Better Together? Faculty, Gender Match, and Credit in Science*

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Abstract

We use unique, linked data on biomedical researchers and an extended Abowd et al. (1999)-style design to study the role of leaders in providing opportunities to researchers. Specifically, we study how women principal investigators (PIs) affect gender disparities among the faculty on their projects. We find that research teams with more women PIs are significantly more supportive of female faculty in three major ways. First, teams with more female leaders employ a larger share of women on their teams. Second, using researcher-year and paper fixed effects to account for unobserved characteristics, we find that teams with women leaders give significantly more credit—in terms of authorship—to female faculty who work on those teams, with the largest effect on high impact papers and in heavily-male fields. Third, the impact of female PIs extends beyond the time female faculty are part of the teams, leading to an increase in the number of co-authored papers with female PIs after female faculty leave the teams. Our estimates are strongest for the most productive women, suggesting that, although women leaders tend to narrow the gender gap in authored papers, they seem to perpetuate within-group inequality in authorship for women.

*We take responsibility for all the mistakes.

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1 Introduction

Observers have pointed to leaders as a way of engaging and generating opportunities for all members of society.[1] This paper leverages linked data that provides unique detailed information on leaders, their teams, and associated outcomes, along with an empirical approach that controls for unobserved characteristics, to examine the influence of women leaders on their team members. Specifically, we analyze how principal investigators (PIs) on biomedical research projects impact the rate at which female faculty collaborators are credited as co-authors on publications, a highly consequential outcome, that affects retention, promotion, tenure, access to resources, and compensation (Ross et al. (2022)).

Our analysis leverages longitudinal, transaction-level UMETRICS data on all people supported on sponsored research projects, including their job titles and effort allocation, at 31 universities covering 40% percent of academic R&D in the United States (Institute for Research on Innovation and Science (IRIS) Research Team (2019)). UMETRICS data allow us to identify the full set of researchers involved in research activities whether or not they ever appear as authors on articles. We link these data to publication data from the Author-ity disambiguation of MEDLINE. The final dataset mimics employer-employee data, allowing us to employ and extend methods akin to Abowd et al. (1999) to obtain plausibly random variation across teams on short-term outcomes.

Biomedicine is a valuable context for studying the role of female leaders on their teams for several reasons. First, there is substantial variation in women's representation across biomedical fields. Second, the leaders of STEM teams can be easily identified from the PIs on NIH grants, allowing for a clear examination of the effect of different leadership composition on credit allocation. Third, broad and full participation can be particularly valuable in biomedicine for progress on women's and minority health (Koning et al. (2020, 2021)).[2]

We begin with a descriptive analysis of how the gender composition of PIs influences who is employed on research projects. Our findings indicate that a higher share of women PIs leads to more women on projects across all five occupations studied: faculty, postdoctoral researchers, graduate students, research staff, and other staff. Focusing on credit attribution, teams led

[1] Matsa and Miller (2011); Bednar and Gicheva (2014); Kunze and Miller (2017); Bertrand et al. (2019); Flabbi et al. (2019); Bossler et al. (2020); Maida and Weber (2022).

[2] See also Nielsen et al. (2017); Dossi (2024); Yang et al. (2022) more broadly.

by men tend to allocate more credit to men than to women across all occupational categories. Teams led by women eliminate or even reverse the gender credit gap seen in male-led teams. The largest increase is seen among faculty, where the credit attribution rate for female faculty more than doubles—from 9% under male PIs to 19% under female PIs.[3]

Motivated by these findings, we focus our empirical analysis on the effects of female PIs on female faculty, employing an enhanced Abowd et al. (1999)-style design. Specifically, we leverage the fact that, in many cases, faculty work on multiple projects at a point in time. This allows us to control for time-varying differences in "motivation" and "ability" using fixed effects for individuals interacted with time and for differences across publications using article fixed effects. Our finding that teams led by women give more authorship credit to women is remarkably robust to the inclusion of these fixed effects. We reinforce our main results by showing that the PIs with the most decision-making authority on an article (those who are included as authors on it) have a stronger influence on female faculty outcomes than all PIs.

Next, we examine several dimensions of heterogeneity in the impact of female PIs on female faculty. First, we investigate how credit attribution varies with the impact of the article and the authorship position. While the failure to provide proper credit is problematic in all cases, its consequences are particularly significant for highly impactful papers and for the most prestigious authorship positions. To examine impact, we categorize papers published by research teams into high- and low-impact groups and find that female PIs have a greater influence on the likelihood of female faculty being credited as authors on high-impact papers. We also examine whether the increased authorship credit is greater or smaller for prestigious first or last authorship positions versus less important middle authorship positions. While the point estimates are larger for middle authorship positions, given the far greater number of middle authors, in percentage terms the effects are larger for first and last authors. Thus, the effects on credit are actually greatest when the likely consequences are largest.

Second, we explore whether women leaders are equally supportive of all female faculty or if they are most supportive of the most or least well-established female faculty. If women PIs tend to support less established women, that would help develop women for future leadership roles

[3]Although all PIs in our sample are faculty, not all faculty are PIs (and even when they are, they might collaborate on projects on which they are not PIs). Throughout the paper, we make this distinction explicit. We also use "male" and "female" as adjectives and "man" and "woman" as nouns.

such as becoming PIs in their own right. On the other hand, if women leaders tend to support the most productive female faculty, that would enhance leadership among successful women, but may be less effective in elevating other women to top positions. Using differences in female faculty's past productivity, we show that women leaders tend to support highly productive women more than less productive women. Thus, while teams with more female PIs tend to reduce the gap between women and men on average, they may increase disparities among women.

Third, we examine whether and how the gender composition of fields mediates the effects of female leaders on the credit received by female faculty. We find that women leaders are particularly valuable in heavily-male fields.[4] This finding echoes recent evidence provided by Funk et al. (2024)–that uses data from three different heavily-male university departments—and shows that when the faculty roster is very gender unbalanced, female students are more likely to enroll in elective courses taught by female instructors. Similarly, our results suggest that in heavily-male fields, female faculty exhibit a preference for collaborating with other women.[5]

We conclude by exploring how having been part of a team with a larger share of women PIs relates to subsequent productivity and collaborations. We find that there is a significant increase in collaborations between female PIs and faculty in the years after female faculty leave the focal research team. Although our design does not allow us to directly address causality, we find that being on a female-led team is associated with prolonged collaborations between female faculty and their female PIs.

Why might the gender of team leaders affect the credit that women receive? First, female leaders may create a more equitable environment, attributing credit in a way that more fully recognizes the contributions of other women. A second possibility is that female leaders might place other women in roles of responsibility to a greater extent than men do or women may be more active on projects with women leaders. In either case, female leaders may lead women to make contributions that justify greater credit. A third possibility is that more productive

[4]Heavily-male research areas are defined as areas where the share of unique female authors is below the median, calculated across all fields.

[5]Funk et al. (2024) also show that female instructors in heavily-male departments receive less favorable teaching evaluations from male students compared to female students. These differences in perceived performances across genders might explain why faculty tend to work with other women faculty in heavily-male fields.

women might be more likely to join female-led teams. The first two explanations involve a causal effect of female PIs while the third explanation is based on selection. Our analysis shows that, in our setting, the causal mechanisms seem more plausible than selection, with female PIs likely treating members of their teams differently rather than attracting the most productive researchers.

Unfortunately, our data do not allow us to assess what is the "right level of equity"—that is, whether female PIs help women because male PIs give too little credit to women or because female PIs give too much credit to women (or both). Having said that, Ross et al. (2022) surveyed authors regarding their contributions to papers and found that women contributed more to the articles that they were credited on than men, suggesting that male PIs (and perhaps even female PIs) may tend to under-include women as authors.

Our paper fits into two literatures. The first literature is on gender disparities in STEM. This literature is quite large and goes beyond our ability to summarize fully.[6] Work in this space generally finds gender gaps in a wide range of outcomes such as earnings (Buffington et al. (2016); Kim et al. (2023)) and promotions (Ginther and Kahn (2004)). Studies have also focused on science-specific outcomes such as authorship,[7] publications (Huang et al. (2020)), citations (Huang et al. (2020), Hofstra et al. (2020)), and funding.[8] A sizeable literature finds evidence for disparities in commercial outcomes including patenting,[9] entrepreneurship,[10] university-industry collaborations (Tartari and Salter (2015)), and technology licensing (Thursby and Thursby (2015)). Work has also sought to unpack the mechanisms that might perpetuate disparities. These include recognition for contributions to group work (Sarsons et al. (2016)), specialization (Leahey et al. (2008)), isolation (Kemelgor and Etzkowitz (2008)), and networks (Cheng and Weinberg (2023)).[11] From this literature, we draw on author inclusion, which was, to the best of our knowledge, first analyzed systematically by Ross et al. (2022).

[6] Prominent examples by non-economists include Wenneras and Wold (2010); Lariviere et al. (2013); Ceci et al. (2014).

[7] See Fong and Wilhite (2017); Lerchenmüller et al. (2018); West et al. (2013); Cikara et al. (2012); Marschke et al. (2018)

[8] See Ley and Hamilton (2008); Ginther et al. (2016).

[9] See Ding et al. (2006); Marx and Fuegi (2021); Whittington and Smith-Doerr (2005).

[10] See Hebert (2023); Blume-Kohout (2014); Guzman and Kacperczyk (2019).

[11] Although less relevant to our context, one line of this larger literature studies gender disparities among academic economists. This literature has explored a wide range of mechanisms, including the refereeing process (Card et al. (2020)), seminar dynamics (Dupas et al. (2021)), and citation patterns (Koffi (2021)).

Our work also fits into a larger literature on the effects of leaders on disparities.[12] Our work belongs to the intersection of these literatures, studying the effects of leaders on disparities in a scientific setting using the richness of data that are uniquely available for academia and outcomes that are highly salient.[13]

The rest of the paper is organized as follows. Section 2 describes our data. Section 3 outlines the empirical model. Section 4 presents our results and section 5 concludes. Additional materials can be found in Appendices.

2 Data, Sample Selection, and Descriptive Statistics

2.1 Data

This section details our two main datasets. The first dataset is the administrative UMETRICS data that provides unprecedented detail on the structure, composition, and inputs of research projects and teams. The second is high-quality, disambiguated, longitudinal data on biomedical publications from Author-ity.

The UMETRICS dataset contains administrative data on over 23 million payroll transactions covering 643,464 unique employees (175,567 of whom were paid on NIH grants) at 31 major research universities between 2001 and 2018 (Institute for Research on Innovation and Science (IRIS) Research Team (2019)). Although these institutions may not be representative of all universities in the U.S., they collectively account for more than 40% of federally funded academic R&D during this time period and cover a wide range of research-intensive institutions (e.g., public and private institutions, institutions with and without medical schools, and institutions with multiple campuses that may be less research intensive). To the best of our knowledge, this is the most comprehensive dataset on how grant funding is allocated among university-based, grant-funded researchers. The administrative nature of UMETRICS data allows us to identify the entire constellation of research teams engaged in conducting research, including people who were not included as authors on articles. The data also allows us to capture detailed information on (i) demographic characteristics of researchers such as gender, race,

[12] See Matsa and Miller (2011); Bednar and Gicheva (2014); Kunze and Miller (2017); Bertrand et al. (2019); Flabbi et al. (2019); Bossler et al. (2020); Maida and Weber (2022).

[13] Kim (2021) studies female department chairs and their impacts on female faculty.

ethnicity (all algorithmically imputed), and birth year; (ii) the time they spent on each grant; and (iii) their occupation. We divide researchers into five groups based on their occupation: faculty (including assistant, associate, and full professors); postdoctoral researchers; graduate students; researchers; and staff.[14] We are also able to identify the PIs of these projects. It should be noted that although all PIs in our sample are faculty, not all faculty are PIs on all projects on which they are employed.

The second dataset that we use is the 2019 release of the Author-ity dataset (Torvik et al. (2005); Torvik and Smalheiser (2009)). Author-ity provides a high-quality disambiguation of the authors in the PubMed database which covers over 30 million publications mostly related to biomedical fields. For each publication, we complement this dataset with information, collected from MEDLINE, on authors, acknowledged grants, and year of publication. By matching the resulting dataset with UMETRICS, we can identify all the papers sponsored by a specific NIH grant and identify which of the researchers paid on each grant are credited as authors on each article, including as first- or last-author.

Matching researchers in the UMETRICS dataset to those in Author-ity based only on names is a challenging task because of variations in the reporting of names and the presence of common names. To overcome this challenge, we adopt a four-step procedure which leverages the fact that in both datasets we observe grants. First, we assign each publication in Author-ity to researchers in UMETRICS based on the grants acknowledged in the publication. Second, we search for the authors listed on the publication among the people who were paid at least once by the acknowledged grants. Limiting the search to authors who are paid by specific grants reduces the search space (and consequently the computational burden) as well as the likelihood of false matches for common names. Each individual identified through this procedure is assigned a unique identifier corresponding to the authored paper and their position on the authorship list. Third, every researcher who was assigned at least one publication in the previous step is linked to their Author-ity cluster, which allows us to identify papers that the researcher published before and after they were paid on any UMETRICS project as well as any that (rightly or wrongly) do not acknowledge NIH funding. Finally, we extend the thus-obtained dataset by looking for authors that we might have missed in the first step by taking advantage

[14] We have data on undergraduates students, but exclude them from the analysis given our focus on publications.

of the network of collaborators. More precisely, we take all the papers associated with the focal researcher and then search for their coauthors among the people who collaborated with that researcher on at least one project (not necessarily the ones acknowledged in the paper). This procedure is repeated until convergence and results in a dataset of 162,195 researchers who were paid on NIH grants between 2001 and 2018.

2.2 Sample Selection and Descriptive Statistics for All Researchers

Given the initial set of 162,195 researchers who were paid on NIH grants that resulted in at least one publication, we further limit our sample to researchers who authored at least one paper during our time frame.[15] Similarly, we exclude undergraduate students from our sample. These restrictions result in a sample of 57,292 researchers. For each researcher, we impute their gender, race, and ethnicity based on their names.[16] Given our interest in credit attribution to researchers according to their gender, our primary results are further limited to the sample of researchers for whom we were able to impute gender, although we provide robustness checks that include people with ambiguous gender imputations.[17] We additionally limit the sample to researchers with unique UMETRICS and Author-ity identifiers. Our final sample consists of 29,472 unique researchers for whom we have a birth year; imputed gender, race, and ethnicity; who have authored at least one paper; who received at least one payment from an NIH-sponsored project in UMETRICS; and who are not undergraduate students.

Our primary analysis defines teams at the paper level. That is, a team in our analysis consists of all researchers who were paid by and were part of NIH grants that were acknowledged by the paper during the year the paper was published or one year before (to allow for a potential lag in the publication process, which tends to be shorter in biomedicine than in economics).[18] This means that if, for example, a paper published in 2005 acknowledges two NIH grants, we

[15] Although this restriction is most relevant for our initial analysis than our main analysis, this sample restriction allows us to drop individuals who are, for instance, responsible for technical support and are unlikely to make contributions that qualify for authorship.

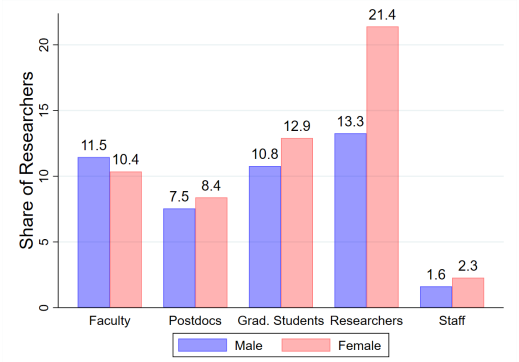
[16] In addition to inaccuracies in these imputations, we note that they are discrete and static and do not necessarily reflect individual self-identification.

[17] Figure A.2 in Appendix A illustrates that approximately 15% of researchers' genders could not be imputed. This limitation is particularly pronounced for Asian names, where the original characters often convey gender information that is lost when translated into the English alphabet.

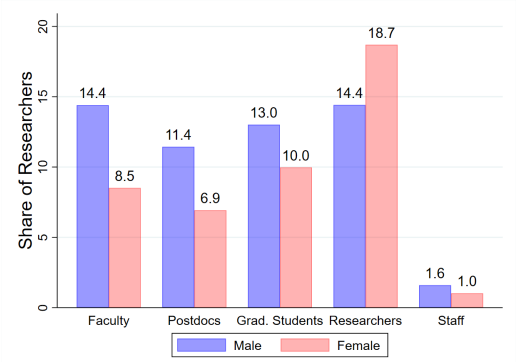
[18] We have explored lags in publications of up to 3 years and our results are robust.

consider all researchers funded by either grant in 2004 or 2005 to be eligible to be authors.[19]

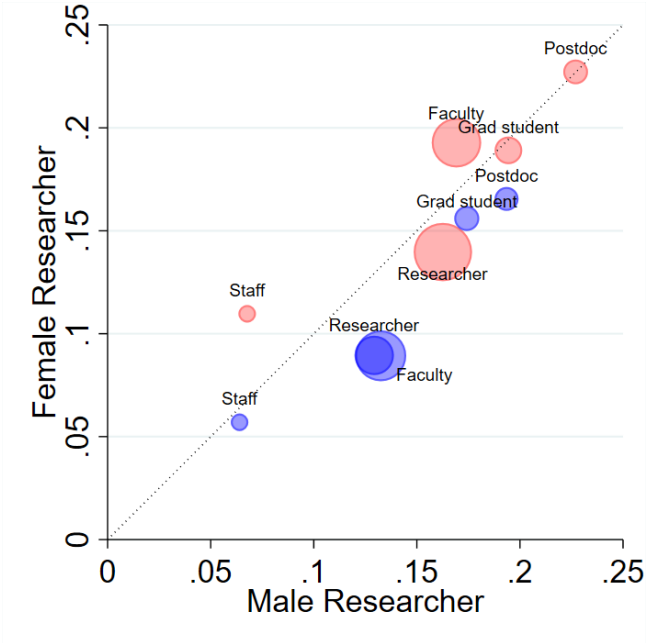
Figure 1. Descriptive Statistics by Researcher and PI Gender



(a) Share of Researchers by Occ. in Female-Led Teams



(b) Share of Researchers by Occ. in Male-Led Teams



(c) Share of Papers Authored by Occ. in Female- and Male-Led Teams

Notes. The Figures present descriptive statistics for researchers in our sample by the gender of PIs. Female-led teams are defined as those teams where half or more of the PIs are women. Panels A and B plot the share of researchers on female-led and male-led teams who are men (blue) and women (pink) by occupation with the all the bars in each Panel summing to 1. The blue (pink) circles in Panel C indicate the share of eligible papers that female researchers in each occupation are credited on relative to male researchers on male-led (female-led) teams. Occupations are sized in proportion to the employment share of that occupation in these teams. Points below the 45-degree line indicate that men in a given occupation are more likely to receive credit than women in the same occupation on a team with a PI of the indicated gender.

For each paper, our primary analysis defines team leaders as the Principal Investigators (PIs) associated with the NIH grants acknowledged in the paper. UMETRICS identifies PIs using the names provided by the NIH. Panel A of Figure A.1 in Appendix A illustrates the

[19]On average, papers in our sample acknowledge 1.7 NIH grants.

distribution of PIs across teams, revealing that approximately 50% of teams have only one PI. However, due to a right-skewed distribution in the number of PIs, the average team has 4 PIs.

We begin our analysis by presenting descriptive statistics for the full sample of 29,472 researchers (including faculty, postdoctoral scholars, graduate students, researchers, and staff). The data are categorized by whether the researchers were part of "female-led" or "male-led" teams, with "female-led" teams defined as those teams where women constitute half or more of the PIs. Panel B of Figure A.1 shows that approximately 20% of the teams in our sample were female-led. Regarding the occupational composition of researchers, Panel A of Figure 1 indicates that female-led teams generally had a higher share of female researchers than male researchers in all occupations except faculty.[20] Panel B, in contrast, shows that male-led teams generally had a higher share of men than women across all occupations except for research staff. Thus, while there are baseline differences in the share of people in each occupation who are women and men, the share of women relative to men is consistently higher in female-led teams compared to male-led teams. This pattern is particularly pronounced among faculty: in male-led teams, 14.4% are male faculty compared to 8.5% female faculty, whereas in female-led teams, the difference narrows significantly to approximately one percentage point (11.5% male faculty versus 10.4% female faculty).

To assess whether PIs tend to attribute credit more to researchers of the same gender, Panel C of Figure 1 explores the extent to which male-led teams are more likely to include men relative to women as authors on articles compared to female-led teams. Blue (pink) dots represent researchers in male-led (female-led) teams and their size is proportional to the employment share of each occupation in these teams. Points below the 45-degree line indicate that men in a given occupation are more likely to receive credit than women in the same occupation. If teams assign authorship equally (i.e., with men and women in each occupation being equally likely to receive credit), all the dots would lie on the 45-degree line. The Panel highlights that, conditional on being eligible, male researchers in male-led teams—with the exception of staff—were more likely to be included as authors on papers than female researchers in the same occupation. For instance, the blue dot for faculty shows that male faculty on male-led teams were authors on 13% of the papers they were eligible to author compared to 9% of female faculty.

[20]Figure A.2 in Appendix A presents analogous results including researchers whose imputed genders are ambiguous.

By contrast, female faculty on female-led teams were more likely to be included as authors compared to their male counterparts. For instance, female faculty on female-led teams are authors on around 19% of the papers, as opposed to 17% for male faculty. Altogether, Panel C shows that female PIs tended to attribute significantly more credit to faculty compared to their male counterparts: 18% vs. 11%. The same pattern holds for researchers in other occupations but to a lesser extent. Considering substantial differences in the likelihood of authorship in female- and male-led teams of faculty of the same gender—that do not seem to be as stark for researchers in other occupations—in the rest of the paper we focus on faculty. (We note that, in percentage terms, the difference between male and female-led teams in the gender gap in attribution for staff is comparable to that for faculty, but the difference is smaller in levels and faculty constitute a considerably larger group than staff.)

2.3 Descriptive Statistics for Faculty

Table 1 reports descriptive statistics for our sample. Columns (1) and (2) report the means and standard deviations for female-led teams and columns (3) and (4) report the means and standard deviations for male-led teams. Panel A reports team-level statistics which show that, on average, male-led teams tend to be larger than female-led teams (24 vs 18 researchers) and were supported by longer grants (3.8 years vs 3.1 years). The substantial differences in the size of male- and female-led teams translate into differences in the number of papers researchers are eligible to be potential authors. Table 1 shows that researchers on male-led teams are eligible to author substantially more papers than their counterparts on female-led teams: 59 vs. 31 papers, on average.

Panels B and C of Table 1 present summary statistics for female and male faculty in our sample, respectively. Panel B indicates that female-led teams tended to have a higher proportion of White faculty, whereas male-led teams had a greater share of Asian faculty (13–15%). Additionally, the Table shows that, on average, faculty on female-led teams were supported for shorter durations (4.3–4.5 years) compared to faculty on male-led teams (5.7–6.2 years). The average number of authors per article was roughly three for both female- and male-led teams. However, female faculty on female-led teams authored an average of 5.52 papers, compared to around 7 papers on male-led teams. Similarly, male faculty authored 6.33 papers on female-led

teams and 7.74 papers on male-led teams.

Table 1: Descriptive Statistics for Researchers in Female- and Male-Led Teams

	Female-Led Teams		Male-Led Teams	
	Mean	St.dev.	Mean	St.dev.
Panel A: Statistics at the Team Level				
Team Size	**17.80**	18.13	**24.38**	24.96
Avg. Grant Duration (Years)	**3.11**	3.79	**3.80**	5.02
Avg. Number of Published Papers	**30.90**	58.22	**58.81**	98.36
Observations	7,724		21,748	
Panel B: Statistics for Female Faculty				
White (Dummy)	**0.88**	0.33	**0.79**	0.41
Asian (Dummy)	**0.06**	0.24	**0.13**	0.33
Hispanic (Dummy)	0.04	0.20	0.05	0.22
Black (Dummy)	0.02	0.15	0.03	0.18
Number of Years on Grants	**4.30**	4.70	**5.77**	7.26
Number of Authors on Papers	**2.93**	1.20	**3.08**	1.11
Number of Authored Papers	**5.52**	5.79	**7.05**	6.97
Share of Authored Papers	**0.19**	0.24	**0.09**	0.15
Above Avg. Prod. (Dummy)	0.49	0.00	0.51	0.00
Observations	762		1,744	
Panel C: Statistics for Male Faculty				
White (Dummy)	**0.85**	0.36	**0.79**	0.41
Asian (Dummy)	**0.10**	0.30	**0.15**	0.36
Hispanic (Dummy)	0.03	0.18	0.03	0.17
Black (Dummy)	0.02	0.13	0.02	0.16
Number of Years on Grants	**4.52**	5.31	**6.21**	7.58
Number of Authors on Papers	**3.04**	1.21	**3.12**	1.14
Number of Authored Papers	**6.33**	6.48	**7.74**	7.18
Share of Authored Papers	**0.17**	0.24	**0.13**	0.19
Above Avg. Prod. (Dummy)	0.47	0.00	0.51	0.00
Observations	865		2,998	

Notes. The Table reports descriptive statistics for faculty in our main sample. Numbers in bold are statistically significantly different between female- and male-led teams at the 10% level. Columns (1) and (2) report the means and standard deviations for female-led teams and columns (3) and (4) report the means and standard deviations for male-led teams. Panel A reports team-level statistics. Panels B and C of Table 1 present summary statistics for female and male faculty.

Despite female faculty in female-led teams authoring fewer papers overall, panel B shows that they were more likely to be credited as authors on a higher share of eligible papers. Specifically, attribution rates for female faculty were 19% on female-led teams and 9% on male-led teams. There are both causal and selection-based factors that might explain why women have higher attribution rates on female-led teams than on male-led teams. On one hand, female PIs may be more likely to allocate credit or responsibilities to women on their teams. On the other hand, more productive female researchers might prefer to join female-led teams. To investigate the plausibility of the selection-based explanation, the last rows of panels B and C in Table 1 examine whether highly productive researchers are more likely

to join female- or male-led teams. We find that highly productive researchers—defined as those who have an above-median number of papers before they joined the team by birth year, race, and the year they entered the team—were actually slightly more likely to join male-led teams. Specifically, among female faculty, 48% of those who joined female-led teams were highly productive, compared to 51% of those who joined male-led teams. This finding suggests that female PIs may not necessarily attract the most productive researchers, paving the way for our empirical analysis that formally explores whether female PIs interact differently with their faculty team members compared to male PIs.

3 The Empirical Model and Its Identification

The central question of this paper is whether the proportion of female leaders—measured as the share of female PIs—in a research team affects the likelihood of team members being credited as authors on publications produced by those teams. A team in our empirical framework is defined as all faculty who were paid by NIH grants that were acknowledged by the paper during the year the paper was published or one year before (to allow for a potential lag in the publication process, which tends to be shorter in biomedicine than in economics).[21]

To estimate the impact of female PIs on credit attribution to faculty, let $\boldsymbol{X}_i$ and μ_{ig} represent the observable (birth year, race/ethnicity, and the logarithm of the number of days employed on the grant) and unobservable characteristics of faculty i who worked on grant g, respectively. Moreover, let $Female_i$ be a binary variable that takes a value of 1 if faculty i is female and 0 otherwise. Additionally, let $\boldsymbol{Paper}_{gp}$ contain observable characteristics of paper p and the set of acknowledged grants g that produced it: the logarithm of the number of potential authors (i.e., all researchers that were employed by the set of grants g), the logarithm of the number of listed authors, the paper's publication year, and university fixed effects. Also, let $ShareFemalePI_p$ capture the share of female PIs on a research team(s) that produced paper p. Additionally, let ν_{gp} include the unobservable characteristics at the paper/grant level. Finally, let ϵ_{igp} represent the error term, which is clustered at both the faculty and paper levels unless specified otherwise. Then faculty i's likelihood of being included as an author on paper p, Y_{ip}, can be represented

[21] In other words, two distinct papers published in the same year and that acknowledge the same set of grants will have the same set of potential authors.

as:

$$\begin{aligned} Y_{igp} =& \alpha_0 + \alpha_1 Female_i \times ShareFemalePI_p + \alpha_2 Female_i \\ &+ \alpha_3 ShareFemalePI_p + \alpha_4 \boldsymbol{X}_i + \alpha_5 \boldsymbol{Paper}_{gp} + \mu_{ig} + \nu_{gp} + \epsilon_{igp} \end{aligned} \tag{1}$$

where α_1 captures the effect of a one percentage point increase in the share of female PIs on a team on the probability that female faculty are included as authors, relative to male faculty.[22]

The estimates obtained using the OLS model in equation (1) may be biased since the selection of researchers into teams with different shares of female PIs may not be random. For instance, female faculty might be more likely to join female-led teams focusing on conditions relevant to women's health. Moreover, the strength of such sorting could vary over time (e.g., be particularly pronounced during periods when women's health issues are receiving more or less attention). Thus, to account for time-varying unobservable characteristics of faculty, we modify equation (1) by including faculty fixed effects interacted with year fixed effects, $Faculty \times PubYearFE_i$. To control for field/paper characteristics, such as quality and field norms, we include paper fixed effects. Note that paper fixed effects subsume team fixed effects and therefore also control for team characteristics such as productivity. These two-way fixed effects estimates are an enhanced version of Abowd et al. (1999), where paper fixed effects play the role of firm fixed effects, which we allow to vary over time. Under the assumption that the faculty × publication year fixed effects adequately control for individual differences in the level of contribution that would justify authorship and that the paper fixed effects control for differences in the probability that team members are included on each article and for other article-related characteristics (e.g., field and number of authors), these estimates can be interpreted causally. Formally, we estimate:

$$\begin{aligned} Y_{igp} =& \beta_0 + \beta_1 Female_i \times ShareFemalePI_p \\ &+ Faculty \times PubYearFE_i + PaperFE_{gp} + \xi_{igp} \end{aligned} \tag{2}$$

where β_1 captures the effect of a one percentage point increase in the share of female PIs on

[22]Note that, the unit of observation in our empirical model is at the faculty-grant-paper level. As a result, each faculty-paper pair appears in the dataset once for every grant that supported the faculty member and is acknowledged in the paper. To avoid double counting, we reweight each observation so that every faculty–paper pair has a total weight of 1. For instance, if a researcher is supported by two grants, both acknowledged in the paper, each corresponding observation is assigned a weight of 0.5.

a paper on female faculty's likelihood of being included as an author relative to male faculty, controlling for both unobservable time-varying faculty and paper characteristics.

4 Empirical Analyses

4.1 Main Analyses

Table 2 presents OLS and FE estimates of the relationship between the gender composition of team leaders and attribution for our main sample that contains 697,251 observations for 6,372 faculty between 2001 and 2018. OLS estimates in Column 1 show that a 10 percentage point (p.p.)–equivalent to 0.42 standard deviations–increase in the share of female PIs on a team is associated with an increase in female faculty's authorship likelihood of 0.5 p.p., which is 29% of the gender gap of 1.7 p.p. In contrast, the share of female PIs appears unrelated to male faculty authorship probabilities (the point estimate is -0.001 and the standard error is 0.008). Additionally, Column 1 shows that authorship attribution is lower on larger teams—a 10% increase in team size corresponds to a 0.9 p.p. reduction in the probability of being credited as an author. Conversely, an increase in the number of authors is associated with a 0.33 p.p. rise in authorship probability. Finally, controlling for the number of days faculty are employed on the grant does not seem to materially alter these results.

In Column 2, we include faculty fixed effects interacted with year fixed effects. These control for time-varying differences across faculty in the probability of being listed as an author caused by potentially time-varying unobserved characteristics such as "ability" or motivation. The overall effect of gender is subsumed in the individual fixed effects, so that we cannot estimate a gender gap in attribution in this specification, but we can still estimate the impact of female PIs on female faculty. The estimates on the share of PIs who are women are slightly lower than those in Column 1, implying that a 10 p.p. change in the share of women PIs is associated with a 0.43 p.p. increase in the attribution rate for women, which is 25% of the gender gap. As in Column 1, an increase in the share of female PIs is unrelated to male faculty's probability of authorship. Moreover, analogous to Column 1, we find that an increase in the number of authors is positively related while team size is negatively related to credit attribution. We also find that the number of days faculty are employed on the grant is not significantly related to

authorship.

Table 2: The Impact of Female PIs on Faculty's Authorship Probability

	(1)	(2)	(3)	(4)
𝟙(Female) × Share of Female PIs	0.050***	0.043***	0.052***	0.054***
	(0.009)	(0.008)	(0.008)	(0.009)
𝟙(Male) × Share of Female PIs	-0.001	-0.005		
	(0.008)	(0.007)		
𝟙(Female)	-0.019***		-0.020***	
	(0.004)		(0.003)	
Log(Number of Days Employed on the Grant)	0.004*	-0.002	0.004***	-0.005*
	(0.002)	(0.003)	(0.002)	(0.003)
Log(Number of Listed Authors)	0.033***	0.030***		
	(0.002)	(0.002)		
Log(Number of Potential Authors)	-0.088***	-0.070***		
	(0.002)	(0.003)		
Mean for Women	0.101	0.101	0.101	0.101
Mean for Men	0.118	0.118	0.118	0.118
Faculty × Publication Year FE		✓		✓
Paper FE			✓	✓
Observations	697,251	691,440	697,251	690,372
Adjusted R^2	0.121	0.378	0.342	0.518

Notes. The Table shows how an increase in the share of female PIs on a team is related to faculty's likelihood of being included as an author on a paper written by the research team.

In Column 3, we drop faculty×year fixed effects, but include paper fixed effects to control for unobservable paper characteristics such as its quality. This slightly increases the coefficient of interest. An increase of 10 p.p. in the share of female PIs is associated with a 0.52 p.p. increase in the attribution rate for women (31% of the gender gap). Similar to our OLS estimates in Column 1, these estimates show that women are 0.02 p.p. less likely to be included as authors compared to men.

Finally, we control for both faculty×year and paper fixed effects. The estimates reported in Column 4 show that, for female faculty, the likelihood of being listed as an author increases in the share of female PIs. Specifically, our results indicate that a 10 p.p. increase in the share of female PIs is associated with a 0.54 p.p. increase in the attribution rate for women, which is 32% of the raw gender gap in attribution. Moreover, moving from a team with only male PIs

to only female PIs more than eliminates the gender gap in attribution.[23]

It is reassuring that the estimates remain fairly stable across specifications. Following the approach in Oster (2019), a "walk-in" analysis often shows a decline in the coefficient of interest as more controls are added to the model. The key question is whether the coefficient of interest would remain both economically and statistically significant if all unobserved variations were accounted for. In our estimates presented in Table 2, moving from Column 1 to Column 4 shows that the variation in the dependent variable explained by our controls increases more than fourfold, as reflected by the adjusted R^2. Despite this substantial increase in explanatory power, the coefficient of interest rises slightly, from 0.050 to 0.054.

Considering the substantial effect of female PIs on female faculty's outcomes, we also explore whether female PIs who are listed as authors on a paper—potentially indicating greater decision-making power over credit attribution—have a stronger impact on credit attribution. It is worth noting that while the main sample contains 697,251 observations, the subsample of papers with at least one PI who is also an author has 322,194 observations. To account for this substantial reduction in sample size, Panel A of Table A.2 re-estimates our baseline regression models with this subsample using the gender mix of all PIs on the team (i.e., regardless of whether they are authors on the focal paper or not). Panel B focuses on the gender composition of PIs who are authors on the paper. The two-way fixed effects estimates in Column 4 of Panel A show that a 10 p.p. increase in the share of female PIs increases female faculty's probability of being included as an author by 1.04 percentage points. Column 4 of Panel B, which focuses only on PIs who are also authors on the paper, reports a point estimate that is around 20% higher than in Panel A. This suggests that increasing the share of female PIs who are also authors—and who likely have greater influence over coauthorship decisions—has a larger impact on the credit given to female faculty than increasing the share of all PIs (including those who are not authors on the paper) who are women.

Altogether, we find that female PIs have a significant impact on credit attribution to female faculty. Moreover, we show that the PIs with the most decision-making authority on an article have a greater impact on female faculty outcomes compared to all PIs.

[23]To address uncertainty in our gender imputations, Table A.1 in Appendix A repeats our results including faculty with missing genders. If anything, this modestly strengthens our results relative to Table 2.

4.2 Heterogeneity Analyses

This subsection examines several dimensions of heterogeneity in the impact of female PIs on female faculty, focusing on three key aspects: the paper's impact and authorship position, faculty productivity, and variations across research fields.

Heterogeneity by the paper's impact and authorship position: Teams produce a range of papers, some of which are more important than others. While failure to provide proper credit is inappropriate and harmful in all cases, its consequences are greatest on the most important papers and for the most prestigious authorship positions. For instance, surveying researchers who were authors on at least one article in the Web of Science, Ross et al. (2022) report that being left off of papers had a significant negative impact on their long-term outcomes, with one particular interviewee stating that her "career would have been quite different with these two *Nature* papers." Given this reality, Table B.2 below investigates whether the effects of the gender of PIs affects authorship only on relatively less important articles or also on the most impactful ones. We measure the impact of articles in two ways. In Panel A, high-impact papers are defined as papers that are above the median in terms of citations compared to all the other papers that were published in the same year and research area. In Panel B, we consider the relative citation ratio (RCR). The RCR is a metric of scientific influence in biomedical research that has a median of 1, is both research area- and time-adjusted, and is benchmarked against NIH-funded papers (Hutchins et al. (2016)).[24] For this analysis, we define high-impact papers as those that have an RCR of over 1. Both panels indicate that female PIs have a larger effect on the probability that female faculty are included as authors on more impactful articles than on less impactful ones. Panel B, for instance, suggests that a 10 p.p. increase in the share of female PIs on a team is associated with an increase in female faculty's authorship probability on low and high-impact papers of 0.35 p.p. and 0.61 p.p. (27% and 32% of the gender gap), respectively. Thus, the greatest effects on authorship probabilities are on the most important and likely most consequential pieces.

[24]For example, an RCR of 2 indicates that the paper received twice as many citations per year compared to the median NIH-funded paper in the same research area (Hutchins et al. (2016)).

Table 3: The Impact of Female PIs on Faculty's Authorship Probability, by the Impact of the Paper

	All	Low Impact	High Impact
Panel A: Results by Log(Number of Citations+1)			
$\mathbb{1}$(Female) × Share of Female PIs	0.054***	0.042***	0.058***
	(0.009)	(0.010)	(0.010)
Mean for Women	0.101	0.099	0.103
Mean for Men	0.118	0.112	0.124
Faculty × Publication Year FE	✓	✓	✓
Paper FE	✓	✓	✓
Observations	690,001	341,746	339,945
Adjusted R^2	0.518	0.534	0.539
Panel B: Results by Relative Citation Ratio			
$\mathbb{1}$(Female) × Share of Female PIs	0.054***	0.035***	0.061***
	(0.009)	(0.010)	(0.010)
Mean for Women	0.101	0.097	0.104
Mean for Men	0.118	0.110	0.123
Faculty × Publication Year FE	✓	✓	✓
Paper FE	✓	✓	✓
Observations	690,001	296,141	385,404
Adjusted R^2	0.518	0.533	0.537

Notes. The Table shows how an increase in the share of female PIs on a team affects female faculty's likelihood of being included as an author on low and high impact papers. In Panel A high impact papers are defined as those that have an above average number of citations compared to all the other papers that were published the same year and the same field. In Panel B, high impact papers are defined as those that have a relative citation ratio (RCR) over 1, where the RCR is a measure of scientific influence that has a median of 1, is both field- and time-adjusted, and is benchmarked against NIH funded papers. The estimates also control for faculty birth year and race/ethnicity fixed effects; the logarithm of the number of days faculty were employed on the grant; the logarithm of the number of potential authors; the logarithm of the number of listed authors; and university fixed effects.

Next, we examine whether the inclusion of women as authors primarily affects the prestigious first or last author positions, or the more marginal middle author positions. In particular, Table B.3 below examines the impact of female PIs and shows that the effect of female PIs on the likelihood of women appearing in all authorship positions is positive and significant. While, at 0.026, the coefficient is larger for for middle authorship than first authorship (0.011) or last authorship (0.018), the probability of being a middle author is more than triple the probability of being a first or last author. In percentage terms, a 10 p.p. increase in the share of PIs who are women increases the probability of a woman being listed as a first author by 6.9%, the probability of last authorship by 10.6%, and the probability of middle authorship by 4.0% (all relative to the baseline rates for women). Thus, once one accounts for differences in the frequency of each type of authorship, in percentage terms the effects are largest for last

authorship, then first authorship, and smallest for middle authorship. Altogether, the results by the paper's impact and the authorship position indicate that the effects are actually greatest when the likely consequences are largest.

Table 4: The Impact of Female PIs on Faculty's Authorship Probability by Authorship Order

	(1)	(2)	(3)
	First Author	Last Author	Middle Author
$\mathbb{1}$(Female) × Share of Female PIs	0.011***	0.018***	0.026***
	(0.002)	(0.004)	(0.006)
Mean for Women	0.016	0.017	0.068
Mean for Men	0.014	0.024	0.080
Faculty × Publication Year FE	✓	✓	✓
Paper FE	✓	✓	✓
Observations	690,372	690,372	690,372
Adjusted R^2	0.371	0.345	0.481

Notes. The Table shows how an increase in the share of female PIs on a team affects faculty's likelihood of being a first, middle, or last author. The estimates also control for faculty birth year and race/ethnicity fixed effects; the logarithm of the number of days faculty were employed on the grant; the logarithm of the number of potential authors; the logarithm of the number of listed authors; and university fixed effects.

Heterogeneity by faculty productivity: Are women leaders equally supportive of all female faculty, or do they tend to be more helpful for either the most established or the least established female faculty? On one hand, if women leaders primarily support less established women, this could help prepare them for future leadership roles. On the other hand, if women leaders focus their support on the most productive female faculty, it might bolster leadership among already successful women but could also increase disparities among women, limiting opportunities for other women to ascend to the top echelons. To shed light on these effects, Table 5 explores heterogeneity by researchers' previous productivity. Productivity of researchers is defined based on the number of papers the researchers published before they joined the teams. Highly productive researchers are those who had more than the median number of papers compared to all researchers who were born the same year, joined the team the same year, and are of the same race and gender. The Table shows that women leaders tend to support highly productive women more than less productive ones. In particular, we find that a 10 p.p. increase in the share of female PIs increases highly productive female faculty's likelihood of authorship by 0.83 p.p. (or 83% of the gender gap). The effect for less productive female faculty, reported in Column 2, is substantially lower and not statistically significant at 0.06 p.p. (or 2.5% of the

gender gap), suggesting that the benefits of women leaders may *not* benefit all female faculty. Thus, while teams with more female PIs tend to reduce the gap between women and men on average, they may increase disparities among women.

Table 5: The Impact of Female PIs on Faculty's Authorship Probability by Faculty's Prior Productivity

	(1)	(2)	(3)
	All	Low Productivity	High Productivity
$\mathbb{1}$(Female) × Share of Female PIs	0.054***	0.006	0.083***
	(0.009)	(0.008)	(0.014)
Mean for Women	0.101	0.087	0.112
Mean for Men	0.118	0.111	0.122
Faculty × Publication Year FE	✓	✓	✓
Paper FE	✓	✓	✓
Observations	690,372	279,425	389,650
Adjusted R^2	0.518	0.580	0.522

Notes. The Table shows how an increase in the share of female PIs on a team affects female faculty's likelihood of being included as an author on a paper based on the faculty member's prior productivity. High productivity researchers are defined as those who have written more than the median number of papers before they joined the teams compared to other researchers who were born the same year, joined the team the same year, and are of the same race. The estimates also control for faculty birth year and race/ethnicity fixed effects; the logarithm of the number of days faculty were employed on the grant; the logarithm of the number of potential authors; the logarithm of the number of listed authors; and university fixed effects.

Heterogeneity across research fields: Table 6 explores whether and how the gender mix of fields mediates the effects of female leaders on the credit received by female faculty. We define heavily-male research areas as those where the share of unique female authors is below the median of 46% calculated across all fields. Column 1 presents results for our main sample. Column 2 presents the findings for women in heavily-male[25] research areas.[26] The Table shows that female faculty in heavily-male fields benefit more, in terms of attribution rates, from having a higher share of female PIs than those in areas that are heavily-female. Specifically, we find

[25]To ensure the accuracy of our classification of fields as heavily-male or heavily-female, we validated our approach against published findings. For instance, in our sample, fields such as gastrointestinal tract and infectious diseases were classified as heavily-male. This is consistent with the results reported by Rabinowitz et al. (2021) and The Lancet Infectious Diseases (2019). An example of a heavily-female field in our sample is animal studies. This classification aligns with findings reported by Slater and Slater (2000) and Lofstedt (2003), which highlight that in the U.S., men constituted 44% of veterinary college applicants in 1985, a figure that declined to just 28% by 1999.

[26]Note that, although researchers were divided equally into heavily-male and heavily-female research areas, the number of observations in Columns 2 and 3 of Table 6 differ since our data are at the (faculty-paper-research grant) level. Hence, if researchers in heavily-female research areas produce more papers or acknowledge more research grants in each paper, the number of observations in Column 3 will be higher even with the same number of researchers.

that increasing the share of female PIs on research teams in heavily-male research areas by 10 p.p. increases the likelihood that female faculty become authors by 0.87 p.p. (or 62% of the gender gap). The results in Column 3 for women in heavily-female research areas, on the other hand, indicate that an equal increase in the share of female PIs results in a significantly smaller increase in the authorship probability of 0.39 p.p. (or 40% of the gender gap).[27] Thus, the Table suggests that women leaders are particularly valuable in heavily-male fields. Our results align with recent evidence provided by Funk et al. (2024) that uses data from three different heavily-male university departments from a Swiss university and shows that when the faculty roster is heavily-male, female students are more likely to enroll in elective courses taught by female instructors. Funk et al. (2024) also shows that female instructors in heavily-male departments receive less favorable teaching evaluations from male students compared to female students. The evaluation gender gap narrows when the faculty is more balanced along a gender dimension. These differences in perceived performances across genders might explain why female faculty tend to work with other female faculty in heavily-male fields.

Table 6: The Impact of Female PIs on Faculty's Authorship Probability by Gender Mix of Fields

	(1)	(2)	(3)
	All	Heavily-Male	Heavily-Female
$\mathbb{1}$(Female) × Share of Female PIs	0.054***	0.087***	0.039***
	(0.009)	(0.015)	(0.011)
Mean for Women	0.101	0.124	0.092
Mean for Men	0.118	0.138	0.102
Faculty × Publication Year FE	✓	✓	✓
Paper FE	✓	✓	✓
Observations	690,372	268,940	406,028
Adjusted R^2	0.518	0.575	0.507

Notes. The Table shows how an increase in the share of female PIs on a team affects female faculty's likelihood of being included as an author on a paper in fields that are heavily male versus heavily female. Heavily-female research areas are defined as those where the share of women on all the articles published in the field are above the median across all fields. The estimates also control for faculty birth year and race/ethnicity fixed effects; the logarithm of the number of days faculty were employed on the grant; the logarithm of the number of potential authors; the logarithm of the number of listed authors; and university fixed effects.

Heterogeneity by faculty productivity *and* research fields: Taken together, the results in Tables 5 and 6 suggest that highly productive female faculty in heavily-male research areas

[27] Note that the sample sizes in Columns 2 and 3 do not add up to the sample size in Column 1 because there are not enough researchers in some of the (birth year, race, publication year, university) cells when we divide the researchers into two sets of research areas causing some observations to be fully captured by fixed effects.

are the ones who benefit the most from having a higher share of female PIs. Table 7 reports estimates by the gender mix of fields interacted with faculty productivity. The estimates show that highly productive women in heavily-male fields experience an increase in the probability of authorship of 1.36 p.p. (or 80% of the gender gap) when the share of female PIs increases by 10 p.p. These estimates are substantially larger than for any other group.

Table 7: Heterogeneity in the Impact of Female PIs on Faculty's Authorship Probability

	(1)	(2)	(3)	(4)	(5)
	All	Low Prod.× Heavily-Male	Low Prod.× Heavily-Fem.	High Prod.× Heavily-Male	High Prod.× Heavily-Fem.
$\mathbb{1}$(Female) × Share of Female PIs	0.054***	0.020	0.003	0.136***	0.058***
	(0.009)	(0.017)	(0.010)	(0.026)	(0.018)
Mean for Women	0.101	0.118	0.077	0.129	0.106
Mean for Men	0.118	0.129	0.095	0.146	0.107
Faculty × Publication Year FE	✓	✓	✓	✓	✓
Paper FE	✓	✓	✓	✓	✓
Observations	690,372	105,866	161,617	146,156	231,039
Adjusted R^2	0.518	0.627	0.566	0.599	0.494

Notes. The Table shows how an increase in the share of female PIs on a team affects female faculty's likelihood of being included as an author on a paper by the gender mix of research areas and prior productivity. Heavily-female research areas are defined as those where the share of women on all the articles published in the field are above the median across all fields. High productivity researchers were defined as those who have written more than the median number of papers before they joined the teams compared to other researchers who were born the same year, joined the team the same year, and are of the same race. The estimates also control for faculty birth year and race/ethnicity fixed effects; the logarithm of the number of days faculty were employed on the grant; the logarithm of the number of potential authors; the logarithm of the number of listed authors; and university fixed effects.

These estimates indicate that the effect of female PIs on female faculty's probability of authorship is mainly concentrated among high-productivity women. The estimates for low-productivity women are small and insignificant for both heavily-male and heavily-female fields. By contrast, a higher share of female PIs increases the authorship probability of high-productivity women in heavily-female fields by 0.058 and the authorship probability of high-productivity women in heavily-male fields by 0.138. Thus, a greater share of women PIs significantly improves authorship of high-productivity female faculty, which narrows the gap in the number of authored papers *between* female and male researchers. However, female PIs also tend to widen the authorship gap between high- and low-productivity female researchers, that is, *within* women, and the results are substantially larger in heavily-male fields.

Summary of heterogeneity analyses: We have shown that an increase in the share of female PIs on the teams that produced a paper substantially increases female faculty's likelihood

of authorship. Second, the impact of female PIs on attribution are largest on highly impactful papers and for being a first or last author. Second, we find the effects on inclusion are greater in heavily-male research areas, suggesting that our effects may stem from supportive research environments. Lastly, we find that the most productive women benefit the most from having a higher share of female PIs. As indicated, this finding suggests that, although an increase in the share of female PIs may narrow the gap in the number of authored papers *between* female and male researchers, it may also perpetuate inequality in authorship among women.

Robustness checks: Our main result include person-by-year fixed effects and paper fixed effects. To ensure that our results are not driven by our selection of paper fixed effects, in Appendix B we report results that account for both unobservable time-varying faculty and grant characteristics using fixed effects. These fixed effects are somewhat more coarse than the paper fixed effects in that the same team could publish more than one article. In keeping with our main results, results in Appendix B demonstrate that our findings do not seem to depend on our choice of fixed effects.

4.3 Post-Research Teams Productivity

This section explores how exposure to female leadership relates to the outcomes of female faculty in the longer term, that is, after they leave the focal research teams. First, we ask whether female leaders are associated with higher productivity among female faculty after leaving those teams. We then explore possible mechanisms. Because our analyses in this section are at the researcher level, we cannot apply our Abowd et al. (1999)-inspired strategy to identify the (plausibly) causal effect of having female PIs on faculty's post-research teams productivity. Thus, these results are more descriptive in nature and should be interpreted accordingly. Throughout this section, in addition to the previous set of observable researcher characteristics, we also control for the number of years we observe researchers' publications after they left their last research team in the UMETRICS dataset. Moreover, instead of calculating the share of female PIs in teams acknowledged for each paper, as in Section 4 above, we estimate the share of female PIs across all teams the researcher was a part of.

Table 8 explores how the share of female PIs is related to researchers' productivity after working with a team, with the standard errors clustered at the level of a set of research grants

the researchers were part of. Given the count nature of the dependent variable and in keeping with the existing literature, we use a Poisson model.[28] We find that a 10% (or around 0.43 of a standard deviation) increase in the share of female PIs on the grants female faculty were part of is associated with an increase in the number of papers they author afterward of 1.2% (or 0.04 additional papers given a baseline output of 3.56 papers). The estimates reported in Columns 2-5[29] show that highly productive female faculty who work in heavily-male research areas tend to experience the largest increase in productivity. In particular, an increase of 10% in the share of female PIs in their teams translates into an increase of 6.8% in the number of papers they author after leaving the team. Although imprecise, in line with our findings in Section 4.2 above, the difference between the estimates in Columns 4 and 2 suggests the possibility that a higher share of female PIs may widen the within-group productivity gap for women in heavily-male research areas.

Table 8: The Relationship between Female PIs and Faculty's Prior Productivity after Leaving a Research Team

	(1)	(2)	(3)	(4)	(5)
	All	Low Prod.× Heavily-Male	Low Prod.× Heavily-Fem.	High Prod.× Heavily-Male	High Prod.× Heavily-Fem.
$\mathbb{1}$(Female) × Share of Female PIs	0.118	-0.333	-0.146	0.679**	0.111
	(0.138)	(0.406)	(0.275)	(0.298)	(0.224)
$\mathbb{1}$(Male) × Share of Female PIs	-0.051	-0.488*	-0.448*	0.209	-0.102
	(0.115)	(0.284)	(0.263)	(0.249)	(0.212)
Mean for Women	3.56	2.00	2.84	3.37	5.26
Mean for Men	4.52	2.71	3.59	4.94	6.91
Observations	4,137	867	1,041	903	908

Notes. The Table shows the relationship between the gender composition of PIs and the productivity of faculty after leaving research teams overall and by faculty productivity and gender composition of research areas. Heavily-female research areas were defined as those where the share of women on all the articles published in the field are above the median across all fields. High productivity researchers were defined as those who have written more than the median number of papers before they joined the teams compared to other researchers who were born the same year, joined the team the same year, and are of the same race. The estimates also control for faculty birth year, race, gender; the number of years we observe researchers' publications after they left their last research team in UMETRICS dataset; university fixed effects; and the logarithm of the number of days faculty worked on all grants.

In Panel A of Table A.3 we examine what share of the papers faculty publish after leaving the teams on which we observe them arises through continued collaborations between these faculty and the female PIs. The estimates suggest that continued collaboration accounts for

[28] When using a Poisson model, we interpret the coefficient of interest β_1 using a first-order Taylor approximation. Specifically, when the estimated coefficient is $\hat{\beta}_1$, a 1% increase in the share of female PIs increases the number of papers researchers have authored after leaving the teams by $(e^{\beta_1} - 1)$ percent or approximately $\hat{\beta}_1$%.

[29] The number of observations in these columns varies slightly due to the clustering of values around the median.

around 46%, of the papers women author after leaving the teams. Focusing on high-productivity women in heavily-male fields, we find that 34% of their post-team papers written come from co-authored work with their former female PIs. Interestingly, although low-productivity women in heavily male fields are less productive after leaving their teams than high-productivity women in those fields, an even larger share of the post-team output of low-productivity women in heavily male fields is with the female PIs on their focal projects. Panel B additionally shows that increased collaboration with female PIs does not seem to come at the expense of decreased collaboration between female faculty and their former co-authors who are not female PIs.

This section provides suggestive evidence that the impact of female PIs on female faculty extends beyond attribution to an increase in the number of authored papers—that is partially driven by continued collaboration between these faculty and female PIs—after female faculty leave the research teams. Similar to our attribution estimates, the strongest relationship is for highly productive women in heavily-male areas. While valuable, the descriptive nature of our results calls for further in-depth analysis in future research.

5 Conclusion

Observers have pointed to leaders as a way of leveraging, engaging, and generating opportunities for all members of society. This paper studies how leaders create opportunities for their teams in a unique setting, where we have clear visibility into leaders and their teams, important outcome variables, as well as an ability to control for unobserved differences. Specifically, we focus on how the gender composition of the leaders of biomedical research teams is related to the employment of women and the credit received by female faculty.

Our unique linked UMETRICS and Author-ity data, show that teams with a higher share of women PIs are significantly more supportive of female faculty in three major ways. First, teams with a greater share of women PIs employ a higher share of women on their teams. Second, using researcher×year and paper fixed effects to control for unobserved factors, we find that teams with a greater share of women among the PIs give significantly more credit—in terms of authorship—to female faculty who work on their teams, with the effect being substantially larger on high impact papers. These effects are significantly higher in heavily-male fields, highlighting the importance of a supportive environment for credit attribution.

Third, we provide suggestive evidence showing that the impact of female PIs on female faculty extends beyond credit attribution to an increase in the number of authored papers–partially due to continued collaboration between these faculty and female PIs–after female faculty leave the research teams. Our analyses also show that prominent female researchers tend to benefit significantly more from having female PIs. Thus, while a greater share of female PIs tends to significantly improve outcomes of female faculty on their teams narrowing the gap in the number of authored papers *between* female and male researchers, they also tend to widen the authorship gap *within* female faculty.

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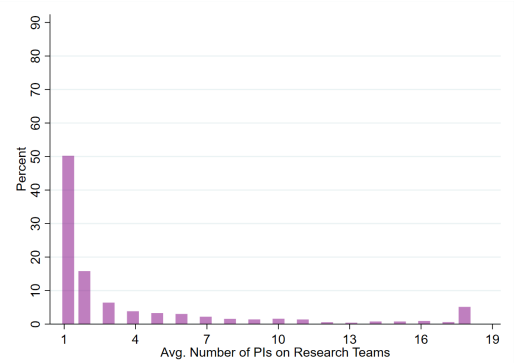
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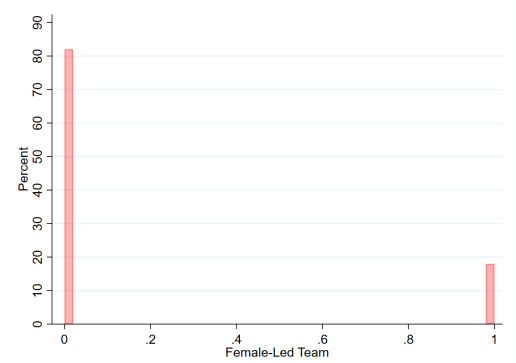
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Appendix A.

Figure A.1: Descriptive Statistics for PIs on Research Teams



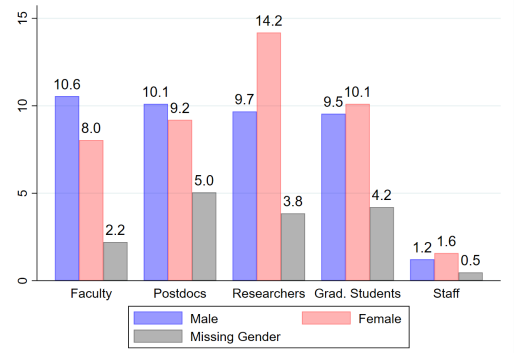
(a) Avg. Number of PIs on Research Teams



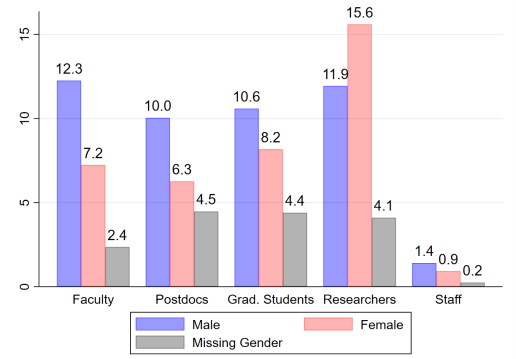
(b) Share of Female-Led Research Teams

Notes. The Figures present descriptive statistics for PIs on research teams that are defined at the paper level. Female-led teams are defined as those teams where half or more of the PIs are women. The Figure in Panel A is winsorized at 2% and 95% levels.

Figure A.2: Descriptive Statistics by Researcher and PI Gender, Including Researchers with Missing Imputed Genders



(a) Share of Researchers by Occ. in Female-Led Teams



(b) Share of Researchers by Occ. in Male-Led Teams

Notes. The Figures present descriptive statistics for the gender of researchers, including researchers with uncertain genders, by PI gender.

Table A.1: The Impact of Female PIs on Faculty's Authorship Probability, Including Faculty with Missing Imputed Genders

	(1)	(2)	(3)	(4)
𝟙(Female) × Share of Female PIs	0.095***	0.052***	0.081***	0.060***
	(0.019)	(0.013)	(0.015)	(0.011)
𝟙(Missing Gender) × Share of Female PIs	0.027	-0.008	0.015	-0.001
	(0.019)	(0.012)	(0.014)	(0.010)
𝟙(Female)	-0.024***	0.000	-0.024***	0.000
	(0.004)	(0.000)	(0.003)	(0.000)
𝟙(Missing Gender)	-0.008		-0.010	
	(0.010)		(0.007)	
Mean for Female	0.090	0.090	0.090	0.090
Mean for Missing Gender	0.129	0.129	0.129	0.129
Mean for Male	0.105	0.105	0.105	0.105
Faculty× Publication Year FE		✓		✓
Paper FE			✓	✓
Observations	842,836	836,110	842,836	834,951
Adjusted R^2	0.128	0.381	0.331	0.513

Notes. The Table shows how an increase in the share of female PIs on a team affects faculty's likelihood of being included as an author on a paper written by the research team. The estimates also control for faculty birth year and race/ethnicity fixed effects; the logarithm of the number of days faculty were employed on the grant; the logarithm of the number of potential authors; the logarithm of the number of listed authors; the paper's publication year fixed effects; and university fixed effects.

Table A.2: The Impact of the Share of Female PIs on Faculty's Authorship Probability for the Subsample of Papers that have PIs who are Also Authors

	(1)	(2)	(3)	(4)
Panel A: The Impact of Female PIs				
𝟙(Female) × Share of Female PIs	0.078***	0.088***	0.077***	0.104***
	(0.014)	(0.015)	(0.014)	(0.017)
𝟙(Male) × Share of Female PIs	-0.001	-0.002		
	(0.012)	(0.014)		
𝟙(Female)	-0.026***		-0.027***	
	(0.008)		(0.006)	
Mean for Women	0.186	0.186	0.186	0.186
Mean for Men	0.20	0.20	0.20	0.20
Faculty × Publication Year FE		✓		✓
Paper FE			✓	✓
Observations	322,194	316,258	322,194	315,141
Adjusted R^2	0.080	0.397	0.371	0.584
Panel B: The Impact of Female PIs who are Also Authors				
𝟙(Female) × Share of Female Author PIs	0.074***	0.103***	0.078***	0.122***
	(0.012)	(0.012)	(0.011)	(0.011)
𝟙(Male) × Share of Female Author PIs	-0.010	-0.017*		
	(0.009)	(0.009)		
𝟙(Female)	-0.027***		-0.027***	
	(0.008)		(0.006)	
Mean for Women	0.186	0.186	0.186	0.186
Mean for Men	0.20	0.20	0.20	0.20
Faculty × Publication Year FE		✓		✓
Paper FE			✓	✓
Observations	322,194	316,258	322,194	315,141
Adjusted R^2	0.081	0.398	0.371	0.584

Notes. The Table shows how an increase in the share of female PIs on a team affects faculty's likelihood of being included as an author on a paper written by the research team for papers that have a PI who is also an author. The top Panel reports estimates for all PIs for the sample for whom we have data on the gender of PIs who are authors. The bottom Panel reports estimates for PIs who are authors on the focal paper. The estimates also control for faculty birth year and race/ethnicity fixed effects; the logarithm of the number of days faculty were employed on the grant; the logarithm of the number of potential authors; the logarithm of the number of listed authors; the paper's publication year fixed effects; and university fixed effects.

Table A.3: The Relationship between Female PIs and Faculty's Post-Research Team Coauthorship

	(1) All	(2) Low Prod.× Heavily-Male	(3) Low Prod.× Heavily-Fem.	(4) High Prod.× Heavily-Male	(5) High Prod.× Heavily-Fem.
Panel A: Share of Papers Written with Female PIs					
𝟙(Female) × Share of Female PIs	0.458***	0.692**	0.592**	0.337*	0.193**
	(0.101)	(0.292)	(0.267)	(0.185)	(0.093)
𝟙(Male) × Share of Female PIs	0.349***	0.539**	0.471***	0.293	0.143**
	(0.077)	(0.260)	(0.128)	(0.261)	(0.069)
𝟙(Female)	0.010	-0.065	-0.004	0.040	0.106**
	(0.036)	(0.080)	(0.100)	(0.085)	(0.051)
Mean Number of Papers for Women	3.56	2.00	2.84	3.37	5.26
Mean Number of Papers for Men	4.52	2.71	3.59	4.94	6.91
Observations	2,422	438	539	560	610
Panel B: Share of Papers Written with Previous Co-Authors Who are Not Female PIs					
𝟙(Female) × Share of Female PIs	0.274*	-0.103	0.421	0.370	-0.145
	(0.152)	(0.581)	(0.327)	(0.396)	(0.230)
𝟙(Male) × Share of Female PIs	-0.273	-0.236	-0.528**	-0.283	-0.447**
	(0.169)	(0.552)	(0.235)	(0.356)	(0.210)
𝟙(Female)	-0.389***	-0.542**	-0.442**	-0.514***	0.041
	(0.087)	(0.265)	(0.175)	(0.179)	(0.163)
Mean Number of Papers for Women	3.56	2.00	2.84	3.37	5.26
Mean Number of Papers for Men	4.52	2.71	3.59	4.94	6.91
Observations	2,422	438	539	560	610

Notes. The Table analyzes heterogeneity in the effect of faculty gender and the share of female PIs on a team on the faculty's post-research teams productivity by faculty's research area and productivity. Heavily-female research areas are defined as those where the share of women on all the articles published in the field are above the median across all fields. High productivity researchers are defined as those who have written more than the median number of papers before they joined the teams compared to other researchers who were born the same year, joined the team the same year, and are of the same race. The estimates also control for faculty birth year, race, gender; fixed effects for the university of employment; and the logarithm of the number of days faculty worked on all grants.

Appendix B. Results Controlling for Faculty×Publication Year and Grant Fixed-Effects

Table B.1: The Impact of Female PIs on Faculty's Authorship Probability

	(1)	(2)	(3)	(4)
𝟙(Female) × Share of Female PIs	0.050***	0.043***	0.030***	0.031***
	(0.011)	(0.010)	(0.008)	(0.008)
𝟙(Male) × Share of Female PIs	-0.001	-0.005	-0.018***	-0.022***
	(0.010)	(0.008)	(0.007)	(0.006)
𝟙(Female)	-0.019***		-0.019***	
	(0.005)		(0.005)	
Log(Number of Days Employed on the Grant)	0.004	-0.002	0.006**	0.002
	(0.002)	(0.003)	(0.002)	(0.005)
Log(Number of Listed Authors)	0.033***	0.030***	0.035***	0.027***
	(0.006)	(0.006)	(0.007)	(0.006)
Log(Number of Potential Authors)	-0.088***	-0.070***		
	(0.003)	(0.004)		
Mean for Women	0.101	0.101	0.101	0.101
Mean for Men	0.118	0.118	0.118	0.118
Faculty × Publication Year FE		✓		✓
Grant FE			✓	✓
Observations	697,251	691,440	696,759	690,902
Adjusted R^2	0.121	0.378	0.272	0.437

Notes. The Table shows how an increase in the share of female PIs on a team is related to faculty's likelihood of being included as an author on a paper written by the research team.

Table B.2: The Impact of Female PIs on Faculty's Authorship Probability, by the Impact of the Paper

	All	Low Impact	High Impact
Panel A: Results by Log(Number of Citations+1)			
𝟙(Female) × Share of Female PIs	0.031***	0.025***	0.034***
	(0.008)	(0.008)	(0.009)
Mean for Women	0.101	0.099	0.103
Mean for Men	0.118	0.112	0.124
Faculty × Publication Year FE	✓	✓	✓
Grant FE	✓	✓	✓
Observations	690,532	342,044	340,184
Adjusted R^2	0.437	0.462	0.464
Panel B: Results by Relative Citation Ratio			
𝟙(Female) × Share of Female PIs	0.031***	0.020***	0.037***
	(0.008)	(0.008)	(0.008)
Mean for Women	0.101	0.097	0.104
Mean for Men	0.118	0.110	0.123
Faculty × Publication Year FE	✓	✓	✓
Grant FE	✓	✓	✓
Observations	690,532	296,467	385,753
Adjusted R^2	0.437	0.462	0.465

Notes. The Table shows how an increase in the share of female PIs on a team affects female faculty's likelihood of being included as an author on low and high impact papers. In Panel A high impact papers are defined as those that have an above average number of citations compared to all the other papers that were published the same year and the same field. In Panel B, high impact papers are defined as those that have a relative citation ratio (RCR) over 1, where the RCR is a measure of scientific influence that has a median of 1, is both field- and time-adjusted, and is benchmarked against NIH funded papers. The estimates also control for faculty birth year and race/ethnicity fixed effects; the logarithm of the number of days faculty were employed on the grant; the logarithm of the number of potential authors; the logarithm of the number of listed authors; and university fixed effects.

Table B.3: The Impact of the Share of Female PIs on Faculty's Authorship Probability by Authorship Order

	(1)	(2)	(3)
	First Author	Last Author	Middle Author
𝟙(Female) × Share of Female PIs	0.008***	0.012***	0.012**
	(0.002)	(0.005)	(0.005)
Mean for Women	0.016	0.017	0.068
Mean for Men	0.014	0.024	0.080
Faculty × Publication Year FE	✓	✓	✓
Grant FE	✓	✓	✓
Observations	690,902	690,902	690,902
Adjusted R^2	0.251	0.274	0.374

Notes. The Table shows how an increase in the share of female PIs on a team affects faculty's likelihood of being a first, middle, or last author. The estimates also control for faculty birth year and race/ethnicity fixed effects; the logarithm of the number of days faculty were employed on the grant; the logarithm of the number of potential authors; the logarithm of the number of listed authors; and university fixed effects.

Table B.4: The Impact of Female PIs on Faculty's Authorship Probability by Faculty's Prior Productivity

	(1)	(2)	(3)
	All	Low Productivity	High Productivity
𝟙(Female) × Share of Female PIs	0.031***	0.013*	0.050***
	(0.008)	(0.007)	(0.013)
Mean for Women	0.101	0.087	0.112
Mean for Men	0.118	0.111	0.122
Faculty× Publication Year FE	✓	✓	✓
Grant FE	✓	✓	✓
Observations	690,902	291,298	399,401
Adjusted R^2	0.437	0.457	0.438

Notes. The Table shows how an increase in the share of female PIs on a team affects female faculty's likelihood of being included as an author on a paper based on the faculty member's prior productivity. High productivity researchers are defined as those who have written more than the median number of papers before they joined the teams compared to other researchers who were born the same year, joined the team the same year, and are of the same race. The estimates also control for faculty birth year and race/ethnicity fixed effects; the logarithm of the number of days faculty were employed on the grant; the logarithm of the number of potential authors; the logarithm of the number of listed authors; and university fixed effects.

Table B.5: The Impact of Female PIs on Faculty's Authorship Probability by Gender Mix of Fields

	(1)	(2)	(3)
	All	Heavily-Male	Heavily-Female
𝟙(Female) × Share of Female PIs	0.031***	0.060***	0.024***
	(0.008)	(0.018)	(0.008)
Mean for Women	0.101	0.124	0.092
Mean for Men	0.118	0.138	0.102
Faculty× Publication Year FE	✓	✓	✓
Grant FE	✓	✓	✓
Observations	690,902	276,874	413,913
Adjusted R^2	0.437	0.454	0.431

Notes. The Table shows how an increase in the share of female PIs on a team affects female faculty's likelihood of being included as an author on a paper in fields that are heavily male versus heavily female. Heavily-female research areas are defined as those where the share of women on all the articles published in the field are above the median across all fields. The estimates also control for faculty birth year and race/ethnicity fixed effects; the logarithm of the number of days faculty were employed on the grant; the logarithm of the number of potential authors; the logarithm of the number of listed authors; and university fixed effects.

Table B.6: Heterogeneity in the Impact of Female PIs on Faculty's Authorship Probability

	(1)	(2)	(3)	(4)	(5)
	All	Low Prod.× Heavily-Male	Low Prod.× Heavily-Fem.	High Prod.× Heavily-Male	High Prod.× Heavily-Fem.
$\mathbb{1}$(Female) × Share of Female PIs	0.031***	0.021	0.012*	0.095***	0.036***
	(0.008)	(0.022)	(0.007)	(0.028)	(0.012)
Mean for Women	0.101	0.118	0.077	0.129	0.106
Mean for Men	0.118	0.129	0.095	0.146	0.107
Faculty× Publication Year FE	✓	✓	✓	✓	✓
Grant FE	✓	✓	✓	✓	✓
Observations	690,902	118,571	172,683	158,251	241,107
Adjusted R^2	0.437	0.447	0.465	0.466	0.423

Notes. The Table above demonstrates how an increase in the share of female PIs on a team affects female faculty's likelihood of being included as an author on a paper by faculty's research area and productivity. Heavily-female research areas were defined as those where the share of women in all the articles published in the field are above the median across all fields. High productivity researchers were defined as those who have written more than median number of papers before they joined the teams compared to other researchers who were born the same year, joined the team the same year, and are of the same race. The Table additionally controls for faculty birth year and race fixed effects; logarithm of the number of days faculty worked on the research team; logarithm of the number of employees who were part of the team; logarithm of the number of authors listed on the paper; paper's publication year fixed effects; and university fixed effects.