

FEDERAL RESERVE BANK OF MINNEAPOLIS

QR

QUARTERLY REVIEW

September 2019

Collaboration and Female  
Representation in Academic Fields

Soohyung Lee  
Benjamin A. Malin

FEDERAL RESERVE BANK OF MINNEAPOLIS

**Quarterly Review** Vol. 39, No.1

ISSN 0271-5287

<https://doi.org/10.21034/qr.3911>

This publication primarily presents economic research aimed at improving policymaking by the Federal Reserve System and other governmental authorities.

*The views expressed herein are those of the authors and not necessarily those of the Federal Reserve Bank of Minneapolis or the Federal Reserve System.*

SENIOR VICE PRESIDENT AND DIRECTOR OF RESEARCH: Mark L. J. Wright

EDITOR: Juan Pablo Nicolini

ARTICLE EDITOR: Joan Gieseke

TECHNICAL SUPPORT: Shawn Hewitt

The *Quarterly Review* is published by the Research Division of the Federal Reserve Bank of Minneapolis. This has become an occasional publication; however, it continues to be known as the *Quarterly Review* for citation purposes. Subscriptions are available free of charge. To subscribe to the journal and be automatically notified whenever a new issue is published, please sign up at <https://www.minneapolis.org/research/>

*Quarterly Review* articles that are reprints or revisions of papers published elsewhere may not be reprinted without the written permission of the original publisher. All other *Quarterly Review* articles may be reprinted without charge. If you reprint an article, please fully credit the source—the Minneapolis Federal Reserve Bank as well as the *Quarterly Review*—and include with the reprint a version of the standard Federal Reserve disclaimer (italicized above). Also, please send one copy of any publication that includes a reprint to the Research Division of the Federal Reserve Bank of Minneapolis.

# Contents

Collaboration and Female Representation in Academic Fields.....	2
--------------------------------------------------------------------	---

*An exploration of a new factor--collaboration--in explaining the  
variation in female representation in academic fields*

# Collaboration and Female Representation in Academic Fields\*

Soohyung Lee  
Associate Professor of Economics  
Sogang University  
and Research Fellow  
IZA

Benjamin A. Malin  
Senior Economist  
Economic Research  
Federal Reserve Bank of Minneapolis

## Introduction

Although gender gaps have shrunk drastically over the past 50 years along some dimensions, such as college enrollment and labor force participation (Goldin 2014), sizable gaps remain elsewhere. An example that has received considerable attention is women’s underrepresentation in (natural) science, technology, engineering, and mathematics (STEM) (Ceci and Williams 2004). A lesser-known fact is that the gender gap varies widely across fields *within* both STEM and non-STEM fields. Using this variation, studies have shown that field-specific factors, such as “math ability” or “ability beliefs,” are highly correlated with the degree to which women are represented in a field (e.g., Ceci et al. 2014 and Leslie et al. 2015). In this paper, we explore a new factor — collaboration — to explain variation in female representation across fields and over time.

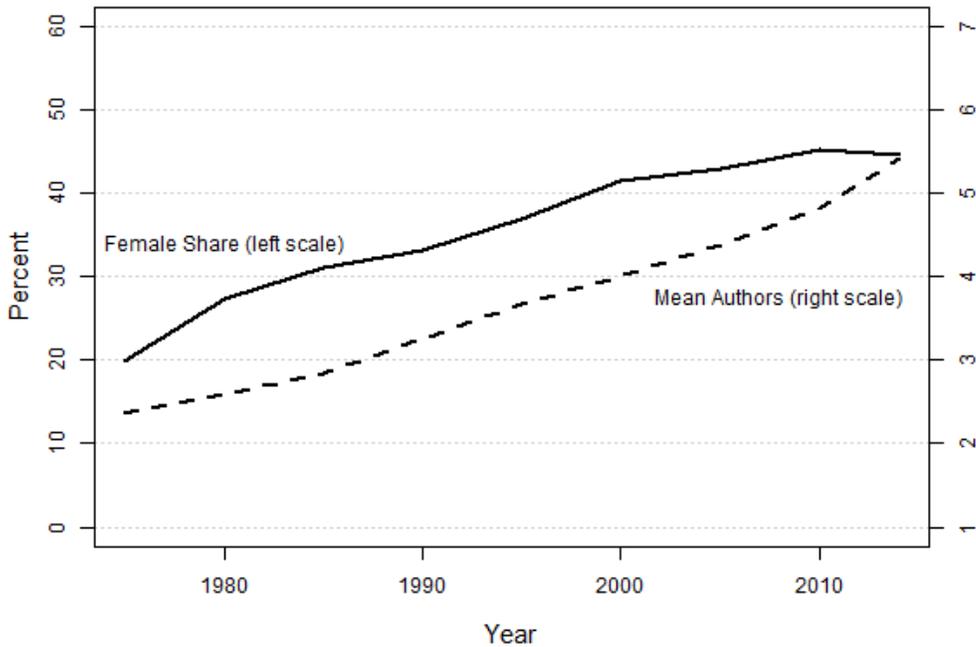
Our focus on collaboration stems from research suggesting that the norms of and approaches to collaboration differ across genders. In particular, men and women exhibit, on average, different preferences for teamwork (Kuhn and Villeval 2015), which, in academic settings, manifests itself in measurable differences between genders in the number of collaborators and network size (Bozeman and Gaughan 2011). These differences suggest that, as the extent of collaboration in academia changes over time, the forces influencing the gender gap may also change. However, as far as we know, no study directly examines the extent to which collaboration and female representation are related. This is the question we take up in this paper.

---

\*This research has been supported by the Basic Science Research Program of the National Research Foundation of Korea (NRF), which is funded by the Ministry of Science, ICT and Future Planning (Grant 2017R1A2B1009094). We thank Claudia Goldin, Claudia Olivetti, and seminar participants at the OECD and IADB for helpful comments, George Krivorotov, Lei Ma, and Margaret Sauer for helpful research assistance, Sara Brandel for assistance in acquiring Web of Science data, and Mark Fiegener for providing data from the National Science Foundation’s Survey on Earned Doctorates. The views expressed herein are those of the authors and not necessarily those of the Federal Reserve Bank of Minneapolis or the Federal Reserve System.

We look for empirical evidence using both time-series and cross-sectional data. We begin by noting that academic collaboration, as measured by coauthorship, has risen markedly in recent decades (e.g., Wuchty, Jones, and Uzzi 2007). This increase has coincided with an increase in female representation. As shown in Figure 1, the mean number of authors per article published in peer-reviewed academic journals increased from around 2.5 in 1975 to 5.5 in 2014, and the female share of new PhD recipients increased from roughly 20 percent in 1975 to 45 percent in 2014.<sup>1</sup> Of course, these aggregate trends may be driven entirely by independent factors and may thus be unrelated. To control for this possibility, the core of our analysis uses disaggregated data to investigate whether the relationship holds *across* academic fields: namely, did fields in which collaboration increased more rapidly also experience a greater increase in female representation?

Figure 1  
**Female representation and coauthorship from 1975 to 2014**



Notes: This figure plots the female share of new PhD recipients at US universities and the mean number of authors per article published in peer-reviewed academic journals for every fifth year from 1975 to 2010, as well as 2014. The data points are weighted averages across academic fields for each year. For female share, the weights are the fields' shares of new PhD recipients. For mean authors, the weights are the fields' shares of published articles.

We compile a dataset with measures of female representation and the prevalence of collaboration across the entire academic spectrum from 1975 to 2014. We include all academic fields (i.e., non-STEM in addition to STEM) because, to the extent that collaboration is related to female representation, it should affect non-STEM fields as well. Using annual data from the National Science Foundation's (NSF) Survey of Doctorate Recipients, we measure female representation as the share of women among new US doctorate recipients.

We measure collaboration by the mean number of authors per article published in a given year and academic field, using data from Thomson Reuters' Web of Science (WoS). The resulting longitudinal dataset covers 30 academic fields for every fifth year from 1975 to 2010, as well as 2014.

We then regress the female share in a given year and academic field on collaboration while controlling for field and year fixed effects. The field fixed effect captures the possibility that some fields may innately attract more women, and the year fixed effect captures any time trend common to academic fields. We find that one additional author on the average published paper is associated with an increase of 2.5 percentage points in the female share of PhD recipients. This estimate suggests that (1) the variation in collaboration across fields in 2014 can account for 25 percent of the variation in female share that year, and (2) the increased collaboration from 1975 to 2014 can account for 31 percent of the increase in female share observed during this period. The findings are robust to analyzing STEM and non-STEM fields separately. Finally, we further explore the relationship between collaboration and female share by analyzing different types of collaboration, controlling for varying norms across fields in how coauthors are ordered, and investigating how collaboration is related to the share of racial/ethnic minorities. These extensions provide suggestive evidence on possible mechanisms that may be driving the relationship between collaboration and female share.

The paper's contributions include documenting the positive relationship between collaboration and female representation across academic fields and employing a dataset that enables us to make methodological contributions to the literature on female representation in academia. Specifically, using longitudinal rather than cross-sectional data, as is typically the case, allows us to account for the possibility that some fields innately attract more women than others and to investigate changes over time in addition to differences across fields at a point in time. That said, our empirical strategy has limitations that are similar to other approaches in the literature; foremost, our analysis uncovers the correlation between collaboration and female representation, but not necessarily the causal impact of the former on the latter.

The paper is organized as follows. We first review the related literature and provide the motivation for our subsequent empirical work. Then we describe our data and methodology before presenting our main findings and discussing the possible mechanisms underlying these findings. The final section concludes.

## Literature Review

This paper is motivated by two separate research literatures. The first strand documents gaps between men and women in academia, investigates the underlying causes of these gaps, and explores mitigating policies. The second literature documents gender differences in collaboration and networking. This paper explores whether the gender differences documented in the second literature are relevant for the gaps documented in the first. We discuss each literature in turn.

### ***Underrepresentation of Women in Academics***

Gender gaps in academia — in terms of both participation and achievement — have been a topic of research and policy debate for decades. Early studies documented that women were underrepresented in science and that women scientists were recognized less often and promoted less frequently than their male counterparts (Long and Fox 1995). More recently, Ceci et al. (2014) survey many dimensions of the gender gap in academic science by taking a broad life cycle view; their analysis explores relevant differences in early-childhood outcomes, in schooling experience (from high school coursework to graduate school), and in various aspects of academic careers, including promotion decisions, publications, and grant funding. In this paper, we focus on one dimension of the gender gap: the female share of new PhD recipients.

At a fundamental level, explanations for female underrepresentation fall into three categories: differences in innate ability (e.g., biologically based differences in spatial and mathematical reasoning), differences in individual preferences (e.g., for specific fields of study or for other pursuits, such as parenthood, that affect career decisions), and societal biases (e.g., discrimination in the assessment of research output and access to key research inputs). Although variation in gender gaps across countries and time suggests that innate ability is unlikely to play a major role, disentangling these categories is otherwise difficult (Penner 2015). Research has thus proceeded by focusing on proximate factors, such as “math ability” or “ability beliefs” (e.g., Ceci et al. 2014 and Leslie et al. 2015), that are quantifiable, vary across academic fields, and can be correlated with female representation. We take a similar approach and investigate a novel factor: collaboration.

Finally, many of the cross-field studies in the literature focus on female representation at a particular point in time. However, a well-documented finding is that gender gaps are not static but have changed over time. In general, gaps have narrowed (e.g., Holden 2001), though significant gender differences remain. We take this fact into account by investigating the relationship between collaboration and female representation both over time and across academic fields.

### ***Collaboration and Gender***

Motivation for our study comes from research that implies that collaboration affects men and women differentially, although the relative effect on women’s representation could be positive or negative.

Studies have found that women are more likely than men to prefer to work in teams — partly because their assessments of prospective teammates’ abilities are more optimistic (Kuhn and Villeval 2015) — and that, after controlling for individual characteristics such as tenure, family status, and doctoral cohort, female academic scientists have more collaborators on average than do men (Bozeman and Gaughan 2011). Other studies document that women respond less favorably to competition and find that this tendency is linked to gender differences in career choices (Niederle and Vesterlund 2011; Buser, Niederle, and Oosterbeek 2014). Indeed, women view academic careers, in some instances, as not sufficiently collaborative (Lober Newsome 2008). Thus, attraction to collaborative fields may be relatively greater for women than for men. Another channel that could produce a

positive relationship between collaboration and female participation is that the “demand” for women’s representation may increase as a field becomes more collaborative. For example, studies of organizational behavior have documented that more diverse teams perform better (Phillips, Liljenquist, and Neale 2008; Sommers 2006). To the extent that these forces apply to academic settings (Freeman and Huang 2015 and Nielsen et al. 2017), researchers in more collaborative fields have greater incentives to seek out colleagues with diverse experiences and perspectives.

On the other hand, increased collaboration could negatively affect females. First, teams need not be diverse: a study of US biology laboratories revealed that elite male faculty trained 10–40 percent fewer women in their laboratories relative to the number of women trained by other investigators, though it was not clear whether the pattern resulted from self-selection by female trainees or from faculty members’ preferences (Sheltzer and Smith 2014). Moreover, in male-dominated fields, women may benefit less from increases in collaboration because they have smaller networks from which to form productive partnerships (McDowell, Singell, and Stater 2006), receive less credit for joint work (Sarsons 2017), or face negative stereotypes that hinder their ability to participate in collaborative efforts (Reuben, Sapienza, and Zingales 2014). Female academics engage less in collaborative activities with industry than do their male colleagues, and the disparity is especially pronounced in departments and fields with lower female representation (Tartari and Salter 2015).

Because of these opposing forces, whether increased collaboration helps or harms female representation in academic fields is an empirical question. We now turn to our approach for answering that question.

## Data and Methodology

Our analysis covers the entire academic spectrum, including both STEM and non-STEM fields. Whereas many studies focus on cross-sectional variation at a point in time, we use longitudinal data, which allows us to exploit both cross-sectional and time variation. This approach is useful because a significant portion of the current cross-sectional variation in the female share of new doctorate recipients comes from differential growth rates in female representation over the past 40 years. For example, the female share of PhD recipients in both aerospace and chemical engineering was less than 1.5 percent in 1975, but in 2014, while the share in aerospace engineering was still below 15 percent, the share in chemical engineering had risen to 30 percent.<sup>2</sup>

Columns (2) and (3) of Table 1 present the female share of new doctorate recipients for each of the 30 academic fields in 1975 and 2014, respectively. Consistent with earlier studies (Leslie et al. 2015), we find that female representation varies considerably within both STEM and non-STEM fields. In 2014, women earned 70 percent of the PhDs in the health sciences but fewer than 15 percent of the PhDs in various engineering fields, such as aerospace and mechanical engineering. Similarly, in non-STEM fields, women earned 71 percent of the PhDs in psychology but only 34 percent in economics. The change in female share from 1975 to 2014 also varies widely across fields. Within STEM fields, aerospace, aeronautical, and astronautical engineering had the smallest increase (13 percentage points), whereas agricultural sciences and natural resources displayed the largest increase (44 percentage points). Within non-STEM fields, foreign languages and literature showed the smallest

Collaboration and Female Representation

Lee and Malin

Table 1

**Female share and collaboration by NSF fields**

NSF Category	STEM	Female share (%)		Mean authors	
		1975	2014	1975	2014
	(1)	(2)	(3)	(4)	(5)
Aerospace, aeronautical, and astronautical engineering	Yes	1.42	14.25	1.88	3.68
Agricultural sciences; natural resources	Yes	4.72	48.31	2.22	5.13
Biological, biomedical sciences	Yes	23.05	53.86	2.52	6.36
Chemical engineering	Yes	1.08	29.77	2.16	4.44
Chemistry	Yes	10.92	38.3	2.65	5.26
Civil engineering	Yes	1.03	23.82	1.78	3.57
Computer and information sciences	Yes	—	19.72	1.76	3.64
Electrical, electronics, and communication engineering	Yes	—	16.77	2.16	4.01
Geosciences	Yes	3.95	41.3	1.97	4.66
Health sciences	Yes	30.95	70.02	2.77	6.88
Industrial and manufacturing engineering	Yes	2.17	29.87	1.88	3.45
Materials science engineering	Yes	3.79	25.6	2.25	5.13
Mathematics	Yes	9.5	28.59	1.33	2.49
Mechanical engineering	Yes	0.62	14.87	1.84	3.42
Other engineering	Yes	2.06	27.35	2.36	4.93
Physics and astronomy	Yes	5.38	20.11	2.48	5.29
Anthropology	No	35.75	62.62	1.41	3.3
Business management and administration	No	3.56	42.49	1.51	2.72
Communication	No	30.3	57.94	1.4	2.31
Economics	No	9.61	34.01	1.31	2.45
Education	No	25.3	64.81	1.54	3.33
Foreign languages and literature	No	49.88	63.2	1.03	1.14
History	No	22.32	44.03	1.35	1.48
Letters	No	39.93	57.57	1.02	1.25
Non-S&E fields not elsewhere classified	No	25.55	57.82	2.07	4.46
Other humanities	No	25.63	45.56	1.08	2.19
Other social sciences	No	20.53	56.65	1.43	2.95
Political science	No	—	44.13	1.21	1.85
Psychology	No	31.73	71.41	1.93	4.06
Sociology	No	30.88	63.42	1.36	2.1

Notes: “—” indicates less than 10 PhD recipients in the particular field-year pair.

increase (13 percentage points), whereas both psychology and education had increases of 40 percentage points.

Table 1 also displays our measure of collaboration — namely, the mean number of authors per article — for each field in 1975 and 2014, respectively.<sup>3</sup> We again see significant variation across fields in both the prevalence of coauthorship at a point in time and the change in coauthorship over time. In 2014, the mean number of authors within STEM fields ranged from 2.5 in mathematics to 6.9 in the health sciences; within non-STEM fields, it ranged from 1.1 in foreign languages and literature to 4.5 in the “Non-S&E (science and engineering) fields not elsewhere classified.” Within their respective categories, these same fields experienced the smallest and largest increases in coauthorship from 1975 to 2014: the mean number of authors increased by 1.2 in mathematics, 4.1 in the health sciences, 0.1 in foreign languages and literature, and 2.4 in the “not elsewhere classified” fields.

Our panel dataset covers 30 academic fields for every fifth year from 1975 to 2010, as well as 2014. We use the following panel regression model to measure the relationship between the degree of collaboration in a field and its female representation:

$$Y_{ft} = \alpha + \beta * Collaboration_{ft} + \delta_f + \theta_t + \epsilon_{ft}, \quad (1)$$

where  $Y_{ft}$  is the female share of PhD recipients in field  $f$  and year  $t$ ,  $Collaboration_{ft}$  is the average number of authors per article, and  $\epsilon_{ft}$  is an error term. The parameter  $\delta_f$  captures the effect of time-invariant characteristics of field  $f$  on the female share (i.e., field fixed effects). For example, if, all else equal, women prefer literature to mechanical engineering, the estimated value of  $\delta_{literature}$  will be greater than  $\delta_{mechanicalengineering}$ . We view the ability to control for the possibility that some fields may be innately more attractive to one gender than the other as a key advantage of using panel data, as opposed to cross-sectional data alone. The parameter  $\theta_t$ , on the other hand, captures any time trend common to all academic fields (i.e., time fixed effects). If, for example, the female share of PhD recipients were to increase by equal amounts in all fields over time, then  $\theta_t$  would also increase by that amount from year to year.

The parameter of interest in our regression is  $\beta$ , which measures the extent to which one additional coauthor per article can account for the variation in the female share of PhD recipients across time and fields. To be precise about what  $\beta$  captures, we consider two examples. First, suppose that field  $f$  has both a larger female share and a higher rate of coauthorship than another field  $f'$ . This may not lead to a positive estimate of  $\beta$  because of the field fixed effects in the model; that is, if the gap in the female share of fields  $f$  and  $f'$  is maintained over time, then this gap will be captured by  $\delta_f - \delta_{f'} > 0$ , not by  $\beta$ . Second, suppose that both the female share and coauthorship increase over time at the same rate across all fields. This correlation between coauthorship and female share would not show up in  $\beta$ , as it would be captured by the time trend  $\theta_t$ . Rather, a positive (negative) estimate of  $\beta$  will result if fields that exhibit faster increases in female share also experience larger (smaller) increases in coauthorship.

Although equation (1) estimates the relationship between contemporaneous female share and collaboration, both variables reflect previous decisions made by individuals: articles are often published several years after collaboration on a project begins, whereas doctorate degrees are typically conferred several years after the decisions to enter and persist in a degree program are made. Because it is not clear what the appropriate dynamic structure

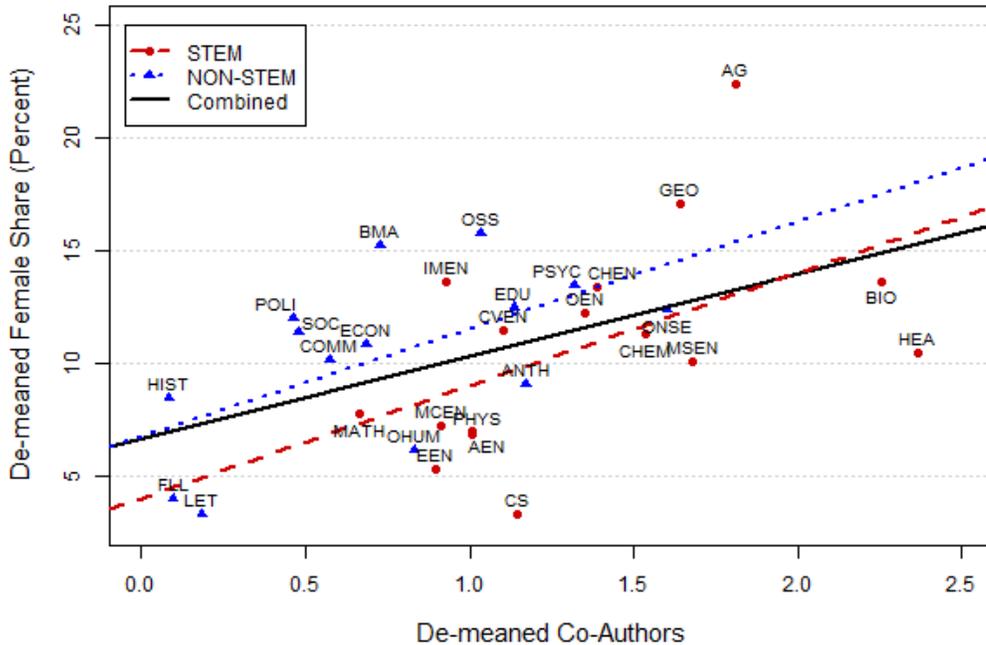
is for these variables, we specify a contemporaneous version as our baseline but will also consider specifications with various lags of the variables as robustness checks.

### Results and Discussion

Before we formally present the regression results, we begin by plotting the underlying data. Under the hypothesis that collaboration affects female representation, the relationship should be apparent along two dimensions: a cross-sectional relationship at a point in time and a time-series relationship within fields.

Figure 2 focuses on the cross-sectional relationship in 2014. Because field-specific traits may be important determinants of the levels of both coauthorship and the female share, we control for such traits by demeaning the 2014 values by their field-specific averages (over time). We split the observations between STEM (red dots) and non-STEM (blue triangles) fields. An estimate of the linear relationship between coauthorship and female share is shown by the plotted lines: the solid black line is estimated using all observations, the dashed red line uses STEM fields, and the dotted blue line uses non-STEM fields. In all cases, a strong positive relationship between coauthorship and female share is evident.

Figure 2  
**Coauthorship and female share of PhD recipients in 2014**



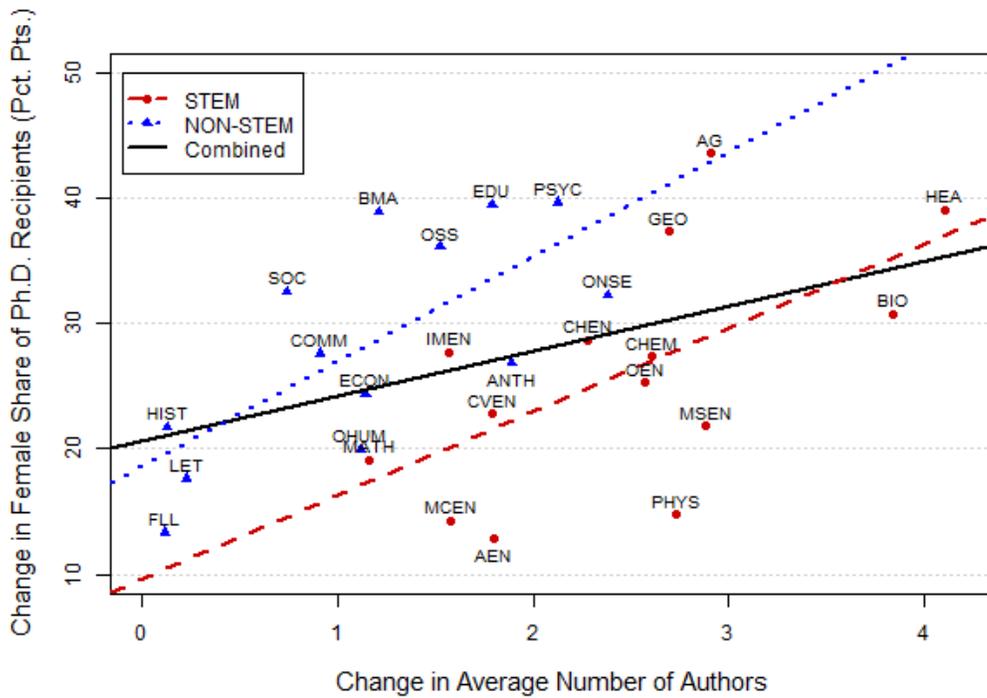
Notes: This figure shows the relationship between coauthorship and the female share of PhD recipients across academic fields in 2014. Variables are expressed relative to their mean value (over time) for each field. The lines represent OLS estimates of the relationship using all fields (solid black line), STEM fields (dashed red line), and non-STEM fields (dotted blue line), respectively. The regression coefficient (standard error) for the various samples is 3.7 (1.2) for all, 5.0 (2.2) for STEM, and 4.8 (1.9) for non-STEM.

QR

Figure 3 shows the relationship between the change in female share and the change in coauthorship over time. For each field, we calculate the change in the respective variables from 1975 to 2014. Because three of our fields are missing some information in 1975, Figure 3 plots data for 27 fields.<sup>4</sup> As in Figure 2, we estimate the relationship between the change in female share and the change in the number of coauthors for all fields and separately for STEM and non-STEM fields. In all cases, we see that fields that had a greater increase in the average number of coauthors from 1975 to 2014 tend to have a greater increase in female share over the same period. All results are statistically significant at the 5 percent level.

Figure 3

**Change in coauthorship and female share of PhD recipients from 1975 to 2014**



Notes: This figure shows the relationship between the change in coauthorship and that in the female share of PhD recipients from 1975 to 2014. The lines represent OLS estimates of the relationship across academic fields using all fields (solid black line), STEM fields (dashed red line), and non-STEM fields (dotted blue line), respectively. The regression coefficient (standard error) for the various samples is 3.5 (1.6) for all, 6.6 (2.6) for STEM, and 8.3 (2.5) for non-STEM .

We now turn to the estimates of our regression model. Panel A of Table 2 reports estimates of  $\beta$  for all fields and separately for STEM and non-STEM fields. For all fields (column 1), one additional author on the average published paper is associated with an increase of 2.5 percentage points in the female share. This positive relationship also holds when we estimate the regression model using STEM and non-STEM fields separately. Columns (2) and (3) show that one additional author on the average published paper is associated with an increase of 3.7 percentage points in the female share among STEM fields and 6.0 percentage points among non-STEM fields, respectively. The average of these two effects is not the same as the result in column (1) because the regression specification

Table 2  
**Female share and collaboration**

	All (1)	STEM (2)	Non-STEM (3)
Panel A. Mean authors	2.51*** [0.81]	3.66*** [1.29]	5.97*** [1.33]
Panel B. Mean authors (restricted)	2.17*** [0.72]	2.90** [1.20]	4.34*** [1.02]
Panel C. Mean institutions (restr.)	11.06*** [2.45]	16.21*** [4.76]	16.64*** [3.04]
Panel D. Mean au. per inst. (restr.)	-0.18 [0.50]	1.00* [0.54]	-1.93** [0.74]
Number of observations	266	141	125

*Notes:* Additional control variables include year dummies (total of 8), NSF-field-specific dummies (total of 29), and a constant. Heteroskedasticity robust standard errors are reported in brackets. Significance: \* 10 percent, \*\* 5 percent, \*\*\* 1 percent.

corresponding to column (1) assumes that the time effects are the same across both STEM and non-STEM fields. That is, if our model allowed for differing time effects for STEM and non-STEM fields, the estimated coefficient would be the same as the (weighted) average of the coefficients in columns (2) and (3).

To gauge the quantitative importance of collaboration, we calculate the share of variation in female representation that may be accounted for by collaboration. In 2014, the difference between the maximum and minimum field female shares was 57.2 percentage points, whereas the corresponding difference for coauthorship was 5.7. The variation in collaboration can thus account for about 25 percent of the variation in female share ( $5.7 * 2.51 / 57.2$ ). A similar calculation can be made over time. The (across-field) average change in female share from 1975 to 2014 was 24.7 percentage points, while the average change in the number of authors per article was 3.1. Thus, increased collaboration can account for 31 percent of the increased female share ( $3.1 * 2.51 / 24.7$ ). The magnitudes are quantitatively similar if we consider STEM and non-STEM fields separately. For STEM fields, collaboration can account for 25 percent of the 2014 cross-sectional variation and 43 percent of the increased female share over time. For non-STEM fields, the results are 53 percent and 36 percent, respectively. In sum, not only are coauthorship and female share positively correlated, but also the variation in coauthorship may account for a sizable portion of the variation in female share across academic fields.

We also check the robustness of these results to alternative specifications of equation (1) by including lagged variables of female share and collaboration in the regressions. Qualitatively, the relationship between contemporaneous correlation and female share is

unaffected. In a first exercise in which we include a single lagged dependent variable, the estimated coefficient for mean authors is 1.52 (standard error of 0.52), which was somewhat smaller than in the baseline regression specification but still statistically significant at the 1 percent level. Adding more lagged values of the dependent variable has little effect, and the additional lags are insignificant. We also consider specifications that include lagged values of the explanatory variable. Again, these lags enter insignificantly and do not alter the contemporaneous relationship between female share and collaboration.

The finding of a positive relationship between coauthorship and female share raises several additional questions. For example, does the correlation reflect a causal relationship,<sup>5</sup> and if so, what are the mechanisms through which these two variables are linked? Further, are some types of collaboration more effective at promoting female representation than others? Although our data do not allow for direct answers to these questions, we conduct some additional exercises that provide hints.

### ***Collaboration within or across Institutions***

We first explore whether female representation is more closely related to collaboration *within* or *across* institutions. Working in the same institution facilitates regular face-to-face interactions, which may be particularly important for senior researchers collaborating with junior researchers. From our WoS data, we calculate two additional collaboration measures: the average number of institutions and the average number of authors per institution for a publication. We use the former as a measure of across-institution collaboration and the latter as a measure of the within variety. Because institutional affiliations are only available for a restricted sample of documents, we first conduct our previous analysis on this restricted sample.<sup>6</sup> In a comparison of panels A and B of Table 2, note that restricting the sample does not significantly alter the results. Turning to the analysis of institutional affiliations, we see that panel C shows that an increase in the number of institutions is associated with a higher female share, whereas panel D indicates that an increase in the number of authors per institution is not.<sup>7</sup> Thus, face-to-face interaction and vertical collaboration, as measured by within-institution coauthorship, may not be especially important for female representation.

### ***Alphabetical versus Contributive Ordering of Authorship***

We next examine whether the possibility of getting less than commensurate credit from coauthored work is associated with lower female representation. Sarsons (2017) documents that in economics — a field in which authors' surnames are generally ordered alphabetically, thus making it difficult to discern an individual's specific contribution to a coauthored paper — women receive less credit than men on papers coauthored with males. In contrast, Sarsons finds that in sociology — a field in which authors are listed in order of contribution — men and women benefit equally from joint work. We note that if female academics perceive they will receive less credit from a coauthored publication that does not indicate their specific contribution, they will be likely to collaborate less on this type of project. Furthermore, because many women value collaboration (as described earlier), women may be less attracted to fields in which the norm is alphabetical ordering of author surnames.

To examine this possibility, we first classify academic fields into two groups: those whose

Table 3  
**Authorship ordering, female share, and collaboration**

Sample	2014 (1)	1975-2014 (2)	1975-2014 (3)
1(f: alphabetical)	-12.84** [5.28]	-8.96*** [2.81]	—
1(f: stem)	-24.32*** [4.62]	-32.39*** [1.88]	—
Mean authors		5.73*** [1.39]	2.52*** [0.84]
Mean authors × 1(f: alphabetical)			0.17 [1.82]
Field fixed effects	No	No	Yes
Year fixed effects	No	Yes	Yes
Number of observations	30	266	266

*Notes:* Specifications with year fixed effects have 8 year dummies. Specifications with field fixed effects have 29 NSF-field-specific dummies. All regressions also include a constant. Heteroskedasticity robust standard errors are reported in brackets. Significance: \* 10 percent, \*\* 5 percent, \*\*\* 1 percent.

primary journals generally list authors' surnames in alphabetical order and those whose journals list authors based on their contribution to the paper (e.g., first author, corresponding author, and so on). A description of our classification is provided in the appendix. We classify only 3 of our 30 academic fields — economics, mathematics, and political science — as alphabetical.

We test two empirical conjectures. First, we hypothesize that the fields that use alphabetical ordering may have lower female shares. Our regression specification is as follows:

$$Y_f = \alpha + \beta * 1(f : \text{alphabetical}) + \gamma * 1(f : \text{STEM}) + \epsilon_f. \quad (2)$$

That is, we regress the female share in a given year on a constant, an indicator variable for whether the field uses alphabetical ordering, and an indicator variable for whether the field is a STEM field. Note that because we only use cross-sectional data, we cannot include field fixed effects, but we do include the STEM-field dummy to control for some heterogeneity across fields. Under our hypothesis, fields with alphabetical ordering will have lower female shares than their peers within STEM (or non-STEM); in other words,  $\beta$  will be negative. Column (1) of Table 3 reports the results based on 2014 data. The fields with alphabetical ordering of author surnames have a smaller female share than other fields.

Column (2) of Table 3 presents the results from a slightly modified regression in which we pool all years of the data. We now include a year fixed effect in the regression specification and also control for the average number of authors corresponding to each (year ×

## QR

field) observation. We find that the fields that use alphabetical ordering have a statistically significant smaller female share of approximately 9 percentage points.

The second conjecture that we test is whether fields with alphabetical ordering exhibit a less positive correlation between collaboration and female share. This could occur because women have less to gain from increased coauthorship in the field than do their male counterparts. Our regression specification is as follows:

$$Y_{ft} = \alpha + \beta_1 * Collaboration_{ft} + \beta_2 * [Collaboration_{ft} \times 1(f : alphabetical)] + \delta_f + \theta_t + \epsilon_{ft}. \quad (3)$$

Compared with equation (1), in equation (3) we add the interaction term  $Collaboration_{ft} \times 1(f : alphabetical)$ . If our conjecture is correct, then  $\beta_2$  will be negative.

Column (3) of Table 3 reports the results. Consistent with our baseline model, the mean number of authors is positively associated with the female share. Turning to our conjecture, we note that the estimated  $\beta_2$  is actually positive, though small and not statistically significant. The lack of statistical significance may be a result of only three fields using alphabetical ordering, thus making it difficult to ensure statistical power. In short, we do not find strong evidence suggesting that collaboration affects women differently in fields with alphabetical ordering compared with those with contributive ordering of authorship.

### ***Collaboration and Racial/Ethnic Minority Shares***

Finally, we expand our analysis to consider how collaboration interacts with the share of minority groups other than women. To the extent that the relationship between collaboration and female share is driven by a greater demand for diversity in more collaborative fields, we would expect to find similar patterns between collaboration and racial/ethnic minorities. Because information on race/ethnicity is only available for PhD recipients who are US citizens or permanent residents, we first redo our primary empirical analysis on this sample.<sup>8</sup> As shown in panel A of Table 4, the relationship between coauthorship and female representation is qualitatively unchanged.

We then estimate the relationship between collaboration and the share of blacks, Asian Americans, and Hispanics, respectively. Panels B and C of Table 4 show that collaboration is positively associated with the share of blacks and Asian Americans (within non-STEM and STEM fields, respectively), although the statistical relationship is not as strong as the one we find for female share. For the estimates that are statistically significant, we calculate the fraction of the variation in representation that can be attributed to collaboration. In 2014, collaboration accounts for 26 percent of the variation in black share across all fields, 76 percent of black share variation across non-STEM fields, and 65 percent of Asian American share variation across STEM fields.

In contrast, Hispanic share (panel D) is not well accounted for by collaboration. We do not have sufficient data to identify the factors that drive these differences across minority groups. It could be that, to the extent that increased collaboration increases demand for diversity, this increased demand does not uniformly apply to all minorities. Alternatively, some minority groups may find collaborative environments more appealing than do others.

Table 4

**Female/minority share and collaboration**

	All (1)	STEM (2)	Non-STEM (3)
Panel A. Female share	3.23*** [0.89]	3.50** [1.44]	7.15*** [1.22]
Panel B. Black share	0.65** [0.26]	0.31 [0.52]	1.83*** [0.49]
Panel C. Asian American share	-0.13 [0.40]	2.16** [0.88]	0.085 [0.36]
Panel D. Hispanic share	-0.21 [0.21]	-0.18 [0.34]	0.07 [0.53]
Number of observations	266	141	125

*Notes:* The shares of various groups are constructed using PhD recipients who are US citizens or permanent residents. Collaboration is measured by mean number of authors. Additional control variables include year dummies (total of 8), NSF-field-specific dummies (total of 29), and a constant. Heteroskedasticity robust standard errors are reported in brackets. Significance: \* 10 percent, \*\* 5 percent, \*\*\* 1 percent.

**Conclusion**

Using panel data for 30 academic fields from 1975 to 2014, we find that academic fields in which coauthorship has expanded rapidly over the past 40 years have also experienced faster growth in female representation; one additional author on the average paper published in a field is associated with an increase of 2.5 percentage points in the female share of PhD recipients in that field.

To be clear, this finding reflects a correlation between coauthorship and female representation and does not establish that increased collaboration causes gender gaps to narrow. That said, a plausible mechanism through which collaboration may increase female share is that women are more likely to collaborate than their male counterparts (Bozeman and Gaughan 2011), so as coauthorship becomes the norm, women engage in collaborative projects relatively more than men do. To the extent that such interactions contribute to success in academia, as suggested by McDowell, Singell, and Stater (2006) and Blau et al. (2010), this effect leads to higher female retention in collaborative fields. At any rate, future research is needed to more fully explore the mechanisms underlying the observed relationship.

Nonetheless, we believe our findings are relevant for the important policy debate about how to improve female representation in academic fields in general and STEM fields in particular. Improving STEM diversity has been a focus of national governments and international organizations for decades. Early efforts, such as those of the US National Science Foundation (NSF) (1982) and the European Commission (2004), focused on collecting sex-disaggregated data to monitor women's participation. Subsequently, these organizations

started initiatives that sought to support women’s careers in science and engineering in various ways, such as providing research funding for women and setting up mentoring networks (Rosser 2008). Policy has also focused on transforming the culture of research institutions. For example, the NSF’s ADVANCE program (Increasing the Participation and Advancement of Women in Academic Science and Engineering Careers), launched in 2001, assists institutions in implementing structural changes to improve underrepresented minorities’ success in STEM fields. These changes range from counteracting gender and ethnic bias in hiring and promotion practices to policies that support work-life balance by offering parental leave and allowing for career breaks.

Despite all of these efforts, the gender gap in STEM fields still exists, and the need to close the gap continues to receive much attention. Indeed, in addition to expanded public policy efforts in recent years,<sup>9</sup> private organizations, such as firms and universities, have also taken steps to improve STEM diversity.<sup>10</sup> This broadened interest may partly be because STEM jobs are projected to grow faster than jobs in other sectors in developed economies — thus requiring a larger pool of educated workers to fill these jobs — and partly because studies have found that more diverse teams perform better than less diverse teams (Phillips, Liljenquist, and Neale 2008). Focusing more narrowly on the context of academic research, we note that having more diversity in any given field may contribute to the intellectual development of ideas. Bayer and Rouse (2016) argue that a lack of diversity can constrain the range of issues addressed by a discipline and may limit its collective ability to understand familiar issues from new and innovative perspectives. Similarly, May, McGarvey, and Kucera (2018) find that male and female economists in the European Union have different perspectives on economy policy and, in light of this, suggest that the greater inclusion of women in economics could potentially lead to a more diverse set of questions being asked and possibly different conclusions being reached on important policy questions.

Our findings are consistent with the view that policies and initiatives that increase opportunities for interaction and collaboration may be beneficial. Policies of this type include public funding that supports mentoring for female scientists and provides opportunities for collaborative efforts,<sup>11</sup> as well as private, grassroots initiatives that seek to create safe and collaborative environments for women to thrive in. One high-profile initiative is LeanIn.org (<https://leanin.org>), which champions small groups for women in which they can express their goals in a supportive environment, form networks, and build the skills necessary to reach their goals. Another source of interactions of this type is professional organizations within academic fields; for example, in economics, the Committee on the Status of Women in the Economics Profession (CSWEP) is a standing committee of the American Economics Association and provides opportunities for mentorship and networking for female economists.

## **Appendix: Data Sources and Construction**

### *Doctorate Recipients by Field of Study*

The annual number of doctorate recipients by field of study, gender, race/ethnicity, and US citizenship status comes from the “Doctorate Recipients from US Universities” reports, which are published annually by the National Science Foundation (NSF).<sup>12</sup> Because information by

field and gender starts in 1966, our sample period ranges from 1966 to 2014. Information on ethnicity and race is available only from 1973 onward. Mark Fiegenger, a project officer in the NSF's National Center for Science and Engineering Statistics, provided us with consistent data over this sample period for 34 academic disciplines.<sup>13</sup>

For each year and academic discipline, we calculate several variables. "Female share" is the number of female doctorates divided by the sum of female and male doctorates. We omit doctorates whose gender is missing. "Female share (US)" is the female share among doctorates with US citizenship or permanent residency. We also calculate racial/ethnic shares as the number of doctorates of a given race/ethnicity (black, Hispanic, or Asian American) divided by doctorates whose race/ethnicity is reported. These shares are calculated from doctorates who are US citizens or permanent residents.

### *Collaboration by Field of Study*

We commissioned Thomson Reuters to construct a panel dataset for us from their Web of Science (WoS) data. Specifically, for each of 251 WoS academic categories and every fifth year from 1970 to 2005 and annually from 2008 to 2014, Thomson Reuters provided the following variables: mean (median) authors per document, mean (median) institutional affiliations per document, mean (median) authors per institution per document, and number of documents.

We placed a few restrictions on the documents that were included in the sample. First, we restricted documents to those classified as "original research," which includes journal articles and book chapters from journal editions. For example, meeting abstracts, editorial material, book reviews, reviews, proceedings papers, and corrections were excluded. Second, as a minimal quality requirement, we restricted our sample to documents that have received at least one citation. We refer to the resulting set of documents as our "full sample."

Additional sample restrictions were made to facilitate the analysis of institutional affiliation. These restrictions differ before and after 2008 because authors are not directly linked to their institutions in the raw WoS data prior to 2008; rather, all institutions affiliated with any of a document's authors are listed together. For pre-2008 publications, our sample is simply restricted to papers that have at least one institutional affiliation. For post-2008 publications, we required documents to have at least one affiliation and also have linked data (to match the author with the institution). We refer to the set of documents that meet these criteria as our "restricted sample." Thomson Reuters constructed all variables — that is, those constructed using the full sample and those that require institutional information — for this sample.

Finally, we construct the institutional affiliation of authors differently before and after 2008. Because authors are not linked to their institution before 2008, the number of institutions for a document is simply the minimum of the number of authors and listed institutions. After 2008, however, we can use linked data to deal with cases in which authors have multiple affiliations.<sup>14</sup> Because we are interested in whether collaboration takes place within or across institutions, we do not want to randomly assign one of the author's institutions to be the primary institution. Instead, we use the following algorithm to identify coauthors' shared institutions, which will produce a lower bound on the number of institutions per document. Namely, for each document:

1. Identify authors with only one affiliation.

## QR

- (a) List those institutions and set the institution count to the number of institutions on that list.
  - (b) Remove any authors, including multiple-institution authors, who have listed affiliations.
2. Identify the most frequently occurring affiliation for the remaining authors.
    - (a) Increment the institution count.
    - (b) Remove all authors associated with that institution.
  3. Repeat previous step until remaining institutions appear only once.
  4. Add the number of remaining authors (not institutions) to the institution count.

*Combining the Data*

We combine the data on doctorate recipients and coauthorship to produce a panel dataset, which covers 30 academic fields for every fifth year from 1975 to 2010, as well 2014, the latest year available. We drop 1970 data because the number of journal categories is significantly lower than in other years (229 versus 248-251), and even though we have data for every year after 2008, we continue to use data from every fifth year for consistency with the earlier part of the sample. Our dataset includes only 30 NSF academic fields (rather than 34) because we merge all education-related fields (i.e., education administration, education research, teacher education, teaching fields, and other education). We do this because the education-related WoS journal categories do not allow for a clean mapping into separate NSF education fields.

To aggregate the 251 WoS journal categories into the 30 NSF major fields, we make use of NSF detailed subfields, which are listed in the NSF's "Table 16. Doctorate recipients, by sex and subfield of study: 2014" (at <http://www.nsf.gov/statistics/2016/nsf16300/data/tab16.pdf>) and assign each journal category to an NSF subfield based on our best judgment. With over 300 NSF subfields, journal categories and subfields are at a similar level of disaggregation, making the mapping straightforward for most categories. The most frequent reason a mapping was less than clear-cut was that the journal category could have been classified as either biological/biomedical sciences or health sciences. Alternative mappings of these categories do not significantly affect our results. We also omit five WoS categories for which the mapping was unclear: Crystallography, Energy & Fuels, Microscopy, Nanoscience & Nanotechnology, and Spectroscopy.

We also drop a few year-by-WoS-category observations that display an exceptionally large number of authors because we are concerned that these outliers could mask the relationship between average collaboration and the composition of doctorates. For example, the mean number of authors per document in "Physics, Particles & Fields" jumped from less than 15 in 2010 (and all previous years) to 47 in 2014. This is an extreme outlier: across WoS categories and years, the mean and standard deviation of authors per document are 3.43 and 2.67, respectively. We drop observations that had a mean number of authors per document more than +/- 5 standard deviations from the cross-sectional mean (i.e., greater than 17 authors). This removes three observations out of 2,259. All three are in 2014: "Astronomy & Astrophysics," "Physics, Nuclear," and "Physics, Particles & Fields."

For each of our 30 academic fields and for each year, we construct the weighted average

of our collaboration statistics (mean authors per article and so on) across journal categories assigned to the field, where the weight is based on the number of documents in the WoS category. Specifically, the weight for a WoS category is its number of documents relative to the number of documents for all WoS categories in the NSF field.

Finally, for analysis involving our primary measure of collaboration (i.e., number of authors), we use our full sample so as to avoid differences in sample selection pre- and post-2008.<sup>15</sup> However, when we analyze the number of institutions and the number of authors per institution, we must use our restricted sample. This approach requires care in how we compare results across time; specifically, it is one reason we include time fixed effects in our regressions.

### *Classification of Fields as Alphabetical versus Contributive Ordering*

To classify fields as alphabetical or contributive ordering, we first selected the five highest-rated journals based on impact factors for each academic field. We then perused the table of contents of at least two issues of each journal and indicated whether the journal used alphabetical ordering of author surnames. Journals in the fields of economics and mathematics used alphabetical ordering, and several (but not all) of the journals in political science did so as well. Some other fields — such as history or business management — had a few journals with alphabetical ordering, but not enough to classify the entire field as using alphabetical ordering.

## **Notes**

1. The increase in coauthorship is not driven by outliers (i.e., a few extremely large sets of coauthors), as a similar pattern emerges for the median (rather than the mean) number of authors.

2. More broadly, we decompose the cross-sectional variance of 2014 female representation into two parts: variance in 1975 levels and variance in differential growth rates from 1975 to 2014. The latter accounts for 29 percent of the variation within all fields and 51 percent within STEM fields.

3. A detailed explanation of how this measure is constructed is provided in the appendix.

4. The three omitted fields include computer and information sciences; political science; and electrical, electronics, and communication engineering.

5. Assessing causality is not feasible with our data, but we did explore the notion of Granger causality. We used the Lopez and Weber (2017) implementation of the Dumitrescu and Hurlin (2012) test for panel datasets, but given the short time dimension of our data set ( $T = 9$ ), we could not reject the null of no Granger causality (in either direction).

6. A detailed explanation of the construction of the restricted sample is provided in the appendix.

7. Although the coefficient estimates in panel C of Table 2 are much higher than those in panel B, the number of institutions varies much less than the number of authors. Thus, the two measures account for similar amounts of the variation in female share.

8. The appendix describes the construction of this sample.

9. Examples include the US Women and Minorities in STEM Booster Act, South Korea's Women in Science, Engineering, and Technology (WISET) program, and UNESCO's STEM and Gender Advancement (SAGA) project. See also Best et al. (2013) for a discussion of programs in Germany.

10. Examples include Intel's Diversity in Technology Initiative, L'Oreal USA's For Women in Science fellowship program, the Athena Scientific Women's Academic Network (SWAN) in the United Kingdom, and Women in Science and Engineering (WISE) programs at universities throughout the United States.

## QR

11. For example, the US Women and Minorities in STEM Booster Act authorizes grants for mentoring and professional development programs that support recruitment and retention of women and minorities in STEM fields.

12. See National Science Foundation, “S & E Doctorate Awards,” <https://www.nsf.gov/statistics/doctorates/>.

13. Data from the NSF’s Survey of Earned Doctorates (SED) are available online, but this information is not suitable for our purposes. In particular, the WebCASPAR system (<https://ncesdata.nsf.gov/webcaspar/>) does not provide data on gender, ethnicity, race, or citizenship after 2006. The SED Tabulation Engine (<https://nces.norc.org/NSFTabEngine/#WELCOME>) performs such tabulations, but currently only from 2006 to 2012. The NSF provided us with the full range of annual SED data (1966-2014), using the classification system of the published tables. Note that the published tables differ somewhat from the online (WebCASPAR) data; specifically, 300+ subfields are aggregated into 47 “Detailed Disciplines” in the WebCASPAR data but into 34 “Major Fields” in the published tables.

14. By “multiple affiliations,” we mean multiple appointments — for example, UCLA and University of Minnesota — and not just parent institutions — for example, the University of California System and UCLA. We deal with the latter case by using only the institution that is on the lowest rung, so to speak.

15. Another reason to focus on the full sample is that WoS policy for assigning institutions appears to have changed in 1998. Documents have a “reprint/corresponding” address (until recently, just one per document) and also “researcher” addresses. The latter are the full address lists from the publication, whereas the former can manifest itself differently in the full text of the article. It appears that, in 1998, publications without researcher addresses but with a reprint address started to have the latter assigned to the former. This led to a big increase in our restricted sample and could cause a spurious drop in the number of authors per document.

## References

- Bayer, Amanda, and Cecilia E. Rouse. 2016. “Diversity in the Economics Profession: A New Attack on an Old Problem.” *Journal of Economic Perspectives* 30 (4): 221–242.
- Best, Kathinka L., Ulrike Sanwald, Susanne Ihnen, and Angela Ittel. 2013. “Gender and STEM in Germany: Policies Enhancing Women’s Participation in Academia.” *International Journal of Gender, Science and Technology* 5 (3): 292–304.
- Blau, Francine D., Janet M. Currie, Rachel T. A. Croson, and Donna K. Ginther. 2010. “Can Mentoring Help Female Assistant Professors? Interim Results from a Randomized Trial.” *American Economic Review: Papers & Proceedings* 100 (2): 348–352.
- Bozeman, Barry, and Monica Gaughan. 2011. “How Do Men and Women Differ in Research Collaborations? An Analysis of the Collaborative Motives and Strategies of Academic Researchers.” *Research Policy* 40 (10): 1393–1402.
- Buser, Thomas, Muriel Niederle, and Hessel Oosterbeek. 2014. “Gender, Competitiveness, and Career Choices.” *Quarterly Journal of Economics* 129 (3): 1409–1447.
- Ceci, Stephen J., Donna K. Ginther, Shulamit Kahn, and Wendy M. Williams. 2014. “Women in Academic Science: A Changing Landscape.” *Psychological Science in the Public Interest* 15 (3): 75–141.
- Ceci, Stephen J., and Wendy M. Williams. 2004. “Understanding Current Causes of Women’s Underrepresentation in Science.” *Proceedings of the National Academy of Sciences* 108 (8): 3157–3162.
- Dumitrescu, Elena-Ivona, and Christophe Hurlin. 2012. “Testing for Granger Non-Causality in Heterogeneous Panels.” *Economic Modelling* 29 (4): 1450–1460.
- European Commission. 2004. *She Figures 2003: Women and Science Statistics and Indicators*. Luxembourg: Office for Official Publications of the European Communities.

- Freeman, Richard B., and Wei Huang. 2015. "Collaborating with People Like Me: Ethnic Coauthorship within the United States." *Journal of Labor Economics* 33 (S1): S289–S318.
- Goldin, Claudia. 2014. "A Grand Gender Convergence: Its Last Chapter." *American Economic Review* 104 (4): 1091–1119.
- Holden, Constance. 2001. "General Contentment Masks Gender Gap in First AAAS Salary and Job Survey." *Science* 294 (5541): 396–411.
- Kuhn, Peter, and Marie C. Villevall. 2015. "Are Women More Attracted to Co-operation Than Men?" *Economic Journal* 125 (582): 115–140.
- Leslie, Sarah-Jane, Andrei Cimpian, Meredith Meyer, and Edward Freeland. 2015. "Expectations of Brilliance Underlie Gender Distributions across Academic Disciplines." *Science* 347 (6219): 262–265.
- Lober Newsome, Jessica. 2008. *The Chemistry PhD: The Impact on Women's Retention*. A report prepared by Jessica Lober Newsome for the UK Resource Centre for Women in SET and the Royal Society of Chemistry.
- Long, J. Scott, and Mary F. Fox. 1995. "Scientific Careers: Universalism and Particularism." *Annual Review of Sociology* 21:45–71.
- Lopez, Luciano, and Silvain Weber. 2017. "Testing for Granger Causality in Panel Data." IRENE Working Paper 17-03, IRENE Institute of Economic Research.
- May, Ann Mari, Mary G. McGarvey, and David Kucera. 2018. "Gender and European Economic Policy: A Survey of the Views of European Economists on Contemporary Economic Policy." *Kyklos* 71 (1): 162–183.
- McDowell, John M., Larry D. Singell, and Mark Stater. 2006. "Two to Tango? Gender Differences in the Decisions to Publish and Coauthor." *Economic Inquiry* 44 (1): 153–168.
- National Science Foundation (NSF). 1982. *Women and Minorities in Science and Engineering*. Washington, DC: National Academies Press.
- Niederle, Muriel, and Lise Vesterlund. 2011. "Gender and Competition." *Annual Review of Economics* 3:601–630.
- Nielsen, Mathias Wullum, Sharla Alegria, Love Börjesson, Henry Etkowitz, Holly J. Falk-Krzesinski, Aparna Joshi, Erin Leahey, Laurel Smith-Doerr, Anita Williams Woolley, and Londa Schiebinger. 2017. "Opinion: Gender Diversity Leads to Better Science." *Proceedings of the National Academy of Sciences* 114 (8): 1740–1742.
- Penner, Andrew M. 2015. "Gender Inequality in Science." *Science* 347 (6219): 234–235.
- Phillips, Katherine W., Katie A. Liljenquist, and Margaret A. Neale. 2008. "Is the Pain Worth the Gain? The Advantages and Liabilities of Agreeing with Socially Distinct Newcomers." *Personality and Social Psychology Bulletin* 35 (3): 336–350.
- Reuben, Ernesto, Paola Sapienza, and Luigi Zingales. 2014. "How Stereotypes Impair Women's Careers in Science." *Proceedings of the National Academy of Sciences* 111 (12): 4403–4408.
- Rosser, Sue Vilhauer. 2008. "Building Two-Way Streets to Implement Policies that Work for Gender in Science." In *Gender Innovations in Science and Engineering*, edited by Londa Schiebinger, 182–197. Stanford, CA: Stanford University Press.
- Sarsons, Heather. 2017. "Recognition for Group Work: Gender Differences in Academia." *American Economic Review: Papers & Proceedings* 107 (5): 141–145.
- Sheltzer, Jason M., and Joan C. Smith. 2014. "Elite Male Faculty in the Life Sciences Employ Fewer Women." *Proceedings of the National Academy of Sciences* 111 (28): 10107–10112.
- Sommers, Samuel R. 2006. "On Racial Diversity and Group Decision Making: Identifying Multiple Effects of Racial Composition on Jury Deliberations." *Journal of Personality and Social Psychology* 90 (4): 597–612.
- Tartari, Valentina, and Ammon Salter. 2015. "The Engagement Gap: Exploring Gender Differences in University–Industry Collaboration Activities." *Research Policy* 44 (6): 1176–1191.
- Wuchty, Stefan, Benjamin F. Jones, and Brian Uzzi. 2007. "The Increasing Dominance of Teams in the Production of Knowledge." *Science* 316 (5827): 1036–1039.