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Is there a differentiated gender effect of collaboration with super-cited authors? Evidence from junior researchers in economics

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Abstract

In recent decades, economists have analyzed different types of gender inequality. Female researchers tend to have lower pay, write fewer articles, and receive fewer citations than their male counterparts. In this paper, we investigate whether there is a medium-term effect of gender on the career of junior researchers who collaborated with a super-cited (SC) author within 5 years of their first publication. We employ a matching model using co-authorship network measurements to compare similar junior collaborators and non-collaborators. We find a positive effect on the impact of all junior collaborators, but there is no statistically significant difference between men and women. Female and male junior collaborators have similar increases in SC co-authorship events and unique SC co-authors relative to non-collaborators, which might help explain this non-differentiated medium-term advantage.

Keywords Super-cited authors · Gender inequality · Co-authorship network · Economics

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Introduction

The economics profession has been no exception to the gender disparities affecting society in various ways, including in representation (Holmes et al., 2008; Sidhu et al., 2009), compensation (Barbezat & Hughes, 2005; Freund et al., 2016), productivity, (Huang et al., 2020; Mueller et al., 2017) and impact (Beaudry & Larivière, 2016; Dorantes-Gilardi et al., 2022; Maliniak et al., 2013). Productivity and impact, measured by a researcher's number of publications and citations, have an important effect on career success, including promotion to a tenured position (Weisshaar, 2017) or receiving salary increases (Leahey & Tuckman, 1975).

Evidence suggests that men and women with similar backgrounds and opportunities may show dissimilar job trajectories because they receive different treatment in the job market or because they self-select for certain positions (Kahn, 1993). Gender differences in promotion, salary, or productivity in many high-skilled occupations lead to a higher dropout rate for women than men, not only in the first stage of their careers, but also later on (Barabási et al., 2020).

Quantitative approaches to evaluating a researcher's career can reduce biases and avoid profiling based on gender, race, and other intrinsic individual characteristics (Acuna et al., 2012). The increased availability of data also makes it possible to conduct more detailed statistical analysis. The use of citation metrics by research committees for purposes of evaluation and promotion has increased the pressure to enhance the impact of publications, leading to controversial practices of self-citation (Ioannidis, 2015). Gender differences in research impact are of fundamental interest to policy-makers, employers, and to female researchers themselves, since the undervaluing of women's research can lead to career attrition and fewer job opportunities (Thelwall, 2018).

One often overlooked aspect of citation distributions is their intrinsic fat-tail behavior. It is a recognized phenomenon that a small group of authors, who we refer to as super-cited (SC), accounts for a disproportionately large number of citations (Redner, 1998). Unlike other distributions, in which observations are gathered around a typical value with minor deviations (Clauset et al., 2009), this distribution of citations means they cannot be characterized with the usual parameters of mean and variance.

In this paper, we focus on two main questions considering researchers in economics. First, we analyze whether co-authorship with an SC author in the early stage of a researcher's career affects the medium-term future outcomes of impact and productivity. Second, we investigate whether the effect of such co-authorship is differentiated by gender.

To answer these questions, we use the publicly available decentralized database RePEc (Research Papers in Economics) to compile articles, citations, and authors in economics. We define junior researchers as those within 5 years of their first publication, what we consider the early career stage, and analyze their outcomes in the medium term (years 6 to 10). We consider only authors with a career of at least 10 years and exclude junior researchers who are SC authors themselves. These restrictions allow us to compare individuals with similar profiles.

However, since junior researchers who have collaborated with an SC author are likely to have different characteristics than those who have not, we use a propensity score matching (PSM) approach that matches on network pre-collaboration measures to create an appropriate control group. Our results show a positive and significant effect on average citations per paper for junior researchers who co-authored with an SC author relative to those who did not. Our analysis by gender finds a positive and significant effect on this measure of impact for both female and male junior collaborators, and we find no gender difference in this effect. We find no statistically significant effect on productivity. Our results are robust to different matching estimators and to the inclusion of authors' sub-field and country controls. We investigate two possible reasons for this non-differentiated effect. We find that female and male junior collaborators have similar increases in SC co-authorship events (collaborations with a SC author) and SC co-authors relative to non-collaborators.

Our study is closely related to that of Li et al. (2019), who show that early co-authorship with SC authors has a positive effect on the junior collaborators' career in the years following the collaboration, considering all authors, but only on the number of citations (impact) and the probability of being SC themselves. However, our analysis includes some crucial differences. We take advantage of the network nature of the co-authorship data to implement the PSM approach, which allows us to use a global perspective on the authors' position instead of one based on one-to-one relationships. We also study whether there is a gender effect, and we use a database that specializes in publications in economics.

Our paper is structured as follows. In "Economics as a discipline" section, we describe the discipline of economics and the background of researchers in the field. In "The importance of co-autorship with SC authors" section, we describe the importance of co-authorship with an SC author. "Data" section presents the data. "Empirical strategy" section describes the empirical strategy, and "Results" section presents the results. Finally, "Conclusions" section offers some concluding remarks.

Economics as a discipline

Economics is considered a social science, although its quantitative methods differ greatly from the methods used in other social sciences. This characteristic affects economists' perception of themselves and their relationship with other areas of knowledge. Economics is a highly competitive discipline in which only the top 10–20% of Ph.D. recipients receive tenure at mid-level research institutions. Receiving a degree from a top department does not guarantee becoming a successful researcher (Conley & Önder, 2014).

Economists are especially concerned with measuring their success and that of their peers. One way to do so is to assess the extent to which their publications appear in influential journals. Economists' evaluations and promotions rely mainly on papers published in well-established journals, with little weight given to books or book chapters (Bardhan, 2003; Heckman & Moktan, 2020; Kuld & O'Hagan, 2018), and the extent to which these papers influence other researchers and shape policy-making and public debate (Hamermesh, 2020).

Journal articles in economics have shown a notable rise in co-authorship[1] in recent years. Kuld and O'Hagan (2018) find a remarkable increase in multi-author and international papers from 1995 to 2014, although two-author papers are still predominant ($\approx$ 40% in 2015), followed by single- and three-author papers ($\approx$ 25% each in 2015). The international papers are mainly collaborations between authors in the US and those in other countries.

[1] The usual practice in economics papers is to list authors' names alphabetically. Kuld and O'Hagan (2018) find no evidence that the ordering of names in multi-author papers signals differences in contributions.

One peculiarity that sets economics apart from other disciplines is the long delay in the journal publishing process. Björk and Solomon (2013) examine the average turnaround time from submission to final publication in different disciplines and find that it is longer in business/economics (18 months) than in social science (14 months), mathematics (13 months), or chemistry (9 months). Furthermore, Ellison (2002) highlights a slowdown in this publication process in the top economics journals, mainly due to journals requiring more extensive revisions.

The peculiarities of the evaluation and publishing processes in economics affect the number of researchers that build a journal-based career. Almost 50% of Ph.D. holders in economics never publish (Conley & Önder, 2014). There are also gender differences in the publishing process: the percentage of men who publish at least once within the 6 years after receiving their Ph.D. is greater than that of women (50% vs. 46%) (Conley et al., 2016). Still, most economists begin to publish after receiving a doctorate. García-Suaza et al. (2020) find that 2 years prior to receiving their degree, the average number of papers is below 0.2; in the fourth year after completing a Ph.D., the average increases to about 0.9 papers per year, and it remains flat until the sixth year. There is evidence that junior male researchers, up to 6 years after completing the Ph.D., publish more papers on average than their female counterparts: 4.18 and 3.13 papers, respectively (Conley et al., 2016).

Gender and geographic differences

In 2019, the American Economic Association released the final report on its Professional Climate Survey,[2] which aimed to shed light on the factors that limit inclusiveness or discourage civility in work environments. The report notes that women and minority groups are under-represented compared to other academic disciplines and that women more frequently reported personal experiences of discrimination or unfair treatment in promotion and compensation, particularly in academia and for-profit organizations.

Little progress has been made in increasing the participation of women in academic positions, and women are less likely to receive tenure than their male counterparts (Antecol et al., 2018; Blau et al., 2010; Lundberg & Stearns, 2019). Ginther and Kahn (2021) show that female researchers in economics are 15% less likely to be promoted to associate professor than their male counterparts, even controlling for productivity and citations. Bayer and Rouse (2016) find that women's presence has increased in the last two decades in the humanities, business, and STEM fields (science, technology, engineering, and math), and also in social sciences, except for economics, which has stagnated at around 30% both for undergraduate and doctoral degrees.

The geographic distribution of exceptionally productive economics researchers is concentrated in the US, where 70% received their Ph.D. and 60% are employed, followed by the EU, with figures of 27% and 30%, respectively (Albarrán et al., 2017). Similarly, Das et al. (2013) show that the geographic focus of empirical studies in economics publications is concentrated on the US and the UK, at 40% and 8.6%, respectively.

[2] https://www.aeaweb.org/resources/member-docs/final-climate-survey-results-sept-2019.

The importance of co-autorship with SC authors

Merton (1968, 1988) found that in co-authored papers, people tend to remember the names they are familiar with and attribute the major findings to them, even if other authors contributed more. However, even though lesser-known co-authors may be overlooked in the short term, the publication with a well-known co-author may help them obtain future recognition in their careers (Merton, 1968).

The issue has become more relevant with the increase in co-authorship in the field, where the proportion of single-author papers has dramatically decreased (Kuld & O'Hagan, 2018), and the number of co-authors increases with the longevity of an author's career (Hollis, 2001). We argue that it is not only the number of co-authors that is essential to receiving more citations, either because having co-authors enables researchers to publish more papers (Li et al., 2013) or because greater collaboration improves a paper's quality (Hollis, 2001). Having highly cited co-authors also helps to receive more citations.

Studies have suggested that social success can be shaped by an individual's local network or by the role they have within a social network (Blansky et al., 2013; Stadtfeld et al., 2019). Relationships among authors play an essential role in defining trajectories of those involved, and their individual benefits may be asymmetric, depending on experience or reputation (Bidault & Hildebrand, 2014; Sarsons, 2017). The selection of co-authors thus becomes an important decision, given that a personal network of high-profile co-authors and publication in top-ranking journals can increase an article's citations (Heckman & Moktan, 2020; Li et al., 2013).

Whenever a researcher co-authors a paper, they create an individual co-authorship network, where each node is an author and the link represents a jointly published paper. The network shows all direct co-authorship relations and contains valuable information on each author's direct and indirect connections (Li et al., 2013). Such networks are well suited to a network science approach (Newman, 2004).

Bidault and Hildebrand (2014) observe that co-authorship between authors of differing academic ages and publication profiles affects their citations differently, depending on their characteristics and the persistence of their relationship. Junior authors benefit from a link with senior authors, which may make their work more visible and attract more citations. Gazni and Thelwall (2014) find that high-impact authors tend to cite their collaborators more than lower-impact authors. Qi et al. (2017) also show that in physics, young researchers who collaborate with outstanding scientists in the early stage of their career experience a positive and persistent effect. Thus, we would expect that a junior researcher who co-authors with an SC author would benefit more than those who did not collaborate.

Li et al. (2019) find that junior collaborators with SC authors consolidate their early competitive advantage by getting more opportunities to continue collaborating with them than non-collaborators. Considering that female junior researchers publish fewer papers than men (Conley et al., 2016), we might expect that women would have fewer opportunities for repeated collaboration with an SC to enlarge an advantage gained early in their careers. Hence, the effect of collaboration might be lower for women than for men.

Moreover, as Bu et al. (2018) find, high-impact authors are more likely to collaborate with researchers having different research topics; thus, the benefits to junior researchers of collaborating with a well-known researcher may not only be tied to the provision of knowledge, experience, and resources, but also to their willingness to engage in new ideas.

It should be noted that co-authorship relationships do not occur at random. The probability of a new collaboration is greater when two authors are closer within an existing collaboration network, since individuals seek to minimize search costs using available information to ensure a better fit in ability and quality (Fafchamps et al., 2010). It is thus important to control for network characteristics in our econometric estimation.

The benefits of collaborating early in one's career with prominent figures or of having access to better resources within a community are not restricted to academia. They have been seen, for instance, in artistic careers, where reputation also plays an essential role. Fraiberger et al. (2018) find that careers in the arts are characterized by a strong path dependence, where those artists beginning in central positions are likely to remain in those positions. Artists in lower positions have higher drop-out rates, but can work their way up the ladder if they remain in their career and have access to prestigious institutions or galleries.

Collaboration with an SC author may not be the only factor increasing the citations of junior researchers. As Ebadi and Schiffauerova (2015) explain, older researchers have greater access to funding, a better-established collaboration network, and better physical resources. One of our robustness tests thus controls by academic age to capture this effect (Barabási et al., 2020; Ebadi & Schiffauerova, 2015). Co-authorship of an article between a junior and an SC researcher may also be a product of mentorship, from which the junior researcher could also benefit from the mentor's influence network.

Data

We obtain information about researchers, publications, co-authorship networks, and citations from Research Papers in Economics (RePEc), an essential bibliographic service for the field of economics. We start with 445,847 articles from the ReDIF-Article feature of RePEc[3] published from 1990 to 2019. Citation data is restricted to the same period.[4] Figure S1 shows a detailed description of RePEc and the articles selected.

Authors whose citations significantly exceed the mean for each year are defined as super-cited (SC) authors, and we consider authors who are outliers.[5] Figure S2 shows that after 1995, SC authors represented approximately 10% of the yearly total. Thus, our definition of an outlier is comparable to the top decile.

In order to study the career effect on junior scientists resulting from a co-authorship with an SC author, we consider cases where this event happens in the early stage of their career. We define the early career stage as the 5 years after the first publication. We define junior researchers as those in the early career stage. We define those who have a co-authored article with an SC author as junior collaborators; those who do not are non-collaborators.

In economics, very few papers are published during the 2 years prior to receiving the Ph.D., and the average number of papers published annually only reaches 0.9 after 4 years ("Economics as a discipline" section). Our definition of the early career stage is close to that of Bazeley (2003), who defines it as the 5 years after completing the Ph.D., and it is the same as that of Jin et al. (2020). Other authors use similar definitions of career stages (e.g., Barabási et al., 2020; Birkmaier & Wohlrabe, 2014; Ductor et al., 2014).

[3] In RePEc, only the journal publisher can index material. See https://ideas.repec.org/t/articletemplate.html.

[4] Articles published prior to 1990 account for less than 1% of the total (Fig. S1).

[5] Number of citations greater than $\mu + 1.5 \times (Q3-Q1)$, where μ is the mean of the distribution and Qi is the ith quartile.

Table 1 Descriptive statistics of junior researchers

Variable	Statistic	Years 0–5		Years 6–10	
		Non-SC collaborator	SC collaborator	Non-SC collaborator	SC collaborator
Articles	Mean	3.8	5.7	7.0	8.0
	S.D.	3.5	4.9	7.0	7.7
Citations	Mean	5.9	14.7	30.8	62.5
	S.D.	6.8	14.3	47.4	65.8
Av. citations per article	Mean	1.8	2.8	4.6	8.9
	S.D.	1.8	2.1	4.6	8.1
Female	%	19	20	19	20
Observations	*n*	2786	1349	2786	1349

We restrict our analysis to all junior researchers with a profile in RePEc whose careers started between 1990 and 2009 and lasted at least 10 years,[6] and who have published at least one co-authored paper every five years.[7] We obtain a list of 4135 junior researchers who are not themselves SC authors.[8]

Table 1 presents summary statistics for junior researchers. Junior collaborators tend to have a greater number of citations,[9] articles, and average citations per article than non-collaborators. In "Empirical strategy" section, we explain how we create a counterfactual to address this imbalance in observable characteristics between junior collaborators and non-collaborators.

As a preliminary analysis, we focus on 1288 junior collaborators who had at least one publication 5 years before and after collaborating with an SC author. Figure 1a and b show for each author the number of citations and articles 5 years before (Year − 5) and 5 years after (Year 5) collaboration with an SC author (Year 0). Figure 1c and d show the mean number of citations and articles for all junior collaborators before and after Year 0.

The average number of citations per author per year (Fig. 1c) is 2.8 in the 5 years before collaborating with an SC author and 11.2 in the 5 years after, nearly a fourfold increase, and the slope seems to be steeper after Year 0. The mean number of articles (Fig. 1d) before Year 0 is smaller (1.8) than after (2.3), but the slope does not seem to change after Year 0. In Fig. 1a, where a darker color represents more citations, the collaboration with an SC author has a visible effect, but we do not see such a notable change in the color representing the number of articles in Fig. 1b. These preliminary results indicate that collaboration with an SC author may positively affect impact but not productivity.

In what follows, we calculate the statistical significance of this effect compared to junior non-collaborators and the possibility of a differential effect by gender.

[6] Following Barabási et al. (2020) and Ebadi and Schiffauerova (2015), career length is calculated as the time between the first and last publication.

[7] We exclude one author who meets these criteria because we do not have subfield information.

[8] The exclusion of SC authors is dictated by the need to find a reasonable balance in covariates between junior collaborators and non-collaborators. Also, we are interested in finding the effect on junior researchers who can benefit the most from co-authorship with an SC author.

[9] In all our analysis, we exclude self-citations.

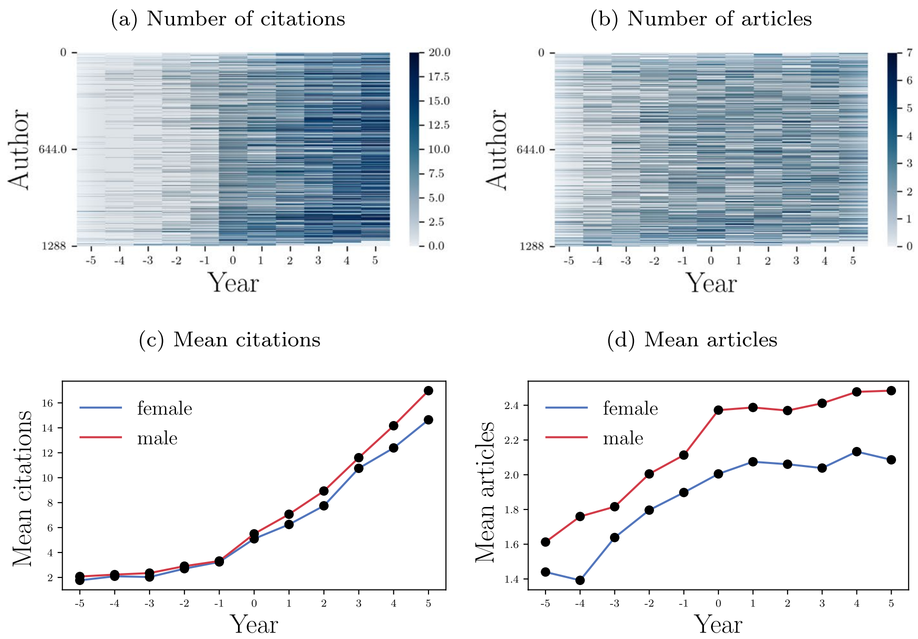

Fig. 1 Effect on citations and articles of junior collaborators

Empirical strategy

To investigate the effect of collaboration with SC authors in the success of male and female junior researchers, we use a propensity score matching procedure to create an appropriate counterfactual. This procedure uses pre-treatment measures of the junior co-authorship network and academic performance, which are shown in Table S3.

Apel and Sweeten (2010) note that both propensity score matching and ordinary least squares (OLS) rely on the assumption that the treatment is random once we condition on observables, what is known as the conditional independence assumption (CIA). However, propensity score matching, unlike OLS, does not assume a linear functional form to estimate treatment effects, and requires the common support assumption, which reveals the overlap in observable characteristics between treated and untreated individuals.

Baser (2007) identifies conditions under which OLS fails to adjust adequately for differences in observed covariates, where it is instead convenient to use propensity score matching. For example, OLS might fail to adjust for observed confounders if: “1. The means of the propensity scores in the two groups are more than one-half a standard deviation apart, unless: (a) distributions of the covariates in both groups are nearly symmetric..., (b) sample sizes of the two groups are approximately the same..., (c) distributions of the covariates in the two groups have similar variances” (pp. 381–382).

In our scenario, the propensity scores of the two groups are 1.1 standard deviations apart (> 0.5). We thus checked the sub-criteria to see whether criterion 1 could be waived. Using the D’Agostino test, we rejected the null hypothesis that the distribution of the covariates was symmetric, since the skewness and kurtosis were significantly different from zero for each variable. Sample sizes were not significantly different: the control group was only

2.1 times larger than the treatment group (criterion b).[10] However, the distributions of the covariates had significantly different variances (criterion c). Overall, the above tests suggest that regression analysis would not adjust for differences in observed characteristics.[11]

As discussed in "The importance of co-autorship with SC authors" section, a co-authorship network embeds information about the nodes and their social status within the network. We thus use co-authorship network measures to proxy important author characteristics, in contrast to other studies that have used explicit job-related or academic characteristics, such as institutional ranking or Ph.D. awarding institution. We describe the construction of the co-authorship network in Sect. S4.

We calculate the propensity score using a probit model (see Sect. S3) that includes the following pre-treatment variables:

- The average degree, or number of direct co-authors, in the co-authorship network during the 5 years after an author's first publication.
- The average closeness centrality in the co-authorship network during the 5 years after an author's first publication. We define the closeness centrality indicator as the inverse of the sum of all shortest paths from a researcher to every other researcher they are connected to. This measure considers all the researchers directly and indirectly linked to them. An author is more centrally located in the co-authorship network when they are closer to every other author, either directly or indirectly. We are aware of the existence of different centrality network measures. However, the number of "steps" between one author and the rest, as captured by closeness centrality, is more relevant in our context than the author's proximity to a path between any two other authors, as captured by other measures such as betweenness centrality. A high closeness centrality indicates that an author has few "degrees of separation" from collaboration with a new researcher, which could have greater implications over the years for a diverse set of co-authors than for someone with a small value.
- The proportion of time the author is in the largest component during the 5 years after their first publication. The largest connected component includes the maximal subnetwork such that a path in the network can connect all authors.
- The number of citations and articles during the 5 years after an author's first publication.

The treatment variable is defined as an indicator function that is equal to one if a junior researcher collaborates with an SC author during the 5 years after their first publication. To calculate the average treatment effect on the treated (ATT), we follow Smith and Todd (2005) and implement the matching estimator as:

$$\hat{\alpha}_M = \frac{1}{n_1} \sum_{i \in I_1 \cap S_P} \left[Y_{1i} - \sum_{j \in I_0} W(i,j) Y_{0j} \right]. \tag{1}$$

Y_1 is the outcome variable conditional on being treated and Y_0 conditional on not being treated. I_1 denotes the set of treated units (junior collaborators), I_0 the set of non-treated

[10] Following Baser (2007), sample sizes are considered significantly different if one group is < 5% the size of the other group.

[11] See Baser (2007) for a detailed explanation.

(junior non-collaborators), and S_P the region of common support. The weights $W(i, j)$ depend on the particular cross-sectional estimator employed.

The idea behind propensity score matching is to compare units that, based solely on their observables, have very similar probabilities of being assigned to treatment. If, conditional on observables, two units have a probability of similar treatment, then we say that they have similar propensity scores. That is, if we compare a unit in the treatment group with a unit in the control group with a similar propensity score, then conditional on the propensity score, all remaining variation between the two is random. However, the probability of observing two units with the same propensity score is initially zero, because the propensity score is a continuous variable. Various propensity score matching methods have been proposed in the literature. We use the kernel, nearest-neighbor, and stratification matching estimators,[12] and the mixed method of OLS and weighting.

In the kernel estimator, all untreated units are used as controls to estimate the counterfactual. The distance between the propensity scores of treated and untreated units in an inversely proportional relationship determines the weights. Specifically,

$$W(i,j) = G\big((P_j - P_i)/a_n\big) / \sum_{k \in I_0 \cap S_P} G\big((P_k - P_i)/a_n\big), \tag{2}$$

where G(.) is a the Gaussian function and a_n is a bandwidth parameter (0.06).

In the nearest neighbor estimator, each treated unit is matched with the control unit with the closest propensity score. The method is applied with replacement, such that a control unit can be the best match for more than one treated unit.

The stratification estimator divides the observations into a set of intervals such that on average, within each range, treated and control units have the same propensity score. In the region of common support, the difference between the average outcomes of the treated and the controls is computed within each block. The ATT is the weighted average of the ATT in each block, with weights given by the fraction of treated units in each block.

These estimators occupy different places in the trade-off between the quantity and quality of the matches. Their joint consideration offers a way to assess the robustness of the estimates (Becker & Ichino, 2002).

Identification of the ATT by the matching estimator requires that outcomes be independent of the treatment, conditional on a set of observable characteristics ($Y_0 \perp\!\!\!\perp D|Z$) and that for all observable characteristics, there should be a positive probability of being treated or not treated, that is, that $0 < Pr(D = 1|Z) < 1$ (the common support assumption).

Imbens (2004) and Hirano et al. (2003) explain how the estimated propensity scores can also be used as weights to obtain a balanced sample of treated and untreated individuals. This mixed-method of OLS and weighting can be estimated using a regression function by weighted least squares:

$$Y_i = \alpha + \tau W_i + \epsilon_i, \tag{3}$$

with weights equal to 1 for treated and $\frac{P_i}{1-P_i}$ for controls to estimate ATT. This weighted least-squares representation suggests that covariates may be added to the regression function (Imbens, 2004). We use this approach to add country[13] and subfield dummies and a time control.

[12] The explanation of these matching estimators closely follows Smith and Todd (2005), Becker and Ichino (2002), Heckman et al. (1998) and Heckman et al. (1997).

[13] An author's country is defined as the country of institutional affiliation.

Results

There are 4135 junior researchers who are not themselves SC in their early career: 1349 collaborators and 2786 non-collaborators. Table S3 shows the results of estimating the propensity score for our sample of junior researchers using the variables detailed above.[14]

Results of the estimation of the propensity score show that the probability of collaborating with an SC author is negatively correlated with the number of articles and the average closeness centrality, while there are nonlinear relationships with citations (quadratic) and average degree (cubic).

We can see in Fig. 2a that the median of the propensity score considering all authors, the horizontal line near the middle of the box, is 0.18 for non-collaborators and and 0.49 for collaborators with the SC authors. As discussed by Becker and Ichino (2002), imposing the common support restriction improves the quality of the matches, since collaborators and non-collaborators have different distributions of the estimated propensity score.[15] The mean of the scores with the common support is 0.326 (SD = 0.241).

If we look separately at male and female researchers (Fig. 2b, c), we see that the probability of being a junior collaborator is roughly the same, at 0.33 and 0.32, respectively. The common support restriction implies that the test of the balancing property is performed on all treated observations plus only those controls whose propensity score lies within the propensity scores of the treatment units.

Tables S4–S6 show that the balancing property is satisfied over the common support region. We report the difference in means and two-sided *p*-values of these *t*-tests for the treatment and control groups in each of the eleven total and seven optimal blocks of the sample. None of these differences is statistically significant at the 99% confidence level.

Table 2, panels A to D report the ATT on impact (log of the number of citations accrued in career years 6–10 and log of the average number of citations received per article published in career years 6–10), productivity (log of the number of articles published in career years 6–10),[16] and the probability of being in the SC group between career years 6 and 10.[17] Bootstrapped standard errors are estimated for all estimators.

In all three groups (all, female, and male), we find that junior collaborators achieve a higher impact than junior non-collaborators. Moreover, the differences with respect to the controls are statistically significant in all cases, except when using the OLS and weighting estimator for the subsample of female researchers and when using total citations as a measure of impact.

In general, we do not find statistically significant differences in terms of productivity. However, we do find suggestive evidence that junior collaborators have a higher probability of becoming SC themselves in career years 6–10 than junior non-collaborators. Testing the difference in the coefficients of the effect of co-authoring with an SC author by gender, we

[14] The propensity score is estimated using the Stata program pscore, developed by Becker and Ichino (2002).

[15] We exclude 19 non-collaborators who fall outside the common support region.

[16] We use a log transformation of the dependent variable given the highly skewed distributions. Although the propensity score matching algorithm does not require normality of the errors, the OLS and weighting approach does. Also, following Criscuolo et al. (2019) and Macurdy and Pencavel (1986), we add one to the values of the variables before taking logs to avoid excluding observations with a value of zero, which make up about half of our observations.

[17] Indicator function with a value of one if the junior researcher was an SC author in any of the years 6–10 of their career.

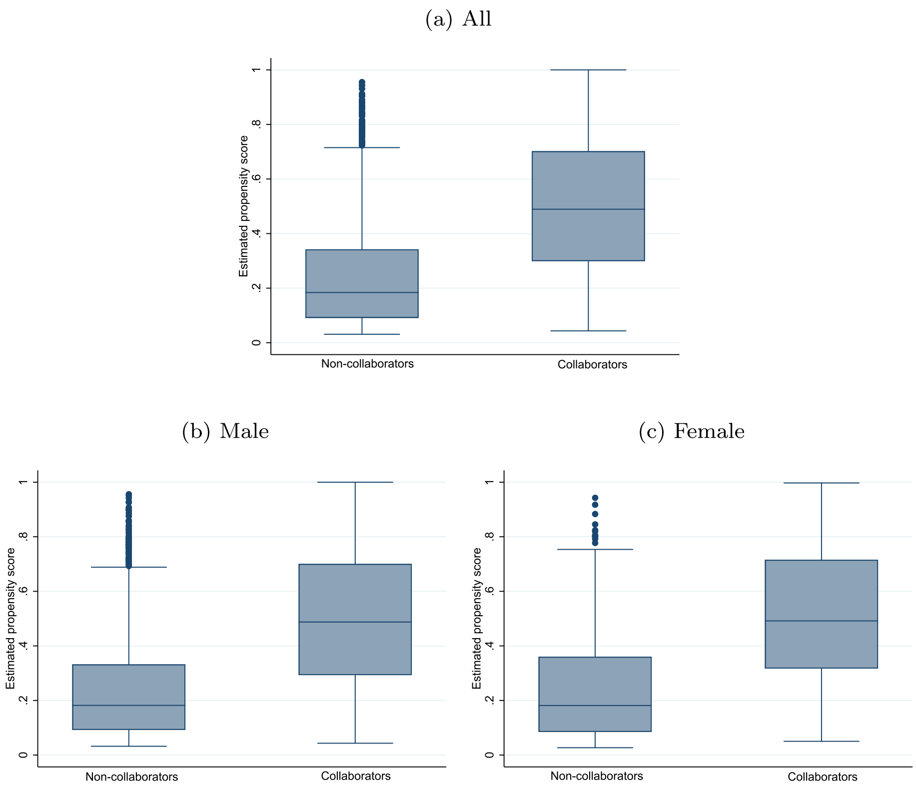

Fig. 2 Estimated propensity scores of junior researchers

cannot reject the null hypotheses that the coefficients in all three groups are equal. It seems that co-authorship with an SC author has the same effect on impact, productivity, and the probability of becoming an SC author, independent of gender. These findings are true for all estimators.

Our results show that co-authorship with an SC author in economics could lead to a medium-term career advantage, in line with the findings of Li et al. (2019) and Qi et al. (2017), who study other disciplines. Unlike these authors, we go one step further and find that this advantage does not differ by gender.

We further explore two potential mechanisms through which this advantage arises. We analyze whether early career SC co-authors have more co-authorship events and unique SC co-authors (the number of different SC collaborators) during years 6–10 of their careers than their control groups. Table 3, panels A to D present the results of this analysis. As shown, the treatment group gets more opportunities to further collaborate with an SC author than the control group, which occurs both in terms of the log of the number of co-authorships with an SC author and the log of the number of unique SC co-authors.

There are statistically significant differences between collaborators and non-collaborators independent of the matching estimator used. The number of SC collaborations in the treated group is between 48 and 39% greater than in the control group, while the number of unique SC co-authors is between 34 and 30% greater.[18] The increase in collaborations with SC co-authors seems to be greater for women than for men. However, this differential effect is not robust.

Robustness

The citation distribution of highly cited articles varies across countries (White et al. 2017) and subfields of economics Bornmann and Wohlrabe (2019), and citations may vary over time. This subsection tests whether our results are robust if we account for intrinsic differences between countries, subfields of economics, and the effects of time effects as factors that influence the number of citations an article receives.

We identify a researcher's subfields, following Moschini et al. (2020), with the Scopus list of journals and subject areas (SAs).[19] For each author, we use the two most common SAs in which they have published as a proxy for subfields (Subfield 1 and Subfield 2). We use the Scopus journal list since it has more comprehensive coverage than Web of Science (WoS), and about 99% of the journals indexed in WoS are also indexed in Scopus (Singh et al., 2021). In S5 we explain in detail the procedure for identifying an author's Subfield 1 and Subfield 2.

It is not surprising that the top research subfield in our sample (Subfield 1) is economics (88.4%), followed by finance and general economics, and econometrics (1.9%), and finance (1.2%). Because of the low variability of Subfield 1, we also use Subfield 2, which has a less concentrated distribution and a more heterogeneous set of subfields.

Next, we estimate the ATT described in Eq. 3, adding as controls a full set of country dummies and Subfield 1 and Subfield 2 dummies. These variables control for differences across countries and subfields that are constant over time. Panel E of Table 2 and of Table 3 show the results of this estimation.

Overall, the results are qualitatively similar to our previous estimates. There is a positive and significant effect on co-authoring with an SC author for both female and male junior researchers, but no effect on productivity or the probability of becoming an SC author. SC junior collaborators have more opportunities to further collaborate with an SC author, both in terms of the numbers of co-authorships and unique SC co-authors. We do not find a differential effect in either of these variables by gender.

Finally, since a paper published in 2000 is more likely to have more citations than one published in 2015, we control for the influence of time by estimating the ATT described in Eq. 3, adding as controls a full set of country dummies, Subfield 1 and 2 dummies, and academic age and academic age-squared to control for time effects (see Table S7).

Following Ebadi and Schiffauerova (2015), we define academic age as the time elapsed between a junior researcher's first publication and 2019, the last year of our data from the RePEc database. As shown in Table S7, our results for log of the number of citations and log of the average number of citations per paper are quantitatively and qualitatively similar to those that do not control for time effects.

[18] Since the dependent variable is in logs, for every one-unit increase in the independent variable, our dependent variable increases by about $(exp^{\beta} - 1) \times 100$.

[19] We determine the subject areas of each journal using the Scopus All Science Journal Classification Codes (ASJC).

Table 2 ATT: productivity, impact and probability of becoming an SC author

	Log citations (years 6–10)	Log articles (years 6–10)	Log av. citations pp (years 6–10)	If super-cited (years 6–10)	Observations	
					Treated	Control
Panel A: kernel						
All	0.283***	– 0.03	0.314***	0.083***	1349	2767
	(0.045)	(0.034)	(0.036)	(0.018)		
Male	0.297***	– 0.01	0.305***	0.087***	1074	2231
	(0.048)	(0.041)	(0.039)	(0.022)		
Female	0.24**	– 0.117*	0.357***	0.076**	275	511
	(0.106)	(0.071)	(0.076)	(0.037)		
t-diff male vs female	0.49	1.33	– 0.61	0.26		
Panel B: nearest neighbor						
All	0.258***	– 0.05	0.31***	0.063**	1349	1286
	(0.062)	(0.047)	(0.044)	(0.027)		
Male	0.189***	– 0.06	0.244***	0.06**	1074	950
	(0.066)	(0.052)	(0.053)	(0.03)		
Female	0.291**	– 0.06	0.353***	0.095**	275	197
	(0.144)	(0.1)	(0.107)	(0.047)		
t-diff male vs female	– 0.64	0.06	– 0.91	– 0.63		
Panel C: stratification						
All	0.243***	– 0.05	0.292***	0.072***	1348	2768
	(0.047)	(0.038)	(0.035)	(0.02)		
Male	0.272***	– 0.02	0.288***	0.085***	1073	2232
	(0.047)	(0.042)	(0.039)	(0.023)		
Female	0.26***	– 0.124*	0.384***	0.092**	275	511
	(0.098)	(0.069)	(0.076)	(0.037)		
t-diff male vs female	0.11	1.32	– 1.12	– 0.16		
Panel D: weighting and regression						
All	0.153**	– 0.072	0.225***	0.049*	1349	2767
	(0.069)	(0.044)	(0.048)	(0.028)		
Male	0.170**	– 0.051	0.220***	0.058*	1073	2232
	(0.076)	(0.050)	(0.052)	(0.031)		
Female	0.121	– 0.149**	0.270**	0.030	275	511
	(0.154)	(0.076)	(0.113)	(0.066)		
t-diff male vs female	0.29	1.08	– 0.40	0.38		
Panel E: weighting and regression + subfield and country controls						
All	0.136**	– 0.031	0.167***	0.034	1313	2635
	(0.058)	(0.039)	(0.044)	(0.024)		
Male	0.152**	– 0.017	0.169***	0.040	1049	2127
	(0.064)	(0.044)	(0.049)	(0.027)		
Female	0.229*	– 0.059	0.288***	0.075*	264	483
	(0.121)	(0.073)	(0.087)	(0.043)		
t-diff male vs female	– 0.56	0.49	– 1.19	– 0.69		

Standard errors in parentheses

$***p < 0.01$, $**p < 0.05$, $*p < 0.1$

Conclusions

Our paper analyzes whether co-authorship with a super-cited (SC) author in the early stages of an academic career affects the future outcomes of impact and productivity in the economics profession. Since the outcomes for collaborators with SC authors are likely to be different from those of non-collaborators, we use a propensity score matching approach that matches network pre-collaboration characteristics to create an appropriate control group.

Our results show how co-authorship with an SC author results in a medium-term career advantage with no difference by gender. Our test of gender differences in the coefficients of co-authoring with a super-cited author finds that we cannot reject the null hypothesis that these coefficients are equal for most estimators. Thus, it seems that co-authorship with an SC author has the same effect on impact, productivity, and probability of being in the SC group, independent of gender.

To explore possible mechanisms of the advantage received from collaboration with an SC author, we analyze whether there are more collaborations with SC authors after the initial one. We find that, for both women and men, those who co-authored within the 5 years after their initial publication receive more opportunities to collaborate with either the same or other SC authors than their counterparts who did not collaborate.

The use of the co-authorship network to perform matching between male and female authors provides a global view of each author's position in the co-authoring space and allows for a fine-grained analysis the different effects of collaboration on junior researchers by gender. It should be noted that we do not attempt to equate co-authorship with mentorship or infer that the SC co-author was the doctoral supervisor of the junior researcher; our database does not provide this level of detail. We acknowledge that co-authorship may arise from formal or informal relationships and that the intensity and duration of collaboration may have different consequences.

Moreover, we understand that the propensity score approach cannot control for the fact that SC authors might attract the best junior researchers, and pre-treatment characteristics might not capture this confounding factor in our analysis. However, our results are sufficiently robust to suggest that our explanations are plausible.

According to the argument of Merton (1968), even if junior researchers who co-author with an SC author are overlooked in the short term, they can obtain recognition in the future, provided they continue to publish. Thus, one issue remains: we do not observe the share of a junior researcher's citations in the medium term that comes from papers co-authored with SC authors versus the share from other papers. The boost in impact may come from the junior researchers' entire portfolio, including papers published prior to the first SC co-authorship, not only from the papers co-authored with the SC author. Investigating this question is a task for future research.

Table 3 ATT: number of SC co-authorships and number of unique SC co-authors

	Log no. SC co-authorships (years 6–10)	Log no. SC co-authors (years 6–10)	Observations	
			Treated	Control
Panel A: kernel				
All	0.391***	0.294***	1349	2767
	0.037	0.025		
Male	0.369***	0.281***	1074	2231
	0.042	0.029		
Female	0.487***	0.346***	275	511
	0.068	0.053		
t-diff male vs female	− 1.48	− 1.08		
Panel B: nearest neighbor				
All	0.356***	0.288***	1349	1286
	0.045	0.034		
Male	0.296***	0.234***	1074	950
	0.05	0.035		
Female	0.523***	0.342***	275	197
	0.087	0.073		
t-diff male vs female	− 2.26	− 1.33		
Panel C: stratification				
All	0.364***	0.279***	1348	2768
	0.038	0.025		
Male	0.36***	0.276***	1073	2232
	0.042	0.029		
Female	0.493***	0.352***	275	511
	0.071	0.054		
t-diff male vs female	− 2.84	− 1.24		
Panel D: weighting and regression				
All	0.332***	0.255***	1349	2767
	(0.048)	(0.034)		
Male	0.309***	0.245***	1073	2232
	(0.055)	(0.038)		
Female	0.450***	0.310***	275	511
	(0.081)	(0.067)		
t-diff male vs female	− 1.44	− 0.84		
Panel E: weighting and regression + subfield and country controls				
All	0.332***	0.241***	1313	2635
	(0.041)	(0.030)		
Male	0.316***	0.239***	1049	2127
	(0.046)	(0.033)		
Female	0.443***	0.295***	264	483
	(0.077)	(0.065)		
t-diff male vs female	− 1.42	− 0.77		

Standard errors in parentheses

$***p < 0.01$, $**p < 0.05$, $*p < 0.1$

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Conflict of interest The authors declare they have no conflicts of interest with respect to this work.

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