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Homophily, Biased Attention, and the Gender Gap in Science

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Abstract

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1 Introduction

In attempting to explain the gender gap in science, and professional labor markets more broadly, much research has focused on the "glass ceiling" – the idea that women hit invisible barriers beyond which they cannot advance when reaching the upper echelons of their organizations or institutional environments (Rosser, 2004). Because this literature focuses on characterizing barriers these "survivors" still face when having climbed near the top of the career ladder (e.g., Hoisl and Mariani, 2016), and perhaps partly because of richer data availability on the trajectory of senior women, recent research has called attention to the fact that we know relatively little about roadblocks women may face much earlier in their careers, both in science (Lerchenmueller and Sorenson, 2018) and in the broader labor market (Fernandez-Mateo and Fernandez, 2016).

Looking at early career stages, conventional wisdom touts the importance of mentorship and more generally working with the "right people". A central mechanism that brings people together is homophily, the tendency to mingle with similar others, which is often prevalent among members of minority groups (McPherson et al., 2001). Indeed, the popular discourse on gender gaps in science and elsewhere frequently centers on the need for senior women sponsoring junior women and, overall, women standing together to overcome barriers in male-dominated fields (e.g., Sandberg, 2013).

In an exploratory study of over 1.4 million academic publications in the life sciences, we find evidence for women working with other women disproportionally, i.e. gender homophily[1]. Figure 1a visually summarizes that women form all-female teams up to 14 times more often than expected given the overall sex distribution of scientists. Men, on the contrary, only form all-men teams less than twice as frequently as expected. This phenomenon is stable when we only consider publications of high quality, as indicated by the authors being sponsored by one of the most prestigious science funding bodies in the world, the U.S. National Institutes of Health (NIH) (Figure 1b).

Figures 1a and 1b

From an economic sociology perspective, what further sparks our interest in homophily is that it has the theoretical potential to both decrease and increase gender gaps. On the one hand, if women

[1] For simplicity, we continue using homophily and gender homophily synonymously in this work, cognizant of the fact that homophily may entail many other dimensions, like age and race.

prefer working with other women, this could mean that women can more easily share information and resources to overcome obstacles and achieve beneficial outcomes (Ody-Brasier and Fernandez-Mateo, 2017), or that senior women will become a mentor for young females, or even inspire young women with high potential to consider a career in academia and other competitive labor markets (Gaule and Piacentini, 2018). On the other hand, women may place themselves at a disadvantage when collaborating with other women in an outsized fashion because, for example, women tend to be part of less resource-rich and influential networks (Burt, 1992) or because women's work may receive less attention than men's, likely harming career progress (Leahey, 2007). Lerchenmueller and Sorenson (2018), for instance, provide evidence for sex differences in returns to similar levels of citations (an indicator for attention from scientific peers) that lowered women's success rate in grant competitions, directly worsening career prospects. Our research question is, therefore, twofold: What is the source of the observed outsized homophily among female scientists (Figure 1) and does it help or hinder women's careers when considering attention to their work as critical for career progress?

To answer our research question, we have to deal with a number of empirical challenges. For starters, it is difficult to disentangle the effect homophily might have on research output from women being forced into female-dominated teams due to (perceived) inferior research output in the past. To deal with this form of reverse causality, we need to identify a fairly homogeneous group of scientists in terms of abilities and examine the evolution of their coauthoring behavior as careers progress.

Moreover, we have to distinguish between sex differences in collaboration choices from differences in collaboration opportunities junior scientists become endowed with when they start their careers. Network evolution occurs, in part, through endogenous social processes, like triadic closure (a scientist recruiting a coauthor from the network of a coauthor). Women may be constrained in acquiring new coauthors because their initial set of coauthors may look less impressive compared to men's, rendering women potentially less attractive as collaborators. We would therefore like to compare male and female scientists who start off with a comparable set of research contacts, and ideally, who have been assigned to this set of potential collaborators in a way that is largely independent of the junior scientists themselves. We tackle the first challenge of comparability through a matched sample approach that exploits variance in tractable research networks and the second challenge of independence through leveraging contextual dynamics of our research setting.

We draw on a granular dataset of a group of junior scientists of equal caliber – recipients of a prestigious F32 postdoctoral research grant awarded by the NIH – to address the outlined empirical tasks. F32 grants are mentored, early career sponsorships and support cohorts of nationally competitive applicants who are committed to pursuing a scientific career (Morgan et al., 2013). Male and female F32 grant recipients start out with comparable research capabilities (Jacob and Lefgren, 2011). Even though similar in terms of ability, we also match the junior scientists on their endowment of research contacts.

Our focus on these scientists further exploits an assignment of research contacts that is largely independent of the F32 scientists. In brief, F32 applicants are required to leave the institution that granted their doctorate and to also expose themselves to a new research domain. This leads to the fact that the senior scientists who mentor the F32 applicants represent a new research environment with a formative set of new research contacts the F32 recipient becomes endowed with on the way to independence[2]. In all, our empirical setting enables us to discern the effect of homophily on research output, accounting for potential reverse causal effects as well as for potential sex differences in opportunities to collaborate.

Using ordinary and weighted least squares regressions, we first document that gender homophily primarily stems from homophily among the leaders of a scientific project. In the life sciences, long established authorship norms list the junior scientist who executed the project as first author and the senior scientist who often conceived of and funded the research as the last author (collectively referred to as lead authors henceforth). Women continue same-sex collaborations as lead authors at about twice the rate compared to men, on average, and in particular when the mentor of the F32 junior scientist is part of the author team or when the focal junior scientist leads the team. Discounting various counterfactuals, including the possibility of women selecting into less attractive research areas and women producing lower quality work, we document that female lead authors receive 11% less citations, on average, irrespective of the gender composition of the coauthors, and up to 29% less citations for work published in the most influential journals.

Taken together, our study identifies outsized homophily among female scientists that is largely

[2] In our data, only 11% of F32 recipients had visible direct contact with the sponsoring mentor prior to the F32 award and over 93% of the remaining F32 recipients did not even have contact through the coauthor network of the sponsoring mentor.

driven by how authors in leading roles choose to assemble their teams. While women's propensity to working with other women may support young women in pursuing an academic career, biased attention may concurrently harm their careers and, in particular, those female scientists who publish in the highest impact journals and who would otherwise be poised to narrowing the gender gap in science. Our contribution is at least threefold. We forward our theoretical understanding of how collaboration dynamics may affect men and women differently at early stages, thereby enhancing a literature that has mostly focused on later career stages. We further bridge literature rooted in economic sociology that presented accounts of positive and negative effects of gender homophily for careers, showing that both a positive effect (sustained and productive collaboration) and negative effect (biased attention) may combine to influence women's careers in science. Finally, we contribute empirically by devising a research design that explicitly tackles challenges of reverse causality and selection that may otherwise undermine empirical evidence for the identified mechanisms.

2 Career Paths and the Gender Gap in Science

Careers in academic science resemble up-or-out career paths found in many other professional labor markets. Men and women first need to clear the entry hurdle to the profession, which, in academic science, generally entails the completion of a graduate degree. Career progress is then marked by critical transitions to increasingly senior roles. Mastering these transitions hinges on several determinants, chiefly among them visible output which generally means cited publications in the sciences (Leahey, 2007). In the life sciences, for example, women complete the required terminal degrees (PhD or MD) at similar rates as men, and women continue to be roughly equally represented at the first career stage when working as a postdoc in the laboratory of a senior researcher. Yet, many women appear to fail in mastering the next career transition to becoming junior faculty, with women accounting for 40% and no more than 30% of assistant and associate professors, respectively (Jena et al., 2015).

The reasons for pronounced excess attrition of women in the early years out of a career have been discussed in different streams of literature. Sociologists have highlighted that career aspirations are formed early on, often during high school and college (Morgan et al., 2013), and may be strongly influenced by, for example, gender stereotypes and gendered career expectations (Correll, 2004).

This literature usefully contributes to our understanding of why fewer women may choose to enroll in certain male-dominated fields, like engineering and math (Shen, 2013). This perspective, however, does not immediately illuminate why women drop out of the life sciences more often than men shortly after having cleared the entry hurdle in similar numbers, for instance. Another perspective suggests that women disproportionally opt-out of an academic career. Reasons vary, but scholars have documented that women more often than men shoulder a larger share of family responsibilities, like child rearing, which may stall their careers (e.g., Craig and Mullan, 2011). Again others have suggested and provided laboratory-based evidence that women tend to shy away from competition more often than men (Croson and Gneezy, 2009), a dynamic that may in itself be influenced by adverse stereotypes, but which may nonetheless explain excess attrition of women from competitive up-or-out careers (Brands and Fernandez-Mateo, 2017). Following this logic, women may not enter or choose to exit the competitive career path.

Furthermore, competitive labor markets may simply weed out those with less visible output. Evidence supporting the conjecture of output differentials between men and women is, however, inconclusive. Most research on the gender gap in science and elsewhere is cross-sectional, pooling individuals across all career stages. Observing a gender gap in the number of publications or citations, for example, might result from comparing more junior women to more senior men since men advance to more senior ranks in larger numbers. Seniority brings with it all kinds of resources, from funding to larger networks of research contacts that aid in the creation of visible output (Shen, 2013). We know since the seminal work of Merton (1968) that even small differences in these resources at an early career stage may accumulate to substantive differences in research output individuals produce over time. As such, observing sex differences in the cross-section may actually obscure that at an early career stage, such sex differences may prove too small to fully account for the observed excess attrition of women. The few longitudinal studies that examine sex differences in career transitions (i.e., promotion rates) indicate that women publish at a somewhat lower rate than men (Lerchenmueller and Sorenson, 2018). And still, even after adjusting for such sex differences in publication records, these studies report a residual effect of gender on the probability of mastering career transitions, indicating that publication records paint an incomplete picture without understanding the underpinning dynamics that contribute to differential research output.

Gender gaps would likely emerge in the presence of differential access to important resources that foster visible output at an early career stage. A key resource at an early career stage is mentorship. Young scientists need support of an established mentor who opens up collaboration opportunities and provides other resources in support of high-quality science and career progress. The up-or-out career ladder in the life sciences is exemplified by the continuous need to acquire substantial funding for the execution of research projects. The typical senior researcher grant awarded by the NIH (the R01 grant), for example, carries an annual budget often exceeding $500,000 to support the expensive lab infrastructure, research material, and human capital involved in a life science project (Li, 2017). By contrast, junior scientists may attract postdoctoral funding, like the NIH F32 grant, which essentially pays the postdoc salary, but hardly ever can junior scientists attract the amounts necessary for the execution of an entire research project until they have become established researchers themselves (Jena et al., 2015). In addition to money, mentors can play a number of important roles, from providing their mentees with a better understanding of how the publication and grant application processes work to introducing them to potential collaborators and to gatekeepers in the field (Preston, 2004).

Beyond mentorship more generally, a determinant of the gender gap in science that has, so far, escaped systematic analysis is working with the "right people". This is surprising, given the extensive work on the relationship between group and team composition and the quality of visible output (e.g., Hoisl et al., 2017). We focus on gender homophily as a central mechanism that brings people together and extract arguments mostly from literature rooted in economic sociology to inform our expectations about how gender homophily might influence the careers of young scientists.

3 Determinants of Gender Homophily at Early Career Stages

Sociologists have long observed that individuals who share similar attributes like to mingle (McPherson et al., 2001). Several factors may underpin this consistent pattern. For starters, gender homophily is related to the cost and the risk of collaboration. Working together with similar others facilitates communication, creates confidence, enables trust, and entails reciprocity (Lincoln and Miller, 1979). It makes the behavior of the collaborators more predictable and collaboration potentially less costly and less risky (Ibarra, 1992). Women, more so than men, tend to avoid risk and uncertainty (Dargnies, 2012). Conversely, men tend to be more confident in their abilities than women, in general, and particularly in situations where success is pretty uncertain, as is the case for academic research (Lichtenstein et al., 1977). Women sometimes even feel inferior to men. Women may, therefore, prefer working with other women due to sex differences in overconfidence and, since in male-dominated fields, women might have a "sense of not belonging" (Shen, 2013).

However, the outsized homophily among women presented in Figure 1 may not only result from women choosing other women as collaboration partners, but also from women being constrained in working more with men, for various reasons. One explanation for facing constraints might be stereotypes. Many studies have documented sex differences in publication rates (Cole and Zuckerman, 1984), in the status of the publishing journals (Lerchenmüller et al., 2018), and in citations the work ends up receiving (Larivière et al., 2013). Again, this evidence stems almost exclusively from cross-sectional data which precludes drawing robust inference as to whether the results hold for cohorts of young scientists, leaving room for women being underestimated despite being capable of achieving equal output (Hoisl and Mariani, 2016).

Besides women potentially being perceived as less competent, which would directly influence their collaboration opportunities, there may also be more subtle ways in which opportunities may become constrained for women. Women may, for example, concentrate in certain fields of research over time, potentially leading to isolation and even to breeding stigma that may limit access to important networks (Etzkowitz et al., 1994). Networks, meanwhile, have been shown to be important for initiating new projects, finding collaboration partners, or getting promoted (e.g., Etzkowitz and Frank-Fox, 1991). This mechanism is consistent with social role theory, according to which women are considered less competent than men because they are underrepresented in particular fields (Ridgeway and Smith-Lovin, 1999). Individuals perceived as experts are more likely to influence decisions, take leadership positions, and get entrusted with important projects (Berger et al., 1992).

An important consideration when viewing mentors as instrumental for endowing junior scientists with research opportunities is whether male and female junior scientists enjoy similar access to mentorship. Evidence on this question is scarce but the few studies that exist point to the possibility that especially elite male faculty mentor female juniors less often than their male peers (Sheltzer and Smith, 2014) and that when mentored, women stand to benefit from being mentored by a senior woman (Gaule and Piacentini, 2018).

In all, the extracted arguments combine to support the idea that gender homophily stems from different sources. Female junior scientists may be constrained in working with men, but they also seem to choose to work with other women. Hence, any credible research design, which aims at relating gender homophily to early career progress, first needs to distinguish potential sex differences in collaboration choices from sex differences in collaboration opportunities junior scientists may enjoy.

4 Attention and Early Career Progress

In the following, we elaborate on the possible relationship between homophily, attention, and career progress. Literature focused on these interrelationships is scarce, and we add to this line of research (e.g., Leahey, 2007) by building our conjectures on the findings on career paths in science and the determinants of homophily, which were summarized in the last two sections.

Economic sociologists have presented different accounts of how homophily may influence economically relevant outcomes, both including negative and positive effects. Studies that suggest that gender homophily might exclude women from powerful networks and from therein contained "know-how" point to a negative effect on women's careers (Ibarra, 1992). Scholars have also shown that women can create their own strategic networks consisting of other women to capitalize on information that primarily flows through these female-dominated groups and that these networks can compensate for potential isolation from male-dominated networks (Ody-Brasier and Fernandez-Mateo, 2017).

The literature on homophilous mentor-mentee relationships and career progress has also not painted a clear picture. Arguments include the possibility that senior women may be more attuned and willing to supporting female careers at an early stage (e.g., Abraham, 2017), or that senior women serve as role models that instill a belief in junior colleagues that the up-or-out career can be mastered (Holman et al., 2018). Homophilous coauthoring with their mentors may be advantageous for junior women if it originates from dedicated support by their senior mentor, which may range from providing the necessary infrastructure for conducting quality research to endowing juniors with collaboration opportunities. It may also further careers if female-dominated teams facilitate women producing quality research more generally. Whatever the reason, these recent findings highlight the potential benefits of homophilous mentorship while also underscoring the need for accounting for the possibility that female and male junior scientists may enjoy differential access to quality mentorship and therefore may also become endowed with different opportunities at the start of their careers, which may well affect career progress.

The preceding arguments regarding networks and mentorship largely take a supply-side perspective on the likely effects homophily might have on junior careers. There may, however, also be a demand-side perspective that informs how homophilous coauthoring differentially influences the careers of female and male junior scientists.

Demand-side influence on early stage careers may stem from various factors. Women may concentrate their research in different fields (Leahey, 2007), and the research being conducted in some fields may be in higher demand (e.g., attract more citations) than the research in other fields. Some recent research suggests, that men and women may differ in the way they self-promote their work to the consumers of research (King et al., 2017), which may also feed into lower citation counts for articles written by women (Bikard and Fernandez-Mateo, 2018). Lerchenmueller and Sorenson (2018) suggest that even if women receive similar amounts of citations for their work as men, they might benefit less from them in terms of career progress. There is also the possibility that women suffer from biased attention to their work, even if the work is of comparable quality. If consumers of research ascribe differential value to the work being conducted by women relative to men, women would obviously experience a substantive disadvantage, particularly at an early career stage. One explanation for such a double-standard in evaluation might be, that the consumers of research have a harder time identifying the work of junior female scientists (e.g., young women may have smaller research networks) or consumers feel less certain when citing this work (e.g., women's networks may serve less as a surrogate indicator of quality) (Botelho and Abraham, 2017).

But the attention disadvantage for young women may equally persist when coauthoring with a female senior scientist. Even low entry and high exit rates of women in science (Hunt, 2016), which lead to a positive selection in terms of motivation and ability of the survivors, might not cancel out stigma or resistant prejudices. Large-scale, cross-sectional research indicates that articles by women may receive less citations, irrespective of the woman appearing in the first author position (i.e., is a junior scientist) or in the last author position (i.e., is a senior scientist) (Larivière et al., 2013).

In sum, prior research has laid bare the importance of producing visible research for career advancement. If junior researchers receive an attention discount when coauthoring in female-dominated teams, this would likely harm the careers of young female scientists who seek to establish their own research identity. It therefore seems pertinent to examine the effect homophilous coauthoring may have on the attention paid to the work of young women, complementing the supply-side with this demand-side perspective.

5 Context

In order to analyze potential differences in and effects of gender homophily at the early stage of an individual's career, we draw on a unique dataset of male and female scientists who receive an F32 postdoctoral grant from the U.S. National Institutes of Health (NIH). The NIH is the largest financier of scientific research globally, with an approximate annual budget of $30 billion[3]. More than 80% of this budget is distributed to scientists through highly competitive grants (Li, 2017).

As part of its charge to develop the life sciences research workforce, the NIH has a long-standing commitment to supporting early career scientists. The Kirchstein National Research Service Award (NRSA) Fellowship program (or F grant mechanism) represents the *only* mechanism through which the NIH directly supports the basic preparation of individuals for careers in the academic life sciences (Mantovani et al., 2006). The F32 is by far the most common of these grants, targeting scientists at the earliest postdoctoral career stage with an average recipient age of approximately 32 years. The fellowship offers up to three consecutive years[4] of mentored research support, with an average annual grant size of about $50,000 (Jacob and Lefgren, 2011). Of note, the F32 fellows are committed to pursuing an academic career, exemplified by about two-thirds of F32 fellows remaining employed in academia eight years after the completion of the fellowship (Mantovani et al., 2006).

The F32 evaluation procedure requires a senior scientist to support the F32 candidate's applica-

[3]In comparison, the U.S. National Science Foundation's budget, that covers not only the life sciences but various disciplines, is roughly a fourth of the NIH's annual budget.

[4]Grant extensions occur, primarily on the grounds of family reasons like child bearing (NIH, 2016).

tion by serving as a dedicated mentor. The mentor is usually an established principal investigator (PI) with an extensive academic track record. This mentor normally remains an influential advisor to the F32 scientist beyond the fellowship (Mantovani et al., 2006). We will exploit this feature as part of our research strategy.

In the following, we analyze the trajectory of these highly skilled junior scientists until they themselves become senior researchers. In the life sciences, the transition to senior researcher is generally marked by moving to the last author position on academic publications, and we can assemble the entire publication histories of F32 recipients up to the transition to last author from a unique connection of previously disparate data sources.

6 Data and Methods

We assemble data from three core sources. The *NIH ExPORTER* records all NIH funded research projects from 1985 to today (NIH, 2017). The *PubMed* database is the most comprehensive listing of articles in the life sciences, including more than 25 million articles and more than 80 million authorships from the 1800s to today (National Library of Medicine, 2017). Finally, we use the *Author-ity* database that assigns author IDs to all authors on *PubMed*-listed articles that were published up to 2009 (Torvik and Smalheiser, 2009).

To build the publication histories of F32 recipients we need to ensure that two scientists with the same name on two different papers actually represent the same individual. Prior research documents that *Author-ity* disambiguates scientists with over 99% accuracy, across different levels of scientists' productivity, ethnicity, and name prevalence, for articles listed in *PubMed* (Lerchenmueller and Sorenson, 2016). We make use of this core data feature to not only assemble the publication histories of the F32 recipients, but also to identify the likely mentors of the F32 recipients as well as the research network of these mentors. This task in essence requires a disambiguation across more than 80 million authorships recorded in *PubMed*.

To identify the mentors of the F32 recipients, we exploit the long standing norm in the authorship order of academic articles in the life sciences: The senior investigator who often heads the laboratory and conceived of the research receives the last authorship position on articles. We identify the first article that acknowledges financial support by the F32 grant and determine the individual who served as the last author on this paper. To increase validity, we only consider individuals as mentors if they have served as last author on articles with at least three coauthors prior to the F32 award[5].

Having identified the mentor of the F32 recipient, we then can also build the mentor's network of research contacts by examining the coauthors on publications of the mentor prior to serving as a mentor on the F32 grant in question. These coauthor networks are time-variant. Consider the case of a mentor sponsoring two F32 recipients at two different time points for which the set of coauthors the mentor had worked with likely differs. To calculate these time-varying coauthor networks, we use high performance cluster computing resources and leverage the author disambiguation. We now turn to our empirical strategy that articulates how we make use of these data and methodological features.

7 Empirical strategy

7.1 Reverse Causality

To forward our theoretical understanding of what mechanisms are more likely to contribute to the ostensible gender homophily depicted in Figure 1, we first need to separate whether gender homophily may be associated with lower visible output or whether lower visible output among female scientists forces women into female-dominated teams – a form of reverse causality. To do so, we need to observe a group of scientists starting from a point in their careers where they have similar levels of output and then follow these scientists over time, observing how their coauthoring behavior evolves.

Our focus on F32 grant recipients is useful for not only observing scientists who start out with similar levels of output, but also with a lower likelihood of sex differences in output as careers unfold relative to a broader population of scientists. This contextual feature further mitigates the aforementioned reverse causal dynamics, while also reducing potential sex differences in career aspirations that could otherwise combine to distorting our analyses.

[5]Requiring three or more coauthors increases the likelihood of identifying a senior author of original research because, in the life sciences, articles with less than three authors more often fall outside of original research (e.g., editorials or reviews). We nonetheless entertain various permutations of this identification approach, including a restriction to articles where the F32 recipient must also be first author, for instance, which lead to similar results available from the authors.

This longitudinal approach is, however, only necessary but possibly not sufficient for discerning the association between gender homophily and research output. More broadly, we need to isolate women's choices (i.e., gender homophily) from women being constrained in their opportunities to join and form author teams. Since researchers are not randomly assigned to research environments, in addition, we need an identification strategy for comparing men and women with similar endowments of research contacts. A core feature of our strategy is to exploit the fact that the F32 fellowship requires a dedicated mentor.

7.2 Assignment of a Mentor and Selection

Ideally, the assignment of a mentor and his or her network of research contacts to F32 recipients would be at random. Although this is practically impossible, we first investigate to what extent the assignment can be considered to be independent of the influence of the F32 applicant. If F32 applicants cannot strategize in their mentor selection, the mentor and the network of the mentor, which we plan to use as a proxy for the initial endowment of research contacts for the F32 applicant, would be plausibly independent of the F32 applicant him- or herself.

The teaming up of an F32 applicant with a potential mentor resembles a two-sided matching problem that suffers from selection. If the pool of F32 applicants is stratified by quality, it stands to reason that the better F32 candidates seek to influence who will serve as a mentor because mentors also have an interest in working with the best junior scientists. By extension, F32 applicants could then also influence the set of research contacts they potentially become endowed with. We first assume that selection is based on observable characteristics of the F32 applicants that are also evaluated by the NIH committees in the grant allocation process (NIH, 2018).

Table 1 summarizes accomplishments of male and female F32 recipients at the time of the F32 award. None of the assessed criteria are statistically distinguishable at the five percent level for female versus male F32 recipients, applying a Kolmogorov-Smirnov test. One can readily see, that the F32 recipients are at the start of their careers with about three years of prior research experience since their first publication was recorded in *PubMed*. The status of the institution the F32 recipient is affiliated with prior to F32 grant receipt[6] is, on average, in the top 5% of the U.S. life science institutions. At this very early career stage, male and female F32 recipients also have

[6] Approximated by the institutions' percentile rankings in terms of receiving major NIH grants.

a similar number of publications, high-impact publications, and coauthors. Taken together, these raw metrics lend credence to our approach for identifying male and female scientists of comparable caliber at the outset of their careers.

The statistics, moreover, indicate that our focus on F32 recipients mitigates selection concerns. The group of F32 recipients is homogeneous and it seems unlikely that they can send quality signals based on these observable and NIH-evaluated characteristics that would affect the F32 recipient-mentor matching. Likewise, conditional upon the capacity for mentoring, the pool of potential mentors should largely be indifferent about who to select for mentoring based on indistinguishable observable characteristics of the male and female F32 recipients.

Table 1

Still, the forming of the F32 mentor-mentee relationship may be influenced by less observable characteristics. F32 applicants might, for instance, try to send quality signals not in form of polished publication records but via working with the targeted mentors *prior* to applying for the F32 grant. However, the NIH expects F32 applicants to move to a new laboratory and even new university instead of applying for an F32 grant at the university where the applicant received the terminal degree. An environment that offers opportunities for new training is a core evaluation criteria for F32 grants (NIH, 2018).

An alternative mechanism may then originate from generally unobservable connections, such as referrals within the network of the F32 applicant's doctoral advisor. Although notoriously difficult to tract, we can mine all articles of the *PubMed* database to identify all members of the scientific community the F32 applicant has published with in the past, and whether any of these individuals is also part of the mentor's coauthor network. Such an indirect connection may serve as an indication for the likelihood that the F32 recipient was connected to the targeted mentor prior to applying for the F32 grant and such a connection would increase the likelihood of selection issues.

Figure 2

Figure 2 discounts both of these endogenous avenues to the forming of the F32 mentor-mentee relationship. Of our sample of F32 recipients, 89% had no direct contact with the scientist who serves as a mentor prior to the F32 award. For those who had direct contact, the frequency distribution tails off swiftly and we account for all these remaining cases in our subsequent analyses. What's more, considering the F32 recipients with no prior contact, 93% of these have also not been connected to their mentor's network of coauthors prior to the F32 award. That is despite the fact that the mentors' networks tend to be broad, including more than 60 unique individuals, on average. Nonetheless, we also control for possible selection effects for those remaining F32 recipients who had contact through the mentors' network prior to the F32 award. Taken together, about nine out of ten F32 recipients had no discernible academic contact with their mentors prior to the F32 award, which confirms the formal NIH expectation of F32 grantees moving to a new research environment and research topic (NIH, 2018).

In all, we conclude that the F32 recipients have had limited opportunity to influence the mentors' mentee selection because the quality of the F32 pool is homogeneous and because the F32 recipients had limited exposure to their chosen mentors prior to the F32 application.

7.3 Matched Sample Approach to Account for Potential Sex Differences in Collaboration Opportunities

Extending from the previous analyses, the F32 applicants appear to have little latitude in determining the formation of a specific mentor-mentee relationship for the F32 fellowship. Therefore, the concomitant assignment of a set of research contacts (the mentor and his or her coauthor network) is plausibly independent of the F32 recipient. Nevertheless, besides controlling for mentor characteristics and the network of the mentor in our regressions, we also employ a matched sample design. We use coarsened exact matching (CEM)[7] to pair male with female F32 grant recipients with observationally equivalent mentors and overall endowments of research contacts. Recent research suggests that CEM has several advantages over other techniques that also match on observable characteristics, such as propensity score matching (for a detailed review, see Iacus et al. (2012)). In essence, we create strata of male and female F32 recipients who are mentored by senior scientists of similar standing and with a comparable network of research contacts. We then account for differences across these strata by including strata fixed effects into our analyses.

[7] We execute matching without replacement (a given female F32 recipient is exactly paired once to a certain male F32 recipient). There is no rule that would govern the choice of a ratio for female to male F32 recipients, but fewer matches per female scientist produce larger standard errors. Our median match ratio female:male F32 recipients across strata is 1:2, but our results remain significant for a 1:1 matching and are available from the authors.

We further account for any remaining differences by employing a weighted least squares regression approach, with more accurate matches receiving greater weights.

Like the variables we used for evaluating the homogeneity of the pool of F32 recipients, we derive the variables for matching from the F32 award evaluation criteria; specifically those criteria used by the NIH committees for evaluating the mentor and collaborators as part of the F32 application (NIH, 2018). We assess *mentor experience* with the years that have passed since the mentor had first published and the F32 grant in question was awarded. We next capture the quality of the mentor's publication record by calculating the share of *high-quality papers*, assessed by the proportion of papers being published in journals with an impact factor exceeding 15[8]. To assess the relevance of the mentor's research expertise for the F32 fellowship, we calculate *content overlap* as the proportion of article key words (called MeSH terms in the life sciences) that overlap between the mentor's body of work and the first publication resulting from the F32 sponsorship. Of note, MeSH terms are not assigned by the authors themselves but by professionally trained librarians of the National Library of Medicine. This exogenous assignment of keywords eliminates bias that might otherwise arise if the authors themselves could influence the keyword nomination (Boudreau et al., 2016). Beyond mentor characteristics, we also match F32 recipients on the sets of potential collaborators they become endowed with when forming the mentor-mentee relationship. We use the time-varying number of *unique coauthors* to capture the network of research contacts, while we calculate the *share of female coauthors* as a measure of gender density that might influence homophilous coauthoring.

Figure 3 depicts the pre- and post-matching distributions of all variables, separately for female and male F32 recipients. We also use statistical testing[9] to compare these distributions. Going down the left column, what may first meet the eye is that the mentors of the male and female F32 recipients appear similar across several characteristics, suggesting that the highly promising F32 applicants get in essence matched to mentors of comparable caliber. Mentors have similar levels of experience and that experience is as relevant to the research of female and male F32 recipients, judged by the content overlap of the mentor's past research with the first publication from the

[8]Adapting this impact factor threshold yielded qualitatively similar results, but a threshold of 15 only includes the most prominent life science field journals and general science journals (Lerchenmüller et al., 2018). Moreover, we use share of high quality papers because the pure number of publications is highly correlated with years of experience.

[9]We apply a Kolmogorov-Smirnov two sample test.

F32 fellowship ($p > 0.10$, respectively). However, mentors of male F32 recipients have statistically higher quality papers compared to mentors of female F32 recipients ($p < 0.05$). With respect to the mentors' network of research contacts, mentors of male and female F32 recipients do not statistically differ in the number of unique coauthors, but they differ markedly in the share of female coauthors that form the network. Female F32 recipients become endowed with a significantly higher density of potential female collaborators ($p < 0.001$). In addition, despite loosing about 17% of F32 scientists that cannot be matched, the pool of 3,233 F32 recipients that remains for analysis is as homogeneous as the pool we started out with. We are thus confident that our matching approach does not systematically select certain individuals over others[10].

Figure 3

The matching approach allows us to hold the initial endowment of research contacts, and with it the set of initial opportunities for coauthoring for the F32 recipients, constant when examining how the F32 recipients choose to extend their network. Research has been profoundly challenged by the difficulties inherent in disentangling choice from opportunity constraints in tie formation, and we do not claim that our approach is immune to these challenges. The econometrician can only account for what is visible, and although our assessment of time-variant sets of research contacts is unusually granular, it cannot capture all possible constraints, including invisible ones[11]. In all, our empirical strategy allows us to account for counterfactual explanations rooted in reverse causality and observable opportunity constraints when seeking to discern the association between gender homophily, scientific collaborations, and ensuing visible research output.

8 Correlates of Scientific Collaboration

To assess the extent of gender homophily among life scientists and potential implications for early stage careers, we create several variables from the detailed publication histories of our F32 scientists. In total, our sample for estimation comprises 3,233 F32 recipients, 2,491 related mentors, and 20,487 publications. Our dataset consists of one observation per publication per person ordered by the publication dates of the articles.

[10] We also ran a selection regression (probit) on the whole set of F32 recipients, with matching status (zero, one) as dependent variable and F32 recipient characteristics as independent variables, obtaining no significant results.

[11] E.g., the mentor-mentee "chemistry" and possible implications for opportunities.

Table 2 provides an overview and definitions of all our variables used for analysis as well as descriptive statistics. Our core dependent and independent variables focus on the sex composition of the author byline. Specifically, we calculate the *percent women* authors on an article and record the sex composition of the leading first (F) and last (L) authors in a set of dummy variables, including *F+L female* for female first and last authors, *F+L male* for male first and last authors, and *F+L mix* for mixed sex lead author teams. We create these variables for the current paper (i.e., at time *t*) as our dependent variables and for the preceding paper (*t-1*) as our key independent variables[12]. Percentage women on the current paper, i.e. the share of female authors, amounts to 32% on average. Percentage women on the preceding paper is marginally smaller and amounts to 31.5%, on average. Only 9% of the current papers, on average, have female lead authors, 52% male lead authors, and 39% list mixed-gender lead authors. The shares are almost the same for the lead authors listed on the preceding paper. Furthermore, the publications of the F32 recipients receive on average 3.8 logged citations.

Table 2

We also include several control variables in addition to the variables on which we match the male and female F32 recipients. To account for the minority of cases where the F32 recipient had prior contact to the senior mentor, either directly or indirectly, we include a dummy variable *pre-grant contact* that is one (9% of the cases) if there was contact and zero otherwise. We also include fixed effects for the *fiscal year* when the F32 grant was awarded to capture potential cohort effects. Similarly, we include fixed effects for the *publishing year* of a given article to account, for example, for changes in the general sex composition of life science authors over time. Beyond our key independent variables that capture the sex composition of the author byline, we also assess potential effects from the F32 recipient being a prestigious *first author* on a paper. The F32 recipients are first author on every other publication (52%), on average. We also control for the overall *number of authors* on a paper, as the importance of female representation may vary with the size of the author team. The average paper is written by about six authors. We account for the quality of the publications, using the *5-year JIF* (journal impact factor) of the publishing journal.

[12]Considering a longer memory of potential gender homophily effects (i.e., prior to *t-1*), does not add substantive explanatory power to our models.

The 5-year JIF on the current and the preceding publications vary between 0 and 56 and amount to 5.5 on average. Hence, we do not observe differences in the average quality of the publications at time t and $t-1$. We further account for extensions of the F32 grant, which would capture a delay in scientists research trajectories due to, for example, family reasons (Lerchenmueller and Sorenson, 2018). We observe that a little less than one-third of publications stem from an extended grant. Finally, we use the information about whether the mentor is amongst the coauthors, which is the case for 59% of the publications in our sample, indicating that the mentor-mentee relationship often extends well beyond the F32 fellowship itself. In addition, we condition our models on the set of matched F32 scientists, thereby controlling for sex-specific characteristics and for the variables on which the scientists are matched.

9 Results

9.1 Factors that Influence Women's Representation on the Author Byline

We first analyze the representation of women on an author team, employing OLS regressions[13]. Exploiting the publication trajectories, we analyze the effect of the share of women on the preceding paper ($t-1$) on the share of women on the current paper (t) of the F32 recipient[14]. Model 1 in Table 3 indicates that a one percentage point increase in the representation of female authors in the past will increase the representation of female authors by over half a percentage point today. This raw homophily effect is, however, independent of gender, since choosing percentage male as a dependent variable would lead to the same outcomes.

To better understand the forces driving the homophily effect by gender, we next add the sex composition of the lead authors, i.e. the authors listed first and last on the paper (Model 2). Switching from male (base category) to female lead authors, increases the representation of women on the author byline, on average, by seven percentage points (about a 50% larger effect compared to switching from male to mixed sex lead authors). Moreover, adding the lead authors' sex reduces

[13]Since most F32 recipients enter our regressions for multiple publications, and since mentors may sponsor more than one F32 recipient, observations are not independent and we therefore cluster standard errors on both F32 recipients and mentors.

[14]We exploit this time-variant structure through regressions in the cross-section of junior scientists with lagged variables. We considered an ordinary panel specification as a potential alternative, however, both the left and right hand side (e.g., share female co-authors in the F32 scientist's network in t and $t-1$) change slowly and provide much less variance.

the raw homophily effect on our lagged variable for overall female representation by 12% (from 0.60 to 0.52). Together, if the average paper in our dataset that is written by six authors was to change from an all-male author byline to a byline with three men and three women (50% female representation) in $t-1$, one would expect the next average paper in t to include at least one woman (six authors $\times 0.5^2$). If, in addition, the added women in $t-1$ were lead authors, one would expect the next average paper in t to include almost two women (six authors $\times(0.5^2+7\%)$). This illustrates the importance of the lead authors' sex composition on the preceding paper for the overall sex composition of the author byline today.

Adding article characteristics as well as time (year of publication and start year of F32 grant) and field fixed effects (20 research fields based on the NIH Institute that funded the F32 fellowship) does not contribute much explanatory power (a reduction of maximum 5% to 0.50; Model 3).

Table 3

Up to here, we have implicitly assumed that the observed effects capture sex-specific collaboration choices made by our scientists. Likely, this assumption is not fully warranted for reasons detailed in our theory development, i.e. because women and men may be endowed with different collaboration opportunities. To empirically disentangle choice from opportunity, we first simply add all our matching variables that capture the set of initial research contacts our F32 recipients are endowed with through their senior mentor (Model 4). Although some of these matching variables exert a significant influence on women's representation on the average paper, adding these variables has surprisingly little influence on the lagged author byline effects (e.g., the effect of lagged female representation drops by about 2% to 0.48).

To better separate sex differences in collaboration choices from opportunities, we next exploit our matching of female and male F32 recipients (Model 5). We now run a weighted least squares regression, including the matching weights from applying coarsened exact matching as well as 593 group fixed effects, one for each strata of matched male and female F32 recipients. This approach yields an effect reduction of about 10% (0.50 to 0.45) for our lagged representation of women on an author team (raw homophily effect) and an even greater reduction (11%) for the lead authors' homophily effect (from 0.073 to 0.065, Models 3 to 5). Even though matching male and female F32 recipients according to their initial set of research contacts can capture part of the environmental constraints, it cannot capture all possible constraints, including invisible constraints[15]. Hence, we cannot interpret the remaining effect as sex-specific collaboration choices per se. Still, even if one assumes that invisible constraints are as important as the visible ones we account for, or even five times as important, the remaining unexplained variance would still indicate the presence of ample choice driving homophilous coauthoring.

In sum, our regressions provide first evidence that outsized gender homophily at least in part stems from how the leaders of scientific projects (first and last authors) choose to assemble their teams. Hence, the lead authors and their collaboration choices deserve closer investigation.

9.2 Factors that Influence Women's Lead Authorship

Given the apparent influence of the lead authors on the sex composition of the overall author byline, we next run regression models predicting the likelihood of a paper being authored by female versus male lead authors. Table 4 summarizes the results of OLS regressions, i.e. linear probability models[16]. Accounting for potential visible sex differences in collaboration opportunities (the endowment of research contacts), we first document that the lead author homophily effect is about twice the size for of female versus male lead authors (Model 6 vs. Model 7). The likelihood of a paper being authored by women in the first and last author position increases by 23 percentage points if the preceding paper has been authored by female relative to male lead authors (Model 6). The corresponding male homophily effect is about 11 percentage points (Model 7), holding article characteristics and set of initial research contacts constant. Similar to our analysis of women's overall representation on the author byline, running the OLS model as a weighted least squares with our matching approach (Models 8 and 9) reduces the homophily effects by about 27% for female lead authors (from 0.23 to 0.17) and by about 37% for male lead authors (from 0.11 to 0.07). Since most endowed networks feature more male than female scientists, a larger portion of the ostensible homophily effect for male lead authors relative to female lead authors is explained by the structure of the initial network of potential collaborators. In other words, the dynamic that

[15] Like differences in the "chemistry" between mentor and mentee.

[16] We also run probit models which lead to results consistent with respect to the size, direction, and significance of the effects (available from the authors). A Probit (or logit) regression has two disadvantages as a primary statistical method in our analysis. First, the large number of intercepts, year and strata fixed effects (>500), raise the possibility of incidental parameters bias and may even prevent the convergence of these models. Second, probit (logit) regressions can overestimate effect sizes as a result of the high leverage of marginal cases, whereas linear probability models average across observations and therefore tend to produce more conservative results.

female lead authorship perpetuates female lead authorship shines even brighter after controlling for sex differences in opportunities to collaborate. We again control for article characteristics, which do not add much explanatory power to these models, and add time and field fixed effects. In all, homophily among female lead authors appears to exceed homophily among male lead authors by a factor of more than two (0.17 versus 0.07; Model 8 versus Model 9).

Table 4

To better understand the choices made by the lead authors, we run the weighted linear probability Models 8 and 9 for female and male lead authors on three subsamples (Table 5). So far, we have not considered the information of who the lead authors actually are. In the regression models displayed in Table 5, we distinguish between three coauthor configurations: (1) the mentor is one of the coauthors and so is the F32 recipient, (2) the mentor is not among the coauthors and the F32 recipient is the first author[17], and (3) the mentor is not among the coauthors and the F32 recipient is not a lead author.

To build intuition, for subsample (1), the mentor rather than the F32 recipient can be expected to drive the author team composition because these papers are either produced by the mentor's laboratory or by another senior scientist in the network of the mentor; these papers likely constrain the F32 recipient in choosing collaborators relative to the mentor. For subsample (2), the mentor is absent and the F32 recipient takes on a leading role, which likely requires the F32 recipient to choose and build ties beyond the mentor's set of contacts. Finally, for subsample (3), neither the mentor is present nor does the F32 recipient serve in a leading role, effectively representing a counterfactual to the proposed dynamics in subsamples (1) and (2). In this case the lead authors' co-author choice should not be driven by the mentor-mentee induced gender homophily.

For female lead authors (Models 10 to 12) we find a significant lead author homophily effect for the subsamples 1 (the mentor is one of the coauthors) and 2 (the F32 recipient is the first author but the mentor is not one of the coauthors). As expected, we do not find a significant lead author homophily effect for subsample 3 (neither the mentor nor the F32 recipient are the lead authors). For male lead authors (Models 13 to 15) we only find a significant lead author homophily effect

[17] We do not consider cases where F32 recipients are the last authors listed on a paper, since we are interested in early career stages. Once the F32 recipient becomes a principal investigator (i.e., moves to the last author position) we exclude this and all subsequent papers from our analysis (right censoring).

for subsample 1. Results also show that, in case the mentor is one of the coauthors (subsample 1) the lead author homophily effect is about 3x larger for female versus male lead authors (Model 10 versus Model 13). But gender homophily appears not just pronounced among senior women. Comparing Models 11 and 14, we observe that junior female F32 recipients also appear to engage in homophilous collaborations when leading as first authors, while there is no corresponding effect for male F32 recipients.

In sum, the results based on the three subsamples provide additional evidence that lead author homophily is stronger for female than male scientists. Our counterfactual regressions (Models 12 and 15) with no significant lagged lead author effects, underline that our earlier results had not just been artifacts of unobserved heterogeneity. Given these regression outcomes, the granular data indicate that lead author homophily is indeed a function of (visible and invisible) endowments of research contacts and of collaboration choices made by the lead authors.

Table 5

9.3 Homophily, Visible Output, and Potential Career Implications

To answer our second research question, i.e. whether outsized gender homophily among female scientists helps or hinders women's careers, we investigate whether women get more or less attention to their work when they work with other women. It is important to note that the following results are correlational and not causal, but derived from a focused set of publications that involve F32 recipients at an early stage in their careers.

Table 6 first documents that research published by female lead authors receives a 18% citation discount (Model 16, $e^{(-0.198)} = 0.82$). This effect already accounts for instances of the mentor being among the coauthors (positive impact on citations) and the relatively inexperienced F32 recipient being a lead author (negative effect). In addition, Model 16 also includes field fixed effects that discount the alternative explanation of women sorting into fields that attract less citations. Next, we add the number of authors on the average paper (Model 17) to account for the possibility that men are, on average, associated with larger research networks[18] that, in turn, may be correlated with the number of people citing the research. Overall, this avenue also seems to partly explain

[18]Of note, for the focal mentors, our matching yields no statistical difference in the size of the research network between those who mentored female and male F32 recipients.

the citation discount received by female lead authors (about a 13% effect reduction from 0.198 to 0.173). Lastly, we entertain the possibility that the underlying work produced by research teams led by women differs in terms of quality to the work produced by men, which would obviously explain a certain discount in citations. To that end, we include 1,830 fixed effects for the journals publishing the work, which reduces the citation discount but does not eliminate it. Model 13 still shows a 11% citation discount experienced by female versus male lead author teams, for work published in the same journal, same field, and same year.

Table 6

Lastly, it seems important to understand under which conditions these adverse effects of female lead author homophily on visible output (citations) is most pronounced. When publishing in less influential journals (journal impact factor ¡ 15), we find a 7% citation discount for female lead authors (controlling for all variables described previously). By contrast, women receive up to 29% less citations for work published in the most influential journals, holding journal, field, and publishing year constant, indicating the presence of tangible, biased attention to women's work.

Figure 4

10 Discussion

We started with the notion that gender homophily can theoretically decrease and increase the gender gap in science. To get a better understanding of homophilous collaboration dynamics and potential consequences for early career researchers, we investigated the publication trajectories of over 3,000 highly qualified postdocs in the life sciences.

Our study sheds light on the dynamics of gender gaps in two novel respects. First, we provide evidence that women disproportionally work with other women. The data discount visible non-choice based explanations for our findings. Outsized gender homophily among women may have resulted from women being forced into female-dominated teams either due to lower research output in the past constraining their future collaboration opportunities or through women starting off with a constrained set of research contacts to begin with. Our empirical strategy discounts both of these explanations. To be clear, we cannot rule out other, particularly invisible, constraints influencing homophilous coauthoring. But even if one assumes that invisible constraints are as or even more important as the visible ones we account for there is substantial remaining variance and considerable room for choice influencing the observed homophily effects.

One of our major findings, confirmed in a split-sample approach, is then that outsized gender homophily is largely driven by lead authors (the first and last authors listed on a publication) deciding how to assemble their teams of coauthors. This finding provides an answer to our first research question asking about the sources of outsized gender homophily among female scientists.

Additionally, we find that women's outsized preference for working with other women is associated with less attention to their work (i.e. less citations), which likely hampers their careers over time. In academia as in many other settings, attention is a key currency for getting hired and promoted. We document up to a 29% discount in citations for women, controlling for a variety of alternative explanations. As outlined in detail, the quality of the individual scientists (both F32 recipients and mentors) is homogeneous across the sexes in our analyses and past research has suggested little-to-no sex difference in career aspirations of the F32 recipients (Mantovani et al., 2006). Moreover, we account for the possibility that women systematically select into fields of research that might draw less attention as well as for the underlying work being of different quality. Still, women appear to suffer from biased attention to their work, particularly those high-potential early career women who publish in the most influential journals and who would otherwise be poised to narrowing gender gaps in science.

Taken together, whereas women's propensity to working with other women may engender the resources and sponsorship needed to keep young women productive and progress their careers, biased attention to their work may hinder their career progress. This finding speaks to our second research question asking whether gender homophily helps or hinders women's careers in science. The obtained results suggest that we might not need to support women in science as much as we might need to stop hindering them.

Our study contributes to the literature on gender gaps in labor markets more broadly. In particular, we complement the existing literature by offering a closer look at the early stages of careers. Existing research, like the work on the "glass ceiling" dynamic (e.g., Hoisl and Mariani, 2016) has mainly focused on later career stages, once women reached the upper echelons of their organizations. Our findings indicate that women's team selection hurts the attention to their work and, consequently, their visibility early on in their careers. The F32 scientists in our samples are at the beginning of their work life and committed to pursuing an academic career long-term. This early window is critical for getting the attention that allows winning independent grants and for opening up the door to a tenure track career (Jena et al., 2015). In other words, women seem to seek out other women during a time when their careers are most vulnerable to lower attention, particularly in markets of cumulative advantage (Merton, 1968). With these results, we add to a line of research that draws our attention to career barriers that women face early (e.g., Lerchenmueller and Sorenson, 2018), relative to an existing and deep literature on barriers women face when having already climbed the career ladder to more senior ranks.

Our finding of a negative coupling of team composition and attention to research outcomes also contributes to literature on how women's position in labor markets may be improved. Counter to most prior research (including our own) that often examines how women's careers are hampered by discrimination, biased resource allocation, and outright exclusion, this study surfaces a potential area that women may influence themselves. At the very least, our findings may sensitize women to more consciously selecting collaborators and to actively promoting their work's visibility. Scholars have started to examine how women can positively influence their career progress through presenting their accomplishments more actively (Bikard and Fernandez-Mateo, 2018), for example. With respect to teaming, recent research has suggested that women's conscious choosing of collaborators may positively influence their careers (Ody-Brasier and Fernandez-Mateo, 2017), and our findings speak to the importance of further defining the scope conditions that determine how conscious teaming and networking may propel women in their careers.

Finally, we contribute methodologically by using an empirical design that, even though not perfect, allows us to explicitly tackle challenges of reverse causality and selection. We are able to separate collaboration choices from (visible) collaboration constraints stemming from an initial endowment of research contacts. This allows us to identify the sources of collaboration dynamics and, finally, to advance our understanding of women's career paths.

As with most empirical research, our study involves trade-offs and limitations. Our key identifying assumption is that the senior author on the first paper coauthored by the F32 recipient serves as a mentor and provides the junior scholar with a network of research contacts. Mentorship is hard to observe in practice, but the stringent F32 grant criteria, requiring a sponsoring mentor by design, and the fact that authorship norms in the life sciences reserve the last author position to the sponsoring senior scholar, lend credence to our approach. Moreover, sensitivity analyses that alter our identification, including thresholds for repeated coauthorship with the first senior author and limiting identification to papers where the F32 recipient is also first author (i.e., holds the second prestigious position on the paper), do not substantively change our results. Still, we do not observe the degree to which the F32 recipient has been able to influence mentor allocation prior to the F32 grant application. This two-sided matching dynamic is a notorious challenge in research on tie formation, and we do not claim that our approach is immune to this challenge. But, selection issues in two-sided matching problems become more pronounced with quality heterogeneity in the two sets of individuals who seek to match. Yet, by design our postdocs represent an unusually homogeneous group of scientists, where more serendipitous factors (e.g., current location, conference meetings, and ultimately the whim of the potential senior mentors) likely play a larger role for the matching than junior scholars' strategic choices. Nonetheless, focusing on F32 recipients potentially reduces generalizability of our findings and we would welcome research that extends our early findings to other cohorts and contexts.

Another limitation of our study is that we can only observe, and therefore account for, part of the constraints junior scientists face. We focus on visible constraints stemming from an initial endowment of research contacts. Networking and social capital more generally have long entered explanations for why women of similar capability may experience differential returns to these capabilities (Brass, 1985). Evidence suggests that the majority of U.S. jobs are found through networking and that this mechanism is often gendered and particularly important for highly qualified knowledge workers (e.g., Rubineau and Fernandez, 2015). Networks help, for example, in identifying new opportunities and influencing key decision-makers (gatekeepers). Nevertheless, other visible and particularly invisible constraints may have an effect, too. At this point we have to leave an even closer look to the (invisible) constraints of female scientists to future research.

In conclusion, we provide the first evidence for female junior scholars selecting into female-dominated teams in an outsized fashion. We further document ensuing tangible negative effects on the attention that women's work ends up receiving. Since these effects appear pronounced early on in women's careers, the identified dynamics conceivably contribute to the gender gap in the life sciences and, potentially, in other professional labor markets.

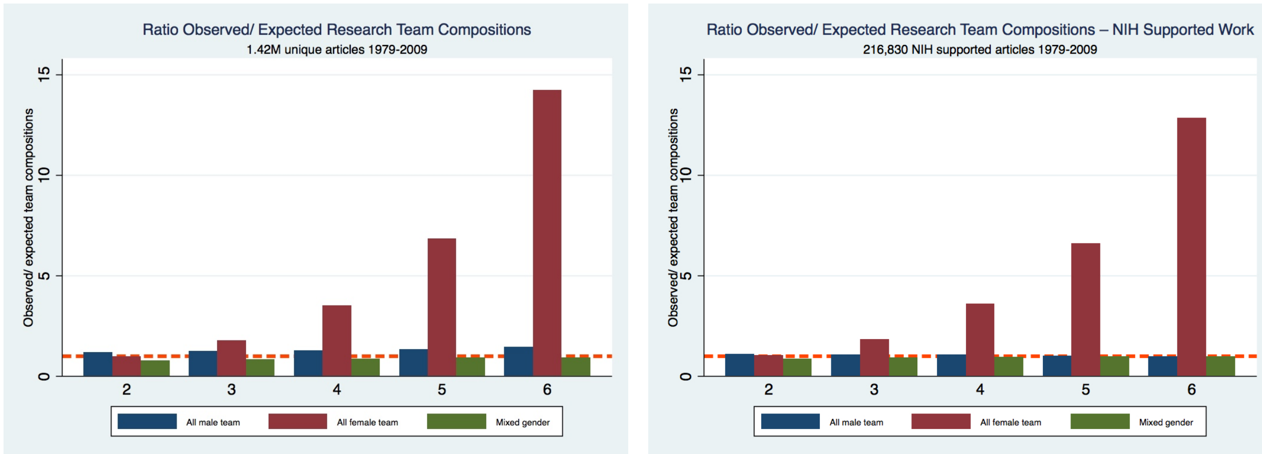

Figure 1: Unadjusted Gender Homophily – Ratio of Observed to Expected Team Compositions
Note: Dashed horizontal line marks point of zero gender homophily.

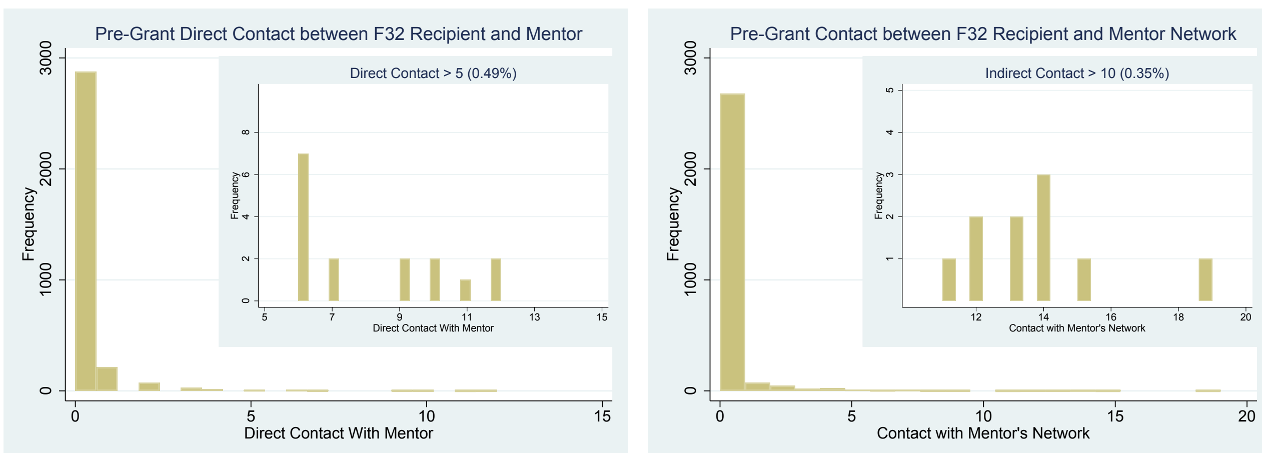

Figure 2: Pre-Grant Contact between F32 Recipient and His/ Her Mentor

Direct contact assessed via the number of junior-mentor scientists' coauthored publications prior to F32 grant receipt: 88.76% with no direct contact.

Indirect contact constructed based on the number of coauthored articles among F32 recipient and another scientist who has been coauthoring with the F32 recipient's mentor prior to the F32 application: 93.08% of those who had no direct contact did also not have any contact with the mentor's network.

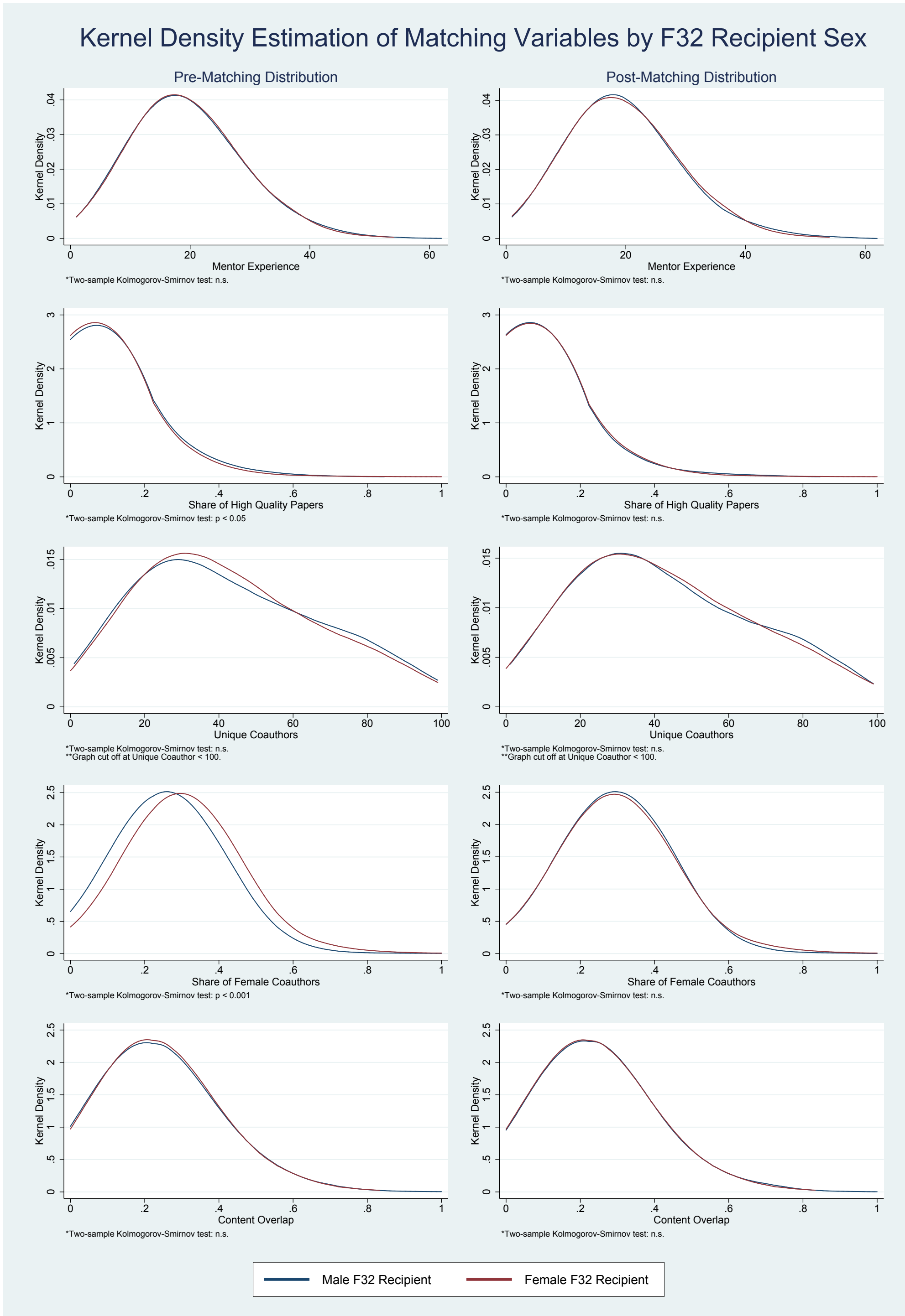

Figure 3: Kernel Density Estimation of Matching Variables Pre- and Post-Matching

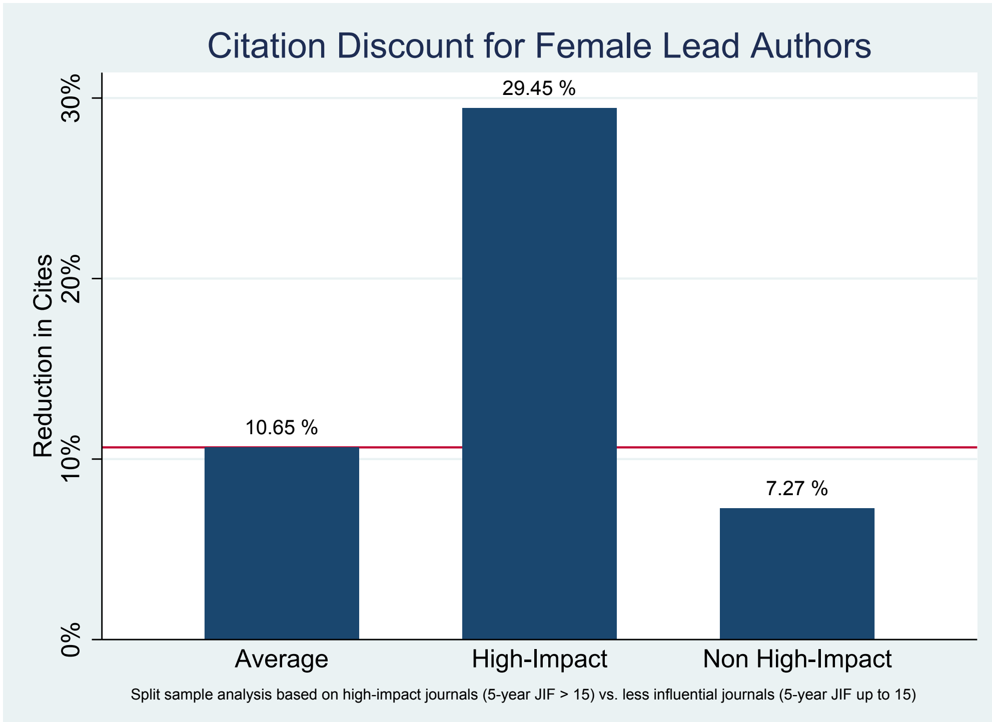

Figure 4: Citation Discount for Female Lead Authors, Stratified by Journal Impact

	Female		Male	
	mean	sd	mean	sd
Experience (in Years)	3.22	3.34	3.33	3.59
Status of Institution*	96.93	7.78	96.72	8.73
Papers Published	2.67	2.54	2.88	2.80
Share of High-Quality Papers (JIF > 15)	0.04	0.15	0.04	0.15
Coauthors	8.77	10.68	9.67	11.86
Unique Coauthors	5.93	6.81	6.30	7.40
Observations	1560		2345	

*Affiliation pre F32 grant (available for 65% of grantees), otherwise F32 institution

Table 1: Characteristics of F32 Recipients

Variable	Description	Type	Mean	Std. Dev.
Pct Women	Percent women on author team	DV/ IV	0.320	0.255
Pct Women (t-1)	Percent women on preceding paper	IV	0.315	0.257
First & Last Authors on Current Paper				
F+L Female	1 if both female; 0 otherwise	DV/ IV	0.090	-
F+L Male	1 if both male; 0 otherwise	DV/ IV	0.519	-
F+L Mixed	1 if mixed sex; 0 otherwise	IV	0.390	-
First & Last Authors on Preceding Paper				
F+L Female (t-1)	1 if both female; 0 otherwise	IV	0.088	-
F+L Male (t-1)	1 if both male; 0 otherwise	IV	0.522	-
F+L Mixed (t-1)	1 if mixed sex; 0 otherwise	IV	0.390	-
Citations (log)	The natural logarithm of citations	DV	3.780	1.143
Pre-Grant Contact	1 if pre-F32 grant contact; 0 otherwise	CV	0.091	-
Fiscal Year*	Fixed Effects for start year of F32 grant	CV	1997	-
Publication Year*	Fixed Effects for year of a publication	CV	2002	-
First Author	1 if F32 was first author; 0 otherwise	CV	0.518	-
No. Authors	Number of authors on a paper	CV	5.674	6.881
5-year JIF	5-year journal impact factor	CV	5.489	7.147
5-year JIF (t-1)	5-year journal impact factor on preceding paper	CV	5.538	7.277
Grant Extended	1 if F32 grant was extended; 0 otherwise	CV	0.290	-
Mentor among Coauthors	1 if mentor is coauthor; 0 otherwise	CV	0.592	-
Mentor Experience	Years since first publication	MV	19.149	8.661
Share of HQ Papers	Articles (%) in journals with impact >15	MV	0.079	0.100
Unique Coauthors (Netw.)	Unique coauthors within 10 years prior to F32 Grant	MV	67.156	61.761
Share of Female Coauthors (Netw.)	Proportion of female coauthors	MV	0.274	0.126
Content Overlap	Share of identical MeSH terms	MV	0.234	0.143
Observations				20,487

*Note: For Fiscal Year and Publication Year we report median instead of mean values

MV (matching variable); DV (dependent variable); IV (independent variable); CV (control variable)

Table 2: Variable Description and Descriptive Statistics

Dependent Variable	*Pct Women*				
	(1)	(2)	(3)	(4)	(5)
Pct Women (t-1)	0.598***	0.524***	0.496***	0.484***	0.446***
	(0.008)	(0.010)	(0.010)	(0.010)	(0.013)
F+L Female (t-1)		0.069***	0.073***	0.072***	0.065***
		(0.009)	(0.009)	(0.008)	(0.010)
F+L Mixed (t-1)		0.0455***	0.047***	0.046***	0.044***
		(0.004)	(0.004)	(0.004)	(0.005)
No. Authors			0.0004*	0.0004*	0.0005*
			(0.000)	(0.000)	(0.000)
First Author			0.0002	-0.0009	-0.001
			(0.003)	(0.003)	(0.004)
Pre-Grant Contact			-0.0005	-0.003	-0.007
			(0.006)	(0.006)	(0.010)
Grant Extended			-0.002	-0.002	0.001
			(0.004)	(0.004)	(0.007)
5-year JIF (t-1)			0.0002	0.0003	0.0002
			(0.000)	(0.000)	(0.000)
Mentor Experience				-0.00005	
				(0.000)	
Share of HQ Papers				-0.0438*	
				(0.019)	
Unique Coauthors (Netw.)				-0.00007*	
				(0.000)	
Share of Female Coauthors (Netw.)				0.162***	
				(0.018)	
Content Overlap				-0.002	
				(0.012)	
Publ. Year Fixed Effects (26 years)			X	X	X
Field Fixed Effects (20 fields)			X	X	X
Fiscal Year Fixed Effects (21 years)			X	X	X
Matching on Network (593 strata)					X
Constant	0.132***	0.131***	0.061	0.043	0.156
	(0.003)	(0.003)	(0.111)	(0.113)	(0.131)
Observations	20487	20487	20487	20487	20487
Adjusted R^2	0.361	0.366	0.376	0.381	0.388

Standard errors (clustered by F32 recipient and mentor) in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Homophily in Co-Authoring Behavior

Dependent Variable	*F+L Female*	*F+L Male*	*F+L Female*	*F+L Male*
	(6)	(7)	(8)	(9)
F+L Female (t-1)	0.228***		0.166***	
	(0.015)		(0.017)	
F+L Male (t-1)		0.109***		0.068**
		(0.018)		(0.022)
F+L Mixed (t-1)	-0.012*	-0.053***	-0.011	-0.051**
	(0.005)	(0.013)	(0.007)	(0.017)
Pct Women (t-1)	0.231***	-0.649***	0.239***	-0.642***
	(0.014)	(0.019)	(0.017)	(0.026)
No. Authors	-0.0003	0.001**	-0.0003	0.001**
	(0.000)	(0.000)	(0.000)	(0.001)
First Author	0.011	-0.043***	0.008	-0.043**
	(0.005)	(0.011)	(0.006)	(0.014)
Pre-Grant Contact	-0.009	0.004	-0.010	0.010
	(0.007)	(0.013)	(0.011)	(0.022)
Grant Extended	-0.004	0.002	-0.0005	-0.010
	(0.005)	(0.008)	(0.009)	(0.014)
5-year JIF (t-1)	-0.0001	-0.0007	-0.00002	-0.0008
	(0.000)	(0.000)	(0.000)	(0.001)
Mentor Experience	-0.0008**	-0.0003		
	(0.000)	(0.000)		
Share of HQ Papers	-0.031	0.060		
	(0.021)	(0.039)		
Unique Coauthors (Netw.)	-0.000001	0.00008		
	(0.000)	(0.000)		
Share of Female Coauthors (Netw.)	0.109***	-0.184***		
	(0.022)	(0.035)		
Content Overlap	0.044*	-0.028		
	(0.017)	(0.027)		
Publ. Year Fixed Effects (26 years)	X	X	X	X
Field Fixed Effects (20 fields)	X	X	X	X
Fiscal Year Fixed Effects (21 years)	X	X	X	X
Matching on Network (593 strata)			X	X
Constant	0.122	1.015***	0.147	0.979***
	(0.114)	(0.135)	(0.133)	(0.127)
Observations	20487	20487	20487	20487
Adjusted R^2	0.161	0.225	0.201	0.246

Standard errors (clustered by F32 recipient and mentor) in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Homophily among Lead Authors

Dependent Variable	*F+L Female*	*F+L Female*	*F+L Female*	*F+L Male*	*F+L Male*	*F+L Male*
	(10)	(11)	(12)	(13)	(14)	(15)
GROUPS						
Mentor among Co-Authors	YES	NO	NO	YES	NO	NO
F32 Recipient First Author	-	YES	NO	-	YES	NO
F+L Female (t-1)	0.184***	0.149**	0.033			
	(0.024)	(0.049)	(0.036)			
F+L Male (t-1)				0.060*	0.028	0.085
				(0.030)	(0.057)	(0.052)
F+L Mixed (t-1)	-0.016	-0.005	0.012	-0.059**	-0.124**	0.050
	(0.009)	(0.017)	(0.015)	(0.021)	(0.042)	(0.045)
Pct Women (t-1)	0.256***	0.308***	0.110**	-0.739***	-0.781***	-0.134*
	(0.025)	(0.049)	(0.040)	(0.036)	(0.071)	(0.068)
No. Authors	0.0003	-0.003	-0.003*	0.0004	0.001	0.005**
	(0.000)	(0.002)	(0.001)	(0.000)	(0.005)	(0.002)
First Author	0.009			-0.043*		
	(0.008)			(0.017)		
Pre-Grant Contact	-0.007	-0.020	0.026	0.015	-0.001	-0.049
	(0.016)	(0.039)	(0.042)	(0.031)	(0.098)	(0.072)
Grant Extended	-0.006	-0.0003	0.010	-0.018	0.008	0.0003
	(0.012)	(0.028)	(0.030)	(0.020)	(0.047)	(0.045)
5-year JIF (t-1)	0.0003	-0.0006	-0.0008	-0.001	-0.001	0.0009
	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Publ. Year Fixed Effects (26 years)	X	X	X	X	X	X
Field Fixed Effects (20 fields)	X	X	X	X	X	X
Fiscal Year Fixed Effects (21 years)	X	X	X	X	X	X
Matching on Network (593 strata)	X	X	X	X	X	X
Constant	-0.012	0.413	-0.099	1.155***	0.731*	0.779**
	(0.042)	(0.291)	(0.107)	(0.099)	(0.339)	(0.298)
Observations	12122	3668	4697	12122	3668	4697
Adjusted R^2	0.307	0.396	0.198	0.336	0.575	0.205

Standard errors (clustered by F32 recipient and mentor) in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Homophily among Lead Authors - Split Sample

Dependent Variable	*Citations (log)*		
	(16)	(17)	(18)
F+L Fem.	-0.198***	-0.173***	-0.113*
	(0.045)	(0.045)	(0.050)
F+L Mixed	-0.0604**	-0.0452*	-0.0623*
	(0.023)	(0.023)	(0.025)
Pct Women	0.0961	0.0645	0.0545
	(0.057)	(0.057)	(0.067)
First Author	-0.232***	-0.175***	-0.137***
	(0.019)	(0.021)	(0.021)
Mentor among Co-Authors	0.238***	0.245***	0.0752*
	(0.024)	(0.024)	(0.029)
No. Authors		0.0226***	0.0129***
		(0.004)	(0.002)
Field Fixed Effects (20 fields)	X	X	X
Publ. Year Fixed Effects (26 years)	X	X	X
Journal Fixed Effects (1830 journals)			X
Constant	2.808***	2.705***	3.147***
	(0.593)	(0.583)	(0.886)
Observations	20487	20487	20487
Adjusted R^2	0.042	0.060	0.415

Standard errors (clustered by F32 recipient and mentor) in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Citation Discount for Female Lead Author Teams

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