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GENDER & COLLABORATION

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Gender and Collaboration

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Abstract

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1 Introduction

Gender disparities in the workplace have attracted considerable attention in recent years. We document gender disparities in research output and connect them to differences in collaboration patterns in economics, using data over the period 1970 to 2017.

We first show that women on average produce 20% fewer articles and 48% less quality weighted research output than men. This output gap remains large – around 19% –even after we control for experience and choice of field (and other observables).

Research is very much a collaborative activity: individuals discuss ideas with each other, present work to colleagues and use the feedback to improve the quality of their work, and they increasingly co-author with others. This leads us to examine the role of networks of co-authorship and how they relate to the gender output gap. In a recent paper, Lindenlaub and Prummer (2014) develop a theoretical model to study the interplay between different network features and their impact on labor market outcomes.[1] They argue that greater connections facilitate access to new ideas, while a higher overlap among connections (higher clustering) and repeated interaction (higher strength of ties) raises peer pressure and trust. These theoretical findings motivate an empirical investigation of network differences between men and women.

We find that, on average, women have 23% fewer connections – degree – than men, controlling for experience, choice of fields, and other observables. Similarly, women have a higher overlap among connections: their clustering coefficient is 6.1% higher than that for men. Women also tend to work more with the same co-authors: their strength of ties is 9.4% higher than men.

[1] Their paper builds on work on the role of social structure in shaping the diffusion of ideas and in the sustenance of social norms, see e.g., Coleman, Katz, and Menzel (1966), Coleman (1988), Granovetter (1973).

These network differences between men and women are closely correlated with research output. Indeed, once we control for network differences, the gender quality weighted output gap goes down by 21%.

These results focus on averages over 48 years, which motivates a closer investigation of how these empirical facts changed over time, especially as the fraction of women grew from 4.4% in 1970 to 28% in 2017. Despite this increase, we find a remarkable persistence in the gender disparity in output as well as in co-authorship networks. We investigate the persistence in network differences further, documenting a number of empirical facts.

First, the persistent difference in degree could be related to women working more on their own compared to men. To investigate this, we look at the share of single-authored papers. The analysis reveals that women write fewer papers on their own, compared to men. Therefore, women's lack in the number of distinct co-authors is not connected to them working on their own.[2]

Second, we ask if the lower degree is due to the lower fraction of women in the population. Our starting point is the evidence in support of gender based homophily: both men and women display gender homophily – the fraction of co-authors of the same gender is larger than the fraction in the population of researchers. Currarini, Jackson, and Pin (2009) argue that in a world with homophily, the gap in degree is larger with a larger gap in the fraction of men versus women. This implies that a more balanced gender composition in economics should lead to a lower degree gap between men and women. We test their prediction in two ways: first, by considering the variation in the share of female authors over time and cohorts and second, by investigating the variation across research fields. We show that across time, cohort and field, the number of distinct co-authors is not affected by a more gender-balanced environment.

[2]In what follows, we use the words economist, author, and researcher interchangeably.

So far, we have focused on the average differences across gender, which leads naturally to the question of whether gender differences emerge for all authors, independently of how much they produce. To study gender differences across authors with different levels of past performance, we rank authors according to their past research output and analyze the differences in network characteristics. It turns out that the gender gap in networks holds across performance levels and that it is even more pronounced for the authors with the highest past output.

Another potentially important heterogeneity is career time. Given the increase in fraction of women over time, the average woman is less senior than the average man. This could potentially relate to network differences between men and women. To address this issue, we study their networks at every stage of career. The analysis reveals that the network differences between men and women continue to hold at every stage of career.

Going one step beyond network patterns of collaboration, we turn to co-authors characteristics. Our principal finding is that women co-author more with more experienced and senior authors at each stage of their career. Finally, we find that for both men and women, their male co-authors have a higher research output.

These differences are striking and we are led to wonder if they are specific to economics. This leads us to study patterns of output and networks in sociology. We study the period 1963 to 1999. We find that, in sociology, the share of women is consistently higher than in economics: it rises to 42% by the end of our sample period. Sociology exhibits the same qualitative, but quantitatively smaller, gender disparities in output, collaboration patterns and co-author characteristics as economics. There is one dimension on which sociology and economics authors appear to differ: male and female sociologists do not exhibit gender homophily in co-authorship, that is both male and female sociologists's

co-authors reflect the gender balance in sociology.

To summarize, we document that the differences in collaboration patterns between men and women are pronounced and remarkably persistent in economics; this is true though to a smaller extent also in sociology. We provide novel evidence highlighting these disparities, with further data being required (such as information on family constraints) to analyse their sources and to derive policy implications.

Related Literature There is a small body of empirical work on gender differences in economics, see e.g., Boschini and Sjögren (2007), McDowell, Singell, and Stater (2006), Sarsons (2015), Wu (2017), Hengel (2016), Chari and Goldsmith-Pinkham (2017), Boring (2017), and Mengel, Sauermann, and Zölitz (2017). Our contribution is to document a set of facts on the relation between gender, research output and collaboration networks. Specifically, 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. Their conclusion is that the share of women is relatively constant. This is quite different from our finding on the growth of fraction of women. A possible explanation may lie in the scope of their work: they restrict attention to US data.

The second fact we present, that women have lower research output as compared to men, also appears to be new; the closest paper here is McDowell, Singell, and Stater (2006). They present evidence on lower output of female authors who are members of the American Economic Association. Turning to network statistics, we are the first to document the long term gender based network differences with respect to degree, strength

and clustering; and to relate these network differences to the gender output gap.[3] For work on degree and clustering in school networks, at the Enron company, and in computer science, see Lindenlaub and Prummer (2014).[4] Turning to characteristics of co-authors, our contribution is to present evidence of gender homophily and differences in the seniority of co-authors.

We contribute to the literature on homophily in social networks. Homophily has been extensively studied in sociology and more recently it has also been studied in economics, see e.g., McPherson, Smith-Lovin, and Cook (2001), Bramoullé, Currarini, Jackson, Pin, and Rogers (2012), Currarini, Jackson, and Pin (2009), and Zeltzer (2020). Our finding on gender-based homophily in co-authorship 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 in the presence of homophily, as elaborated in Currarini, Jackson, and Pin (2009).

The rest of the paper proceeds as follows: Section 2 lays out the empirical strategy, describes the data and defines the variables. Section 3 presents our findings for economics. Section 4 provides an overview of the persistence and stability of co-authorship patterns. Section 5 briefly summarizes the evidence from sociology. We conclude in Section 6.

2 Methodology

We first discuss our empirical strategy to estimate gender differences in output, gender differences in collaboration networks, and the importance of networks in explaining the

[3] Contrary to Boschini and Sjögren (2007), we find that women co-author a larger share of their publications. Boschini and Sjögren (2007) focused on three journals, while we use publications in over 1600 journals, over a period of 47 years.

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

gender output gap. We then describe our data set and define measures of research output and coauthor networks.

2.1 Empirical Strategy

A key parameter of interest in each regression is the coefficient of an indicator variable for gender (which equals one if the author is female). We include a number of control variables in all of our regressions. First, we control for experience through career time dummies, which are defined as the number of years since the first publication by the author.[5] We further control for field of research. Following Fafchamps, Goyal, and van der Leij (2010), we categorize 19 different fields using the first digit of JEL codes and include a measure of the proportion of publications in each JEL code. These codes capture the fields of specialization of the author. We also include time fixed effects to account for time trends. We denote the set of controls, including a constant, by x_{it} for author i at time t. Research output is denoted by q_{it}, network measures by z_{it}; these measures will be defined in Section 2.2. Standard errors are clustered at the author level as both research output and network measures are correlated over time. We use Pooled OLS (POLS) as our baseline estimation, but also estimate a variety of other models to ensure robustness.[6]

We start with the gender output gap in research:

$$q_{it} = \rho F_i + x_{it}\beta + \varepsilon_{it}, \tag{1}$$

[5] While the Ph.D. graduation date is arguably a better proxy for experience, since the timing of the first publication may differ across gender, we refrain from doing so as gathering this information for over 367,000 authors is prohibitively costly.

[6] We also studied a random effect model, a correlated random effect model, and a negative binomial model; the results, presented in the Supplementary Appendix, show that our results are robust to model specification.

where F_i, an indicator for being female, is our main variable of interest.

We then turn to gender differences in network statistics. To capture differences in past academic performance across gender, we additionally control for past output, the accumulated research output from the first publication of the author until $t-5$, captured by an amended vector of controls x'_{it}. Research output is lagged to avoid a simultaneity problem with the network variable.[7] The estimated model is:

$$z_{it} = \rho F_i + x'_{it}\beta + \varepsilon_{it}, \tag{2}$$

Finally, we study the association between the network differences and future output. For this purpose, we consider the future output model proposed in Ductor, Fafchamps, Goyal, and van der Leij (2014). Specifically, we first estimate a baseline model, where the dependent variable is the accumulated output from $t+1$ to $t+5$, defined as q_{it+5}. In addition to experience and field, we control for both past output (the accumulated output from first publication until $t-5$) and recent output (the output accumulated from $t-4$ to t), the new vector of controls is denoted by x''_{it}. We take the log of the output variables plus one, as in Ductor, Fafchamps, Goyal, and van der Leij (2014), since the distribution is highly right-skewed:

$$log(1 + q_{it+5}) = \rho F_i + x''_{it}\beta + \varepsilon_{it}. \tag{3}$$

We add a network variable – z_{it} – to model (3) to investigate the association between the gender output gap and collaboration patterns:

$$log(1 + q_{it+5}) = \rho F_i + x''_{it}\beta + \theta z_{it} + \varepsilon_{it}. \tag{4}$$

[7] In the Supplementary Appendix, we also add the number of papers published from $t-4$ to t to the network model. The results are qualitatively similar.

A comparison of coefficients on the gender dummy between models (3) and (4) captures the extent of the influence of the network variables.

2.2 Data

Data Description Our main 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 921,976 articles published between 1970 and 2017, in 1990 journals. We do not cover working papers and work published in books.[8] For further information on the journals included, see https://www.aeaweb.org/econlit/journal_list.php.

Each article registered in the EconLit has information about the journal (including name of the journal, volume, issue, first and last page), title, the last and first name of each author, affiliations of each author, JEL codes, keywords and the abstract.[9] Authors are identified by their first and last name, as in Goyal, Van Der Leij, and Moraga-González (2006). Using information about all the articles published by an author in our sample period, 1970-2017, we construct a panel that starts for each individual with their first publication and extends to the last observed publication of the author (or to 2017).

To provide additional measures of research performance, we supplement the EconLit data with citations and references from the Web of Science (hereafter, WoS) (Clarivate Analytics, 2018). For this latter exercise, we focus on the 100 most established journals in economics according to IDEAS/RePEc, see also Ductor, Goyal, v. der Leij, and Paez

[8] 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 articles with four or more authors are included.

[9] Affiliations are only available for articles published after 1989. Abstracts are only available for articles published after 1999.

(2020).[10] The citation and reference data set includes information on 275,670 articles and the number of citations they received yearly until 2017.

We identify the gender of an author using their first names and the *gender-api.com*, a source that provides first names and the estimated gender for 201 countries. We identify an author's gender if the author's first name is associated with a single estimated gender in the 201 countries, at least 95% of the time. This allows us to identify the gender of 78% of the authors (367,441 out of 470,309 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.

To make meaningful comparisons on output, we focus on authors who are active for a significant period of time. This leads us to restrict attention to authors who are present for at least 5 years after their first publication. This means that every author in our sample has a first paper (which is when they make their appearance in the data set) and then at least one more paper published five or more years after the first paper. This rules out a large fraction of authors: 60% of the authors in EconLit only publish one article during the sample period.

Definition of Variables It is well known that there are long lags in publication (Ellison, 2002). Moreover, the average number of papers per author is small: 0.68 papers per year. We therefore need a reasonable time window over which to consider research output: this motivates our five-year window. We have also considered three and ten-year windows. Our results are robust to alternative time intervals, see the Supplementary

[10] More precisely, we take the top 100 journals from the Simple Rank list over all years.

Appendix.

Research Output: It is natural to start with the count of publications of author i during the period $t-4$ to t. However, not all articles are of equal standing. To take quality into account, we define the research output of an author i at time t 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. We use the quality measure introduced in Ductor, Fafchamps, Goyal, and van der Leij (2014) that covers 1627 journals, and builds on the quality journal index developed by Kodrzycki and Yu (2006). It is a fairly common practice to measure the quality of the article using the journal where it was published as a proxy. For instance, the Research Excellent Framework in the UK use the British ABS Academic Journal Guide to evaluate the research performance of departments. As this index does not vary over time, we consider citations and references from the WoS to construct a time varying quality index: the 'article influence score'. The formal definition of the article influence score index and the results that confirm our baseline findings are provided in the Supplementary Appendix.

Research output is discounted by the number of authors in paper p, since we want to analyze differences in output not driven by disparities in co-authorship, such as differential numbers of co-authors per paper across gender.[11]

Network Variables: We construct a network, where two authors i and j have a link in the

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

co-authorship network, $g_{ij,t} = 1$, if they have at least one joint publication in the period $t-4$ to t. We consider three network measures: degree, clustering and strength of tie. The degree d_{it} is the number of distinct co-authors in the network over $t-4$ to t:

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

Degree is treated as missing if the author does not have publications from $t-4$ to t.[12] The clustering coefficient measures how many co-authors of an agent are themselves co-authors.

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

In regressions for the clustering coefficient, we restrict attention to authors with at least two links as it is otherwise undefined.

The strength of ties measures the number of papers written with a co-author. Denote the number of papers written between i and j as $n_{ij,t}$. The strength of an author is given by the average strength across all his ties, over the past five years, $t-4$ 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 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.

[12] Results are robust to replacing 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.

Descriptive Statistics Table 1 provides summary statistics of both our output measures as well as network variables. We use as output measures research output, number of publications as well as number of citations per paper. Across all measures, women perform worse. Women publish on average 20% fewer articles than men. Taking into account the quality of the journal, leads to an even larger output gap with women producing almost 50% less compared to men. The gender gap for number of citations per paper is somewhat smaller, with women attracting 34% fewer citations per article than men.

Men and women do not only differ in terms of their research output but also with regard to their collaboration patterns. Women have an 8% lower degree than men (i.e., fewer distinct co-authors). They have 27% higher clustering coefficient than men, implying that a higher share of their co-authors are themselves collaborators. Lastly, women are more likely to work repeatedly with the same co-authors, reflected in their strength of ties being 17% higher than men's.

3 Findings

We start with the gender output gap, before turning to the gender difference in co-authorship networks. We then connect the two and show that accounting for network differences is associated with a lower gender output gap. Last, we provide a number of robustness checks for our findings.

3.1 Gender and Research Output

We first estimate model (1) to document the gender output gap; the results are presented in Table 2. Independently of our measure of research performance, women have a lower

output: this difference is significant, when we consider number of papers and research output weighted by the journal quality. Of independent interest is our finding that the gender difference in citations per paper is statistically insignificant.

Column 2 in Table 2 shows that there is a negative coefficient of 1.60 on women's research output. Recalling from Table 2 that the output of women is 4.43, yields us the finding that the output of men is 36% higher than the output of women, after controlling for experience and research fields. Controlling for these observables reduces the gender gap in research output by 50% (to see this compare the coefficient on the gender dummy between columns 1 and 2). So, career time and choice of fields matter, but there still remains a large and significant unexplained gap in research output.[13]

3.2 Gender and Collaboration

Inspired by the theoretical literature on the role of networks in shaping peer effects and the diffusion of new ideas – for references, see the introduction – we now examine network differences across gender. Table 3 presents network statistics for men and women, estimated from equation (2).

Our principal findings are as follows:

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

   Column 2 shows that women have 0.54 less collaborators than men; recall from Table 1 that average degree of men is 2.41; thus women have 23% (0.54/2.31) lower degree than men.[14]

[13] Following a suggestion of one of the referees, we considered the effects of allowing a slightly longer window for women, partly as a way to take into account time for child care. The research output of women over 6 years is 2.66 and the research output for a period of 7 years is 3.08. Recall that men's output for a 5 year period is 2.80. This means that women's output over 6 years is lower than men's output over 5 years – the difference is 0.14 (2.66 versus 2.80). On the other hand, the output of women over 7 years is *larger* than the output of men over 5 years: 3.08 versus 2.80.

[14] 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

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

   Column 4 shows that women's clustering coefficient is 0.054 higher than men; recall from Table 1 that men's clustering is 0.51. Thus women's clustering is 10.6% (0.054/0.51) higher than that of men. Goyal, Van Der Leij, and Moraga-González (2006) and Jackson and Rogers (2007) have shown that there is a negative correlation between degree and clustering in the co-author network. So, in principle, the higher clustering of women could be explained by their lower degree. Indeed, degree differences are important: if we compare the female coefficients in columns 4 and 5, we see that degree explains 43% of the gender difference in clustering. However, these results also show that the gender difference in clustering remain large, even after we control for degree: indeed, women's clustering is then 6.1% (0.031/0.51) higher than that of men.

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

   Column 3 shows that female authors' normalised strength is 0.060 lower than that of men. Recalling from Table 1 that men's strength is 0.64. This means that women have a 9.4% (0.060/0.64) higher strength than men, controlling for observable factors.

3.3 Gender, Output and Collaboration

Having established that research output and network differences across gender are large and persistent, we now analyze the association between current networks and gender difference in future output. For this purpose, we compare the coefficients of the female indicator of the baseline model (3) with model (4), which additionally controls for network characteristics. In this analysis, we focus on the sample of authors that have a defined

results are available in the Supplementary Appendix; they show that while the gender difference in degree is increasing along the degree distribution, it holds for every quantile.

clustering, i.e. those with at least two co-authors from $t-4$ to t, since we want to compare the correlation of each network variable with the future gender output gap and in that sample, degree and strength are also well defined. These results are reported in Table 4.

If we control for degree then there is 18% ((0.067-0.055)/0.067) fall in the future gender output gap (see columns 1 and 2 of Table 4). If we add strength of ties, we find that the female coefficient declines by 12% ((0.067-0.059)/0.067; based on a comparison of columns 1 and 3). If we add clustering, this decline is 4% ((0.067-0.064)/0.067); this is based on a comparison of the female coefficients between columns 1 and 4 in Table 4. If we control for all network characteristics simultaneously, that leads to a 21% ((0.067-0.053)/0.067) decline in the coefficient on gender (compare the female coefficients between columns 1 and 5). These results show that networks help to explain variation in future output differences across gender, over and above recent and past output.

3.4 Robustness Checks

Given our data, we cannot establish a causal relationship between network structure and research output. In this section, we will show that the correlation between the network variables and output difference is robust.

First, we examine the role of institutions in relation to the gender gaps in research output and collaboration by using a sample of 395 affiliations. One standard problem with affiliations is that authors tend to report an affiliation with different names, this is particularly problematic 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 and network models described in section 2. The results presented

in the Supplementary Appendix show that the role of institutions in explaining gender differences in output and collaboration is minor.

Second, we consider a research-stream authors sample, those publishing at least three papers every five years. The results, presented in the Supplementary Appendix, show that the gender differences in research output and collaboration are even larger when we focus on relatively active researchers. The correlation between networks and the gender output gap is also stronger in this sample.

Third, we focus on journals that are available in the EconLit for the entire sample period, 1970-2017. The results, presented in the Supplementary Appendix, confirm that the gender differences in output and collaboration are not driven by journal selection.

Fourth, we show in the Supplementary Appendix that the gender differences in output and collaboration patterns persist using different models, correlated random effects, random effects and non-linear models. We also consider a time-varying quality impact factor (article influence score) to measure research output.

Fifth, we consider three and ten-year output and network variables, the output and network differences are robust to different time aggregation. The results are qualitatively identical. Details can be found in the Supplementary Appendix.

4 Collaboration and Output Over Time

So far, we have focused on average disparities between female and male authors in terms of collaboration and output. This may mask important changes in economics over the 48 year period under investigation. Therefore, we turn to an investigation of the stability and persistence of output and collaboration patterns and supplement our findings with a number of empirical facts documenting other novel differences in collaboration between

female and male economists.

Women in Economics First, there has been a significant increase in the share of women in the economics profession, a finding opposite to what the literature focussed on the US has found so far (Ginther and Kahn (2004)). The fraction of women grew from 6% in the period 1971-1975 to 29% in 2011-2015. Plot (a) in Figure 1 illustrates this development.

Gender Differences in Ouput Over Time Despite this increase in the share of women, the gender output gap remains remarkably stable over time, see columns 5, 6 and 7 in Table 5 with women producing 25% to 30% fewer articles than men over the entire period. The difference is larger but equally persistent if we take into account the quality of journals: the difference in quality-weighted research output was roughly 45% at the start in 1971-1975, it fell to 28% in 1990-1994, and was 25% in the period 2011-2015. Plot (b) in Figure 1 shows the ratios of average number of papers and average quality-weighted output between men and women, over time.

Gender Differences in Networks Over Time Similarly, gender differences in networks persist over time. To examine the stability of gender disparities across time, we add interaction terms between gender and year dummies to our baseline model (2). Figure 2 presents the coefficients and 95% confidence interval of these interaction terms. All the estimates are relative to the base year 1980. 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 from -0.24 in 1980 to -1.15 in 2017, i.e. women have roughly one co-author less than men in 2017.

Co-authored Papers and Co-authors per Paper Women having a lower degree may be related to women co-authoring less, instead they may write more single-authored papers. To address this, we calculate the ratio between the number of co-authored papers and the total number of articles. We find that women write fewer solo-authored papers compared to men, see column 1 in Table 3. The gender difference in the share of co-authored articles relative to solo papers is positive and small, 0.012 (women produce 1.2 percentage points more co-authored papers than men). Our result may also be due to men having a higher number of co-authors per paper. We therefore investigate gender differences in collaborators per paper and we find that in fact women have 20% (1.38/1.15) more coauthors per paper than men, see Table 1.

Gender Homophily As women co-author to a greater extent, the influx of women in the profession together with gender homophily (McPherson et al. (2001)) could have ameliorated the gender differences in co-authorship networks. We first check whether authors display gender homophily based on two commonly used measures, *relative homophily* and *inbreeding homophily* (Coleman (1958)).[15]

Men display relative homophily if the average share of male co-authors among men is higher than the fraction of male authors in the population; similarly for women. We compute the percentage of links within gender and find that, on average, 80.5% of men's collaborations are with other men: this is higher than the fraction of men in the population 70.5%. Women also exhibit relative homophily as their collaboration with other women, 34.1% is larger than the fraction of women in the population 29.5%. Therefore,

[15] An alternative measure has been suggested by Zeltzer (2020). His measure is similar to the relative homophily we consider but primarily pertains to directed networks (we consider undirected networks). His index is defined as the difference in the share of male collaborators of men versus women; in our setting, this can be computed to be equal to 14.6% (80.5% − 65.9%).

both women and men exhibit relative homophily.[16]

While relative homophily does not take into account the varying shares of men and women in the profession, *inbreeding homophily* incorporates this change. It measures 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. 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. Inbreeding homophily is then given by

$$IH_s = \frac{H_s - w_s}{1 - w_s}, \quad \text{for } s = \{f, m\}. \tag{5}$$

Observe that positive IH_s indicates homophily while a negative IH_s indicates heterophily.

Figure 3 presents the average inbreeding homophily of authors per year by gender and 95% confidence intervals. The figure shows that there is inbreeding homophily for men and women, and that it is *persistent* and *stable* across the entire sample period.

Building on Currarini, Jackson, and Pin (2009), we note that gender-based homophily together with a more gender balanced environment would imply a fall in the gender difference in degree: men co-author less, women co-author more, as the share of women increases. We examine this prediction.

We first exploit variation in gender shares across time. From Table 5, we know that women became more representative in the profession over time. But contrary to the prediction of the model, we find in Figure 2 that the gender difference in degree is actually increasing for the most recent periods.

[16]This homophily may reflect a greater proportion of gender specific shared activities, see Graham (2016).

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 120 different fields. We then de-trend degree by regressing degree on time dummies, the residual from this regression is the de-trended degree.[17] We find that the link between degree and that fraction of women in a field is insignificant.[18] Figure 4 shows the relationship between the de-trended degree and the fraction of women across fields, after pooling all the years together.[19] This implies that a higher share of women in a field is not associated with a larger number of distinct co-authors for women.

So, despite the homophily observed in the data, there is no relationship between degree and gender balance.

Heterogeneity in Research Output So far, our argument focuses on averages across gender, which may neglect that different collaboration patterns emerge due to observables. One such observable is differences in research output, which begs the question of whether gender differences emerge for all authors, independently of how much they produce. To investigate this, we follow Ductor, Fafchamps, Goyal, and van der Leij (2014) and divide authors into five groups based on their past output, the output accumulated from the first publication until $t-5$. We define four dummy variables, the dummy past output 99th is equal to one for authors in the top 1% of past output. Similarly, we create a dummy for those in the 95-99, the 80-94, and the 50-79 percentiles of past output, respectively. The reference category is authors with past output equal or below the median. We interact the tier group dummy variables with the female dummy variable to quantify the difference

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

[18] Regressing the degree detrended on the fraction of women, we obtain: $\widehat{degreedet} = -.004 + 0.014 w_f$, the p-value of the intercept and slope coefficients are 0.01 and 0.18, respectively.

[19] The same pattern is observed if we define fields using the first digit of the JEL code, 19 different fields.

in networks between female and male authors belonging to the same past output group.

Table 6 presents our results: differences in degree persist for authors with high research output. For instance, the gender difference in degree for authors in the 80-94th percentile is almost twice the gender difference for authors whose past output is below the median.

Heterogeneity in Career Time Another important heterogeneity that should be taken into account is career time. Given the rise in fraction of women, the average woman is more junior than the average man. We therefore investigate whether women's networks differ at each stage of their career from men's collaboration patterns. For that purpose, we add interaction terms between career time dummies and the female dummy to the network model defined in equation 2. Figure 5 presents the coefficients and 95% confidence intervals of the interaction terms. The estimates are interpreted relative to the base career time, six years of experience. The plots show that the degree difference is stable along the career of authors. A similar picture emerges for clustering and strength which are stable for the majority of the career, but then significantly decrease after 20 years.[20]

To assess the importance of generational effects, we study if gender differences in networks vary across cohorts. The results are in line with what we find across career time, see the Supplementary Appendix.[21] Last, we analyze if the career time effects vary across cohorts. The results presented in the Supplementary Appendix document that life cycle patterns in networks for both men and women remained stable across cohorts, with the exception of degree, where the gender difference increased along the career of

[20]The p-values of the F-tests on the joint significant of the interaction terms in the degree, strength and clustering models are 0.23, 0.00 and 0.02, respectively.

[21]The results show that the gender differences in clustering and strength are stable across cohorts. The gender difference in degree was higher for authors with a first publication in the 90s or 00s, but otherwise stable.

the author for the cohorts 1990-1994 and 2000-2004.

Characteristics of Co-Authors Going one step beyond network patterns of collaboration, we turn to co-authors characteristics; in particular their research output and seniority, and analyze how they differ across gender. Figure 6 presents the cumulative average co-authors' research output distribution by gender for male (left plot) and female (right plot) authors. Male co-authors have, on average, a higher past research output than female co-authors, both for men and women; a difference that is significant at the 1% level.[22] Figure 7, right plot, highlights average co-authors' experience by gender across career time: we note that *at every stage of their career*, women tend to work, with co-authors that have more experience, relative to men. 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).

5 Sociology

The patterns on gender output and gender differences in coauthor networks in economics are striking. In this section, we will show that similar empirical patterns also hold in sociology. Due to space constraints, the descriptive statistics, the Tables and the Figures pertaining to sociology are presented in the Supplementary Appendix (see Section A).

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

[22] We also observe that articles published exclusively by men are those with the highest journal quality impact factor and number of citations, both for co-author teams of two and three individuals, see the Supplementary Appendix.

sociology. Sociological Abstracts limits coverage to journal articles, neglecting conference presentations, book reviews, essays, or books. We use keywords of the articles as a proxy for fields. The quality index that we use for the journals in Sociological Abstract is the Scimago JR (Scopus, 2016) impact factor. Table A.1 presents summary statistics for sociology focusing on averages, while Table A.2 documents the changing environment in sociology.

Our first point concerns fraction of women and differences in output. The fraction of women was 13% in 1963 and moved up to 42% in 1999, see Plot (a) in Figure A.1. The ratio of per capita papers started around 0.70 in 1963, but by the end of the period in 1999, the ratio was close to 0.92. However, the difference in quality-weighted research output is larger and more persistent: in the early years, around 1970, women were producing 60% less than men. This difference declined significantly and was around 20% by 1980. However, it has remained unchanged after that until 1999. Table A.3 shows that these 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 (see Table A.4). Women have lower degree: the conditional average difference in degree is -0.19. This is 8% (0.19/2.37) of the average degree of men. Women have a higher clustering coefficient: the conditional difference in clustering is 0.017, taking the correlation with degree into account. This is 2.2% (0.017/0.76) of the average clustering of men. Women also tend to work more often with the same co-authors: the conditional difference in strength is 0.022; this is roughly 2.7% (0.022/0.82) of the average strength for men. Thus, although the same qualitative patterns emerge in sociology, the magnitude of the differences in degree,

clustering and strength are substantially smaller than in economics: indeed, the gender differences in networks are roughly three times larger in economics than in sociology.

Table A.5 presents the correlations between networks and gender difference in future output in sociology. Consider the effect of adding degree: comparing the coefficients of the female dummy, between the baseline model (equation (4) estimated in column 1) and a regression that adds a degree to the baseline model in column 2, we find that the gender gap in output declined by 21% ((0.014-0.011)/0.014). If we add strength, this decline is 29%, and if we add clustering, then the decline is 21%. Finally, the decline is 36% when we add all the network variables simultaneously to the baseline model.[23]

Our third observation is about the types of co-authors that men and women have. We find that collaboration does not exhibit homophily in sociology. Men exhibit relative heterophily, on average, 48% of men's collaborations are with other men: this is lower than the fraction of men in the population, 64%. Similarly, women exhibit relative heterophily as their collaboration with other women, 28%, is lower than the fraction of women in the population, 36%.[24] As in economics, we also find that women have more senior co-authors, at every point in their career. In particular, compared to men, women have co-authors that are 0.9 years more experienced (this is presented in Figure A.3).

To summarize: sociology exhibits the same qualitative – but quantitatively smaller – gender disparities in output, collaboration patterns and co-author characteristics as economics. A key difference is that sociologists do not display gender homophily.

[23]Notice that the future output gap in sociology (1.4%) is substantially smaller than in economics (6.7%); moreover, taking into account network characteristics reduces the future output gap in sociology to 0.9%.

[24]The inbreeding homophily indexes for women and men are negative and persistent over time, see Figure A.2.

6 Concluding Remarks

This paper examined gender disparity in economics research over the period 1970-2017. The share of women publishing in economics grew roughly four times, but there remains a large gender difference in research output: women produced 20% fewer articles and 48% less quality-weighted research output than men over the period. This output gap is associated with large and persistent differences in the co-author networks of men and women: women tend to have fewer co-authors (and collaborate more often with the same co-authors) and exhibit greater overlap in their co-authors. Women also tend to have a higher share of co-authored work and they co-author more with senior colleagues. We further show that gender homophily is not a driver of collaboration patterns.

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Figures and Tables

Table 1: Summary Statistics in Economics: 1970-2017

Variable	Gender	(1) Mean	(2) Standard Deviation
# of publications	Female	2.21	2.71
	Male	2.77	3.86
	All	2.68	3.70
	Ratio	0.80	0.70
Research output	Female	4.43	14.50
	Male	8.59	24.89
	All	7.71	24.89
	Ratio	0.52	0.58
# of citations per paper	Female	3.96	14.61
	Male	6.01	27.30
	All	5.52	24.84
	Ratio	0.66	0.54
Degree	Female	2.13	2.34
	Male	2.31	3.05
	All	2.30	2.95
	Ratio	0.92	0.77
Clustering	Female	0.65	0.39
	Male	0.51	0.41
	All	0.55	0.41
	Ratio	1.27	0.95
Strength	Female	0.75	0.30
	Male	0.64	0.34
	All	0.67	0.33
	Ratio	1.17	0.88
Co-authorship	Female	0.73	0.38
	Male	0.66	0.40
	All	0.68	0.39
	Ratio	1.11	0.95
Coauthors per paper	Female	1.38	1.13
	Male	1.15	1.03
	All	1.23	1.07
	Ratio	1.2	1.1

The sample includes authors publishing in the EconLit from 1970 to 2017. All the variables are obtained using publications in a five-year window, from $t-4$ to t. All the averages and standard deviations differences between male and female are statistically significant at the 1% level. Ratio is the average/standard deviation of women to men.

Table 2: Gender Differences in Performance

VARIABLES	(1) Output	(2) Output	(3) # Papers	(4) $\frac{Output}{\#Papers}$	(5) $\frac{Citations}{\#Papers}$
Female	-3.257***	-1.604***	-0.515***	-0.139***	-0.243
	(0.156)	(0.137)	(0.020)	(0.034)	(0.169)
Observations	1,069,809	1,069,809	1,069,809	776,943	546,557
Career-time FE		✓	✓	✓	✓
Year FE		✓	✓	✓	✓
JEL codes FE		✓	✓	✓	✓

The sample consists of authors who have a career time of at least six years. 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 Co-author Networks

VARIABLES	(1) Co-authorship	(2) Degree	(3) Strength	(4) Clustering	(5) Clustering
Female	0.012***	-0.538***	0.060***	0.054***	0.031***
	(0.003)	(0.029)	(0.003)	(0.003)	(0.003)
Degree					-0.035***
					(0.001)
Past output$_{t-5}$	0.000***	0.008***	-0.001***	-0.001***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	672,171	672,171	560,533	422,512	422,512
Career-time FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
JEL codes shares	✓	✓	✓	✓	✓

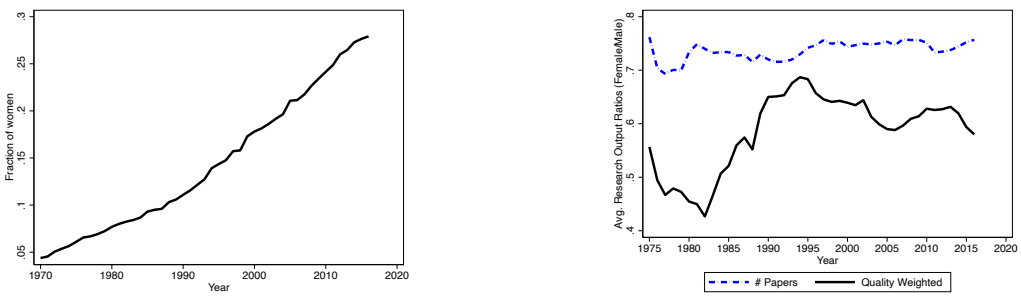
The sample consists of authors who have a career time of at least six years. All the results are obtained using the POLS. Co-authorship and Degree are undefined for periods without publications. Clustering is undefined for sole authors and authors with only one co-author; strength is undefined for periods without co-authored publications. Clustered standard errors at the author level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Gender, Networks and Future Output

	Dependent Variable: Future Output				
	(1)	(2)	(3)	(4)	(5)
Female	-0.067***	-0.055***	-0.059***	-0.064***	-0.053***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Degree		0.027***			0.024***
		(0.001)			(0.001)
Strength			-0.227***		-0.104***
			(0.015)		(0.023)
Clustering				-0.096***	0.009
				(0.010)	(0.015)
Recent Output	0.594***	0.569***	0.566***	0.583***	0.560***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Past Output	0.182***	0.182***	0.185***	0.182***	0.183***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	224,604	224,604	224,604	224,604	224,604
Career-time FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
JEL codes shares	✓	✓	✓	✓	✓

The sample consists of authors who have a career time of at least six years and at least two co-authors. Results estimated using POLS models. The dependent variable, future output, is accumulated output in logs from $t+1$ to $t+5$. Recent output is the accumulated output in logs from $t-4$ to t and Past Output is the accumulated output from the first publication of the author in logs to $t-5$. Clustered standard errors at the author level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Figure 1: Participation of women and research output, 1970-2016



(a) Participation of Women: 1970-2016 (b) Research Output Ratio (Female/Male)

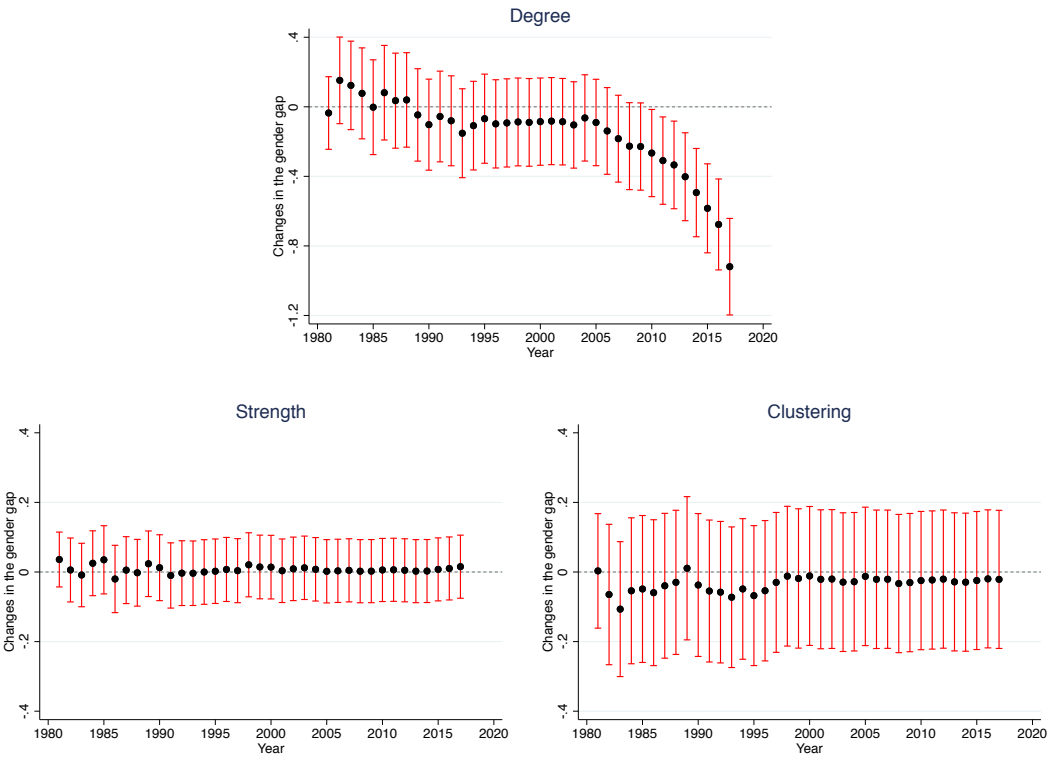
Note: Share of women publishing in EconLit per year in plot (a). Average research output ratio between women and men for each year in plot (b). We identify the gender of 78% of the authors using their first names and the *gender-api.com*.

Table 5: Number of journals, articles and authors, 1970-2017

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
					Per capita articles		
Year	Journals	Articles	Women	Men	Women	Men	Ratio
1971-1975	252	28460	975	15062	2.72	3.47	0.78
1976-1980	276	36602	1893	21656	1.70	2.42	0.70
1981-1985	351	45103	2954	27181	1.57	2.15	0.73
1986-1990	382	51609	4159	31565	1.49	2.12	0.70
1991-1995	587	67381	6829	40578	1.56	2.19	0.71
1996-2000	804	95750	12360	55604	1.77	2.40	0.74
2001-2005	1017	118017	19157	69591	1.83	2.48	0.74
2006-2010	1260	159421	31467	92816	2.04	2.77	0.74
2011-2015	1474	229034	51641	123597	2.59	3.50	0.74
2016-2017	1312	85533	26753	66201	3.64	4.86	0.75
1970-2017	1990	921976	101536	265905	2.21	2.77	0.80

The sample includes all articles published in the EconLit from 1970 to 2017. 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 number of papers per author for women across periods, column 6 presents the average number of papers for men across periods, column 7 shows the ratio between women's average number of papers to men's average number of papers. The last row, 1970-2017, presents the average across all the entire sample, 1970-2017 (thus, the numbers in columns 5-7 of the last row are *not* an average of the numbers for the individual periods reported in the respective columns). We identify the gender of 78% of the authors using their first names and the *gender-api.com*.

Figure 2: Network Differences Across time



Note: The plots show the coefficients and 95% confidence intervals of the interaction terms between year dummies and the female dummy of a network model estimated using POLS, the base year is 1980. The gender gaps in degree, strength and clustering in the base year 1980 are -0.236, 0.065, 0.067 and respectively. The p-values, obtained using the of F-tests on the joint significant of all the interaction terms are: 0.000 in the degree model; 0.149 in the strength model; 0.447 in the clustering model.

Figure 3: Inbreeding Homophily

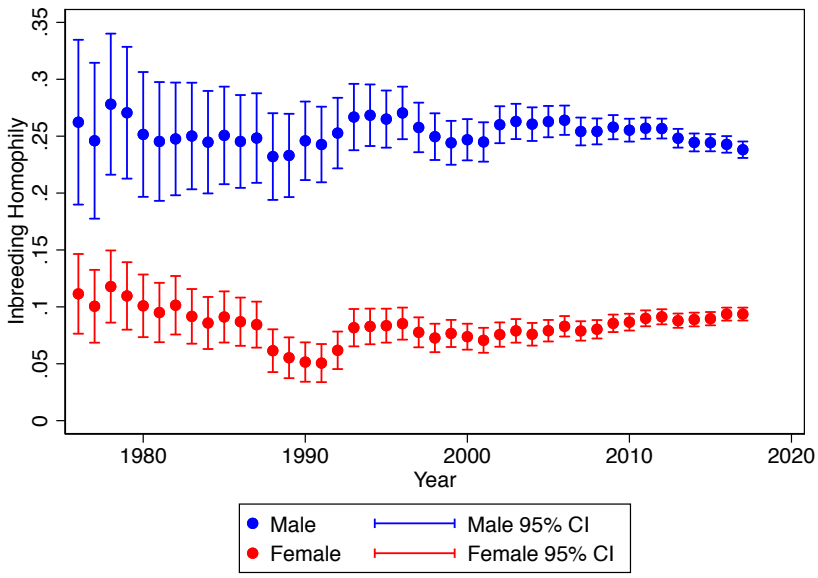
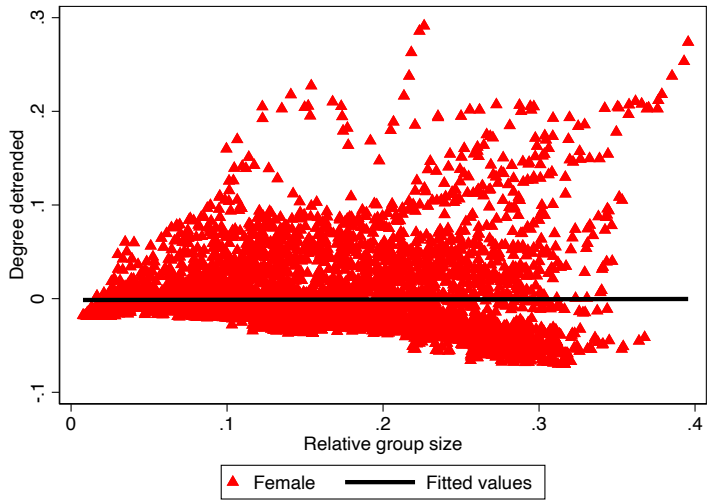


Figure 4: Degree and Fraction of Women, Across Fields



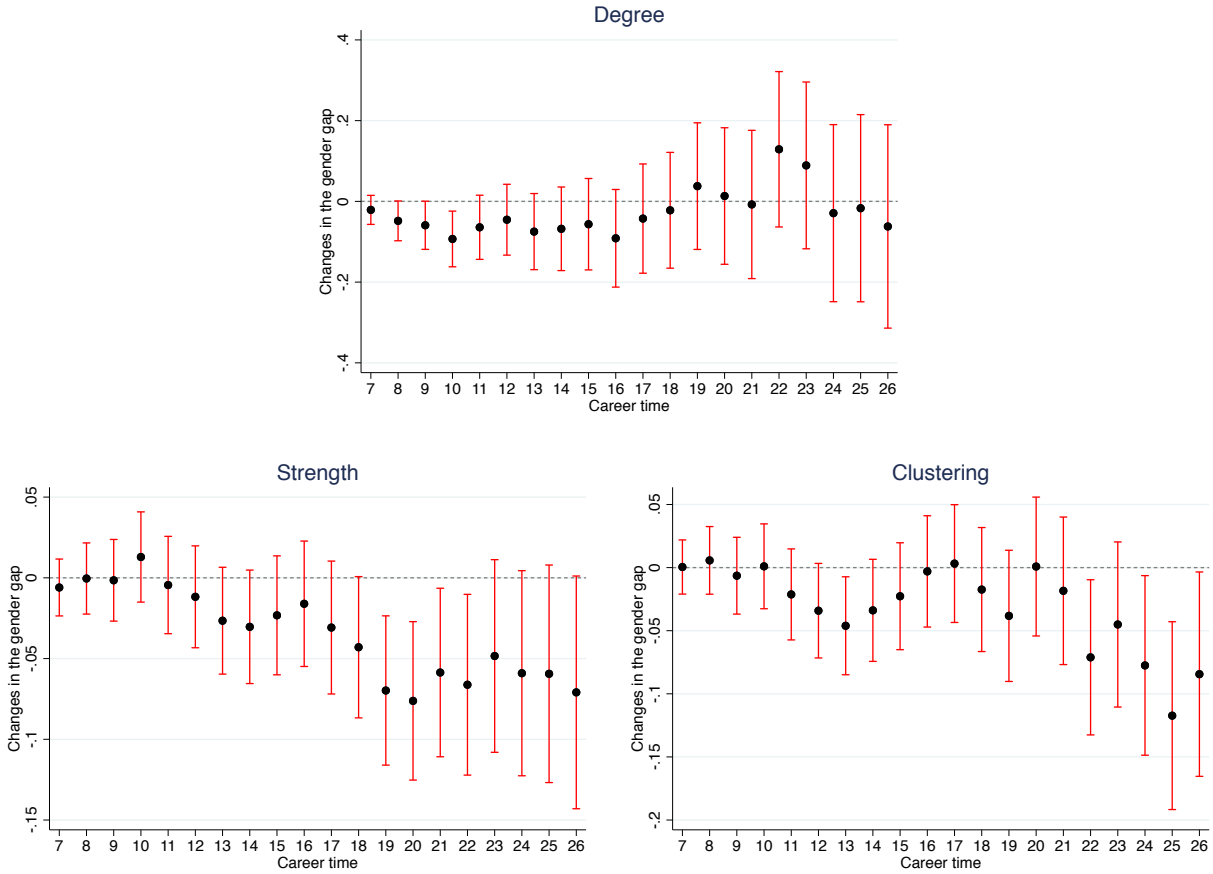
Note: Degree is detrended is the residual of a linear regression of degree on year dummies. Regressing the degree detrended on relative group size, we obtain: $\widehat{degreedet} = -.004 + 0.014w_f$, the p-value of the intercept and slope coefficients are 0.01 and 0.18, respectively.

Table 6: Network Differences Across Past Output Levels

VARIABLES	Degree	Strength	Clustering
Female	-0.395***	0.139***	0.109***
	(0.026)	(0.009)	(0.011)
(Dummy 50th-79th)*female	-0.088*	0.033**	0.004
	(0.049)	(0.015)	(0.016)
(Dummy 80th-94th)*female	-0.371***	0.057**	0.007
	(0.092)	(0.023)	(0.022)
(Dummy 95th-99th)*female	-0.154	-0.046	0.017
	(0.247)	(0.043)	(0.039)
(Dummy >99th)*female	-0.563	-0.068	-0.012
	(0.809)	(0.114)	(0.085)
Past output$_{t-5}$	0.004***	-0.066***	-0.041***
	(0.001)	(0.006)	(0.005)
Observations	641,486	533,718	401,756
Career-time FE	✓	✓	✓
Year FE	✓	✓	✓
JEL codes share	✓	✓	✓

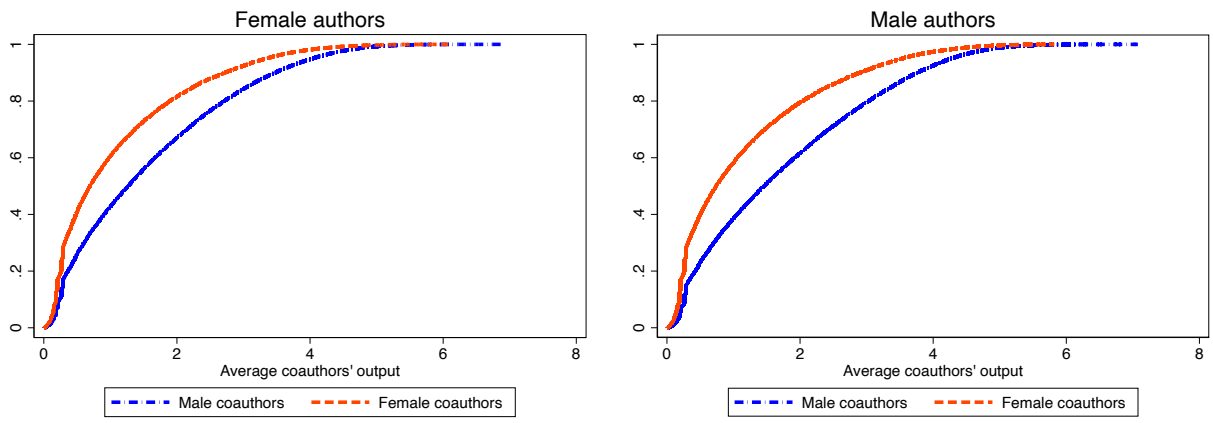
The sample consists of authors who have a career time of at least six years. All the results are obtained using the POLS model. Degree is undefined for periods without publications. Clustering is undefined for sole authors and authors with only one co-author; strength is undefined for periods without co-authored publications. All the variables except the dummies are standardized. The dummy past output $> 99th$ is equal to one for authors in the top 1% in terms of past output. Dummy past output $99th - 95th$ is equal to one for authors in the 95-99 percentiles of past output. The dummy past output $95th - 80th$ is one for the 80-94 percentiles, the dummy past output $80th - 50th$ is for authors in the 50-79 percentiles and the reference category if for authors below the median. To compute these dummies we excluded observations where recent output is 0. Past output$_{t-5}$ is the accumulated research output from the first publication till $t - 5$. Clustered standard errors by author in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Figure 5: Gender Differences in Networks, Across Career



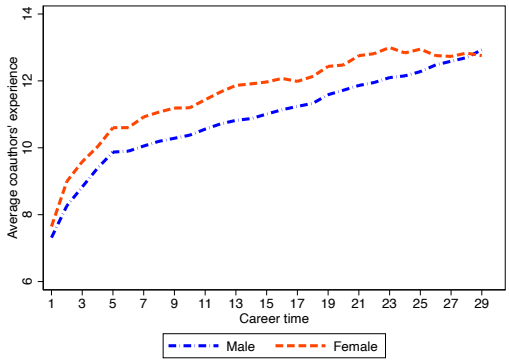
Note: The plots show the coefficients and 95% confidence intervals of the interaction terms between career time dummies and the female dummy of a network model estimated using POLS, the base career time age is 6. The gender gaps in degree, strength, clustering in the base career time age are -0.5020, 0.201 and 0.151, respectively. The p-values of F-tests on the joint significant of all the interaction terms are: 0.230 in the degree model; 0.002 in the strength model; 0.020 in the clustering model. Authors with less than six years of experience are excluded from the sample since past output is not defined.

Figure 6: Cumulative Distributions of Co-authors' Output, By Gender



Note: Research output is in log plus one, $log(x+1)$. We only consider observations with positive values. Using a Kolmogorov-Smirnov test we reject the null that the distributions across gender are equal at the 1%.

Figure 7: Co-authors' Experience, By Gender



Note: Co-authors experience by gender is obtained using all the articles published in the EconLit from 1974 to 2017 where the gender of at least one author is identified. The gender difference is statistically significant except for authors with more than 17 years of career time.

Gender & Collaboration: Supplementary Appendix

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February 12, 2020

Contents

A Sociology

This section presents the descriptive statistics and the Tables/Figures pertaining to our analysis of gender differences in sociology.

Table A.1: Summary Statistics in Sociology, 1963-1999

Variable	Gender	(1) Mean	(2) Standard Deviation
# of publications	Female	1.57	1.80
	Male	1.57	2.04
	All	1.56	1.95
	Ratio	1	0.88
Research output	Female	0.65	1.61
	Male	0.80	1.90
	All	0.74	1.78
	Ratio	0.81	0.85
Degree	Female	2.42	1.92
	Male	2.37	2.06
	All	2.38	1.99
	Ratio	1.02	0.93
Clustering	Female	0.85	0.30
	Male	0.76	0.36
	All	0.80	0.34
	Ratio	1.12	0.83
Strength	Female	0.88	0.24
	Male	0.82	0.28
	All	0.85	0.26
	Ratio	1.07	0.86
Co-authorship	Female	0.64	0.44
	Male	0.55	0.45
	All	0.58	0.45
	Ratio	1.21	0.98
Coauthors per paper	Female	1.30	1.45
	Male	0.98	1.27
	All	1.10	1.36
	Ratio	1.33	1.14

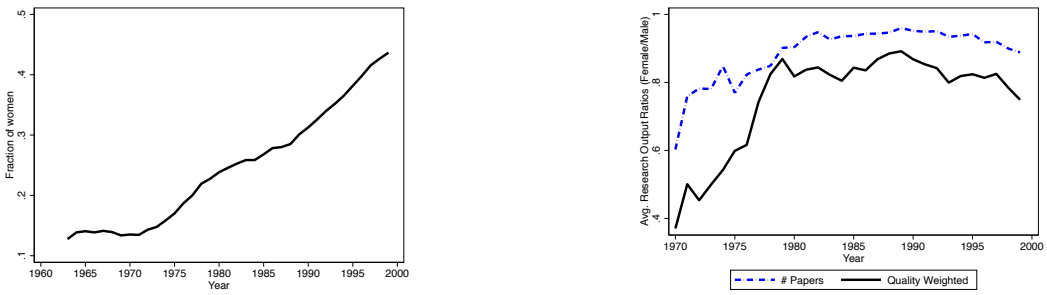
The sample includes authors publishing in Social Abstracts from 1963 to 1999. All the variables are obtained using publications in a five-year window, from $t-4$ to t. All the averages and standard deviations differences between male and female are statistically significant at the 1% level. Ratio is the average/standard deviation of women to men.

Table A.2: Number of Journals, Authors and Papers in Sociology, 1963-1999

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
					Per capita papers		
Year	Journals	Articles	Women	Men	Women	Men	Ratio
1965-1969	29	180	1345	8022	1.24	1.77	0.70
1970-1974	438	11001	2635	13444	0.89	1.14	0.78
1975-1979	884	28585	6952	23303	1.19	1.38	0.86
1980-1984	949	28689	9681	26488	1.34	1.45	0.92
1985-1989	1260	33121	12880	29202	1.12	1.18	0.95
1990-1994	1599	56269	22000	38978	1.44	1.51	0.95
1995-1999	1921	73178	33540	46684	2.07	2.24	0.92
1963-1999	2865	231066	52711	92512	1.57	1.57	1

The sample includes all articles published in Social Abstract from 1963 to 1999. 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 number of papers per author for women across periods, column 6 presents the average number of papers for men across periods, column 7 shows the ratio between women's average number of papers to men's average number of papers. We identify the gender of 80% of the authors using their first names and the *gender-api.com*.

Figure A.1: Participation of Women and Research Output Ratio: Sociology



(a) Participation of Women: 1963-1999

(b) Research Output Ratio, 1970-1999

Note: Share of women publishing in Sociological Abstracts per year in plot (a). Average research output ratio between women and men for each year in plot (b). The journal quality impact factor to compute research output is available only after 1966. There is great fluctuation in the number of papers before 1970; so we start the output plot in 1970. We identify the gender of 80% of the authors using their first names and the *gender-api.com*

Table A.3: Gender Differences in Performance in Sociology

VARIABLES	(1) Output	(2) Output	(3) # Papers
Female	-0.147***	-0.046***	-0.115***
	(0.017)	(0.016)	(0.014)
Observations	469,953	469,953	469,953
Career-time FE		✓	✓
Year FE		✓	✓
Field FE		✓	✓

The sample consists of authors who have a career time of at least six years and publish in Social Abstract from 1963 to 1999. 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. Field FE are obtained using keywords of the article. Clustered standard errors by authors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.4: Gender and Co-author Networks in Sociology

VARIABLES	(1) Co-authorship	(2) Degree	(3) Strength	(4) Clustering	(5) Clustering
Female	-0.014***	-0.191***	0.022***	0.030***	0.017***
	(0.004)	(0.021)	(0.003)	(0.004)	(0.004)
Degree					-0.046***
					(0.001)
Past output$_{t-5}$	-0.002***	0.063***	-0.016***	-0.015***	-0.012***
	(0.000)	(0.006)	(0.001)	(0.001)	(0.001)
Observations	334,386	334,386	250,298	147,912	147,912
Career-time FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Field FE	✓	✓	✓	✓	✓

All the results are obtained using POLS. Field FE are obtained using keywords of the articles. Columns 1, 2 and 3 show the results from estimating gender differences in degree, strength, and clustering, respectively. Coauthorship and degree are undefined for periods without publications. Clustering is undefined for sole authors and authors with only one co-author; strength is undefined for periods without co-authored publications. Clustered standard errors at the author level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.5: Gender, Networks and Future Output in Sociology

	Dependent Variable: Future Output				
	(1)	(2)	(3)	(4)	(5)
Female	-0.014***	-0.011**	-0.010**	-0.011**	-0.009**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Degree		0.010***			0.004***
		(0.001)			(0.001)
Strength			-0.194***		-0.181***
			(0.008)		(0.013)
Clustering				-0.101***	0.000
				(0.006)	(0.009)
Recent Output	0.325***	0.313***	0.265***	0.295***	0.264***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
Past Output	0.129***	0.128***	0.125***	0.126***	0.125***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Observations	147,912	147,912	147,912	147,912	147,912
Career-time FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
JEL codes shares	✓	✓	✓	✓	✓

The sample consists of authors who have a career time of at least six years and at least two co-authors; publications from 1968 to 1999 in Sociological Abstract. Results estimated using POLS models. The dependent variable, future output, is accumulated output in logs from $t+1$ to $t+5$. Recent output is the accumulated output in logs from $t-4$ to t and Past Output is the accumulated output in logs from the first publication of the author to $t-5$. Clustered standard errors at the author level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Figure A.2: Inbreeding Homophily

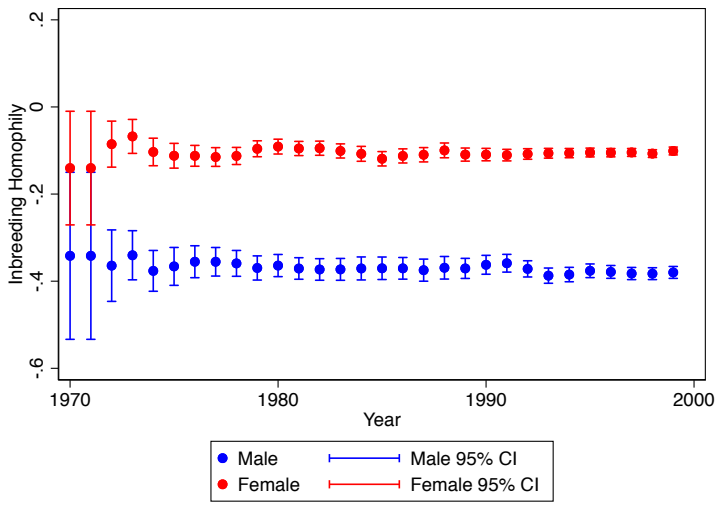
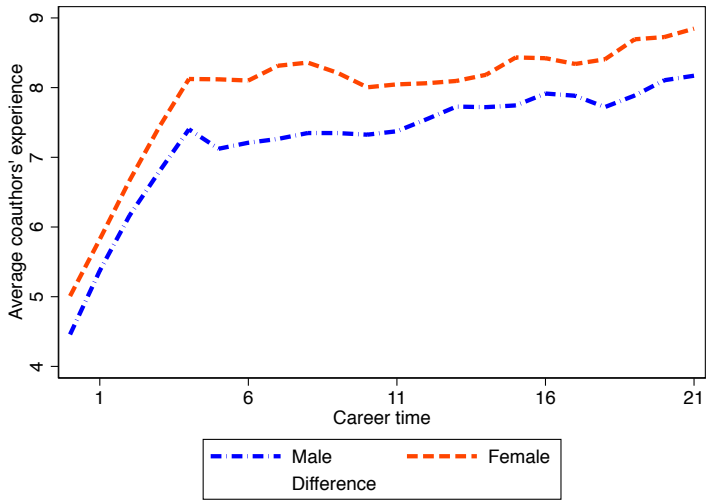


Figure A.3: Average co-authors' experience by gender



Note: Co-authors' experience by gender is obtained using all the articles published in Sociological Abstracts from 1963 to 1999 where the gender of at least one author is identified. The gender difference is statistically significant for every year.

B Robustness: Research Output

We document the robustness of the gender gap in research output. First, we show that gender differences in research output are robust to accounting for institutions, to alternative academic performance measures and different econometric models. We then consider a research stream of authors – those who publish at least three papers in every five year period – and find that the gender difference in output is larger for researchers in this set. Next, we restrict attention to the set of journals that were published throughout the entire sample period; for this sample, again, gender disparities in output persist. Finally, we carry out quantile regressions: the gender output gap emerges across the entire distribution of output.

B.1 Institutions

We control for institutional affiliation, using a sample of 395 affiliations over the period 1990-2011. EconLit provides information about the affiliation of each author publishing a research article in a journal listed in EconLit during that time period. A problem with affiliations is that authors tend to report affiliations with different names. This is particularly problematic for institutions located in non-English speaking countries. To mitigate this problem we 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 model 1 of the main text. The results in Table B.6 show that differences in institutions account for 8.6% 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), highlighting the limited impact of institutions.

B.2 Alternative Measure for Journal Quality

The quality index considered in the main text does not reflect changes in the quality of the journal over time. In this section we consider the *influence per publication* as an additional measure of quality that varies over time. We follow Ductor et al. (2020) and use a database of 100 journals in economics that provides information on citations. This allows us to define a citation matrix which changes over time. In this matrix, each cell ij corresponds to the fraction of articles in journal i in year t that refer to articles published in journal j between

Table B.6: 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	-4.310***	-4.122***	-2.516***	-0.628***	-0.161***	-0.299
	(0.326)	(0.307)	(0.280)	(0.037)	(0.059)	(0.244)
Observations	369,413	369,413	369,413	369,413	291,665	291,665
Career-time FE			✓	✓	✓	✓
Year FE			✓	✓	✓	✓
JEL codes FE			✓	✓	✓	✓
Institutions FE		✓	✓	✓	✓	✓

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

years $t-1$ to $t-6$.[1] Based on this definition, we calculate $c_{ij,t}$, which is the number of articles in journal i that cite journal j in year t. Let $s_{it} = \sum_j c_{ij,t}$ be the total number of citations from articles published in journal i.

Following Bergstrom et al. (2008), we calculate the eigenfactor of journal i in year t, as the solution to

$$EF_{it} = \sum_{j \in \mathcal{I}} \frac{c_{ij,t}}{s_{it}} EF_{jt}. \tag{1}$$

The number of citations is influenced by the number of articles a journal publishes. We would like to control for the pure size effect. Denote the number of papers in a journal i in year t by a_{it}. Our second measure of journal quality, the Article Influence Score (AIS) is given by:

$$AIS_{it} = \frac{EF_{it}}{a_{it}}. \tag{2}$$

The advantage of the AIS is that it is time varying, it excludes self-citations, and it considers the influence of the citing journal (see Bergstrom et al. (2008) for further discussion on the virtues of AIS).[2]

The results presented in Table B.7 are consistent with the journal quality index presented in the paper. Women have a research output that is roughly 40% lower than that of men (the output of women is 0.028, that of men is 0.049; so the ratio of the difference is 0.21/0.49). This difference in output is larger than the research output measure obtained using a time

[1] Computing a time-varying impact factor for the 1990 journals listed in EconLit is computationally infeasible as most of these journals are new. Therefore, citations are not easily available.

[2] The AIS is used in some universities – e.g., the Erasmus University of Rotterdam – to evaluate the research performance of their faculty.

invariant journal quality index.

Table B.7: Gender Differences in Performance: Article Influence Score

VARIABLES	(1) Output-AIS
Female	-0.013***
	(0.001)
Observations	1,069,809
Career-time FE	✓
Year FE	✓
JEL codes FE	✓

Publications from 100 journals from 1970-2017. The sample consists of authors who have a career time of at least six years. 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

B.3 Alternative Econometric Models

We first show that the gender differences in research output are robust to the use of different econometric models. In Table B.8 we show the gender differences in academic performance using the correlated random effect (CRE) model. 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:

$$q_{it} = \rho F_i + x_{it}\beta + \bar{x}_i\gamma + \varepsilon_{it}, \tag{3}$$

where $l = 1, ..., 19$, q_{it} is the research output of author i over the period $t-4$ to t and $\bar{x}_{it}$ includes the average proportion of articles published in each JEL code by author i during her career. The correlated random effect model does not require the time-varying covariates and the author fixed effect to be orthogonal. 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.

Table B.8: Gender Differences in Performance: Correlated Random Effect Model

VARIABLES	(1) Output	(2) Output	(3) # Papers	(4) $\frac{Output}{\#Papers}$	(5) $\frac{Citations}{\#Papers}$
Female	-2.402***	-1.217***	-0.500***	-0.103***	0.112
	(0.092)	(0.088)	(0.017)	(0.022)	(0.131)
Observations	1,069,809	1,069,809	1,069,809	776,943	776,943
Career-time FE		✓	✓	✓	✓
Year FE		✓	✓	✓	✓
JEL codes FE		✓	✓	✓	✓

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 negative effect of gender might be driven by authors with a high output, as output is quite skewed. We estimate research output as $log(q_{it}+1)$ to mitigate the impact of authors with high output, as in Ductor et al. (2014). The results presented in columns 1 (obtained using the POLS) and 2 (obtained using the CRE) of Table B.9 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 next turn to number of publications. Number of publications is a discrete variables that do not follow normal distributions, so count data models might be more appropriate. Column 3 of Table B.9 shows the incidence rate ratio (IRR) of women for number of publications using a count data model, the negative binomial (NB). The results are qualitatively similar to those obtained using the CRE model. The publication rate is 19.7% lower for women.

B.4 Not Discounting for Number of Co-authors

We 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:

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

Table B.9: Gender Differences in Performance: Non-linear Models

VARIABLES	(1) POLS $log(1+q_{it})$ Coeff.	(2) CRE $log(1+q_{it})$ Coeff.	(3) NB # Papers IRR
Female	-0.108***	-0.098***	-0.197***
	(0.007)	(0.006)	(0.009)
Observations	1,016,658	1,016,658	1,016,658
Career-time FE	✓	✓	✓
Year FE	✓	✓	✓
JEL codes FE	✓	✓	✓

Column 1 presents the coefficient of the gender difference in research output, the dependent variable being $log(q_{it}+1)$, model estimated using the Pooled OLS; in column 2 the dependent variable is $log(q_{it}+1)$ and the model is estimated using the correlated random effect model. Columns 3 and 4 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

Table B.10 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 B.10: Gender Differences in Performance: Non-Discounted Output

VARIABLES	(1) POLS q_{it}	(2) POLS $log(1+q_{it})$	(3) RE q_{it}	(4) CRE q_{it}
Female	-3.138***	-0.120***	-3.246***	-2.417***
	(0.251)	(0.008)	(0.171)	(0.168)
Observations	1,069,809	1,069,809	1,069,809	1,069,809
Career-time FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
JEL codes shares	✓	✓	✓	✓

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, $log(q_{it}+1)$, 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

B.5 Research-Stream Sample

We focus on research active authors, i.e. those who publish at least three articles every five years. The sample includes 22,478 authors. Table B.11 shows that the gender differences in research output are quantitatively larger when we focus on active researchers.

Table B.11: Gender Differences in Performance: Research-stream sample

VARIABLES	(1) Output	(2) Output	(3) # Papers	(4) $\frac{Output}{\#Papers}$	(5) $\frac{Citations}{\#Papers}$
Female	-11.162***	-2.818***	-1.040***	-0.111	0.310
	(0.871)	(0.724)	(0.086)	(0.090)	(0.279)
Observations	129,256	129,256	129,256	129,256	129,256
Career-time FE		✓	✓	✓	✓
Year FE		✓	✓	✓	✓
JEL codes shares		✓	✓	✓	✓

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

B.6 Restricted Set of Journals

We document that gender differences in output hold if we restrict attention to journals that were published throughout the entire sample period, from 1970 to 2011, see Table *B*.12. The gender differences in output are larger when we focus on historical journals in economics.

Table B.12: Gender Differences in Performance: Fixed Set of Journals

VARIABLES	(1) Output	(2) Output	(3) # Papers	(4) $\frac{Output}{\#Papers}$	(5) $\frac{Citations}{\#Papers}$
Female	-5.083***	-2.782***	-0.198***	-0.680***	-1.271
	(0.584)	(0.498)	(0.025)	(0.222)	(0.934)
Observations	187,995	187,995	187,995	123,167	123,167
Career-time FE		✓	✓	✓	✓
Year FE		✓	✓	✓	✓
JEL codes shares		✓	✓	✓	✓

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

B.7 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 B.13, 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. The gender gap persists, though, and is significant in all of our specifications.

Table B.13: 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	-1.881***	-0.903***	-6.184***	-3.419***
	(0.081)	(0.070)	(0.394)	(0.351)
Observations	1,316,874	1,316,874	641,244	641,244
Career-time FE		✓		✓
Year FE		✓		✓
JEL codes FE		✓		✓

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

B.8 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 regression models, see Table B.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. We do not include JEL codes in the output models estimated in Table B.14 to ensure convergence of the iterative simplex method used to estimate the quantiles.

Table B.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	-0.204***	-1.319***	-7.105***	-13.853***
	(0.006)	(0.025)	(0.115)	(0.264)
Career time	-0.026***	0.014**	0.292***	0.573***
	(0.001)	(0.006)	(0.030)	(0.065)
Career time^2	0.001***	0.001***	-0.003***	-0.005***
	(0.000)	(0.000)	(0.001)	(0.002)
Observations	1,069,809	1,069,809	1,069,809	1,069,809
Linear time trend	✓	✓	✓	✓

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

C Robustness: Gender Differences in Networks

We show that gender differences in networks are robust to accounting for institutions and alternative econometric specifications. Gender differences in networks also arise for the stream of research active authors and if we restrict attention to the journals published across our entire sample. Next, we show that these gender differences arise in networks measured across three and ten years. Finally, these differences emerge across the entire distribution.

C.1 Institutions

We use a sample of 395 affiliations over the period 1990-2011 to test the role of institutional factors in explaining gender differences in collaboration patterns. The results presented in Table C.15 show that the role of institutions is minor.

C.2 Alternative Econometric Models

C.2.1 Correlated random effect, Randon effects and Negative binomial

We show that our results hold when we 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. The correlated random effect model is:

$$z_{it} = \rho F_i + x'_{it}\beta + \theta \bar{x}'_{it} + \varepsilon_{it}, \tag{4}$$

where z_{it} is a network variable as defined in section 2 of the main text, $\bar{x}'_{it}$ includes the average proportion of articles published in each JEL code by author i during her career and the average research output of an author, $\bar{q}^c_{it}$. The correlated random effect model does not require the time-varying covariates and the author fixed effect to be orthogonal. The rest of regressors are defined as in the main text.

Tables C.16 and C.17 show the results and highlight the robustness of our findings.

C.2.2 Additional control factors

We check if the documented gender differences in networks hold once we add number of publications from t-4 to t as an additional control in the network model presented in model (2) of the paper. The results presented in Table C.18 show that the documented gender differences in degree and strength are smaller, but still highly significant.

C.3 Research-stream sample

We focus again on research active authors. As in subsection B.5, we define a research active author as an author who publishes at least three articles every five years. Table C.19 shows our results are similar to our main specification.

C.4 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 *C*.20.

Table C.15: Gender and Collaboration: Accounting for Institutions

VARIABLES	(1) Coauthorship	(2) Coauthorship	(3) Degree	(4) Degree	(5) Strength	(6) Strength	(7) Clustering	(8) Clustering
Female	0.007	0.007	-0.566***	-0.535***	0.068***	0.065***	0.031***	0.032***
	(0.005)	(0.005)	(0.041)	(0.041)	(0.004)	(0.004)	(0.005)	(0.005)
Degree							-0.036***	-0.036***
							(0.001)	(0.001)
Past Output	0.000***	0.000***	0.007***	0.007***	-0.001***	-0.001***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	256,033	256,033	261,373	261,373	218,234	218,234	164,698	164,698
Career-time FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
JEL codes FE	✓	✓	✓	✓	✓	✓	✓	✓
Institutions FE		✓		✓		✓		✓

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

Table C.16: 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	0.017***	-0.162***	-0.389***	0.043***	0.024***
	(0.003)	(0.009)	(0.020)	(0.002)	(0.003)
Degree					-0.030***
					(0.001)
Past Output	0.000***	0.002***	0.002***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	672,171	672,171	672,171	560,533	422,512
Career-time FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
JEL codes FE	✓	✓	✓	✓	✓

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. Clustered standard errors at the author level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C.17: Networks and Gender: Random Effect

VARIABLES	(1) Co-authorship	(2) Degree	(3) Strength	(4) Clustering
Female	0.015***	-0.466***	0.059***	0.038***
	(0.003)	(0.022)	(0.002)	(0.003)
Degree				-0.031***
				(0.001)
Past Output	0.000***	0.004***	0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	672,171	672,171	560,533	422,512
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. Clustered standard errors at the author level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C.18: Gender and Collaboration: adding number of articles as an additional control

VARIABLES	(1) Co-authorship	(2) Degree	(3) Strength	(4) Clustering
Female	0.016***	-0.058***	0.022***	0.022***
	(0.003)	(0.019)	(0.002)	(0.003)
Degree				-0.013***
				(0.001)
Number of articles	0.005***	0.663***	-0.046***	-0.026***
	(0.000)	(0.010)	(0.001)	(0.001)
Past Output	0.000***	0.000*	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	672,171	672,171	560,533	422,512
Career-time FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
JEL codes shares	✓	✓	✓	✓

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

Table C.19: Networks and Gender: Research-stream sample

VARIABLES	(1) Co-authorship	(2) Degree	(3) Strength	(4) Clustering
Female	0.020***	-0.942***	0.042***	0.027***
	(0.006)	(0.105)	(0.004)	(0.004)
Degree				-0.010***
				(0.000)
Past Output	-0.000***	0.001	-0.000***	-0.000***
	(0.000)	(0.001)	(0.000)	(0.000)
Observations	106,778	106,778	103,577	98,066
Career-time FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
JEL codes shares	✓	✓	✓	✓

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

Table C.20: Networks and Gender: Fixed Set of Journals

VARIABLES	(1) Co-authorship	(2) Degree	(3) Strength	(4) Clustering
Female	-0.004	-0.145***	0.054***	0.041***
	(0.005)	(0.027)	(0.007)	(0.010)
Degree				-0.069***
				(0.002)
Past Output	-0.000	0.003***	-0.001***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	179,003	179,003	90,503	56,590
Career-time FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
JEL codes shares	✓	✓	✓	✓

The sample includes authors publishing in journals that existed froom 1970 to 2017. It includes authors who have a career time of at least six years. All the results are obtained using the POLS. Co-authorship and Degree are undefined for periods without publications. Clustering is undefined for sole authors and authors with only one co-author; strength is undefined for periods without co-authored publications. Clustered standard errors at the author level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

C.5 Networks Across 3 & 10 Years

In the main text of the paper, 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 C.21 indicate that the gender differences in co-authorship and degree are smaller in magnitude compared to the five-year network results presented in Table 4 of the main text. The gender difference in clustering is larger in the three-year network period. Overall, the results of our main specification continue to hold.

Table C.21: Networks and Gender: 3 Year Period

VARIABLES	(1) Co-authorship	(2) Degree	(3) Strength	(4) Clustering
Female	0.005**	-0.184***	0.060***	0.038***
	(0.002)	(0.013)	(0.003)	(0.004)
Degree				-0.061***
				(0.001)
Past Output	0.000***	0.003***	-0.001***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	581,272	581,272	476,677	202,259
Career-time FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
JEL codes shares	✓	✓	✓	✓

All the results are obtained using correlated random effects. 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 C.22. 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.

C.6 Quantile Regressions

In the main text of the paper we 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 C.23). 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 the gender difference in clustering along

Table C.22: Networks and Gender: 10 Year Period

VARIABLES	(1) Co-authorship	(2) Degree	(3) Strength	(4) Clustering
Female	0.012***	-0.286***	0.041***	0.023***
	(0.003)	(0.019)	(0.002)	(0.004)
Past Output	0.000***	0.009***	-0.001***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Degree				-0.024***
				(0.000)
Observations	852,348	852,348	693,786	371,356
Career-time FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
JEL codes shares	✓	✓	✓	✓

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

its distribution (see Table C.24). 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 C.25).

Table C.23: Degree and Gender: Quantile Regressions

Variables/Percentile:	(1) 25th pc.	(2) Median	(3) 75th pc.	(4) 90th pc.
Female	-0.097***	-0.255***	-0.576***	-1.023***
	(0.004)	(0.008)	(0.013)	(0.025)
Career time	0.021***	0.033***	0.059***	0.081***
	(0.001)	(0.002)	(0.003)	(0.006)
Career time^2	-0.001***	-0.001***	-0.002***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
Past output	0.005***	0.009***	0.014***	0.021***
	(0.000)	(0.000)	(0.000)	(0.000)
Linear time trend	0.048***	0.082***	0.138***	0.203***
	(0.000)	(0.000)	(0.001)	(0.001)
Observations	672,171	672,171	672,171	672,171
JEL codes shares	✓	✓	✓	✓

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

Table C.24: Clustering and Gender: Quantile Regressions

	(1)	(2)	(3)	(4)
Variables/Percentile:	25th pc.	Median	75th pc.	90th pc.
Female	0.027***	0.047***	0.127***	0.000*
	(0.001)	(0.001)	(0.004)	(0.000)
Career time	-0.004***	-0.010***	-0.029***	-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***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Linear time trend	0.005***	0.004***	-0.002***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	422,512	422,512	422,512	422,512
JEL codes shares	✓	✓	✓	✓

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

Table C.25: Strength and Gender: Quantile Regressions

	(1)	(2)	(3)	(4)
Variables/Percentile:	25th pc.	Median	75th pc.	90th pc.
Female	0.054***	0.044***	0.005***	0.000
	(0.001)	(0.001)	(0.002)	(0.000)
Career time	-0.004***	-0.006***	-0.001**	0.000
	(0.000)	(0.000)	(0.000)	(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***	-0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	560,533	560,533	560,533	560,533
JEL codes shares	✓	✓	✓	✓

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

D Robustness: Gender, Output and Collaboration

We highlight now that the association between networks and the gender output gap is robust if we account for institutions. Further, it emerges if we restrict attention to research active authors and journals published throughout our entire sample. Additionally, the association is also found in networks measured across three and ten years.

D.1 Institutions

The association between gender differences in networks and the gender output gap are significant and large after controlling for gender differences in affiliations, see Table D.26.

D.2 Research-Stream Sample

We show that the association between networks and the gender output gap continues to hold when we focus on research active authors, i.e., those publishing at least three articles every five years: however, adding information about the networks reduces the gender output gap by 23% ((0.044-0.034)/0.044). Table D.27 reports our results.

D.3 Restricted Set of Journals

The association between gender differences in networks and the gender output gap is robust to restricting attention to the set of journals that existed throughout the entire sample period,

Table D.26: Gender, Networks and Future Output: Accounting for Institutions

	Dependent Variable: Future Output				
	(1)	(2)	(3)	(4)	(5)
Female	-0.052***	-0.043***	-0.045***	-0.049***	-0.041***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Degree		0.019***			0.017***
		(0.001)			(0.001)
Strength			-0.186***		-0.097***
			(0.018)		(0.027)
Clustering				-0.078***	0.005
				(0.012)	(0.017)
Recent Output	0.489***	0.470***	0.466***	0.480***	0.461***
	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)
Past Output	0.159***	0.158***	0.160***	0.159***	0.159***
	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)
Observations	164,698	164,698	164,698	164,698	164,698
Career-time FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
JEL codes shares	✓	✓	✓	✓	✓

The sample consists of authors who have a career time of at least six years. Results estimated using POLS models. The dependent variable, future output, is accumulated output in logs from $t+1$ to $t+5$. Recent output is the accumulated output in logs from $t-4$ to t and Past Output is the accumulated output from the first publication of the author in logs to $t-5$. Clustered standard errors at the author level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

see Table D.28.

Table D.27: Gender, Networks and Future Output: Research-stream authors

	Dependent Variable: Future Output				
	(1)	(2)	(3)	(4)	(5)
Female	-0.044***	-0.037***	-0.035**	-0.041***	-0.034**
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Degree		0.009***			0.007***
		(0.001)			(0.001)
Strength			-0.286***		-0.147***
			(0.038)		(0.052)
Clustering				-0.098***	-0.008
				(0.022)	(0.028)
Recent Output	0.522***	0.510***	0.509***	0.518***	0.506***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Past Output	0.179***	0.185***	0.184***	0.180***	0.187***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Observations	98,066	98,066	98,066	98,066	98,066
Career-time FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
JEL codes shares	✓	✓	✓	✓	✓

The sample consists of authors who have a career time of at least six years and at least two co-authors. Results estimated using POLS models. The dependent variable, future output, is accumulated output in logs from $t+1$ to $t+5$. Recent output is the accumulated output in logs from $t-4$ to t and Past Output is the accumulated output from the first publication of the author in logs to $t-5$. Clustered standard errors at the author level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table D.28: Gender, Networks and Future Output: Fixed Set of Journals

	Dependent Variable: Future Output				
	(1)	(2)	(3)	(4)	(5)
Female	-0.080***	-0.071**	-0.074***	-0.078***	-0.071**
	(0.029)	(0.028)	(0.029)	(0.029)	(0.028)
Degree		0.044***			0.043***
		(0.004)			(0.005)
Strength			-0.168***		-0.071
			(0.031)		(0.056)
Clustering				-0.046**	0.048
				(0.021)	(0.034)
Recent Output	0.471***	0.447***	0.448***	0.465***	0.445***
	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)
Past Output	0.240***	0.243***	0.245***	0.241***	0.244***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Observations	56,590	56,590	56,590	56,590	56,590
Career-time FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
JEL codes shares	✓	✓	✓	✓	✓

The sample consists of authors who have a career time of at least six years and at least two co-authors. Results estimated using POLS models. The dependent variable, future output, is accumulated output in logs from $t+1$ to $t+5$. Recent output is the accumulated output in logs from $t-4$ to t and Past Output is the accumulated output from the first publication of the author in logs to $t-5$. Clustered standard errors at the author level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table D.29: Gender, Networks and Future Output: 3 Year Period

	Dependent Variable: Future Output				
	(1)	(2)	(3)	(4)	(5)
Female	-0.076***	-0.065***	-0.063***	-0.069***	-0.060***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Degree		0.039***			0.028***
		(0.001)			(0.002)
Strength			-0.338***		-0.211***
			(0.012)		(0.020)
Clustering				-0.173***	-0.008
				(0.008)	(0.013)
Recent Output	0.604***	0.579***	0.561***	0.581***	0.558***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Past Output	0.174***	0.176***	0.179***	0.175***	0.178***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	202,259	202,259	202,259	202,259	202,259
Career-time FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
JEL codes shares	✓	✓	✓	✓	✓

The sample consists of authors who have a career time of at least six years and at least two co-authors. Results estimated using POLS models. The dependent variable, future output, is accumulated output in logs from $t+1$ to $t+5$. Recent output is the accumulated output in logs from $t-4$ to t and Past Output is the accumulated output from the first publication of the author in logs to $t-5$. Clustered standard errors at the author level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

D.4 Networks Across 3 & 10 Years

We now show that the correlation between network and the output gap documented in the main text hold when we use three and ten-year networks. Adding three-year network variables declined the output gap by 21% ((0.076-0.060)/0.076), see Table D.29. The explanatory power of the network is even larger when we consider 10-year network period. The output gap declines by 32% ((0.05-0.034)/0.05) after controlling for degree, clustering and strength simultaneously, see Table D.30.

Table D.30: Gender, Networks and Future Output: 10 Year Period

	Dependent Variable: Future Output				
	(1)	(2)	(3)	(4)	(5)
Female	-0.050***	-0.037***	-0.041***	-0.046***	-0.034***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Degree		0.026***			0.023***
		(0.001)			(0.001)
Strength			-0.286***		-0.149***
			(0.012)		(0.015)
Clustering				-0.117***	-0.003
				(0.008)	(0.010)
Recent Output	0.563***	0.538***	0.546***	0.558***	0.532***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Past Output	0.191***	0.181***	0.181***	0.186***	0.177***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	366,547	366,547	366,547	366,547	366,547
Career-time FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
JEL codes shares	✓	✓	✓	✓	✓

The sample consists of authors who have a career time of at least six years and at least two co-authors. Results estimated using POLS models. The dependent variable, future output, is accumulated output in logs from $t+1$ to $t+5$. Recent output is the accumulated output in logs from $t-4$ to t and Past Output is the accumulated output from the first publication of the author in logs to $t-5$. Clustered standard errors at the author level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

E Further Analysis

This section takes up three issues: one, the decline of quality weighted output, two, changes in collaboration patterns across cohorts, and three, the distribution of article quality by gender composition of authorship.

E.1 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 E.4. 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 5 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 E.5. 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.

E.2 Gender & Collaboration Across Cohorts

We study if the gender differences have changed across cohorts. For this purpose, we define a cohort dummy equal to one for the year of the first publication of the author and add interaction terms between the cohort dummy variables and the female dummy to the degree,

Figure E.4: Research output by gender over time

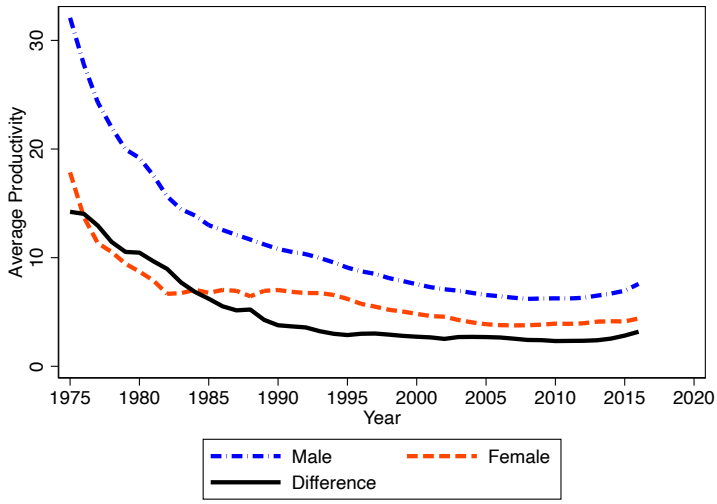
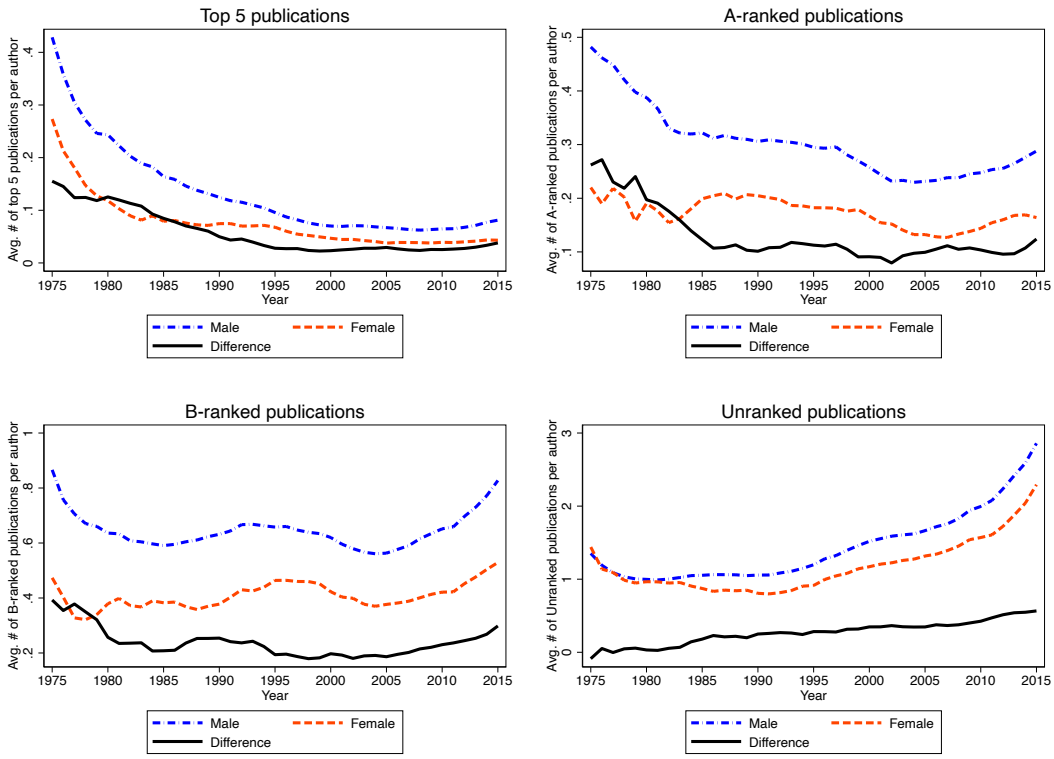


Figure E.5: Average number of publications per author across journal quality

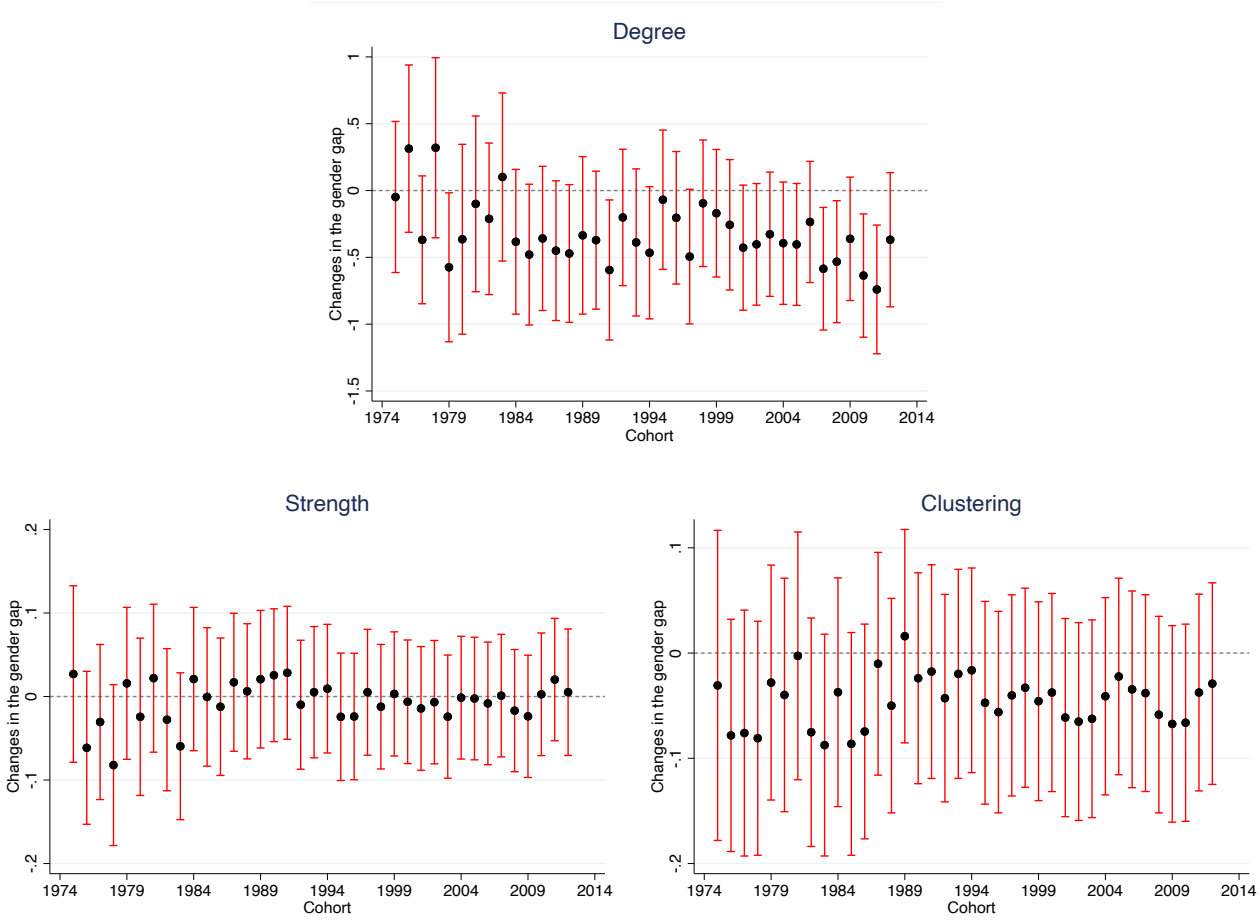


Note: Average number of publications per author in four different journal categories according to the Tinbergen Institute Journal List. *Top*5 publications include articles published in *American Economic Review*, *Econometrica*, *Journal of Political Economy*, *Quarterly Journal of Economics* and the *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.

strength and clustering network models. Figure E.6 shows the coefficients and 95% confidence interval of the interaction terms between the cohort dummies and the female dummy. All the estimates are relative to the base cohort, 1974. The gender differences in clustering and strength are quite stable across authors of different cohorts, the p-value of an F-test on the joint significance of the coefficients of the interaction terms of gender and cohort dummies is 0.13 and 0.15 in the clustering and strength models, respectively. However, the gender difference in degree has changed across cohorts, it was lower for cohorts starting in the 70s, 80s and 90s, and it has increased for cohorts starting in the early 2000s, the p-value of an F-test on the joint significance of the interaction terms is 0.04 in the degree model.

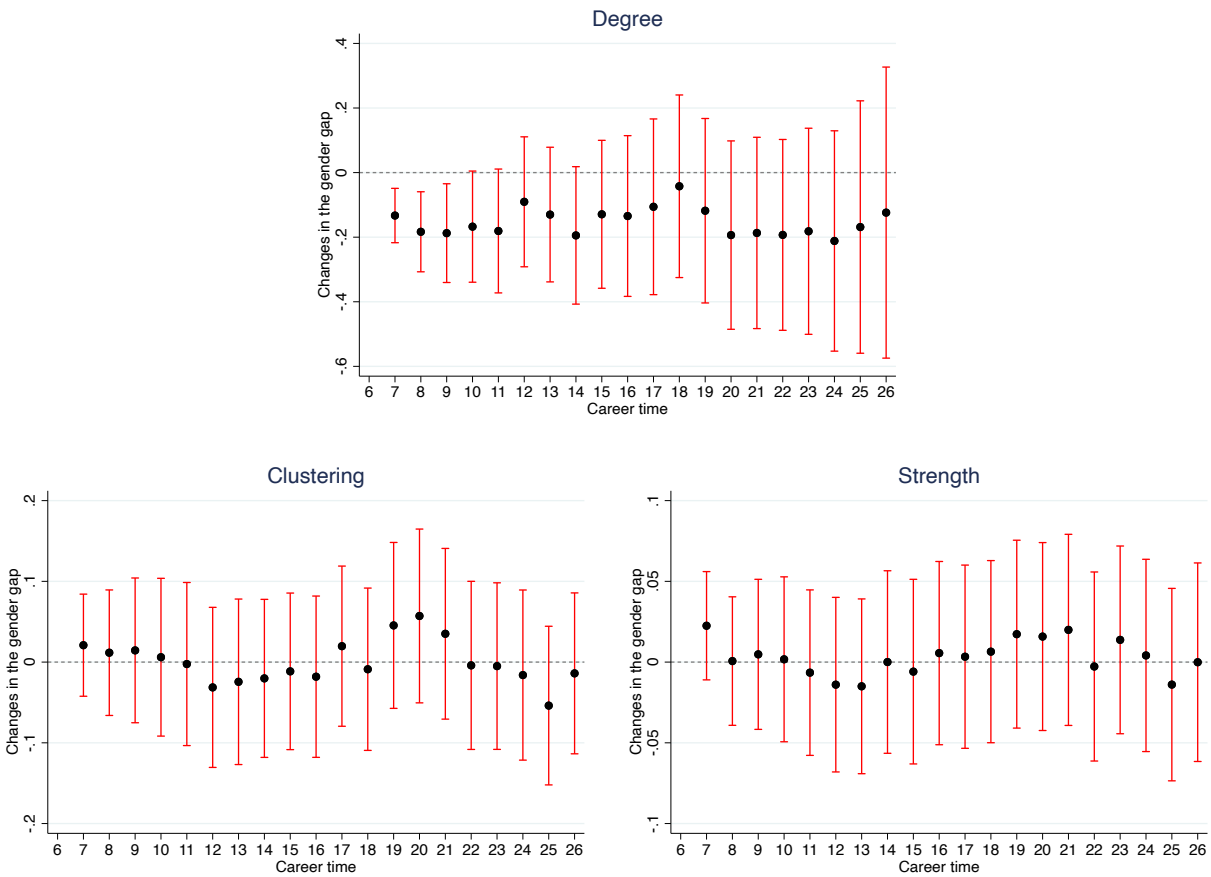
Last, we show that the gender differences across career time are stable for all cohorts. We add interaction terms between career time dummies and the female dummy to the network model, defined in equation (2) of the main text, and restrict our sample to different cohorts: 1980-1984, 1990-1994 and 2000-2004, where a cohort is defined as the year of the first publication. Figure E.7-E.9 present the coefficients and 95% confidence intervals of the interaction terms. The estimates are interpreted relative to the base career time, six years of experience. Thus, gender differences in network patterns are stable along the career of an author for each cohort, with the exception of degree, where the gender difference increased along the career of the author for the cohorts 1990-1994 and 2000-2004.

Figure E.6: Network differences across cohorts



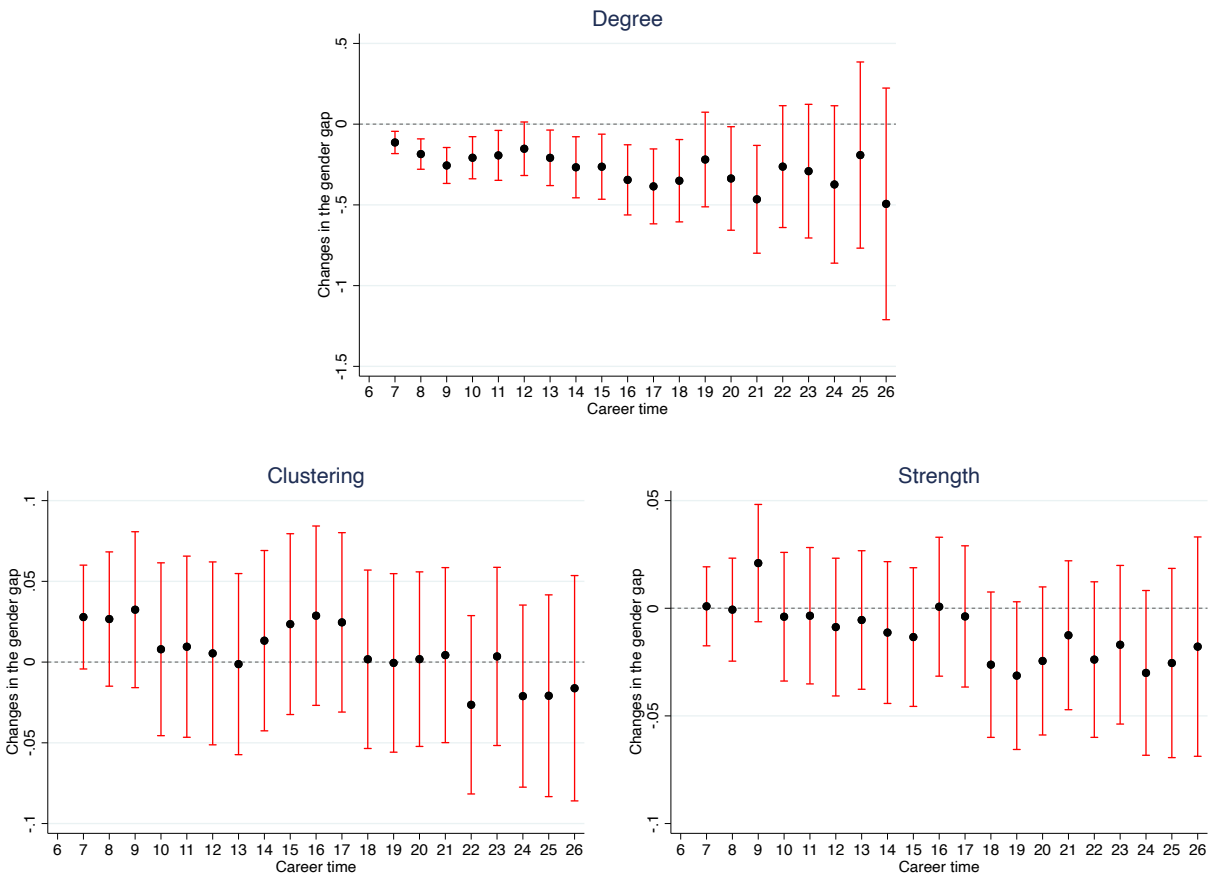
Note: The plot shows the coefficients and 95% confidence intervals of the interaction terms between cohort dummies and the female dummy of a degree model estimated using POLS. All the estimates are relative to the base cohort 1974. The gender gap in the base cohort is -0.20, 0.21 and 0.24 for degree, strength and clustering, respectively. The p-value of a F-test on the joint significant of all the interaction terms between the cohort dummies and female is 0.18, 0.19 and 0.02 in the degree, strength and clustering models, respectively. Standard errors are clustered at author level.

Figure E.7: Gender Differences in Networks Across Career Time: Cohort 1980-1984



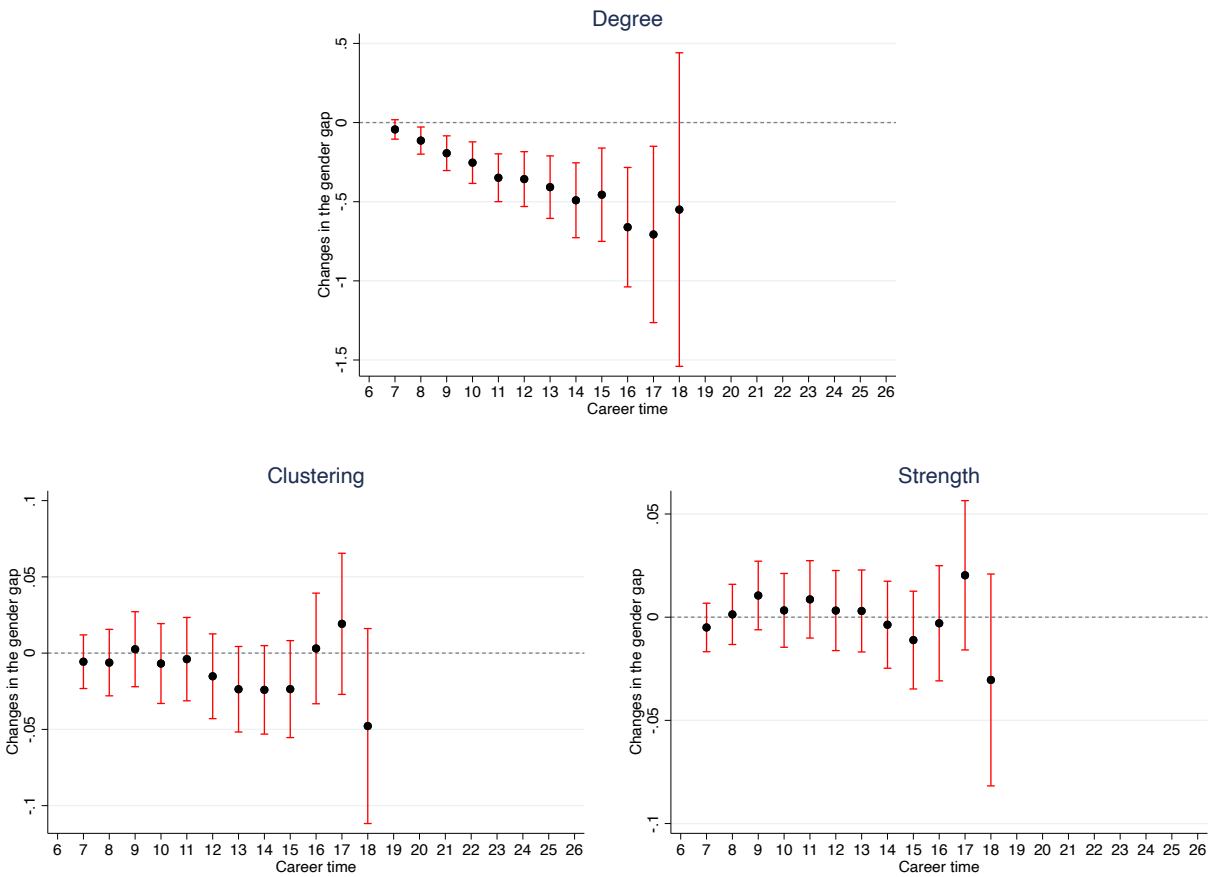
Note: The plots show the coefficients and 95% confidence intervals of the interaction terms between career time dummies and the female dummy of a network model estimated using correlated random effects, the base career time age is 6. The gender gaps in degree, strength, clustering in the base career time age are -0.13, 0.04, 0.05, respectively.

Figure E.8: Gender Differences in Networks Across Career Time: Cohort 1990-1994



Note: The plots show the coefficients and 95% confidence intervals of the interaction terms between career time dummies and the female dummy of a network model estimated using correlated random effects, the base career time age is 6. The gender gaps in degree, strength, clustering in the base career time age are -0.12, 0.05, 0.06, respectively.

Figure E.9: Gender Differences in Networks Across Career Time: Cohort 2000-2004

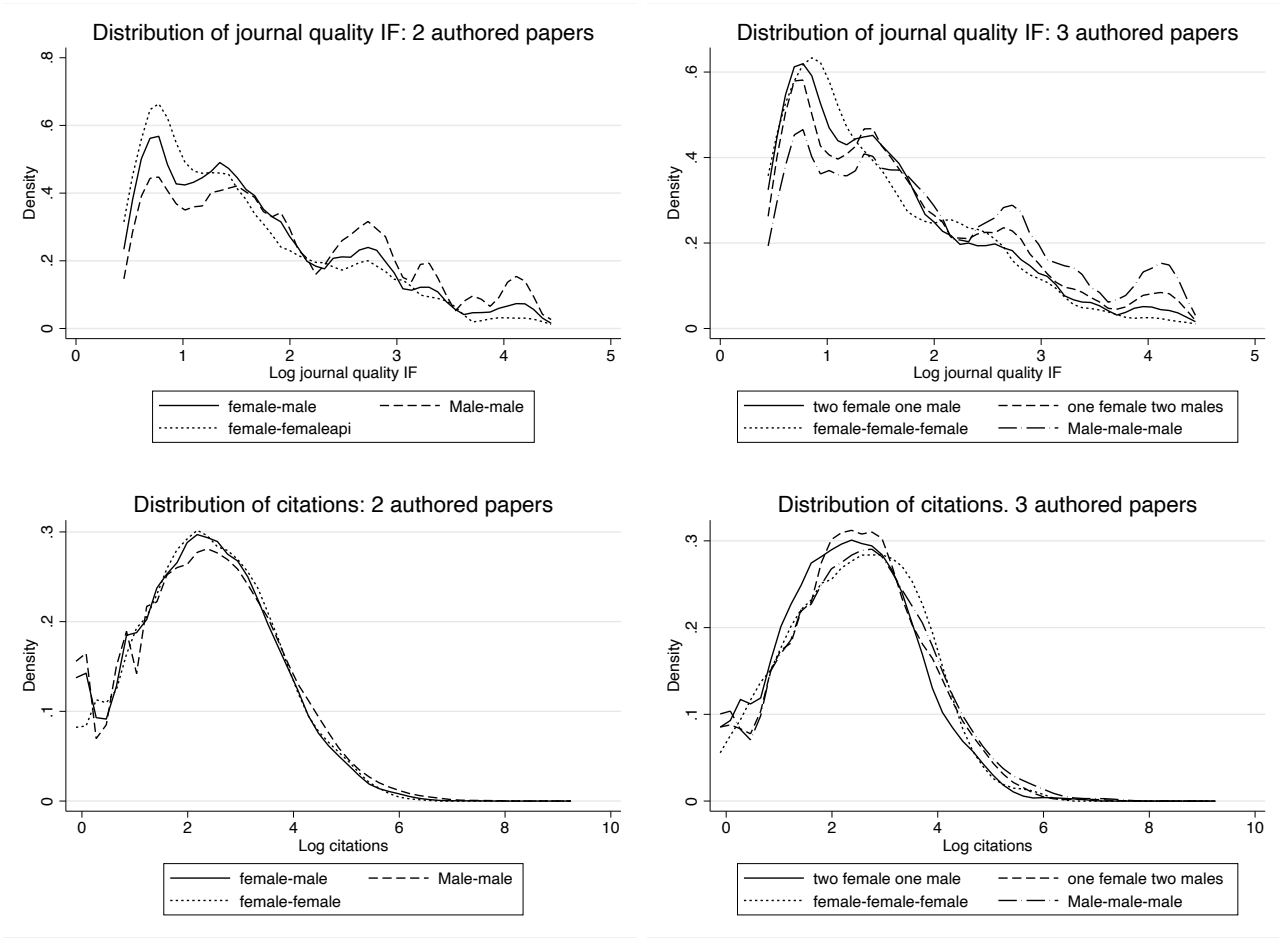


Note: The plots show the coefficients and 95% confidence intervals of the interaction terms between career time dummies and the female dummy of a network model estimated using correlated random effects, the base career time age is 6. The gender gaps in degree, strength, clustering in the base career time age are -0.19, 0.05, 0.03, respectively.

E.3 Distribution of articles' quality by gender composition

We observe that articles published exclusively by men are those with the highest journal quality impact factor and number of citations, both for co-author teams of two and three individuals.

Figure E.10: Distribution of articles' research quality and journal quality impact factor by gender composition and number of authors



Note: Article as the unit of analysis. Journal quality impact factors and citations are in logs. Female-female are two authored articles published by two females, Male-male are two authored articles published by two males, female-male are two authored articles published by one female and one male, Female-female-female are three authored articles published by three females, Male-male-male are three authored articles published by three males, Female-female-male are three authored articles published by two females and one male, Female-male-male are three authored articles published by two males and one female.

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