Gender & Collaboration

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Abstract

The fraction of women in economics has grown significantly over the last forty years. In spite of this, the differences in research output between men and women are large and persistent. These output differences are related to 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. Moreover, women collaborate more and do so with more senior co-authors. Standard models of homophily and discrimination cannot account for these differences. We discuss how differences in risk aversion and an adverse environment for women can explain them.

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

Keywords: Gender Inequality, Network Formation, Discrimination, Homophily, Risk Taking.

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1 Introduction

Gender inequality in the work place has 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. Overall, research in economics has grown greatly: there has been a big increase in the number of journals and in the number of authors. This increase has been accompanied by a significant change in the share of women in the profession: the fraction of female economists grew from 8% to 29% over this period. Turning to research output, after a fall until 1990, the output difference between men and women has remained essentially unchanged until 2011: men have produced 50% more output then women throughout the period under study.

In principle, the lower performance of women could be explained by women sorting in fields with lower impact or by women leaving the profession at a differential rate and research output being related to career time. Our analysis of the data suggests that there remain large differences in output even after we control for experience and choice of field (and other observable factors). This motivates an examination of alternative explanations.

Research is a 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. It is natural then to suppose that the collaborations of an individual will shape their performance. This leads us to examine the role of networks of co-authorship. A long and distinguished body of research argues that the structure of social networks plays an important role in the diffusion of ideas and information and in the sustenance of social norms and trust (Coleman, Katz, and Menzel (1966), Coleman (1988), Granovetter (1973), Dasgupta and Serageldin (2001)). In a recent paper, Lindenlaub and Prummer (2014) formally study the interplay between different network features and these effects. They argue that the number of connections and centrality in the network facilitates access to new ideas, while a higher overlap among connections (higher clustering coefficient) and repeated interaction (higher strength of ties) sustains greater peer pressure and trust. These theoretical findings are our point of departure for the analysis of network differences across gender. We identify large and persistent network differences: women have lower degree and centrality and higher clustering and strength than men, implying that women choose networks connected to lower future output.

We then examine two potential explanations for these patterns: homophily (the desire of women to collaborate with other women, and for men to work with other men) and discrimination (a preference for male co-authors) and investigate whether they can account for the observed network differences. Homophily would predict that a significant increase in the fraction of women should lead to a large fall in degree difference between men and women. This is rejected by the data. A taste for co-authoring with men predicts that female co-authors should be more productive than male co-authors: again, this is rejected by the data.[1]

We then turn to differences in risk taking between men and women. The differences in risk taking can arise out of differences in preferences and differences in the environment (men and women may face a different distribution of rewards from the same actions). The first observation is that the variance in output is significantly greater for men as compared to women. This offers us a first suggestion that differences in risk taking may be playing a role. We now elaborate on the implications of risk taking for decisions on co-authorship. Suppose men and women with similar ability decide on how to carry out a set of projects: whether to work alone or with others. It is reasonable to suppose that solo work is more uncertain than joint work: this leads to a negative correlation between risk taking and share of research that is co-authored. Co-authoring with senior co-authors is less risky than co-authoring with junior co-authors, so lower risk taking should be correlated with a higher fraction of senior co-authors. These two correlations are observed in our data: women coauthor a larger share of their research and they coauthor with more senior colleagues. We now draw out the implications of differences in risk taking for network structure: someone who takes less risks would be more inclined to continue working with a known collaborator rather than to write a paper with a new unknown person. Finally, a lower inclination to take on risks will lead to a greater reliance on introductions through co-authors, leading to a higher clustering coefficient. Taken together, therefore, a difference in risk taking with regard to project selection and partner choice offers a parsimonious explanation for the observed network differences between men and women.

Our paper contributes to a better understanding of gender inequality in the work place (Blau and Kahn (2016) and Bertrand (2011)). Over the years, researchers have explored a number of alternative explanations such as discrimination (Black and Strahan (2001), Goldin and Rouse (2000)), differences in preferences (in particular risk aversion and competitiveness) (Eckel and Grossman (2008), Croson and Gneezy (2009)), and family constraints (Bertrand, Goldin, and Katz (2010), Albanesi and Olivetti (2009), Adda, Dustmann, and Stevens (2011)). 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, Sauermann, and Zölitz (2017)). We make three contributions to this literature. Our first contribution is to establish trends in female participation and persistent productivity differences between men and women across over a four decade period. Our second contribution is to link this to differences in specific features of co-author networks. And our third contribution

[1] We also do not find support for statistical discrimination or for a major role of family engagements as shaping network differences.

is to show that differences in risk taking between men and women can account for these network differences.

We contribute to the literature on networks (Azoulay, Graff Zivin, and Wang (2010), Goyal, Van Der Leij, and Moraga-González (2006)). In their early work on network formation, Bala and Goyal (2000) and Jackson and Wolinsky (1996) assume the benefits of links to be the same across individuals. More recent work has explored the implications of relaxing this assumption. One way to relax this assumption would be to say that everyone has higher rewards from linking with men: this would be an interpretation of discrimination in our context. We show that this theory is rejected in our empirical context. Another way to relax this assumption is to say that individuals exhibit homophily: they link with others of the same gender, see e.g., Currarini, Jackson, and Pin (2009), Bramoullé, Currarini, Jackson, Pin, and Rogers (2012). Our analysis suggests that gender based homophily is not an important driving force for co-authoring among economists. Instead, we build on the influential literature dealing with risk preferences and gender and propose that it is differences in risk taking between men and women that provide a parsimonious account for the striking patterns in the data on collaboration. For an overview of the research on preferences and gender, see Croson and Gneezy (2009) and Charness and Gneezy (2012). Kovářík and Van der Leij (2014) relate gender based differences in risk preferences to observed patterns of clustering in friendship networks of undergraduates. Our paper shows that differences in risk taking can have powerful and very wide-ranging effects for collaboration in economics: on the share of co-authored work, on partnering with senior authors, on number of co-authors and on the strength of ties (in addition to the effects on clustering that they note).

The rest of the paper proceeds as follows: Section 2 discusses trends and highlights differences in research output among men and women. Section 3 connects these differences to gender disparities in patterns of collaboration. Section 4 investigates the sources of the gender disparities in co-authorship. Section 5 concludes with a brief discussion on policy implications.

2 Gender & Research Output

2.1 Data Description

Our data is drawn from the EconLit database, a bibliography of journals in economics compiled by the editors of the *Journal of Economic Literature*. The database provides information on all articles published between 1970 and 2011 in 1,627 journals in economics.[2] For further information

[2] EconLit does not report the names of all the authors for articles published by more than three authors before 1999; therefore, we exclude these articles from the analysis for the period 1970-1999. Articles published by four or more authors represent 1.6% of all the articles published between 1970-1999. Goyal et al. (2006). show that the co-authorship network statistics are unaffected when (for a subset of the data) articles with four or more authors

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. 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. Further details on how names are identified are provided in the Appendix. Authors with missing gender are not included in the panel data, but are used to obtain our network measures. Put differently, if an author has a co-author, whose gender is not identified, then we still take into account that this co-author exists, rather than dropping him from the sample entirely.

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

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

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

where p denotes a publication and P_{it} is the total number of articles published by author i from $t-4$ to t. The variable $quality_p$ is a measure of journal quality in which the article p was published. This quality measure was introduced in Ductor, Fafchamps, Goyal, and van der Leij (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.[3] The number of authors of paper p is the denominator.

are included. A similar data set was studied in Ductor (2015).

[3]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), which leads us to believe that this assumption does not impact our key results.

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.[4]

2.2 Gender Differences in Research Output

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 women economists has grown from 8% in the period 1971-1975 to 29% in 2006-2010. Figure 1 plots this development.

We now turn to patterns in research output. Table 2 presents the average research output. Average output has declined across time. Consider male economists: in the period 1976-1980, the average output was 18.94 but this declined to 9.55 in the period 2006-2010. A similar trend is observable for women. This fall is driven by the large increase in the number of journals and authors, and the relatively stable number of high-quality journals: in our measure this is reflected in a fall in the fraction of 'high quality' articles over time. We provide a more detailed discussion of this trend in the 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 summarize, *despite the significant increase in the fraction of female economists, large gender differences in research output persist.*

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.

As we are interested in gender, a time-invariant variable, we cannot use the fixed effect estimator and therefore use a correlated random effects model (Mundlak (1978)). In line with

[4]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.

this 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.[5] We estimate the following research output model:

$$q_{it} = \alpha_i + \rho F_i + C_{it}\omega + \sum_{l=1}^{L} \beta_r JEL_{lit} + \mu_t + \varepsilon_{it}, \quad (1)$$

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

Our approach, the correlated random effect model, improves upon a standard pooled OLS or a random effects model as we do not require the time-varying covariates and the author fixed effect μ_i to be orthogonal.

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. Following Fafchamps, Leij, and Goyal (2010), we categorize 19 different subfields 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. $\overline{JEL}_{li}$ is the average proportion of articles published in JEL code l by author i during her career. Year dummies, μ_t, account for time effects. Finally, μ_i is an individual fixed effect, 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 3. Column 2 shows that on average men have a research output that is 28% higher than the average research output of women, after controlling for the specified observables. While differences in experience and choice of field, among other observables can explain 43% of the gender difference in research output (see columns 1 and 2), there still remains a large and significant unexplained gap in research output.

Our estimates can be interpreted as a lower bound of the gender difference, as both random effects and pooled OLS indicate a larger gender gap in research output due to unobservable factors. Moreover, the result carries over if we measure differences in output by the number of publications or citations. For all of these measures, the differences between men and women remain large and persistent, after controlling for various observables. This leads us to a closer

[5]We also consider a random effect model, pooled OLS and a negative binomial model, see Supplementary Appendix.

examination of other possible explanations.

3 Gender, Networks & Output

A large and distinguished body of research argues 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 network in shaping research output, see Ductor et al. (2014)). The potential effects of different network characteristics have been theoretically studied by Lindenlaub and Prummer (2014). Building on this body of work, we focus attention on network statistics such as degree and centrality that are, on a priori grounds, more correlated with access to new scientific ideas, and we examine strength of ties and clustering due to their potential to create peer pressure and to foster trust.

We now introduce some additional network terminology. We assume that 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

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

Degree is treated as missing if the author does not have publications from $t-4$ to t.[6]

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

[6]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.

of an author is given by the average strength across all his ties $t-4$ to t, d_{it},

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

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

Betweenness: Let $\tau_{it}(jk)$ be the number of shortest paths between authors j and k that i lies on and let $\tau_t(jk)$ be the total number of shortest paths between jk at time t. Betweenness is then the frequency of shortest paths between any two individuals passing through author i, relative to all shortest paths between two agents:

$$B_{it} = \sum_{j \neq k: i \notin \{j,k\}} \frac{\tau_{it}(jk)}{\tau_t(jk)}.$$

We restrict attention to betweenness for authors who are in the giant component, the largest component in the network. We also discuss other measures of centrality such as closeness and eigenvector centralities in the Supplementary Appendix. We choose betweenness as the main centrality measure because, as shown in Ductor et al. (2014), this is the centrality measure with the largest predictive power on future output.

We start by studying the correlation between current network characteristics, measured between $t-5$ to $t-1$, and future research output, as defined in section 2.1, using publications from t to $t+4$. Table 4 presents the results of a random effect model estimating the effect of the network characteristic on future output, controlling for past research output (from $t-5$ to $t-1$), proportion of papers published in each JEL code, career time fixed effects and year fixed effects.[7]

In line with the work of Ductor et al. (2014) we find that degree and betweenness are positively correlated while clustering and strength are negatively correlated with research output. These correlations are consistent with the theoretical predictions of Lindenlaub and Prummer (2014). They show that a lose network is particularly valuable in a setting with high uncertainty- such as Academia. As lose networks provide better information, agents can fine-tune their effort and this is more important under greater uncertainty than peer pressure.

Equipped with these findings, we turn to a study of gender differences in network structure. Figure 3 provides the unconditional differences in average networks characteristics between men and women. The upper plots present network characteristics for measures that are more corre-

[7] We do not use the correlated random effect model because is not appropriate for forecasting purposes.

lated with access to new ideas: degree and betweenness. The lower plots show network measures that are more correlated with peer pressure: clustering and strength. It is clear that women have lower degree and centrality and higher clustering and strength than men. As in the case of research output, the disparities in network characteristics too are large and persistent.

We then examine if these differences hold 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.

We use a correlated random effect model. The model estimated is:

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

where $\alpha_i = \phi + a_i + \varphi \bar{y}_i + \sum_{l=1}^{L} \gamma_l \overline{JEL}_{lit}$.

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

Table 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 0.30 more collaborators than women; this is 16% of the average degree.[8]

[8] 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.

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

   Women's clustering coefficient is 0.07 standard deviations higher than men's: this is roughly 5.7% of the average clustering. 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 0.14 standard deviation higher than male authors controlling for observable factors; this is 6.9% of the average strength.

4. *Women have a lower betweenness than men.*

   Women have a betweenness centrality that is 0.06 standard deviations lower than men controlling for observable factors and degree; this is 6% of the average centrality. As expected, the association between degree and betweenness is strong and positive.

We next perform various robustness checks. First, we use alternative models, pooled OLS and random effects. Second, we consider three and ten-year network variables. Third, we focus on a fixed set of journals, those available in the EconLit for the entire sample period, 1970-2011. All our results are qualitatively similar and quantitatively larger and are presented in the Supplementary Appendix.

Finally, adding interaction terms between female and year dummies to our baseline regression presented in (2) allows us to examine how gender network difference vary across time. Figure 4 presents the coefficients and 95% confidence interval of these interaction terms. All the estimates are relative to the base year 1979. Remarkably, the network differences are *persistent* despite the increase in the share of women over time. The average gender difference in degree conditional on observable factors has even increased by 0.20 from 1979 to 2011. The only network difference that has declined over time is the conditional average gender difference in betweenness centrality, which has significantly decreased by 0.36 from 1979 to 2011, but nevertheless persists.[9]

We have established that networks are correlated with output and that network differences across gender are large and persistent. We now analyze the association between gender differences in future output and gender differences in networks. For this purpose, we regress future research output, as defined in section 2.1, using publications from t to $t+4$, on past research output (from $t-5$ to $t-1$), proportion of papers published in each JEL codes (from $t-5$ to $t-1$), career

[9]The p-values of F-tests on the joint significance of all the interaction terms are: 0.02 in the degree model and 0.04 in the betweenness model.

time dummies, year dummies and a female dummy; we call this model the baseline model. We then compare the female coefficients between the baseline model and a regression that adds a network variable to the baseline model. The results presented in columns 1 and 2 of Table 6 show that the female coefficient declines by 0.145 (1.936-1.791), which is a 7.5% fall in the gender future output gap, when we add degree to the future output model. This result is in line with the findings in Azoulay et al. (2010), who document a 5-8% drop in a author's research output if his/her superstar co-author suddenly died. Comparing the female coefficients between columns 3 and 4 we find that the female coefficient declines by 8.41% (2.070-1.896) when we add strength to the baseline model. This decline is 4.25% (2.234-2.139) when we add clustering to the baseline model (compare the female coefficients between columns 5 and 6) and 7.27% (2.876-2.667) when we control for betweenness (compare the female coefficients between columns 7 and 8).[10] These results show that networks help to explain variation in future output differences across gender over and above past output. Note that the drop in the coefficient we observe is a lower bound on the importance of network characteristics. Network structure may affect how successful a first paper will be published and thus affects output in research first years. This in turn influences output in later years. Therefore, the fact that past output is a strong predictor of current output may be partially attributed to network structure.

These findings motivate an investigation into the origin of network differences.

4 Drivers of Collaboration

We discuss three potential explanations of network differences in turn, namely, (i) homophily, that is the preference to work with gender-identical co-authors, (ii) discrimination, where we distinguish between taste-based and statistical discrimination and last, (iii) family engagements, which differ for men and women. We argue that neither of these explanations can help understand the differences in network structure. We then turn to disparities in risk taking, which may be caused by differences in risk aversion or environmental factors (such as women facing a more adverse environment).

[10] We add all the network variables simultaneously in the Supplementary Appendix, the results show that the female coefficient decreases by 10.04% (2.818-2.535) once we account for differences in networks. For robustness, we also provide in the supplementary appendix results from a Oaxaca-Blinder decomposition of future research output. We use that framework to test if the differences between the coefficients of the network model relative to the baseline model are statistically significant. The results show that the decrease in the gender coefficient is indeed significant.

4.1 Homophily

We have established that female economists have fewer distinct co-authors than their male colleagues; this is true even once we control for past output and a variety of other factors. We explore the role of 'homophily' in explaining this difference in degree. Homophily means that individuals prefer to form links with others of their own type (McPherson, Smith-Lovin, and Cook (2001)). In our setting, homophily implies that men prefer male co-authors, whereas women prefer female collaborators.

As a first step, we present aggregate data on same gender co-authorship. 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 $H_f > w_f$. Table 7 presents the percentage of links within gender for the sample period, 1974-2011. On average, 81% of men's collaborations are with other men: this is higher than the fraction of men in the population 72%. Similarly, women exhibit relative homophily as their collaboration with other women, 33% is larger than the fraction of women in the population (27%). Therefore, women and men tend to collaborate with authors of the same gender over and above the relative size of their gender group.

Following Coleman (1958), we define another measure of homophily, *inbreeding homophily*. Inbreeding homophily compares the proportion of collaborations with the same gender with the fraction of this gender in the sample and normalizes this 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 5 shows that on average there is inbreeding homophily for both men and women.

Since both men and women display significant relative and inbreeding homophily, we perform a closer examination of the role of homophily in explaining the observed difference in degree between men and women.

As a guide, we use the model of Currarini et al. (2009) that studies the role of homophily in shaping the number of connections. In their setting, both men and women prefer to form ties to their own type and there are costs to waiting to match, which induces each agent to accept everyone he/she meets. So, an individual of a more prevalent type will meet more people of his/her own type than someone of a less common type in the population. Therefore, an agent of the common type will spend more time on matching, as he gains higher utility from new connections which are of the same type. This generates a positive correlation between the relative size of a group in the population and its (average) degree. As the fraction of men has consistently been larger than that of women this could explain the difference in degree observed in the data. We test their prediction in our data.

First, we exploit variation in gender shares across time. From Figure 1 we know that women became more representative in the profession over time. Currarini et al. (2009) predict that gender differences in degree decrease as we move across cohorts, i.e. as the share of women increases. To investigate this possibility, 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 network model. Figure 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. Contrary to Currarini et al. (2009)' s prediction, we find that the gender difference in degree is even increasing for the most recent cohort of economists: women who published their first article in 1974 (1974 cohort) have 0.14 fewer co-authors than men, while women of the 2005 cohort have 0.54 fewer co-authors than men.[11]

Second, we exploit variation in gender shares across fields. Here we use the first two digits of the JEL codes, to define 124 different fields.[12] In Figure 7, we observe that the relationship between degree and relative group size is weak. Regressing average degree per field on the relative group size per field we obtain a slope coefficient of 0.057, which is significant at the 0.1% level. The effect is quantitatively negligible, though. In particular, a 10% point increase in relative group size would lead to an increase in degree by 0.0057, which is 1.3% of the degree difference in the 2000s.[13]

So, despite the homophily observed in the data, the relationship between degree and gender shares is weak. We conclude that homophily is not a key driver of gender difference in degree in our setting.

[11] The p-value of an F-test on the joint significance of the coefficients of the interaction terms of gender and time is 0.01 suggesting that the observed increase in degree over recent cohorts is jointly significant.

[12] We de-trend degree by regressing degree on time dummies, the residual from this regression is the de-trended degree. The results are robust to other de-trending methods.

[13] We also check if there is any relationship between degree and group share when we exclude the male authors group sizes from the sample. We find that the link between degree and group size becomes negative. Regressing the de-trended degree on relative group size excluding males, we obtain: $\widehat{d_l^{det}} = -.013 - .044 w_l$, both coefficients statistically significant at the 1% level. This is quantitatively insignificant. The corresponding figure is available in the Supplementary Appendix.

4.2 Discrimination

Female economists with the same ambitions and ability as men may have less opportunities to collaborate with others because of the prejudices and stereotypes that society and, more specifically, economists have about women.[14] These prejudices may form the basis for discrimination: women might be less desirable as co-authors than men.

To assess the role of discrimination in generating the observed network patterns, we distinguish between taste-based and statistical discrimination.

Taste-Based Discrimination: We examine the hypothesis of taste-based discrimination: economists, both male and female, prefer to work with men rather than women (Becker (1957)). In the presence of taste-based discrimination, an economist would work with a female colleague only if there is evidence that she has higher productivity. This leads us to examine the role of past output: we interpret the tase-based discrimination hypothesis as implying that past research output of female co-authors should be higher than that of male co-authors. Figure 8 presents the 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. This is inconsistent with taste-based discrimination.[15]

We now turn to a slightly different aspect of taste-based discrimination: it may still be the case that women are less supported by senior colleagues, who might prefer working with junior men. If this is the case, then we would expect women to co-author more with junior co-authors. Figure 9 presents the average co-authors' experience by gender across career time. It reveals 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 statistically significant at the 5% for every year of career time (except for authors with over 17 years of experience).

Finally, we examine a more direct implication of taste-based discrimination: if this were a major factor then, other things being equal, we would expect women to co-author less than men. The empirical pattern is exactly the opposite: column 1 of Table 5 shows that, between 1970-2011, the fraction of co-authored work is 1.2% points higher for women as compared to men.

[14] As an instance of this, in a recent paper, Reuben, Sapienza, and Zingales (2014) show that women are less likely to be hired (for mathematical tasks), even after controlling for past performance.

[15] Our prediction relies on the assumption that working with more productive women leads to better outcomes in terms of quality and impact. However, it might be the case that articles written jointly with women are published better and cited more even if women generate less output per se. Figure 11 shows 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. Thus, the fact that women find male co-authors despite the lower return from working with them does not support taste-based discrimination.

Statistical Discrimination: We next take up the issue of information-based (statistical) discrimination. Authors who have limited information about the skills and ability of a potential co-author may use observable characteristics such as gender to infer expected ability. This may disadvantage female economists, potentially due to stereotypes, but also because women tend to generate less research output. Therefore, the prior beliefs about the capabilities of women may be below those of men. To test this theory, we conduct the following thought experiment: we focus on highly productive economists and ask if there are network differences across gender. Our idea here is that top female economists are more known to other academics in the profession, compared to their less productive female colleagues. So if statistical discrimination were a major factor then network differences would be smaller between top male and female economists as compared to average economists. To identify the importance of statistical discrimination in explaining gender difference in networks, 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 defined 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 are for 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 difference 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.[16] Then, higher output mechanically leads to 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 1.112 (95% CI: 1.103-1.122), 1.173 (95% CI: 1.151-1.200), 1.233 (95% CI: 1.193-1.278), 1.089 (95% CI: 1.001-1.212), and 1.225 (95% CI: 1.034-1.707) 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

[16]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.

is also increasing for tier groups 50-80th and 80-95th. Taken together, these findings show that statistical discrimination is not a dominant driver of the network differences across gender.

We therefore conclude that there is little evidence in favor of statistical or taste-based discrimination.

4.3 Family engagements

We turn next to the role of child bearing in explaining network differences. In recent research, it has been shown that male professors with children younger than two years old invest less in child-rearing than female professors (Rhoads and Rhoads (2012)) and that motherhood before the age of 30 has a detrimental effect on women's productivity (Krapf, Ursprung, and Zimmermann, 2017).

Unfortunately, we do not have information about marriage status and the presence of children to directly analyze whether family engagements impact the gender differences in output and networks. To provide circumstantial evidence about the role of having children in explaining the networks differences across gender we examine if these differences vary along the career of an author. For that purpose, we add interaction terms between career time dummies and the female dummy to the network model defined in equation 2. We expect that if child rearing is an important factor then the differences in networks should vary along the career of an author, increasing in periods where women are more likely to have children, first ten years, and decreasing as the children matures in later stages of the author's career. Figure 10 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 network differences on betweenness, clustering and strength are stable along the career of authors, while the difference in degree increases during the first nine years of the career of an author.[17] This is inconsistent with child-rearing and family engagements being the main drivers of the gender differences in networks.

4.4 Risk Taking

We now turn to differences in risk taking as a possible explanation for the observed differences in co-authorship between men and women.

Section 2 showed that men have on average a higher research output, more publications and their papers receive a higher number of citations compared to women. We analyze now if women

[17] 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 has not changed across cohorts.

choose less risky projects by studying the dispersion of research output and citation distributions, respectively. The standard deviation of research output and citations is significantly lower for women: it is 17.96 for women whereas it is 27.07 for men. In terms of citation, women's standard deviation is less than half of that of men. Table 9 and 12 in the Appendix present the distribution of research output and citations. These results provide circumstantial evidence that women are less likely to choose risky projects, which results in a narrower distribution of the quality of their publications. At the same time, men who are more willing to take on risky projects, need to be compensated for the risk they bear. Thus, it must be that the expected payoff of the risky option outweighs the benefit from the safe option, in line with the evidence. This finding suggests that men and women differ in terms of their project choices.

Equipped with these findings we now turn to the implications of differential risk-taking on patterns of collaboration.

An individual's choices reflect their preferences and the rewards from different actions. So differences in risk taking may be due to disparities in risk aversion or they may be due to different choice and reward opportunities. We now elaborate on these two routes for differential risk taking.

We begin with differences in risk preferences. There is a wide ranging literature on differences in risk aversion between men and women, for a survey see Croson and Gneezy (2009) and Charness and Gneezy (2012). Researchers in sociology and psychology have explored differences in risk aversion between men and women across a wider range of domains, for overviews see Eckel and Grossman (2008) and Weber, Blais, and Betz (2002).

We now turn to differences in environment. We have ruled out gender homophily and discrimination against women in terms of co-authorship, but there are other channels for institutional biases that may lead to women receiving different rewards as compared to men (Ginther and Kahn (2004)). For instance, Sarsons (2015) presents evidence that female economists receive less credit for work done jointly with co-authors, Wu (2017) highlights misogyny on the Econ Job Market Rumours web-site, while Hengel (2016) shows that female authors face a longer review time in journals. In a similar spirit, and Mengel et al. (2017) shows that female economists obtain on average lower teaching evaluations. These pieces of evidence suggest that women may face a different – more challenging and possibly more uncertain – environment as compared to men.[18] If their expected rewards differ from those of men, due to discrimination in the publish-

[18]It is known that beliefs and perceptions about the riskiness of a project affect the willingness to take on risk (Weber et al. (2002), Harris, Jenkins, and Glaser (2006)). Additionally, familiarity and enjoyment of an activity affect how much risk taking is displayed (Loewenstein, Weber, Hsee, and Welch (2001), Slovic, Fischhoff, and Lichtenstein (2000)). In this respect, a more adverse environment may shape individual's risk taking by changing their beliefs.

ing process, then it may be beneficial to choose a different collaboration strategy and to select different, potentially less risky projects. Thus even if women had similar risk preferences as men, women might find it optimal to choose a different strategy in collaboration as compared to men, as an insurance against perceived and actual discrimination.

4.4.1 Collaboration Strategy and Output

We now examine the implications of differences in risk taking — which may be due to innate differences in risk aversion or due to an adverse environment — for patterns of collaboration. We distinguish between gender as well as seniority, as junior and senior economists may differ in their motivations and opportunities for collaboration. We assume further that every author has a fixed time budget he/she can allocate to different projects. Every author can pursue (i) a project on his/her own, (ii) a project jointly with another junior or (iii) a project with a senior co-author.

Women write fewer single-authored papers: We take the view that a single authored paper is a more risky undertaking compared to a co-authored paper. The benefits of a successful single-authored publication may outweigh those of a co-authored one, but a single-authored project has a greater potential to fail. Therefore, other things being equal, a more risk averse author is more likely to collaborate than to work alone. Similarly, if women face greater adversity when writing on their own, we would expect women to co-author more. Sarsons (2015) documents that women are less likely to present a single authored paper compared to a co-authored paper. This finding indicates that a solo work receives less attention, which may make it harder to publish.

Additionally, Sarsons (2015) has shown that women receive less credit from co-authoring with men, which would go against co-authorship. However, in the survey she conducts, she also asks whether individuals are aware of women receiving less credit for co-authored projects and this is *not* the case. Taking these considerations together, we would expect women to write fewer single-authored papers. This is consistent with our evidence.

Women collaborate more with seniors, at every stage of their career: We now turn to gender differences in seniority of co-authors. For simplicity, assume that each author can decide to enter a matching pool, either with juniors or seniors. Upon entering a matching pool, an author is randomly matched to a collaborator. If he/she undertakes a project with a junior, then this is more risky than collaborating with a senior. A senior-co-author with more experience is likely to have a better sense of whether the idea is promising and how to best approach the work. However, there is a potential downside of working with a senior co-author: a junior may receive less credit from the collaboration, even if the project is successful. So there is a potential tradeoff: working with a senior coauthor brings a more assured but possibly a lower reward. A related consideration is that there is more information available on a senior academic: in other words there is less uncertainty on ability and working ethos. This may be more appealing to someone who is less inclined to take risks. Putting together these two observations we predict that women are more likely to choose senior co-authors. This is consistent with the evidence.

Women display a lower degree, higher clustering and higher strength: Consider an author who is looking to start a new project: he or she can (i) continue to work with current co-authors, (ii) team up with unknown new co-authors chosen at 'random' or (iii) rely on their current co-authors to find new co-authors. There is likely to be less uncertainty about the co-author of a current co-author as compared to someone who is not known to any of their current co-authors. So lower risk taking would be associated with preferring options (i) and (iii) over option (ii). If women take less risk than they should have a lower degree and higher strength and higher clustering. This is exactly what we find in the data.

5 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 less risky choices with regard to collaboration. The differences in risk taking may be due to differences in risk preferences and in the environment men and women face.

In recent years, professional bodies have begun to take steps to facilitate changes to make the economics profession more welcoming to women, e.g. the American Economic Association forum to take steps against the misogyny on Econ Job Rumours, and debates about providing child care at conferences and mentor programs for women.[20] Our work suggests that creating a fairer environment in which men and women face similar constraints, and where women also *perceive* these constraints to be the same, is an important challenge for economics.

[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.

[20] See https://www.aeaweb.org/news/statement-of-the-aea-executive-committee-oct-20-2017 and https://www.eeassoc.org/index.php?site=&page=192&trsz=206.

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

Year	(1) Journals	(2) Articles	(3) Women	(4) Men
1971-1975	252	24292	1293	14530
1976-1980	276	31643	2378	20411
1981-1985	351	39363	3646	25219
1986-1990	382	45536	4907	28884
1991-1995	586	59400	7797	36610
1996-2000	803	84354	13616	49439
2001-2005	1017	103974	20147	59619
2006-2010	1260	138727	30702	74049
1970-2011	1627	557290	59661	161390

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.

Figure 1: Participation of Women: 1970-2010

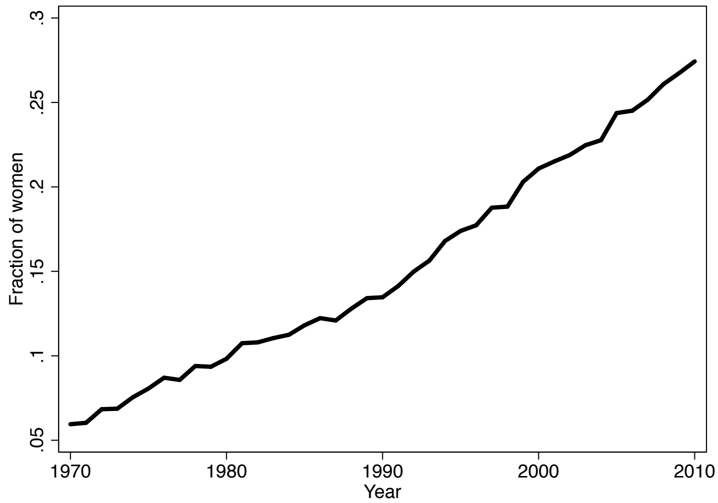


Table 2: Research output across time

Year/Gender:	(1) Women	(2) Men	(3) % difference
1971-1975	15.25	28.57	87%
1976-1980	8.69	18.94	118%
1981-1985	6.98	13.24	90%
1986-1990	7.35	11.20	52%
1991-1995	6.62	9.59	45%
1996-2000	5.27	8.21	56%
2001-2005	4.54	7.63	68%
2006-2010	6.20	9.55	54%
1970-2011	5.82	10.72	84%

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

Figure 2: Research output by gender over time

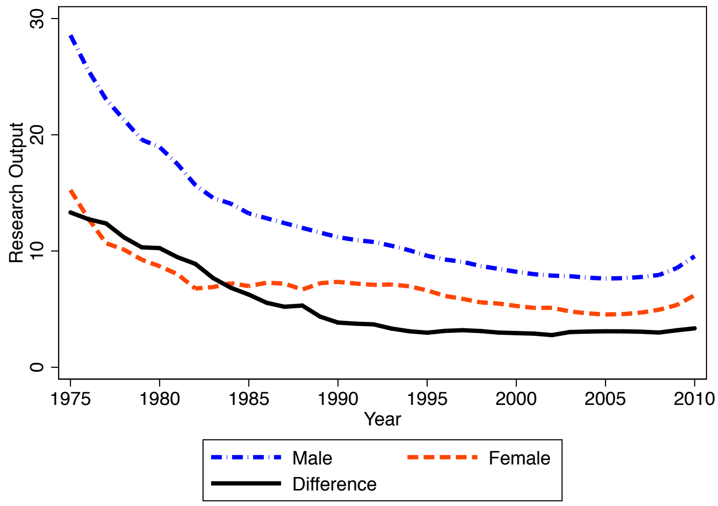


Table 3: Gender Differences in Performance

VARIABLES	(1) Output	(2) Output	(3) # Papers	(4) Citations
Female	-2.792***	-1.580***	-0.399***	-2.492***
	(0.150)	(0.145)	(0.021)	(0.445)
Observations	625,518	625,518	625,518	457,074
Number of authors	62,961	62,961	62,961	62,961
Career-time FE	NO	YES	YES	YES
Year FE	NO	YES	YES	YES
JEL codes FE	NO	YES	YES	YES

Results estimated using correlated random effect models. Column 1 presents the gender difference in research output without control factors; column 2 presents the gender difference in research output controlling for observable factors; column 3 presents the gender difference in total number of publications; column 4 shows gender differences in the number of citations. Clustered standard errors by authors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Output and Networks

	Dependent Variable: Future Output				
VARIABLES	(1)	(2)	(3)	(4)	(5)
Degree_{t-1}	0.439***				0.030
	(0.049)				(0.090)
Strength_{t-1}		-3.621***			-5.550***
		(0.317)			(0.966)
Clustering_{t-1}			-0.038***		-0.001
			(0.005)		(0.016)
Betweenness_{t-1}				0.047***	0.011
				(0.006)	(0.017)
$\text{Recent Output}_{t-1}$	0.331***	0.343***	0.358***	0.380***	0.376***
	(0.010)	(0.011)	(0.011)	(0.011)	(0.012)
Constant	7.018***	11.185***	9.227***	12.476**	15.248**
	(1.377)	(2.198)	(3.278)	(5.756)	(6.646)
Observations	255,616	200,732	138,969	116,018	98,054
Number of authors	34,312	28,883	22,170	19,867	17,277
Career-time FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
JEL codes shares	YES	YES	YES	YES	YES

Results estimated using random effect models. The dependent variable, future output, is accumulated output from t to $t + 4$. Clustering is undefined for sole authors and authors with only one co-author; strength is undefined for periods without co-authored publications; betweenness is only defined for authors in the giant component. Clustered standard errors at the author level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Figure 3: Networks over time

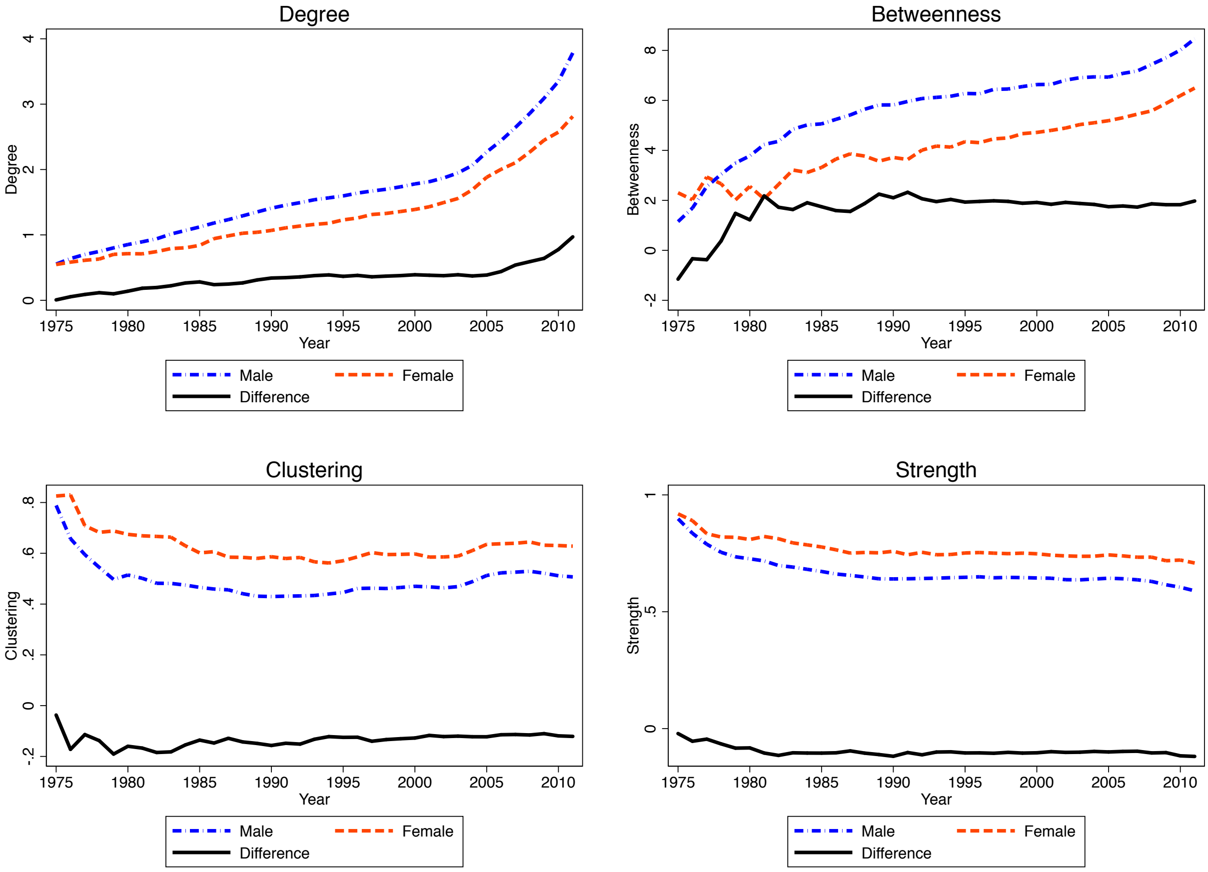


Table 5: Gender and Collaboration

VARIABLES	(1) Co-authorship	(2) Degree	(3) Strength	(4) Clustering	(5) Betweenness
Female	0.013***	-0.295***	0.142***	0.068***	-0.064***
	(0.004)	(0.022)	(0.009)	(0.010)	(0.009)
Degree				-0.207***	0.372***
				(0.005)	(0.008)
Past output$_{t-5}$	0.0001***	0.001***	0.0784***	0.0196***	-0.0356***
	(0.0000)	(0.0004)	(0.0055)	(0.0046)	(0.0051)
Avg. Past output	0.0000	0.0106***	-0.3324***	-0.1324***	0.1147***
	(0.0000)	(0.0004)	(0.0116)	(0.0071)	(0.0064)
Observations	394,113	394,113	316,145	226,078	191,784
Number of authors	56,949	56,949	48,936	38,757	33,121
Career-time FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
JEL codes shares	YES	YES	YES	YES	YES

All the results are obtained using the correlated random effect model. Column 1 presents the results of co-authorship defined as the fraction of co-authored articles. Columns 2, 3, 4 and 5 show the results from estimating gender differences in degree, strength, clustering and betweenness, respectively. All the continuous variables in the models estimated in columns 3, 4 and 5 are standardized. Betweenness is in $log(B_{it}+1)$. Clustered standard errors at the author level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Gender, Networks and Future Output

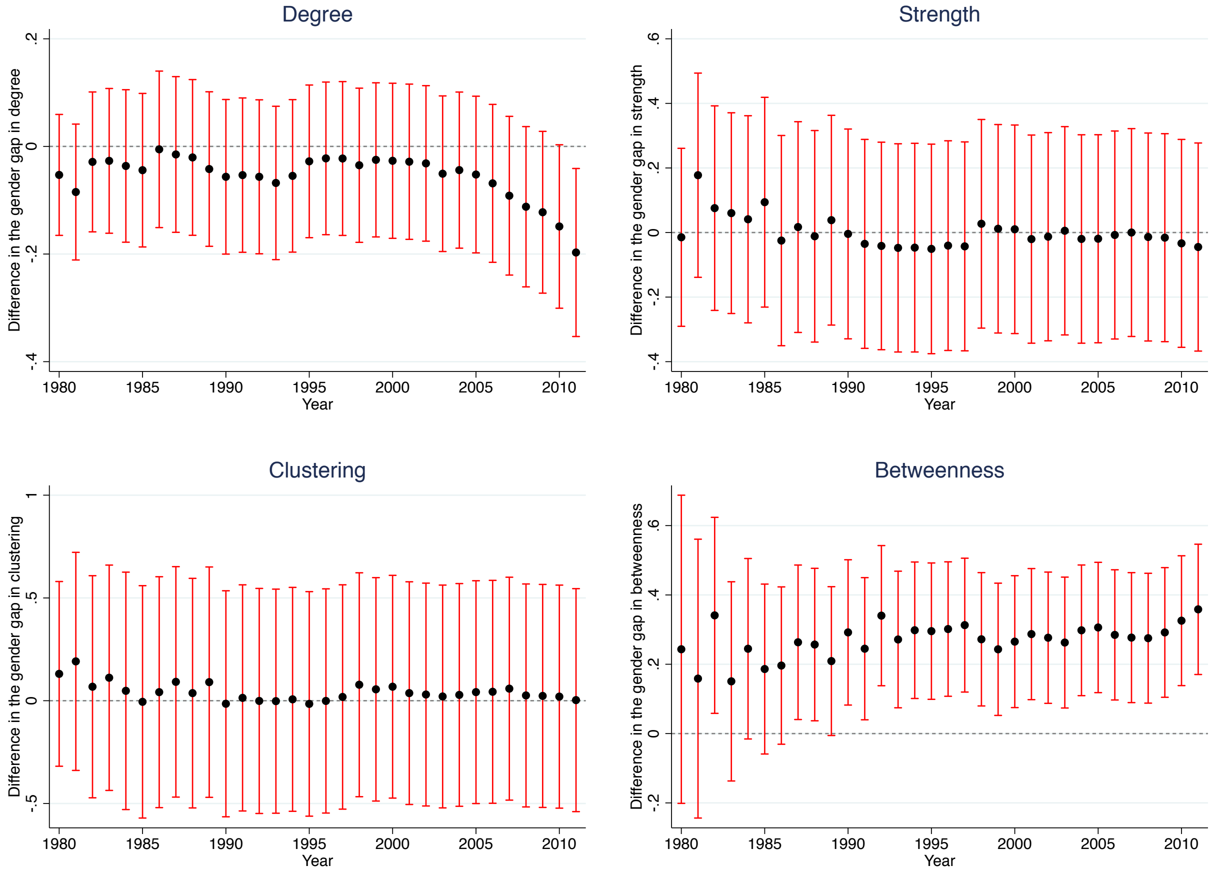
	Dependent Variable: Future Output							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-1.936***	-1.791***	-2.070***	-1.896***	-2.234***	-2.139***	-2.876***	-2.667***
	(0.239)	(0.236)	(0.280)	(0.278)	(0.373)	(0.372)	(0.427)	(0.426)
Degree_{t-1}		0.431***						
		(0.055)						
Strength_{t-1}				-3.659***				
				(0.356)				
Clustering_{t-1}						-2.241***		
						(0.293)		
Betweenness_{t-1}								0.214***
								(0.024)
Recent Output_{t-1}	0.342***	0.335***	0.356***	0.346***	0.360***	0.356***	0.388***	0.382***
	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Observations	216,416	216,416	170,187	170,187	117,944	117,944	98,543	98,543
Number of Authors	28,448	28,448	23,949	23,949	18,418	18,418	16,554	16,554
Career-time FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
JEL codes shares	YES	YES	YES	YES	YES	YES	YES	YES

Results estimated using random effect models. The dependent variable, future output, is accumulated output from t to $t+4$. The centrality measure betweenness at $t-1$ is in $log(B_{it}+1)$. Clustering is undefined for sole authors and authors with only one co-author; strength is undefined for periods without co-authored publications; betweenness is only defined for authors in the giant component. Clustered standard errors at the author level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7: 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

Figure 4: 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 correlated random effects, the base year is 1979. The gender gaps in degree, strength, clustering and betweenness in the base year 1979 are -0.04, 0.16, 0.07 and -0.44, respectively. The p-values of F-tests on the joint significant of all the interaction terms are: 0.02 in the degree model; 0.34 in the strength model; 0.42 in the clustering model; and 0.04 in the betweenness model.

Figure 5: Inbreeding Homophily Across Time

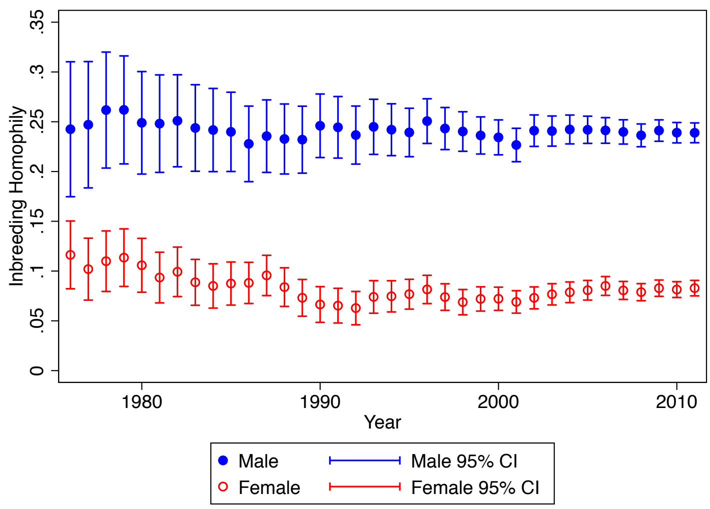
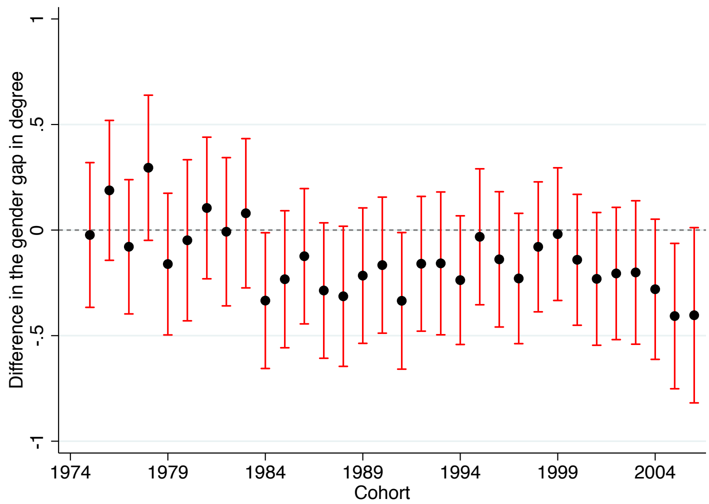
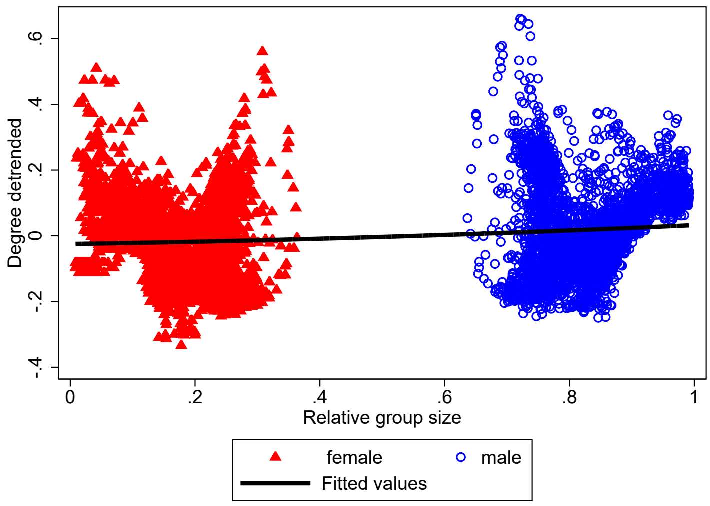


Figure 6: Gender differences in degree across cohorts



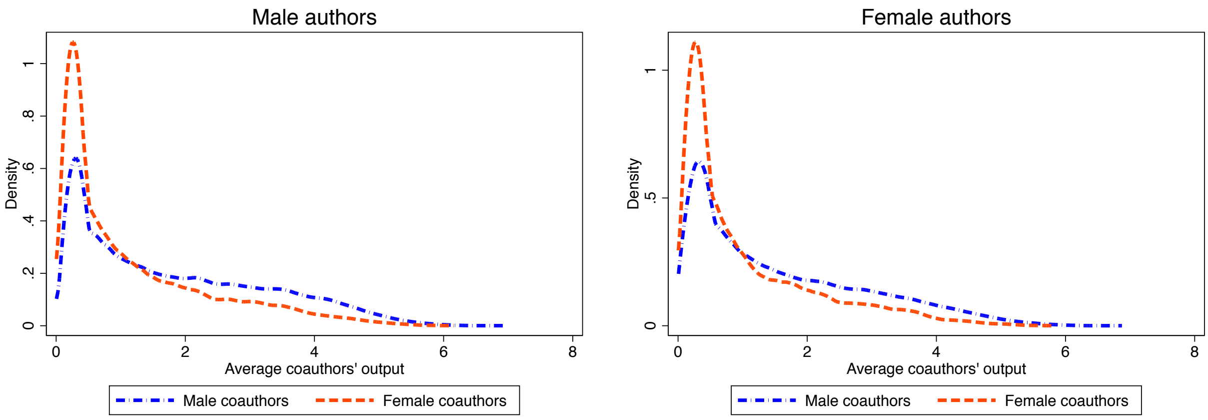
Note: The plot shows the coefficients and 95% confidence intervals of the interaction terms between cohort dummies and the female dummy of a degree model estimated using correlated random effects. All the estimates are relative to the base cohort 1974. The degree gender gap in the base cohort is -0.14. The p-value of a F-test on the joint significant of all the interaction terms is 0.01. Standard errors are clustered at author level.

Figure 7: Degree and fraction of women across fields



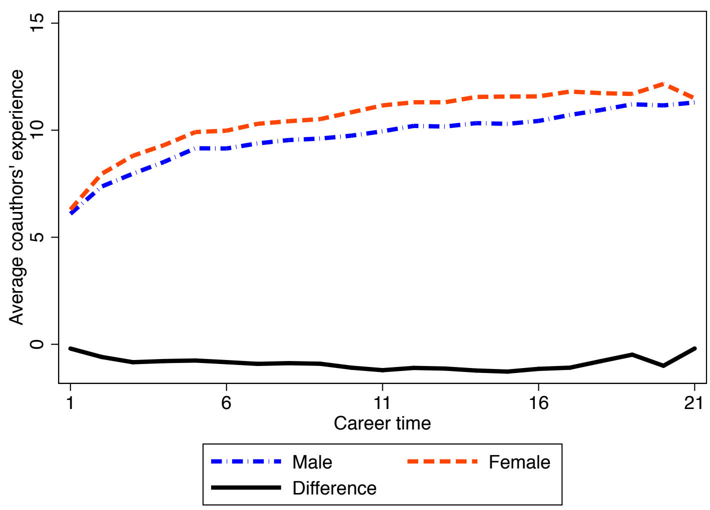
Note: De-trended degree is the residual of a linear regression of degree on year dummies. Regressing the de-trended degree on relative group size, we obtain: $\widehat{d_l^{det}} = -.028 + 0.057w_l$, both coefficients are statistically significant at the 1% level.

Figure 8: Distribution of co-authors' output 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. Average co-authors' output is the total research output produced by all the co-authors from $t-4$ to t divided by the number of co-authors. The average co-authors' output is in log plus one, $log(x+1)$. The dash-dot line shows the average co-authors' output of male co-authors. The dash line presents the average co-authors' output of female co-authors.

Figure 9: Average co-authors' experience by gender



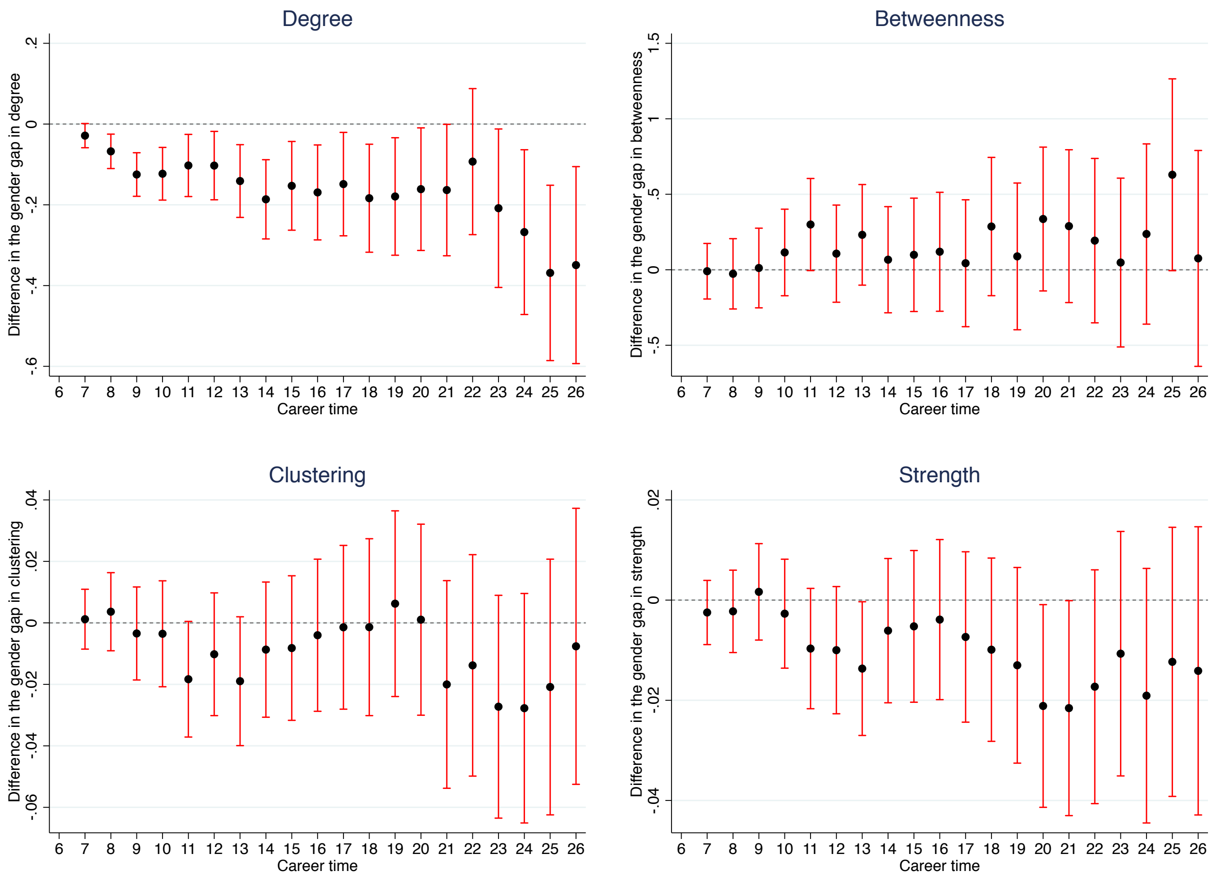
Note: Coauthors productivity by gender is obtained using all the articles published in the EconLit from 1974 to 2011 where the gender of at least one author is identified. The gender difference is statistically significant except for authors with more than 17 years of career time.

Table 8: Network Differences Across Output Levels

VARIABLES	Degree	Strength	Clustering	Betweenness
Female	-0.209***	0.133***	0.100***	-0.131***
	(0.024)	(0.012)	(0.015)	(0.016)
(Dummy 50th-80th)*female	-0.163***	0.017	-0.004	-0.023
	(0.024)	(0.018)	(0.023)	(0.022)
(Dummy 80th-95th)*female	-0.354***	0.053**	-0.008	-0.012
	(0.087)	(0.026)	(0.031)	(0.030)
(Dummy 95th-99th)*female	-0.049	-0.022	0.059	-0.003
	(0.246)	(0.050)	(0.058)	(0.055)
(Dummy >99th)*female	-0.303	-0.045	0.084	0.036
	(0.457)	(0.097)	(0.096)	(0.111)
Past output$_{t-5}$	0.001*	0.058***	-0.002	-0.018***
	(0.0008)	(0.006)	(0.005)	(0.007)
Avg. past output	0.008***	-0.339***	-0.157***	0.170***
	(0.0004)	(0.012)	(0.007)	(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 correlated random effect 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

Figure 10: 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 correlated random effects, the base career time age is 6. The gender gaps in degree, strength, clustering and betweenness in the base career time age are -0.20, 0.05, 0.05 and -0.95, respectively. The p-values of F-tests on the joint significant of all the interaction terms are: 0.00 in the degree model; 0.12 in the strength model; 0.89 in the clustering model; and 0.08 in the betweenness model. Authors with less than six years of experience are excluded from the sample since past output is not defined.

References

Adda, J., C. Dustmann, and K. Stevens (2011). The Career Costs of Children.

Albanesi, S. and C. Olivetti (2009, January). Production, Market Production and the Gender Wage Gap: Incentives and Expectations. *Review of Economic Dynamics 12*(1), 80–107.

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.

Azoulay, P., J. S. Graff Zivin, and J. Wang (2010). Superstar extinction. *The Quarterly Journal of Economics 125*(2), 549–589.

Bala, V. and S. Goyal (2000). A noncooperative model of network formation. *Econometrica 68*(5), 1181–1229.

Becker, G. (1957). The economics of discrimination. chicago: Univ.

Bertrand, M. (2011). *New Perspectives on Gender*, Volume 4 of *Handbook of Labor Economics*, Chapter 17, pp. 1543–1590. Elsevier.

Bertrand, M., C. Goldin, and L. F. Katz (2010). Dynamics of the Gender Gap for Young Professionals in the Financial and Corporate Sectors. *American Economic Journal: Applied Economics*, 228–255.

Black, S. E. and P. E. Strahan (2001). The division of spoils: rent-sharing and discrimination in a regulated industry. *American Economic Review*, 814–831.

Blau, F. D. and L. M. Kahn (2016). The gender wage gap: Extent, trends, and explanations. Technical report, National Bureau of Economic Research.

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.

Card, D. and S. DellaVigna (2013). Nine facts about top journals in economics. *Journal of Economic Literature 51*(1), 144–161.

Card, D. and S. DellaVigna (2014). Page limits on economics articles: Evidence from two journals. *The Journal of Economic Perspectives 28*(3), 149–167.

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.

Coleman, J., E. Katz, and H. Menzel (1966). Medical innovation: A diffusion study. Bobbs-Merril Co, New York.

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

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.

Goldin, C. and C. Rouse (2000). Orchestrating impartiality: The impact of "blind" auditions on female musicians. *The American Economic Review 90*(4), 715–741.

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.

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

Harris, C. R., M. Jenkins, and D. Glaser (2006). Gender differences in risk assessment: why do women take fewer risks than men? *Judgment and Decision making 1*(1), 48.

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.

Jackson, M. O. and A. Wolinsky (1996). A strategic model of social and economic networks. *Journal of economic theory 71*(1), 44–74.

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.

Krapf, M., H. W. Ursprung, and C. Zimmermann (2017). Parenthood and productivity of highly skilled labor: evidence from the groves of academe. *Journal of Economic Behavior & Organization*.

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

Loewenstein, G. F., E. U. Weber, C. K. Hsee, and N. Welch (2001). Risk as feelings. *Psychological bulletin 127*(2), 267.

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.

Mundlak, Y. (1978). On the pooling of time series and cross section data. *Econometrica: journal of the Econometric Society*, 69–85.

Reuben, E., P. Sapienza, and L. Zingales (2014). How stereotypes impair women's careers in science. *Proceedings of the National Academy of Sciences 111*(12), 4403–4408.

Rhoads, S. E. and C. H. Rhoads (2012). Gender roles and infant/toddler care: Male and female professors on the tenure track. *Journal of Social, Evolutionary, and Cultural Psychology 6*(1), 13.

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

Slovic, P., B. Fischhoff, and S. Lichtenstein (2000). Rating the risks in: P. slovic (ed.) the perception of risk.

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.

Data Appendix

Identification of Names

The US Social Security Administration (http://www.ssa.gov/oact/babynames/) allows to identify the gender of the author from first names. We assume we can identify an author's gender if the author's first name is associated with a single gender in social security records at least 95% of the time. By this method we are able to assign gender to 238800 from 373437 authors (64%). We identify the gender of some remaining (non-US) authors using internet search engine to find out their gender through academic profiles or CVs. The final sample consist of 80% of the total number of authors.

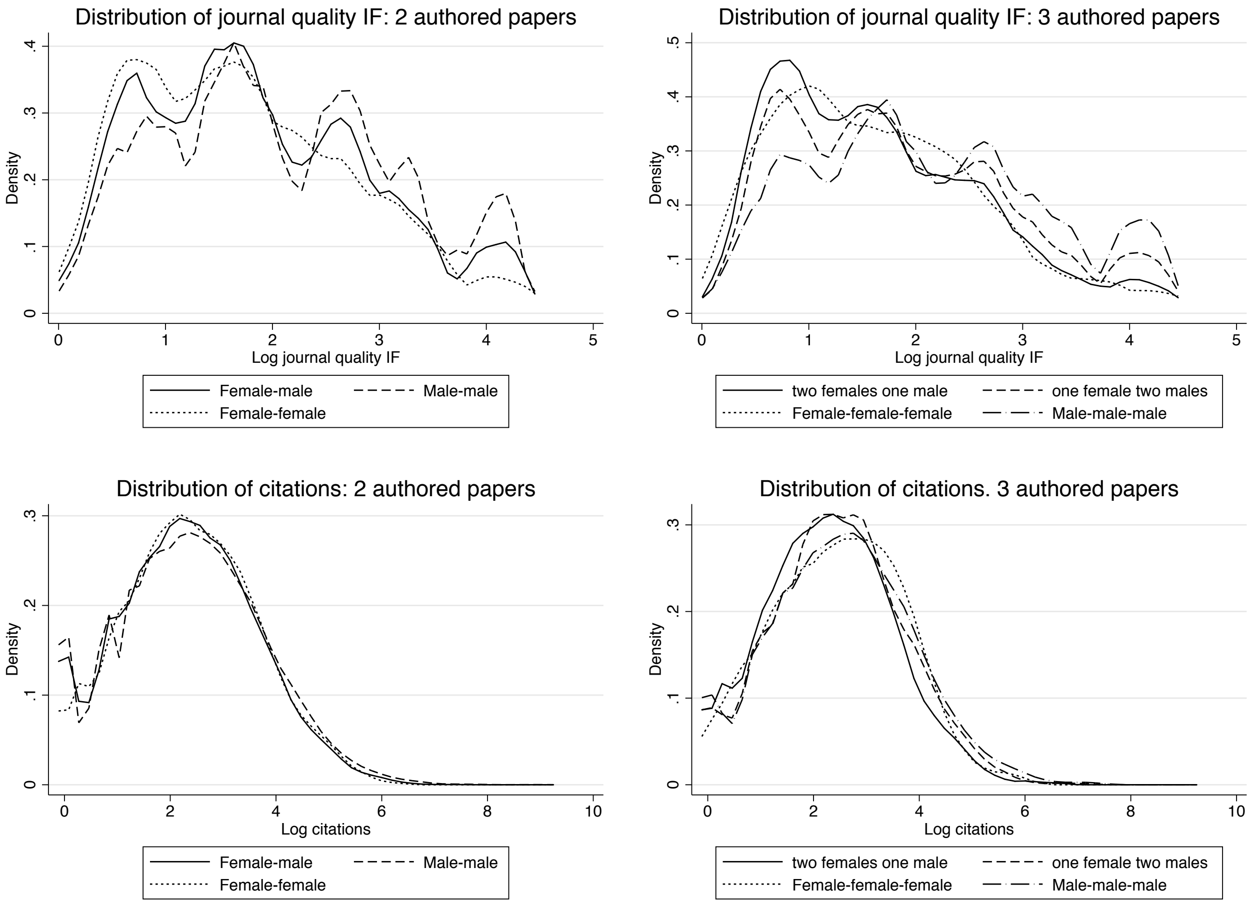
Summary Statistics

Table 9: Summary Statistics: 1970-2011

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

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

Figure 11: Distribution of articles' research quality and journal quality impact factor by gender composition and number of authors

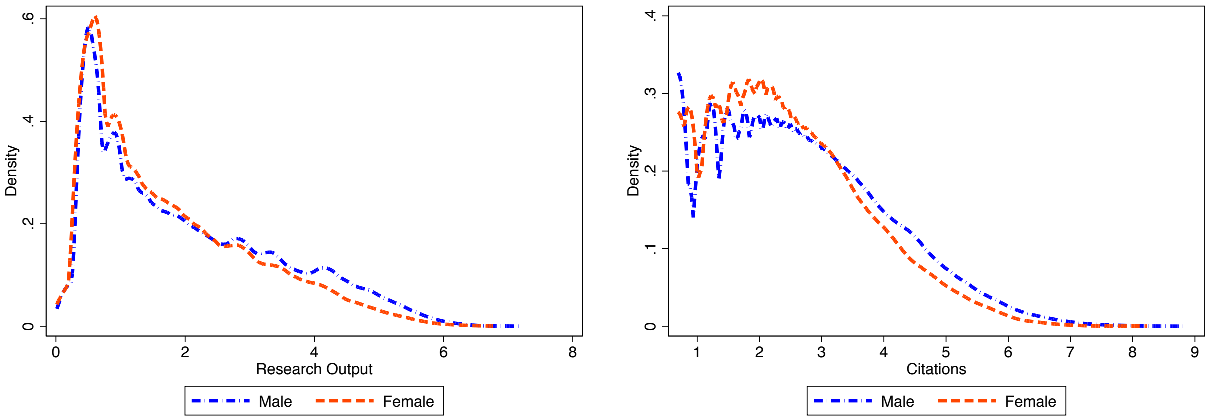


Note: Article as the unit of analysis. Journal quality impact factors and citations are in logs. Female-female are two authored articles published by two females, Male-male are two authored articles published by two males, female-male are two authored articles published by one female and one male, Female-female-female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

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 2. 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

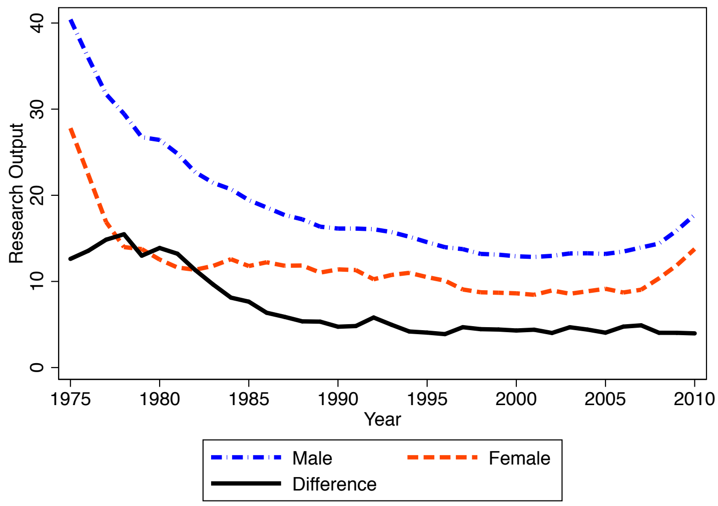
Figure 12: Distribution of academic performance by gender



Note: Research output and citations are 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%.

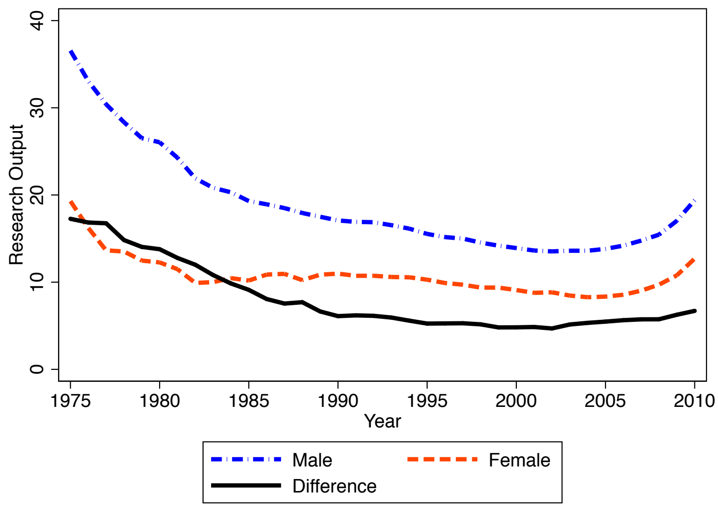
information on the number of submissions. As such figures are hard to collect systematically for our large journal sample, we use as a proxy the number of unique authors that publish in the EconLit database. Table 1 suggests that the number of submissions has increased much more than the number of published 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 Table 9 and Figure 15. Figure 13 also shows that 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, see Figure 14. These findings lead us to conclude that the fall in average research output is mainly driven by a reduction in top 5 publications and an increase in publications in lower ranked journals caused by an increase in competition.

Figure 13: Average research output over time. Journals since 1970



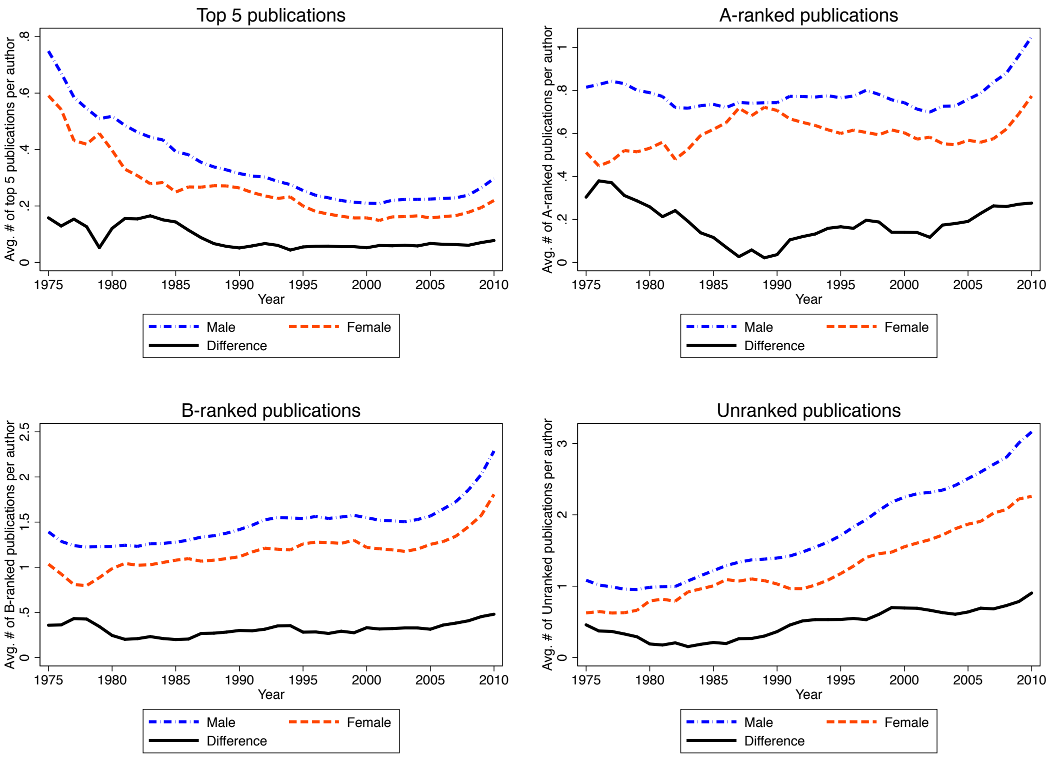
Note: The sample includes articles published in a journal available in the EconLit from 1970 to 2011: 70 journals.

Figure 14: Non-discounted average research output over time



Note: Research output is the sum of publications from $t-4$ to t weighted by journal quality. The sample includes all articles published in journals listed in the EconLit from 1970 to 2011 where the gender of at least one author is identified.

Figure 15: 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.

Gender & Collaboration: Supplementary Appendix

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Contents

1 Research Output

We show that the gender differences in research output are robust to alternative academic performance measures. Additionally, we highlight that different econometric models lead to larger gender disparities than presented in the main paper. We then restrict attention to the set of journals published throughout our entire sample period; for this sample, again, gender disparities in output persist. Moreover, we show that the gender gap in output does not only exist for the authors with highest output, but throughout the entire distribution.

1.1 Non-Discounted Output

We first 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:

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

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

Table 1: Gender Differences in Performance: Non-Discounted Output

VARIABLES	(1) CRE q_{it}^{n}	(2) CRE $log(1+q_{it}^{n})$	(3) RE q_{it}^{n}	(4) OLS q_{it}^{n}
Female	-2.779***	-0.103***	-3.792***	-3.577***
	(0.260)	(0.009)	(0.263)	(0.403)
Observations	625,518	625,518	625,518	625,518
Number of authors	62,961	62,961	62,961	62,961
Career-time FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
JEL codes FE	YES	YES	YES	YES

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

1.2 Restricted Set of Journals

We further document that gender differences in output increase if we restrict attention to journals that were published throughout the entire sample period, from 1970 to 2011, see Table 2.

Table 2: Gender Differences in Performance: Fixed Set of Journals

VARIABLES	(1) CRE Research Output	(2) CRE Research Output	(3) CRE # Papers	(4) CRE Citations
Female	-4.262***	-3.388***	-0.204***	-13.267***
	(0.491)	(0.474)	(0.028)	(2.766)
Observations	150,338	150,338	150,338	103,530
Number of authors	14,704	14,704	14,704	14,704
Career-time FE	NO	YES	YES	YES
Year FE	NO	YES	YES	YES
JEL codes	NO	YES	YES	YES

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

1.3 Alternative Econometric Models

We now show that the gender differences in research output are robust to the use of different econometric models. In Table 3 we show the gender differences in academic performance using pooled OLS and random effect models. The results from the POLS and RE are consistent with those presented in Table 3 in the main text, though as expected the gender differences are larger here.[1]

Table 3: Gender Differences in Performance: Pooled OLS

VARIABLES	(1) RE Output	(2) POLS Output	(3) RE # Papers	(4) POLS # Papers	(5) RE Citations	(6) POLS Citations
Female	-2.131***	-2.049***	-0.487***	-0.480***	-3.596***	-5.308***
	(0.146)	(0.229)	(0.022)	(0.028)	(0.441)	(0.842)
Observations	625,518	625,518	625,518	625,518	457,074	457,074
Number of authors	62,961	62,961	62,961	62,961	62,961	62,961
Career-time FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
JEL codes FE	YES	YES	YES	YES	YES	YES

Odd columns present the results of estimating a research performance variable using the random effect model. Even columns show the gender difference in a research performance variable using pooled OLS. Clustered standard errors by authors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

As a next step, we address potential concerns that the the negative effect of gender might be driven by authors with a high output, as output is quite skewed. We estimate research

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

output in $log(q_{it}+1)$ to mitigate the impact authors with high output, as in Ductor et al. (2014). The results presented in column 1 of table 4 show that women have on average a research output that is approximately 10% lower than the research output of men, that is we find suntil a substantial gap.

We now turn to number of publications and citations. These are discrete variables that do not follow normal distributions, so count data models might be more appropriate. Columns 2 and 3 of Table 4 show the incidence rate ratio (IRR) of female for number of publications and citations using a count data model, the negative binomial (NE). The results are qualitatively similar to those obtained using the CRE model. The publication and citation rates of are 17.2% and 22.9% lower for women, respectively.

Table 4: Gender Differences in Performance. Non-linear models

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

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

1.4 Quantile Regressions

As the distribution of output is strongly right-skewed, we estimate the gender gap in research output across different percentiles of the distribution using quantile regressions, see Table 5. In particular, we estimate the median output and the percentiles 75, 90 and 95. While the gender gap in output is higher at the right tail of the distribution, it also emerges at the median, establishing that our results are not driven by differences among top authors.

Table 5: Research Output and Gender: Quantile Regressions

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

The dependent variable is $log(q_{it}+1)$, output is the sum of publications in the EconLit adjusted by the journal quality and discounted by the number of authors. Past output is the accumulated output from the first publication until $t-1$. Robust standard errors. *** p<0.01, ** p<0.05, * p<0.1

2 Gender Differences in Networks

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

2.1 Alternative Econometric Models

We show that using alternative econometric models to measure the gender gap in network characteristics leads to a larger discrepancy for men and women. We document this using a pooled OLS as well as a random effect model. We also consider the negative binomial for degree, which is a discrete variable.[2] Tables 6 and 7 show the results, which highlight the robustness of our findings.

Table 6: Networks and Gender: Pooled OLS and Negative Binomial

VARIABLES	(1) POLS Co-authorship	(2) NB Degree	(3) POLS Degree	(4) POLS Strength	(5) POLS Clustering	(6) POLS Betweenness
Female	0.003	-0.158***	-0.407***	0.165***	0.066***	-0.068***
	(0.004)	(0.012)	(0.030)	(0.011)	(0.010)	(0.009)
Past Output	0.000***	0.002***	0.007***	-0.156***	-0.053***	0.037***
	(0.000)	(0.000)	(0.000)	(0.006)	(0.003)	(0.004)
Degree					-0.238***	0.379***
					(0.005)	(0.008)
Observations	394,113	394,113	394,113	316,145	226,078	191,784
Career-time FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
JEL codes FE	YES	YES	YES	YES	YES	YES

The results presented in columns 3, 4 and 5 are standardized. Column 1 presents the results of co-authorship defined as the fraction of co-authored articles. Columns 2, 3, 4 and 5 show the results from estimating gender differences in degree, strength, clustering and betweenness, respectively. Past output is the accumulated research output from the first publication until $t-5$. Clustering is only defined for authors who have a degree larger than one. Betweenness is only defined for authors who are in the giant component. Betweenness is in $log(B_{it}+1)$. Authors who have less than five years of experience are not included. The first five observations of the authors are also excluded. Clustered standard errors at the author level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

2.2 Restricted Set of Journals

If we restrict attention to the set of journals that existed throughout the entire sample period, the gender differences in networks are qualitatively unchanged, see Table 8. Only the gender

[2] We choose the correlated random effect model in the main text because it allows to relax the assumption in the pooled OLS and random effect models that the authors fixed effects are orthogonal to the time varying regressors.

Table 7: Networks and Gender: Random Effect

VARIABLES	(1) Co-authorship	(2) Degree	(3) Strength	(4) Clustering	(5) Betweenness
Female	0.011***	-0.337***	0.170***	0.087***	-0.072***
	(0.004)	(0.023)	(0.010)	(0.010)	(0.009)
Past Output	0.000***	0.003***	0.025***	-0.004	-0.002
	(0.000)	(0.000)	(0.004)	(0.004)	(0.004)
Degree				-0.209***	0.375***
				(0.005)	(0.008)
Observations	394,113	394,113	316,145	226,078	191,784
Number of authors	56,949	56,949	48,936	38,757	33,121
Career-time FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
JEL codes FE	YES	YES	YES	YES	YES

All the results are obtained using random effects. The results presented in columns 3, 4 and 5 are standardized. Column 1 presents the results of co-authorship defined as the fraction of co-authored articles. Columns 2, 3, 4 and 5 show the results from estimating gender differences in degree, strength, clustering and betweenness, respectively. Past output is the accumulated research output from the first publication until $t - 5$. Clustering is only defined for authors who have a degree larger than one. Betweenness is only defined for authors who are in the giant component. Betweenness is in $log(B_{it} + 1)$. Authors who have less than five years of experience are not included, the first five observations of the authors are also excluded. Clustered standard errors at the author level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

difference in co-authorship becomes insignificant.

Table 8: Networks and Gender: Fixed Set of Journals

VARIABLES	(1) co-authorship	(2) Degree	(3) Strength	(4) Clustering	(5) Betweenness
Female	-0.001	-0.178***	0.227***	0.113***	-0.064**
	(0.009)	(0.034)	(0.022)	(0.027)	(0.029)
Degree				-0.242***	0.404***
				(0.008)	(0.013)
Past Output	0.000	0.001			
	(0.000)	(0.000)			
Average Past Output			0.023***	-0.039***	0.014
			(0.006)	(0.010)	(0.011)
Observations	88,826	88,826	76,949	42,004	16,466
Number of authors	13,430	13,430	11,866	8,018	4,136
Career-time FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
JEL codes FE	YES	YES	YES	YES	YES

All the results are obtained using correlated random effects. The results presented in columns 3, 4 and 5 are standardized. Column 1 presents the results of co-authorship defined as the fraction of co-authored articles. Columns 2, 3, 4 and 5 show the results from estimating gender differences in degree, strength, clustering and betweenness, respectively. Past output is the accumulated research output from the first publication until $t - 5$. Clustering is only defined for authors who have a degree larger than one. Betweenness is only defined for authors who are in the giant component. Betweenness is in $log(x + 1)$. Authors who have less than five years of experience are not included, the first five observations of the authors are also excluded. Clustered standard errors at the author level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

2.3 Networks Across 3 & 10 Years

In the analysis so far, we have assumed that a link between two authors lasts for 5 years, from $t-4$ to t. In this section, we document that our results are robust to considering three and ten-year networks. We first consider three-year network. In these networks two authors have a link in the co-authorship network, if they have at least one joint publication in the period $t-2$ to t. The results presented in Table 9 indicate that the gender differences in networks are larger in magnitude compared to the five-year network results presented in Table 4 of the main text.

Table 9: Networks and Gender: 3 Year Period

VARIABLES	(1) Co-authorship	(2) Degree	(3) Strength	(4) Clustering	(5) Betweenness
Female	0.018***	-0.266***	0.152***	0.078***	-0.075***
	(0.002)	(0.019)	(0.009)	(0.010)	(0.009)
Past Output			0.084***	0.026***	-0.024***
			(0.006)	(0.005)	(0.005)
Average past output			-0.317***	-0.146***	0.093***
			(0.010)	(0.008)	(0.006)
Constant	0.672***	0.939***	-0.019	0.110	-1.201***
	(0.018)	(0.096)	(0.051)	(0.088)	(0.117)
Observations	267,119	267,119	267,119	177,160	123,303
Number of authors	48,214	48,214	48,214	36,737	27,624
Career-time FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
JEL codes FE	YES	YES	YES	YES	YES

All the results are obtained using correlated random effects. The results presented in columns 3, 4 and 5 are standardized. Column 1 presents the results of co-authorship defined as the fraction of co-authored articles. Columns 2, 3, 4 and 5 show the results from estimating gender differences in degree, strength, clustering and betweenness, respectively. Past output is the accumulated research output from the first publication until $t-5$. Clustering is only defined for authors who have a degree larger than one. Betweenness is only defined for authors who are in the giant component. Betweenness is in $log(B_{it}+1)$. Authors who have less than five years of experience are not included, the first five observations of the authors are also excluded. 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 10. In these networks two authors have a link if they have at least one joint publication in the period $t-9$ to t. Again, network differences are robust to this time aggregation and the gender differences in degree and betweenness are substantially larger in magnitude than the five-year network results presented in Table 4 of the paper, while the gender differences in strength and clustering are slightly smaller under this 10-year window.

Table 10: Networks and Gender: 10 Year Period

VARIABLES	(1) co-authorship	(2) Degree	(3) Strength	(4) Clustering	(5) Betweenness
Female	0.013***	-0.460***	0.111***	0.062***	-0.079***
	(0.003)	(0.031)	(0.008)	(0.009)	(0.009)
Past Output			-0.000	0.004	-0.004
			(0.002)	(0.004)	(0.003)
Average past output			-0.230***	-0.097***	0.121***
			(0.008)	(0.005)	(0.005)
Constant	0.470***	0.565***	-0.358***	-0.197***	-0.387***
	(0.016)	(0.147)	(0.028)	(0.044)	(0.046)
Observations	338,766	341,527	338,766	279,692	258,596
Number of authors	50,295	50,414	50,295	42,773	38,975
Career-time FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
JEL codes FE	YES	YES	YES	YES	YES

All the results are obtained using correlated random effects. The results presented in columns 3, 4 and 5 are standardized. Column 1 presents the results of co-authorship defined as the fraction of co-authored articles. Columns 2, 3, 4 and 5 show the results from estimating gender differences in degree, strength, clustering and betweenness, respectively. Past output is the accumulated research output from the first publication until $t-5$. Clustering is only defined for authors who have a degree larger than one. Betweenness is only defined for authors who are in the giant component. Betweenness is in $log(B_{it}+1)$. Authors who have less than five years of experience are not included, the first five observations of the authors are also excluded. Clustered standard errors at the author level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

2.4 Quantile Regressions

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

We first estimate gender differences in degree in the 25th percentile, median, 75th percentile and 90th percentile using quantile regressions (see Table 11). The results show that the gender difference in degree increases along the degree distribution and it is highest for authors in the 90th percentile. Second, we analyse using quantile regressions the gender difference in clustering along its distribution (see Table 12). 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. Third, we find that the gender difference in strength diminishes along its distribution (see Table 13). Finally, the gender difference in betweenness is lowest at the lower tail of the betweenness distribution and highest at the median (see Table 14).

Table 11: Degree and Gender: Quantile Regressions

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

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

Table 12: Clustering and Gender: Quantile Regressions

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

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

Table 13: Strength and Gender: Quantile Regressions

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

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

Table 14: Betweenness and Gender: Quantile Regressions

	(1)	(2)	(3)	(4)
Variables/Percentile:	25th pc.	Median	75th pc.	90th pc.
Female	-0.036***	-0.548***	-0.351***	-0.301***
	(0.010)	(0.023)	(0.015)	(0.015)
Career time	0.007**	0.106***	0.063***	0.048***
	(0.003)	(0.005)	(0.003)	(0.004)
Career time^2	-0.000***	-0.003***	-0.002***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Past output	0.018***	0.004***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
Linear time trend year	0.004***	0.133***	0.116***	0.109***
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	191,784	191,784	191,784	191,784
JEL codes shares	YES	YES	YES	YES
Avg. JEL codes shares	YES	YES	YES	YES

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

3 Alternative Centrality Measures

We show in Table 15 that gender differences also emerge for other centrality measures, namely closeness and eigenvector centrality. Formally, these centrality measures are defined as follows:

Closeness Centrality $C_{i,t}$ is the inverse of the average distance of a node to other nodes within the giant component. The distance between to nodes i and j is denoted by $l(i, j)$. Then, closeness is given by

$$C_{it} = \frac{M_t - 1}{\sum\limits_{j \neq i} l_t(i,j)}$$

where M_t is the size of the giant component in year t. Because C_{it} has fat tails, we use $\log(1 + C_{i,t})$ as the regressor instead.

Eigenvector Centrality. This measure is based on the intuition that a node's centrality is determined by the centrality of its neighbors. More formally, the centrality of a node is proportional to the sum of the centrality of its neighbors, $\lambda C_i^e(g_t) = \sum_j g_{ij} C_j^e(g_t)$, where g_{ij} is one if i and j are neighbors and zero otherwise. In matrix notation:

$$\lambda C^e(g_t) = g C^e(g_t)$$

Thus, $C^e(g_t)$ is the eigenvector of the network g_t and λ is its corresponding eigenvalue.

Table 15 shows that women have both a lower closeness and eigenvector centrality.

Table 15: Centrality and Gender

VARIABLES	(1) Closeness	(2) Eigenvector
Female	-0.067***	-0.020***
	(0.011)	(0.008)
Past Output	0.009**	0.005**
	(0.004)	(0.002)
Observations	191,784	191,784
Number of auth	33,121	33,121
Career-time FE	YES	YES
Year FE	YES	YES
JEL codes FE	YES	YES

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

4 Gender, Networks & Output

We document that networks can explain even more of the gender disparity in output if we allow for alternative econometric specifications. To investigate more systematically the impact of networks on output, we conduct an Oaxaca-Blinder decomposition. Last, we allow for the networks effect on output to differ across gender.

4.1 Alternative Econometric Specifications

We now document that the results presented in Table 6 in the main text are robust if we use a POLS model instead of the CRE. We find that networks can explain a larger share of the gender gap in output in the POLS compared to the CRE model. We further include all network variables in one regression

Table 16 presents the results. We regress future research output using publications from t to $t+4$, on past research output (from $t-5$ to $t-1$), proportion of papers published in each JEL codes, career time dummies, year dummies and a female dummy; we call this model the baseline model. We then compare the female coefficients between the baseline model and a regression that adds a network variable to the baseline model. The results presented in column 9 and 10 shows that controlling for gender differences in networks reduces the gender future output gap by 19%. We also include all network variables simultaneously to the specification presented in the main paper, in column 11 and 12, the results show that the female coefficient decreases by 10.04% (2.818-2.535) once we account for differences in networks. This results suggest that individual unobserved heterogeneity, which is modeled in the random effect model, accounts for an important fraction of the predictive power of networks for forecasting future output.

4.2 Blinder-Oaxaca Decomposition

In order to investigate the importance of networks in explaining gender differences in output more systematically, we use a Blinder-Oaxaca decomposition. This approach decomposes the difference in future average research output between female and male authors into (i) an explained component given by differences in characteristics, including differences in experience, past performance, field of specialization and network characteristics, (ii) an unexplained component given by differences in coefficients and (iii) an interaction term. Formally, let q_{it}^{f}

Table 16: Gender, Networks and Future Output

	Dependent Variable: Future Output											
	Pooled OLS										CRE	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Female	-0.893***	-0.660***	-1.027***	-0.872***	-1.119***	-1.034**	-1.709***	-1.485***	-1.479***	-1.199**	-2.818***	-2.535***
	(0.238)	(0.236)	(0.288)	(0.287)	(0.409)	(0.408)	(0.479)	(0.478)	(0.570)	(0.565)	(0.498)	(0.496)
Degree_{t-1}		0.659***								0.452***		-0.020
		(0.054)								(0.105)		(0.101)
Strength_{t-1}				-3.258***						-1.572		-5.596***
				(0.354)						(1.217)		(1.077)
Clustering_{t-1}						-2.045***				-1.610		-0.445
						(0.292)				(1.045)		(1.008)
Betweenness_{t-1}								0.234***		-0.087		-0.019
								(0.027)		(0.082)		(0.075)
Past Output_{t-1}	0.585***	0.569***	0.588***	0.579***	0.592***	0.588***	0.582***	0.576***	0.587***	0.577***	0.380***	0.377***
	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	(0.014)
Observations	216,416	216,416	170,187	170,187	117,944	117,944	98,543	98,543	83,337	83,337	83,337	83,337
Career-time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
JEL codes shares	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Results estimated using pooled OLS. The centrality measure betweenness at $t-1$ is in $log(x+1)$. Clustered standard errors at the author level in parentheses. *** p<0.01, ** p<0.05, * p< 0.1. The dependent variable, future output, is accumulated discounted output from t to $t+4$.

be a woman's future output (accumulated research output from t to $t+4$) and q_{it}^m a man's future output. We consider the following regressions per gender group:

$$q_{it}^f = x_{it}^f \beta_f + u_{it}^f \quad (1)$$

$$q_{it}^m = x_{it}^m \beta_m + u_{it}^m \quad (2)$$

where x_{it}^g, $g \in \{f, m\}$ is a vector of covariates: career time dummies, share of past publications in each field, past output (accumulated output from $t-5$ to $t-1$), degree, clustering, strength and betweenness. We can define the average difference in future output between females and males as:

$$\bar{q}^m - \bar{q}^f = (\bar{x}^f - \bar{x}^m)\beta_f + \bar{x}^f(\beta_f - \beta_m) + (\bar{x}^f - \bar{x}^m)(\beta_f - \beta_m). \quad (3)$$

Thus, the average difference between future output of men and women can be decomposed in three components: the part of the difference due to group differences in observables (the endowment effect) $(\widehat{x}^f - \widehat{x}^m)\beta_f$, the differences in the coefficients and an interaction term that accounts for the fact that differences in endowments and coefficients exist simultaneously between the two groups.

In Table 17 we present the results of the Oaxaca-Blinder decomposition. The difference in future output between between men and women ranges from of 4.119 to 7.230 depending on the sample (see row Total difference). Around 6.75 of this difference is explained by differences in observed characteristics between female and male in the model where we include all the network variables (see column 5). In this model, differences in past output (accumulated output from $t-5$ to $t-1$) are associated with a 5.941 gender gap in future output, whereas differences in degree is related to a 0.407 of the gender gap in future output. In the models where we add one network variable, columns 1-4, differences in network characteristics are significantly associated to differences in future research output, with the exception of strength. However, for the strength variable, we find that differences in returns (unexplained difference) are strongly negatively associated with the gender gap in future output, i.e. collaborating repeatedly with the same authors tends to be more detrimental in terms of future output for men than women.

Table 17: Contributions of differences in average network characteristics to the gender difference in mean future output.

VARIABLES	(1) Degree	(2) Strength	(3) Clustering	(4) Betweennes	(5) All networks
Avg. male future output	12.908	14.934	18.095	21.267	22.795
Avg. female future output	8.789	10.022	12.312	14.055	15.564
Total difference	4.119***	4.912***	5.78***	7.212***	7.230***
Difference explained by covariates	3.917***	4.471***	5.337***	6.313***	6.750***
Difference explained by coefficients	0.739***	0.939***	1.109***	1.573***	1.286***
Difference explained by interaction	-0.536**	-0.498	-0.663***	0.546	-0.807
Explained difference:					
Past Output	3.251***	3.983***	4.883***	5.591***	5.941***
Degree	0.256***				0.407***
Strength		0.068			-0.121
Clustering			.034*		-0.074
Betweenness				.187***	0.057
Unexplained difference:					
Past Output	-0.102	-0.237	-0.426	-0.264	-0.604
Degree	0.037				-1.313
Strength		-1.349***			-1.571
Clustering			-0.637*		-1.066
Betweenness				0.488	-1.782
Observations	216,416	170,187	117,944	98,543	83,337

Total difference shows the average difference in future output between men and women. Explained difference is the difference in future output across gender explained by differences in observable characteristics. Unexplained difference shows the difference in future output across gender explained by differences in the coefficients. The dependent variable is the accumulated output from t to $t+4$. Past Output is the lagged dependent variable, which is the accumulated output from $t-5$ to $t-1$. Clustered standard errors at the author level. *** p<0.01, ** p<0.05, * p<0.1

4.3 Differences in Network Effects Depending on Gender

That strength has a different effect for men and women is also confirmed when we look at whether the returns from a specific network characteristic differ across gender by adding an interaction between the female dummy and the network variable to the future research output model described above. The results presented in Table 18 shows that the effect of degree, clustering and betweenness on research output is the same across gender. However, the effect of strength on future output is lower for women. In particular, a 0.10 increases in strength is associated with a decline of 0.39 in future output for men and a decline of 0.18 in future output for women.

Table 18: Gender, Networks and Future Output: Random Effects

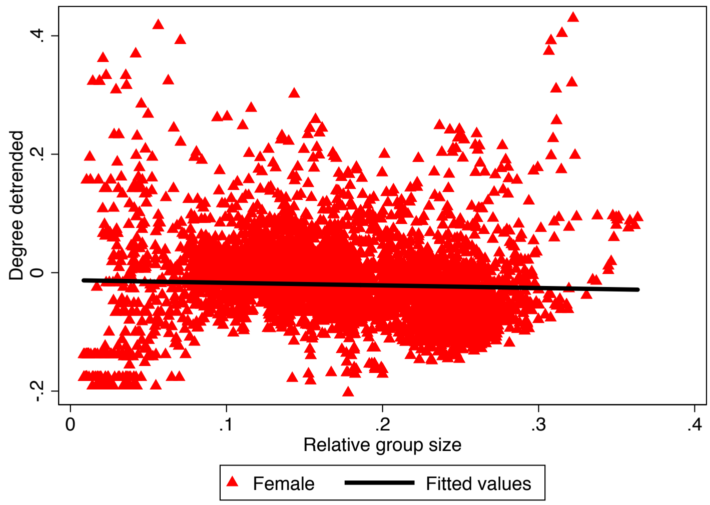
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-1.936***	-1.991***	-3.120***	-2.070***	-2.464***	-2.234***	-2.876***	-2.679***
	(0.239)	(0.285)	(0.621)	(0.280)	(0.529)	(0.373)	(0.427)	(0.415)
Degree_{t-1}		0.421***						
		(0.059)						
$\text{Female*Degree}_{t-1}$		0.100						
		(0.142)						
Strength_{t-1}				-3.958***				
				(0.384)				
$\text{Female*Strength}_{t-1}$				2.157***				
				(0.742)				
Clustering_{t-1}						-2.354***		
						(0.322)		
$\text{Female*Clustering}_{t-1}$						0.821		
						(0.664)		
Betweenness_{t-1}								0.214***
								(0.027)
$\text{Female*Betweenness}_{t-1}$								0.002
								(0.060)
Past Output_{t-1}	0.342***	0.335***	0.356***	0.346***	0.360***	0.356***	0.388***	0.382***
	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Constant	0.041	0.063	0.124	0.116	0.126	0.117	0.198	0.224
	(0.058)	(0.058)	(0.087)	(0.086)	(0.132)	(0.132)	(0.224)	(0.224)
Observations	216,416	216,416	170,187	170,187	117,944	117,944	98,543	98,543
Number of authors	28,448	28,448	23,949	23,949	18,418	18,418	16,554	16,554
Career-time FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
JEL codes shares	YES	YES	YES	YES	YES	YES	YES	YES

Results estimated using random effect models, all the variables are standardized. The centrality measure betweenness at $t-1$ is in $log(B_{it}+1)$. Clustered standard errors at the author level in parentheses. *** p<0.01, ** p<0.05, * p< 0.1. The dependent variable, future output, is accumulated discounted output from t to $t+4$.

5 Homophily

We show that there is a negative relationship between degree and the share of women across fields when we exclude the share of men. Regressing the de-trended degree on relative group size of women, yields: $\widehat{d_l^{det}} = -.013 - .044w_l$, with both coefficients statistically significant at the 1% level. Figure 1 replicates Figure 7 of the main text excluding the share of men.

Figure 1: Degree & Share of Women Across Fields

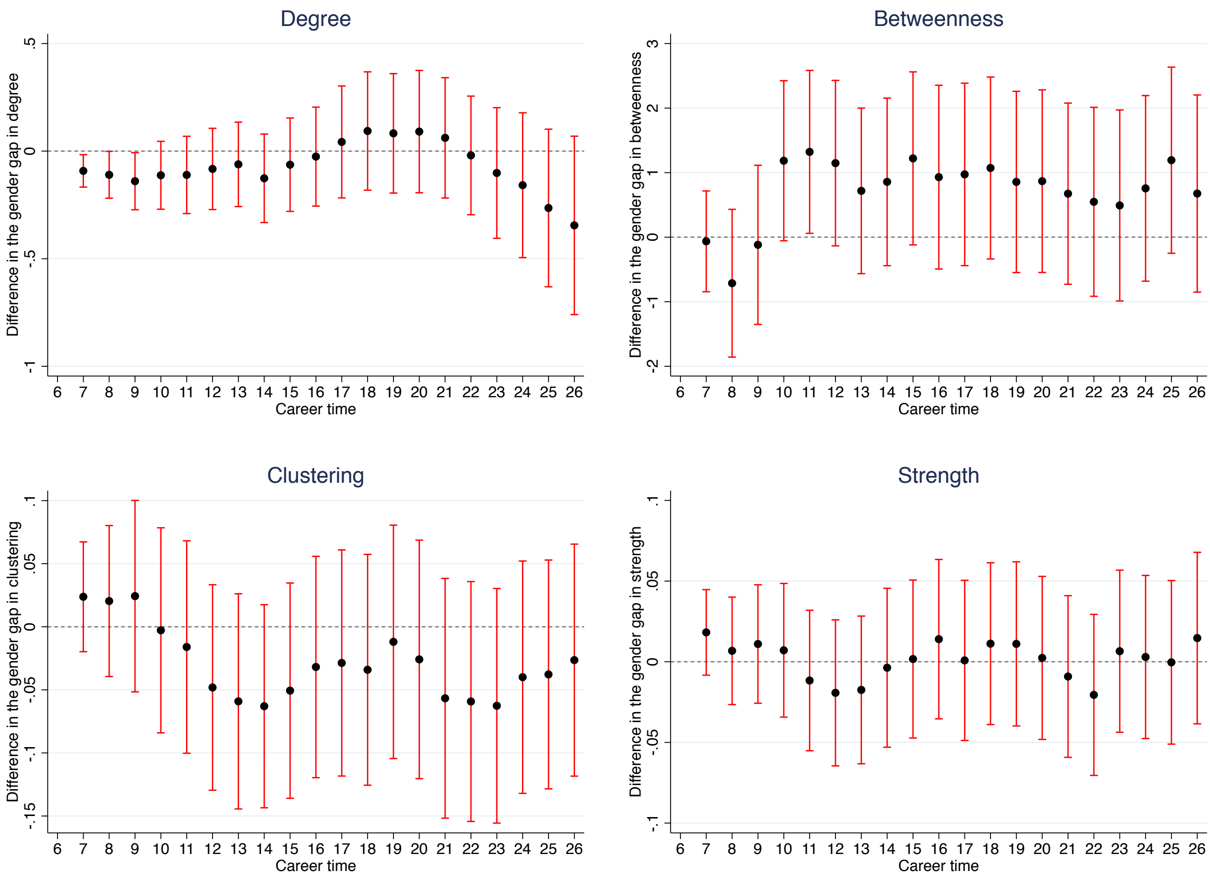


Note: De-trended degree is the residual of a linear regression of degree on year dummies.

6 Family engagements

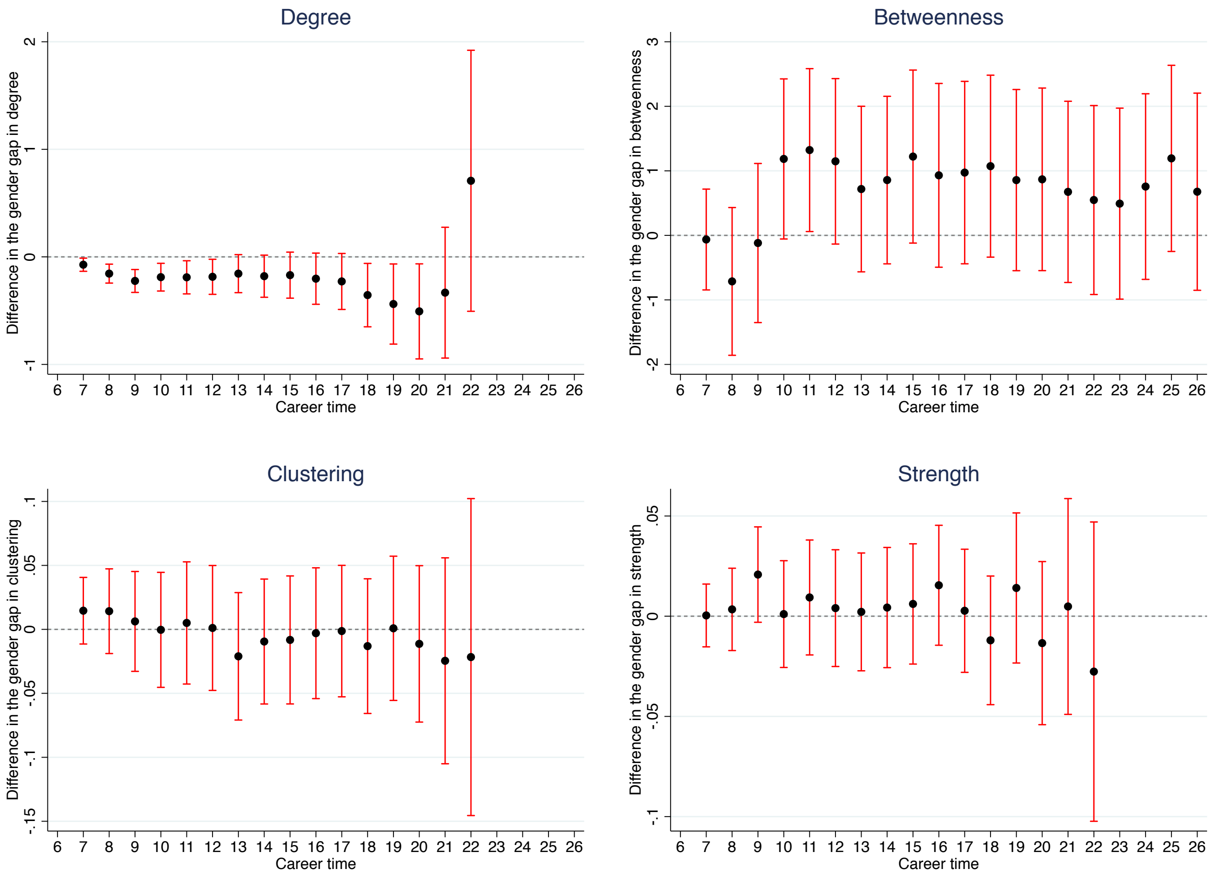
Last, we show that the gender differences across career time are stable for all cohorts. We add interaction terms between career time dummies and the female dummy to the network model, defined in equation (2) of the main text, and restrict our sample to different cohorts: 1980-1984, 1990-1994 and 2000-2004, where a cohort is defined as the year of the first publication. Figure 2-4 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.

Figure 2: Gender Differences in Networks Across Career Time: Cohort 1980-1984



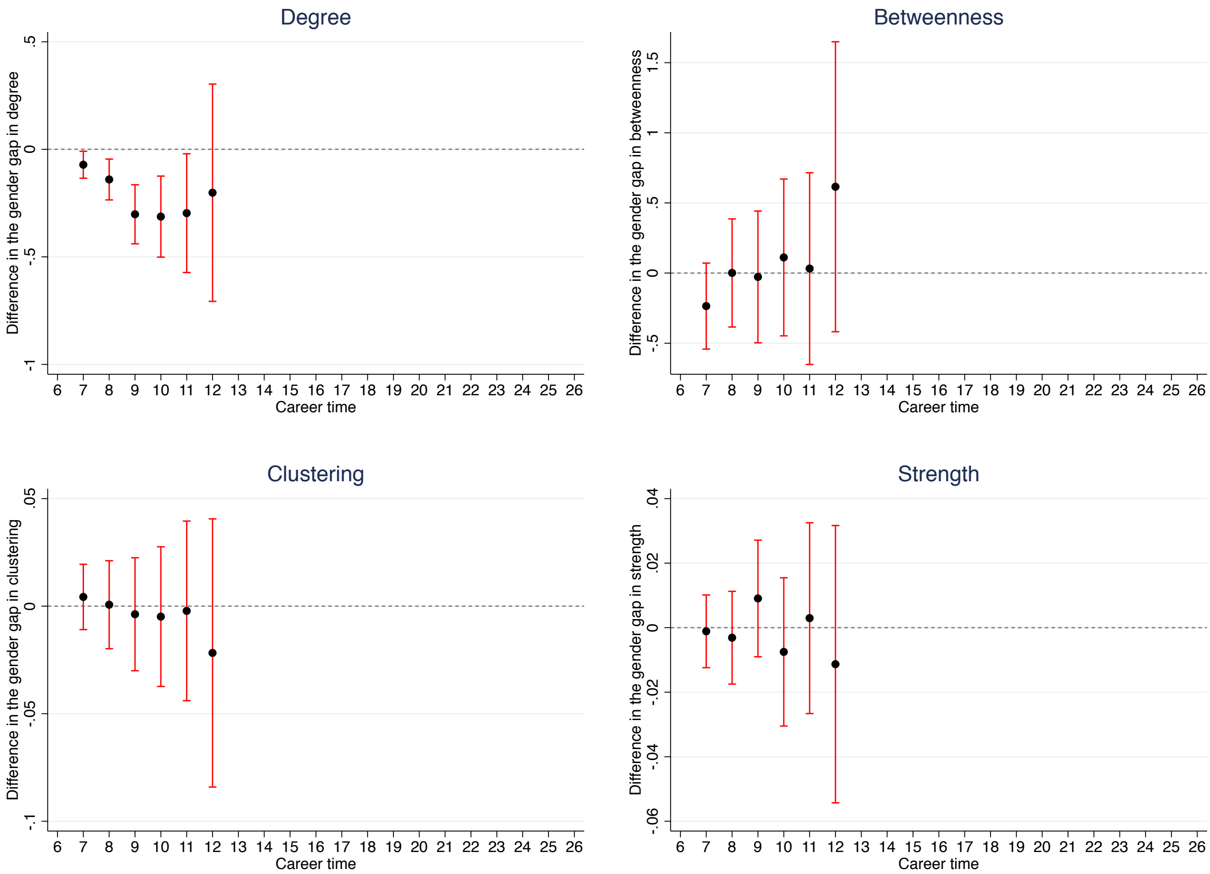
Note: The plots show the coefficients and 95% confidence intervals of the interaction terms between career time dummies and the female dummy of a network model estimated using correlated random effects, the base career time age is 6. The gender gaps in degree, strength, clustering and betweenness in the base career time age are -0.13, 0.04, 0.05 and -1.48, respectively.

Figure 3: 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 and betweenness in the base career time age are -0.12, 0.05, 0.06 and -1.08, respectively.

Figure 4: 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 and betweenness in the base career time age are -0.19, 0.05, 0.03 and -0.61, respectively.

References

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.