	−0.268	p = 0.133
Computer science	0.072	p = 0.529
Observational study	−0.154	p = 0.111
Heart disease	0.021	p = 0.836
Epidemiology	−0.106	p = 0.104
Obstetrics	0.158	p = 0.133
Pregnancy	−0.140	p = 0.040
Fishery	0.026	p = 0.839
Alternative medicine	−0.243	p = 0.041
Logistic regression	0.385	p = 0.00003
Offspring	0.196	p = 0.031
Mood	−0.287	p = 0.002
Bacteria	0.127	p = 0.248
Prostate cancer	−0.400	p = 0.00004
Evolutionary biology	0.130	p = 0.114
Phenomenon	0.022	p = 0.821
Longitudinal study	0.027	p = 0.758
Genome	0.088	p = 0.191
Mutation	0.204	p = 0.012
Pedagogy	−0.283	p = 0.101
Dementia	−0.186	p = 0.046
Relative risk	0.121	p = 0.109

Microeconomics	0.536	p = 0.003
Odds	0.004	p = 0.968
Feeling	0.451	p = 0.00004
Oceanography	−0.095	p = 0.376
Emergency medicine	0.029	p = 0.759
Personality	−0.023	p = 0.804
Prospective cohort study	−0.212	p = 0.0003
Hippocampus	−0.046	p = 0.650
Greenhouse gas	0.006	p = 0.948
Biomarker medicine	0.409	p = 0.00002
Myocardial infarction	−0.135	p = 0.140
Socioeconomics	0.297	p = 0.015
Drug	0.290	p = 0.004
Environmental science	−0.368	p = 0.0003
Epigenetics	−0.382	p = 0.0002
Inorganic chemistry	−0.233	p = 0.020
Emergency department	−0.205	p = 0.028
Medical prescription	0.270	p = 0.002
Phenotype	0.076	p = 0.450
Constant	0.968	p = 0.000
Observations	524,052	
Log Likelihood	-255,530.5	
Akaike Inf. Crit.	511,537.0	
Bayesian Inf. Crit.	514,195.3	

APPENDIX C

Supplemental Materials for Chapter 4

C.1 Supplementary Figures

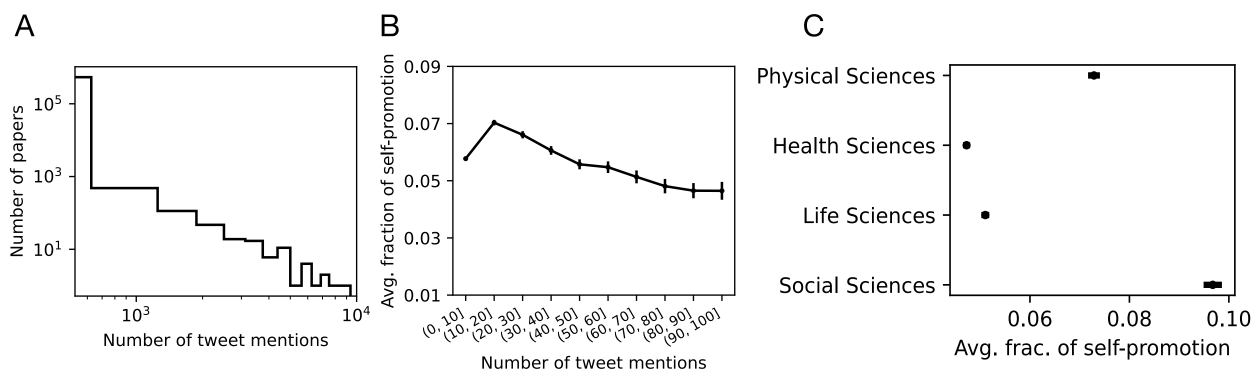

Figure C.1: **A**, The histogram of a paper's total number of tweet mentions. **B**, The average fraction of a paper's tweets that are about self-promotion from its authors, as a function of the paper's total number of tweets (the x-axis). **C**, The average fraction of self-promotional tweets *per paper*, for papers in each of the four broad disciplines. Error bars indicate 95% confidence intervals.

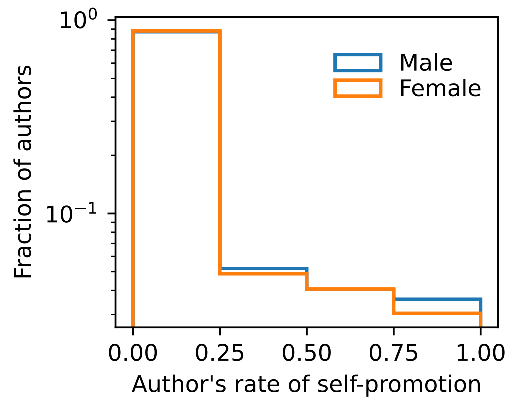

Figure C.2: Histogram (normalized) of the self-promotion rate per author, which is calculated as the fraction of an author's papers they have self-promoted. Only authors with at least five publications are included in the analysis.

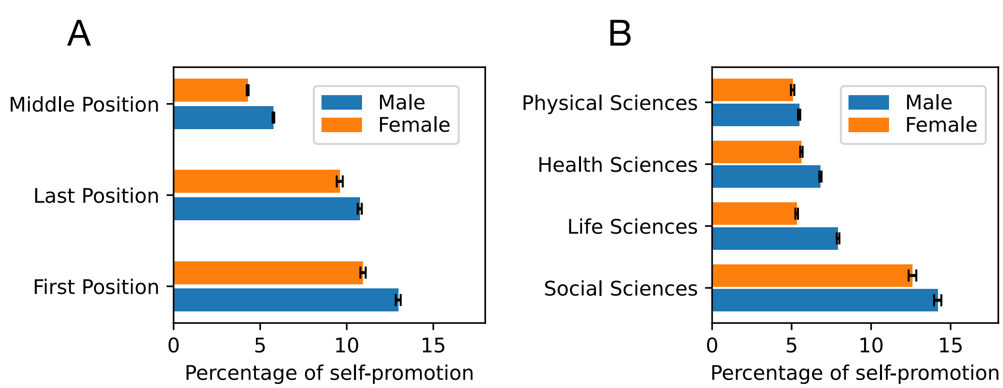

Figure C.3: Each (paper, author) pair is an observation, with the dependent variable indicating whether the author has self-promoted the paper or not. **A**, The x-axis shows the percentage of self-promotion grouped by author gender and authorship position. **B**, the same as **A**, but for the breakdown by papers' discipline. Error bars indicate 95% confidence intervals.

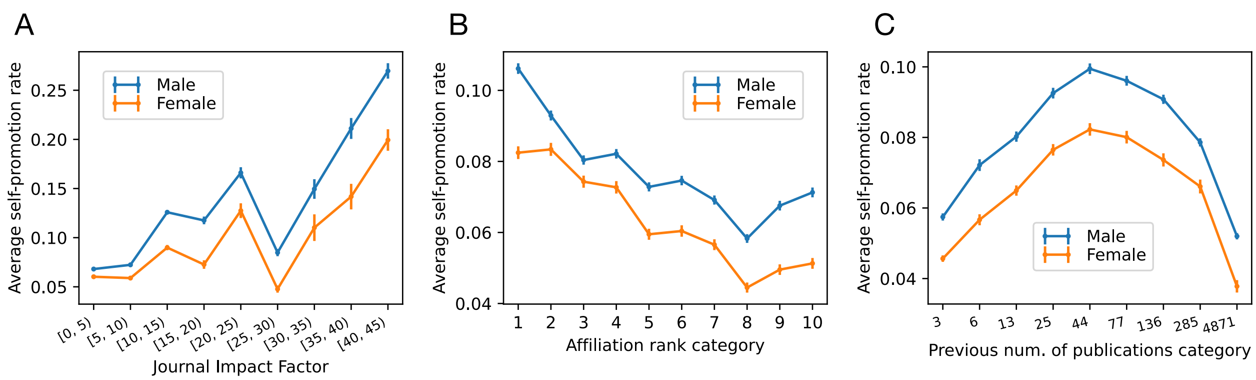

Figure C.4: Average probability of self-promotion by gender in the raw data as a function of **A**, journal impact factor, **B**, author's affiliation rank category, and **C**, author productivity category, measured as the author's total number of publications before the publication year of the paper in each (paper, author) observation.

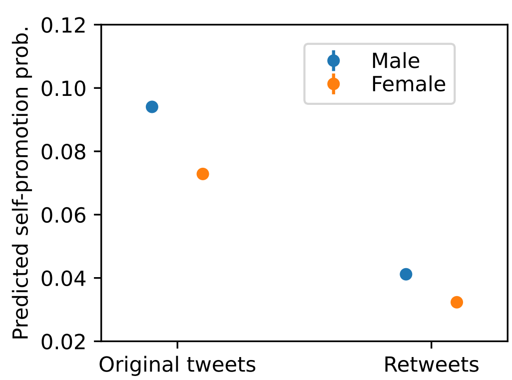

Figure C.5: Predicted probability of self-promotion after controlling for confounding factors. The x-labels indicate the type of tweets (original tweets vs. retweets) based on which the binary dependent variable, self-promotion status, is coded in the mixed effects logistic regression. Promotions based on original tweets come directly from the authors, whereas retweet-based promotions originate from others. Error bars indicate 95% bootstrapped confidence intervals.

C.2 Supplementary Tables

F1 Score	**China**	**non-China**	**All Countries**
Female	0.61	0.90	0.83
Male	0.80	0.98	0.95

Table C.1: The gender prediction accuracy based on authors' self-reported gender in the IOP Publishing data. There are 71,869 authors from China and 361,019 authors from outside China.

Table C.2: Coefficients of a mixed effects logistic regression model that predicts whether the author has self-promoted the paper or not (2,375,419 observations). The model includes the random effect for each paper. Significance levels: *** p<0.001, ** p<0.01, and * p<0.05.

genderFemale	−0.277***	p = 0.000
authorship_posfirst_position	0.335***	p = 0.000
authorship_posmiddle_position	−0.674***	p = 0.000
authorship_possolo_author	0.764***	p = 0.000
author_pub_count_cate	0.247***	p = 0.000
I(author_pub_count_cate^2)	−0.026***	p = 0.000
affiliation_rank_cate	−0.053***	p = 0.000
affiliation_cateinternational	0.034***	p = 0.00001
num_authors	−0.002***	p = 0.000
journal_impact	0.035***	p = 0.000
Social_Sciences	0.960***	p = 0.000
Materials_Science	−0.157***	p = 0.000
Engineering	−0.381***	p = 0.000
Chemistry	−0.343***	p = 0.000
Biochemistry__Genetics_and_Molecular_Biology	−0.162***	p = 0.000
Medicine	−0.288***	p = 0.000
Nursing	0.208***	p = 0.000
Agricultural_and_Biological_Sciences	0.438***	p = 0.000
Pharmacology__Toxicology_and_Pharmaceutics	−0.513***	p = 0.000
Neuroscience	0.027	p = 0.156
Business__Management_and_Accounting	−0.254***	p = 0.000
Economics__Econometrics_and_Finance	−0.432***	p = 0.000
Chemical_Engineering	0.185***	p = 0.000
Physics_and_Astronomy	−0.720***	p = 0.000
Computer_Science	0.074**	p = 0.005
Decision_Sciences	−0.581***	p = 0.000
Health_Professions	0.922***	p = 0.000
Psychology	−0.639***	p = 0.000
Immunology_and_Microbiology	−0.107***	p = 0.00000
Dentistry	−1.116***	p = 0.000
Earth_and_Planetary_Sciences	−0.077***	p = 0.0004
Environmental_Science	0.154***	p = 0.000
Mathematics	−0.372***	p = 0.000
Arts_and_Humanities	−0.212***	p = 0.00000
Energy	−0.353***	p = 0.000
Veterinary	−0.846***	p = 0.000
General	0.334***	p = 0.000
Constant	−2.753***	p = 0.000

Table C.3: Coefficients of all variables in a mixed effects logistic regression model that predicts whether the author has self-promoted the paper or not. The model is fitted to 374,320 observations for which the author has ever self-promoted any of their papers in our data. For these authors, we are sure they have a Twitter account. The model includes the random effect for each paper. Significance levels: *** p<0.001, ** p<0.01, and * p<0.05.

genderFemale	-0.070^{***}	p = 0.000
authorship_posfirst_position	0.259^{***}	p = 0.000
authorship_posmiddle_position	-0.741^{***}	p = 0.000
authorship_possolo_author	0.359^{***}	p = 0.000
author_pub_count_cate	-0.397^{***}	p = 0.000
I(author_pub_count_cate^2)	0.008^{***}	p = 0.000
affiliation_rank_cate	0.015^{***}	p = 0.000
affiliation_cateinternational	0.247^{***}	p = 0.000
num_authors	-0.001^{***}	p = 0.000
journal_impact	0.024^{***}	p = 0.000
Social_Sciences	0.561^{***}	p = 0.000
Materials_Science	-0.050	p = 0.195
Engineering	0.030	p = 0.384
Chemistry	0.047	p = 0.093
Biochemistry__Genetics_and_Molecular_Biology	-0.185^{***}	p = 0.000
Medicine	-0.491^{***}	p = 0.000
Nursing	-0.022	p = 0.514
Agricultural_and_Biological_Sciences	0.260^{***}	p = 0.000
Pharmacology__Toxicology_and_Pharmaceutics	-0.241^{***}	p = 0.000
Neuroscience	-0.006	p = 0.791
Business__Management_and_Accounting	0.051	p = 0.328
Economics__Econometrics_and_Finance	0.068	p = 0.231
Chemical_Engineering	0.308^{***}	p = 0.000
Physics_and_Astronomy	-0.096^{**}	p = 0.005
Computer_Science	0.261^{***}	p = 0.000
Decision_Sciences	-0.248^{**}	p = 0.003
Health_Professions	0.582^{***}	p = 0.000
Psychology	-0.592^{***}	p = 0.000
Immunology_and_Microbiology	0.068^{*}	p = 0.013
Dentistry	-0.394^{**}	p = 0.003
Earth_and_Planetary_Sciences	-0.156^{***}	p = 0.00000
Environmental_Science	0.012	p = 0.597
Mathematics	0.037	p = 0.484
Arts_and_Humanities	0.069	p = 0.335
Energy	0.062	p = 0.334
Veterinary	-0.410^{***}	p = 0.00000
General	0.402^{***}	p = 0.000
Constant	1.772^{***}	p = 0.000

Table C.4: Coefficients of all variables in a negative binomial regression model that predicts the total number of tweets for each paper. The model is fitted to all 2.3M observations and includes the interaction term between gender and self-promotion. Significance levels: *** p<0.001, ** p<0.01, and * p<0.05.

genderFemale	0.018***	p = 0.000
self_promotionTrue	1.566***	p = 0.000
authorship_posfirst_position	−0.004	p = 0.252
authorship_posmiddle_position	0.268***	p = 0.000
authorship_possolo_author	−0.204***	p = 0.000
author_pub_count_cate	0.014***	p = 0.000
affiliation_rank_cate	−0.025***	p = 0.000
affiliation_cateinternational	−0.115***	p = 0.000
num_authors	0.0001***	p = 0.000
journal_impact	0.094***	p = 0.000
Social_Sciences	0.220***	p = 0.000
Materials_Science	−0.662***	p = 0.000
Engineering	−0.618***	p = 0.000
Chemistry	−0.764***	p = 0.000
Biochemistry__Genetics_and_Molecular_Biology	−0.179***	p = 0.000
Medicine	−0.013***	p = 0.000
Nursing	0.292***	p = 0.000
Agricultural_and_Biological_Sciences	0.366***	p = 0.000
Pharmacology__Toxicology_and_Pharmaceutics	−0.511***	p = 0.000
Neuroscience	0.010*	p = 0.040
Business__Management_and_Accounting	−0.329***	p = 0.000
Economics__Econometrics_and_Finance	−0.086***	p = 0.000
Chemical_Engineering	0.045***	p = 0.000
Physics_and_Astronomy	−0.418***	p = 0.000
Computer_Science	−0.312***	p = 0.000
Decision_Sciences	−0.713***	p = 0.000
Health_Professions	0.686***	p = 0.000
Psychology	−0.193***	p = 0.000
Immunology_and_Microbiology	−0.057***	p = 0.000
Dentistry	−1.305***	p = 0.000
Earth_and_Planetary_Sciences	−0.274***	p = 0.000
Environmental_Science	−0.053***	p = 0.000
Mathematics	0.049***	p = 0.000
Arts_and_Humanities	−0.010	p = 0.533
Energy	−1.125***	p = 0.000
Veterinary	−0.563***	p = 0.000
General	0.416***	p = 0.000
genderFemale:self_promotionTrue	0.033***	p = 0.00002
Constant	1.730***	p = 0.000

Table C.5: Coefficients of all variables in a negative binomial regression model that predicts the total number of tweets for each paper. The model is fitted to 173,594 observations that involve self-promotion (thus the self-promotion variable and its interaction term with gender are dropped). The model additionally controls for the author's follower count on Twitter. Significance levels: *** p<0.001, ** p<0.01, and * p<0.05.

genderFemale	0.066***	p = 0.000
authorship_posfirst_position	0.055***	p = 0.000
authorship_posmiddle_position	0.411***	p = 0.000
authorship_possolo_author	−0.251***	p = 0.000
matched_tid_follower_cn_log	0.108***	p = 0.000
author_pub_count_cate	0.0005	p = 0.724
affiliation_rank_cate	−0.010***	p = 0.000
affiliation_cateinternational	−0.126***	p = 0.000
num_authors	0.001***	p = 0.000
journal_impact	0.054***	p = 0.000
Social_Sciences	−0.232***	p = 0.000
Materials_Science	−0.593***	p = 0.000
Engineering	−0.281***	p = 0.000
Chemistry	−1.042***	p = 0.000
Biochemistry__Genetics_and_Molecular_Biology	−0.030***	p = 0.001
Medicine	−0.058***	p = 0.000
Nursing	0.047*	p = 0.027
Agricultural_and_Biological_Sciences	0.117***	p = 0.000
Pharmacology__Toxicology_and_Pharmaceutics	−0.500***	p = 0.000
Neuroscience	−0.055***	p = 0.0002
Business__Management_and_Accounting	−0.436***	p = 0.000
Economics__Econometrics_and_Finance	−0.002	p = 0.954
Chemical_Engineering	0.076**	p = 0.003
Physics_and_Astronomy	−0.654***	p = 0.000
Computer_Science	−0.401***	p = 0.000
Decision_Sciences	−0.302***	p = 0.000
Health_Professions	0.571***	p = 0.000
Psychology	−0.010	p = 0.596
Immunology_and_Microbiology	−0.072***	p = 0.00002
Dentistry	−1.296***	p = 0.000
Earth_and_Planetary_Sciences	−0.450***	p = 0.000
Environmental_Science	−0.195***	p = 0.000
Mathematics	0.138***	p = 0.00001
Arts_and_Humanities	−0.051	p = 0.127
Energy	−0.719***	p = 0.000
Veterinary	−0.939***	p = 0.000
General	0.541***	p = 0.000
Constant	2.523***	p = 0.000

Table C.6: Coefficients of all variables in a negative binomial regression model that predicts the total number of tweets for each paper. The model includes the interaction term between gender and self-promotion and is fitted to 30,417 observations for which the paper is solo-authored. Significance levels: *** $p<0.001$, ** $p<0.01$, and * $p<0.05$.

genderFemale	0.079***	p = 0.0001
self_promotionTrue	1.563***	p = 0.000
author_pub_count_cate	0.053***	p = 0.000
affiliation_rank_cate	−0.016***	p = 0.000
affiliation_cateinternational	−0.205***	p = 0.000
journal_impact	0.048***	p = 0.000
Social_Sciences	0.082***	p = 0.0003
Materials_Science	−0.662***	p = 0.000
Engineering	−0.459***	p = 0.000
Chemistry	−0.484***	p = 0.000
Biochemistry__Genetics_and_Molecular_Biology	0.063*	p = 0.047
Medicine	−0.073**	p = 0.002
Nursing	0.032	p = 0.589
Agricultural_and_Biological_Sciences	0.201***	p = 0.00000
Pharmacology__Toxicology_and_Pharmaceutics	−0.713***	p = 0.000
Neuroscience	0.464***	p = 0.000
Business__Management_and_Accounting	−0.390***	p = 0.000
Economics__Econometrics_and_Finance	−0.006	p = 0.880
Chemical_Engineering	0.103	p = 0.341
Physics_and_Astronomy	−0.223***	p = 0.00000
Computer_Science	−0.278***	p = 0.00000
Decision_Sciences	−0.198*	p = 0.034
Health_Professions	0.502***	p = 0.00000
Psychology	−0.171***	p = 0.00003
Immunology_and_Microbiology	0.052	p = 0.365
Dentistry	−0.688**	p = 0.008
Earth_and_Planetary_Sciences	−0.385***	p = 0.000
Environmental_Science	0.041	p = 0.359
Mathematics	−0.154***	p = 0.0005
Arts_and_Humanities	−0.269***	p = 0.000
Energy	−1.076***	p = 0.000
Veterinary	−0.435**	p = 0.007
General	0.371***	p = 0.00000
genderFemale:self_promotionTrue	−0.022	p = 0.581
Constant	1.616***	p = 0.000

Table C.7: Coefficients of all variables in a negative binomial regression model that predicts the total number of tweets for each paper. The model is fitted to 117,535 observations that involve self-promotion, which is defined as an author advertising their paper within one day after the paper's publication. The model additionally controls for the author's follower count on Twitter. Significance levels: *** p<0.001, ** p<0.01, and * p<0.05.

genderFemale	0.078***	p = 0.000
authorship_posfirst_position	0.144***	p = 0.000
authorship_posmiddle_position	0.441***	p = 0.000
authorship_possolo_author	−0.152***	p = 0.000
matched_tid_follower_cn_log	0.115***	p = 0.000
author_pub_count_cate	0.001	p = 0.413
affiliation_rank_cate	−0.012***	p = 0.000
affiliation_cateinternational	−0.067***	p = 0.000
num_authors	0.001***	p = 0.000
journal_impact	0.057***	p = 0.000
Social_Sciences	−0.261***	p = 0.000
Materials_Science	−0.596***	p = 0.000
Engineering	−0.250***	p = 0.000
Chemistry	−1.078***	p = 0.000
Biochemistry__Genetics_and_Molecular_Biology	−0.018	p = 0.090
Medicine	−0.116***	p = 0.000
Nursing	−0.017	p = 0.484
Agricultural_and_Biological_Sciences	0.054***	p = 0.00001
Pharmacology__Toxicology_and_Pharmaceutics	−0.474***	p = 0.000
Neuroscience	−0.196***	p = 0.000
Business__Management_and_Accounting	−0.457***	p = 0.000
Economics__Econometrics_and_Finance	−0.034	p = 0.303
Chemical_Engineering	0.111***	p = 0.0001
Physics_and_Astronomy	−0.656***	p = 0.000
Computer_Science	−0.355***	p = 0.000
Decision_Sciences	−0.224***	p = 0.00001
Health_Professions	0.607***	p = 0.000
Psychology	0.008	p = 0.722
Immunology_and_Microbiology	−0.177***	p = 0.000
Dentistry	−1.430***	p = 0.000
Earth_and_Planetary_Sciences	−0.514***	p = 0.000
Environmental_Science	−0.162***	p = 0.000
Mathematics	−0.124***	p = 0.001
Arts_and_Humanities	−0.041	p = 0.312
Energy	−0.808***	p = 0.000
Veterinary	−1.041***	p = 0.000
General	0.510***	p = 0.000
Constant	2.376***	p = 0.000

Table C.8: Coefficients of all variables in a negative binomial regression model that predicts the number of scientists ("researcher") who have mentioned each paper. Note that the types of Twitter audiences are categorized by in-house experts from Altmetric. The model is fitted to all 2.3M observations and includes the interaction term between gender and self-promotion.

genderFemale	0.021***	p = 0.000
self_promotionTrue	1.590***	p = 0.000
authorship_posfirst_position	−0.008	p = 0.075
authorship_posmiddle_position	0.294***	p = 0.000
authorship_possolo_author	−0.219***	p = 0.000
author_pub_count_cate	0.011***	p = 0.000
affiliation_rank_cate	−0.043***	p = 0.000
affiliation_cateinternational	−0.117***	p = 0.000
num_authors	0.0001***	p = 0.000
journal_impact	0.099***	p = 0.000
Social_Sciences	0.288***	p = 0.000
Materials_Science	−0.734***	p = 0.000
Engineering	−0.734***	p = 0.000
Chemistry	−0.417***	p = 0.000
Biochemistry__Genetics_and_Molecular_Biology	0.093***	p = 0.000
Medicine	−0.506***	p = 0.000
Nursing	0.286***	p = 0.000
Agricultural_and_Biological_Sciences	0.467***	p = 0.000
Pharmacology__Toxicology_and_Pharmaceutics	−0.743***	p = 0.000
Neuroscience	−0.033***	p = 0.00000
Business__Management_and_Accounting	−0.438***	p = 0.000
Economics__Econometrics_and_Finance	−0.161***	p = 0.000
Chemical_Engineering	0.048***	p = 0.00000
Physics_and_Astronomy	−0.192***	p = 0.000
Computer_Science	−0.354***	p = 0.000
Decision_Sciences	−0.734***	p = 0.000
Health_Professions	0.897***	p = 0.000
Psychology	−0.205***	p = 0.000
Immunology_and_Microbiology	0.134***	p = 0.000
Dentistry	−1.804***	p = 0.000
Earth_and_Planetary_Sciences	−0.189***	p = 0.000
Environmental_Science	−0.068***	p = 0.000
Mathematics	0.470***	p = 0.000
Arts_and_Humanities	−0.193***	p = 0.000
Energy	−1.168***	p = 0.000
Veterinary	−1.133***	p = 0.000
General	0.544***	p = 0.000
genderFemale:self_promotionTrue	0.075***	p = 0.000
Constant	0.284***	p = 0.000

Table C.9: Coefficients of all variables in a negative binomial regression model that predicts the number of non-scientists (including "member of the public", "practitioner", and "science communicator") who have mentioned each paper. The model is fitted to all 2.3M observations and includes the interaction term between gender and self-promotion.

genderFemale	0.019***	p = 0.000
self_promotionTrue	1.500***	p = 0.000
authorship_posfirst_position	0.0001	p = 0.967
authorship_posmiddle_position	0.237***	p = 0.000
authorship_possolo_author	−0.193***	p = 0.000
author_pub_count_cate	0.015***	p = 0.000
affiliation_rank_cate	−0.021***	p = 0.000
affiliation_cateinternational	−0.121***	p = 0.000
num_authors	0.0001***	p = 0.000
journal_impact	0.091***	p = 0.000
Social_Sciences	0.185***	p = 0.000
Materials_Science	−0.676***	p = 0.000
Engineering	−0.582***	p = 0.000
Chemistry	−0.925***	p = 0.000
Biochemistry__Genetics_and_Molecular_Biology	−0.254***	p = 0.000
Medicine	0.076***	p = 0.000
Nursing	0.400***	p = 0.000
Agricultural_and_Biological_Sciences	0.330***	p = 0.000
Pharmacology__Toxicology_and_Pharmaceutics	−0.419***	p = 0.000
Neuroscience	0.071***	p = 0.000
Business__Management_and_Accounting	−0.420***	p = 0.000
Economics__Econometrics_and_Finance	0.022	p = 0.075
Chemical_Engineering	0.040***	p = 0.00000
Physics_and_Astronomy	−0.430***	p = 0.000
Computer_Science	−0.326***	p = 0.000
Decision_Sciences	−0.646***	p = 0.000
Health_Professions	0.603***	p = 0.000
Psychology	−0.116***	p = 0.000
Immunology_and_Microbiology	−0.131***	p = 0.000
Dentistry	−1.132***	p = 0.000
Earth_and_Planetary_Sciences	−0.265***	p = 0.000
Environmental_Science	−0.075***	p = 0.000
Mathematics	−0.166***	p = 0.000
Arts_and_Humanities	0.003	p = 0.846
Energy	−1.115***	p = 0.000
Veterinary	−0.415***	p = 0.000
General	0.441***	p = 0.000
genderFemale:self_promotionTrue	0.018*	p = 0.016
Constant	1.407***	p = 0.000

Table C.10: Coefficients of a mixed effects logistic regression model that predicts whether the author has self-promoted the paper or not. The data exclude authors whose names are predicted to be East Asian ethnicities. The model includes the random effect for each paper. Significance levels: *** p<0.001, ** p<0.01, and * p<0.05.

genderFemale	-0.254^{***}	p = 0.000
authorship_posfirst_position	0.334^{***}	p = 0.000
authorship_posmiddle_position	-0.657^{***}	p = 0.000
authorship_possolo_author	0.684^{***}	p = 0.000
author_pub_count_cate	0.224^{***}	p = 0.000
I(author_pub_count_cateˆ2)	-0.025^{***}	p = 0.000
affiliation_rank_cate	-0.047^{***}	p = 0.000
affiliation_cateinternational	0.094^{***}	p = 0.000
num_authors	-0.002^{***}	p = 0.000
journal_impact	0.034^{***}	p = 0.000
Social_Sciences	0.848^{***}	p = 0.000
Materials_Science	-0.064^{*}	p = 0.016
Engineering	-0.356^{***}	p = 0.000
Chemistry	-0.327^{***}	p = 0.000
Biochemistry__Genetics_and_Molecular_Biology	-0.140^{***}	p = 0.000
Medicine	-0.330^{***}	p = 0.000
Nursing	0.175^{***}	p = 0.000
Agricultural_and_Biological_Sciences	0.387^{***}	p = 0.000
Pharmacology__Toxicology_and_Pharmaceutics	-0.504^{***}	p = 0.000
Neuroscience	0.009	p = 0.642
Business__Management_and_Accounting	-0.262^{***}	p = 0.000
Economics__Econometrics_and_Finance	-0.416^{***}	p = 0.000
Chemical_Engineering	0.186^{***}	p = 0.000
Physics_and_Astronomy	-0.768^{***}	p = 0.000
Computer_Science	0.074^{**}	p = 0.005
Decision_Sciences	-0.490^{***}	p = 0.000
Health_Professions	0.886^{***}	p = 0.000
Psychology	-0.629^{***}	p = 0.000
Immunology_and_Microbiology	-0.112^{***}	p = 0.00000
Dentistry	-1.181^{***}	p = 0.000
Earth_and_Planetary_Sciences	-0.119^{***}	p = 0.00000
Environmental_Science	0.157^{***}	p = 0.000
Mathematics	-0.428^{***}	p = 0.000
Arts_and_Humanities	-0.223^{***}	p = 0.00000
Energy	-0.334^{***}	p = 0.000
Veterinary	-0.896^{***}	p = 0.000
General	0.295^{***}	p = 0.000
Constant	-2.581^{***}	p = 0.000

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