Gender and Collaboration

Lorenzo Ductor [*] Sanjeev Goyal [†] Anja Prummer [‡]

December 25, 2018

Abstract

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

JEL Codes: D8, D85, J7, J16, O30

Keywords: Gender Inequality, Networks, Homophily, Risk Taking.

[*]Universidad de Granada and Middlesex University London. E-mail: `lductor@ugr.es`

[†]University of Cambridge and Christ's College. Email: `sg472@cam.ac.uk`

[‡]Queen Mary University London. Email: `a.prummer@qmul.ac.uk`

We are very grateful to Gustavo Paez for excellent research assistance. We are indebted to Sebastian Axbard, Leonie Baumann, Yann Bramoullé, Gary Charness, Sihua Ding, Eliana Ferrara, Uri Gneezy, Willemien Kets, Kai Liu, Meg Meyer, Sujoy Mukerji, Noriko Amano Patino, Barbara Petrongolo, Ludovic Renou, Brian Rogers, Adam Szeidl and Marco van der Leij for helpful suggestions. We thank participants at Baleares, Bocconi, Cambridge (Economics & Gender Studies), Essex, Oxford, Paris Dauphine, Yale, Barcelona GSE Summer Forum, Annual Conference on Network Science in Economics (St Louis), BiNoMa workshop (Malaga), Toulouse, and European Networks Workshop (UCL) for useful comments.

1 Introduction

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

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

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

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

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

The paper concludes with a brief discussion on potential sources of these differences in collaboration patterns. Our point of departure is the recent work on gender differences in reward mechanisms, in journal review processes in economics as well as differences in teaching evaluations (Sarsons (2015), Hengel (2016), Mengel, Sauermann, and Zölitz (2017)), all of which indicate that women face adversity in each aspect of the profession. This may lead them to adjust their collaboration patterns to insure against the adversity, the distinct risks, they are facing. There is also evidence on gender differences in risk taking, which is affected by beliefs and perceptions, background risk (potentially due to family constraints) as well as differences in risk preferences (Croson and Gneezy (2009), Charness and Gneezy (2012)). This will also lead to different co-author choices (Kovářík and Van der Leij (2014)).[1]

We build on these two strands of work to argue that, taking them together, could lead to different collaboration choices by women as compared to men. This can help account for lower average output and a lower variance among women, the differences in co-authors networks as well as distinct co-author characteristics.

There is a small body of work on gender differences in economics, see e.g., Boschini and Sjögren (2007), McDowell, Singell, and Stater (2006), Sarsons (2015), Wu (2017) and Hengel (2016)) and Mengel et al. (2017)). Our contribution is to provide a set of striking facts about the relation between gender, research output and collaboration networks. We briefly discuss the novelty of these facts now. There is some work on gender proportions but as far as we are aware the growth in fraction of women in economics research has not been systematically documented; for instance, in Ginther and Kahn (2004) the concern is that the share of women admitted to PhDs is stagnating and so their conclusion is that the share of women is relatively constant. Their study is based on US data. The second fact that women have lower mean and a lower standard deviation of research output as compared to men also appears to be new; the closest paper here is McDowell et al. (2006) that presents evidence on lower mean output of female economists who are members of the AEA. Turning to network statistics, our work is the first long term study of gender based network differences on degree, strength and clustering; for a related paper that discusses degree and clustering in school networks and computer science, see Lindenlaub and Prummer (2014).[2] Turning to characteristics of coauthors, our paper is, to the best of our knowledge, the first to present data on gender homophily and on differences in seniority of coauthors.

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

[1] Kovářík and Van der Leij (2014) relate gender based differences in risk preferences to observed patterns of clustering in friendship networks of undergraduates.

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

with homophilous preferences, as elaborated in Currarini et al. (2009).

The rest of the paper proceeds as follows: Section 2 presents the aggregate facts on gender composition and output. Section 3 presents the facts on differences in collaboration. Section 4 investigates differences in co-authors' characteristics. Section 5 briefly summarizes the evidence from sociology. Section 6 discusses differences in risk taking as a potential explanation for these differences. We conclude in Section 7.

2 Gender Participation & Research Output

Our data is drawn from the EconLit database, a bibliography of journals in economics compiled by the editors of the *Journal of Economic Literature*. The database provides information on all articles published between 1970 and 2011 in 1,627 journals in economics.[3] For further information on the journals included, see `https://www.aeaweb.org/econlit/journal_list.php`. We do not cover working papers and work published in books and we identify authors by their last and first names. We then construct a panel that starts for each individual with their first publication and extends to the last observed publication of the author, or to 2011.

We identify the gender of an author using their first names and the US Social Security Administration records. We identify an author's gender if the author's first name is associated with a single gender in the social security records at least 95% of the time.[4] If the first names are ambiguous, we search for the exact co-author online in order to minimize sample selection. This allows us to identify the gender of 80% of all authors. Authors with missing gender are not included in the panel data, but are used to obtain our network measures. Put differently, if an author has a co-author, whose gender is not identified, then we still take into account that this co-author exists, rather than dropping him from the sample entirely.

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

The research output of an author i at time t is measured as the number of publications during

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

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

the period $t-4$ to t, weighted by journal quality and discounted by the number of co-authors:

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

where p denotes a publication and P_{it} is the total number of articles published by author i from $t-4$ to t. The variable $quality_p$ is a measure of journal quality in which the article p was published. This quality measure was introduced in Ductor, Fafchamps, Goyal, and van der Leij (2014), and builds on the quality journal index developed by Kodrzycki and Yu (2006). The journal index is based on the citations received by all articles published in a journal weighted by the importance of the citing journal and excluding self-citations. See Ductor et al. (2014) for a detailed description of the index.[5] The number of authors of paper p is the denominator. In our analysis of academic performance, we also consider number of publications and number of citations. Citations were retrieved for 121 journals listed in the Tinbergen Institute Journal list. Citations are missing if the author has no publications from $t-4$ to t, the other academic performance variables are zero for periods without publications.[6]

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

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

We now turn to patterns in research output. Columns 5, 6 and 7 of Table 1 present the average research output of women and men and its percentage difference. Average output has declined across time. Consider male economists: in the period 1976-1980, the average output was 18.94 but this declined to 9.55 in the period 2006-2010. A similar trend is observable for women. This fall is driven by the large increase in the number of journals and authors, and the relatively stable number of high-quality journals: in our measure this is reflected in a fall in the fraction of 'high quality' articles over time. We provide a more detailed discussion of this trend

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

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

in the Supplementary Appendix. In spite of the large change in the share of female economists, after a fall in output from 1976 until 1990, the output difference between men and women has remained essentially unchanged: men produced 118% more than women in 1976-1980, and this went down to 52% in 1986-1990, but it has remained stable after that and the difference was 54% in 2006-2010.

To get a first impression of the sources of these gender differences in research output, we examine the role of research field and experience. The observed lower academic performance of women could be explained by women sorting in fields with lower impact or gender differences in experience. We use Pooled OLS (POLS).[7] We estimate the following research output model:

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

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

The main variable of interest, F_i, is a dummy equal to one, if the author is female. The parameter ρ captures the conditional difference in the average research output across gender. The regressors further include experience, C_{it}, and field of research, given by the JEL codes. Career time dummies C_{it}, are included to control for the experience of the author and are dummy variables for each value of career time defined as the number of years since the first publication of the author.[8] Following Fafchamps, Goyal, and van der Leij (2010), we categorize 19 different sub-fields using the first digit of the JEL codes and include in our output model the proportion of publications in each JEL code over the time period $t-4$ to t, JEL_{lit}. These JEL codes capture the fields of specialization of the author. Year dummies, μ_t, account for time effects. Finally, ε_{it} is the time varying error term, and α is an intercept. We cluster standard errors at the author level since research output is correlated over time.

The results are presented in Table 2. Column 2 shows that on average men have a research output that is 36% higher than the average research output of women, after controlling for the specified observables.[9] While differences in experience and choice of field, among other observables can explain 44% of the gender difference in research output (see columns 1 and 2), there still remains a large and significant unexplained gap in research output. We also find that the journal quality index per paper is 0.23 lower for women (see column 4) and that women receives 0.58 fewer citations per paper than men (see column 5).

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

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

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

We perform a number of robustness checks. First, we control for institutional affiliation, using a sample of 395 affiliations over the period 1990-2011. The EconLit provides information about the affiliation of each author publishing a research article in a journal listed in the EconLit from 1990 to 2011. This allows us to examine the role of institutions in explaining the gender gaps in research output. One standard problem with affiliations is that authors tend to report an affiliation with different names, this is 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 model described in equation 1 of the main text. The results presented in Table 3 shows that differences in institutions account for 2.5% of the unconditional gender gap in research output (see column 1 and column 2) while experience and fields account for 39% of the gender gap conditional on institutions (see columns 2 and 3). We also consider a research active sample, those publishing at least a paper every five year, to check if the documented gender differences in output is driven by different rates of attrition between women and men. The results, presented in the Supplementary Appendix, show that the gender differences in research output are larger when we focus on active researchers. Further, we focus on journals that are available in the EconLit for the entire sample period, 1970-2011. For this sample, gender differences in output are larger than those presented here. Details can be found in the Supplementary Appendix.

3 Gender & Collaboration

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

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

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

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

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

Degree is treated as missing if the author does not have publications from $t-4$ to t.[10]

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

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

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

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

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

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

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

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

F_i is a dummy equal to one if the author is female. Career time dummies, C_{it}, are included

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

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

Table 5 displays the magnitude of the difference in network statistics for men and women estimated from equation (2). Strength, clustering and betweenness are standardized to ease the interpretation. We find the following gender differences in collaboration patterns:

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

   Column 2 of Table 5 shows that men have 0.41 more collaborators than women; this is 21% of the average degree of men.[11]

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

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

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

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

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

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

gender difference in degree conditional on observable factors has even increased by 0.83 from 1979 to 2011.

It is worth noting that these gender differences cannot be attributed to women collaborating less with their colleagues. The gender difference in the share of co-authored articles relative to solo papers is not statistically significant, see Table 7, column (1).

We conduct various robustness checks. First, it could be that women are disproportionately in non-academic jobs and consequently have tighter network. We use a sample of 395 affiliations over the period 1990-2001 to test the role of institutional factors in explaining gender differences in collaboration patterns. The results presented in Table 6 shows that the role of institutions is minor. Second, we mitigate potential attrition problems by restricting attention to authors who publish at least one paper every five years. The results presented in the Supplementary Appendix shows that the gender differences in collaboration patterns are larger when we focus on this subsample. The gender difference in co-authorship is significant in this sample with women co-authoring a significantly larger share of their papers. Third, we show that the gender differences in collaboration patterns persist using different models, correlated random effects, random effects and non-linear models. Fourth, we consider three and ten-year network variables, the network differences are robust to different time aggregation. Fifth, we focus on a fixed set of journals, those available in the EconLit for the entire sample period, 1970-2011 and show that the gender differences in collaboration patterns are not driven by new journals coming into the profession. Details of these robustness checks are presented in the Supplementary Appendix.

3.1 Heterogeneity

We have focused so far on the averages in collaboration patterns, which may obfuscate heterogeneity in collaboration patterns. In order to address this, we first consider network patterns across the distribution of previous output.

We follow Ductor et al. (2014) and divide the observations into five tier groups based on their past output, the output accumulated from the first publication, $t = 0$, to $t - 5$. We define four dummy variables, the dummy past output $> 99th$ is equal to one for authors in the top 1% in terms 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. The reference category to 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 in networks between female and male authors belonging to the same tier group. Table 8 shows gender differences in network characteristics across categories. The network differences persist for women with a high research output. For degree and strength the gender differences are even larger for some high output tier groups. For example, the gender difference in degree for authors in the 80-94th percentile of past output distribution is almost twice the gender difference for authors whose past output is below the median.

The differences presented in the table are absolute differences and could be higher for those with higher output as they form additional collaborations. This is the case if both men's and women's degree increases in past output according to the same ratio.[12] Then, higher output mechanically leads to a higher gender gap in degree. To rule this out, we check if the gender ratios in degree increase across output groups. We obtain the predicted ratios for each tier group from the model estimated in column 1 of Table 8. These ratios are 1.159 (95% CI: 1.149-1.172), 1.164 (95% CI: 1.145-1.184), 1.167 (95% CI: 1.134-1.201), 1.053 (95% CI: 1.00-1.169), and 1.225 (95% CI: 0.841-1.737) for authors who are below the median, 50-80th, 80-95th, 95-99th and top 1% of past output distribution, respectively. This indicates that the degree ratio is also increasing for tier groups 50-80th and 80-95th.

Taken together, these findings show that network differences in degree is larger for highly productive individuals. This implies that even the women with the highest past research output have significantly different networks compared to male economists.

We now study if the gender differences in networks change along the career of academics. For that purpose, we add interaction terms between career time dummies and the female dummy to the network model defined in equation 2. Figure 6 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, while the difference in strength and clustering tend to decrease after 20 years of the career of an author.[13] However, the decline in the gender differences in clustering and strength is not statistically significant, since the interaction terms between career time dummies and female dummies are jointly insignificant in all the network models. The p-values of the F-tests in the degree, strength and clustering models are 0.13, 0.10 and 0.21, respectively.[14]

[12] Suppose, as an example, that women with low past output form one collaboration, but men two and for both sexes it is scaled up by a factor of ten.

[13] We also study if the gender differences in networks vary across cohorts in the Supplementary Appendix. The results show that the gender differences in degree and strength are stable across cohorts, but the gender difference in clustering was higher for authors with a first publication in the 70s or 80s.

[14] We also analyze if the career time effects by gender vary across cohorts. The results presented in the Supplementary Appendix show that life cycle patterns in network measures of both genders have not changed across cohorts.

4 Characteristics of Co-Authors

We now turn to our third set of facts that pertain to characteristics of co-authors. We start with the gender composition of coauthors. Gender based homophily means that individuals prefer to form links with others of their own gender (McPherson et al. (2001)). Denote the fraction of male authors in the population as w_m and the share of women by $w_f = 1 - w_m$. Let H_m denote the average share of male co-authors among men. Then, men exhibit *relative homophily* if $H_m > w_m$. Similarly, women exhibit relative homophily if $H_f > w_f$. We compute the percentage of links within gender and find that, on average, 81% of men's collaborations are with other men: this is higher than the fraction of men in the population 72%, see Table 9. Similarly, women exhibit relative homophily as their collaboration with other women, 33% is larger than the fraction of women in the population (27%). Therefore, women and men tend to collaborate with authors of the same gender over and above the relative size of their gender group.[15]

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

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

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

Building on the work of Currarini et al. (2009), we note that gender based homophily together with increases in the fraction of women would imply a fall in difference in degrees across gender. We examine this prediction. We exploit variation in gender shares across time. From Table 1 we know that women became more representative in the profession over time. But contrary to the prediction of the model, we find in Figure 1 that the gender difference in degree is actually increasing for the most recent periods. We then check if there is any relationship between degree and the share of women exploiting variation across fields. Here we use the first two digits of the JEL codes, to define 124 different fields. We then de-trend degree by regressing degree on

[15] It is worth noting that homophily here may reflect a greater proportion of gender specific shared activities, see Graham (2016).

time dummies, the residual from this regression is the de-trended degree.[16] We find that the link between degree and group size is negative. Regressing the degree detrended on relative group size excluding men, we obtain: $\widehat{degreedet} = -.013 - .044w$, both coefficients statistically significant at the 1% level. Figure 3 shows the relationship between the de-trended degree and the fraction of women across fields.[17] This implies that a higher share of women is correlated with lower homophily, although the effect is economically negligible. Despite the increase in the share of women in the profession overall as well as in certain fields, the gender gap in the number of co-authors has risen. Put differently, even though there is a greater share and number of women and women prefer working with women, the gender gap is slightly *increasing*. This seems to indicate that a higher share of women in economics will not automatically lead to a reduction in gender gaps.

Finally, we study if the coauthors' of women and men differ in terms of output and seniority. Figure 4 presents the cumulative average co-authors' research output distribution by gender for male (left plot) and female (right plot) authors. The empirical evidence is that male co-authors have, on average, a higher past research output than female co-authors for both women and men. We also observe that articles published exclusively by males 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, Figure 7.

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

5 Sociology

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

We use the database compiled by Moody (2004), that considers all the English journal articles in Sociological Abstracts that were published between 1963 and 1999. This comprises not only of journals in sociology, but also articles published by sociologists in other journals, and thus allows us to gain more comprehensive data on publishing in sociology. Sociological Abstracts limits coverage to journal articles, neglecting conference presentations, book reviews, essays, or

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

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

books.

Our first point concerns fraction of women and differences in output. The fraction of women was 15% in 1963 and moved up to 50% in 1999, see Table 10. This implies that sociology reached gender balance. Despite this, the research output difference between men and women has remained stable from 1984 to 1999: men produced 69% more than women in 1965-1969, and this decreased to 31% in 1985-1989, but it has remained constant after that and the difference was 30% in 1995-1999. This lower output for women is accompanied with a lower variation: the standard deviation for women is 18% lower than that for men. These large differences in output remain after we control for experience and choice of field (and other observable factors), see Table 11.

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 12. Women have fewer distinct co-authors (the conditional average difference in degree is -0.18, which is 7.6% of the average degree of men) and a higher clustering coefficient (the conditional difference in clustering is 2.6% of the average clustering of men). They also tend to work repeatedly with the same co-authors (the conditional difference in strength is 2.8% of the average strength of men). Although the same qualitative patterns emerge in sociology, the magnitude of the differences are substantially smaller than in economics. Specifically, the gender differences in degree, clustering and strength are roughly three times larger in economics than in sociology.

Our third observation is about the types of coauthors that men and women have. We find that collaboration does not exhibit homophily in sociology, the imbreeding homophily index as shown in Table 13 is zero. But, as in economics, we also find that women have more senior co-authors, at every point in their career. In particular, women have co-authors that are 0.9 years more experienced than men, see Figure 8.

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

6 Discussion

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

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

We next turn to the issue of gender differences in risk preferences. Researchers have documented evidence, based on experimental and observational data, that across a wide range of decision making contexts, women choose to take fewer risks. For surveys on this work, see Croson and Gneezy (2009), Charness and Gneezy (2012), Eckel and Grossman (2008) and Weber, Blais, and Betz (2002).[18] These differences in risk taking can be due to (i) differences in beliefs and perception, (ii) differences in background risk, such as family constraints and (iii) differences in risk preferences, risk aversion.

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

If women face discrimination at the publishing stage, then it is rational to respond to this by either sending their papers to lower ranked journals or by investing more time to ascertain that the standards of the journal are met. The latter is consistent with Hengel (2016)'s finding that women put in more effort even at the first stage of submission. Additionally, it implies that women's beliefs and perceptions regarding the risk of aiming for a certain journal are very different to men's. This affects their risk taking and skews their choices to more secure and certain, but lower payoffs. Last, it may simply be that women, due to their more pronounced family constraints, choose a different submission strategy; one that is less time intensive in producing a steady stream of output. As beliefs and background risk affect risk taking, women will make less risky choices. All of these potential explanations predict the same: women will have a lower, but less variable output. This is consistent with the data.

Second, consider network differences. If women are exposed to discrimination within their collaborations, women may be more careful in finding new co-authors. They may rather stick with co-authors they already worked with or collaborators of existing co-authors, who can provide

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

information and vouch for the new co-author. Moreover, if women believe that an unsuccessful collaboration can be very costly for them, more so then for men, then women will take fewer risks. In particular, women will be more reluctant to collaborate with someone unknown rather than a previous collaborator or someone recommended by a co-author. Background risk due to family constraints can be another source of differences in risk taking: women may have higher absences which may lead them to choose to work on several projects with the same person. With repeated collaborations, the work across all the projects will even out, even though this may not be the case for each project. Again, all of these factors push towards fewer coauthors, repeat coauthoring and higher clustering. This is exactly what we find in the data.

Third, we turn to characteristics of coauthors: here we focus on seniority of coauthors. If women face biases in the publication process, they may choose more senior co-authors that can help overcome these biases. This is in line with Burt (1992, 1998), who argues that social capital can be borrowed. Moreover, for a more senior co-author there is more information available, in terms of his past collaborative behavior, which may be more important given women's beliefs and perceptions. Additionally, a more senior co-author may be more understanding about family constraints compared to a more junior one, who may face greater pressure to publish quickly. Based on these factors, we predict that women will prefer senior co-authors. This is consistent with the evidence, see Figure 5.

Fourth, the differences in output and collaboration patterns emerge both in economics and sociology, with the gaps in sociology being smaller. We speculate that this may be due to female sociologists facing a less adverse environment; at least sociology is perceived to be more female friendly, one indicator being the higher share of women who pursue a sociology degree. Another indicator is that male sociologists exhibited heterophily, a preference for working with women when the share of women was small, see Figure 9. These disparities may lead to different perceptions which in turn effects an adjustment in risk taking, resulting in lower gender gaps in sociology.

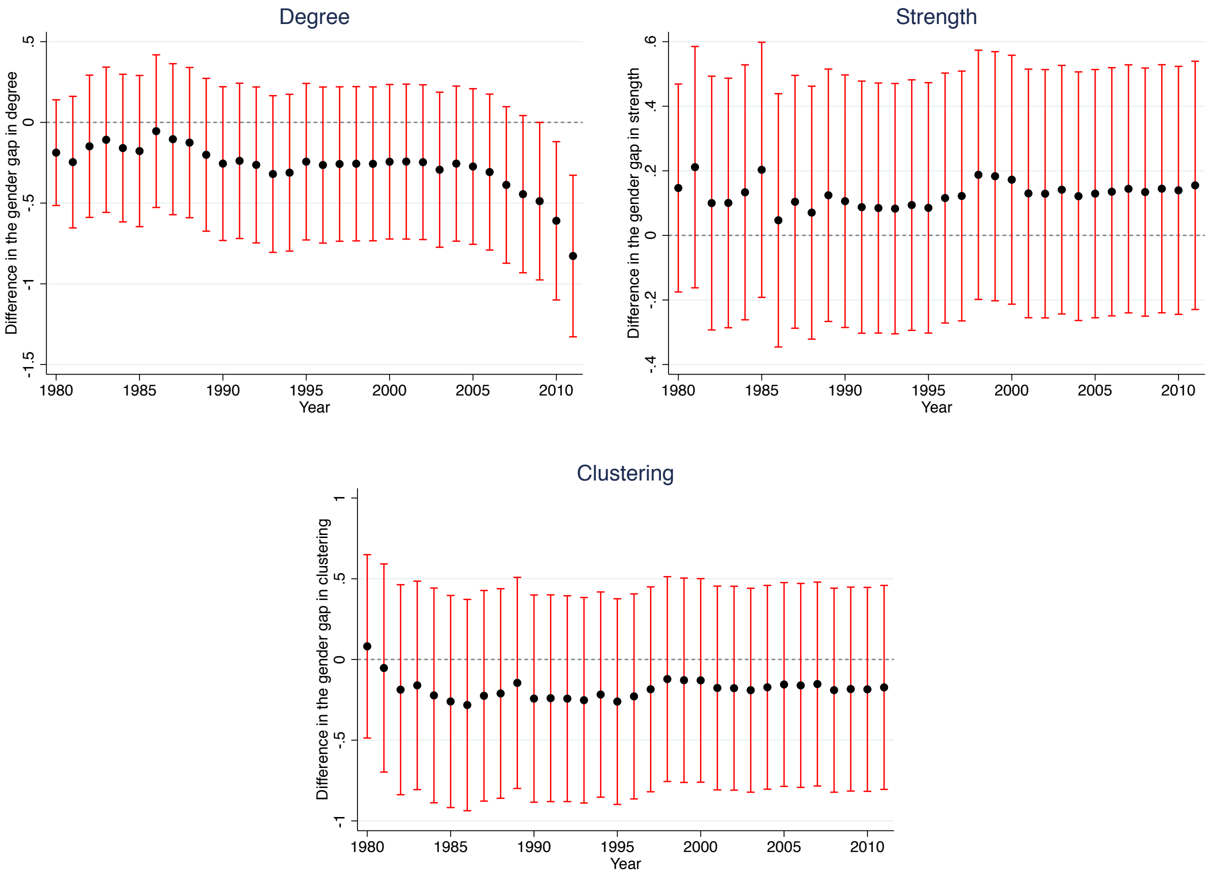
7 Concluding Remarks

We have examined gender disparity in economics research over a forty year period, 1970-2010. The share of women publishing in economics grew roughly four times, but there remains a large gender difference in research output: men produce 50% more than women. The persistence in output gap is accompanied by large and persistent differences in the co-author networks of men and women: women have a higher share of co-authored work and they co-author more with senior colleagues. They also tend to have fewer co-authors (and co-author more often with the same co-authors) and exhibit greater overlap in their co-authors.[19] These differences in networks are consistent with the view that women make different, less risky choices with regard to collaboration.

[19]We have also examined collaboration patterns in sociology. In line with the findings of the present paper we find that, in sociology too, women have lower output as compared to men and that their networks are different: they have lower degree, higher clustering and higher strength. The magnitude of these differences is however significantly lower.

Figures and Tables

Figure 1: 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 1979. The gender gaps in degree, strength, and clustering in the base year 1979 are -0.06, 0.34 and 0.03, respectively. The p-values, obtained using the of F-tests on the joint significant of all the interaction terms are: 0.00 in the degree model; 0.36 in the strength model; 0.09 in the clustering model.

Figure 2: Inbreeding Homophily

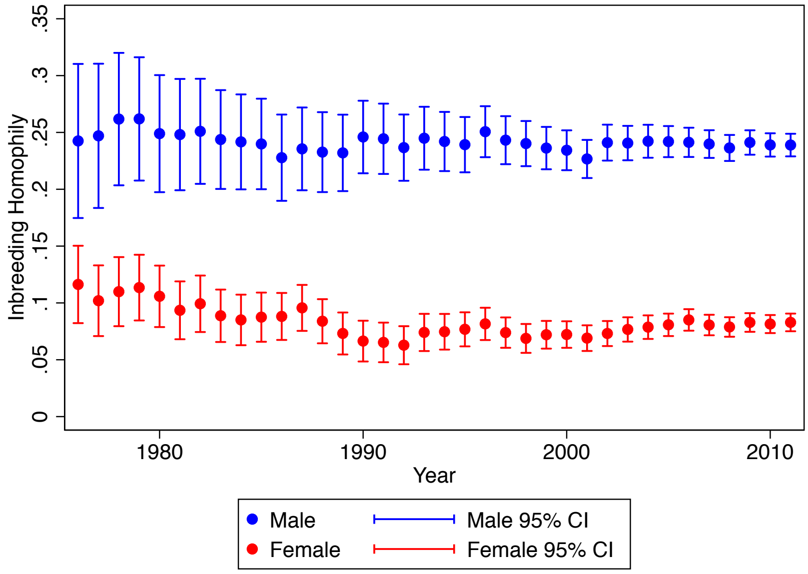
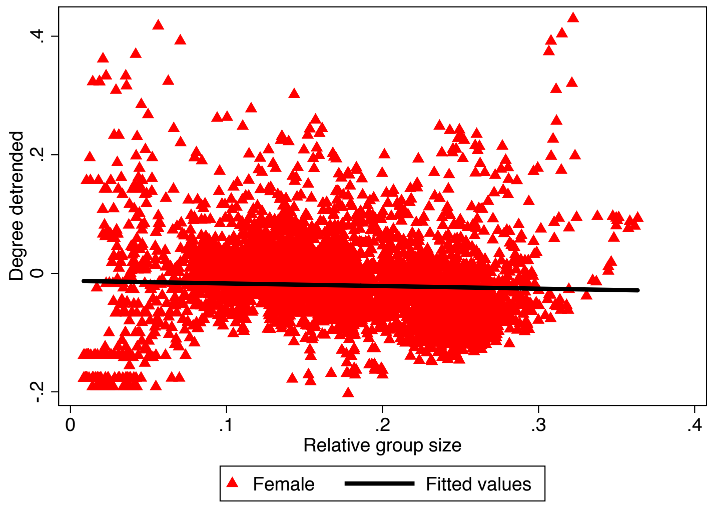
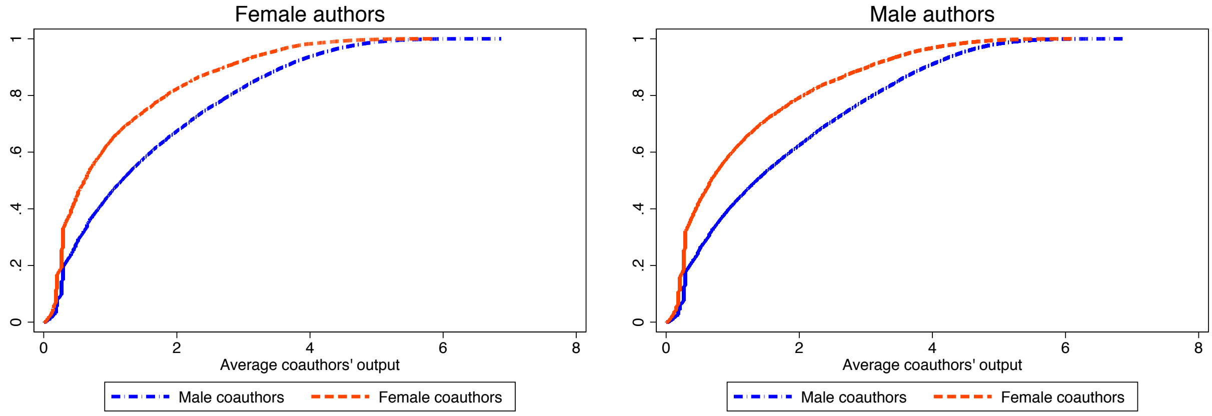


Figure 3: Degree and fraction of women across fields



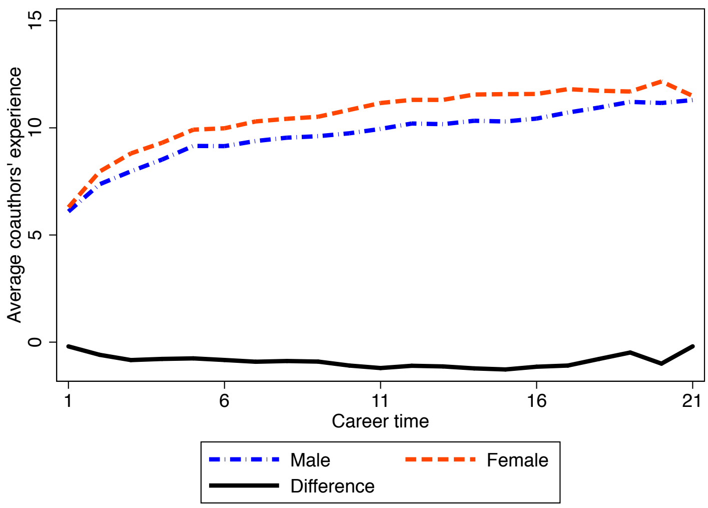
Note: Degree detrended is the residual of a linear regression of degree on year dummies. Regressing the degree detrended on relative group size, we obtain: $\widehat{degreedet} = -.013 - .044w$, both coefficients statistically significant at the 1% level.

Figure 4: Cumulative distributions of coauthors' research output by gender



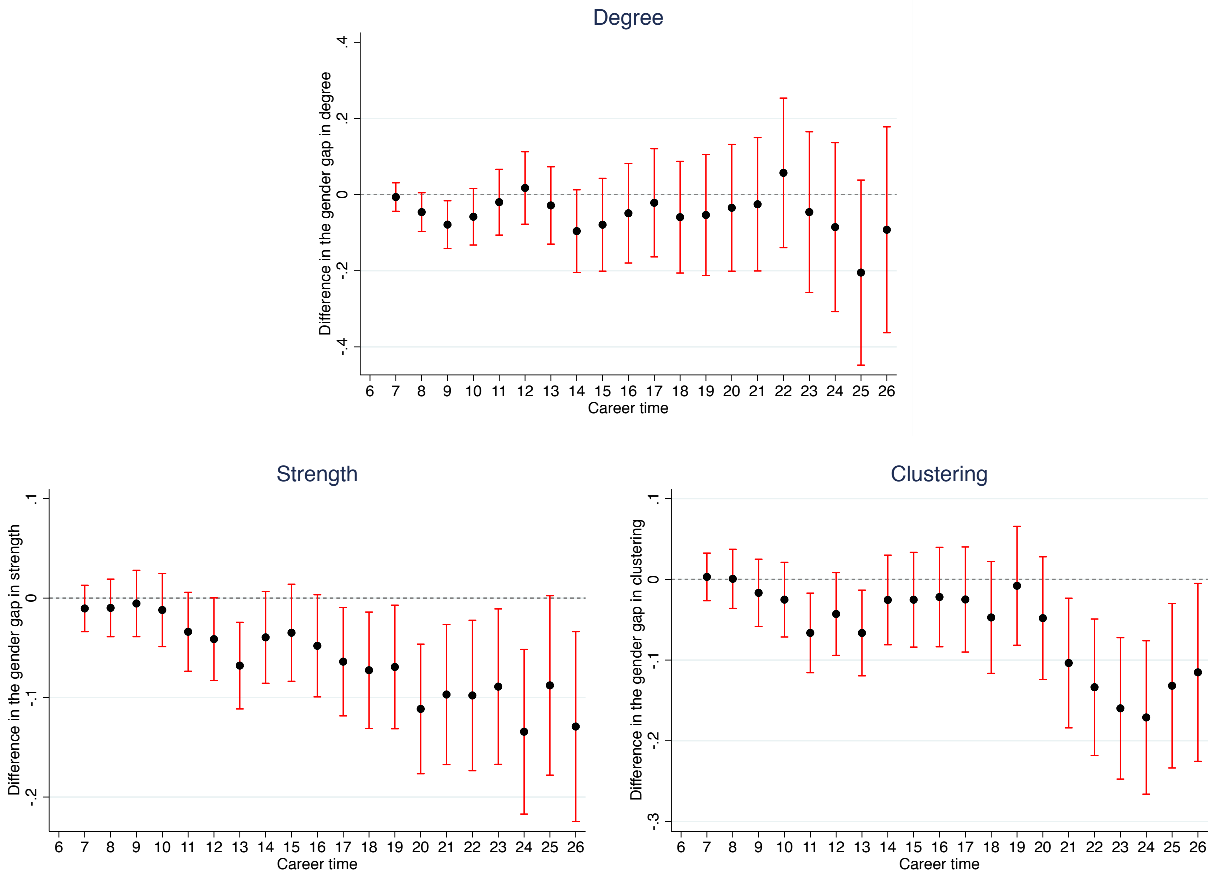
Note: Research output is in log plus one, $log(x + 1)$. We only consider observations with positive values. Using a Kolmogorov-Smirnov test we reject the null that the distributions across gender are equal at the 1%.

Figure 5: Average co-authors' experience by gender



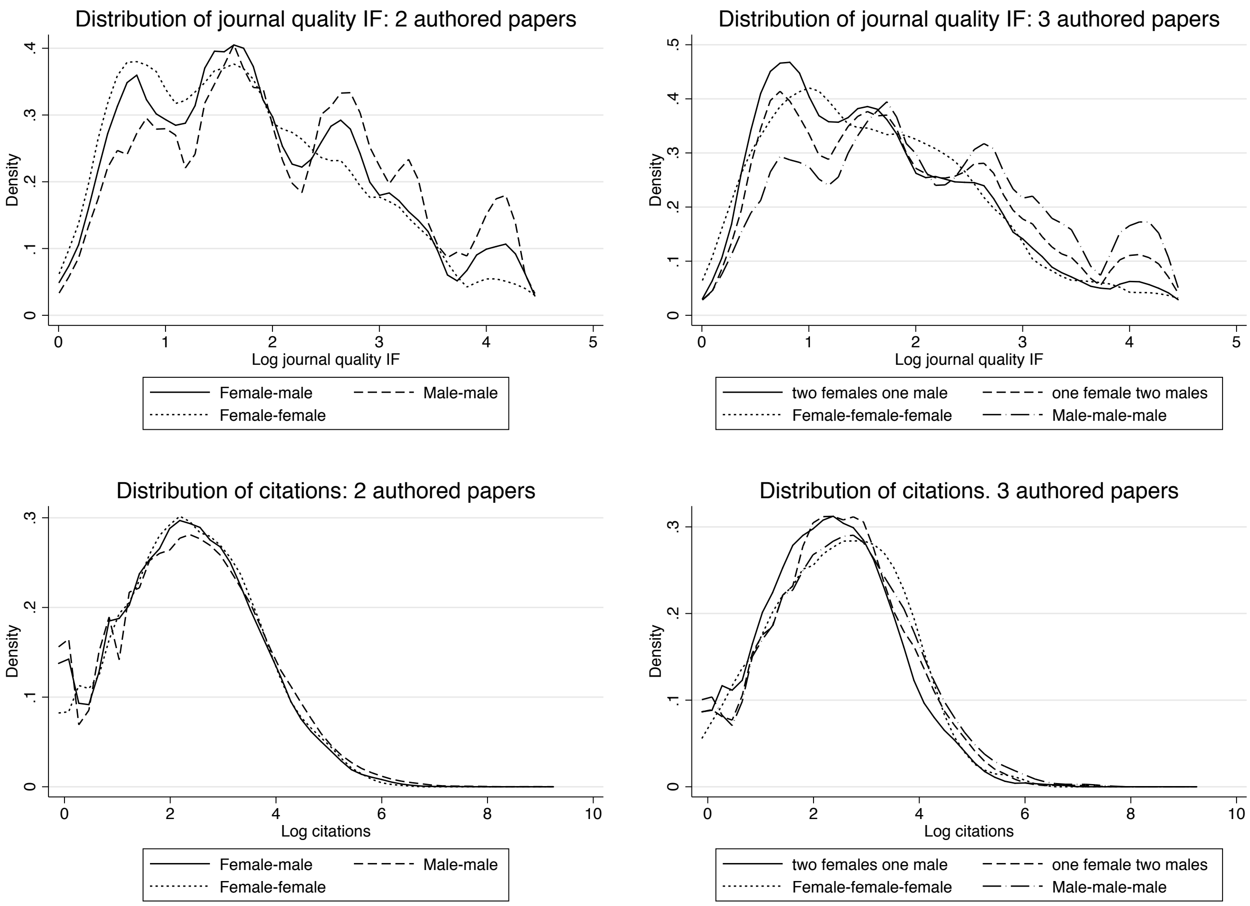
Note: Coauthors productivity by gender is obtained using all the articles published in the EconLit from 1974 to 2011 where the gender of at least one author is identified. The gender difference is statistically significant except for authors with more than 17 years of career time.

Figure 6: Gender differences in networks across career time age



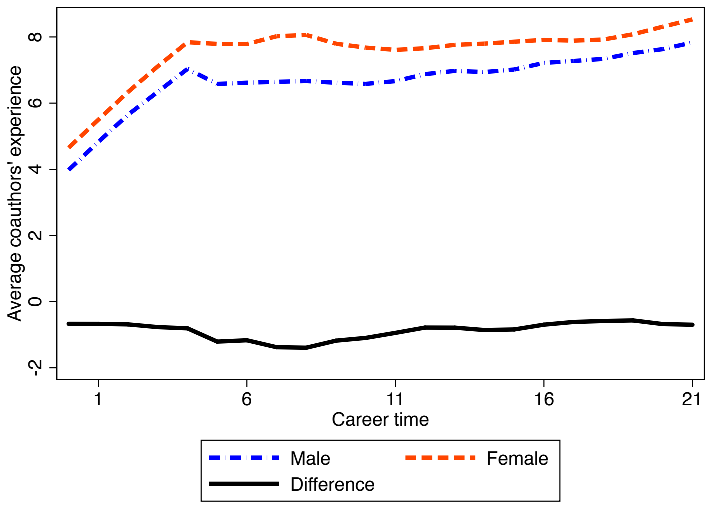
Note: The plots show the coefficients and 95% confidence intervals of the interaction terms between career time dummies and the female dummy of a network model estimated using POLS, the base career time age is 6. The gender gaps in degree, strength, clustering in the base career time age are -0.378, 0.202 and 0.148, respectively. The p-values of F-tests on the joint significant of all the interaction terms are: 0.13 in the degree model; 0.1032 in the strength model; 0.206 in the clustering model. Authors with less than six years of experience are excluded from the sample since past output is not defined.

Figure 7: 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.

Figure 8: Average co-authors' experience by gender in Sociology



Note: The gender difference is statistically significant at the 1% level, except for authors with more than 10 years of career time.

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

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

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

Table 2: Gender Differences in Performance

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

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

Table 3: Gender Differences in Performance: Accounting for Institutions

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

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

Table 4: Gender Differences in Performance: Active Researchers

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

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

Table 5: Gender and Collaboration

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

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

Table 6: Gender and Collaboration: Accounting for Institutions

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

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

Table 7: Gender and Collaboration: Active sample

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

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

Table 8: Network Differences Across Output Levels

VARIABLES	Degree	Strength	Clustering	Betweenness
Female	-0.278***	0.129***	0.100***	-0.142***
	(0.025)	(0.012)	(0.015)	(0.016)
(Dummy 50th-80th)*female	-0.128***	0.032*	0.003	-0.026
	(0.047)	(0.019)	(0.022)	(0.023)
(Dummy 80th-95th)*female	-0.249***	0.043	-0.008	-0.018
	(0.092)	(0.027)	(0.028)	(0.030)
(Dummy 95th-99th)*female	0.005	-0.074	-0.032	0.051
	(0.275)	(0.051)	(0.047)	(0.051)
(Dummy >99th)*female	0.114	-0.119	-0.052	0.076
	(0.833)	(0.102)	(0.084)	(0.139)
Past output$_{t-5}$	0.005***	-0.078***	-0.051***	0.045***
	(0.001)	(0.008)	(0.005)	(0.007)
Observations	389,201	311,950	222,979	189,540
Number of authors	54,681	46,968	37,237	32,065
Career-time FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
JEL codes share	YES	YES	YES	YES

All the results are obtained using the POLS model. 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. Past output$_{t-5}$ is the accumulated research output from the first publication till $t - 5$. Avg. Past output is the time average of past output stock. Clustered standard errors by author in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 9: Percentage of links across gender

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

Table 10: Number of authors and research output across time in Sociology

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

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

Table 11: Gender Differences in Performance in Sociology

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

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

Table 12: Gender and Collaboration in Sociology

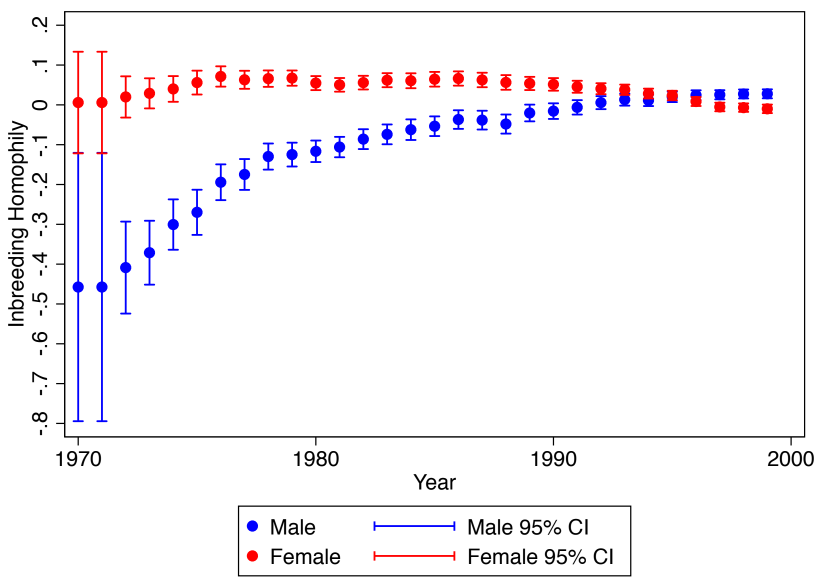
VARIABLES	(1) Degree	(2) Strength	(3) Clustering
Female	-0.185***	0.088***	0.057***
	(0.022)	(0.010)	(0.012)
Degree			-0.302***
			(0.006)
Past output	0.077***	-0.249***	-0.131***
	(0.005)	(0.008)	(0.007)
Observations	252,982	252,982	149,929
Number of auth	75,501	75,501	46,469
Career-time FE	YES	YES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

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. All the continuous variables in the models estimated in columns 2 and 3 are standardized. Clustered standard errors at the author level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 13: Percentage of links across gender in Sociology

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

Figure 9: Inbreeding Homophily Sociology



References

Althouse, B. M., J. D. West, C. T. Bergstrom, and T. Bergstrom (2009). Differences in impact factor across fields and over time. *Journal of the Association for Information Science and Technology 60*(1), 27–34.

Boschini, A. and A. Sjögren (2007). Is team formation gender neutral? evidence from coauthorship patterns. *Journal of Labor Economics 25*(2), 325–365.

Bramoullé, Y., S. Currarini, M. O. Jackson, P. Pin, and B. W. Rogers (2012). Homophily and long-run integration in social networks. *Journal of Economic Theory 147*(5), 1754–1786.

Burt, R. (1992). *Structural Holes: The Social Structure of Competition*. Harvard University Press.

Burt, R. S. (1998). The gender of social capital. *Rationality and society 10*(1), 5–46.

Charness, G. and U. Gneezy (2012). Strong evidence for gender differences in risk taking. *Journal of Economic Behavior & Organization 83*(1), 50 – 58. Gender Differences in Risk Aversion and Competition.

Coleman, J. (1958). Relational analysis: the study of social organizations with survey methods. *Human organization 17*(4), 28–36.

Coleman, J. (1988). Social Capital in the Creation of Human Capital. *American journal of sociology*, 95–120.

Croson, R. and U. Gneezy (2009). Gender differences in preferences. *Journal of Economic Literature 47*(2), 448.

Currarini, S., M. O. Jackson, and P. Pin (2009). An economic model of friendship: Homophily, minorities, and segregation. *Econometrica 77*(4), 1003–1045.

Dasgupta, P. and I. Serageldin (2001). *Social capital: a multifaceted perspective*. World Bank Publications.

Ductor, L. (2015). Does co-authorship lead to higher academic productivity? *Oxford Bulletin of Economics and Statistics 77*(3), 385–407.

Ductor, L., M. Fafchamps, S. Goyal, and M. J. van der Leij (2014). Social networks and research output. *Review of Economics and Statistics 96*(5), 936–948.

Eckel, C. and P. Grossman (2008). Men, Women and Risk Aversion: Experimental Evidence. *Handbook of experimental economics results 1*, 1061–1073.

Ellison, G. (2002). The slowdown of the economics publishing process. *Journal of Political Economy 110*(5), 947–993.

Fafchamps, M., S. Goyal, and M. J. van der Leij (2010). Matching and network effects. *Journal of the European Economic Association 8*(1), 203–231.

Friebel, G., M. Lalanne, B. Richter, P. Schwardmann, and P. Seabright (2017). Women form social networks more selectively and less opportunistically than men.

Ginther, D. K. and S. Kahn (2004). Women in economics: moving up or falling off the academic career ladder? *The Journal of Economic Perspectives 18*(3), 193–214.

Goyal, S., M. J. Van Der Leij, and J. L. Moraga-González (2006). Economics: An emerging small world. *Journal of political economy 114*(2), 403–412.

Graham, B. S. (2016). Homophily and transitivity in dynamic network formation. Technical report, National Bureau of Economic Research.

Granovetter, M. (1973). The Strength of Weak Ties. *American Journal of Sociology*, 1360–1380.

Hengel, E. (2016). Publishing while female. Technical report, Technical report, University of Liverpool.

Jackson, M. O. and B. W. Rogers (2007). Meeting strangers and friends of friends: How random are social networks? *The American economic review 97*(3), 890–915.

Kodrzycki, Y. K. and P. Yu (2006). New approaches to ranking economics journals. *The BE Journal of Economic Analysis & Policy 5*(1).

Kovářík, J. and M. J. Van der Leij (2014). Risk aversion and social networks. *Review of Network Economics 13*(2), 121–155.

Larivière, V., C. Ni, Y. Gingras, B. Cronin, and C. R. Sugimoto (2013). Bibliometrics: Global gender disparities in science. *Nature News 504*(7479), 211.

Lindenlaub, I. and A. Prummer (2014). Gender, social networks and performance.

McDowell, J. M., L. D. Singell, and M. Stater (2006). Two to tango? gender differences in the decisions to publish and coauthor. *Economic inquiry 44*(1), 153–168.

McPherson, M., L. Smith-Lovin, and J. M. Cook (2001). Birds of a feather: Homophily in social networks. *Annual review of sociology 27*(1), 415–444.

Mengel, F., J. Sauermann, and U. Zölitz (2017). Gender bias in teaching evaluations.

Moody, J. (2004). The structure of a social science collaboration network: Disciplinary cohesion from 1963 to 1999. *American sociological review 69*(2), 213–238.

Sarsons, H. (2015). Gender differences in recognition for group work. *Harvard University 3*.

Weber, E. U., A.-R. Blais, and N. E. Betz (2002). A domain-specific risk-attitude scale: Measuring risk perceptions and risk behaviors. *Journal of behavioral decision making 15*(4), 263–290.

Wu, A. H. (2017). Gender stereotyping in academia: Evidence from economics job market rumors forum.