Gender and Collaboration

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Abstract

We document persistent gender disparities in economics. The fraction of women in economics has grown significantly over the last forty years but the difference in research output between men and women remains large. There are significant differences in the co-authorship networks of men and women: women have fewer collaborators, collaborate more often with the same co-authors, and a higher fraction of their co-authors are co-authors of each other. Both men and women exhibit homophily in their co-authorship relations. Finally, women collaborate with more senior co-authors. Similar output and collaboration patterns obtain in sociology.

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1 Introduction

Gender disparities in the work place have attracted considerable attention in recent years. In this paper we study this issue in a specific context: research output of economists over the period 1970 to 2011. We document a set of empirical facts relating to gender, output and collaboration.

Our first observation is that there has been a significant increase in the share of women in the profession: the fraction of female economists grew from 8% to 29% over this period. But, after a fall until 1990, the research output difference between men and women has remained essentially unchanged until 2011: men have produced 50% more output than women throughout the period under study. These large differences in output remain after we control for experience and choice of field (and other observable factors). This difference in average output goes alongside a lower variation: women have a standard deviation of output that is roughly 50% lower than men.

Our second observation pertains to patterns of collaboration: we find that there are large and persistent differences between men and women controlling for experience, past output and choice of fields. Women have fewer distinct co-authors (lower degree): women have an average degree 21% lower than that for men. Women have a higher overlap among connections (higher clustering coefficient), their average clustering coefficient is 6% higher than that for men. They also tend to work repeatedly with the same co-authors (higher strength of ties), women have an average strength 8.7% higher than that for men.

Our third observation is about the types of coauthors that men and women have. We find that collaboration exhibits homophily: men tend to work more with men and women more with other women, on average. We also find that women have more senior co-authors, at every point in their career. This difference in seniority is almost equal to 1 year.

These differences are striking and we are led to wonder if they are specific to economics or if they are obtained more broadly. This motivates a study of sociology over the period 1963-1999. In sociology, the share of women is higher than in Economics: it rises to almost 50% by the end of our sample period. Nevertheless, female sociologists have a lower research output, display the same collaboration networks as female economists, and also co-author with more senior co-authors. There is one dimension on which sociologists and economists appear to differ: male and female sociologists do not display homophily in their coauthorships.

The paper concludes with a brief discussion on potential sources of these differences. Our point of departure is the recent work on gender differences in reward mechanisms, in journal review processes in economics as well as differences in teaching evaluations (Sarsons (2015), Hengel (2016), Mengel, Sauermann, and Zölitz (2017)) and the body of work on gender difference in risk preferences (Croson and Gneezy (2009), Charness and Gneezy (2012)). We build on this

work to argue that, taking them together, could lead to lower risk taking by women as compared to men. This can help account for lower average output and a lower variance among women. And it can also help account for differences in collaboration patterns.

There is a small body of work on gender differences in economics, see e.g., Boschini and Sjögren (2007), McDowell, Singell, and Stater (2006), Sarsons (2015), Wu (2017) and Hengel (2016)) and Mengel et al. (2017)). Our contribution is to provide a set of striking facts about the relation between gender, research output and collaboration networks. We briefly discuss the novelty of these facts now. There is some work on gender proportions but as far as we are aware the growth in fraction of women in economics research has not been systematically documented; for instance, in Ginther and Kahn (2004) the concern is that the share of women admitted to PhDs is stagnating and so their conclusion is that the share of women is relatively constant. Their study is based on US data. The second fact that women have lower mean and a lower standard deviation of research output as compared to men also appears to be new; the closest paper here is McDowell et al. (2006) that presents evidence on lower mean output of female economists who are members of the AEA. Turning to network statistics, our work is the first long term study of gender based network differences on degree, strength and clustering; for a related paper that discusses degree and clustering in school networks and computer science, see Lindenlaub and Prummer (2014).[1] Turning to characteristics of coauthors, our paper is, to the best of our knowledge, the first to present data on gender homophily and on differences in seniority of coauthors.

We contribute to the literature on homophily in social networks. Homophily has been extensively studied in sociology and more recently has also been studied by economists, see e.g., (McPherson, Smith-Lovin, and Cook (2001), Bramoullé, Currarini, Jackson, Pin, and Rogers (2012), and Currarini, Jackson, and Pin (2009). Our finding on gender based homophily in coathorship in economics is novel. Moreover, the persistence of degree difference in spite of large changes in gender proportions goes against the prediction of the models of network formation with homophilous preferences, as elaborated in Currarini et al. (2009).

The rest of the paper proceeds as follows: Section 2 presents the aggregate facts on gender composition and output. Section 3 presents the facts on differences in collaboration. Section 4 briefly summarizes the evidence from sociology. Section 5 discusses differences in risk taking as a potential explanation for these differences.

[1] Our finding on average output is consistent with the finding of Larivière, Ni, Gingras, Cronin, and Sugimoto (2013), who study all articles published in the Web of Science for the period 2008 to 2012.

2 Gender Participation & Research Output

Our data is drawn from the EconLit database, a bibliography of journals in economics compiled by the editors of the *Journal of Economic Literature*. The database provides information on all articles published between 1970 and 2011 in 1,627 journals in economics.[2] For further information on the journals included, see https://www.aeaweb.org/econlit/journal_list.php. We do not cover working papers and work published in books and we identify authors by their last and first names. We then construct a panel that starts for each individual with their first publication and extends to the last observed publication of the author, or to 2011.

We identify the gender of an author using their first names and the US Social Security Administration records. We identify an author's gender if the author's first name is associated with a single gender in the social security records at least 95% of the time.[3] If the first names are ambiguous, we search for the exact co-author online in order to minimize sample selection. This allows us to identify the gender of 80% of all authors. Authors with missing gender are not included in the panel data, but are used to obtain our network measures. Put differently, if an author has a co-author, whose gender is not identified, then we still take into account that this co-author exists, rather than dropping him from the sample entirely.

Turning now to research output, we note that the average annual number of papers per author is small. It is also well known that there are long lags in publication (Ellison, 2002). We therefore need a reasonable time window over which to consider gender differences in academic performance: this motivates the use of a five-year window. Our results are qualitatively similar to other intervals of aggregation (e.g. three and ten-year); these patterns are reported in the Supplementary Appendix.

The research output of an author i at time t is measured as the number of publications during the period $t-4$ to t, weighted by journal quality and discounted by the number of co-authors:

$$q_{it} = \sum_{p=1}^{P_{it}} \frac{\text{quality}_p}{\#\text{ of authors}_p},$$

where p denotes a publication and P_{it} is the total number of articles published by author i from $t-4$ to t. The variable $quality_p$ is a measure of journal quality in which the article p was published. This quality measure was introduced in Ductor, Fafchamps, Goyal, and van der Leij

[2] EconLit does not report the names of all the authors for articles published by more than three authors before 1999; therefore, we exclude these articles from the analysis for the period 1970-1999. Articles published by four or more authors represent 1.6% of all the articles published between 1970-1999. Goyal, Van Der Leij, and Moraga-González (2006) show that the co-authorship network statistics are unaffected when (for a subset of the data) articles with four or more authors are included. A similar data set was studied in Ductor (2015).

[3] By this method we are able to assign gender to 238800 from 373437 authors (64%).

(2014), and builds on the quality journal index developed by Kodrzycki and Yu (2006). The journal index is based on the citations received by all articles published in a journal weighted by the importance of the citing journal and excluding self-citations. See Ductor et al. (2014) for a detailed description of the index.[4] The number of authors of paper p is the denominator. In our analysis of academic performance, we also consider number of publications and number of citations. Citations were retrieved for 121 journals listed in the Tinbergen Institute Journal list. Citations are missing if the author has no publications from $t-4$ to t, the other academic performance variables are zero for periods without publications.[5]

Table 1 presents an overview of the broad empirical trends on journals and articles. The number of journals has grown from 252 in the period 1971-1975 to $1,260$ in 2006-2010, while the number of articles has grown from $24,292$ during the period 1971-1975 to $138,727$, in 2006-2010. There was also a large increase in the number of authors: from $15,823$ in 1971-1975 to $104,751$ in the period 2006-2010.

The growth in the economics research community has been accompanied by a significant change in the share of women in the profession: the fraction of female economists has grown from 8% in the period 1971-1975 to 29% in 2006-2010.

We now turn to patterns in research output. Columns 5, 6 and 7 of Table 1 present the average research output of women and men and its percentage difference. Average output has declined across time. Consider male economists: in the period 1976-1980, the average output was 18.94 but this declined to 9.55 in the period 2006-2010. A similar trend is observable for women. This fall is driven by the large increase in the number of journals and authors, and the relatively stable number of high-quality journals: in our measure this is reflected in a fall in the fraction of 'high quality' articles over time. We provide a more detailed discussion of this trend in the Supplementary Appendix. In spite of the large change in the share of female economists, after a fall in output from 1976 until 1990, the output difference between men and women has remained essentially unchanged: men produced 118% more than women in 1976-1980, and this went down to 52% in 1986-1990, but it has remained stable after that and the difference was 54% in 2006-2010.

To get a first impression of the sources of these gender differences in research output, we examine the role of research field and experience. The observed lower academic performance of

[4]The journal index measure does not vary over time. Computing a time-varying impact factor is only feasible for the journals listed in the Web of Science, a small subset of the journals in EconLit. In addition, journal impact factors in economics are quite stable, both in absolute term and relatively to other disciplines, see Althouse, West, Bergstrom, and Bergstrom (2009). We also show that the results are qualitatively similar when we use a time varying quality measure: citations of the articles.

[5]For robustness, the Supplementary Appendix presents research output measures that do not discount output by the number of authors and show that research patterns are robust to this adjustment.

women could be explained by women sorting in fields with lower impact or gender differences in experience. We use the Pooled OLS (POLS).[6] We estimate the following research output model:

$$q_{it} = \alpha + \rho F_i + C_{it}\omega + \sum_{l=1}^{L} \beta_l JEL_{lit} + \mu_t + \varepsilon_{it}, \tag{1}$$

where $l = 1, ..., 19$, q_{it} is the research output of author i over the period $t-4$ to t.

The main variable of interest, F_i, is a dummy equal to one, if the author is female. The parameter ρ captures the conditional difference in the average research output across gender. The regressors further include experience, C_{it}, and field of research, given by the JEL codes. Career time dummies C_{it}, are included to control for the experience of the author and are dummy variables for each value of career time defined as the number of years since the first publication of the author.[7] Following Fafchamps, Goyal, and van der Leij (2010), we categorize 19 different sub-fields using the first digit of the JEL codes and include in our output model the proportion of publications in each JEL code over the time period $t-4$ to t, JEL_{lit}. These JEL codes capture the fields of specialization of the author. Year dummies, μ_t, account for time effects. Finally, ε_{it} is the time varying error term, and α is an intercept. We cluster standard errors at the author level since research output is correlated over time.

The results are presented in Table 2. Column 2 shows that on average men have a research output that is 36% higher than the average research output of women, after controlling for the specified observables.[8] While differences in experience and choice of field, among other observables can explain 44% of the gender difference in research output (see columns 1 and 2), there still remains a large and significant unexplained gap in research output. We also find that the journal quality index per paper is 0.23 lower for women (see column 4) and that women receives 0.58 fewer citations per paper than men (see column 5).

We perform a number of robustness checks. First, we control for institutional affiliation, using a sample of 395 affiliations over the period 1990-2011. This does not change our estimates. Further, we focus on journals that are available in the EconLit for the entire sample period, 1970-2011. For this sample, gender differences in output are larger than those presented here. We also consider a research active sample, those publishing at least a paper every five year, to check if the documented gender differences in output is driven by different rates of attrition between women and men. The results in this sample are qualitatively the same. Details can be

[6] We also consider a random effect model, a correlated random effect model and a negative binomial model, see Supplementary Appendix. The results are qualitatively similar.

[7] The Ph.D. graduation date could be a better proxy for experience, since the timing of the first publication might differ across gender. We do not consider the Ph.D. graduation date as a proxy for experience because gathering this information for over 220,000 authors would be prohibitively costly.

[8] Summary Statistics are reported in Table 1 in the Supplementary Appendix.

found in the Supplementary Appendix.

3 Gender & Collaboration

Male and female economists differ not only in their research output but also in terms of their collaboration patterns. We first investigate gender disparities in co-authorship networks and then take up differences in co-author's characteristics.

One motivation for the study of collaboration networks is the view that social networks play an important role in the diffusion of ideas and information and in the sustenance of social norms and trust (Coleman (1988), Granovetter (1973), Burt (1992), Dasgupta and Serageldin (2001)). For a recent empirical investigation of the role of networks in shaping research output, see Ductor et al. (2014). They find that degree is positively correlated while clustering is negatively correlated with research output. The potential effects of different network characteristics have been theoretically studied by Lindenlaub and Prummer (2014). They show that a loose network is particularly valuable in a setting with high uncertainty- such as Academia. As loose networks provide better information, agents can fine-tune their effort and this is more important under greater uncertainty than peer pressure. Building on this body of work, we examine gender differences in degree, strength of ties, and clustering.

To present these results, we introduce some additional network terminology. Two agents i and j have a link in the co-authorship network, $g_{ij,t} = 1$, if they have at least one joint publication in the period $t-4$ to t. The network measures of interest are then as follows:

Degree: The degree d_{it} is the number of distinct co-authors in the network over five years, formally

$$d_{it} = \left| j : g_{ij,t} = 1 \right|.$$

Degree is treated as missing if the author does not have publications from $t-4$ to t.[9]

Clustering Coefficient: The clustering coefficient measures how many co-authors of an agent are themselves co-authors. Formally, the clustering coefficient for author i is defined as

$$CC_{it} = \frac{\sum_{j \neq i; k \neq j; k \neq i} g_{ij,t} g_{ik,t} g_{jk,t}}{\sum_{j \neq i; k \neq j; k \neq i} g_{ij,t} g_{ik,t}}.$$

[9]Results are robust to replace these missing periods by zero, but this replacement would treat sole-authored periods and periods with zero output as equivalent and difference in degree would be capturing difference in the frequency of publication.

The clustering coefficient is undefined for sole authors and authors with only one co-author; thus, in the clustering analysis we focus on authors with at least two co-authors from $t-4$ to t.

Strength of Ties: The strength of ties is given by the number of articles written between two authors. We denote the number of papers written between i and j as $n_{ij,t}$. Then, the strength of an author is given by the average strength across all his ties $t-4$ to t, d_{it},

$$s_{it} = \frac{1}{d_{it}} \sum_{j:g_{ij,t}=1} n_{ij,t}.$$

We further normalise the strength by the number of publications, in order to capture time that is spent between co-authors. This normalized strength is denoted by $\overline{s}_{it} = s_{it}/P_{it}$. Strength is undefined for periods without co-authored publications from $t-4$ to t.

We now turn to a study of gender differences in network structure, controlling for trends in co-authorship, gender differences in experience, fields of specialization (measured by the share of papers published in a given field) and past output. The dependent variable z_{it} is a network measure as defined above and obtained using publications from $t-4$ to t. The estimated model is:

$$z_{it} = \phi + \mu_t + \rho F_i + C_{it}\omega + \sum_{l=1}^{L} \beta_l JEL_{lit} + \psi y_{it-5} + \varepsilon_{it}, \tag{2}$$

F_i is a dummy equal to one if the author is female. Career time dummies, C_{it}, are included to control for differences in experience across gender. The proportion of publications in each JEL code l at the first digit level from $t-4$ to t, JEL_{lit}, captures that women specialize in different fields with potentially distinct collaboration patterns than men. Past output y_{it-5} is the accumulated research output from the first publication of the author until $t-5$ and captures differences in past academic performance across gender. This variable is lagged to avoid a simultaneity problem with the network variable. An implication of considering past output accumulated until $t-5$ is that we loose the first five observations of every author and we exclude authors with less than five years of experience. Year dummies μ_t control for time aggregate effects. Since networks are correlated over time, we cluster standard errors by authors. The main parameter of interest is ρ, which captures the conditional gender difference in networks.

Table 3 displays the magnitude of the difference in network statistics for men and women estimated from equation (2). Strength, clustering and betweenness are standardized to ease the interpretation. We find the following gender differences in collaboration patterns:

1. *Women have fewer distinct co-authors than men.*

   Column 2 of Table 3 shows that men have 0.41 more collaborators than women; this is 21%

of the average degree of men.[10]

2. *Women have a higher clustering than men.*

   Women's clustering coefficient is 0.07 standard deviations higher than men's: this is roughly 6% of the average clustering of men. The results also show that the association between the authors' degree and the clustering coefficient in the scientific networks is negative. This is in line with the negative correlation between degree and clustering noted by Goyal et al. (2006), Jackson and Rogers (2007). The gender difference in clustering remains large, once we control for a number of factors, including degree.

3. *Women collaborate more with the same co-authors.*

   Female authors' normalised strength of ties is 0.17 standard deviation higher than male authors controlling for observable factors; this is 8.8% of the average strength of men.

We also examine how gender network difference vary across time by adding interaction terms between female and year dummies to our baseline regression presented in (2). Figure 1 presents the coefficients and 95% Bonferroni corrected confidence interval of these interaction terms. All the estimates are relative to the base year 1979. Remarkably, as in the case of research output, the network differences are *persistent* despite the increase in the share of women over time. The average gender difference in degree conditional on observable factors has even increased by 0.83 from 1979 to 2011.

It is worth noting that these gender differences cannot be attributed to women not being able to find co-authors, since the gender difference in the share of co-authored articles relative to solo papers is not statistically significant, see Table 3, column (1).

We conduct various robustness checks, which are presented in the Supplementary Appendix. First, it could be that women are disproportionately in non-academic jobs and consequently have tighter network. We show using a sample of 395 affiliations over the period 1990-2011 that the role of institutional factors in explaining gender differences in collaboration patterns is negligible. Second, we use alternative models: correlated random effects, random effects and non-linear models. Third, we consider three and ten-year network variables. Fourth, we focus on a fixed set of journals, those available in the EconLit for the entire sample period, 1970-2011. The gender differences in co-authorship networks are significant in all our specifications. We also show that the gender differences in degree is larger for highly productive women. This implies that even the women with the highest research output in the past 5 years have significantly different networks compared to male economists.

[10]The degree distribution is highly right-skewed; we check if the gender difference in degree is mainly driven by male authors who collaborate with many different co-authors using quantile regressions. The results are available in the Supplementary Appendix and show that the gender difference in degree is increasing along the degree distribution.

We now turn to our third set of facts that pertain to characteristics of co-authors. We start with the gender composition of coauthors. Gender based homophily means that individuals prefer to form links with others of their own gender (McPherson et al. (2001)). Denote the fraction of male authors in the population as w_m and the share of women by $w_f = 1 - w_m$. Let H_m denote the average share of male co-authors among men. Then, men exhibit *relative homophily* if $H_m > w_m$. Similarly, women exhibit relative homophily if $H_f > w_f$. We compute the percentage of links within gender and find that, on average, 81% of men's collaborations are with other men: this is higher than the fraction of men in the population 72%. Similarly, women exhibit relative homophily as their collaboration with other women, 33% is larger than the fraction of women in the population (27%). Therefore, women and men tend to collaborate with authors of the same gender over and above the relative size of their gender group.[11]

As gender proportions are changing sharply over our sample period, it is useful to consider a measure that accounts for this change. Following Coleman (1958), we define *inbreeding homophily*: this measure compares the proportion of collaborations with the same gender against the fraction of this gender in the sample and then normalizes the difference by the maximum bias that a gender could have. Formally,

$$IH_s = \frac{H_s - w_s}{1 - w_s} \quad \text{for } s = \{f, m\}. \tag{3}$$

We shall say that there is inbreeding homophily if the index is positive, heterophily if it is negative. Figure 2 shows that there is inbreeding homophily for men and women, and that it is *persistent* across the entire sample period.

Building on the work of Currarini et al. (2009), we note that gender based homophily together with increases in the fraction of women would imply a fall in difference in degrees across gender. We examine this prediction. We exploit variation in gender shares across time. From Table 1 we know that women became more representative in the profession over time. But contrary to the prediction of the model, we find in Figure 1 that the gender difference in degree is actually increasing for the most recent periods. Similarly, we find that the gender difference in degree is larger in fields where the fraction of women is higher.[12] A potential explanation for conflict with the theory is that gender based homophily is sensitive to the fraction of women in the profession. However, Figure 2 shows that inbreeding homophily is persistent over time (note that inbreeding homophily normalizes for changes in gender composition).

[11] Table 25 in the Supplementary Appendix presents the percentage of links. It is worth noting that homophily here may reflect a greater proportion of gender specific shared activities, see Graham (2016).

[12] See Figure 4 in the Supplementary Appendix.

The final observation pertains to the seniority of co-authors; Figure 2, right plot, presents average co-authors' experience by gender across career time: we note that *at every stage of their career* women tend to work, relative to men, with co-authors that have more experience. The gender difference in co-authors' seniority is around 1 year and it is statistically significant at the 5% level for every year of career time (except for authors with over 17 years of experience).

4 Sociology

The patterns on output and collaboration in economics are striking. In this section we will show that similar patterns obtain in sociology.

We use the database compiled by Moody (2004), that considers all the English journal articles in Sociological Abstracts that were published between 1963 and 1999. This comprises not only of journals in sociology, but also articles published by sociologists in other journals, and thus allows us to gain more comprehensive data on publishing in sociology. The results of this section are presented in the Supplementary Appendix, due to space constraints.

Our first point concerns fraction of women and differences in output. The fraction of women was 15% in 1963 and moved up to 50% in 1999. The research output difference between men and women has remained stable from 1984 to 1999: men produced 69% more than women in 1965-1969, and this decreased to 31% in 1985-1989, but it has remained constant after that and the difference was 30% in 1995-1999. This lower output for women is accompanied with a lower variation: the standard deviation for women is 18% lower than that for men. These large differences in output remain after we control for experience and choice of field (and other observable factors).

Our second observation pertains to patterns of collaboration: as in economics, we find that there are persistent differences between men and women, after controlling for differences in past output, experience and fields. Women have fewer distinct co-authors (the conditional average difference in degree is -0.18, which is 7.6% of the average degree of men) and a higher clustering coefficient (the conditional difference in clustering is 2.6% of the average clustering of men). They also tend to work repeatedly with the same co-authors (the conditional difference in strength is 2.8% of the average strength of men).[13]

Our third observation is about the types of coauthors that men and women have. We find that collaboration does not exhibit homophily in sociology. But, as in economics, we also find that women have more senior co-authors, at every point in their career. In particular, women have co-authors that are 0.9 years more experienced than men.

[13] See Table 5 in the Supplementary Appendix.

To summarise: gender disparities in sociology have the same qualitative features as in economics (except on the dimension of homophily).

5 Discussion

Our analysis of the data in economics reveals a number of striking patterns. In this section we build on two strands of recent research – one, that women face a relatively more adverse environment as compared to men in economics, and, two, that there are gender differences in risk preferences – to propose a potential explanation for them.

A recent strand of work argues that women in economics face a different and more adverse environment as compared to their male colleagues. Sarsons (2015) presents evidence that female economists receive less credit for work done jointly with co-authors, Wu (2017) highlights misogyny on the Econ Job Market Rumours web-site, while Hengel (2016) shows that female authors face a longer review time in journals. In a related context, Mengel et al. (2017) show that female economists obtain on average lower teaching evaluations. Taken together, these papers suggest that women may face a different – more challenging and possibly more uncertain – environment as compared to men.

We next turn to the issue of gender differences in risk preferences. Researchers have documented evidence, based on experimental and observational data, that across a wide range of decision making contexts, women are more risk averse as compared to men. For surveys on this work, see Croson and Gneezy (2009), Charness and Gneezy (2012), Eckel and Grossman (2008) and Weber, Blais, and Betz (2002).[14].

Taking these two factors together, we suggest that women may make less risky choices both on projects and on partners. These differences in risk taking will lead to different publication and collaboration patterns.

First, we note that less risky project choice should mean lower and less variable output: this is consistent with the data.

Second, consider network differences. An author looking to start a new project who takes less risk is likely to continue working with current coauthors and if given a choice will prefer to start a new collaboration with a common co-author rather than someone chosen at random. This suggests that lower risk taking will push toward fewer coauthors, repeat coauthoring and higher clustering. This is exactly what we find in the data.

Third, we turn to characteristics of coauthors: here we focus on seniority of coauthors.

[14]For a study of the evolutionary basis for these differences, see e.g., Friebel, Lalanne, Richter, Schwardmann, and Seabright (2017)

Someone who takes less risk is more likely to work with people who have a clearer track record of past work and past collaborations. This suggests a preference for senior coauthors in favour of young coauthors who have less of a track record. A related consideration is that there is more information available on a senior academic: in other words there is less uncertainty about how they treat female co-authors. Putting together these two observations we predict that women will prefer senior co-authors. This is consistent with the evidence, see Figure 2.

Table 1: Number of authors, articles, journals and output across time

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Number		Output		
Year	Journals	Articles	Women	Men	Women	Men	% diff.
1971-1975	252	24292	1293	14530	15.25	28.57	87%
1976-1980	276	31643	2378	20411	8.69	18.94	118%
1981-1985	351	39363	3646	25219	6.98	13.24	90%
1986-1990	382	45536	4907	28884	7.35	11.20	52%
1991-1995	586	59400	7797	36610	6.62	9.59	45%
1996-2000	803	84354	13616	49439	5.27	8.21	56%
2001-2005	1017	103974	20147	59619	4.54	7.63	68%
2006-2010	1260	138727	30702	74049	6.20	9.55	54%
1970-2011	1627	557290	59661	161390	5.82	10.72	84%

Column 1 shows the number of journals in our sample across periods, column 2 presents the number of articles in our sample across periods, column 3 shows the number of unique women across time and column 4 presents the number of unique men across periods. Column 5 shows the average research output per author for women across periods, column 6 presents the average research output per author for men across periods, column 7 shows the percentage difference between the average research output of men and women relative to women's output.

Table 2: Gender Differences in Performance

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Output	Output	# Papers	$\frac{Output}{\#Papers}$	$\frac{Citations}{\#Papers}$
Female	-3.654***	-2.049***	-0.480***	-0.225***	-0.577***
	(0.249)	(0.229)	(0.028)	(0.048)	(0.161)
Observations	240,897	240,897	240,897	240,897	240,897
Career-time FE	NO	YES	YES	YES	YES
Year FE	NO	YES	YES	YES	YES
JEL codes FE	NO	YES	YES	YES	YES

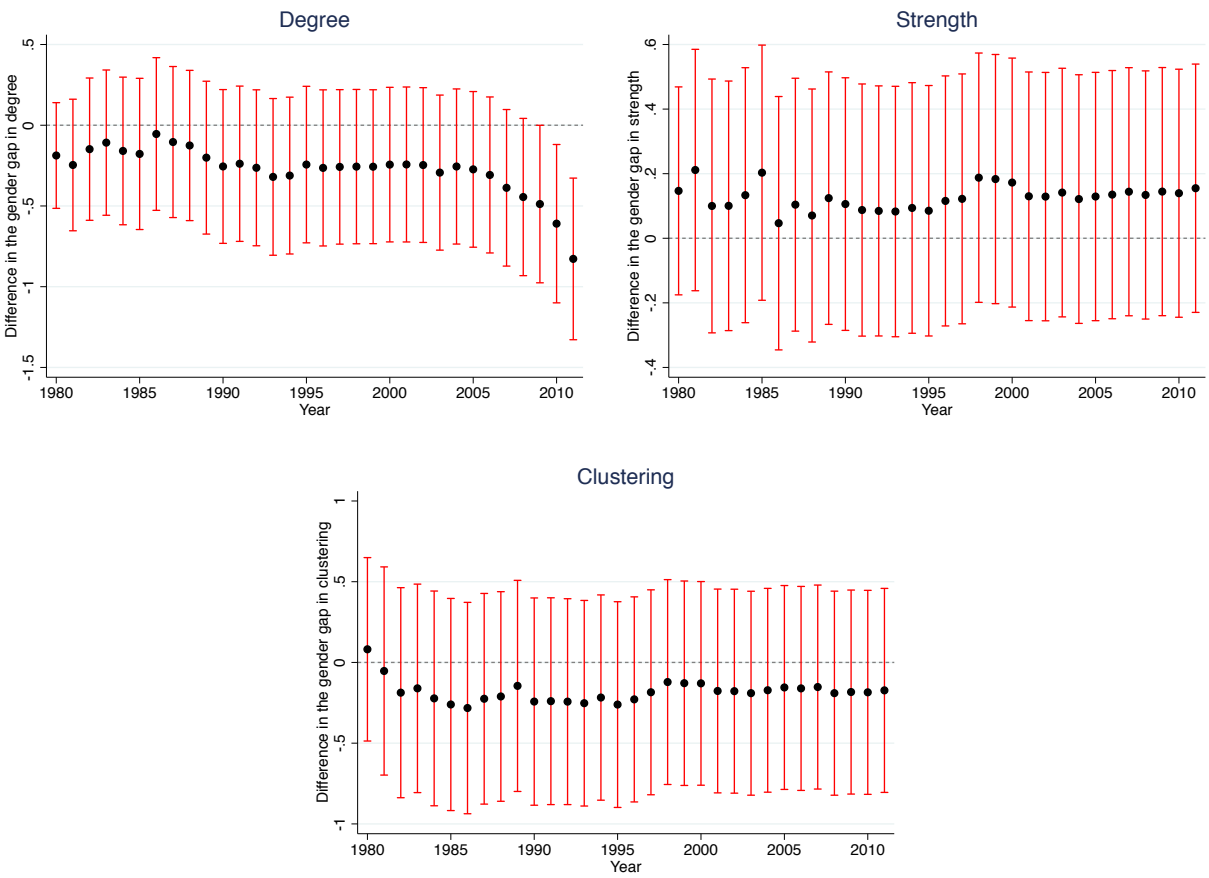
Results estimated using POLS. Column 1 presents the gender difference in research output without control factors; column 2 presents the gender difference in research output controlling for observable factors; column 3 presents the gender difference in total number of publications; column 4 shows the gender difference in journal quality impact factor per paper; column 5 shows gender differences in the number of citations per paper. The dependent variables in columns 4 and 5 are undefined for periods without publications. Clustered standard errors by authors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3: Gender and Collaboration

VARIABLES	(1) Co-authorship	(2) Degree	(3) Strength	(4) Clustering
Female	0.003	-0.407***	0.165***	0.066***
	(0.004)	(0.030)	(0.011)	(0.010)
Degree				-0.238***
				(0.005)
Past output$_{t-5}$	0.0001	0.007***	-0.156***	-0.053***
	(0.00002)	(0.0004)	(0.006)	(0.003)
Observations	394,113	394,113	316,145	226,078
Number of authors	56,949	56,949	48,936	38,757
Career-time FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
JEL codes shares	YES	YES	YES	YES

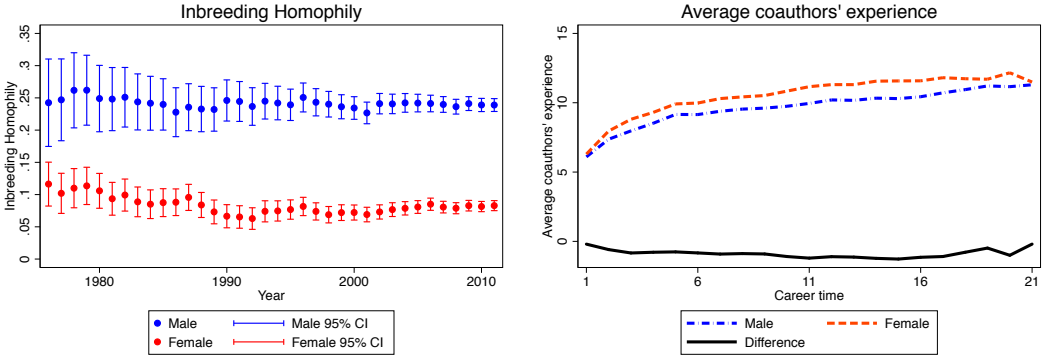
All the results are obtained using the POLS. Column 1 presents the results of co-authorship defined as the fraction of co-authored articles. Columns 2, 3, 4 show the results from estimating gender differences in degree, strength and clustering, respectively. All the continuous variables in the models estimated in columns 3 and 4 are standardized. Clustered standard errors at the author level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Figure 1: Network differences across time



Note: The plots show the coefficients and 95% confidence intervals, obtained using the Bonferroni correction, of the interaction terms between year dummies and the female dummy of a network model estimated using POLS, the base year is 1979. The gender gaps in degree, strength, clustering and betweenness in the base year 1979 are -0.04, 0.16, 0.07 and -0.44, respectively. The p-values, obtained using the of F-tests on the joint significant of all the interaction terms are: 0.02 in the degree model; 0.27 in the strength model; 0.09 in the clustering model.

Figure 2: Inbreeding Homophily and Coauthors experience



The gender difference in coauthor seniority is statistically significant except for authors with more than 17 years of career time.

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Gender and Collaboration: Supplementary Appendix

Lorenzo Ductor, Sanjeev Goyal, Anja Prummer

Contents

1 Data Appendix

1.1 Summary Statistics

In this section, we provide some statistics about our data. Table 1 shows the mean, standard deviation, the minimum and maximum of the network and performance variables by gender.

Table 1: Summary Statistics: 1970-2011

Variable	Gender	(1) Mean	(2) Standard Deviation	(3) Min.	(4) Max
# of publications	Female	2.22	2.74	0	45
	Male	2.78	3.69	0	90
	All	2.68	3.53	0	90
# of top 5 publications	Female	0.06	0.39	0	15
	Male	0.10	0.53	0	20
	All	0.09	0.49	0	20
Research output	Female	5.69	17.96	0	470.15
	Male	9.34	27.07	0	892.91
	All	8.41	25.09	0	832.91
# of citations	Female	5.45	35.02	0	3763
	Male	12.86	72.67	0	7009
	All	10.39	63.37	0	7009
Co-authorship	Female	0.70	0.45	0	1
	Male	0.65	0.46	0	1
	All	0.67	0.45	0	1
Degree	Female	1.72	1.95	0	39
	Male	1.96	2.49	0	87
	All	1.91	2.38	0	87
Clustering	Female	0.62	0.41	0	1
	Male	0.49	0.41	0	1
	All	0.53	0.42	0	1
Strength	Female	0.74	0.31	0.03	1
	Male	0.64	0.34	0.01	1
	All	0.67	0.33	0.01	1
Betweenness	Female	5.22	5.90	0	16.58
	Male	6.85	5.93	0	18.33
	All	6.39	5.99	0	18.33

Research output and network variables are obtained using publications in a five-year window, from $t-4$ to t. All the averages and standard deviations between male and female are statistically significant at the 1% level.

1.2 Drivers of the fall in research output

A striking feature in our data is the substantial decrease in the average research output per author from 1970 to 2000, see Figure 1. The decay in research output per author could be explained by the increase in the number of low-quality journals over time, increase in the number of authors per paper and increased competition. Previously documented patterns consistent with increased competition include an increase in the number of submissions to the top 5 (Card and DellaVigna (2013)), in number of co-authors (Ductor (2015)), in papers' length (Card and DellaVigna (2014)) and in turnaround time (Ellison (2002)). To get an idea of the increase in competition one needs information on the number of submissions. As such figures are hard to collect systematically for our large journal sample, we use as a proxy the number of unique authors that publish in the EconLit database. Table 1 of the main text suggests that the number of submissions has increased much more than the number of published articles, consistent with an increase in competition. This increase in competition has led to a substantial decrease in the number of top 5 publications per capita and to an increase in publications in lower ranked-journals (B-ranked and unranked publications), see Figure 2. The decay in average research output holds if we fix a set of journals that have been in the sample for the whole sample period, 1970-2010. This decrease also emerges if we do not discount research output by the number of authors. These findings lead us to conclude that the fall in average research output is mainly driven by a reduction in top 5 publications and an increase in publications in lower ranked journals caused by an increase in competition.

Figure 1: Research output by gender over time

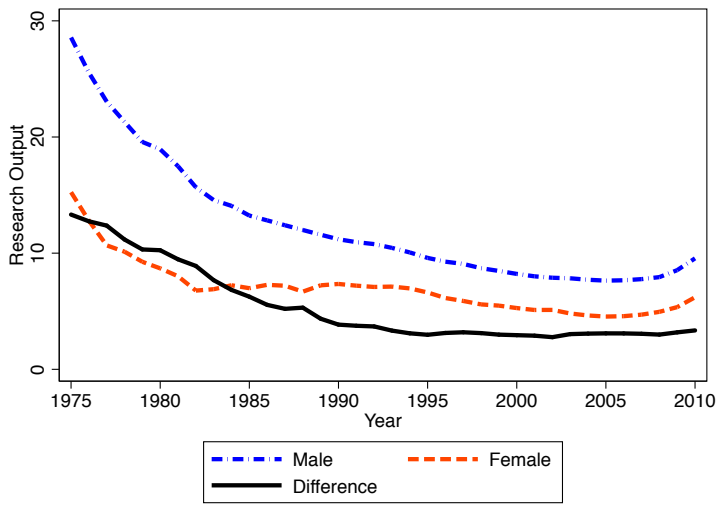
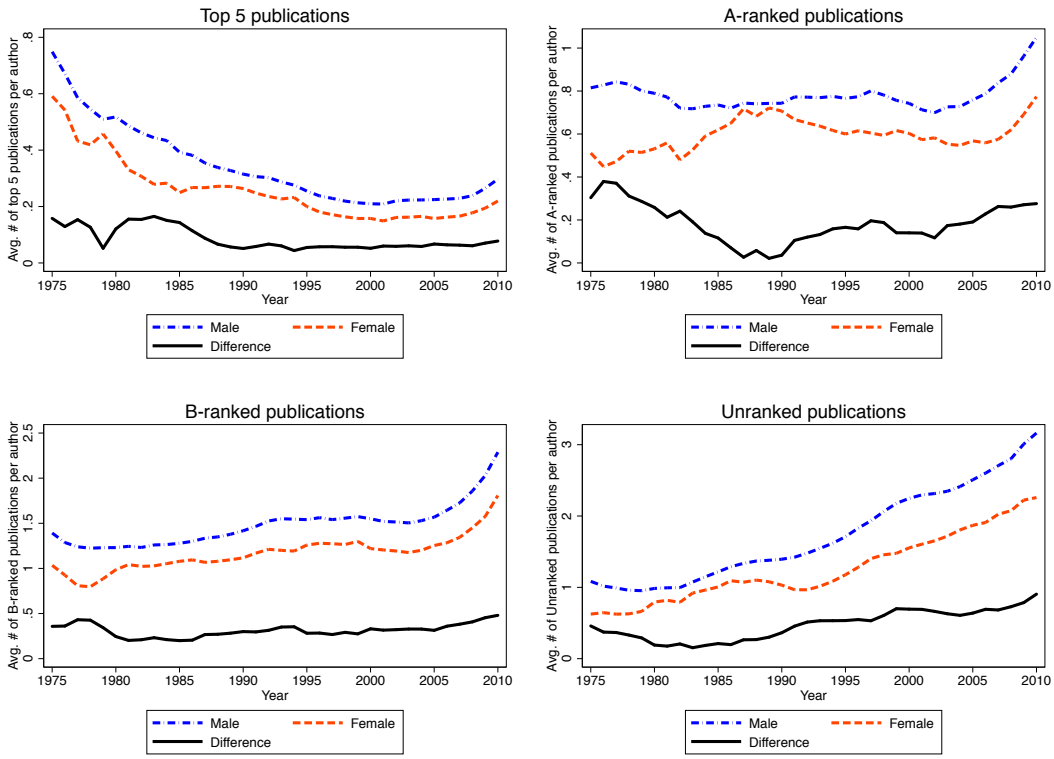


Figure 2: Average number of publications per author across journal quality



Note: Average number of publications per author in four different journal categories according to the Tinbergen Institute Journal List. *Top*5 publications include articles published in *American Economic Review*, *Econometrica*, *Journal of Political Economy*, *Quarterly Journal of Economics* and the *Review of Economic Studies*; A-ranked include articles published in a journal ranked as A in the Tinbergen Institute Journal List; B-ranked publications include articles published in a journal ranked as B in the Tinbergen Institute Journal List; and Unranked are publications in a journal not included in the Tinbergen Institute Journal list.

2 Sociology

This section presents the statistics and results presented in section 4 of the main text. Table 2 documents the large increase in the fraction of women over time. In table 3 we show summary statistics of the network and output variables of interest.

In table 4, we present gender differences in research output and number of papers controlling for experience, time trends and gender differences in fields. We define research output as in economics, see definition in section 2.1. in the main text, but the quality index for the sociology journals is obtained from the journal impact factor of the Journal Citations Reports (JCR) (ISI Web of Knowledge, 2017). We assign an impact factor of 0.1 to journals that are not listed in the JCR. The results show that women write 0.12 fewer papers than men per year and that their research output is 8% lower than the average.

We then estimate equation 2 of the main text using the sociology data. The results presented in Table 5 show that, as in economics, women have lower degree, higher strength and higher clustering.

We also check if there is evidence of homophily in sociology, using the definition presented in equation 3 of the main text. Contrary to the findings in economics, there is no evidence of homophily in sociology (see Table 6); the share of women and women's collaborators is essentially the same.

Finally, in Figure 3 we present the average coauthors' experience of women and men. As in economics, women collaborate with more seniors, on average.

Table 2: Number of authors and reseach output across time

	(1)	(2)	(3)	(4)	(5)
	Number		Output		
Year	Men	Women	Men	Women	% diff.
1965-1969	7823	1509	1.02	0.60	69%
1970-1974	13055	2952	1.09	0.69	58%
1975-1979	22661	7688	0.88	0.62	42%
1980-1984	25687	10736	0.97	0.70	39%
1985-1989	28118	14243	0.79	0.60	31%
1990-1994	37068	24195	0.80	0.61	32%
1995-1999	43873	36555	0.80	0.62	30%
1963-1999	87734	57698	0.87	0.62	40%

Column 1 shows the number of unique men across time and column 2 presents the number of unique women across periods. Column 3 shows the average research output per author for men across periods, column 4 presents the average research output per author for women across periods, column 5 shows the percentage difference between the average research output of men and women relative to women's output.

Table 3: Summary Statistics: 1970-2011

Variable	Gender	(1) Mean	(2) Standard Deviation	(3) Min.	(4) Max
# of publications	Female	1.56	1.79	0	40
	Male	1.58	2.05	0	63
	All	1.56	1.95	0	63
Research output	Female	0.68	1.58	0	108.28
	Male	0.85	1.91	0	54.39
	All	0.78	1.78	0	108.28
Co-authorship	Female	0.63	0.48	0	1
	Male	0.53	0.49	0	1
	All	0.56	0.49	0	1
Degree	Female	2.41	1.91	0	43
	Male	2.37	2.07	0	54
	All	2.38	1.99	0	54
Clustering	Female	0.85	0.30	0	1
	Male	0.76	0.37	0	1
	All	0.80	0.34	0	1
Strength	Female	0.88	0.24	0.07	1
	Male	0.82	0.28	0.04	1
	All	0.85	0.26	0.04	1

Research output and network variables are obtained using publications in a five-year window, from $t-4$ to t. All the averages and standard deviations between male and female are statistically significant at the 1% level.

Table 4: Gender Differences in Performance

VARIABLES	(1) Output	(2) Papers
Female	-0.062***	-0.121***
	(0.016)	(0.014)
Observations	472,117	472,117
Number of authors	83,487	83,487
Career-time FE	YES	YES
Year FE	YES	YES
JEL codes FE	YES	YES

Results estimated using POLS. Column 1 presents the gender difference in research output controlling for observable factors; column 2 presents the gender difference in total number of publications. Clustered standard errors by authors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Gender and Collaboration

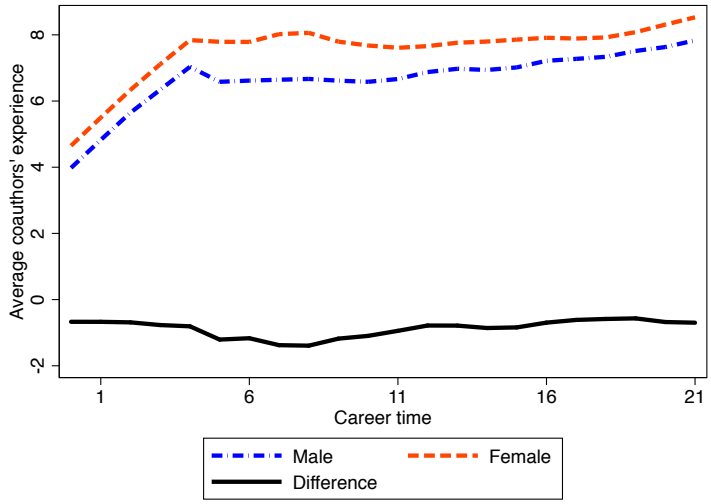
VARIABLES	(1) Degree	(2) Strength	(3) Clustering
Female	-0.185***	0.088***	0.057***
	(0.022)	(0.010)	(0.012)
Degree			-0.302***
			(0.006)
Past output	0.077***	-0.249***	-0.131***
	(0.005)	(0.008)	(0.007)
Observations	252,982	252,982	149,929
Number of auth	75,501	75,501	46,469
Career-time FE	YES	YES	YES
Year FE	YES	YES	YES
JEL codes FE	YES	YES	YES

All the results are obtained using POLS. Columns 1, 2 and 3 show the results from estimating gender differences in degree, strength, and clustering, respectively. All the continuous variables in the models estimated in columns 2 and 3 are standardized. Clustered standard errors at the author level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Percentage of links across gender

	Men	Women
Population Share	43.1%	56.9%
Men's Collaborators	44.7%	55.3%
Women's Collaborators	43%	57%
Inbreeding Homphily	0.0002	0.0000

Figure 3: Average co-authors' experience by gender



Note: The gender difference is statistically significant at the 1% level.

3 Robustness: Research Output

We show that the gender differences in research output are robust to different econometric models and alternative academic performance measures. We then restrict attention to the set of journals published throughout our entire sample period; for this sample, again, gender disparities in output persist. We also show that the role of institutions in explaining the gender gap in research output is minor. We find that the gender difference in output is larger for researchers who publish at least an article every five year, active sample. Moreover, we show that the gender gap in output does not only exist for the authors with highest output, but throughout the entire distribution.

3.1 Alternative Econometric Models

We first show that the gender differences in research output are robust to the use of different econometric models. In Table 7 we show the gender differences in academic performance using the correlated random effect models. In line with the correlated random effect approach, we include the mean over time of the time varying regressors in our estimation as a proxy for time invariant unobservable factors, such as innate ability. We estimate the following research output model:

$$q_{it} = \alpha_i + \rho F_i + C_{it}\omega + \sum_{l=1}^{L} \beta_l JEL_{li} + \mu_t + \varepsilon_{it}, \tag{1}$$

where $l = 1, ..., 19$, q_{it} is the research output of author i over the period $t-4$ to t and $\alpha_i = \phi + a_i + \sum_{l=1}^{L} \gamma_l \overline{JEL}_{li}$.

The correlated random effect model does not require the time-varying covariates and the author fixed effect α_i to be orthogonal. $\overline{JEL}_{li}$ is the average proportion of articles published in JEL code l by author i during her career, the rest of regressors are defined as in the main text.

The results from the CRE are consistent with those presented in Table 3 in the main text, though as expected the gender differences in the CRE are smaller.[1]

Table 7: Gender Differences in Performance: Correlated Random Effect Model

VARIABLES	(1) Output	(2) Output	(3) # Papers	(4) $\frac{Output}{\#Papers}$	(5) $\frac{Citations}{\#Papers}$
Female	-2.793***	-1.580***	-0.399***	-0.145***	-0.301*
	(0.150)	(0.145)	(0.021)	(0.034)	(0.156)
Observations	625,518	625,518	625,518	457,074	457,074
Number of auth	62,961	62,961	62,961	62,961	62,961
Career-time FE	NO	YES	YES	YES	YES
Year FE	NO	YES	YES	YES	YES
JEL codes FE	NO	YES	YES	YES	YES

Results estimated using correlated random effect models. Column 1 presents the gender difference in research output without control factors; column 2 presents the gender difference in research output controlling for observable factors; column 3 presents the gender difference in total number of publications; column 4 shows the gender difference in journal quality impact factor per paper; column 5 shows gender differences in the number of citations per paper. The dependent variables in columns 4 and 5 are undefined for periods without publications. Clustered standard errors by authors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

As a next step, we address potential concerns that the the negative effect of gender might be driven by authors with a high output, as output is quite skewed. We estimate research output in $log(q_{it} + 1)$ to mitigate the impact authors with high output, as in Ductor et al. (2014). The results presented in column 1 of Table 8 show that women have on average a research output that is approximately 10% lower than the research output of men, that is we find a substantial gap.

We now turn to number of publications and citations. These are discrete variables that do not follow normal distributions, so count data models might be more appropriate. Columns 2 and 3 of Table 8 show the incidence rate ratio (IRR) of female for number of publications and citations using a count data model, the negative binomial (NE). The results are qualitatively similar to those obtained using the CRE model. The publication and citation rates of are 17.2% and 22.9% lower for women, respectively.

[1] The CRE model accounts for average JEL codes, which proxy for authors' time invariant characteristics.

Table 8: Gender Differences in Performance: Non-linear Models

VARIABLES	(1) CRE $log(1+q^n_{it})$ Coeff.	(2) NB # Papers IRR	(3) NB Citations IRR
Female	-0.097***	0.828***	0.771***
	(0.008)	(0.010)	(0.029)
Observations	562,557	562,557	394,113
Number of authors	56,949	56,949	56,949
Career-time FE	YES	YES	YES
Year FE	YES	YES	YES
JEL codes$_{t-5}$	YES	YES	YES

Column 1 presents the coefficient of the gender difference in research output, the dependent variable being $log(q_{it}+1)$, model estimated using the correlated random effect model; columns 2 and 3 present the incidence rate ratio from estimating the gender difference in number of publications and citations, respectively, using a negative binomial model. Clustered standard errors by authors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

3.2 Non-Discounted Output

We then document that gender differences in research output are unchanged, if we do not discount by the number of authors on a paper. Formally, the non-discounted research output of an author i at time t is measured as the number of publications during the period $t-4$ to t, weighted by journal quality:

$$q^n_{it} = \sum_{p=1}^{P_{it}} \text{quality}_p.$$

Table 9 shows the results from estimating output without discounting by the number of authors. We consider different models and specification: a pooled OLS (POLS) model (see column 1), a POLS with logged output (see column 2), a random effect (RE) model (see column 3), and correlated random effect (CRE) model (see column 4). The gender difference in non-discounted output is substantially larger than the discounted differences presented in the main text.

Table 9: Gender Differences in Performance: Non-Discounted Output

VARIABLES	(1) POLS q^n_{it}	(2) POLS $log(1+q^n_{it})$	(3) RE q^n_{it}	(4) CRE q^n_{it}
Female	-3.577***	-0.126***	-3.792***	-2.779***
	(0.403)	(0.011)	(0.263)	(0.260)
Observations	625,518	625,518	625,518	625,518
Number of authors	62,961	62,961	62,961	62,961
Career-time FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
JEL codes FE	YES	YES	YES	YES

Column 1 presents gender difference in non-discounted research output using POLS; column 2 presents the results of estimating log of non-discounted research output plus one, $log(q^n_{it}+1)$, using a POLS; column 3 and 4 show the gender difference in non-discounted research output using a random effect and correlated random effect model, respectively. Clustered standard errors by authors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

3.3 Restricted Set of Journals

We further document that gender differences in output increase if we restrict attention to journals that were published throughout the entire sample period, from 1970 to 2011, see Table 10.

Table 10: Gender Differences in Performance: Fixed Set of Journals

VARIABLES	(1) Output	(2) Output	(3) # Papers	(4) $\frac{Output}{\#Papers}$	(5) $\frac{Citations}{\#Papers}$
Female	-5.202***	-4.696***	-0.333***	-0.905***	-2.430**
	(0.711)	(0.705)	(0.044)	(0.227)	(0.975)
Observations	150,338	150,338	150,338	103,530	103,530
Career-time FE	NO	YES	YES	YES	YES
Year FE	NO	YES	YES	YES	YES
JEL codes	NO	YES	YES	YES	YES

Clustered standard errors by authors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

3.4 Output Across 3 & 10 Years

In the main text, we consider a five-year research output measure obtained using publications from $t-4$ to t. We now check if the results are robust to a shorter and longer time horizon: three and ten-years. The three-year research output is obtained using publications from $t-2$ to t and the ten-year considers publications from $t-9$ to t. In Table 11, we show that, unsurprisingly, the gender difference in research output is lower for the shorter horizon, see columns 1 and 2, and larger for the 10-year output variable, see columns 3 and 4.

Table 11: Gender Differences in Performance: 3 and 10 Years Period

VARIABLES	(1) 3-year Output	(2) 3-year Output	(3) 10-year Output	(4) 10-year Output
Female	-2.107***	-1.150***	-6.821***	-4.292***
	(0.128)	(0.117)	(0.645)	(0.601)
Observations	773,001	773,001	365,100	365,100
Career-time FE	NO	YES	NO	YES
Year FE	NO	YES	NO	YES
JEL codes FE	NO	YES	NO	YES

Results estimated using POLS. Column 1 presents the gender difference in research output obtained using publications from $t-2$ to t without control factors; column 2 presents the gender difference in research output from $t-2$ to t controlling for observable factors; column 3 shows the gender difference in research output obtained using publications from $t-9$ to t without control factors; column 2 presents the gender difference in research output from $t-9$ to t controlling for observable factors. Clustered standard errors by authors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

3.5 Institutions

The EconLit provides information about the affiliation of each author publishing a research article in a journal listed in the EconLit from 1990 to 2011. This allows us to examine the role of institutions in explaining the gender gaps in research output. One standard problem with affiliations is that authors tend to report an affiliation with different names, this is specially a problem for institutions located in non-English speaking countries. To mitigate this problem we have manually cleaned 395 institutions from the list of affiliations obtained from the research articles. We then add institutional dummies to the research output model described in equation 1 of the main text. The results presented in Table 12 shows that differences in institutions account for 2.5% of the unconditional gender gap in research output (see column 1 and column 2) while experience and fields account for 39% of the gender gap conditional on institutions (see columns 2 and 3). As in the main text, we find significant differences in the number of publications and citations across gender.

Table 12: Gender Differences in Performance: Accounting for Institutions

VARIABLES	(1) Output	(2) Output	(3) Output	(4) # Papers	(5) $\frac{Output}{\#Papers}$	(6) $\frac{Citations}{\#Papers}$
Female	-4.787***	-4.668***	-2.843***	-0.622***	-0.198***	-0.859***
	(0.453)	(0.431)	(0.406)	(0.049)	(0.071)	(0.290)
Observations	263,582	263,582	263,582	263,582	211,630	211,630
Career-time FE	NO	NO	YES	YES	YES	YES
Year FE	NO	NO	YES	YES	YES	YES
JEL codes FE	NO	NO	YES	YES	YES	YES
Institutions FE	NO	YES	YES	YES	YES	YES

Results based on 395 affiliations. Results estimated using POLS. The dependent variables in columns 5 and 6 are undefined for periods without publications. Clustered standard errors by authors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

3.6 Active sample

An author is in the panel data till the last observed publication or 2011 and women tend to leave academia earlier than men, so our results might be affected by gender differences in attrition. In this section, we mitigate potential attrition problems by focusing on research active authors. We define a research active as an author who publish at least one paper every five year. Table 13 shows that the gender differences in research output is larger when we focus on active researchers.

Table 13: Gender Differences in Performance: Active Researchers

VARIABLES	(1) Output	(2) Output	(3) # Papers	(4) $\frac{Output}{\#Papers}$	(5) $\frac{Citations}{\#Papers}$
Female	-7.673***	-3.203***	-0.777***	-0.198***	-0.452**
	(0.566)	(0.524)	(0.058)	(0.071)	(0.203)
Observations	240,897	240,897	240,897	240,897	240,897
Career-time FE	NO	YES	YES	YES	YES
Year FE	NO	YES	YES	YES	YES
JEL codes FE	NO	YES	YES	YES	YES

Results estimated using POLS. Sample restricted to authors publishing a paper every five years. The dependent variables in columns 4 and 5 are undefined for periods without publications. Clustered standard errors by authors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

3.7 Quantile Regressions

As the distribution of output is strongly right-skewed, we estimate the gender gap in research output across different percentiles of the distribution using quantile regressions, see Table 14. In particular, we estimate the median output and the percentiles 75, 90 and 95. While the gender gap in output is higher at the right tail of the distribution, it also emerges at the median, establishing that our results are not driven by differences among top authors.

Table 14: Research Output and Gender: Quantile Regressions

Variables/Percentile:	(1) Output Median	(2) Output 75th pc.	(3) Output 90th pc.	(4) Output 95th pc.
Female	-0.112***	-0.631***	-3.461***	-8.648***
	(0.004)	(0.026)	(0.133)	(0.306)
Career time	0.072***	0.197***	0.391***	0.317***
	(0.002)	(0.009)	(0.044)	(0.103)
Career time^2	-0.002***	-0.005***	-0.009***	-0.007**
	(0.000)	(0.000)	(0.001)	(0.003)
Observations	562,557	562,557	562,557	562,557
Linear time trend	YES	YES	YES	YES
JEL codes shares	YES	YES	YES	YES

The dependent variable is $log(q_{it} + 1)$. Robust standard errors. *** p<0.01, ** p<0.05, * p<0.1

4 Robustness: Gender Differences in Networks

We highlight now that the gender differences in networks are robust to alternative econometric specifications. They emerge if we restrict attention to the journals published across our entire sample. Additionally, the gender differences arise in networks measured across three and ten years. Gender differences in networks also emerge across the entire network distribution. Last, we show that gender differences in networks also emerge for other centrality measures.

4.1 Alternative Econometric Models

We show that our results holds using alternative econometric models to measure the gender gap in network characteristics. We document this using random effect (RE) and correlated random effect models (CRE). We also consider the negative binomial (NB) for degree, which is a discrete variable.[2] The correlated random effect model is:

$$z_{it} = \alpha_i + \mu_t + \rho F_i + C_{it}\omega + \sum_{l=1}^{L} \beta_l JEL_{lit} + \psi y_{it-5} + \varepsilon_{it}, \tag{2}$$

where $\alpha_i = \phi + a_i + \varphi \bar{y}_i + \sum_{l=1}^{L} \gamma_l \overline{JEL}_{li}$ and $l = 1, ..., 19$. The rest of the variables are defined as in equation 2 of the main text.

Tables 15 and 16 show the results, which highlight the robustness of our findings.

Table 15: Networks and Gender: Correlated Random Effect and Negative Binomial

VARIABLES	(1) CRE Co-authorship	(2) NB Degree	(3) CRE Degree	(4) CRE Strength	(5) CRE Clustering
Female	0.013***	-0.158***	-0.295***	0.142***	0.068***
	(0.004)	(0.012)	(0.022)	(0.009)	(0.010)
Past Output	0.0001***	0.002***	0.001***	0.0784***	0.0196***
	(0.000)	(0.000)	(0.0004)	(0.0055)	(0.0046)
Avg. Past output	0.0000	–	0.0106***	-0.3324***	-0.1324***
	(0.0000)	–	(0.0004)	(0.0116)	(0.0071)
Degree					-0.207***
					(0.005)
Observations	394,113	394,113	394,113	316,145	226,078
Career-time FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
JEL codes FE	YES	YES	YES	YES	YES

Column 2 shows the results from estimating degree using a negative binomial model. The results presented in columns 1, 3-5 are obtained using the correlated random effect model. The results presented in columns 4 and 5 are standardized. Clustered standard errors at the author level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

[2] We choose the POLS in the main text because is easier to interpret.

Table 16: Networks and Gender: Random Effect

VARIABLES	(1) Co-authorship	(2) Degree	(3) Strength	(4) Clustering
Female	0.011***	-0.337***	0.170***	0.087***
	(0.004)	(0.023)	(0.010)	(0.010)
Past Output	0.000***	0.003***	0.025***	-0.004
	(0.000)	(0.000)	(0.004)	(0.004)
Degree				-0.209***
				(0.005)
Observations	394,113	394,113	316,145	226,078
Number of authors	56,949	56,949	48,936	38,757
Career-time FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
JEL codes FE	YES	YES	YES	YES

All the results are obtained using random effects. The results presented in columns 3, 4 and 5 are standardized. Clustered standard errors at the author level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4.2 Restricted Set of Journals

If we restrict attention to the set of journals that existed throughout the entire sample period, the gender differences in networks are qualitatively unchanged, see Table 17.

Table 17: Networks and Gender: Fixed Set of Journals

VARIABLES	(1) Co-authorship	(2) Degree	(3) Strength	(4) Clustering
Female	-0.006	-0.202***	0.196***	0.085***
	(0.009)	(0.046)	(0.021)	(0.028)
Degree				-0.263***
				(0.008)
Past Output	-0.00001	0.003***	-0.121***	-0.077***
	(.00004)	(0.0003)	(0.007)	(0.008)
Observations	88,826	88,826	97,439	42,004
Career-time FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
JEL codes FE	YES	YES	YES	YES

All the results are obtained using correlated random effects. The results presented in columns 3, 4 and 5 are standardized. Clustered standard errors at the author level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4.3 Networks Across 3 & 10 Years

In the analysis so far, we have assumed that a link between two authors lasts for 5 years, from $t-4$ to t. In this section, we document that our results are robust to considering three and ten-year networks. We first consider three-year network. In these networks two authors have a link in the co-authorship network, if they have at least one joint publication in the period $t-2$ to t. The results presented in Table 18 indicate that the gender differences in networks are larger in magnitude compared to the five-year network results presented in Table 3 of the main text.

Table 18: Networks and Gender: 3 Year Period

VARIABLES	(1) Co-authorship	(2) Degree	(3) Strength	(4) Clustering
Female	0.018***	-0.346***	0.184***	0.081***
	(0.002)	(0.026)	(0.011)	(0.010)
Past Output	-0.000***	0.004***	-0.154***	-0.063***
	(0.000)	(0.000)	(0.005)	(0.004)
Observations	267,119	267,119	267,119	177,160
Number of authors	48,214	48,214	48,214	36,737
Career-time FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
JEL codes FE	YES	YES	YES	YES

All the results are obtained using correlated random effects. The results presented in columns 3, 4 and 5 are standardized. Clustered standard errors at the author level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Second, we present the results from a ten-year network in Table 19. In these networks two authors have a link if they have at least one joint publication in the period $t-9$ to t. Again, network differences are robust to this time aggregation and the gender differences in degree and betweenness are substantially larger in magnitude than the five-year network results presented in Table 4 of the paper, while the gender differences in strength and clustering are slightly smaller under this 10-year window.

4.4 Institutions

In this section, we analyse the importance of affiliations in explaining the gender difference in collaboration patterns documented in the main text. The sample is restricted to men and women affiliated to 395 institutions. The results presented in Table 20 shows that the role of institutions is minor. Comparing the results obtained without institutions (column 3) with those obtained controlling for institutions fixed effect (column 4), the difference in degree declines by 2.8% when we account for differences in affiliations. The gender gap in

Table 19: Networks and Gender: 10 Year Period

VARIABLES	(1) Co-authorship	(2) Degree	(3) Strength	(4) Clustering
Female	0.008**	-0.661***	0.125***	0.049***
	(0.003)	(0.047)	(0.009)	(0.009)
Past Output	-0.000***	0.012***	-0.134***	-0.034***
	(0.000)	(0.001)	(0.005)	(0.003)
Degree				-0.053***
				(0.001)
Observations	338,766	341,527	338,766	279,692
Number of authors	50,295	50,414	50,295	42,773
Career-time FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
JEL codes FE	YES	YES	YES	YES

All the results are obtained using correlated random effects. The results presented in columns 3, 4 and 5 are standardized. Clustered standard errors at the author level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

strength declines by 3.8% when we control for institutions fixed effects (see columns 5 and 6). However, institutions do not play any significant role in explaining gender differences in clustering.

Table 20: Gender and Collaboration: Accounting for Institutions

VARIABLES	(1) Coauthorship	(2) Coauthorship	(3) Degree	(4) Degree	(5) Strength	(6) Strength	(7) Clustering	(8) Clustering
Female	-0.002	-0.001	-0.527***	-0.512***	0.173***	0.168***	0.079***	0.078***
	(0.005)	(0.005)	(0.049)	(0.049)	(0.015)	(0.015)	(0.014)	(0.014)
Degree							-0.195***	-0.196***
							(0.006)	(0.006)
Past Output	0.000*	0.000*	0.006***	0.006***	-0.114***	-0.114***	-0.040***	-0.040***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)	(0.005)	(0.003)	(0.003)
Observations	190,087	190,087	190,087	190,087	161,236	161,236	123,436	123,436
Career-time FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
JEL codes FE	YES	YES	YES	YES	YES	YES	YES	YES
Institutions FE	NO	YES	NO	YES	NO	YES	NO	YES

All the results are obtained using POLS. Clustered standard errors at the author level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

4.5 Active sample

We now mitigate potential attrition problems by considering research active authors. As in the subsection 3.5, we define a research active as an author who publish at least one paper every five year. Table 21 shows that the gender differences in collaboration patterns are larger when we focus on active researchers. The gender difference in co-authorship is significant in this research active sample, women co-author a larger share of their papers.

Table 21: Gender and Collaboration

VARIABLES	(1) Co-authorship	(2) Degree	(3) Strength	(4) Clustering
Female	0.014***	-0.489***	0.157***	0.061***
	(0.005)	(0.048)	(0.012)	(0.011)
Degree				-0.177***
				(0.005)
Past output$_{t-5}$	-0.000	0.004***	-0.094***	-0.030***
	(0.000)	(0.000)	(0.005)	(0.004)
Observations	206,595	206,595	181,089	145,668
Career-time FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
JEL codes shares	YES	YES	YES	YES

All the results are obtained using the POLS. All the continuous variables in the models estimated in columns 3 and 4 are standardized. Clustered standard errors at the author level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4.6 Quantile Regressions

In the main paper we have estimated the average gender difference in network characteristics. In this section, we examine the gender difference in networks at the 25th percentile, the median, the 75th percentile and 90th percentile of the network variables distributions.

We first estimate gender differences in degree in the 25th percentile, median, 75th percentile and 90th percentile using quantile regressions (see Table 22). The results show that the gender difference in degree increases along the degree distribution and it is highest for authors in the 90th percentile. Second, we analyse using quantile regressions the gender difference in clustering along its distribution (see Table 23). We find that the gender gap in clustering is largest in the upper half of the clustering distribution and it is lowest in the tails. Finally, we find that the gender difference in strength diminishes along its distribution (see Table 24).

Table 22: Degree and Gender: Quantile Regressions

	(1)	(2)	(3)	(4)
Variables/Percentile:	25th pc.	Median	75th pc.	90th pc.
Female	-0.076***	-0.232***	-0.480***	-0.790***
	(0.006)	(0.008)	(0.014)	(0.024)
Career time	0.022***	0.025***	0.039***	0.051***
	(0.002)	(0.002)	(0.004)	(0.008)
Career time^2	-0.001***	-0.001***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Past output	0.004***	0.008***	0.013***	0.018***
	(0.000)	(0.000)	(0.000)	(0.000)
Linear time trend	0.041***	0.071***	0.121***	0.176***
	(0.000)	(0.000)	(0.001)	(0.001)
Observations	394,113	394,113	394,113	394,113
JEL codes shares	YES	YES	YES	YES
Avg. JEL codes shares	YES	YES	YES	YES

Robust standard errors. *** p<0.01, ** p<0.05, * p<0.1

Table 23: Clustering and Gender: Quantile Regressions

	(1)	(2)	(3)	(4)
Variables/Percentile:	25th pc.	Median	75th pc.	90th pc.
Female	0.013***	0.046***	0.160***	0.000***
	(0.002)	(0.002)	(0.005)	(0.000)
Career time	-0.003***	-0.011***	-0.034***	-0.000***
	(0.000)	(0.000)	(0.001)	(0.000)
Career time^2	0.000***	0.000***	0.001***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Past output	-0.000***	-0.000***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Linear time trend	0.041***	0.071***	0.121***	0.176***
	(0.000)	(0.000)	(0.001)	(0.001)
Observations	226,078	226,078	226,078	226,078
JEL codes shares	YES	YES	YES	YES
Avg. JEL codes shares	YES	YES	YES	YES

Robust standard errors. *** p<0.01, ** p<0.05, * p<0.1

Table 24: Strength and Gender: Quantile Regressions

	(1)	(2)	(3)	(4)
Variables/Percentile:	25th pc.	Median	75th pc.	90th pc.
Female	0.051***	0.042***	0.010***	0.000**
	(0.001)	(0.001)	(0.003)	(0.000)
Career time	-0.003***	-0.005***	-0.001	-0.000
	(0.000)	(0.000)	(0.001)	(0.000)
Career time^2	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Past output	-0.000***	-0.001***	-0.001***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Linear time trend	-0.001***	-0.002***	-0.001***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	316,145	316,145	316,145	316,145
JEL codes shares	YES	YES	YES	YES
Avg. JEL codes shares	YES	YES	YES	YES

Robust standard errors. *** p<0.01, ** p<0.05, * p<0.1

5 Homophily

We first present in Table 25 the share of men's and women's collaborators per gender.

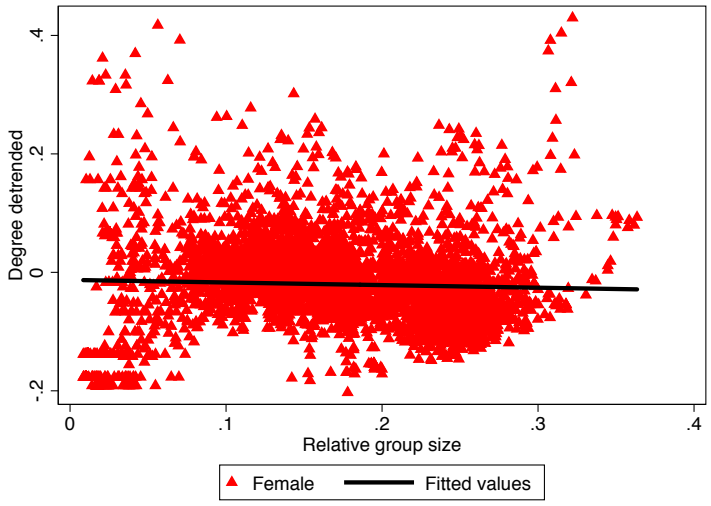
Table 25: Percentage of links across gender

	Men	Women
Population Share	72.72%	27.28%
Men's Collaborators	81.01%	18.99%
Women's Collaborators	67.28%	32.72%
Inbreeding Homphily	0.3039	0.0748

We then check if there is any relationship between degree and the share of women exploiting variation across fields. Here we use the first two digits of the JEL codes, to define 124 different fields. We then de-trend degree by regressing degree on time dummies, the residual from this regression is the de-trended degree.[3] We find that the link between degree and group size is negative. Regressing the degree detrended on relative group size excluding males, we obtain: $\widehat{degreedet} = -.013 - .044w$, both coefficients statistically significant at the 1% level. Figure 4 shows the relationship between the de-trended degree and the fraction of women across fields.

[3]The results are robust to other de-trending methods.

Figure 4: Degree and fraction of women across fields



Note: Degree detrended is the residual of a linear regression of degree on year dummies. Regressing the degree detrended on relative group size, we obtain: $\widehat{degreedet} = -.013 - .044w$, both coefficients statistically significant at the 1% level.

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