DEPARTMENT OF ECONOMICS
JOHANNES KEPLER UNIVERSITY OF LINZ

Gender Homophily, Collaboration, and Output

by

Anja PRUMMER
Lorenzo DUCTOR

Working Paper No. 2302
February 2023

Johannes Kepler University of Linz
Department of Economics
Altenberger Strasse 69
A-4040 Linz - Auhof, Austria
www.econ.jku.at

anja.prummer@jku.at

Gender Homophily, Collaboration, and Output

Lorenzo Ductor * Anja Prummer †

February 10, 2023

Abstract

We consider the implications of gender homophily in Economics, which has persisted despite the significant increase in women in the field. As women remain underrepresented, gender homophily may serve as a constraint in collaboration. It could also lead to less gender diverse co-author teams than may be optimal in terms of generating high quality research papers. We show that gender homophily neither constrains collaboration nor prevents higher quality output.

JEL Codes: D85, J16, O30

Keywords: Homophily, Collaboration, Diversity, Research Quality

*Universidad de Granada. E-mail: lductor@ugr.es

†Johannes Kepler University Linz, Queen Mary University London. Email: anja.prummer@jku.at
We are indebted to Sanjeev Goyal for helpful comments and his contribution to the homophily section. We are grateful to René Böheim, Matthias Fahn, Erin Hengel, Nagore Iriberri, Michael Rose and Rudolf Winter-Ebmer for their valuable comments. Thi Phuong Anh Doan provided excellent research assistance. We thank various audiences for comments and suggestions. Lorenzo Ductor acknowledges the financial support of the *Fundación Ramón Areces*, and the Ministry of Science and Innovation of Spain, project PID2019-111708GA-I00 financed by MCIN/ AEI /10.13039/501100011033. This research was funded in whole or in part by the Austrian Science Fund (FWF) V 991-G.

1 Introduction

Many workplaces strive to attract women. More female colleagues increase the share of women in teams. The influx of women either leads to greater gender diversity or more collaboration between women. The level of gender diversity observed may depend on which teams produce the best results. If collaborators are chosen freely, then preferences or differential interaction rates between men and women could also affect the gender composition of a team, potentially inducing too little diversity.

In this paper, we describe how female and male economists collaborate across gender from 1970 to 2017 and connect gender diversity to research output.

Authors may display gender homophily, meaning that they collaborate relatively more with authors of the same gender. In contrast, if authors work disproportionately with Economists of the opposite gender, they exhibit heterophily. As in Currarini, Jackson, and Pin (2009), we interpret homophily as an equilibrium phenomenon that does not only depend on preferences but also interaction rates between men and women.[1] The simplest measure of homophily, *Relative Homophily*, compares the share of same-gender co-authors with the share of same-gender authors among all economists. Both men and women display relative homophily. However, economics has become significantly more gender-balanced. At the beginning of our sample period, in 1970, only 5% of authors were female. This share has increased to almost 30% in 2017 (Ductor, Goyal, and Prummer (2021)). Therefore, both female and male authors have now more opportunitiesto co-author with women. This increase in the share of female authors requires us to use a measure of homophily that takes into account the varying gender composition in our population, *Inbreeding Homophily*. This measure normalises the same gender co-authors by their share in the population. Both male and female economists display inbreeding homophily, collaborating disproportionately with same-gender co-authors. Men display a higher level of homophily compared to women. Remarkably, the level of homophily has remained stable throughout our observation period. The influx of women has neither led to a relative increase in female or male co-authors; rather, the proportions remained unchanged for both men and women in economics.

The stability and persistence of homophily leads us to investigate whether the predominantly same-gender collaborations have implications for research output. We consider two

[1] For a detailed discussion of homophily, see McPherson, Smith-Lovin, and Cook (2001).

channels, namely (i) the smaller number of same type co-authors for women and (ii) the association between team diversity and research quality.

In the presence of homophily, women, as the underrepresented group in Economics, face a smaller pool of potential collaborators. The number of collaborators is a key factor in predicting research output: a higher number of co-authors is tied to more high-quality publications in the future (Ductor et al. (2021)).[2] If homophily was indeed a factor limiting the number of collaborators, then an increase in the share of women would ameliorate the shortage of co-authors, an idea formalised by Currarini et al. (2009). We test this prediction using the variation in the share of women over time as well as across fields. Different fields in Economics attract distinct shares of women. Perhaps surprisingly, women's average number of collaborators is unaffected by the share of female authors present. This implies that women's number of collaborators has not increased over time relative to men's and the gender gap in number of collaborators is unaffected by research field. Even though economists display homophily, it does not impact the gap in the number of collaborators. This implies that the mere increase in the share of women has not lead women to acquire more co-authors relative to men. Our findings show that a higher number of women in Economics will not per se decrease the gender gap in number of collaborators, which in turn is an important contributor to the continued gender gap in research.[3]

Homophily has implications for the gender diversity of the research team. While homophily and team diversity are related, they differ in how they are constructed. Homophily is an *author-specific* measure, while team diversity is assessed for each research team that produces an article, making it *article-specific*. Male teams write 47% of all articles, while all-female teams only make up 2%. Mixed teams account for 18% of publications.[4] Gender diverse teams make up for a lower share of publications relative to same-gender teams, consistent with homophily.

Research teams exclusively comprised of men publish higher quality articles compared to

[2]Note that the number of co-authors is based on previous and current collaboration, while research output is assessed in future periods to rule out simultaneity.

[3]Ductor et al. (2021) show that the gender differences in past number of collaborators explain approximately 10% of the variation in research output differences across gender, over and above past performance. Doan, Ductor, and Rascon-Ramirez (2023) shows that the relationship between number of collaborators and research output is causal. They found that loosing a co-author leads to a decline in long-run output of 11%.

[4]For the remainder, the gender composition cannot be identified. If we cannot identify an author's gender, then we can also not assess the gender composition of the research teams.

mixed teams, which perform as well as all-female teams for our sample of 100 journals in Economics.[5] All-female teams publish articles in journals with 8.6% lower impact than all-male teams.

In contrast, female teams are connected to 20% higher citations compared to male teams, controlling for article quality and other observables. There is no significant difference between male and mixed teams.

Confirming the findings of Card, DellaVigna, Funk, and Iriberri (2020), our results similarly raise questions about the correct metric for evaluating research contributions given the notable gender differences between measures.

Crucially, there is no benefit to collaborate with authors of a different gender. If a male author works with a female author, then the article they produce is associated with a lower journal quality, while at the same time the cross-gender publication does not lead to higher citations. Similarly, if a female author opts to work with a male collaborator, then the publication quality does not improve relative to a paper written with a female author, but the cross-gender collaboration tends to acquire lower citations.

While both men and women display gender homophily, homophily does not seem to be limiting them both in terms of finding collaborators as well as publishing as gender diversity does not improve research quality. While an increase in the share of women in Economics is an important goal in and of itself, it does not seem sufficient to erase gender disparities.

Related Literature We contribute to the literature on homophily in social networks. Homophily has been extensively studied in sociology (for a summary see McPherson, Smith-Lovin, and Cook (2001)). In Economics, gender homophily has been shown to arise in job search networks (Torres and Huffman (2002), Zhu (2018)), referral networks (Beaman, Keleher, and Magruder (2013), Zeltzer (2020)) as well as in the lab (Mengel (2020)). Jackson, Nei, Snowberg, and Yariv (2023) document gender homophily among college students, distinguishing between friendships and study groups. We complement their findings by documenting gender homophily in team formation. Concurrently to this paper, Davies (2022) shows gender homophily in NBER working papers, while we cover all journals in Economics over a 47 year period.

[5] We use the Top 100 journals and follow in our classification of journal quality Ductor, Goyal, v. der Leij, and Paez (2020).

More broadly, we add to the literature documenting the constraints women in economics face, see e.g., Ginther and Kahn (2004), Sarsons, Gërxhani, Reuben, and Schram (2021a), Wu (2018), Hengel (2016), Chari and Goldsmith-Pinkham (2017), Boring (2017), Mengel, Sauermann, and Zölitz (2019), Card et al. (2020), Paredes, Paserman, and Pino (2020), Dupas, Modestino, Niederle, Wolfers, et al. (2021). Ductor, Goyal, and Prummer (2018) shows that differing network structures between men and women can account for a substantial part of the gender gap in research output. In particular, a higher number of co-authors is a key predictor for future research output. We document gender homophily and investigate whether its serves as a constraint on finding collaborators for women in Economics.

Currarini, Jackson, and Pin (2009), Bramoullé, Currarini, Jackson, Pin, and Rogers (2012) model matching processes that tie homophily to the number of connections, formalising the idea that homophily can serve as a constraint for underrepresented groups. Our paper highlights that the influx of women in Economics has not reduced the gender differences in the number of co-authors. This contrasts with Currarini, Jackson, and Pin (2009)' finding on interracial friendships, emphasising the importance of distinguishing between (i) friendship ties and work collaborations and (ii) race and gender.

Our finding on gender team diversity and research output confirms Card et al. (2020), who show that publications of women attract a higher number of citations in four journals. This citations gap is robust in that it persists for the Top 100 journals in Economics. The gap also emerges if we exclusively consider publications in Top 5 journals as in Hengel and Moon (2020).[6]

In light of Koffi (2021), our result can be interpreted as a lower bound on the citations gap. She documents that papers with a more female co-author team are cited less relative to the citations they should be receiving, according to the quality of the article (measured using the degree of novelty of the article). To assess the quality and novelty of an article, Koffi (2021) relies on textual analysis techniques and machine learning tools. While we find that women are cited more, the citation bias documented by Koffi (2021) could indicate that women should be cited even more.[7]

The gender composition of teams has been analysed in the context of boardrooms, in

[6]In contrast to both Hengel and Moon (2020) and us, Maddi and Gingras (2021) find that gender-diverse teams are associated with higher citations in economics, not controlling for journal quality of the publication.

[7]We take into account a measure of article quality but do not assess novelty.

committees and in experiments, see the surveys by Azmat and Petrongolo (2014), Azmat and Boring (2020). Results as to whether gender diversity is beneficial for better outcomes are mixed, in line with the theory (Lazear (1999), Prat (2002)), which postulates that the specific environment matters. This warrants an investigation into economics. There, gender diversity in teams does not seem to be rewarded.

The rest of the paper proceeds as follows: Section 2 describes our data. In Section 3 we outline the empirical strategy. Our findings are presented in Section 4. Section 5 discusses our results and concludes.

2 Data

Data Sources We use two data sets for our analysis, EconLit and the Web of Science, which we describe in turn.

The EconLit database is a bibliography of journals in economics compiled by the editors of the *Journal of Economic Literature*. The database provides information on 921,976 articles published between 1970 and 2017, in 1990 journals. We do not cover working papers and work published in books. We focus on research papers with at most 3 co-authors as 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.[8]

Each article registered in EconLit contains information on the journal (including name of the journal, volume, issue, first and last page), title, the last and first name of each author, affiliations of each author, JEL codes, keywords and the abstract.[9] Authors are identified by their first and last name, as in Goyal, Van Der Leij, and Moraga-González (2006), leaving us with 470,309 authors. Using information about all the articles published by an author in our sample period, 1970-2017, we construct a panel that starts for each individual with their first publication and extends to the last observed publication of the author (or to 2017). This allows us to describe an author's collaborators.

[8] Goyal, Van Der Leij, and Moraga-González (2006) show that the co-authorship network statistics are unaffected when articles with four or more authors are included.

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

For our measures of research quality, we supplement the EconLit data with citations and references from the Web of Science (hereafter, WoS) (Clarivate Analytics, 2018). For this latter exercise, we focus on the 100 most established journals in economics according to IDEAS/RePEc, see also Ductor, Goyal, v. der Leij, and Paez (2020).[10] The citation and reference data set includes information on $275,670$ articles and the number of citations they received yearly until 2017.

We identify the gender of an author using their first names and *gender-api.com*, a source that provides first names and the estimated gender for 201 countries. We identify an author's gender if the author's first name is associated with a single estimated gender in the 201 countries, at least 95% of the time. Using this standard approach allows us to identify the gender of 78% of the authors (367,441 out of 470,309 authors).[11]

Homophily To measure gender homophily, we calculate the share of co-authors of the same gender and compare it to the share of all same-gender authors, omitting authors whose gender is not identified.

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, while H_f is women's average share of female collaborators. Then, women exhibit *relative homophily* if their share of female collaborators is larger than the share of women among authors. Formally, $H_f > w_f$. Similarly, men exhibit relative homophily if $H_m > w_m$, that is if men's share of male co-authors is greater than the share of men in our population.[12]

Following Coleman (1958), we define another measure of homophily, *inbreeding homophily*. Inbreeding homophily normalises the share of same-gender collaborations by taking into account the share of men and women in the population. Considering that the share of female authors in economics has increased substantially, we measure the share of each gender across a 5-year window and index this measure with t, implying that the share of each gender is the number of authors with a certain gender, present in year $t-4$ to year t. We select a 5-year window in line with Ductor et al. (2018), to capture the

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

[11]Given that our data spans the universe of authors publishing in Economics over a 47 year horizon, it is prohibitively costly to conduct a google search to identify the gender of the remaining 100 000 authors.

[12]An alternative measure has been suggested by Zeltzer (2020). His measure is similar to the relative homophily we consider but primarily pertains to directed networks (we consider undirected networks). His index is defined as the difference in the share of male collaborators of men versus women. Therefore, his index contains the same information as relative homophily.

available collaborators at the beginning of a project. We focus on a five-year time frame as it is well known that there are long lags in publication. Therefore, available co-authors of a paper do not coincide with the publication date.[13] The proportion of collaborators of gender $s \in \{f, m\}$ at time t is denoted by H_{st}, while w_{st} denotes the proportion of authors of gender s at time t. The inbreeding homophily h_{st} at time t for gender s is then formally defined by

$$h_{st} = \frac{H_{st} - w_{st}}{1 - w_{st}}. \tag{1}$$

We shall say that there is inbreeding homophily if the index is positive, inbreeding heterophily if it is negative.[14] Intuitively, the index compares the proportion of collaborations with the same gender with the fraction of this gender in the sample, weighted by the maximal gender bias authors could display.

The measure h_{st} provides the average inbreeding homophily for men and women. To capture the gender diversity of an author's collaboration network, we additionally measure inbreeding homophily at the author level: we replace the overall share of same-gender collaborations with H_{it}, the number of same-gender collaborators author i has and obtain h_{it}.[15]

Gender Diversity While homophily is measured at the author level, we also track gender diversity at the research team or article level.

We create a categorical variable for which we classify teams as male if they exclusively consist of men, female if only women collaborate and mixed if there are female and male co-authors. If we can identify one author as male, another one as female, while the third remains unidentified, the team is categorised as mixed.[16] We further create a variable that measures the share of women on a research team as well as an explicit measure of gender diversity, the Blau index, for details see the Supplementary Appendix.

Research Quality We assess the connection between gender team diversity and output quality. We focus on two measures for the quality of the research output. Our first

[13] Alternative time windows lead to qualitatively identical results.

[14] Note that the index lies between $-\frac{w_{st}}{1-w_{st}}$ and 1.

[15] We omit here an explicit marker of gender as we keep track of it through the individual author.

[16] Our classification of teams differs from Card et al. (2020) and Hengel and Moon (2020) as we focus explicitly on gender diversity.

measure is the article influence score, a time-varying impact factor of the journal an article is published in. We construct the article influence score, AIS_p, for each article p following Ductor et al. (2020), where we provide a detailed discussion of the numerous virtues of the article influence score as a measure of research quality. Second, we consider the number of citations an article attracts.

3 Empirical Strategy

We first examine gender homophily. We then assess whether homophily serves as a constraint on collaboration and the production of high quality research output.

Homophily We focus here on the homophily for a given author, taking into account their observable characteristics. We estimate the following regression using Pooled OLS,

$$h_{it} = \alpha + x_{it}\beta + \epsilon_{it}, \tag{2}$$

separately for each gender. As defined above, individual inbreeding homophily is denoted by h_{it} for author i at time t. We control for a number of variables collected in x_{it}. Authors may display different collaboration patterns over the course of their career. We therefore account for experience through career time indicators, which are defined as the number of years since the first publication by the author.[17] Collaboration could also vary across fields of research. We therefore control for it. Following Fafchamps, Goyal, and van der Leij (2010), we categorize 19 different fields using the first digit of JEL codes and include a measure of the proportion of publications in each JEL code. These codes capture the fields of specialisation of the author. We also include year fixed effects to account for time trends as collaborations have changed over time. Further, we control for past research output, which is the accumulated output from the first publication until $t-1$, evaluated by their article influence score. This takes into account that some collaborators may be more appealing due to past output, which could also affect their homophily. Formally,

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

past research output is defined as

$$Q_{it} = \sum_{p=1}^{P} \frac{AIS_p}{\#\text{authors}_p}, \tag{3}$$

where P are all publications of author i up to time $t-1$ and AIS_p denotes the article influence score. We weight every article by the number of authors.

Overall, the empirical model described by (2) allows us to generate a conditional homophily measure.

Homophily and Collaboration We analyse if homophily limits collaboration opportunities. Collaborations are increasingly important in Economics. In particular, a higher number of co-authors is associated with a higher quality research output (Ductor et al. (2018), for a theoretical foundation, see Lindenlaub and Prummer (2021)). Taking the underrepresentation of women in economics together with homophily, women may collaborate less compared to male authors. This argument has been formalised by Currarini et al. (2009), who study the role of homophily in shaping the number of connections.[18] 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. 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. Currarini et al. (2009) assume that each individual gains higher utility from new connections which are of the same type. Taken together, an agent of the common type will spend more time on matching. The advantage of this model is that it explicitly allows for the type of agent, contrary to other models of network formation. Additionally, it generates a clear empirically testable prediction, namely a positive correlation between the relative size of a group in the population and the average number of co-authors.[19] We test their prediction in our data by first exploiting the variation in the share of women over time and second, the variation in women across fields. We study if the gender gap in the number of coauthors from $t-4$ to t diminishes over time, as the share of women in economics increases. The number of collaborators is denoted by d_{it}, which abbreviates the degree of the author. We focus on

[18] Other models of network formation do not condition on distinct types of nodes.

[19] Currarini et al. (2009) take their model to the data and find support for their hypothesis in the context of race. It seems natural to ask whether their prediction is equally valid in the context of gender.

cohorts as co-authorship may also be driven by similarity in career time. Specifically, we estimate the following model:

$$d_{it} = \alpha F_i + \sum_{c=1975}^{2017} \gamma_c C_{itc} + \sum_{c=1975}^{2017} \delta_c F_i \times C_{itc} + x_{it}\beta + \epsilon_{it}, \tag{4}$$

The variable F is an indicator variable equal to one if the author is female. The cohort denoted by C is an indicator variable equal to one for the year of first publication. The additional controls are identical to those included in empirical model (2) and as such are denoted once again by x_{it}. In this specification, we define past output as the accumulated output from the first publication until $t-5$ to avoid simultaneity with the number of co-authors. We focus on the coefficients of the interaction terms between female and the cohort indicator variables. They capture if the gender gap in the number of co-authors is changing across cohorts allowing us to investigate whether an increase in the share of women can erase potential disparities in terms of the number of collaborators.

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 and obtain the average number of co-authors per JEL code, l, and the share of women per JEL code, w_{fl}. We de-trend degree by regressing degree on year indicators, the residual from this regression is the de-trended degree.[20] Finally, we estimate the association between de-trended degree d_l^{det} and the share of women in a field using the linear model

$$d_l^{det} = \alpha + \beta w_{fl} + \epsilon_l. \tag{5}$$

Homophily, Team Composition and Research Output We examine gender diversity at the team level and its relationship to research quality. Gender homophily has implications for the gender composition of research teams, which in turn affects research quality, q_{pt}. Research quality can either refer to the article influence score or the number of citations. We use Pooled OLS to estimate

$$log(q_{pt}) = \rho D_p + x'_{pt}\beta + \epsilon_{pt}, \tag{6}$$

[20]The results are robust to other de-trending methods, available upon request.

where D_p denotes the team diversity. We include once again a number of controls, which contain a constant, and denote them by x'_{pt}. We control for the number of authors on the team as a larger team may allow for different skills, potentially affecting research quality. Additionally, we control for the specialisation of the research team. This captures how many articles the collaborators have published previously, taking into account the research field. Having more experience of publishing in a given field may relate to quality. As in Ductor (2015), we count the number of papers the research team has published in a given field and calculate the Herfindahl index $\sum_{l=1}^{F}\left(\frac{n_{lt}}{n_t}\right)^2$, where n_{lt} denotes the number of publications in field l and n_t the overall number of publications by the the research team of article p up to t. Articles with multiple JEL codes are assigned proportionally to each field. If there is no previous article published by a given team, we normalise the Herfindahl index to zero.

We further control for the past output of the research team, defined in the same spirit as past output per author: we count the overall number of papers, weighted by journal quality, published by the team that produced article p. This variable captures the track record of the team. We also take into account the average past output of the co-authors. As above, we calculate the past output for each co-author and take its average. This variable control for the track record of the team's members.[21]

We include team experience as the number of years since the first publication of the research team, which relates to seniority. We take into account the length of the article p by counting the number of pages which has shown to be related to quality (Card and DellaVigna (2013)). In addition, we include year and field fixed effects, the latter measured by JEL codes. Standard errors are clustered at the team level as research quality is correlated over time.

We focus here on team characteristics given that this is the relevant unit of observation. We further provide results that take into account individual characteristics, for instance, each author's past output, and experience in the Supplementary Appendix.[22]

[21] We focus here on averages. Alternatively, we could control for the highest output of a co-author or the highest seniority of the co-author team. Including such controls does not affect our results.

[22] Our sample consists of papers with two and three authors. To control for author-specific characteristics we are required to make an assumption about the missing third author's characteristics on a two-researcher team as e.g. his past output is not defined. We set missing characteristics of the third author to zero and include an indicator for a two person team.

4 Gender Diversity in Economics

We first document gender homophily, before investigating whether gender homophily constitutes a constraint. Gender homophily could lead to a lack of co-authors or inefficiently few gender-diverse research teams, which in turn could have implications for research quality.

4.1 Homophily

Men display relative homophily if their average share of male co-authors is higher than the fraction of male authors in the population. We compute in Table 1 the percentage of links within gender and find that on average 80.5% of men's collaborations are with other men: this is higher than the fraction of men in the population, 72%. Women also exhibit relative homophily as their collaboration with other women, 34.1% exceeds the fraction of women in the population, 28%. Therefore, both men and women display relative homophily.[23]

Table 1: Summary Statistics

	Men	Women	Men-Women
Population Share	0.72	0.28	0.44***
Men's Collaborators (share)	0.805	0.195	0.610***
Women's Collaborators (share)	0.659	0.341	0.318***
Inbreeding Homophily	0.30	0.08	0.22***
# Co-authors	2.31	2.13	0.18***
Co-authorship	0.66	0.72	-0.06***
Experience	10.37	7.08	3.29***
Past output	1.13	0.68	0.45***

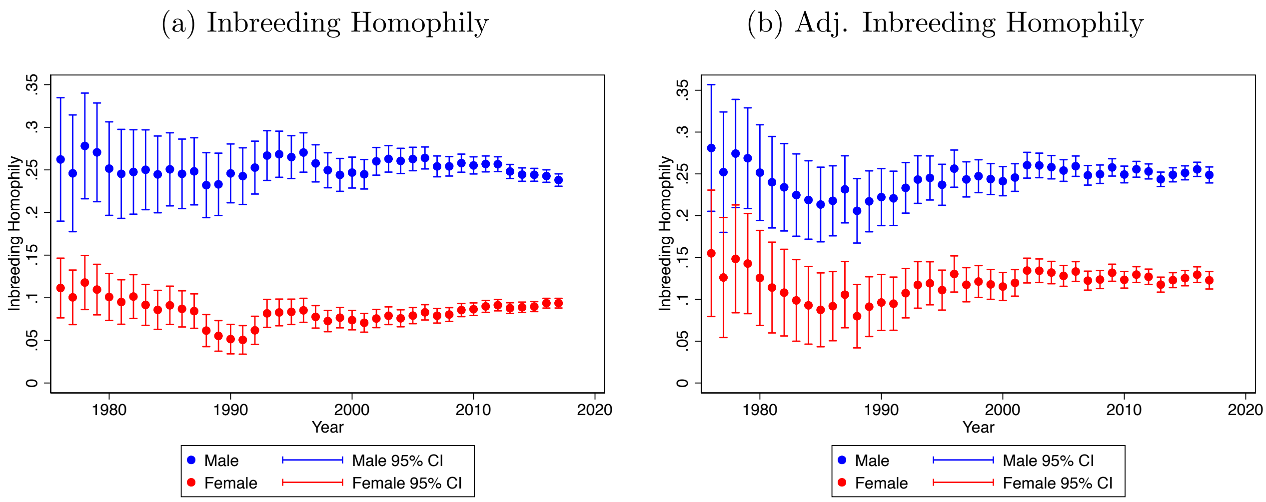
Note: The sample includes all articles published in EconLit from 1970 to 2017, where the gender of at least one author is identified. The unit of analysis is at the author level. The # coauthors is the number of different coauthors accumulated from $t-4$ to t. Coauthorship is the ratio between the number of coauthored articles and the total number of articles published from $t-4$ to t. Experience refers to time since first publication, past output as defined in expression (3). Column 3 shows the differences in means between men and women. ***p<0.01 implies that the difference between men and women is significant at the 1% level.

While relative homophily does not take into account the varying shares of men and women in the profession, inbreeding homophily incorporates this change. Figure 1a documents that both men and women exhibit inbreeding homophily, collaborating more with authors of the same gender. This pattern is more pronounced for men whose inbreeding

[23]Figure A.1 in the Supplementary Appendix highlights that relative homophily exists for the entire sample period.

homophily is higher compared to the one for women. Remarkably, the level of inbreeding homophily is stable over time, both for men and women. Considering the whole sample period, 1970-2017, the inbreeding homophily of men and women are equal to 0.30 and 0.08 (see Table 1), respectively. Inbreeding homophily remains stable even if we control

Figure 1: Inbreeding Homophily



Note: Adjusted inbreeding homophily is the conditional mean of inbreeding homophily, calculated from model (2). Controls include career time, share of JEL codes, past research output, and year.

for experience, field of research, past research output and year fixed effects, see Figure 1b, which is based on empirical model (2).

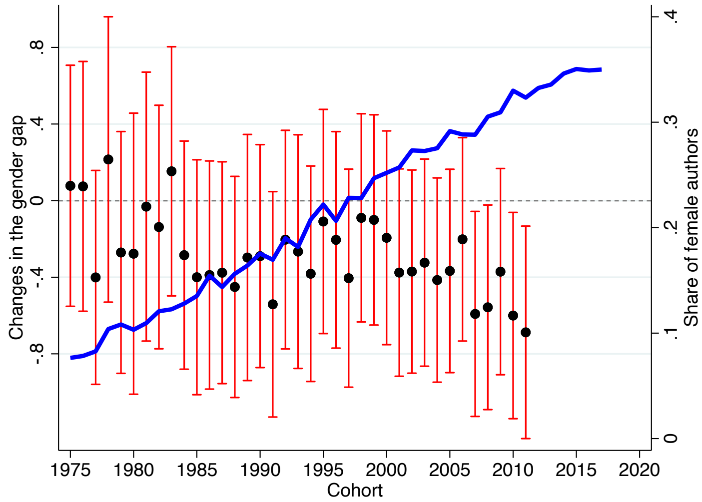
Our result highlights that despite the increase in the share of women in Economics, authors' share of male and female collaborators has remained unchanged. Interestingly, the increase in the share of women has not led to a higher share of female co-authors, both for men and women.

4.2 Homophily and Collaboration

We ask whether homophily serves as a constraint for women in finding collaborators. Men have a significantly higher number of co-authors relative to women, see Table 1: the average number of co-authors for men amounts to 2.31 while women's average number across a five-year period is 2.13. This gap matters as a higher number of collaborators is associated with a higher research output (Ductor et al. (2021)). If the discrepancy is driven by gender homophily, then a possibility to reduce the gender gap would be to increase the share of women in the profession.

We first investigate the relationship between the share of women in a given cohort as

Figure 2: Gender Gap in # of Co-authors Across Cohort



Note: The blue line shows the share of female authors across different cohorts. The black dots and red lines are the coefficients and 95% confidence intervals of the interaction terms between cohort indicators and the female indicator added to the degree network model 4 estimated using POLS, the base cohort year is 1974.

well as the change in the gender gap in the number of collaborators. Our findings are presented in Figure 2. The right vertical axis refers to the share of female authors in a given cohort, that is the share of women who published for the first time in a given year. The share of women publishing has been steadily increasing over the years. While women account for less than 10% of authors in the 1975 cohort, they represent 35% of first publications at the end of our sample.[24]

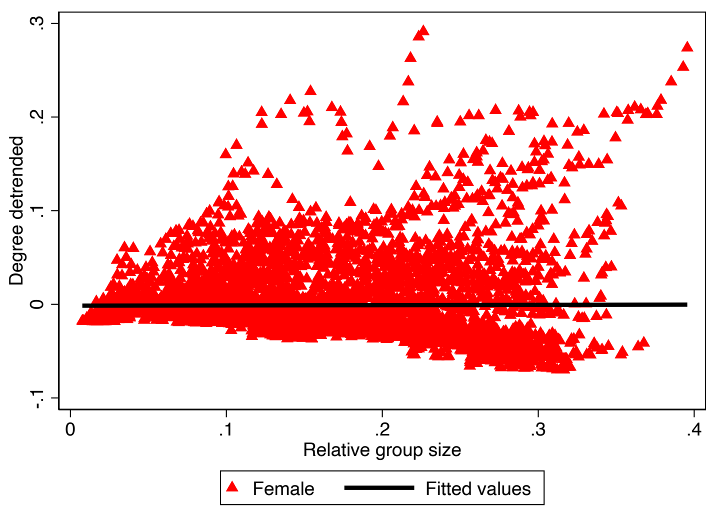
We estimate the relationship between the number of co-authors and the share of women per cohort using the empirical model described in (4). To evaluate how the gender gap evolved throughout our period of observation, we provide the coefficients as well as the 95% confidence interval of the interaction terms between the cohort indicators and the female indicator on the left vertical axis of Figure 2. 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 the number of collaborators is even increasing for the most recent cohort of economists: women who published their first article in 1974 have 0.18 fewer co-authors than men, while women of the 2011 cohort have 0.87 fewer co-authors than men.[25] We find that the discrepancy in the number of collaborators for men and women

[24] This is consistent with the higher share of women in Economics documented in Ductor et al. (2021).

[25] The p-value of an F-test on the joint significance of the coefficients of the interaction terms of gender and time is 0.09 suggesting that the observed increase in degree over recent cohorts is jointly significant

was less pronounced in 1974 than in 2017. This documents that the gender collaboration gap has increased despite the rise in the share of women.[26]

Figure 3: Degree and Fraction of Women, Across Fields



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

Second, we exploit variation in gender shares across fields and tie it to the number of collaborators using empirical model (5). In Figure 3, we observe that the relationship between degree and relative group size is weak. Regressing the average degree per field on the relative group size per field we obtain a slope coefficient of 0.014, which is statistically insignificant (p-value=0.18).

An increase in the share of women in the Economics profession does not ameliorate the gender gap in collaboration, which is key to a reduction in the output gap. Even though economists display gender homophily, the influx in the number of female economists has not led to a higher number of collaborators for women, and thus in turn, it has not helped close the gender output gap.

at the 9% level.

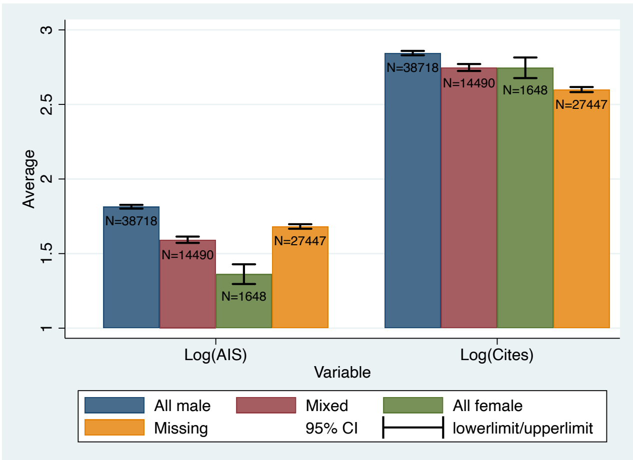
[26]Our results provide a lower bound on the gender gap in the number of collaborators: if we focus instead on the share of women at a given time and how it relates to the number of collaborators, we see an even larger increase in the gender gap.

4.3 Gender Diversity in Research Teams

Homophily shapes the gender diversity of teams. We, therefore, begin by providing descriptive statistics on the gender composition of research teams, before connecting it to the quality of research output. As citations are not available for all journals listed in EconLit, we restrict attention to articles published in the 100 most established journals in economics.[27]

Descriptive statistics for research teams, or equivalently, at the article level are provided in Figure 4. We focus on research teams consisting of two and three authors.[28]

Figure 4: Gender Team Composition: Descriptive Statistics



Note: Sample includes all articles published by two and three authors in the 100 leading journals from 1970 to 2017, and with an estimated gender for each author. *Men* corresponds to articles published only by male authors, *Mixed* is a research team composed of male and female authors, *Women* include articles published only by female authors. The left-bars present the average Log(AIS) and 95% confidence interval for each gender team composition, the right bars show the average Log(Cites+1) and 95% confidence interval for each gender team composition.

Exclusively male teams make up 47% of all collaborations. In comparison, only 2% of all research teams are entirely female. Mixed teams comprise 33%, and the remainder are teams with a missing gender composition.

We find unconditional differences in the quality of the research output according to

[27] This reduces our sample from 367k authors to 327k authors. We opted to use all available information to measure homophily. Our homophily results remain unchanged if we perform our analysis for the authors that published at least once in one of the Top 100 journals.

[28] Articles published by more than three authors represent 4.3% of all the articles published between 1970 to 2017 in the 100 journals. We include single-authored articles as a robustness check when we consider the fraction of women as independent variable, see Tables B.1 and B.2 in the Supplementary Appendix. Our results are qualitatively unchanged, but do not capture the impact of team diversity on research output.

gender team composition. The article influence score is significantly higher for male teams compared to mixed teams. In turn, gender-diverse teams possess a significantly higher article influence score compared to purely female teams. This pattern partially carries over to citations: male teams produce research articles that are more highly cited relative to those written by mixed or female teams. However, there is no distinction between the average number of citations that mixed vs female teams produce, see column 1 of Table 3.[29]

Moving beyond descriptives, we estimate model (6) using the article influence score as the dependent variable. Our results are presented in Table 2.

When controlling for observables, a mixed team publishes, on average, articles in journals with 6.6% lower article influence score than those published by male team, while female teams publishes on journals with 8.6% lower AIS than those of male teams. The gap between mixed and male teams is not significantly smaller than between female and male teams.

A higher number of authors on a team correlates with a lower article influence score.[30] Authors' average past output and team past output are positively associated with journal quality, which may reflect a positive impact of past success on publications. Controlling for authors' past output and team past output, team experience is negatively associated with journal quality. Authors that collaborate with the same coauthors tend to publish in worse journals than authors who collaborate with a different set of coauthors. This seems to indicate that diversity matters– just not in terms of gender. Consistent with Card and DellaVigna (2013), the length of an article is positively associated with the article influence score.

We turn to citations and relate gender team composition to the number of citations the article receives. Our results are presented in Table 3. While male teams unconditionally generate higher citations, this pattern is reversed once we control for observables. A female team tends to receive higher citations, see column (2) of Table 3, which indicates that all-female teams publish articles that are 20% more cited than those of all-male teams. The gender gap in citations persists if we additionally control for the article influence score,

[29]Research teams with a missing gender composition have predominantly Asian last names. It seems like Asian research teams are cited less compared to other papers.

[30]This is in contrast to the results of Bramoullé and Ductor (2018) who find a positive relationship between the number of authors and journal impact. This difference is driven by the exclusion of single-authored papers.

Table 2: Team Gender Composition and Article Influence Score

Variables	Dependent Variable Log(AIS) (1)	(2)
Mixed	-0.221***	-0.066***
	(0.015)	(0.010)
Female	-0.452***	-0.086***
	(0.039)	(0.031)
Missing gender	-0.132***	-0.057***
	(0.012)	(0.008)
Past output team		0.427***
		(0.051)
Avg. past output authors		0.827***
		(0.008)
Team specialization		-0.001
		(0.021)
Team experience		-0.023***
		(0.002)
Pages		0.026***
		(0.000)
# authors		-0.031***
		(0.008)
Constant	1.814***	1.378***
	(0.008)	(0.074)
Year FE	–	✓
JEL codes FE	–	✓
Test Mixed=Female (p-value)	32 (0.00)	0.40(0.53)
Observations	82,303	82,303
R-squared	0.006	0.409

Note: In columns 1 to 2, we estimate the relationship between Article Influence Score and gender diversity, the dependent variable is in log. Sample restricted to two- and three-authored papers. Pages is the number of pages of the article; Number of authors is the number of authors publishing the article; Team specialisation is a Herfindahl index obtained using the shares of past publications in different fields in economics, as defined by the first digit of the JEL codes; Past output team is the number of papers adjusted by quality that the research team has published together in the past; Avg. past output authors is the average number of papers adjusted by quality published by the authors of the research team in the past. All the regressions use clustered standard errors at the team level.*** p<0.01, ** p<0.05, * p<0.10.

that is the journal quality in which the paper was published. Then a hypothetical switch from a male to an otherwise observationally equivalent all-female team is associated to an increase in citations by 21%.

Authors' past average output as well as the team's past output are positively associated with citations. In contrast, team experience is negatively associated with the number of citations, consistent with the findings presented in Table 2. Specialisation is positively related to citations, in line with the existence of positive returns to specialisation in the publication process. Papers written by more authors are also more cited.

In sum, we find that a woman on the team ties in with a lower article influence score. However, conditional on authors' and team characteristics, female teams generate a higher number of citations.

4.4 Alternative Measures, Methods and Samples

Given our data, we cannot establish a causal relationship between team composition and research quality. However, we document in this section that our correlations are robust to alternative measures of diversity and estimation methods. These results are provided in the Supplementary Appendix.

First, we show that our results are robust to a different measure of gender team diversity. We consider the fraction of women on a team as the independent variable of interest. Our results are presented in Tables B.1 and B.2. Once again, having a higher share of women is related to a lower article influence score, but a higher number of citations. Moving from a team without a woman to an all-female team is related to a decrease in the article influence score by 7.5%, while citations rise by 11%.

We then use the Blau diversity index instead of the indicator variable for gender composition. Note that the Blau diversity is difficult to interpret as all female and male teams are assigned the same number– despite the differences in research quality these teams are connected with. With this caveat, we find that gender team diversity is negatively associated with the article influence score. Moving from a gender- homogeneous team to a gender-balanced one is related to a 4.5% lower article influence score. We further find that the association between team diversity and citations is positive and statistically significant, but as with the article influence score, the effect is quantitatively small. Switching from zero diversity to gender balance is associated with a 3.5% increase in citations. This

Table 3: Team Gender Composition and Citations

Variables	Dependent Variable Log(Citations+1)		
	(1)	(2)	(3)
Mixed	-0.097***	0.001	0.011
	(0.016)	(0.013)	(0.013)
Female	-0.099**	0.197***	0.211***
	(0.041)	(0.029)	(0.029)
Missing gender	-0.245***	-0.120***	-0.111***
	(0.013)	(0.011)	(0.011)
Team specialisation		0.054**	0.054**
		(0.025)	(0.025)
Past output team		0.641***	0.574***
		(0.063)	(0.064)
Avg. past output authors		0.309***	0.178***
		(0.010)	(0.010)
Team experience		-0.030***	-0.026***
		(0.002)	(0.002)
# authors		0.148***	0.153***
		(0.010)	(0.010)
Pages		0.031***	0.027***
		(0.000)	(0.000)
Log(AIS)			0.159***
			(0.004)
Constant	2.844***	1.677***	1.458***
	(0.009)	(0.076)	(0.075)
Year FE	–	✓	✓
JEL codes FE	–	✓	✓
Test Mixed=Female (p-value)	0.00(0.96)	43(0.00)	44(0.00)
Observations	82,303	82,303	82,303
R-squared	0.006	0.334	0.345

Notes: In columns (1) to (3), we estimate the relationship between cumulative citations from year of publication to 2017 and gender diversity, the dependent variable is in $\log(x+1)$. Sample restricted to two- and three-authored papers. Pages is the number of pages of the article; Number of authors is the number of authors publishing the article; Team specialisation is a Herfindahl index obtained using the shares of past publications in different fields in economics, as defined by the first digit of the JEL codes; Past output team is the number of papers adjusted by quality that the research team has published together in the past; Avg. past output authors is the average number of papers adjusted by quality published by the authors of the research team in the past. All the regressions use clustered standard errors at the team level.*** p<0.01, ** p<0.05, * p<0.10.

positive association between diversity and citation becomes statistically insignificant when we use the negative binomial model, which is appropriate as citations are by definition count data.

We also estimate the negative binomial for citations and other measures of gender team composition. Our results remain qualitatively unchanged, see Table D.6.

We further control for individual past output and individual experience instead of team characteristics. The results presented in Tables C.4 and C.5 are robust to these different control factors.

Finally, we restrict attention to Top 5 publications, which are summarised in the Supplementary Appendix, Section E. These findings are qualitatively in line with our findings for 100 leading journals in Economics, as well as with Hengel and Moon (2020).

5 Discussion

We document that gender homophily is present in Economics and has remained remarkable stable over a 47 year period. Unfortunately, our data does not permit us to distinguish between the potential drivers of homophily, such as differential meeting rates within groups, preferences or a mix of the two. This is a common issue in the literature on the evaluation of homophily, see for instance Graham (2016). Recently, Jackson et al. (2023) have tackled these questions, focusing on malleable (for instance hours playing video games) and permanent characteristics (such as gender). They find that both matter. Therefore, we follow the interpretation that homophily is an equilibrium phenomenon, shaped by both preferences and differential meeting rates. It is worth noting that one side may be instrumental in limiting interactions. If either men or women did not work with the other gender, then this increases the other gender's homophily as well.[31]

Gender homophily together with the under-representation of women in Economics may contribute to the gender gap in collaborators which is in turn a key predictor for research output.[32] Women have a smaller number of co-authors (see 1 for the difference across a 5-year window), which is an important predictor of research output. However, a higher share of women does not decrease the gender gap in number of collaborators. Therefore,

[31] Mechanically, if women were not willing to work with men, then there are few men that work with women, increasing men's homophily.

[32] Doan et al. (2023) document a causal effect of number of collaborators on research output, e.g. loosing a coauthor leads to a long-run decline in research output of approximately 11%.

while increasing the share of women in Economics may be a necessary condition to tackle existing gender inequalities, our findings indicate that it may not be sufficient in closing the gap in the number of collaborators. This gender gap in co-authors has instead been exacerbated by the me too movement (Gertsberg (2022)). There, women collaborate less with their colleagues at their own universities and are not able to increase the number of co-authors from outside their institution.[33] We can merely speculate as to the reasons why gender homophily and the increase in the share of women has not improved the gender gap in collaboration. If preferences and meeting rates has stayed the same, women would have experienced an uptick in the number of collaborators. Consequently, one of these two factors (or both) seems to have changed over time.

Gender homophily has implications for the gender composition of research teams, which are often homogeneous. Gender homogeneous teams generally outperform gender-diverse teams: male teams outperform female and mixed teams in terms of journal quality, while articles written by women attract the highest citations across the 100 leading journals in Economics.[34] This implies that both men and women have little incentive to work with the other gender. The lack of incentive to work across gender is in line with Sarsons, Gërxhani, Reuben, and Schram (2021b), who show that women do not receive credit for papers co-authored with men. Note that the time frame of our data is before the profession became aware of Sarsons et al. (2021b)'s surprising finding.

Why gender diversity is not an asset in economics, remains for future research. Possible explanations derive from both the supply and demand side. Prat (2002) demonstrates theoretically that if the input of different team members are complementary it is better for the team to be homogeneous. This means that if the research output is dependent on all team members doing their part well, then research teams should be homogeneous. Moreover, Lazear (1999) points out that similarities facilitate communication. A common advantage of more diversity are better predictions (Hong and Page (2001)), which may not be driven by gender differences. Notably, racial, age, educational and gender diversity can have distinct implications for labour market outcomes (see for instance Ilmakunnas and Ilmakunnas (2011)) and it may be that gender differences are relatively less important in terms of making better predictions.

[33] Female academics across disciplines collaborate more locally in general, see Kwiek and Roszka (2021) and online interactions do not seem to have ameliorated this problem.

[34] Our finding confirms Card et al. (2020), who document the same pattern for four journals.

The usual demand side explanations may be at play as well, such as women being held to higher standards in publishing (Ferber and Teiman (1980), Hengel (2016)), and therefore attracting fewer male collaborators.

We leave a systematic investigation of the sources of gender homophily as well as the implications of gender diversity on research to future work. This paper instead documents that despite the increase in the share of women in Economics, women have not reduced the gender gap in the number of collaborators. There is also no discernible positive effect of collaboration across gender. Our findings do not imply that outcomes are efficient as Ductor et al. (2018) demonstrated that more collaborators predict more papers and better publications. Our findings merely indicate that increasing the share of women is not enough to address existing gender gaps.

References

Azmat, G. and A. Boring (2020). Gender diversity in firms. *Oxford Review of Economic Policy 36*(4), 760–782.

Azmat, G. and B. Petrongolo (2014). Gender and the labor market: What have we learned from field and lab experiments? *Labour Economics 30*, 32–40.

Beaman, L., N. Keleher, and J. Magruder (2013). Do Job Networks Disadvantage Women? Evidence from a Recruitment Experiment in Malawi. Working Paper.

Boring, A. (2017). Gender biases in student evaluations of teaching. *Journal of public economics 145*, 27–41.

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.

Bramoullé, Y. and L. Ductor (2018). length. *Journal of Economic Behavior & Organization 150*, 311–324.

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

Card, D., S. DellaVigna, P. Funk, and N. Iriberri (2020). Are referees and editors in economics gender neutral? *The Quarterly Journal of Economics 135*(1), 269–327.

Chari, A. and P. Goldsmith-Pinkham (2017). Gender representation in economics across topics and time: Evidence from the nber summer institute. Technical report, National Bureau of Economic Research.

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

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

Davies, B. (2022). Sex-based sorting among economists: Evidence from the nber.

Doan, T. P. A., L. Ductor, and E. Rascon-Ramirez (2023). The effect of networks on research output. Technical report, Mimeo.

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

Ductor, L., S. Goyal, and A. Prummer (2018). Gender & collaboration. Technical report, Working Paper.

Ductor, L., S. Goyal, and A. Prummer (2021, 10). Gender and Collaboration. *The Review of Economics and Statistics*, 1–40.

Ductor, L., S. Goyal, M. v. der Leij, and G. Paez (2020). On the influence of top journals. unpublished.

Dupas, P., A. S. Modestino, M. Niederle, J. Wolfers, et al. (2021). Gender and the dynamics of economics seminars. Technical report, National Bureau of Economic Research.

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

Ferber, M. A. and M. Teiman (1980). Are women economists at a disadvantage in publishing journal articles? *Eastern Economic Journal 6*(3/4), 189–193.

Gertsberg, M. (2022). The unintended consequences of# metoo-evidence from research collaborations. *Available at SSRN 4105976*.

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

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

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

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

Hengel, E. and E. Moon (2020). Gender and equality at top economics journals.

Hong, L. and S. E. Page (2001). Problem solving by heterogeneous agents. *Journal of economic theory 97*(1), 123–163.

Ilmakunnas, P. and S. Ilmakunnas (2011). Diversity at the workplace: Whom does it benefit? *De Economist 159*(2), 223–255.

Jackson, M. O., S. M. Nei, E. Snowberg, and L. Yariv (2023). The dynamics of networks and homophily. Technical report, National Bureau of Economic Research.

Koffi, M. (2021). Innovative ideas and gender inequality. Technical report, Working Paper Series.

Kwiek, M. and W. Roszka (2021). Gender disparities in international research collaboration: A study of 25,000 university professors. *Journal of Economic Surveys 35*(5), 1344–1380.

Lazear, E. P. (1999). Culture and language. *Journal of political Economy 107*(S6), S95–S126.

Lindenlaub, I. and A. Prummer (2021). Network structure and performance. *The Economic Journal 131*(2), 851–898.

Maddi, A. and Y. Gingras (2021). Gender diversity in research teams and citation impact in economics and management. *Journal of Economic Surveys*.

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. (2020). Gender differences in networking. *The Economic Journal 130*(630), 1842–1873.

Mengel, F., J. Sauermann, and U. Zölitz (2019). Gender bias in teaching evaluations. *Journal of the European Economic Association 17*(2), 535–566.

Paredes, V. A., M. D. Paserman, and F. Pino (2020). Does economics make you sexist? Technical report, National Bureau of Economic Research.

Prat, A. (2002). Should a team be homogeneous? *European Economic Review 46*(7), 1187–1207.

Sarsons, H., K. Gërxhani, E. Reuben, and A. Schram (2021a). Gender differences in recognition for group work. *Journal of Political Economy 129*(1), 101–147.

Sarsons, H., K. Gërxhani, E. Reuben, and A. Schram (2021b). Gender differences in recognition for group work. *Journal of Political Economy 129*(1), 101–147.

Torres, L. and M. L. Huffman (2002). Social networks and job search outcomes among male and female professional, technical, and managerial workers. *Sociological Focus 35*(1), 25–42.

Wu, A. H. (2018). Gendered language on the economics job market rumors forum. In *AEA Papers and Proceedings*, Volume 108, pp. 175–79.

Zeltzer, D. (2020). Gender homophily in referral networks: Consequences for the medicare physician earnings gap. *American Economic Journal: Applied Economics*, forthcoming.

Zhu, M. (2018). Job networks through college classmates: effects of referrals for men and women. Technical report, Working Paper.

Gender Homophily, Collaboration, and Output

Lorenzo Ductor *   Anja Prummer †

February 10, 2023

Contents

*Universidad de Granada. E-mail: lductor@ugr.es

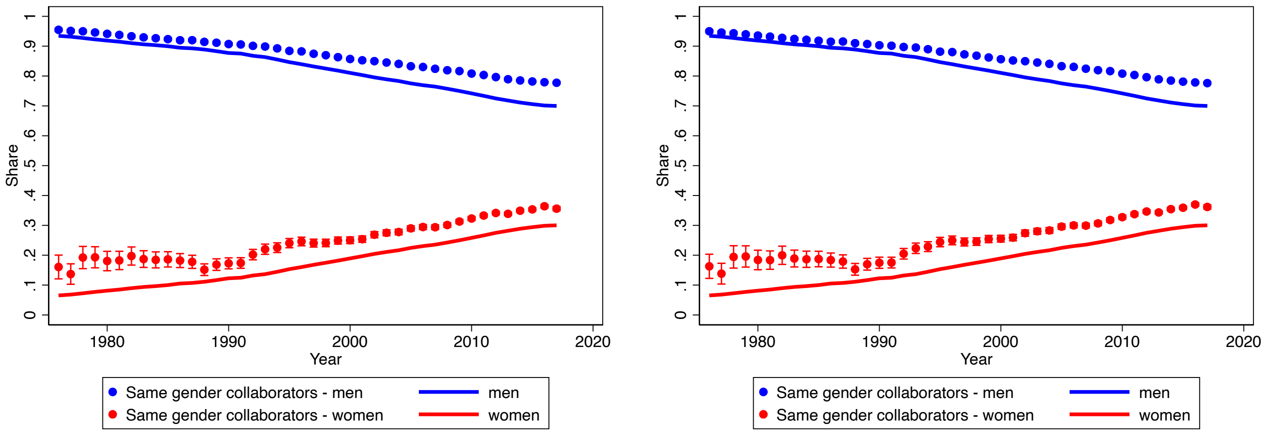
†Johannes Kepler University Linz and Queen Mary University London. Email: anja.prummer@jku.at.

A Relative Homophily

In this section, we show that relative homophily persists over time. To determine whether relative homophily exists, we compare the share of co-authors of the same gender and the share of all same-gender authors. Figure A.1 shows the unconditional and conditional share of collaborators of the same gender, and the share of men and women for each year. At each point in time, men work relatively more with men, compared to their share in the population. Similarly, women work more with women, relative to the share of women among economists. Therefore, both men and women display relative homophily. Relative homophily does not allow us to draw conclusions about the relative change in the gender composition of collaborators relative to the varying gender shares in Economics, unlike inbreeding homophily, which we discuss in the main text.

Figure A.1: Share of same gender collaborators

(a) Same gender collaborators (b) Adj. Same gender collaborators



Note: Adjusted same gender collaborators is the conditional mean calculated from model (2) and using as the dependent variable the share of collaborators with the same gender as the author. Controls include career time, share of JEL codes, past research output, and year.

B Alternative Measures of Gender Team Diversity

In this section, we show that our results are robust to a different measure of gender team diversity. We use the fraction of women on a team as the independent variable of interest. The fraction is not well defined for the research teams where all the authors have missing gender, for this sample we replace missing observations with zero and include an indicator, *All missing gender*, equal to one for these research teams. The results are robust if we remove from our sample research teams with at least one missing gender or those where the gender is missing for all team members.

The results presented in Tables B.1 and B.2 show that having a higher share of women is related to a lower article influence score, but a higher number of citations, in line with our findings in the main text.

We further consider the Blau index, a normalised Herfindahl index, to capture the level of gender diversity. The Blau index of team p is defined as,

$$D_p = 2(1 - p_f^2 - p_m^2), \tag{1}$$

where p_f and p_m are the share of women and men of team p, respectively.[1] The index is a bounded ratio between zero and one. It takes value one if all team members have the same gender. The Blau index is zero if there is an equal number of men and women. The index is not well defined for the research teams where all the authors have missing gender, for this sample, we replace missing observations for zero and include an indicator variable to keep track of these research teams.[2] One shortcoming of the Blau index, and for that matter, any diversity measure is that it does not keep track of whether the team skews towards men or men. A team with a Blau index of one is either entirely female or male. Table B.3 shows that gender team diversity is negatively associated with the article influence score, but positively with citations, once again confirming our results presented in the main text.

C Alternative Control Factors

In the main text we use the average past output of the authors as a control for the ability and skill of the research team. We now check if our results are robust to controlling for the individual past output of each author and individual experience instead. For a two-authored paper, we replace missing characteristics of the third author with zero and include an indicator for a two-author paper. The individual past output is defined as the sum of the article influence scores of all the articles published by the author from the first

[1] To see that this index is a function of the Herfindahl index widely used in the literature to measure concentration, recall that the Herfindahl index is defined as $HI_p = p_f^2 + p_m^2$.

[2] The results are robust if we remove from our sample research teams with at least one missing gender or with all the members with missing gender.

Table B.1: Team Gender Composition and Fraction of women.

Variables	Dependent Variable Log(AIS)		
	(1)	(2)	(3)
Team specialization		-0.004	0.114***
		(0.021)	(0.012)
Fraction women	-0.372***	-0.075***	-0.036***
	(0.019)	(0.014)	(0.010)
All missing gender	-0.213***	-0.036**	-0.036***
	(0.026)	(0.017)	(0.010)
# authors = 2			0.386***
			(0.090)
# authors = 3			0.353***
			(0.090)
Past output team		0.428***	0.083***
		(0.051)	(0.013)
Avg. past output authors		0.827***	0.757***
		(0.008)	(0.006)
Team experience		-0.023***	-0.007***
		(0.002)	(0.001)
Pages		0.026***	0.027***
		(0.000)	(0.000)
# authors		-0.039***	
		(0.008)	
Constant	1.785***	1.383***	0.803***
	(0.006)	(0.074)	(0.099)
Year FE	–	✓	✓
JEL codes FE	–	✓	✓
Observations	82,303	82,303	146,968
R-squared	0.007	0.409	0.369

Notes: In columns 1 to 2, we estimate the relationship between the Article Influence Score and gender diversity, the dependent variable is in log. Sample restricted to two- and three-authored papers. In column 3 we include sole-authored articles. Pages is the number of pages of the article; Number of authors is the number of authors publishing the article; Team specialisation is a Herfindahl index obtained using the shares of past publications in different fields in economics, as defined by the first digit of the JEL codes; Past output team is the number of papers adjusted by quality that the research team has published together in the past; Avg. past output authors is the average number of papers adjusted by quality published by the authors of the research team in the past. All the regressions use clustered standard errors at the team level.*** p<0.01, ** p<0.05, * p<0.10.

Table B.2: Team Gender Composition and Fraction of women.

Variables	Dependent Variable Log(Citations+1)			
	(1)	(2)	(3)	(4)
Fraction women	-0.134***	0.093***	0.105***	0.100***
	(0.021)	(0.016)	(0.016)	(0.011)
All missing gender	-0.458***	-0.158***	-0.153***	-0.125***
	(0.030)	(0.021)	(0.021)	(0.011)
Team specialization		0.050*	0.050**	0.020
		(0.025)	(0.025)	(0.014)
# authors = 2				0.689***
				(0.126)
# authors = 3		0.126***	0.132***	0.825***
		(0.010)	(0.010)	(0.126)
Past output team		0.643***	0.574***	0.063***
		(0.064)	(0.065)	(0.019)
Avg. past output authors		0.311***	0.179***	0.211***
		(0.010)	(0.010)	(0.008)
Team experience		-0.029***	-0.026***	-0.002*
		(0.002)	(0.002)	(0.001)
Pages		0.031***	0.027***	0.033***
		(0.000)	(0.000)	(0.000)
Log(AIS)			0.160***	0.164***
			(0.004)	(0.003)
Constant	2.783***	1.944***	1.736***	0.812***
	(0.007)	(0.073)	(0.071)	(0.134)
Year FE	–	✓	✓	✓
JEL codes FE	–	✓	✓	✓
Observations	82,303	82,303	82,303	146,968
R-squared	0.004	0.332	0.344	0.300

Notes: In columns 1 to 3, we estimate the relationship between the citations and gender diversity, the dependent variable is in log(x+1). Sample restricted to two- and three-authored papers. In columns 4, we include sole-authored articles. Pages is the number of pages of the article; Number of authors is the number of authors publishing the article; Team specialisation is a Herfindahl index obtained using the shares of past publications in different fields in economics, as defined by the first digit of the JEL codes; Past output team is the number of papers adjusted by quality that the research team has published together in the past; Avg. past output authors is the average number of papers adjusted by quality published by the authors of the research team in the past. All the regressions use clustered standard errors at the team level.*** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table B.3: Team Diversity and Research Quality

Variables	Dependent Variable Log(AIS) (1)	Log(cites+1) (2)	Log(cites+1) (3)
Team diversity	-0.045***	0.028**	0.035***
	(0.010)	(0.012)	(0.012)
All missing gender	-0.032*	-0.169***	-0.164***
	(0.017)	(0.021)	(0.021)
Past output team	0.426***	0.647***	0.579***
	(0.051)	(0.064)	(0.065)
Avg. past output authors	0.829***	0.307***	0.175***
	(0.008)	(0.010)	(0.010)
Team specialization	-0.006	0.053**	0.054**
	(0.021)	(0.025)	(0.025)
Team experience	-0.023***	-0.030***	-0.026***
	(0.002)	(0.002)	(0.002)
Pages	0.026***	0.031***	0.027***
	(0.000)	(0.000)	(0.000)
# authors	-0.035***	0.124***	0.129***
	(0.008)	(0.010)	(0.010)
Log(AIS)	–	–	0.160***
			(0.004)
Constant	1.370***	1.709***	1.491***
	(0.074)	(0.076)	(0.075)
Year FE	✓	✓	✓
JEL codes FE	✓	✓	✓
Observations	82,303	82,303	82,303
R-squared	0.409	0.332	0.344

Note: In column (1), we estimate the relationship between Article Influence Score and gender diversity, the dependent variable is in log. In columns (2) to (3), we estimate the relationship between cumulative citations from year of publication to 2017 and gender diversity, the dependent variable is in $\log(x+1)$. Sample restricted to two- and three-authored papers. Pages is the number of pages of the article; Number of authors is the number of authors publishing the article; Team specialisation is a Herfindahl index obtained using the shares of past publications in different fields in economics, as defined by the first digit of the JEL codes; Past output team is the number of papers adjusted by quality that the research team has published together in the past; Avg. past output authors is the average number of papers adjusted by quality published by the authors of the research team in the past. Team diversity is set to 0 for teams with unidentified gender, we included a dummy for teams where all members have a missing gender, All missing gender, in column (3). All the regressions use clustered standard errors at the team level.*** p<0.01, ** p<0.05, * p<0.10.

publication till $t-1$. Tables C.4 and C.5 show that the results are robust to individual author control factor instead of research team.

D Alternative Econometric Model

We show that the association between team gender diversity and citations is robust to the use of different econometric models. Citations are a discrete variable that does not follow normal distributions, so count data models might be more appropriate. In Table D.6, we estimate the number of citations using the negative binomial (NB) model. Columns 1-5 of Table D.6 show the incidence rate ratio (IRR) of each variable. The results are qualitatively similar to those obtained using the Pooled OLS. The citations are 13.1% higher for female research teams once we account for observable factors.

Table C.4: Team Gender Composition and Article Influence Score

Variables	Dependent Variable Log(AIS)		
	(1)	(2)	(3)
Mixed	-0.221***	-0.062***	
	(0.015)	(0.010)	
Female	-0.452***	-0.133***	
	(0.039)	(0.031)	
Missing gender	-0.132***	-0.060***	
	(0.012)	(0.008)	
Team diversity			-0.040***
			(0.010)
All missing gender			-0.061***
			(0.017)
Team specialization		-0.089***	-0.093***
		(0.020)	(0.020)
# authors		-0.086***	-0.091***
		(0.011)	(0.011)
Past output team		-0.234***	-0.231***
		(0.035)	(0.035)
Past output author 1		0.594***	0.594***
		(0.009)	(0.009)
Past output author 2		0.593***	0.595***
		(0.009)	(0.009)
Past output author 3		0.422***	0.422***
		(0.014)	(0.014)
Experience author 1		-0.015***	-0.015***
		(0.001)	(0.001)
Experience author 2		-0.016***	-0.015***
		(0.001)	(0.001)
Experience author 3		-0.009***	-0.009***
		(0.001)	(0.001)
Pages		0.024***	0.024***
		(0.000)	(0.000)
Constant	1.814***	1.842***	1.833***
	(0.008)	(0.077)	(0.077)
Observations	82,303	82,303	82,303
Year FE	–	✓	✓
JEL codes FE	–	✓	✓
Test Mixed=Female (p-value)	32 (0.00)	5.06(0.02)	–
Observations	82,303	82,303	82,303
R-squared	0.006	0.430	0.429

Notes: In columns 1 to 2, we estimate the relationship between Article Influence Score and gender diversity, the dependent variable is in log. Sample restricted to two- and three-authored papers. Pages is the number of pages of the article; Team specialisation is a Herfindahl index obtained using the shares of past publications in different fields in economics, as defined by the first digit of the JEL codes; Past output team is the number of papers adjusted by quality that the research team has published together in the past; past output author 1 is the number of papers adjusted by quality published by author 1 from the first publication til $t-1$. Experience 1 is the career time of author 1. All the regressions use clustered standard errors at the team level.*** p<0.01, ** p<0.05, * p<0.10.

Table C.5: Team Gender Composition and Citations

Variables	Dependent Variable Log(Citations+1) (1)	(2)	(3)	(4)	(5)
Mixed	-0.097***	-0.004	0.005		
	(0.016)	(0.013)	(0.013)		
Female	-0.099**	0.166***	0.186***		
	(0.041)	(0.029)	(0.029)		
Missing gender	-0.245***	-0.126***	-0.117***		
	(0.013)	(0.011)	(0.011)		
Team diversity				0.025**	0.031***
				(0.012)	(0.012)
All missing gender				-0.192***	-0.183***
				(0.021)	(0.021)
Team specialization		-0.028	-0.015	-0.028	-0.015
		(0.026)	(0.025)	(0.026)	(0.025)
# authors		0.181***	0.193***	0.155***	0.168***
		(0.013)	(0.013)	(0.013)	(0.013)
Past output team		0.093	0.126**	0.102*	0.136**
		(0.057)	(0.057)	(0.057)	(0.057)
Past output author 1		0.289***	0.204***	0.288***	0.202***
		(0.011)	(0.011)	(0.011)	(0.011)
Past output author 2		0.264***	0.179***	0.265***	0.179***
		(0.011)	(0.011)	(0.011)	(0.011)
Past output author 3		0.105***	0.044**	0.106***	0.045***
		(0.017)	(0.017)	(0.017)	(0.017)
Experience author 1		-0.012***	-0.010***	-0.012***	-0.010***
		(0.001)	(0.001)	(0.001)	(0.001)
Experience author 2		-0.012***	-0.010***	-0.012***	-0.010***
		(0.001)	(0.001)	(0.001)	(0.001)
Experience author 3		-0.005***	-0.003***	-0.005***	-0.003***
		(0.001)	(0.001)	(0.001)	(0.001)
Pages		0.030***	0.027***	0.030***	0.027***
		(0.000)	(0.000)	(0.000)	(0.000)
Log(AIS)			0.144***		0.145***
			(0.005)		(0.005)
Constant	2.844***	2.205***	1.964***	2.186***	1.947***
	(0.009)	(0.074)	(0.072)	(0.074)	(0.072)
Year FE	–	✓	✓	✓	✓
JEL codes FE	–	✓	✓	✓	✓
Test Mixed=Female (p-value)	0.00(0.96)	33(0.00)	36(0.00)	–	–
Observations	82,303	82,303	82,303	82,303	82,303
R-squared	0.006	0.339	0.348	0.338	0.347

Notes: In columns 1 to 3, we estimate the relationship between cumulative citations from year of publication to 2017 and gender diversity, the dependent variable is in log(x+1). Sample restricted to two- and three-authored papers. Pages is the number of pages of the article; Number of authors is the number of authors publishing the article; Team specialisation is a Herfindahl index obtained using the shares of past publications in different fields in economics, as defined by the first digit of the JEL codes; Past output team is the number of papers adjusted by quality that the research team has published together in the past; Avg. past output authors is the average number of papers adjusted by quality published by the authors of the research team in the past. All the regressions use clustered standard errors at the team level.*** p<0.01, ** p<0.05, * p<0.10.

Table D.6: Gender Differences in Performance: Negative Binomial

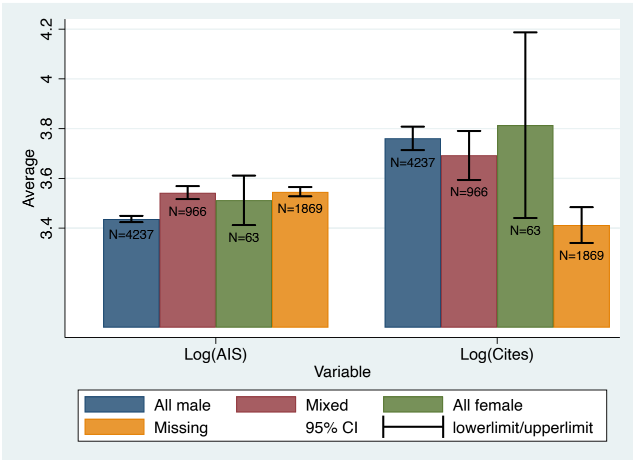
VARIABLES	(1) NB # citations IRR	(2) NB # citations IRR	(3) NB # citations IRR	(4) NB # citations IRR	(5) NB # citations IRR
Mixed	0.788***	0.970	0.979		
	(0.025)	(0.020)	(0.020)		
Female	0.739***	1.114***	1.131***		
	(0.040)	(0.041)	(0.042)		
Missing gender	0.704***	0.848***	0.855***		
	(0.021)	(0.016)	(0.016)		
Team diversity				1.012	1.018
				(0.018)	(0.019)
All missing gender				0.760***	0.767***
				(0.023)	(0.024)
Past output team		1.738***	1.675***	1.749***	1.685***
		(0.150)	(0.154)	(0.153)	(0.158)
Avg. past output authors		1.404***	1.229***	1.401***	1.225***
		(0.022)	(0.022)	(0.022)	(0.021)
Team specialization		0.969	0.984	0.964	0.979
		(0.042)	(0.043)	(0.042)	(0.043)
Team experience		0.974***	0.977***	0.975***	0.978***
		(0.004)	(0.004)	(0.004)	(0.004)
Pages		1.034***	1.030***	1.034***	1.030***
		(0.001)	(0.001)	(0.001)	(0.001)
# authors		1.135***	1.143***	1.100***	1.109***
		(0.018)	(0.018)	(0.017)	(0.017)
Log(AIS)			1.147***		1.148***
			(0.009)		(0.009)
Year FE	–	✓	✓	✓	✓
JEL codes FE	–	✓	✓	✓	✓
Observations	82,303	82,303	82,303	82,303	82,303

Columns 1-3 present the incidence rate ratio from estimating the association between team gender diversity and total citations of the article, using a negative binomial model. Clustered standard errors by authors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

E Top 5 sample

In this section, we restrict attention to the top 5 journals and authors publishing in the top 5. We remove Papers &Proceedings from the *American Economic Review*. The descriptive statistics for the Top 5 journals are presented in Figure E.2.

Figure E.2: Gender Team Composition: Descriptive Statistics. Top 5 sample



Note: Sample includes all articles published by two and three authors on the Top 5 journals from 1970 to 2017: *American Economic Review*, *Journal of Political Economy*, *Econometrica*, *Quarterly Journal of Economics*, and *Review of Economic Studies*. *Men* corresponds to articles published only by male authors, *Mixed* is a research team composes of male and female authors, *Women* include articles published only by female authors. The left-bars present the average Log(AIS) and 95% confidence interval for each gender team composition, the right-bars show the average Log(Cites+1) and 95% confidence interval for each gender team composition.

We then estimate the relationship between publishing in Top 5 journals and gender team composition based on empirical model (6) using OLS.

Columns (1)-(2) of Table E.7 presents the coefficients of the OLS estimation when we use gender team composition dummies. The results show that a female team is associated with a 1.9 higher percentage point probability to publish in a top 5 journal relative to male team, and 2.4 relative to mixed gender teams. Interestingly, mixed teams perform the worst. This finding is robust to the use of alternative measures of team diversity, the results presented in column (3) using the Blau index show that gender diversity does not affect the probability of publishing in a top 5 journal.

When we restrict attention to Top 5 journals, our measure of team composition is unrelated to citations. However, if we account for the fraction of women on a team, then a higher share of women is still related to a higher number of citations, see Table E.8.[3] Taken together, while there may be gender gaps in terms of citations, publishing in Top 5 journals does not seem less likely for female teams, while mixed teams perform worst. Once again, the result illustrates that gender diversity is not an asset.

Table E.7: Gender Differences in Performance: Publishing in a Top 5 Journal

Variables	Dep. Variable: Publishing in Top 5		
	(1)	(2)	(3)
Mixed	-0.035***	-0.005*	
	(0.003)	(0.003)	
Female	-0.033***	0.019***	
	(0.008)	(0.007)	
Missing gender	-0.046***	-0.019***	
	(0.003)	(0.002)	
Team diversity			-0.000
			(0.003)
All missing gender			-0.015***
			(0.004)
Past output team		0.179***	0.179***
		(0.020)	(0.020)
Avg. past output authors		0.137***	0.137***
		(0.003)	(0.003)
Team specialization		-0.033***	-0.033***
		(0.006)	(0.006)
Team experience		-0.008***	-0.008***
		(0.000)	(0.000)
# authors		-0.002	-0.005**
		(0.002)	(0.002)
Pages		0.001***	0.001***
		(0.000)	(0.000)
Constant	0.127***	0.456***	0.455***
	(0.002)	(0.033)	(0.033)
Year FE	–	✓	✓
JEL codes FE	–	✓	✓
Observations	82,303	82,303	82,303

Note: Columns (1) and (2) show the result from estimating the association between team gender diversity and the probability of publishing an article in a Top 5 journal using OLS. Team diversity is set to 0 for teams with unidentified gender, we included a dummy for teams where all members have a missing gender, All missing gender, in column (3).Clustered standard errors at the team level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

[3] Note that our sample differs from Card, DellaVigna, Funk, and Iriberri (2020) and Hengel and Moon (2020) as we omit single-authored papers, which reduces the number of all female teams, making our results less precise.

Table E.8: Team Gender Composition and Citations: Top 5 sample

Variables	Dependent Variable Log(Citations+1)				
	(1)	(2)	(3)	(4)	(5)
Mixed	-0.069	0.024	0.023		
	(0.059)	(0.040)	(0.040)		
Female	0.053	0.106	0.100		
	(0.221)	(0.120)	(0.120)		
Missing gender	-0.349***	-0.135***	-0.134***		
	(0.048)	(0.035)	(0.035)		
Team diversity				0.066*	
				(0.039)	
All missing gender					-0.165*
					(0.099)
Fraction women					0.148**
					(0.060)
Team specialization		-0.224**	-0.218**	-0.224**	-0.226**
		(0.089)	(0.089)	(0.088)	(0.089)
Past output team		0.081	0.084	0.081	0.076
		(0.100)	(0.100)	(0.102)	(0.101)
Avg. past output authors		0.238***	0.237***	0.237***	0.241***
		(0.028)	(0.028)	(0.028)	(0.028)
Team experience		-0.018***	-0.018***	-0.018***	-0.017***
		(0.006)	(0.006)	(0.006)	(0.006)
# authors		0.072**	0.071**	0.051	0.056*
		(0.033)	(0.033)	(0.033)	(0.033)
Pages		0.032***	0.033***	0.033***	0.033***
		(0.001)	(0.002)	(0.002)	(0.002)
Log(AIS)			-0.134**	-0.135**	-0.132**
			(0.056)	(0.056)	(0.056)
Constant	3.761***	2.095***	2.519***	2.648***	2.629***
	(0.026)	(0.216)	(0.282)	(0.270)	(0.271)
Year FE	–	✓	✓	✓	✓
JEL codes FE	–	✓	✓	✓	✓
Test Mixed=Female (p-value)	0.29(0.59)	0.44(0.51)	0.39(0.53)	–	–
Observations	7,135	7,135	7,135	7,135	7,135
R-squared	0.009	0.445	0.445	0.444	0.445

Notes: In columns 1 to 3, we estimate the relationship between cumulative citations from year of publication to 2017 and gender diversity, the dependent variable is in log(x+1). Sample restricted to two- and three-authored papers published on the Top 5 journals: *American Economic Review*, *Journal of Political Economy*, *Econometrica*, *Quarterly Journal of Economics*, and *Review of Economic Studies*. In column 4, we use the fraction of female in the research team and the sample includes sole-,two- and three-authored articles published on the Top 5 journals. Pages is the number of pages of the article; Number of authors is the number of authors publishing the article; Team specialisation is a Herfindahl index obtained using the shares of past publications in different fields in economics, as defined by the first digit of the JEL codes; Past output team is the number of papers adjusted by quality that the research team has published together in the past; Avg. past output authors is the average number of papers adjusted by quality published by the authors of the research team in the past. All the regressions use clustered standard errors at the team level.*** p<0.01, ** p<0.05, * p<0.10.

References

Card, D., S. DellaVigna, P. Funk, and N. Iriberri (2020). Are referees and editors in economics gender neutral? *The Quarterly Journal of Economics 135*(1), 269–327.

Hengel, E. and E. Moon (2020). Gender and equality at top economics journals.