Cracking the Code: The Networking Matrix of Finance Academia

Kuntara Pukthuanthong* Sujiao (Emma) Zhao†

June 1, 2023

Abstract

This research delves into social networks among finance academics from 1980 to the present. Engagement in social networks positively correlates with productivity, with co-authors and student-advisor networks having the most significant impact, followed by post-Ph.D. and Ph.D. networks. Focusing on existing relationships rather than expanding connections and connecting with prominent researchers has proven more effective. Scholars with strong networks produce higher-quality research and receive better compensation. Our findings on editorial favoritism are complex. Co-authors of editors and Ph.D. colleagues are less likely to have their papers accepted, while student advisors are more likely. There is no evidence to support bias toward female scholars, but discrimination against Asian and Hispanic females and favoritism towards White females and Hispanic males is evident.

JEL classification: G21

Keywords: Social Network, Top-Tier Publications, Citations, Favoritism, Bias, Discrimination, Races, Gender

*University of Missouri, phone: 1-619- 807-6124, e-mail: pukthuanthongk@missouri.edu

†Banco de Portugal. The University of Porto, School of Economics and Management, and CEF.UP, e-mail: szhao@bportugal.pt

Acknowledgement

The views and opinions expressed in this work are those of the authors and do not necessarily reflect the views or positions of Banco of Portugal or the Eurosystem. All errors are ours.

1 Introduction

The recognition of networking as a beneficial practice entailing the exchange of resources, information, and assistance has grown substantially in recent times. Increasingly, data converge to demonstrate that social networks serve as a basis for professions and boost productivity. However, networks' full impact on individual and collective performance has yet to be comprehensively investigated. In this regard, we utilize the field of financial academics as a research domain, where scholars circulate through a network of peers, colleagues, and acquaintances. Our research investigates the effects of social networks formed during graduate school, employment, and tenure on scholars' research output and quality, utilizing an impressive data set of over 24,671 publications co-authored by 4,223 researchers in finance from 46 top journals over four decades.

Social networks have become a ubiquitous presence in U.S. academia. However, women and minority scholars are less likely to associate with established scholars than their white male counterparts (bozeman2011men).[1] Their works get fewer cited than men (Larivière et al. 2013). The underrepresentation of women in co-authorship networks exacerbates this citation imbalance. Disparities in other disciplines have also been identified, with studies revealing that men cite papers written by men (Dworkin et al. 2020, Fulvio et al. 2021, Caplar et al. 2017, and Chatterjee and Werner 2021). In addition, many scholars in all fields are produced only from some dominant colleges (Wapman et al. 2022).

Further research has shown that women scientists are likelier to be favored throughout the editorial process. Moreover, co-authoring with influential authors increases the likelihood of accepting finance papers (see Squazzoni et al. 2021; Borsuk et al. 2009; Tudor and Yashar 2018; Fox and Paine 2019). The most recent study by Bethmann et al. (2023) finds that the top two journals in economics, the Journal of Political Economy (JPE) and the Quarterly Journal of Economics (QJE), tend to publish studies conducted by authors associated with the University of Chicago and Harvard/MIT, respectively. Furthermore, the study highlights more significant bias in the QJE than in the JPE, indicating that the quality of works published in the QJE is not adequately justified.

While these findings demonstrate that inequalities exist in academia, researchers have not examined the link between the work on biases in productivity and the quality of research as a function of social network structure. We reexamine whether such inequalities exist in finance and investigate the relationship between these disparities and social networks.

[1] Brown and Samuels (2018) explain studies conducted in women's studies have found that women are less likely to attend conferences and be invited to join teams or form collaborations, leading to fewer citations for women's studies publications than for those produced by men.

The knowledge exchange between co-authors, colleagues, and academic advisors should facilitate the creation of high-quality research and publication in prestigious journals for networked authors. The assertion that networking increases the number of prestigious publications is overly simplistic. Building a network requires an investment. Socializing, traveling, and attending meetings demand significant amounts of time, a valuable commodity for academics with limited time to complete high-quality work within the tenure system. Attending social gatherings during business trips is often counterproductive and a distraction. A question is which network is more advantageous for researchers and worth cultivating. We strive to answer the question of which types of social networks improve productivity and which types impede it.

We utilize Social Network Analysis (SNA) to evaluate the relationships between academic advisors, Ph.D. colleagues, and post-Ph.D. colleagues, and co-authors within each scholar's network by considering size, closeness, and prestige. We employ the number of publications in the top journals in finance as productivity and the number of citations as quality. We also use xxx as an alternative measure of paper quality. Networks are susceptible to endogeneity, which we address by incorporating various fixed effects, such as author and affiliation-fixed effects, in our primary analyses. We further employ Difference-in-Difference (DiD) modeling to examine the effects of exogenous shocks, such as deaths and editor job transitions, and find that our results are robust.

Our research shows that social networks substantially impact the productivity and quality of academic publications. Building solid relationships with colleagues is more advantageous than merely increasing one's network or connecting with renowned scholars. The study reveals that closer and larger student-advisor relationships, followed by those with co-authors and post-PhD colleagues, lead to higher productivity and quality. Additionally, having influential advisors and post-PhD colleagues can boost productivity and quality. Our use of DiD and the authors' death as an exogenous shock demonstrates that networking, particularly among co-authors, impacts productivity.

Furthermore, we investigate two potential channels underlying the relationship between networking, productivity, and quality. First, we consider the possibility that these well-networked researchers may receive a high salary, resulting in a light teaching load and more time to conduct high-quality research. Second, we examine the relationships these researchers have with journal editors and editorial boards, which may result in preferential treatment for publication. Our results indicate that the mechanism underlying the causal link is pay, with scholars with extensive networks earning more money, particularly those with more prominent and prestigious networks. This effect is most pronounced among scholars at the top 10, top 50, and top 100 schools.

The issue of editorial bias in scholarly publishing has sparked much discussion. While some argue that articles published in top-tier journals are often written by scholars who have personal connections with the editorial team, Brogaard et al. (2014) find that this is mostly due to the high quality of their work. Our research delves deeper into this topic, specifically examining connections within networks. We have discovered that, even with the same level of quality, scholars who are linked to editors through their Ph.D. colleagues and co-authors have a lower acceptance rate. On the other hand, those who connect to editors through student advisors are viewed more positively. Our findings also show that the level of editorial favoritism varies depending on the type of connection. Editors' Ph.D. colleagues and co-authors seem discriminated against, while editors' student-advisors are given preferential treatment. To confirm this, we have applied the editors' job transitions as a shock in a DiD framework. The results indicate that authors with a student-advisor relationship with the editor experience decreased productivity for the next ten years. This implies that being tied to an editor, mainly through a student-advisor relationship, impacts a scholar's productivity.

Turning to citation bias, studies have shown that in specific fields like neurology, astronomy, medicine, physics, and economics, men tend to cite papers written by other men ((Dworkin et al., 2020; Caplar et al., 2017; Chatterjee and Werner, 2021; Teich et al., 2022; Dion et al., 2018).). Additionally, scholars with close networks also tend to cite each other's works. We find this does not necessarily mean there is bias because the papers produced by these scholars are often high-quality, as demonstrated by weighted citations and Who cites whom. Fong et al. (2023) reveals that papers citing editors' work tend to be more accepted. We show the quality of these papers in finance justifies their acceptance, indicating no bias.

Our investigation has also shed light on the co-author's status bias and elite school bias. While Huber et al. (2022) have shown that finance research papers written by eminent authors tend to have higher acceptance rates, our findings suggest that this is due to the superior quality of their work rather than any bias.[2] Similarly, Wapman et al. (2022) have demonstrated that a disproportionate number of new hires graduate from a few elite schools. In contrast, we find no evidence of this bias. Papers produced by graduates of these top universities tend to be of high quality. Any conclusions that suggest otherwise may be premature and ignore the papers' quality.

Centering on issues of gender and race, we have observed no evidence of gender bias in favor of females, contrary to the findings of Squazzoni et al. (2021) and others. Instead, we observe female scholars who are co-authors with editors or post-Ph.D. colleagues tend to have fewer top-tier publications despite producing

[2]Huber et al. (2022) recruited over 3300 authors and examined their willingness to review papers with and without known scholars. Their results demonstrate strong evidence for status bias, as more reviewers agreed to assess papers when a prominent researcher's name was present. The likelihood of recommending rejection increased from 23% to 48% when the authors were anonymous and increased to 65% when the authors were relatively unknown.

work of comparable quality. When examining specific racial groups, we discern editorial favoritism towards White females, editors' Ph.D. colleagues, and Hispanic males. In contrast, Asian female editors' post-Ph.D. colleagues and Hispanic female scholars who are editors' students and advisors appear to face discrimination.

Contribution. We make three contributions. Firstly, we engage in a contentious debate surrounding the unequal treatment of individuals across gender and co-authorship status. Dworkin et al. (2020) examine five broad-scope journals and discover that papers authored first and/or last by women receive fewer citations than expected. Fulvio et al. (2021) build upon the findings of Dworkin et al. (2020) and extend them to neuroscience papers, observing a similar trend. According to Caplar et al. (2017), research authored by women receives 10.4 +/- 0.9% fewer citations than men with the same non-gender-specific attributes. Additionally, Chatterjee and Werner (2021) examine gender bias in the top five medical journals and reveal that articles authored by female primary and senior authors receive approximately half as many citations as articles produced by male primary and senior authors.

Teich et al. (2022), Wang et al. (2021), and Maliniak et al. (2013) report comparable findings in physics, communication, and international affairs, respectively. Notably, Dworkin et al. (2020) and Chatterjee and Werner (2021) utilize citations in their research, while Caplar et al. (2017) estimate over-citations. The question of how citation reflects the quality of a paper remains unresolved. Female-authored studies may be perceived as lower quality, leading to reduced referencing. We investigate this issue.

The extant literature has established that females tend to have smaller professional networks and garner fewer citations, albeit without experimentation. Conversely, empirical evidence in biology, health, and physical sciences suggests that research co-authored by women receives more lenient peer review (ibid.)(see Squazzoni et al. (2021); Borsuk et al. (2009); Tudor and Yashar (2018); Fox and Paine (2019)).

In this study, we conduct an extensive social network analysis encompassing multiple forms of collaboration, including co-authors, Ph.D. colleagues, post-Ph.D. colleagues, and student advisors, to elucidate the underlying mechanisms linking networking, publishing in prestigious outlets, and the attainment of quality markers such as citations.

Second, we apply the SNA to finance. SNA has been implemented in virtually every area of finance, including the venture capital industry, initial public offerings, corporate governance, banking, and global trade. Numerous studies have demonstrated the importance of network centrality in achieving better performance, higher portfolio returns, and improved stock performance. Using SNA, we analyze the collaborations of finance scholars. We examine two plausible causal processes underlying the association between networking, prestigious publishing, and quality (citations): remuneration and editorial ties. By analyzing these collaborations, we contribute to understanding the role of networking in finance research, providing insights into the impact of network centrality on research quality and career success.

Third, our study contributes explicitly to favoritism research. The impact of editorial connections on publishing has been widely studied, with past research seeking to differentiate favoritism and excellence in journal publications. For instance, Laband and Piette (1994) use citation analysis to demonstrate how editors utilize their professional connections to publish high-impact papers, including subpar works written by colleagues and graduate students. Medoff (2003) also finds that related articles receive more citations over time than unconnected ones. In contrast, Brogaard et al. (2014) (henceforth, BEP) provides evidence challenging editorial nepotism, demonstrating that linked papers receive significantly higher citation counts and editors are more selective in accepting their colleagues' papers.

Similarly, Chan et al. (2015) (hereafter CCC) present equivalent evidence in the top three finance journals, finding that co-authors who had previously worked with journal editors had lower citation counts. In contrast, articles by authors affiliated with the same institutions as editors receive more citations. Our study presents more nuanced findings and determines the connections between various academic networks, including student-advisors, co-authors, Ph.D. colleagues, post-Ph.D. colleagues, and editors. Unlike previous studies, our network measurement is continuous and utilizes size, proximity, and prestige to measure network centrality. Expanding networks significantly impacts publishing outcomes, particularly after obtaining tenure. Factoring in network closeness and size, the student-advisor and co-author networks play pivotal roles in increasing high-quality publications, whereas considering prestige, student-advisor, and post-Ph.D. colleague networks contribute most significantly to enhancing quality. Our study emphasizes the importance of strengthening existing relationships while expanding networks in all areas.

In brief, the methodologies employed by BEP and CCC exclusively rely on the editor network. CCC define a coauthor network as the frequency with which each author (or coauthor) of a publication has collaborated with the editor (of the published journal) in the sampled journals on or before the year of publication. They employ the same journal network variable as the number of authors who are current board members of the journal, in which they published during the specific year, and an editor colleague variable equal to one if one of the authors is the editor's colleague. Conversely, Brogaard et al. (2014) eschews the use of SNA. It formulates two primary variables: the Colleague-Connected Article, which is a binary variable equal to one if the author of the publication is affiliated with the same institution as the editor of the journal, and the Any-Connected Article, which is the maximum value of Colleague-Connected Article and Co-author-Connected Articles.

In contrast to BEP and CCC, our research delves into the connections between student advisors, coauthors, Ph.D. colleagues, post-Ph.D: colleagues, and the relationships between these networks and editors. Furthermore, our approach differs from BEP's in that our network measurement is continuous, allowing us to draw fresh economic insights. We gauge network centrality through size, proximity, and prestige. We find that the student-advisor and coauthor networks are the most critical in increasing the number of high-quality publications.Although strengthening all forms of networks is advantageous, reinforcing current relationships is more beneficial.

2 Academic network centrality and data

2.1 Academic network centrality

This section describes the centrality metrics we use to characterize scholar networks. Our research question is whether well-connected authors have tremendous success regarding the number of top-tier publications and publication quality. We compute three network connectivity metrics: Degree, Closeness, and Eigenvector.

Freeman (1977) and Freeman et al. (2002) present two metrics for determining centrality in a social network: Degree (number of direct ties) and Closeness (small number of steps between actors/nodes). The third dimension, as proposed by Bonacich (1987), determines an academic's position of influence. The degree of centrality measures the size of an author's network without considering the effect of other nodes. The closeness of an author's network captures how close each person is and the eigenvector, which also accounts for the influence of the network. For instance, an author may be connected to a large size of the network (high Degree) but isolated from the remainder of the network (low Closeness).

In contrast, an author may only be related to a few other authors (low Degree) and be geographically isolated from the rest of the network (low Closeness). However, he or she may have a high Eigenvector centrality if he or she is connected to a significant player in the network. The definition of proximity is "the average length of the shortest path from one author to all other authors." The eigenvector awards more points to more influential authors. That is, everything else being equal, it is deemed more beneficial to contact influential authors who have more prominent and extensive networks.

According to the SNA literature, the central location of an agent in a network and the nature and extent of its connections to other agents in that network influence the flow of information to and from that agent.

Lazarsfeld et al. (1944) find social networks play a crucial role in the dissemination of information between individuals. Katz and Lazarsfeld (1964) elaborate on this notion and highlight the role of opinion leaders (someone who convey their information to other people who are less informed). They show that networked individuals can affect the voting and purchasing decisions of others.

We compute centrality measures over two years, considering the structure of academia, the change in composition, and the extent of each scholar's communication with others. In the SNA literature, several centrality concepts capture distinct features of social and economic networks. Our measurements reflect the number of relationships a researcher has with other individuals. The greater a researcher's number of connections, the more central he is in his network. Our measures are comparable to determining the number of links based on the premise that indirect connections are also significant.

To compute the centrality measures, we generate an N-by-N adjacency matrix X, where N is the number of scholars in the network, and each cell takes the value one if two scholars are co-authors, Ph.D. advisors, Ph.D. colleagues, or post-PhD colleagues over the two years ($x_{ij} = 1$ if scholar i is a co-author, Ph.D. or advisor, Ph.D. colleagues, or post-PhD colleagues with scholar j). We assume that in these four relations, two scholars equally lead; thus, $x_{ij} = x_{ji} = 1$.

2.1.1 Degree centrality

Degree centrality or network size represents the researcher's number of peer connections. It is the most straightforward and transparent centrality metric.

Because they have access to or provide more resources and opportunities, scholars with more direct links to others are thought to be more influential. In this instance, the center network node, "5", is directly connected to five other network nodes (Figure 1, Panel (a)). The least central nodes in the network are only connected to one other node. The degree of this "5" node is equal to five, while nodes 1, 2, and 4 are equal to one, and nodes 3 and 6 equal to two. The core concept is that the more connections a researcher has, the more central he is inside his network. Given the adjacency matrix X, the following formula can be used to calculate the degree centrality of scholar i at time t:

$$Degree_{i,t} = \sum_{j=1}^{N} x_{i,j,t} \tag{1}$$

where x is the individual who links academics i and j. It presents the total number of rows (or columns). The networks we are interested in are comprised of scholars who have been connected over the past two years.

Consequently, the Degree counts the total number of academics who are coauthors, Ph.D. colleagues, post-Ph.D colleagues, and students/advisors on a high-impact article. Degree centrality is a simple measure that measures the amount of information or the number of sources of knowledge a central scholar has. More information is provided as the significance of the scholar's degree increases. According to Davis and Greve (1997), direct connections provide access to insider information regarding the decision-making process of other actors (or other scholars in a social network) that is not readily available to stakeholders, such as business process innovation or effective corporate practices.

2.1.2 Closeness centrality

The difficulty with Degree centrality is that it does not sufficiently reflect the direction and flow of information. We employ Closeness centrality to solve this issue. Closeness centrality measures a node's proximity to other nodes in a network. More central nodes can communicate with others in the network faster and more readily than less central nodes. More central nodes have lower proximity centrality ratings and do not require as much path trip to reach other nodes. Nodes with high closeness centrality ratings are more central and require less path travel to reach other nodes. The number of steps between them determines the distance between the two scholars. In Figure 1, Panel (b), the turquoise circle has a closeness score of 2.

Closeness evaluates the strength of connections similarly to Degree centrality but considers both direct and indirect connections. It is determined as the reciprocal of the sum of the shortest paths between the scholar and all other scholars in the network.

$$Closeness_{i,t} = \frac{\left[\sum_{j=1}^{N} d(i,j)\right]^{-1}}{N-1} \tag{2}$$

where $d(i,j)$ is the shortest length between two scholars i and j. Closeness is an inverse of the sum of all the shortest pathways connecting two scholars, where N is the number of scholars in the network. The centrality of proximity improves the overall network's flow the quickest. By decreasing the distance between researchers, proximity reduces the time required to share information and increases the rate of resource exchange. It represents an author's "closeness" to all other writers in the network based on the shortest path between them. Closeness identifies influencers, or those best positioned to affect the transmission of information, or those that are closest to everyone.

2.1.3 Eigenvector centrality

Eigenvector centrality is our final network centrality metric. Like degree centrality, eigenvector centrality measures a node's influence based on the number of links it has to other nodes in a network. Eigenvector centrality then goes a step further by considering how highly connected a node is, how many interconnections their connections have, and so on via the network.

It evaluates a scholar's prominence and influence inside the network. If a scholar has a high degree of centrality, but most of his connections are too poorly connected scholars, his power within his network will be limited. He will substantially impact the network if connected to well-connected or more central scholars. Connection to higher-status (well-connected scholars) in a network can enhance a scholar's prestige while connecting to lower-status scholars might diminish it (Podolny, 1993). Eigenvector centrality, which measures the connection of a researcher based on the connectedness of its direct relationship, is calculated as follows:

$$Eigenvector_{i,t} = \frac{1}{\lambda} \sum_{j=1}^{N} x(i,j) \times e(j) \tag{3}$$

where λ is a constant represented by the biggest eigenvalue of the adjacency matrix and e_j is the Eigenvector centrality score. $\sum_{j=1}^{N} x(i,j)$ is the sum of connecting individuals between scholar i and j. Contrary to Equation (1), if a scholar is associated with another scholar with high centrality, this will boost his influence in the network.

Eigenvector centrality allows a scholar to boost in prominence. When well-connected nodes reach out to outside peers, such as through direct and indirect interactions with editors, associate editors, colleagues, co-authors, etc., the power and control of core scholars are strengthened.

In short, the degree indicates the number of finance professionals he knows. The closeness reflects how close he is to his connection, which influences the rate of information transmission. The eigenvector represents the overall prominence of each scholar's connections.

2.2 Data

Our sample consists of 4,223 authors who published in the top four finance journals from 1980. We further collect their publications and citation records in 48 finance and economics journals to have more encompassing measures of authors' characteristics. We measure authors' productivity only using publications in the top eleven journals. [3] We gather the following information about each author:

- Authors' first and family names: We infer the author's gender using the gender dictionary provided by genderize.io and forecast the author's race using Bayesian prediction of a racial category based on the author's names. In cases of ambiguity, we validate the author's gender and race by verifying the author's personal or/and school web pages and the author's Web of Science page of publishing data.
- Education: We cover the author's ultimate degree-granting institution (bachelor's, master's, Ph.D.) and their graduation dates.
- The advisory information: We collect the composition and date of the author's doctoral committee and the students for whom the author worked as a Ph.D. advisor.
- Professional information: We gather the author's associations and associated dates since earning a bachelor's degree.

We use this data to generate the Ph.D. colleague, post-Ph.D. colleagues, co-authors, and student-advisor networks. The data collected after this stage contains information about collaborative works by an author and publication since 1980. After completing these methods, we obtain a final sample of 4,228 authors with sufficient information to generate network matrices. Then, we collect each author's publication records and paper citations from the Web of Science.

We collect the following characteristics of author's papers published in 48 economics and finance journals (Appendix Table A1): publication year, journal, number of authors, paper length, whether an essay listed authors in alphabetical order, whether an article is published in special issues, and whether a paper is a lead paper (first three papers in a specific journal issue) and annual citations from 1980.

Our sample is limited to journal papers; therefore, proceedings, corrections, editorial posts, and book reviews are excluded. We cleanse the publication data set by removing duplicates (i.e., papers appearing in

[3] The top four journals in finance are the Journal of Finance (JF), Journal of Financial Economics (JFE), Review of Financial Studies (RFS), and Journal of Financial and Quantitative Analysis (JFQA). The top seven journals in economics are the Quarterly Journal of Economics (QJE), Journal of Political Economy (JPE), American Economic Review (AER), Econometrica, Journal of Economic Literature (JEL), Journal of Economic Growth (JEG), and Review of Economic Studies (RES).

multiple journals with identical names and authors), resulting in a final sample size of 24,672 publications.

In addition to the number of citations, we collect detailed information regarding which papers cite which. In other words, we collect their cited publications, authors, journals, publication year, and paper citations.

We collect scholars' salaries. AACSB is where we obtain our salary information. Members of the AACSB have access to pay data for business school academics of various ranks (assistant professor, associate professor, and full professor). Any business school with AACSB accreditation must disclose the salaries of faculty members at each rank and department. We concentrate on the finance department, and annual data is accessible. Although Glassdoor.com provides compensation data at the School-rank level, it is crucial to note that it is based on the average wage of all disciplines and is not specific to finance. We complement our salary from AACSB with the salaries collected from the public domains.[4]

Due to our finance concentration, we must collect the average salaries of professors at different ranks within financial departments. Because all our analyses of author salaries are conducted at the school-rank level, author characteristics, including network factors, must likewise be aggregated at this level.

AACSB does not disclose the salary of a particular university but rather the average salary of six universities at a time. To obtain a rough approximation of the salary for our focal sample, we select our focal university and the five universities adjacent to our focus university. The W.P. Carey Business School maintains the rank of the finance department at Arizona State University. Although there are other business school rankings from US News, Business Week, and Financial Times, we use the Arizona State University ranking since it evaluates the department based on publications in top-tier journals, which is aligned with the goal of our analysis.

We also collect historical information on the editorial boards of the top four finance journals, including the journal editors, their roles in the journal (e.g., editors, co-editors, associate editors), their relationship with the sample authors (advisor-student, Ph.D. colleague, Post Ph.D. colleague, co-author), deaths, and changes in editorial teams (i.e., editor turnover).

Our final sample contains 4,228 authors, 291 Ph.D. schools, 1,070 affiliations, and 24,672 papers published in 48 leading finance, accounting, and economics journals from 1980. Table 1 reports the descriptive statistics of our sample authors' research records and network features. Publishing in scientific literature is a long and winding process (Björk and Solomon, 2013). The typical author publishes 0.4 papers yearly after her

[4]For instance, we collect state university employees in California from https://www.sacbee.com/news/databases/state-pay/article229468549.html/

Ph.D. and only 0.24 in top finance and economics journals yearly.[5] Note that this is not specific to young researchers, as the authors in our sample have an experience 15 years of in academics. Their networks are relatively large - the typical author has 39 connections, among which two are his/her advisors/students, 8 are Ph.D. colleagues, and 21 are post-Ph.D. colleagues, and 3 are coauthors. On average, post-Ph.D. colleagues network has the highest closeness and prestige.

3 Does networking improve an author's research outcomes?

Our analyses are conducted at various levels determined by data availability and dependent variables. The analysis of productivity is conducted at the author-year level, whereas the analysis of citations (paper quality) is conducted at the paper-author-year level. Salary information enables us to operate only at the school-rank-year level. The editorial process and bias are then carried out at the author-year level. Brogaard et al. (2014) use school-journal-year-level data when analyzing productivity but switch to paper-journal-year-level data when calculating citations, as they wish to control for paper characteristics.

3.1 Does networking improve research productivity?

3.1.1 Network improves research productivity

We perform author-level panel data regression as follows:

$$\begin{aligned} Research\,Output_{i,t} =& \beta_1 Author\,Network_{i,t-2} + \\ & \alpha Author\,Controls_{i,t-2} + \rho_i + \gamma_j + \theta_t + \varepsilon_{i,t} \end{aligned} \tag{4}$$

where the dependent variable $Research\,Output_{i,t}$ is the total top publications of author i in year t. $Network_{i,t-2}$ are Degree, Closeness, and Eigenvector centralities measured at year t-2 considering the average turnaround time (e.g., Brogaard et al. (2014)). Authors' controls include the 5-year cumulative citations, total number of lead articles, and experience (years elapsed after the Ph.D.); they are log-transformed.

[5]We identify top papers as those published in 4 top finance (Journal of Finance, Journal of Financial Economics, Review of Financial Studies, and Journal of Financial and Quantitative Analysis) and 7 top economics journals (American Economic Review, Econometrica, Quarterly Journal of Economics, Journal of Political Economy, Journal of Economic Growth, Journal of Economic Literature, and Journal of Monetary Economics).

Our main specification includes author-fixed effects (ρ_i) and affiliation-fixed effects (γ_j) to capture time-invariant author and affiliation characteristics. Year-fixed effects (θ_t) are included to control for factors that are constant across authors but vary over time (e.g., technologies that alter research productivity). We cluster standard errors at the author level to correct for serial correlation within each author. For robustness, we also examine a specification that uses the author's Ph.D. school fixed effects instead of the author fixed effects to account for a school reputation effect. We do not have both in the exact specifications because Ph.D. School FEs are perfectly collinear with author FEs. – an author only has one Ph.D. school. The results are presented in columns (1), (2), (4), (5), (7), and (8) of Table 2.

Our results show that closeness is most significantly associated with log (total publications) and log (total citations) (top publications). A standard deviation above the mean improves leading publications by 22% (column (4) of Table 2) and increases citations by 14% (column (3) of Panel A, Table 3). The network size has a secondary impact, followed by the prestige of people you know.

3.1.2 Which network is more relevant?

Next, we examine which network is the most impactful to productivity. The results are presented in columns (3), (6), (9) of Table 2

Under degree and closeness, which indicates the size and proximity of everyone's network, and eigenvector measuring a network's prestige (influence), the advisor-student network has the most significant favorable influence on leading publications, followed by coauthor and post-Ph.D. colleague. The Ph.D. colleague network has no impact on author productivity.

Post-Ph.D. colleagues exert the most impact for prestige, followed by advisor-student. The negative coefficient, although insignificant, on Ph.D. colleagues when assessing the impact of network closeness is puzzling. A possible explanation is that this variable may capture the effect of an omitted/unobserved variable, "size of Ph.D. programs" - large Ph.D. programs lead to less favorable outcomes.

In order of importance, the most crucial aspect of all relationships is proximity, network size, and prestige. This suggests nurturing the current connection is more important than expanding it or connecting with influential scholars. The exception is the network of advisor-student, where network size has a more significant impact than network proximity. On the other hand, proximity has the most negligible impact on the co-authors' network. Having a notable co-author substantially affects the paper's success, supporting Huber et al. (2022). In the following part, we analyze whether publications written by renowned writers are also of higher quality.

3.2 Does networking increase research quality?

We examine if networking enhances the quality of the papers in this study using article-level panel data regression:

$$\begin{aligned} Research\,Quality_{p,t} = &\beta_1 Author\,Network_{p,t-2} + \\ &\alpha Author\,Controls_{p,t-2} + \\ &\gamma Paper\,Controls_{p} + \rho_{j,t} + \theta_{life} + \varepsilon_{p,t} \end{aligned} \tag{5}$$

The dependent variable, $Research\,Quality_{p,t}$ is the logarithm of cumulative paper citations p in year t. $Author\,Network_{p,t-2}$ are the paper's average author network centrality (degree, closeness, and eigenvector) two years before the publication or citation. We control for paper characteristics such as the number of authors, paper length, number of years after publication, a nonalphabetic dummy variable for papers that do not list authors in alphabetical order, a dummy variable for articles published in special issues, and a dummy variable for lead papers (first three papers in a specific journal issue). We additionally control for average author characteristics, including the logarithm of cumulative publications, the logarithm of top cumulative publications, the logarithm of star papers, and the logarithm of author experience (years since the Ph.D.), which are all measured two years before publication. We use journal x year fixed effects (denoted by $\rho_{j,t}$ to exclude the citation effect of omitted components that are constant at the journal-year level. To make our method more adaptable, we make no assumptions regarding the shape of the citation growth curve. We offer a collection of paper life-years after publication dummies (θ_{life}) to control for the bias from articles published long ago. Utilizing residual citation to fit a third-degree polynomial function based on paper age (where paper age is defined as years elapsed since publication) does not influence our findings.[6] The standard errors are clustered at the article level. Our coefficient of interest is β_1. It evaluates how the author's network centrality affects the quality of the author's study.

We measure the author's network at publication (Panel A of Table 3) and a citation (Panel B of Table 3). The former addresses the endogeneity concern due to the reputation effect, while the latter evaluates the

[6] We collect the residual of the regression od ln(cumulative citation) on Age^3, Age^2, and Age. See $https://www.dropbox.com/s/2hucdt7dnp172lm/Fit_polynimial.png?dl=0$

reputation effect explicitly. An author's network expands naturally as their publications accumulate, resulting in a reputation effect that may influence the citation process.

We find that the quality of the article is enhanced by cultivating relationships with network members in general. The effect is strengthened significantly after publication with the growth in the author's network, consistent with the reputation effect. For instance, the effect of network prestige tripled after measuring the author's network at citation - in column (5), the coefficient of network prestige increases from 0.038 in Panel A to 0.116 in Panel B.

However, this quality-enhancing networking effect is not valid for the coauthor network. Papers published by authors with a more extensive network are of lower quality. In particular, papers of authors with higher closeness centrality at publication have significantly lower quality. (see column (4) of Table 3). Since the network at citation is endogenous and confounded by the reputation effect, we focus on the network at a publication for the rest of the analyses. The result remains intact when we focus the sample only on the top four finance journals and when we use a variable, $Research\,Quality_{p,t}$ is the logarithm of cumulative residual citations of paper p in year t with residual citation estimated by fitting a polynomial function of author's publication experience (see Tables A4 and A5 in the Appendix, respectively).[7]

3.3 Non-linear effects of networking

Figure 2 plots the point estimates and confidence intervals for the network deciles (the 1st decile serves as the reference group, therefore, is not estimated) estimating the research productivity specification 4 (left panel) and the research quality specification 5 (right panel). On the one hand, the author network is positively and linearly correlated with productivity (measured by the number of top publications). On the other hand, the effect of networking on research quality is non-linear - networking improves research quality only for authors in the highest network deciles.

4 Underlying mechanism

So far, we show scholars with a better network are associated with more top publications, and those publications have more citations, suggesting highly networked papers have better quality. We find that

[7]The top four journals include the Journal of Finance, Review of Financial Studies, Journal of Financial Economics, and Journal of Financial and Quantitative Analysis.

among relationships, the student-advisor relationship is the most important. While closeness, followed by network size and prestige, is the most important for all connection types, prestige is the most critical network for the co-author's network. This section explains why a network is associated with productivity and paper quality. We propose two mechanisms.

4.1 Networks improve salary

First, authors with extensive networks may earn high salaries. In academia, it is known that institutions with high salaries offer faculty members with less teaching load, and as a result, they have time to do research. Research schools tend to offer higher salaries and a lighter teaching load but also demand more top-tier publications. We perform the following school and academic rank panel data regression:

$$\begin{aligned} Salary_{i,t} =& \beta_1 Author\ Network_{i,t-2} + \\ & \alpha Author\ Controls_{i,t-2} + \\ & + \rho_i + \Psi_r + \tau_l + \theta_t + \varepsilon_{i,t} \end{aligned} \tag{6}$$

where the dependent variable $Salary_{i,t}$ is the logarithm of author i's salary in year t. We collect salary data from AACSB and augmented them by manually collecting it from the public domains. The data is only available at the school-rank-year level. We, therefore, estimate an author's yearly salary based on the average salary of researchers in the same school rank and the same year. We rely on Arizona State University's ranking of department finance because they rank each finance department based on the same criterion as we do: top-tier publications. $Author\ Network_{i,t-2}$ is the average author network centrality (degree, closeness, and eigenvector), measured in year $t-2$. Moving forward, we will showcase the results using the network measurement taken at the publication for the citation regression analysis. As demonstrated in Table 3, the network at the citation stage could also reflect a reputation effect, which the network itself may intrinsically influence.

We control for average author characteristics, including the logarithm of 5-year cumulative citations, the logarithm of cumulative publications, the logarithm of top cumulative publications, the total number of lead articles, and the logarithm of author experience (years since the Ph.D.), all of which are measured in year t-2. We include school location and author rank fixed effects (τ_l and Ψ_r) to capture time-invariant unobservable within each country-state and author rank (assistant professor, associate professor, and full professor).[8] Year-fixed results (θ_t) are included to control for factors constant across the school and author rank but vary over time (e.g., inflation and availability of public funds). We cluster standard errors at the author level to correct for possible serial correlation across authors.

The results in Table 4 indicate a positive role of networking in affecting the author's salary. A standard deviation increase in network centrality over the past two years leads to an increase in the author's wage by about 4.2%-4.7%. Post-Ph.D. colleagues generate the most amplified effect when evaluating the author's network by size and prestige. Advisor-Student generates the most amplified effect when evaluating the author's network by closeness.

Columns (10)-(12) of Table 4 include dummies from the top ten, top fifty, and top one hundred universities interacting with networking factors. Generally, the top ten schools pay more, followed by the top fifty, and then the top one hundred. We find that the effect of networking is enhanced by school ranking. Researchers with larger and closer networks are valued more in top schools. There is no evidence that school ranks add to the effect of network prestige (i.e., the influence of an author in the network) on salary, probably due to the self-enhancing effect of influential researchers. When an author is already influential enough in the network, it doesn't matter if he/she works in a top school for him/her to receive a higher salary. Notably, the effect of networking on salary is muted or even reversed in schools that ranked lower than 100. Moreover, the mediation effect of school ranking is more pronounced in schools that ranked between 50 and 100, followed by those between 10 and 50, and lastly, the top 10 schools.

4.2 Are higher salary-connected authors more likely to publish in the top tiers?

Now that we have proven that writers who engage in networking are compensated more, we investigate if higher compensation encourages authors to publish more in top-tier journals. To investigate this, we regress the log of papers published in leading journals on salary, network, and their interaction in Table 5.

[8] County-state FE captures effects of geographical factors; for instance, the pay of the same position in California is higher than in Kentucky. Author rank FEs capture the fact that full professors are paid higher than associate professors and assistant professors.

$$
\begin{aligned}
Research\,Output_{i,t} = &\beta_1 Author\,Network_{i,t-2} + \\
&\beta_2 Author\,Salary_{i,t-2} + \\
&\beta_3 Author\,Salary_{i,t-2} \times Author\,Controls_{i,t-2} + \\
&\alpha Author\,Controls_{i,t-2} + \rho_i + \gamma_j + \theta_t + \varepsilon_{i,t}
\end{aligned}
\tag{7}
$$

Built on Specification 4), we interact the network variables with the author's salary to infer whether a higher wage leads to more top publications and whether the effect accelerates with the size and depth of the author's network. We include the same author controls and author, affiliation, and year-fixed effects similar to Eq.4.

Interestingly, a higher salary is not associated with more top publications after controlling for a wide range of author characteristics and fixed effects. Note that the coefficient on salary in column (1) of Table 5 is insignificant. Yet, we learn from all features that higher-paid academics with deeper networks are likelier to publish scholarly works of the highest quality. In particular, the coefficients of network closeness and prestige change signs when the interaction terms are included, thus suggesting salary is an underlying channel. This implies that, for scholars with a lower salary, networks decrease the quality of the paper. Given that they have less time left due to a heavy teaching load, networking might take away their time to focus on good quality work.

4.3 Is there any editorial favoritism?

This section analyzes whether the network, top publications, and paper quality relationship is channeled through the specific network with editors or the editorial team. We perform the following regression:

$$
\begin{aligned}
Publication_{i,j,t} = &\beta_1 Editor\,Connection_{i,j,t-2} + \\
&\alpha Author\,Controls_{i,t-2} + \zeta_{i,j} + \theta_t + \varepsilon_{i,j,t}
\end{aligned}
\tag{8}
$$

where the dependent variable $Publication_{i,j,t}$ is the dummy for published papers by the author i in journal j in year t.[9] $Editor\,Connection_{i,j,t-2}$ is a dummy variable that takes a value of 1 if author i has at least one

[9] In this specification, we have many zeros, making the log transformation undesirable (see Chen and Roth (2022)). Using a

connected editor in journal j. The author controls consist of the logarithms of 5-year cumulative citations, cumulative publications, top cumulative publications, cumulative lead articles, and author experience (years elapsed after the Ph.D.). All of these variables are measured in year $t-2$ and log-transformed. We include author-journal fixed effects ($\zeta_{i,j}$)to account for author-journal relationships that are not observable (other than the author's relationship with the journal's editors). We also adjust for year-fixed effects (θ_t) to account for time-dependent author and journal characteristics. We estimate the parameters using the linear probability model. Standard errors are clustered at the author level.

Overall, no significant evidence exists that authors connected with editors are likelier to publish their papers with the connected journal (column (1), Panel A of Table 6). Yet, after examining each network type, we find the network with the editor through student-advisor and post-PhD colleague relationships increases the probability of publication with the connected journal (column (2) and column (4), Panel A of Table 6). In contrast, the editor network through Ph.D. colleagues and co-author relations significantly decreases the chance of publishing in the editor's journal (column (3) and column (5), Panel A of Table 6).

The next concern is whether these academics will receive preferential treatment. To answer this question, we examine whether editor-networked papers also have high quality. If having a network with the editor increases the paper's productivity and quality, then there is no bias in the editorial process. If otherwise, there is editorial nepotism.

$$\begin{aligned} Research\ Quality_{p,t} =& \beta_1 Editor\ Connection_{p,j,t-2} + \\ & \alpha Author\ Controls_{p,t-2} + \\ & \gamma Paper\ Controls_p + \rho_{j,t} + \theta_{life} + \varepsilon_{p,t} \end{aligned} \tag{9}$$

where $Research\ Quality_{p,t}$ is the logarithm of cumulative citations of paper p in year t. $Editor\ Connection_{p,j,t-2}$ is a dummy variable that takes a value of 1 if authors of paper p have at least one connected editor in J=journal j two years before publication. Adjustments are made for paper characteristics such as the number of authors, paper length, number of years since publication, absence of an alphabetic dummy for papers that do not list authors in alphabetical order, a dummy variable for articles published in special issues, and a dummy variable for lead papers (first three papers in a specific journal issue). We also control for average author characteristics measured two years before publication, such as the logarithm of cumulative publications, top cumulative

dummy also makes the interpretation easier. We have also tested the log specification, and the results remain robust.

publications, star papers, and author experience (years since Ph.D.). We include $journal - year$ fixed effects (denoted by $\rho_{j,t}$) to eliminate any citation effect of the omitted variables at the journal-year level. To make our method more adaptable, we make no assumptions regarding the shape of the citation growth curve. We offer a collection of paper life - years after publication θ_{life}

Panel B of Table 6 elucidates that manuscripts boasting editorial connections exhibit superior quality, predominantly propelled by the post-doctorate colleague network. Intriguingly, connections established with editors through student-advisor networks suggest an undercurrent of favoritism, as these publications fail to garner additional citations despite the increased probability of acceptance. Conversely, discrimination affects Ph.D. colleagues and co-authors associated with editors, as their equally meritorious works experience diminished publication opportunities. This phenomenon might stem from imposing stringent standards or competitive dynamics among doctoral peers.

Owing to the inconclusive nature of the evidence, we exercise caution in ascribing editorial bias. Our findings lend nuance to Brogaard et al. (2014)'s assertion regarding the absence of nepotism in the review process, highlighting that editorial favoritism constitutes a less potent mechanism than remuneration and prestigious academic affiliations.

5 Is there any bias in citations?

5.1 Is there any network favoritism in citations?

The literature in non-finance disciplines finds there is a bias in a citation. Men cited papers written by men in the fields of neurology, astronomy, medicine, physics, and economics, according to Dworkin et al. (2020), Caplar et al. (2017), Chatterjee and Werner (2021), Teich et al. (2022), and Dion et al. (2018), respectively.

In this section, we examine whether connected authors tend to cite each other by estimating the following specification:

$$
\begin{aligned}
Citation_{i,j,t} = &\beta_1 Author\ Connection_{i,j,t-2} + \\
&\alpha_1 CitedAuthor\ Controls_{i,t-2} + \\
&\alpha_2 CitingAuthor\ Controls_{j,t-2} + \\
&+ \rho_i + \rho_j + \gamma_i + \gamma_j + \theta_t + \varepsilon_{p,t}
\end{aligned} \tag{10}
$$

where the dependent variable $Citations_{i,j,t}$ is the logarithm of cumulative citations of cited author i by citing author j in year t. We control for characteristics of cited and citing authors. Cited and citing authors' fixed effects (ρ_i and ρ_j) are also controlled for, as well as the affiliation fixed effects (γ_i and γ_j) to capture observable and time-invariant characteristics that are specific to cited and citing authors and their affiliations. Year-fixed effects (θ_t) are included to control for constant factors across authors but vary over time. We cluster standard errors at the cited author-citing author level to correct for serial correlation within each relationship.

The results are presented in Panel A, Table 7. All network types reference one another. Co-authors cite each other the most (0.331). This can be interpreted that these researchers are 39% more likely to cite their coauthors (exp(0.331)-1)*100. The Ph.D. and post-Ph.D. colleagues tend to cite less with each other, presumably due to competition.

Given the evidence that authors are more likely to cite their relationships, we examine the possibility of favoritism, like the empirical specification used in Section 3.2, with the inclusion of a dummy variable indicating if a publication is mentioned by the author(s)' connections (advisor, students, Ph.D. colleagues, Post Ph.D. colleagues, and coauthors, or any of these types).

$$
\begin{aligned}
Research\ Quality_{p,t} = &\beta_1 Author\ Connection_{p,t-2} + \\
&\alpha Author\ Controls_{p,t-2} + \\
&\gamma Paper\ Controls_p + \rho_{j,t} + \theta_{life} + \varepsilon_{p,t}
\end{aligned} \tag{11}
$$

Panel B, Table 7 shows that papers cited by connected authors have superior quality, in line with the private information channel. Among the four relation types, papers cited by students/advisors are of relatively lower quality than others.

5.2 Is there any editorial favoritism from citing editors' papers?

In addition, scholars may rig the system by citing editors' works to gain favor during the editorial process. To assess this hypothesis, we build on Equation 8 and Equation 9, including the variable $EditorCiting$ (the number of editor papers cited) and its interaction term with $EditorConnection$.

$$
\begin{aligned}
Publication_{i,j,t} = &\beta_1 Editor\ Connection_{i,j,t-2} + \\
&\beta_2 Editor\ Citing_{i,j,t} + \\
&\beta_3 Editor\ Connection_{i,j,t-2} \times Editor\ Citing_{i,j,t} + \\
&\alpha Author\ Controls_{i,t-2} + \zeta_{i,j} + \theta_t + \varepsilon_{i,t}
\end{aligned}
\tag{12}
$$

$$
\begin{aligned}
Research\ Quality_{p,t} = &\beta_1 Editor\ Connection_{p,j,t-2} + \\
&\beta_2 Editor\ Citing_{p,j} + \\
&\beta_3 Editor\ Connection_{p,j,t-2} \times Editor\ Citing_{p,j} + \\
&\alpha Author\ Controls_{p,t-2} + \\
&\alpha Author\ Controls_{p,t-2} + \\
&\gamma Paper\ Controls_p + \rho_{j,t} + \theta_{life} + \varepsilon_{p,t}
\end{aligned}
\tag{13}
$$

We observe that, on the whole, editor citing is associated with a higher likelihood of publication in editors' journals and higher paper quality (Table 8).

However, those connected to editors who cite editors' papers receive fewer top publications, although their work is of equal quality to that of other scholars, except for the connection via the Ph.D. colleagues' network. Editors do not seem to favor papers from their Ph.D. colleagues that cite their work, but if they do so, the papers are of lower quality. Overall, the quality of papers that cite the work of editors is higher; therefore, we cannot conclude that there is citation bias.

6 Gender and race

This section examines the role of gender and race in finance academics. Researchers find that studies co-authored by women receive a lenient review process in biology, health, and physical sciences (see Squazzoni et al. (2021); Borsuk et al. (2009); Tudor and Yashar (2018); Fox and Paine (2019)). We examine whether there is editorial nepotism across genders and races.

We project race and gender using "predict race", a user-written R function that uses U.S. Census data to forecast the race and gender of a surname or first name. Next, we utilize "NamSor" to complete the gender and racial predictions. In cases where "predict race" and "NamSor" return different answers, we validate the author's CV and biography by hand. We focus on gender first and finish the paper with gender and race.

6.1 Network features

We characterize the network statistics across genders and races in Appendix A3. White males dominate our sample. There are 3,620 male authors and 608 female authors in our sample. Regarding the separation by race, there are 2,502 white authors and 1,726 nonwhite authors. Men have a more incredible research record in almost every facet and contact, but their social networks do not seem more extensive and more profound than women. Males have a larger coauthor network but are less close to their coauthors than females. Males are close to all the connection types in the network than females. Men also have more influential co-authors, as evidenced by their more significant eigenvectors. Brown and Samuels (2018) state that males are more interconnected than females.

Like females, nonwhites are more centralized in the network regarding closeness. Yet, whites have a more influential network than nonwhites, except for the Ph.D. colleagues network, for which no difference is found. Females and nonwhites have a more extensive and closer advisor-student network, but whites have a more influential one. Collectively, the gap in the network is more significant between white and non-white individuals. We include the detailed results for more granular races, including African American, Asian, Hispanic, and white, in Appendix A2.

6.2 Male vs. Female/ White vs. Non-White

To disentangle the role of gender and race in mediating the effect of networking on research output and quality, we augment the specification outlined in Section 3.1.1 and Section 3.2, including the gender/race dummy and its interaction with the author's network centrality.

$$
\begin{aligned}
Research\,Output_{i,t} = & \beta_1 Author\,Network_{i,t-2} + \\
& \beta_2 Author\,Minority_i \times Network_{i,t-2} + \\
& \alpha Author\,Controls_{i,t-2} + \rho_i + \gamma_j + \theta_t + \varepsilon_{i,t}
\end{aligned}
\tag{14}
$$

$$
\begin{aligned}
Research\,Quality_{p,i,t} = & \beta_1 Author\,Network_{i,t-2} + \\
& \beta_2 Author\,Minority_i + \\
& \beta_3 Author\,Minority_i \times Network_{i,t-2} + \\
& \alpha Author\,Controls_{i,t-2} + \\
& \gamma Paper\,Controls_p + \rho_{j,t} + \theta_{life} + \varepsilon_{p,t}
\end{aligned}
\tag{15}
$$

The results in Table 9 suggest discrimination against female researchers with a more centralized and influential network. Female researchers with higher network prestige are less inclined to publish in top finance and economics journals even though their papers are of higher quality. Moreover, our results show that non-white authors with influential networks do not publish more, but their papers tend to receive more citations if they do.

6.3 Editorial process toward different races and genders

This section examines whether editorial nepotism exists across genders and races. Empirical evidence in biology, health, and physical sciences suggests that research co-authored by women receives more lenient peer review (see Squazzoni et al. (2021), Borsuk et al. (2009), Tudor and Yashar (2018), and Fox and Paine (2019)), so this section examines this evidence in finance. We execute the following specifications, deriving from those in Section 4.3.

$$
\begin{aligned}
Publication_{i,j,t} = &\beta_1 Editor\ Connection_{i,j,t-2} + \\
&\beta_2 Author\ Minority_i \times Editor\ Connection_{i,j,t-2} + \\
&\alpha Author\ Controls_{i,t-2} + \zeta_{i,j} + \theta_t + \varepsilon_{i,t}
\end{aligned} \tag{16}
$$

$$
\begin{aligned}
Research\ Quality_{p,t} = &\beta_1 Editor\ Connection_{p,j,t-2} + \\
&\beta_2 Author\ Minority_p + \\
&\beta_3 Author\ Minority_p \times Editor\ Connection_{p,j,t-2} + \\
&\alpha Author\ Controls_{p,t-2} + \\
&\gamma Paper\ Controls_p + \rho_{j,t} + \theta_{life} + \varepsilon_{p,t}
\end{aligned} \tag{17}
$$

In a nutshell, with the same paper quality, we show female authors who are editors post-Ph.D. colleagues have fewer top publications, although their papers are not of lower quality, thereby suggesting discrimination against female scholars which contrasts with the finding of non-finance literature.[10] There is, however, no favoritism against editors' woman coauthors.

The results in Table 10 Panel A find a significant difference in the impact of networking across genders on the number of top publications. Female authors who are connected with journal editors via the post-Ph.D. colleagues and coauthor networks are less likely than their male peers to publish in connected journals.

Table 10 Panel B further reveals that papers of female researchers accepted by the connected journals via the coauthor network have lower quality, indicating no unfairness to editors' female coauthors. However, editors' post-Ph.D. female colleagues do not seem to publish lower-quality papers, despite the lower probability of publication, implying discrimination rather than favoritism in other fields.

There is a caveat. The editorial discrimination against post-Ph.D. colleagues linked to editors shown in Table 10 Panel A is more driven by females. This does not mean that discrimination does not occur among men. It is more evident to female scholars.

We do not find any evidence of discrimination against non-whites. The coefficients of the non-white dummy interacted with the editor connection dummy are never statistically significant in the research output results.

[10] The coefficient of Connection in this spec represents the impact of networking on quality for males.

They are only marginally significant (at 10%) in the research quality results for the post-Ph.D—colleague network.

We also examine the relationship between network and productivity (and quality) at granular races, including African American, Asian, Hispanic, and white.

Table A6 shows White male scholars have lower quality than the others while black males have higher quality. Black female scholars have fewer top publications, although their quality is indifferent to the quality of the research work done by other races.

It is worth mentioning some nuances. With the same number of top publications, African American males and Hispanic females with a prestigious network and Hispanic females with a more prominent network size have better quality work. We do not suggest there is discrimination against them. With the same quality, discrimination seems more evident for African American females with fewer publications. See Appendix A2.

Turning to editorial favoritism, Table A7 shows a white female who connects with editors in the form of Ph.D. colleagues who have lower quality. Hispano male researchers who have any relationships with editors have more papers published, but their work quality is not different from the others. In contrast, with the same quality work, Hispano females have fewer top-tier publications. The results are strong and statistically significant at the 1% level. Interestingly, black male researchers who are editors' co-authors have more papers accepted at the top tiers, but their works justify as they have higher quality. Asian female researchers who have any connection with editors get fewer papers published, but we also observe that editors' co-authors have lower quality works. In sum, we see the editorial favoritism toward white females and Hispano male and discrimination against Hispano female scholars.

Table A6 reveals that White male scholars typically produce lower quality work than their counterparts, whereas Black male scholars generally exhibit higher quality. Despite the comparable quality of their research, Black female scholars have fewer top-tier publications than scholars of other races.

Subtle distinctions are worth noting. With an equivalent number of top-tier publications, African American males and Hispanic females with prestigious networks and Hispanic females with larger network sizes produce superior quality work. This is not indicative of discrimination against these demographics. However, when considering the same level of quality, discrimination appears more pronounced for African American females, who have fewer publications. Please refer to Appendix A2 for more details.

Moving to editorial favoritism, Table A7 indicates that White females who are editors' Ph.D. colleagues typically exhibit lower-quality work. Conversely, Hispanic male researchers who have any form of relationship with editors have more papers published, although their work's quality aligns with the general standard. In contrast, with comparable quality, Hispanic females attain fewer top-tier publications. These results are robust and statistically significant at the 1% level. Interestingly, Black male researchers who have co-authored with editors secure more top-tier acceptances, justified by their higher-quality work. Asian female researchers with any editor connection have fewer published papers, and those who co-author with editors generally produce lower-quality work. Strikingly, Asian females who are editors post-Ph.D. colleagues have higher quality work. In summary, we observe editorial favoritism towards White females and Hispanic males and discrimination against Hispanic and Asian female scholars who are editors' post-Ph.D. colleagues.

7 Causality

7.1 Networking and productivity

Identifying the impact of author networking is empirically challenging due to the likelihood that the network is endogenous to productivity. For instance, authors earn notoriety through their publications; hence, authors with more research output are likely to have a more significant and extensive network, raising concerns regarding reverse causality. In this section, we demonstrate causation by examining an author's network disruption due to the unexpected death of an author's link. We perform the following:

$$\begin{aligned} Research\,Output_{i,t} = & \sum_{s=-1}^{-3} \beta_s Pre - Shock_{i,s,t} + \varphi_1 Shock_{i,t} + \\ & \beta_1 Author\,Network_{i,t-2} + \\ & \alpha Author\,Controls_{i,t-2} + \rho_i + \gamma_j + \theta_t + \varepsilon_{i,t} \end{aligned} \tag{18}$$

Our coefficient of interest is φ_1 which captures how an author's research output evolves after the sudden death of the author's connection. To check pre-trends, we estimate the impact of connection decreases on the connected author's productivity s years before the decreasing event captured by β_s. We collect scholars' deaths from the public domain and the American Finance Association website. $Shock_{i,t}$ takes the one if author i has a connection that deceased in the past, and 0 otherwise. As the disruption effect on productivity may take time to materialize, we only consider announced author decrease events that occurred five years before the end of our sample period, so we observe an author's publication activity after the decrease of his/her connection to estimate the effect of the network shock.

Sudden deaths of the author's connection are exogenous events as it is arguably unanticipated, therefore, can be considered random and orthogonal to the research output of a given author. We expect φ_1 to be negative if authors suffer from network loss. One can argue that deaths caused by a medical condition or illness (such as cancer) can be anticipated. An author can adjust his publication strategy to alleviate possible loss from the death of his/her connection. If this is the case, it will only make φ_1 weaker (i.e., less negative).

Our main identification challenge is that the authors in the control group may not represent a proper counterfactual. The concern is that the announcement of decease events may be biased towards connections with higher visibility, inducing selection into treatment. To guarantee that treatment and control groups are comparable, we implement coarsened exact matching on characteristics of authors before the shock, i.e., gender, ethnicity, number of total publications, number of top publications, experience, and cumulative citations in the past five years. The final sample includes 249 treated authors (authors with a connection deceased in the past) and 249 control authors that are of the same gender and have similar publication records compared to the treated authors.

Table 11 finds that the abrupt dissolution of co-author networks decreases leading publications, and the effect remains ten years after the connection decease. Further, a lower coefficient in column (10) than in column (5) suggests that the shock has a long-term effect on authors' productivity[11].

7.2 Editorial process

The connection to the editor may also be endogenous; thus, we apply a transition of journal editor as an exogenous shock in a similar difference-in-differences framework.

$$\begin{aligned} Publication_{i,j,t} = \sum_{s=-1}^{-3} \beta_s Pre-Shock_{i,s,t} + \varphi_1 Shock_{i,t} + \\ \alpha Author\,Controls_{i,t-2} + \zeta_{i,j} + \theta_t + \varepsilon_{i,j,t} \end{aligned} \tag{19}$$

[11] The pre-trends look reasonable except for post-Ph.D. colleagues. This suggests omitted variables possibly positively related to the post-Ph.D. network. Post-Ph.D. network is the most significant network type, which may suffer from measurement errors (we do not know all of the scholars' post-Ph.D. colleagues, for example)

where our coefficient of interest is φ_1 which captures how the chance of an author publishing in a top journal changes after the turnover of the author's connected editor, $Shock_{i,t}$ takes the value of one of the author i's associated editors ceased to serve journal j and 0 otherwise. β_s evaluates the pre-trends, the impact of editor turnover on the connected author's productivity s years before the event.

Similarly, we perform matching as in Section 7.1 and break down the connection into four networks. Only when an advisor stops being an editor hurts the top publication. The significance is at 5%, and the effect remains strong ten years after the shock (Table 12).

So far, the outcomes of networking with editors have been mixed. On one side, increased productivity is observed when the editor is connected through student, advisor, and post-Ph.D—colleague networks. However, connections with Ph.D. colleagues and co-authors seem to have a negative impact. Conversely, papers linked via Ph.D. colleagues and post-Ph.D. colleague networks demonstrate higher quality, while those connected through student-advisor and coauthor networks do not appear to exhibit superior quality. This suggests the presence of favoritism via student-advisor and post-Ph.D. colleague connections, while discrimination occurs against the editor's students, advisors, and co-authors.[12]

8 Conclusion

We find that the network enhances scholars' productivity and paper quality. Network proximity is more significant than network size and prestige.

The most significant ties are coauthors and student-advisors, followed by post-Ph.D. and Ph.D. networks. We employ co-author deaths as a shock in DiD analysis to address endogeneity concerns, and the effect is most remarkable for co-author networks. We show that compensation accounts for this causation. Scholars with extensive connections receive a higher salary, produce more prominent publications, and perform superior research. As their research is correlated with quality, there is no hint of favoritism at elite universities. We find no apparent evidence of editorial bias in finance. Regardless of their connection, researchers close to the editor get their articles approved more often, but their work is also of excellent quality. There are several intricacies among the relationships. With equal quality, co-author and Ph.D. editor colleagues are accepted less often than student-advisor and post-PhD editors. The result is robust using editor transition as an exogenous shock.

Our study focuses on the contentious issue of inequality. According to non-finance literature, males are

[12] if we do not perform any matching, the coefficient is also significant for post colleagues and marginally for coauthors. See the results here: https://www.dropbox.com/s/nauaqkqip7cbfa6/reg$_{e}ditorial_{p}rocess_{D}iD.csv?dl = 0$

cited more often than women. We show that scholars with the same network reference each other more frequently, which is connected with higher quality. The paper quality of scholars referencing editors' work is also outstanding. There is no citation favoritism.

We focus primarily on gender and race. Women have fewer connections and networks than men. The disparity between whites and non-whites is considerably more significant, with whites having stronger ties in nearly all aspects.

In contrast to the research in other fields indicating that women get favorable editorial treatment, we find that it depends on the connection type with editors. Female scholars who have post-PhD colleague connections with editors are discriminated against. They received less prestigious publications, although the quality of their work is comparable to that of others. On the other hand, female scholars who are editors' Ph.D. colleagues and co-author have lower quality works but get the same number of publications accepted.

The disparity is economically significant. One standard deviation increase in females and proximity to editors reduces the number of leading publications by 0.02. [13]

We find discrimination against Asian females who are editors post-Ph.D. colleagues. We also find evidence for Hispanic females who are editor's student-advisors. In contrast, we find favoritism toward white females' Ph.D. colleagues with editors and Hispanic males.

Our findings suggest that students should not avoid networking due to potential bias in their work, as expanding and nurturing their current network is crucial for achieving success in publishing. Additionally, we recommend that academics collaborate with exceptional professors as co-authors, which will likely result in mutual benefits. Our conclusions can be applied to other organizations, indicating that companies should consider investing in their employees' relationships to enhance overall firm performance.

[13] According to column (5) of Table 10, editors' coauthors are not likely to get their paper accepted in the editor's journal, neither males nor females, as evidenced by the negative coefficients on Connection and Female x Connection. However, editors' female coauthors are even less likely to get their paper accepted, as evidenced by the negative coefficients on Female x Connection.

References

Bethmann, D., Bransch, F., Kvasnicka, M., and Sadrieh, A. (2023). Home bias in top economics journals.

Björk, B.-C. and Solomon, D. (2013). The publishing delay in scholarly peer-reviewed journals. *Journal of Informetrics*, 7(4):914–23.

Bonacich, P. (1987). Power and centrality: A family of measures. *American journal of sociology*, 92(5):1170–1182.

Borsuk, R. M., Aarssen, L. W., Budden, A. E., Koricheva, J., Leimu, R., Tregenza, T., and Lortie, C. J. (2009). To name or not to name: The effect of changing author gender on peer review. *BioScience*, 59(11):985–989.

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

Brown, N. E. and Samuels, D. (2018). Introduction to gender in the journals, continued: Evidence from five political science journals. *PS: Political Science & Politics*, 51(4):847–848.

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

Chan, K. C., Chang, C.-H., and Chang, Y. (2015). The network effects of publishing in finance. *The North American Journal of Economics and Finance*, 33:305–316.

Chatterjee, P. and Werner, R. M. (2021). Gender disparity in citations in high-impact journal articles. *JAMA Network Open*, 4(7):e2114509–e2114509.

Chen, J. and Roth, J. (2022). Log-like? identified ates defined with zero-valued outcomes are (arbitrarily) scale-dependent.

Davis, G. F. and Greve, H. R. (1997). Corporate elite networks and governance changes in the 1980s. *American journal of sociology*, 103(1):1–37.

Dion, M. L., Sumner, J. L., and Mitchell, S. M. (2018). Gendered citation patterns across political science and social science methodology fields. *Political analysis*, 26(3):312–327.

Dworkin, J. D., Linn, K. A., Teich, E. G., Zurn, P., Shinohara, R. T., and Bassett, D. S. (2020). The extent and drivers of gender imbalance in neuroscience reference lists. *Nature neuroscience*, 23(8):918–926.

Fong, E. A., Patnayakuni, R., and Wilhite, A. W. (2023). Accommodating coercion: authors, editors, and citations. *Research Policy*, 52(5):104754.

Fox, C. W. and Paine, C. T. (2019). Gender differences in peer review outcomes and manuscript impact at six journals of ecology and evolution. *Ecology and Evolution*, 9(6):3599–3619.

Freeman, L. C. (1977). A set of measures of centrality based on betweenness. *Sociometry*, pages 35–41.

Freeman, L. C. et al. (2002). Centrality in social networks: Conceptual clarification. *Social network: critical concepts in sociology. Londres: Routledge*, 1:238–263.

Fulvio, J. M., Akinnola, I., and Postle, B. R. (2021). Gender (im) balance in citation practices in cognitive neuroscience. *Journal of Cognitive Neuroscience*, 33(1):3–7.

Huber, J., Inoua, S., Kerschbamer, R., König-Kersting, C., Palan, S., and Smith, V. L. (2022). Nobel and novice: Author prominence affects peer review. *Proceedings of the National Academy of Sciences*, 119(41).

Katz, E. and Lazarsfeld, P. F. (1964). *Personal Influence, The part played by people in the flow of mass communications*. Transaction publishers.

Laband, D. N. and Piette, M. J. (1994). The relative impacts of economics journals: 1970-1990. *Journal of economic Literature*, 32(2):640–666.

Larivière, V., Ni, C., Gingras, Y., Cronin, B., and Sugimoto, C. R. (2013). Bibliometrics: Global gender disparities in science. *Nature*, 504(7479):211–213.

Lazarsfeld, P. F., Berelson, B., and Gaudet, G. (1944). *The People's Choice. How the Voter Makes Up His Mind in a Presidential Campaign*. Columbia University Press.

Maliniak, D., Powers, R., and Walter, B. F. (2013). The gender citation gap in international relations. *International Organization*, 67(4):889–922.

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

Squazzoni, F., Bravo, G., Grimaldo, F., García-Costa, D., Farjam, M., and Mehmani, B. (2021). Gender gap in journal submissions and peer review during the first wave of the covid-19 pandemic. a study on 2329 elsevier journals. *PloS one*, 16(10):e0257919.

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

Tudor, C. L. and Yashar, D. J. (2018). Gender and the editorial process: World politics, 2007–2017. *PS: Political Science & Politics*, 51(4):870–880.

Wang, J., Liu, Y., and Wang, X. E. (2021). Are gender-neutral queries really gender-neutral? mitigating gender bias in image search. *arXiv preprint arXiv:2109.05433*.

Wapman, K. H., Zhang, S., Clauset, A., and Larremore, D. B. (2022). Quantifying hierarchy and dynamics in US faculty hiring and retention. *Nature*, 610(7930):120–127.

Tables and Figures

	Mean	Std. Dev.	P25	Median	P75
Panel A: Research Record					
Total publications	5.57	6.02	1.83	3.58	7.03
Total publications per year	0.40	0.36	0.15	0.31	0.55
Top publications	3.06	3.59	1.00	1.81	3.67
Top publications per year	0.24	0.24	0.08	0.16	0.32
Lead papers	1.58	1.84	0.00	1.00	2.21
Lead papers per year	0.12	0.13	0.00	0.08	0.18
Star Papers	0.14	0.48	0.00	0.00	0.00
Star Papers per year	0.01	0.03	0.00	0.00	0.00
5-year Cumulative citations	64.99	170.06	6.80	20.73	57.71
3-year Cumulative citations	44.57	113.86	4.88	15.04	40.15
Experience: Number of years after PhD	14.98	8.26	9.00	14.00	19.50
Panel B: Network Centrality					
Network Size:					
All networks	39.46	35.00	11.89	28.95	58.46
Advisor-Student	2.03	2.53	0.00	1.00	3.00
Ph.D. Colleague	7.78	10.49	0.00	3.00	11.00
Post Ph.D Colleague	21.34	25.08	0.00	12.65	33.00
Coauthor	3.03	4.81	1.00	2.00	3.51
Network Closeness:					
All networks	0.30	0.07	0.25	0.30	0.35
Advisor-Student	0.08	0.07	0.00	0.09	0.14
Ph.D. Colleague	0.01	0.01	0.00	0.00	0.01
Post Ph.D Colleague	0.18	0.13	0.00	0.22	0.28
Coauthor	0.09	0.05	0.07	0.10	0.13
Network Prestige:					
All networks	0.09	0.14	0.01	0.02	0.11
Advisor-Student	0.01	0.04	0.00	0.00	0.00
Ph.D. Colleague	0.01	0.09	0.00	0.00	0.00
Post Ph.D Colleague	0.04	0.11	0.00	0.00	0.03
Coauthor	0.01	0.10	0.00	0.00	0.00

Table 1: **Summary statistics.** This table reports summary statistics for the variables used in our main analysis. Our sample contains 4 228 authors, 291 Ph.D. schools, 1 070 affiliations, and 24 672 papers published in the 48 top finance, accounting, and economics journals. The sample period is from 1980 to 2014.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Size			Closeness			Prestige	
All Network	0.105***	0.113***		0.220***	0.189***		0.065***	0.049***	
	(0.009)	(0.009)		(0.019)	(0.015)		(0.008)	(0.007)	
Advisor-Student			0.107***			0.087***			0.026***
			(0.008)			(0.008)			(0.007)
Ph.D. Colleague			0.006			-0.005			0.007
			(0.007)			(0.007)			(0.007)
Post Ph.D Colleague			0.057***			0.081***			0.044***
			(0.008)			(0.008)			(0.008)
Coauthor			0.064***			0.086***			0.010
			(0.012)			(0.009)			(0.010)
Author Chars	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Affiliation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Author FE	No	Yes	No	No	Yes	No	No	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	73 812	73 766	73 812	73 812	73 766	73 812	73 812	73 766	73 812
Adjusted R^2	0.664	0.940	0.685	0.664	0.940	0.676	0.657	0.939	0.656

Table 2: **Networking and productivity.** This table reports the estimates for β_1 in Specification (4). The standard errors are heteroscedasticity-consistent and clustered at the author level. Standard errors are in parentheses and *, **, *** denote statistical significance at the 5%, 1%, and 0.1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Size		Closeness		Prestige	
	Panel A: Network at Publication					
Network	0.090***		0.144***		0.038***	
	(0.011)		(0.029)		(0.010)	
Advisor-Student		0.027**		-0.020		0.038***
		(0.011)		(0.014)		(0.011)
Ph.D. Colleague		0.028***		0.031***		-0.010
		(0.011)		(0.010)		(0.009)
Post Ph.D Colleague		0.063***		0.047***		0.033***
		(0.011)		(0.013)		(0.010)
Coauthor		0.008		-0.064***		0.018
		(0.013)		(0.015)		(0.012)
Paper Chars	Yes	Yes	Yes	Yes	Yes	Yes
Author Chars	Yes	Yes	Yes	Yes	Yes	Yes
Journal × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Paper Life FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	179 029	179 029	179 029	179 029	179 029	179 029
Adjusted R^2	0.588	0.588	0.587	0.587	0.587	0.587
	Panel B: Network at Citation					
Network	0.149***		0.225***		0.116***	
	(0.012)		(0.024)		(0.010)	
Advisor-Student		0.078***		0.082***		0.070***
		(0.012)		(0.014)		(0.008)
Ph.D. Colleague		0.014		0.026**		-0.015*
		(0.010)		(0.010)		(0.008)
Post Ph.D Colleague		0.100***		0.063***		0.041***
		(0.012)		(0.013)		(0.009)
Coauthor		0.041***		0.056***		0.043***
		(0.015)		(0.016)		(0.014)
Paper Chars	Yes	Yes	Yes	Yes	Yes	Yes
Author Chars	Yes	Yes	Yes	Yes	Yes	Yes
Journal × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Paper Life FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	179 029	179 029	179 029	179 029	179 029	179 029
Adjusted R^2	0.592	0.594	0.590	0.590	0.591	0.590

Table 3: **Networking and Quality.** This table reports the estimates for β_1 in Specification (5). Author network centrality is measured at publication in Panel A and at citation in Panel B. The standard errors are heteroscedasticity-consistent and clustered at the paper level. Standard errors are in parentheses and *, **, *** denote statistical significance at the 5%, 1%, and 0.1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		Size			Closeness			Prestige		Size	Closeness	Prestige
Network	0.047***	0.024***		0.042***	0.012*		0.043***	0.018***		-0.008	-0.028***	0.016
	(0.004)	(0.005)		(0.006)	(0.007)		(0.004)	(0.004)		(0.014)	(0.010)	(0.012)
Advisor-Student			0.010***			0.022***			0.001			
			(0.003)			(0.004)			(0.001)			
Ph.D. Colleague			0.018***			0.021***			0.009***			
			(0.003)			(0.004)			(0.002)			
Post Ph.D Colleague			0.036***			-0.010***			0.026***			
			(0.003)			(0.003)			(0.003)			
Coauthor			0.004			-0.000			0.003			
			(0.003)			(0.004)			(0.003)			
Top 10										0.588***	0.584***	0.572***
										(0.023)	(0.023)	(0.023)
Top 50										0.399***	0.399***	0.394***
										(0.022)	(0.021)	(0.021)
Top 100										0.250***	0.257***	0.244***
										(0.021)	(0.022)	(0.021)
Top 10 × Network										0.027**	0.057***	-0.001
										(0.013)	(0.006)	(0.012)
Top 50 × Network										0.034***	0.067***	0.003
										(0.013)	(0.005)	(0.012)
Top 100 × Network										0.052***	0.076***	-0.017
										(0.018)	(0.008)	(0.022)
Author Chars	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Title FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School Location FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Author FE	No	Yes	No	No	Yes	No	No	Yes	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	32 953	32 867	32 953	32 953	32 867	32 953	32 953	32 867	32 953	32 867	32 867	32 867
Adjusted R^2	0.687	0.948	0.687	0.681	0.948	0.678	0.684	0.948	0.678	0.957	0.959	0.957

Table 4: **Networking and Salary.** This table reports the estimates for β_1 in Specification (6) and the estimates for the interaction between the dummies for top universities and the network metrics. The standard errors are heteroscedasticity-consistent and clustered at the author level. Standard errors are in parentheses and *, **, *** denote statistical significance at the 5%, 1%, and 0.1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Size		Closeness		Prestige	
Salary	-0.013	-0.031**	-0.031**	-0.019	-0.032**	-0.020	-0.023
	(0.015)	(0.014)	(0.014)	(0.015)	(0.014)	(0.015)	(0.014)
Network		0.154***	0.151**	0.117***	-0.061	0.072***	-0.102**
		(0.015)	(0.064)	(0.018)	(0.052)	(0.013)	(0.049)
Salary × Network			0.000		0.034***		0.031***
			(0.010)		(0.009)		(0.009)
Author Chars	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Affiliation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Author FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28 095	28 095	28 095	28 095	28 095	28 095	28 095
Adjusted R^2	0.976	0.977	0.977	0.977	0.977	0.976	0.977

Table 5: **Is salary positively associated with top publications?** This table reports the estimates for β_1, β_2, β_3 in Specification (7). The standard errors are heteroscedasticity-consistent and clustered at the author level. Standard errors are in parentheses and *, **, *** denote statistical significance at the 5%, 1%, and 0.1% levels, respectively.

Panel A: Do connections to editors increase author's chance to publish in top tiers?

	Publication Dummy				
	(1)	(2)	(3)	(4)	(5)
Connection Type	Any	Student-advisor	Ph.D. Colleague	Post Ph.D. Colleague	Coauthor
Connection	0.001	0.036***	-0.012***	0.004**	-0.010***
	(0.001)	(0.005)	(0.003)	(0.002)	(0.003)
Author Chars	Yes	Yes	Yes	Yes	Yes
Author-Journal FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	321 634	321 634	321 634	321 634	321 634
Adjusted R^2	0.109	0.110	0.109	0.109	0.109

Panel B: Does connection to editors lead to favoritism?

	log(Cumulative Citations+1)				
	(1)	(2)	(3)	(4)	(5)
Connection Type	Any	Student-advisor	Ph.D. Colleague	Post Ph.D. Colleague	Coauthor
Connection	0.084***	-0.013	0.075**	0.108***	0.037
	(0.026)	(0.035)	(0.034)	(0.026)	(0.033)
Paper Chars	Yes	Yes	Yes	Yes	Yes
Author Chars	Yes	Yes	Yes	Yes	Yes
Journal-Year FE	Yes	Yes	Yes	Yes	Yes
Paper Life FE	Yes	Yes	Yes	Yes	Yes
Observations	114 791	114 791	114 791	114 791	114 791
Adjusted R^2	0.531	0.530	0.530	0.531	0.530

Table 6: **Is there any editorial favoritism?** This table reports the estimates for β_1 in Specification (8) and Specification (9). The standard errors are heteroscedasticity-consistent and clustered at the author level. Standard errors are in parentheses and *, **, *** denote statistical significance at the 5%, 1%, and 0.1% levels, respectively.

Panel A: Do connected authors tend to cite each other?

Connection Type	(1) Any	(2) Student-advisor	(3) Ph.D. Colleague	(4) Post Ph.D. Colleague	(5) Coauthor
Connection	0.194***	0.179***	0.097***	0.105***	0.331***
	(0.007)	(0.021)	(0.012)	(0.007)	(0.007)
Cited Author Chars	Yes	Yes	Yes	Yes	Yes
Citing Author Chars	Yes	Yes	Yes	Yes	Yes
Cited Author Affiliation FE	Yes	Yes	Yes	Yes	Yes
Citing Author Affiliation FE	Yes	Yes	Yes	Yes	Yes
Cited Author FE	Yes	Yes	Yes	Yes	Yes
Citing Author FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	2 870 759	2 870 759	2 870 759	2 870 759	2 870 759
Adjusted R^2	0.216	0.210	0.209	0.211	0.231

Panel B: Do papers cited by connected authors of better quality?

Connection Type	(1) Any	(2) Student-advisor	(3) Ph.D. Colleague	(4) Post Ph.D. Colleague	(5) Coauthor
Connection	0.499***	0.235***	0.412***	0.456***	0.413***
	(0.026)	(0.038)	(0.033)	(0.028)	(0.026)
Paper Chars	Yes	Yes	Yes	Yes	Yes
Author Chars	Yes	Yes	Yes	Yes	Yes
Journal × Year FE	Yes	Yes	Yes	Yes	Yes
Paper Life FE	Yes	Yes	Yes	Yes	Yes
Observations	179 029	179 029	179 029	179 029	179 029
Adjusted R^2	0.599	0.587	0.591	0.595	0.595

Table 7: **Who cite whom** This table reports the estimates for β_1 in Specification (10) and Specification (11). The standard errors are heteroscedasticity-consistent and clustered at the citing author-cited author level in Panel A and at the paper level in Panel B. Standard errors are in parentheses and *, **, *** denote statistical significance at the 5%, 1%, and 0.1% levels, respectively.

Panel A: Does citing editors' works increase author's chance to publish in top tiers?

	(1)	(2)	(3)	(4)	(5)	(6)
Connection Type		Any	Student-advisor	Ph.D. Colleague	Post Ph.D. Colleague	Coauthor
Editor Citing	0.147***	0.177***	0.156***	0.149***	0.166***	0.165***
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Connection		0.005***	0.025***	-0.004	0.008***	0.004
		(0.001)	(0.005)	(0.002)	(0.002)	(0.003)
Connection × Editor Citing		-0.053***	-0.045***	-0.015	-0.047***	-0.063***
		(0.007)	(0.009)	(0.013)	(0.007)	(0.007)
Author Chars	Yes	Yes	Yes	Yes	Yes	Yes
Author-Journal FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	321 634	321 634	321 634	321 634	321 634	321 634
Adjusted R^2	0.333	0.340	0.336	0.333	0.339	0.342

Panel B: Does citing editors' works lead to favoritism?

	(1)	(2)	(3)	(4)	(5)	(6)
Connection Type		Any	Student-advisor	Ph.D. Colleague	Post Ph.D. Colleague	Coauthor
Editor Citing	0.027***	0.022***	0.031***	0.033***	0.021***	0.021***
	(0.005)	(0.008)	(0.006)	(0.005)	(0.006)	(0.006)
Connection		0.064**	-0.005	0.142***	0.084***	-0.020
		(0.030)	(0.043)	(0.043)	(0.031)	(0.039)
Connection × Editor Citing		0.006	-0.012	-0.029**	0.009	0.016*
		(0.009)	(0.010)	(0.012)	(0.009)	(0.009)
Paper Chars	Yes	Yes	Yes	Yes	Yes	Yes
Author Chars	Yes	Yes	Yes	Yes	Yes	Yes
Journal-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Paper Life FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	114 791	114 791	114 791	114 791	114 791	114 791
Adjusted R^2	0.532	0.532	0.532	0.532	0.533	0.532

Table 8: **Does citing journal editors lead to editorial favoritism?** This table reports the estimates for β_1, β_2,and β_3, in Specification (12) and Specification (13). The standard errors are heteroscedasticity-consistent and clustered at the author level. Standard errors are in parentheses and *, **, *** denote statistical significance at the 5%, 1%, and 0.1% levels, respectively.

Panel A: Productivity

	(1) Size	(2) Closeness	(3) Prestige	(4) Size	(5) Closeness	(6) Prestige
Network	0.115***	0.190***	0.053***	0.110***	0.191***	0.043***
	(0.009)	(0.015)	(0.008)	(0.010)	(0.015)	(0.009)
Female × Network	-0.031	-0.025	-0.055**			
	(0.029)	(0.016)	(0.023)			
Non-white × Network				0.010	-0.009	0.021
				(0.015)	(0.008)	(0.015)
Author Chars	Yes	Yes	Yes	Yes	Yes	Yes
Affiliation FE	Yes	Yes	Yes	Yes	Yes	Yes
Author FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	73 766	73 766	73 766	73 766	73 766	73 766
Adjusted R^2	0.940	0.940	0.939	0.940	0.940	0.939

Panel B: Research Quality

	(1) Size	(2) Closeness	(3) Prestige	(4) Size	(5) Closeness	(6) Prestige
Network	0.090***	0.133***	0.038***	0.090***	0.147***	0.023*
	(0.012)	(0.029)	(0.011)	(0.013)	(0.030)	(0.012)
Female	0.002	-0.020	0.005			
	(0.040)	(0.043)	(0.039)			
Female × Network	0.006	0.095**	-0.005			
	(0.035)	(0.037)	(0.034)			
Non-white				-0.025	-0.028	-0.033
				(0.025)	(0.025)	(0.025)
Non-white × Network				-0.000	-0.015	0.046**
				(0.022)	(0.023)	(0.023)
Paper Chars	Yes	Yes	Yes	Yes	Yes	Yes
Author Chars	Yes	Yes	Yes	Yes	Yes	Yes
Journal × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Paper Life FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	179 029	179 029	179 029	179 029	179 029	179 029
Adjusted R^2	0.588	0.587	0.587	0.588	0.587	0.587

Table 9: **The role of minority authors: Productivity and quality.** This table reports the estimates for β_1 and β_2 in Specification (14) (Panel A) and the estimates for β_1, β_2, and β_3 in Specification (15) (Panel B). The standard errors are heteroscedasticity-consistent and clustered at the author level in Panel A and the paper level in Panel B. Standard errors are in parentheses and *, **, *** denote statistical significance at the 5%, 1%, and 0.1% levels, respectively.

Panel A: Do connections to journal editors increase author's chance to publish in top tiers?

Connection Type	(1) Any	(2) Student-advisor	(3) Ph.D. Colleague	(4) Post Ph.D. Colleague	(5) Coauthor
Connection	0.002	0.038***	-0.012***	0.005**	-0.009***
	(0.002)	(0.006)	(0.003)	(0.002)	(0.003)
Female × Connection	-0.008	-0.016	-0.005	-0.015**	-0.020*
	(0.005)	(0.015)	(0.007)	(0.007)	(0.011)
Author Chars	Yes	Yes	Yes	Yes	Yes
Author-Journal FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	321 634	321 634	321 634	321 634	321 634
Adjusted R^2	0.109	0.110	0.109	0.109	0.109

	(1) Any	(2) Student-advisor	(3) Ph.D. Colleague	(4) Post Ph.D. Colleague	(5) Coauthor
Connection	0.001	0.034***	-0.013***	0.003	-0.009*
	(0.003)	(0.009)	(0.004)	(0.004)	(0.005)
Non-white × Connection	0.000	0.003	0.000	0.000	-0.002
	(0.003)	(0.011)	(0.005)	(0.004)	(0.006)
Author Chars	Yes	Yes	Yes	Yes	Yes
Author-Journal FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	321 634	321 634	321 634	321 634	321 634
Adjusted R^2	0.109	0.110	0.109	0.109	0.109

Panel B: Does connection to editors lead to favoritism?

Connection Type	(1) Any	(2) Student-advisor	(3) Ph.D. Colleague	(4) Post Ph.D. Colleague	(5) Coauthor
Female	0.056	0.023	0.093**	0.029	0.080*
	(0.056)	(0.048)	(0.047)	(0.049)	(0.046)
Connection	0.086***	-0.029	0.111***	0.101***	0.060*
	(0.028)	(0.037)	(0.037)	(0.028)	(0.035)
Female × Connection	-0.023	0.168	-0.360***	0.101	-0.345**
	(0.088)	(0.115)	(0.129)	(0.103)	(0.146)
Paper Chars	Yes	Yes	Yes	Yes	Yes
Author Chars	Yes	Yes	Yes	Yes	Yes
Journal-Year FE	Yes	Yes	Yes	Yes	Yes
Paper Life FE	Yes	Yes	Yes	Yes	Yes
Observations	114 791	114 791	114 791	114 791	114 791
Adjusted R^2	0.531	0.530	0.531	0.531	0.530
Connection Type	(1) Any	(2) Student-advisor	(3) Ph.D. Colleague	(4) Post Ph.D. Colleague	(5) Coauthor
Non-white	0.073*	0.040	0.057*	0.081**	0.059*
	(0.039)	(0.031)	(0.031)	(0.034)	(0.031)
Connection	0.124***	-0.048	0.145**	0.187***	0.093
	(0.044)	(0.059)	(0.064)	(0.048)	(0.060)
Non-white × Connection	-0.062	0.053	-0.108	-0.120*	-0.085
	(0.057)	(0.081)	(0.086)	(0.062)	(0.078)
Paper Chars	Yes	Yes	Yes	Yes	Yes
Author Chars	Yes	Yes	Yes	Yes	Yes
Journal-Year FE	Yes	Yes	Yes	Yes	Yes
Paper Life FE	Yes	Yes	Yes	Yes	Yes
Observations	114 791	114 791	114 791	114 791	114 791
Adjusted R^2	0.531	0.530	0.530	0.531	0.530

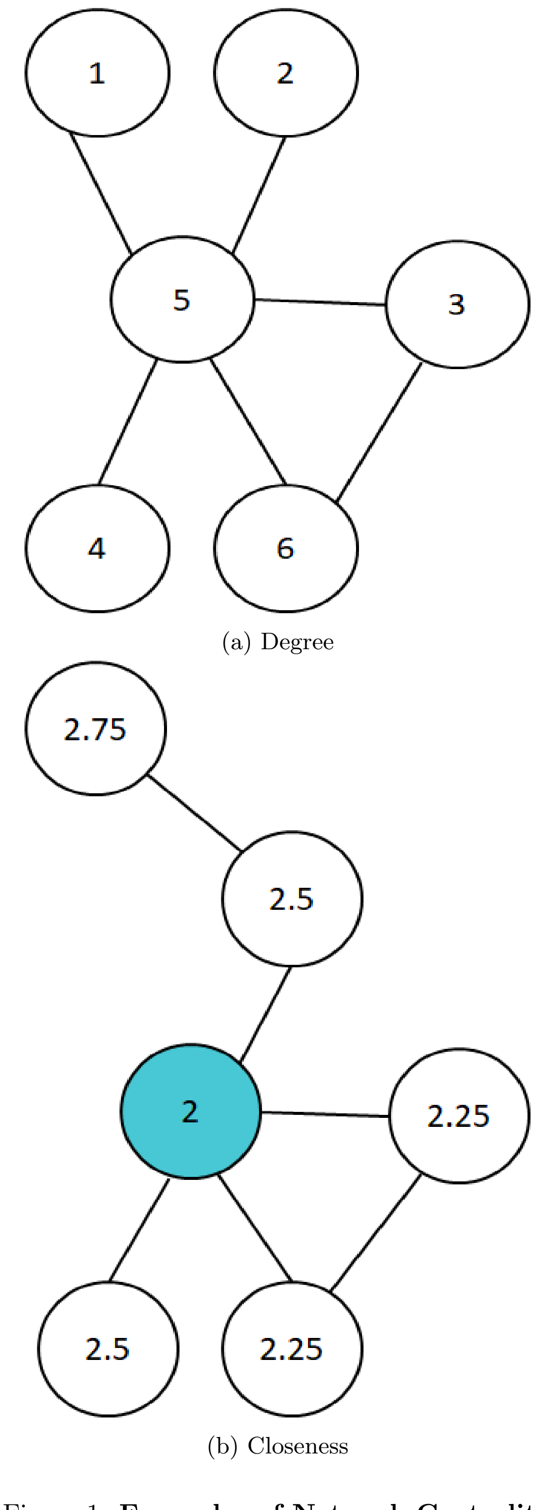
Table 10: **Does connection to editors lead to favoritism?** This table reports the estimates for β_1 and β_2 in Specification (16) (Panel A) and β_1, β_2, and β_3 in Specification (17) (Panel B). The standard errors are heteroscedasticity-consistent and clustered at the author level in Panel A and at the paper level in Panel B. Standard errors are in parentheses and *, **, *** denote statistical significance at the 5%, 1%, and 0.1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Five Years after Connection Decease					Ten Years after Connection Decease				
Shock - 3	-0.007	-0.031	-0.054	0.034	-0.024	-0.006	-0.031	-0.040	0.035	-0.025
	(0.014)	(0.035)	(0.041)	(0.021)	(0.022)	(0.015)	(0.035)	(0.042)	(0.022)	(0.022)
Shock - 2	0.003	-0.035	-0.051	0.043*	-0.017	0.004	-0.035	-0.044	0.046**	-0.017
	(0.017)	(0.042)	(0.049)	(0.023)	(0.027)	(0.017)	(0.043)	(0.049)	(0.023)	(0.028)
Shock - 1	0.004	0.039	-0.064	0.042*	-0.032	0.005	0.039	-0.057	0.047**	-0.033
	(0.016)	(0.045)	(0.053)	(0.022)	(0.025)	(0.016)	(0.045)	(0.052)	(0.023)	(0.025)
Shock	-0.000					-0.006				
	(0.018)					(0.020)				
Shock: Advisor/Student		0.008					-0.000			
		(0.053)					(0.053)			
Shock: Ph.D. Colleague			0.012					-0.011		
			(0.051)					(0.052)		
Shock: Post Ph.D. Colleague				0.049**					0.046*	
				(0.024)					(0.027)	
Shock: Coauthor					-0.054*					-0.064**
					(0.028)					(0.030)
Author Network	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Affiliation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8 802	9 694	9 731	9 133	9 586	9 787	9 787	9 787	9 787	9 787
Adjusted R^2	0.947	0.948	0.948	0.948	0.948	0.948	0.948	0.948	0.948	0.948

Table 11: **Networking and productivity: A DiD design.** This table reports the estimates for φ_1 in Specification (18). The standard errors are heteroscedasticity-consistent and clustered at the author level. Standard errors are in parentheses and *, **, *** denote statistical significance at the 5%, 1%, and 0.1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Five Years after Editor Turnover					Ten Years after Editor Turnover				
Shock - 3	-0.009	-0.023	0.002	-0.006	0.004	-0.009	-0.023	0.002	-0.005	0.004
	(0.006)	(0.027)	(0.014)	(0.008)	(0.018)	(0.006)	(0.026)	(0.014)	(0.008)	(0.018)
Shock - 2	-0.012*	-0.026	-0.002	-0.009	-0.007	-0.012*	-0.025	-0.002	-0.009	-0.007
	(0.006)	(0.027)	(0.012)	(0.008)	(0.017)	(0.006)	(0.027)	(0.013)	(0.008)	(0.017)
Shock - 1	-0.003	-0.004	-0.006	0.004	0.016	-0.002	-0.003	-0.007	0.004	0.016
	(0.007)	(0.027)	(0.012)	(0.008)	(0.019)	(0.007)	(0.027)	(0.012)	(0.008)	(0.019)
Shock	-0.014***					-0.015***				
	(0.005)					(0.005)				
Shock: Advisor-Student		-0.043**					-0.039**			
		(0.019)					(0.018)			
Shock: Ph.D. Colleague			0.008					0.012		
			(0.010)					(0.011)		
Shock: Post Ph.D. Colleague				-0.007					-0.006	
				(0.005)					(0.005)	
Shock: Coauthor					-0.001					-0.001
					(0.012)					(0.012)
Author Chars	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Author-Journal FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	170 144	172 231	173 055	170 747	171 441	173 412	173 099	173 308	173 049	171 441
Adjusted R^2	0.102	0.101	0.101	0.102	0.101	0.102	0.102	0.102	0.102	0.101

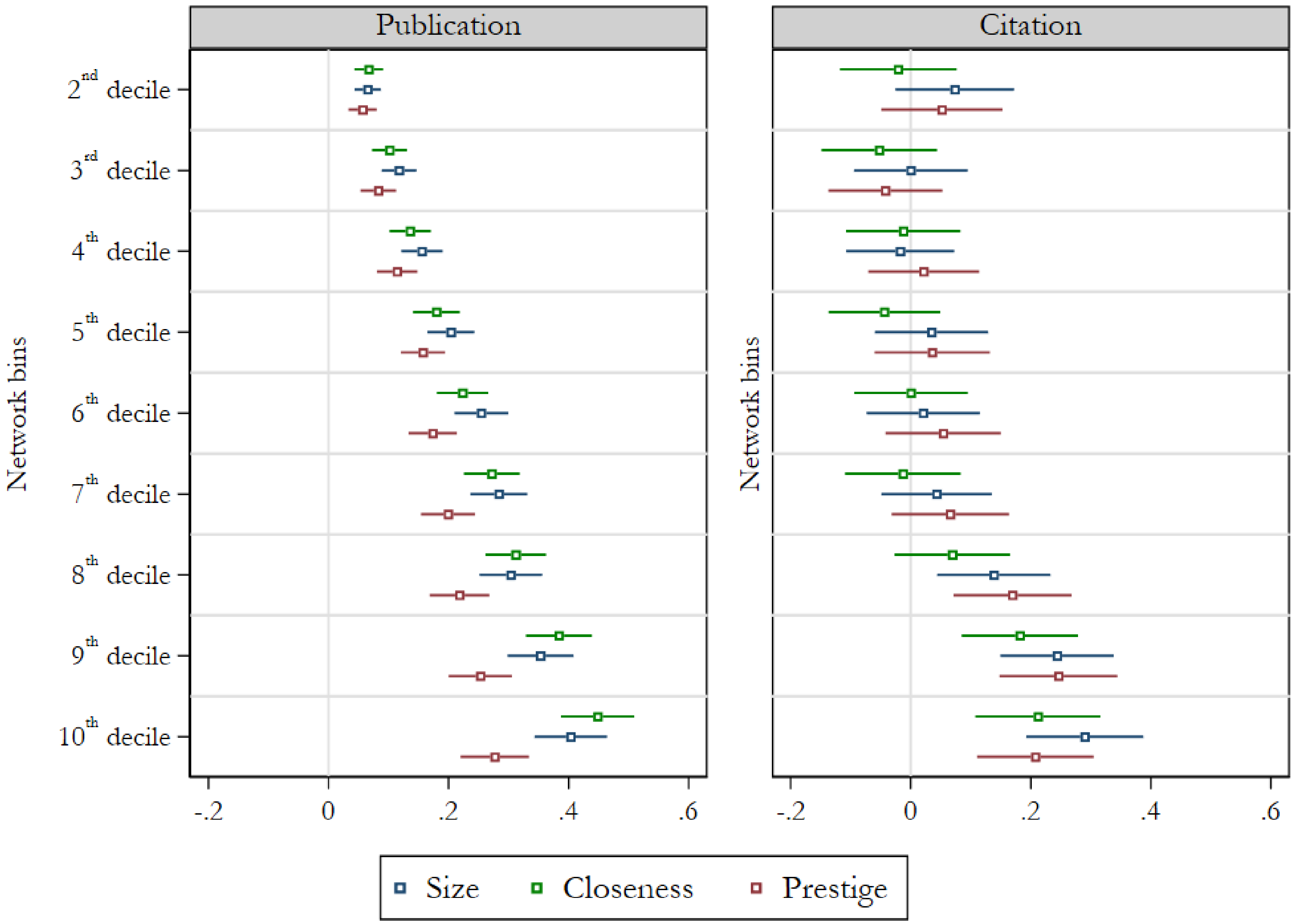
Table 12: **Editorial process: A DiD design.** This table reports the estimates for φ_1 in Specification (19). The standard errors are heteroscedasticity-consistent and clustered at the author level. Standard errors are in parentheses and *, **, *** denote statistical significance at the 5%, 1%, and 0.1% levels, respectively.



(a) Degree

(b) Closeness

Figure 1: **Examples of Network Centrality**



(a) Degree

Figure 2: **Networking effects across the network deciles** This figure shows point estimates and 90% confidence intervals for the coefficients of the networking deciles following Specification (4) and Specification (5). The first decile is the reference group and is omitted from the estimation. The dependent variable is i) the logarithm of top publications for each author over time, ii) the logarithm of cumulative citations for each paper over time. Standard errors are clustered at the author level in the left-hand side panel and at the paper level in the right-hand side panel.

Appendices

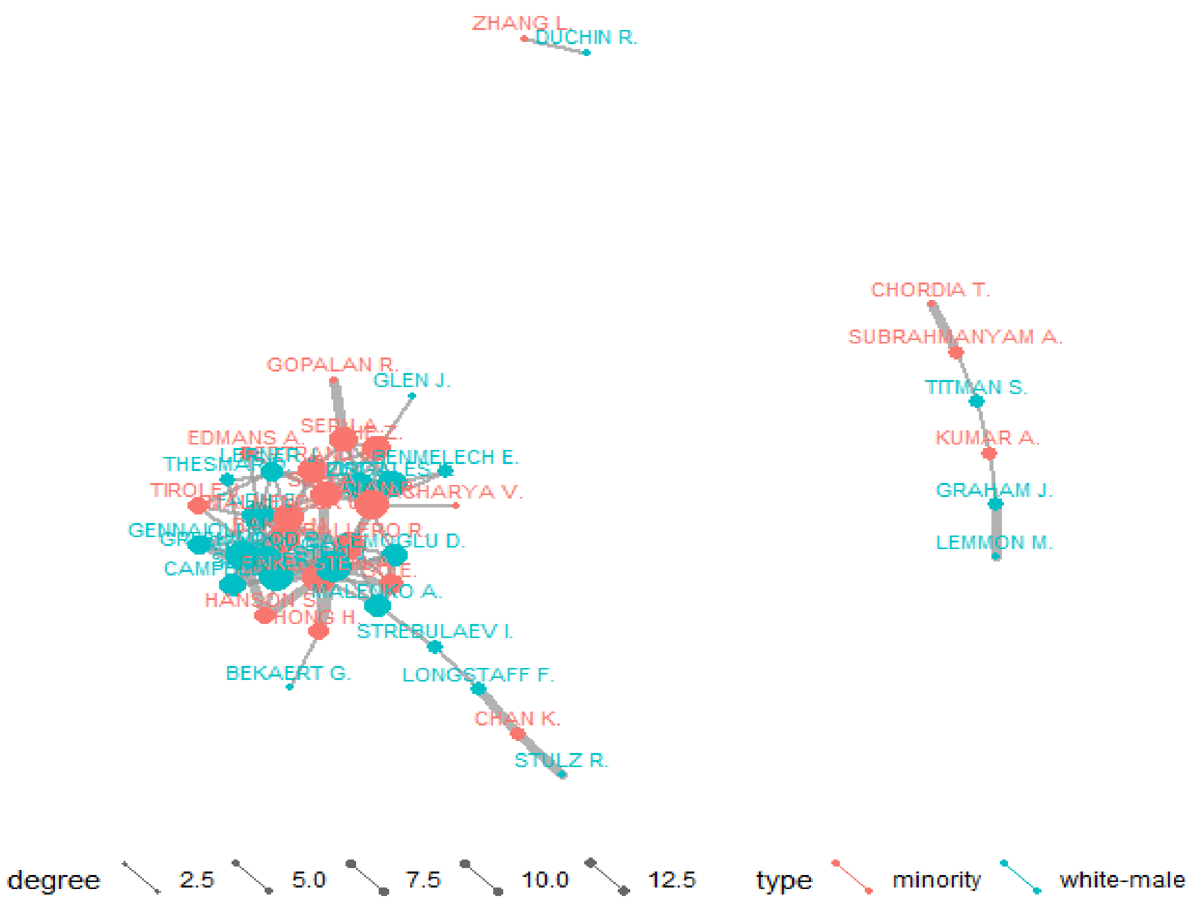
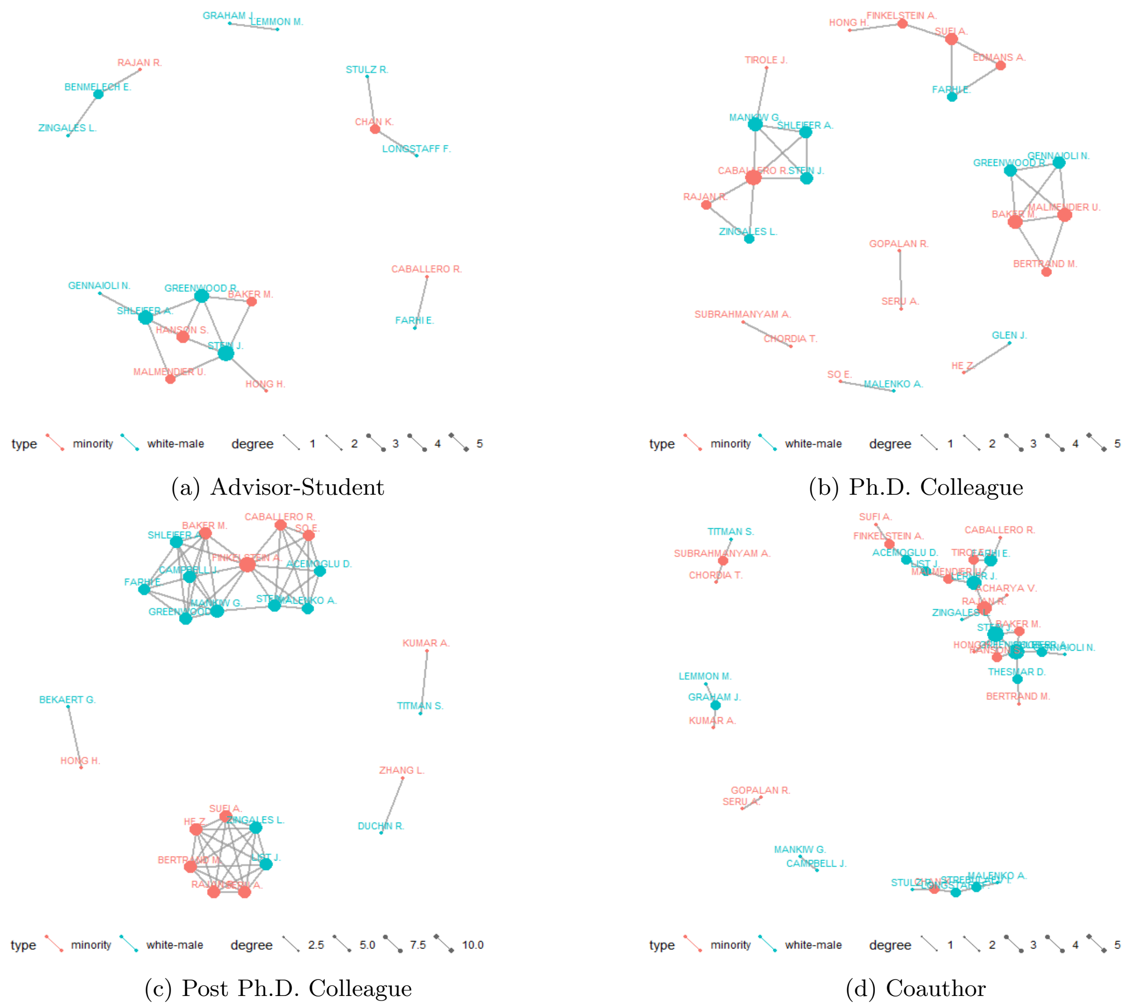


Figure A1: **Network of Top Authors** This figure plots the general network of the top 50 authors in our sample. Top authors are identified based on the number of top publications per year after their Ph.D.



(a) Advisor-Student

(b) Ph.D. Colleague

(c) Post Ph.D. Colleague

(d) Coauthor

Figure A2: **Sub-Network of Top Authors** This figure plots the sub-network of the top 50 authors in our sample. Top authors are identified based on the number of top publications per year after PhD.

Table A1: Papers by journal.

Journal Title	Number of Papers
JOURNAL OF FINANCE	3 417
JOURNAL OF FINANCIAL ECONOMICS	1 958
JOURNAL OF BANKING & FINANCE	1 720
AMERICAN ECONOMIC REVIEW	1 417
REVIEW OF FINANCIAL STUDIES	1 343
JOURNAL OF FINANCIAL AND QUANTITATIVE ANALYSIS	1 221
FINANCIAL MANAGEMENT	794
JOURNAL OF MONEY CREDIT AND BANKING	739
JOURNAL OF PORTFOLIO MANAGEMENT	703
JOURNAL OF FUTURES MARKETS	649
JOURNAL OF MONETARY ECONOMICS	604
JOURNAL OF ECONOMIC THEORY	551
JOURNAL OF ECONOMETRICS	522
JOURNAL OF BUSINESS	520
ECONOMETRICA	510
REVIEW OF ECONOMICS AND STATISTICS	500
JOURNAL OF INTERNATIONAL MONEY AND FINANCE	491
JOURNAL OF POLITICAL ECONOMY	471
QUARTERLY JOURNAL OF ECONOMICS	470
JOURNAL OF CORPORATE FINANCE	411
JOURNAL OF ECONOMIC LITERATURE	397
ECONOMIC JOURNAL	388
REVIEW OF ECONOMIC STUDIES	385
JOURNAL OF BUSINESS & ECONOMIC STATISTICS	356
JOURNAL OF PUBLIC ECONOMICS	332
JOURNAL OF ECONOMIC PERSPECTIVES	311
JOURNAL OF FINANCIAL INTERMEDIATION	283

Continued on next page

Table A1 – continued from previous page

Journal Title	Number of Papers
RAND JOURNAL OF ECONOMICS	281
JOURNAL OF INTERNATIONAL ECONOMICS	277
INTERNATIONAL ECONOMIC REVIEW	275
FINANCIAL ANALYSTS JOURNAL	268
JOURNAL OF FINANCIAL RESEARCH	239
JOURNAL OF FINANCIAL SERVICES RESEARCH	212
JOURNAL OF LAW & ECONOMICS	209
GAMES AND ECONOMIC BEHAVIOR	183
JOURNAL OF FINANCIAL MARKETS	180
ECONOMIC THEORY	173
JOURNAL OF APPLIED ECONOMETRICS	159
EUROPEAN FINANCIAL MANAGEMENT	128
JOURNAL OF BUSINESS FINANCE & ACCOUNTING	127
JOURNAL OF LABOR ECONOMICS	119
JOURNAL OF INDUSTRIAL ECONOMICS	117
JOURNAL OF EMPIRICAL FINANCE	110
JOURNAL OF HUMAN RESOURCES	95
PACIFIC-BASIN FINANCE JOURNAL	55
REVIEW OF ECONOMIC DYNAMICS	45
ACCOUNTING AND FINANCE	45
JOURNAL OF ECONOMIC GROWTH	26

	White		Black		Hispano		Asian	
	Male	Female	Male	Female	Male	Female	Male	Female
Panel A: Research Record								
Total publications	6.256	3.869	6.852	4.220	5.024	2.949	4.741	2.996
Total publications per year	0.417	0.336	0.420	0.311	0.408	0.312	0.396	0.357
Top publications	3.429	2.323	3.652	2.509	2.688	1.792	2.551	1.790
Top publications per year	0.247	0.214	0.235	0.204	0.229	0.197	0.232	0.236
Lead papers	1.729	1.191	1.844	1.170	1.396	0.921	1.461	0.953
Lead papers per year	0.120	0.103	0.114	0.093	0.113	0.107	0.124	0.111
Star Papers	0.166	0.082	0.223	0.043	0.127	0.120	0.074	0.033
Star Papers per year	0.010	0.007	0.013	0.005	0.009	0.014	0.006	0.004
5-year Cumulative citations	75.912	40.662	82.193	43.154	77.136	49.043	43.932	28.509
3-year Cumulative citations	51.499	29.014	54.790	30.111	54.070	35.904	30.972	21.633
Experience: Number of years after PhD	16.490	12.744	17.827	15.000	13.045	10.800	12.417	9.645
Panel B: Network Centrality								
Network Size								
All networks	40.585	43.838	36.456	43.762	42.125	40.687	36.501	33.384
Advisor-Student	1.955	1.887	2.214	1.924	1.710	1.506	2.267	2.278
Ph.D. Colleague	7.183	9.902	5.744	8.563	10.529	9.621	8.502	8.427
Post Ph.D Colleague	23.219	23.518	20.444	25.019	20.302	22.076	17.251	15.370
Coauthor	3.342	2.259	3.436	1.977	2.236	1.788	2.834	2.372
Network Closeness								
All networks	0.287	0.314	0.273	0.303	0.311	0.324	0.307	0.324
Advisor-Student	0.071	0.082	0.069	0.076	0.076	0.080	0.095	0.110
Ph.D. Colleague	0.005	0.007	0.004	0.006	0.008	0.007	0.006	0.006
Post Ph.D Colleague	0.184	0.201	0.168	0.180	0.193	0.215	0.169	0.182
Coauthor	0.089	0.097	0.083	0.092	0.091	0.095	0.104	0.118
Network Prestige:								
All networks	0.094	0.100	0.076	0.106	0.099	0.098	0.069	0.058
Advisor-Student	0.010	0.008	0.009	0.003	0.009	0.009	0.006	0.004
Ph.D. Colleague	0.013	0.018	0.010	0.026	0.012	0.030	0.013	0.007
Post Ph.D Colleague	0.054	0.044	0.038	0.051	0.041	0.036	0.028	0.021
Coauthor	0.016	0.004	0.017	0.001	0.001	0.000	0.005	0.001

Table A2: **Summary statistics for authors by gender and race** This table reports means for the variables used in our analysis. Our sample contains 2 209 white males, 293 white females, 382 black males, 67 black females, 231 Hispano males, 45 Hispano females, 798 Asian males, and 203 Asian females. The sample period is from 1980 to 2014.

	Male	Female	Diff.	P-Value	White	Non-white	Diff.	P-Value
Panel A: Research Record								
Total publications	5.906	3.548	2.358***	0.000	5.976	4.974	1.002***	0.000
Total publications per year	0.412	0.338	0.074***	0.000	0.408	0.393	0.015	0.165
Top publications	3.212	2.126	1.085***	0.000	3.299	2.702	0.597***	0.000
Top publications per year	0.241	0.219	0.023***	0.010	0.243	0.231	0.012	0.109
Lead papers	1.661	1.089	0.572***	0.000	1.666	1.452	0.214***	0.000
Lead papers per year	0.119	0.105	0.015***	0.006	0.118	0.117	0.001	0.868
Star Papers	0.149	0.064	0.085***	0.000	0.156	0.109	0.047***	0.001
Star Papers per year	0.010	0.006	0.003***	0.007	0.010	0.008	0.002**	0.043
5-year Cumulative citations	69.603	37.499	32.104***	0.000	71.784	55.133	16.651***	0.001
3-year Cumulative citations	47.485	27.181	20.305***	0.000	48.866	38.332	10.535***	0.002
Experience: Number of years after PhD	15.513	11.814	3.699***	0.000	16.051	13.431	2.620***	0.000
Panel B: Network Centrality								
Network Size:								
All networks	39.348	40.106	-0.759	0.621	40.966	37.268	3.698***	0.001
Advisor-Student	2.036	1.994	0.042	0.663	1.947	2.149	-0.201***	0.010
Ph.D. Colleague	7.535	9.241	-1.706***	0.000	7.501	8.186	-0.684**	0.035
Post Ph.D Colleague	21.424	20.856	0.568	0.602	23.254	18.572	4.682***	0.000
Coauthor	3.169	2.231	0.939***	0.000	3.215	2.773	0.443***	0.002
Network Closeness								
All networks	0.291	0.317	-0.025***	0.000	0.290	0.302	-0.012***	0.000
Advisor-Student	0.076	0.091	-0.015***	0.000	0.072	0.087	-0.015***	0.000
Ph.D. Colleague	0.006	0.007	-0.001***	0.001	0.006	0.006	-0.001**	0.042
Post Ph.D Colleague	0.179	0.193	-0.014**	0.018	0.186	0.175	0.010***	0.009
Coauthor	0.092	0.103	-0.011***	0.000	0.090	0.099	-0.009***	0.000
Network Prestige								
All networks	0.087	0.086	0.001	0.884	0.095	0.076	0.019***	0.000
Advisor-Student	0.009	0.006	0.002*	0.075	0.009	0.007	0.002**	0.022
Ph.D. Colleague	0.013	0.016	-0.004	0.387	0.014	0.013	0.001	0.631
Post Ph.D Colleague	0.045	0.037	0.009*	0.059	0.053	0.032	0.020***	0.000
Coauthor	0.013	0.002	0.010***	0.000	0.014	0.006	0.008***	0.003

Table A3: **Test of differences in author characteristics by gender and race** This table reports means for the variables used in our analysis. Our sample contains 2 209 male white authors, 1 411 male non-white authors, 293 female white authors, and 315 female non-white authors. The sample period is from 1980 to 2014. Differences in means are assessed with the t-test.

Panel A: Productivity

	(1)	(2)	(3)	(4)	(5)	(6)
	Size		Closeness		Prestige	
All Network	0.081***		0.106***		0.023***	
	(0.007)		(0.009)		(0.005)	
Advisor-Student		0.086***		0.065***		0.012***
		(0.009)		(0.007)		(0.004)
Ph.D. Colleague		-0.005		-0.018***		0.005
		(0.006)		(0.006)		(0.006)
Post Ph.D Colleague		-0.002		0.026***		0.015**
		(0.007)		(0.007)		(0.007)
Coauthor		0.064***		0.063***		0.011
		(0.010)		(0.006)		(0.008)
Author Chars	Yes	Yes	Yes	Yes	Yes	Yes
Affiliation FE	Yes	Yes	Yes	Yes	Yes	Yes
Author FE	Yes	No	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	71 817	71 952	71 817	71 952	71 817	71 952
Adjusted R^2	0.941	0.717	0.941	0.704	0.940	0.691

Panel B: Research Quality

	(1)	(2)	(3)	(4)	(5)	(6)
	Size		Closeness		Prestige	
Network	0.086***		0.121***		0.049***	
	(0.014)		(0.033)		(0.013)	
Advisor-Student		0.012		-0.343		0.041***
		(0.015)		(0.320)		(0.015)
Ph.D. Colleague		0.029**		4.782***		-0.012
		(0.013)		(1.741)		(0.012)
Post Ph.D Colleague		0.062***		0.406***		0.046***
		(0.013)		(0.155)		(0.012)
Coauthor		-0.001		-1.980***		0.015
		(0.014)		(0.400)		(0.012)
Paper Chars	Yes	Yes	Yes	Yes	Yes	Yes
Author Chars	Yes	Yes	Yes	Yes	Yes	Yes
Journal $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Paper Life FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	114 791	114 791	114 791	114 791	114 791	114 791
Adjusted R^2	0.532	0.532	0.531	0.532	0.531	0.532

Table A4: **Robustness checks: Top 4 finance journals.** This table reports the estimates for β_1 in Specification (4) and the estimates for β_1 in Specification (5) for the top 4 finance journals. Network centrality is measured two years before publication. The standard errors are heteroscedasticity-consistent and clustered at the author level. Standard errors are in parentheses and *, **, *** denote statistical significance at the 5%, 1%, and 0.1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Size		Closeness		Prestige	
Network	0.007		-0.176***		0.005	
	(0.011)		(0.013)		(0.010)	
Advisor-Student		0.001		-1.818***		0.610***
		(0.004)		(0.242)		(0.155)
Ph.D. Colleague		-0.004***		1.936		-0.170*
		(0.001)		(1.491)		(0.101)
Post Ph.D Colleague		0.001**		-0.213*		0.242***
		(0.001)		(0.128)		(0.066)
Coauthor		0.002		-2.869***		0.185***
		(0.002)		(0.327)		(0.071)
Paper Chars	Yes	Yes	Yes	Yes	Yes	Yes
Author Chars	Yes	Yes	Yes	Yes	Yes	Yes
Journal × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	179 029	179 029	179 029	179 029	179 029	179 029
Adjusted R^2	0.452	0.452	0.460	0.462	0.452	0.454

Table A5: **Alternative citation measure.** This table reports the estimates for β_1 in Specification (5). The dependent variable, $Research\,Quality_{p,t}$ is the logarithm of cumulative residual citations of paper p in year t with residual citation estimated by fitting a polynomial function of author' publication experience. Author network centrality is measured at publication. The standard errors are heteroscedasticity-consistent and clustered at the paper level. Standard errors are in parentheses and *, **, *** denote statistical significance at the 5%, 1%, and 0.1% levels, respectively.

	Panel A: Productivity			Panel B: Research Quality		
	(1) Size	(2) Closeness	(3) Prestige	(4) Size	(5) Closeness	(6) Prestige
Network	0.116***	0.180***	0.055***	0.003***	1.370***	0.414***
	(0.014)	(0.016)	(0.012)	(0.001)	(0.310)	(0.110)
White male				0.034	0.030	0.065**
				(0.038)	(0.058)	(0.029)
White male × Network	-0.004	0.013	-0.009	0.000	0.037	-0.272**
	(0.015)	(0.008)	(0.014)	(0.001)	(0.216)	(0.138)
Network	0.114***	0.190***	0.051***	0.003***	1.341***	0.247***
	(0.009)	(0.015)	(0.008)	(0.000)	(0.284)	(0.068)
White female				-0.070	-0.216*	-0.057
				(0.082)	(0.122)	(0.060)
White female × Network	-0.029	-0.023	-0.047*	0.000	0.699	-0.005
	(0.038)	(0.021)	(0.028)	(0.001)	(0.426)	(0.275)
Network	0.116***	0.191***	0.048***	0.003***	1.436***	0.185***
	(0.010)	(0.015)	(0.008)	(0.000)	(0.286)	(0.068)
Black male				0.023	0.057	-0.018
				(0.055)	(0.079)	(0.044)
Black male × Network	-0.027	-0.018*	0.001	0.000	-0.109	0.512**
	(0.020)	(0.011)	(0.021)	(0.001)	(0.325)	(0.215)
Network	0.114***	0.189***	0.050***	0.003***	1.381***	0.251***
	(0.009)	(0.015)	(0.007)	(0.000)	(0.281)	(0.067)
Black female				0.052	-0.173	0.072
				(0.151)	(0.271)	(0.111)
Black female × Network	-0.085***	-0.042*	-0.072***	-0.000	1.180	-0.145
	(0.030)	(0.025)	(0.027)	(0.002)	(1.108)	(0.367)
Network	0.111***	0.188***	0.047***	0.003***	1.420***	0.262***
	(0.009)	(0.015)	(0.008)	(0.000)	(0.282)	(0.066)
Hispano male				0.075	0.209	0.114
				(0.101)	(0.160)	(0.077)
Hispano male × Network	0.053	0.020	0.053	-0.001	-0.678	-0.483
	(0.047)	(0.026)	(0.036)	(0.002)	(0.545)	(0.346)
Network	0.113***	0.188***	0.049***	0.003***	1.401***	0.244***
	(0.009)	(0.015)	(0.007)	(0.000)	(0.281)	(0.065)
Hispano female				-0.048	-0.249	0.078
				(0.307)	(0.736)	(0.224)
Hispano female × Network	0.099	0.093	-0.005	0.008	1.888	1.949*
	(0.122)	(0.105)	(0.061)	(0.005)	(2.259)	(1.121)
Network	0.108***	0.189***	0.044***	0.003***	1.428***	0.205***
	(0.009)	(0.015)	(0.008)	(0.000)	(0.282)	(0.070)
Asian male				-0.117**	-0.150*	-0.159***
				(0.052)	(0.088)	(0.036)
Asian male × Network	0.040*	0.002	0.038*	-0.000	0.024	0.247
	(0.023)	(0.012)	(0.022)	(0.001)	(0.318)	(0.206)
Network	0.112***	0.189***	0.049***	0.003***	1.395***	0.249***
	(0.009)	(0.015)	(0.007)	(0.000)	(0.283)	(0.066)
Asian female				0.108	-0.155	0.086
				(0.120)	(0.229)	(0.092)
Asian female × Network	0.062	-0.044	-0.068	-0.000	0.864	-0.055
	(0.094)	(0.039)	(0.119)	(0.002)	(0.721)	(0.532)

Table A6: **Gender and race at a granular level: Networking, productivity and research quality.** This table reports the estimates for β_1 and β_2 in Specification (14) (Panel A) and the estimates for β_1, β_2, and β_3 in Specification (15) (panel B). The standard errors are heteroscedasticity-consistent and clustered at the author level in Panel A and at the paper level in Panel B. Standard errors are in parentheses and *, **, *** denote statistical significance at the 5%, 1%, and 0.1% levels, respectively.

Panel A: Do connections to journal editors increase author's chance to publish in top tiers?

Connection Type	(1) Any	(2) Student-advisor	(3) Ph.D. Colleague	(4) Post Ph.D. Colleague	(5) Coauthor
Network	0.000	0.034***	-0.014***	0.002	-0.011**
	(0.003)	(0.008)	(0.004)	(0.003)	(0.005)
White male × Network	0.002	0.004	0.002	0.003	0.001
	(0.003)	(0.011)	(0.005)	(0.004)	(0.006)
Network	0.002	0.036***	-0.012***	0.004**	-0.010***
	(0.002)	(0.006)	(0.003)	(0.002)	(0.003)
White female × Network	-0.007	-0.005	-0.007	-0.014*	-0.023
	(0.006)	(0.019)	(0.008)	(0.008)	(0.015)
Network	0.001	0.035***	-0.012***	0.003	-0.013***
	(0.002)	(0.006)	(0.003)	(0.002)	(0.003)
Black male × Network	0.004	0.013	-0.011	0.006	0.021**
	(0.005)	(0.019)	(0.008)	(0.006)	(0.011)
Network	0.001	0.036***	-0.013***	0.003*	-0.010***
	(0.001)	(0.005)	(0.003)	(0.002)	(0.003)
Black female × Network	0.006	-0.028	0.006	0.020*	0.003
	(0.009)	(0.031)	(0.019)	(0.012)	(0.023)
Network	0.001	0.037***	-0.013***	0.003*	-0.011***
	(0.002)	(0.005)	(0.003)	(0.002)	(0.003)
Hispano male × Network	0.016**	-0.023	0.009	0.009	0.012
	(0.008)	(0.031)	(0.012)	(0.010)	(0.020)
Network	0.001	0.036***	-0.012***	0.004**	-0.010***
	(0.001)	(0.005)	(0.003)	(0.002)	(0.003)
Hispano female × Network	0.005	-0.041***	-0.004	0.012	-0.016
	(0.023)	(0.013)	(0.027)	(0.035)	(0.043)
Network	0.002	0.035***	-0.013***	0.004**	-0.009***
	(0.002)	(0.006)	(0.003)	(0.002)	(0.003)
Asian male × Network	-0.006	0.002	0.002	-0.005	-0.010
	(0.005)	(0.013)	(0.007)	(0.006)	(0.008)
Network	0.002	0.037***	-0.012***	0.004**	-0.010***
	(0.001)	(0.005)	(0.003)	(0.002)	(0.003)
Asian female × Network	-0.023**	-0.026	-0.004	-0.066***	-0.028
	(0.011)	(0.029)	(0.018)	(0.020)	(0.019)

Panel B: Does connection to editors lead to favoritism?

Connection Type	(1) Any	(2) Student-advisor	(3) Ph.D. Colleague	(4) Post Ph.D. Colleague	(5) Coauthor
Network	0.103**	-0.021	0.061	0.171***	0.063
	(0.041)	(0.054)	(0.058)	(0.045)	(0.057)
White male	0.059	0.044	0.043	0.073**	0.051*
	(0.038)	(0.031)	(0.030)	(0.034)	(0.031)
White male × Network	-0.033	0.014	0.023	-0.103*	-0.041
	(0.056)	(0.081)	(0.084)	(0.061)	(0.077)
Network	0.091***	-0.023	0.107***	0.111***	0.049
	(0.027)	(0.036)	(0.036)	(0.027)	(0.034)
White female	0.057	-0.026	0.071	0.024	0.028
	(0.071)	(0.063)	(0.060)	(0.063)	(0.059)
White female × Network	-0.142	0.161	-0.494***	-0.080	-0.310
	(0.116)	(0.145)	(0.159)	(0.142)	(0.192)
Network	0.064**	-0.027	0.068*	0.096***	-0.006
	(0.027)	(0.037)	(0.036)	(0.028)	(0.035)
Black male	-0.022	0.038	0.045	0.017	0.000
	(0.064)	(0.050)	(0.050)	(0.058)	(0.051)
Black male × Network	0.176*	0.128	0.080	0.095	0.360***
	(0.092)	(0.129)	(0.136)	(0.096)	(0.125)
Network	0.082***	-0.017	0.080**	0.103***	0.045
	(0.026)	(0.035)	(0.034)	(0.026)	(0.033)
Black female	0.034	0.038	0.103	-0.026	0.142
	(0.161)	(0.125)	(0.125)	(0.138)	(0.124)
Black female × Network	0.074	0.328	-0.315	0.291	-0.646*
	(0.232)	(0.366)	(0.338)	(0.242)	(0.342)
Network	0.082***	-0.013	0.059*	0.104***	0.034
	(0.026)	(0.035)	(0.035)	(0.027)	(0.033)
Hispano male	0.063	0.077	0.034	0.051	0.066
	(0.091)	(0.072)	(0.073)	(0.079)	(0.073)
Hispano male × Network	0.055	0.058	0.394*	0.138	0.157
	(0.138)	(0.233)	(0.214)	(0.162)	(0.229)
Network	0.081***	-0.013	0.075**	0.106***	0.034
	(0.026)	(0.035)	(0.034)	(0.026)	(0.033)
Hispano female	-0.051	0.272	0.270	0.113	0.182
	(0.277)	(0.222)	(0.211)	(0.274)	(0.199)
Hispano female × Network	0.621*	0.026	0.149	0.376	0.908*
	(0.350)	(0.458)	(0.373)	(0.341)	(0.474)
Network	0.095***	0.016	0.067*	0.103***	0.053
	(0.029)	(0.041)	(0.039)	(0.029)	(0.037)
Asian male	-0.131***	-0.138***	-0.162***	-0.162***	-0.149***
	(0.046)	(0.037)	(0.036)	(0.040)	(0.037)
Asian male × Network	-0.064	-0.133	0.039	0.019	-0.072
	(0.067)	(0.087)	(0.106)	(0.074)	(0.084)
Network	0.083***	-0.014	0.072**	0.104***	0.044
	(0.026)	(0.035)	(0.034)	(0.027)	(0.033)
Asian female	0.072	0.076	0.073	0.051	0.131*
	(0.092)	(0.080)	(0.077)	(0.080)	(0.077)
Asian female × network	0.083	0.115	0.219	0.379**	-0.471**
	(0.150)	(0.170)	(0.276)	(0.186)	(0.225)

Table A7: **Gender and race at a granular level: Does connection to editors lead to favoritism?** This table reports the estimates for β_1, β_2, and β_3 in Specification (17). The standard errors are heteroscedasticity-consistent and clustered at the author level. Standard errors are in parentheses and *, **, *** denote statistical significance at the 5%, 1%, and 0.1% levels, respectively.