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Is there a differentiated gender effect of collaboration with super-cited authors? Evidence from early-career economists.

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Abstract

Several inequalities between genders have been reported over the last decades in academia. Female researchers tend to have a lower pay, write fewer articles and receive fewer cites than their male counterparts, among other disparities. Co-authorship with highly cited scholars tend to give an advantage to early career researchers. Indeed, the impact of researchers that collaborate with super-cited (SC) authors at their early career stage tends to be greater than for those scientists who do not. The question of whether this advantage is favors male or female scientists has not been addressed yet. By conditioning on career length (at least ten years), we study the effect on male and female economists from collaborating with a SC author within the first five years of their career. Since collaboration is not likely random, we employ a matching model using pre-collaboration network characteristics to compare similar authors. We find a positive effect on the impact and the probability of being SC afterward; however, this effect is not statistically different between men and women. On the

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productivity side, we do not find an effect for any gender. To further explore these results, we study whether repeated collaboration with SC co-authors may be a possible mechanism in the years that follow.

Keywords: super-cited authors, gender inequality, collaboration network, economics.

1 Introduction

Academia is no exception to gender disparities across a wide variety of topics, including representation (Sidhu et al., 2009; Holmes et al., 2008), compensation (Freund et al., 2016; Barbezat and Hughes, 2005), productivity (Mueller et al., 2017; Huang et al., 2020) and impact (Beaudry and Larivière, 2016; Maliniak et al., 2013). Productivity and impact, measured by an author's number of publications and cites have an important effect on career success, such as being promoted to a tenure track position (Weisshaar, 2017) or receiving salary increments (Leahey and Tuckman, 1975).

Evidence suggests that men and women with similar backgrounds and opportunities may show dissimilar job trajectories because each one receives different treatment in the job market or auto-select to certain positions (Kahn, 1993). Even more, striking gender differences (e.g., promotion, salaries, or productivity) in many high-skilled occupations point out to a higher drop-out rate of women than men in the first stage of their career and later on as well (Barabási et al., 2020).

Quantitative approaches to evaluate a researcher's career provide unbiased results that largely avoid profiling based on gender, race or other intrinsic individual characteristics (Acuna et al., 2012). Furthermore, the increased availability of data makes possible a more detailed statistical analysis. The use of citation metrics in research committees for evaluation and promotion has raised the pressure to enhance the impact of the publications, even by diverse controversial practices of self-citation (Ioannidis, 2015). Gender differences in research impact are of primordial interest for policy-makers, employers, and for female researchers' expectations since if female-authored work is undervalued, it can lead to career attrition or fewer job opportunities (Thelwall, 2018).

Particularly in the economics profession, little progress has been made to increase the participation of women in academic positions, and women are less likely to receive tenure than their male counterparts (Lundberg and Stearns, 2019; Antecol et al., 2018; Blau et al., 2010; Ginther and Kahn, 2021). 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 by productivity and cites.

One aspect of citation distributions that is often overlooked is the endemic fat-tail behavior where usual parameters cannot characterize observations (mean and variance), unlike other well-known distributions in which observations are gathered around a typical value with minor deviations (Clauset et al., 2009). It is a recognized phenomenon that a small group of authors accounts for a disproportionate large number of cites received (Redner, 1998). We refer to those authors as super-cited (SC), as described in detail in Section 3.

Our paper analyzes whether co-authorship with a SC in the early stages of an academic career affects future outcomes (i.e., impact and productivity) in the economics profession. We define the authors' early career stage as the first five years after their first publication. We only consider young SC co-authors who were not SC themselves before the collaboration and who had a publishing career length of at least ten years. Moreover, we investigate whether the effect of a collaboration with a SC author is different by gender; thus, we perform the econometric analysis using three groups: all, female and male.

We expect that the alliance of SC author with a young not SC author will benefit the second one due to the access to new resources and the more beneficial utilization of its means (Bidault and Hildebrand, 2014). Since collaborators of SC authors are likely to have different characteristics from non-collaborators, we use a propensity score matching (PSM) approach that matches on network pre-collaboration measures to create an appropriate control group.

In intensive-research universities, tenure decisions are usually made after a probationary fixed time (approx. seven years) after hiring, where candidates are expected to show a publishing portfolio that signals their actual productivity and impact (Antecol et al., 2018). Additionally, female researchers tend to drop out of the publishing career more than their male counterparts due to a variety of reasons (e.g. Kahn, 1993; Geisler and Kaminski, 2012; Gaule and Piacentini, 2018; Antecol et al., 2018). Therefore, if we control for career length (at least ten years), we expect to observe more similar female and male groups than if we mix all sorts of career lengths (short and long).

Consequently, by studying only authors with a career length of at least ten years, we implicitly observe researchers who remained in the academic career. Within this group, we want to investigate whether, while being junior, they benefit from collaborating with a SC co-author compared to their same-gender counterparts who did not collaborate,s and if this benefit is indistinguishable between genders.

Our central hypothesis is that the popularity of the SC co-author can benefit the junior collaborator by yielding a higher impact compared to similar researchers who are not collaborators (Li et al., 2019; Gaule and Piacentini, 2018). On the other hand, we do not necessarily expect to find a similar increase in productivity of SC collaborators as the SC influence may boost popularity but not productivity.

We use the publicly open RePEc (Research Papers in Economics) decentralized database to obtain articles, cites, and authors in economics (see Zimmermann, 2013). To perform the PSM, we use 4,136 young authors with a career length of at least ten years, in which 1,349 collaborated with a SC within the first five years after the first publication (Section 3). To measure the effect of a SC co-authorship, from year 6 to year 10, we take advantage of the collaboration network in which we calculate different network measures to find similar researchers who did not collaborate with a SC author.

We find an advantage of early female researchers who collaborated with a SC regarding their female colleagues with similar backgrounds who did not collaborate. This positive effect is only on impact, the probability of being SC later on, and the number of collaborations with SC authors, but not on productivity. Results are similar when we analyze only men. Moreover, the magnitudes of the positive effects between men and women are not statistically different.

Our paper is closely related to Li et al. (2019), who show that early co-authorship (within three years from first publication) with SC authors does have a positive effect on the juniors' career in the following five years after the collaboration, considering all authors, but only in the number of cites (impact) and in the probability of being SC themselves. However, there are some crucial differences to consider where we innovate. 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 of the authors' position instead of using one-to-one relationships. We study women and men separately, and we use a different database that specializes in economics.

It is worth noting that we do not attempt to equal co-authorship with mentorship or affirm that the SC co-author was the doctoral supervisor of the junior researcher. We acknowledge that co-authorship may happen due to formal or informal relationships and that the intensity and duration of contact may have different consequences.

Our paper is structured as follows: in Section 2 we present the importance of analyzing the collaboration with a SC author, Section 3 describes the data and the empirical strategy, Section 4 shows the results of the empirical strategy, and Section 5 concludes.

2 Why care about collaboration with SC authors?

Merton (1968, 1988) noticed that, in co-authored papers, people tend to remember the names they are familiar with and to attribute them the principal contribution even if others contributed more, “the Matthew effect”. Therefore, the Matthew effect involves a misallocation of credit where there is an over-recognition of the already prominent ones, the rich get richer. Therefore, we would expect that an already highly cited author would attract more cites.

Due to the Matthew effect, we could reasonably argue that the name of the most recognizable co-author serves as a known brand that may help attract attention to a paper in which they appear and reach a wider audience. In this sense, young researchers who collaborate with a well-known researcher are usually overlooked in the short term, but if they continue in the publishing career, they can obtain future recognition (Merton, 1968). Tol (2013) finds evidence for the Matthew effect in Economics, using the RePEc database as well, in which this effect can be considered as increasing returns to scale. Birkmaier and Wohlrabe (2014) show that those economists that present a Matthew effect are not only those with highly cited papers but also with low self-citation rates and longer careers.

On the other hand, in areas of knowledge where the majority of members are men or perceived as male-related, even if women are responsible for influential discoveries, they would be often overlooked, and their contribution minimized, “the Matilda effect” (Rossiter, 1993). Most academic authors would receive few cites for their work, even if it is of high quality, not only women. This phenomenon could only exacerbate the Matilda effect in male-dominated fields. Thus, if men are primarily prevalent in the economics profession, one crucial question is whether the collaboration with a highly recognized author, mainly a male one, positively affects both genders equally.

The issue becomes relevant since there has been a substantial rise in co-authorship in economics, where sole-author papers have dramatically decreased as a share of the total (McDowell and Melvin, 1983; Kuld and O'Hagan, 2018), and the number of co-authors increases with the longevity of the career (Hollis, 2001). However, we may argue that not only the number of co-authors is essential to achieve more cites—either because authors can publish more papers in a given period (Li et al., 2013), or because the quality of their products increases (Hollis, 2001)—but also the level of influence of those co-authors.

In general, social success can also be determined by the local network of people or the role one has within a social network (Stadtfeld et al., 2019; Blansky et al., 2013). Relationships among scientific authors play an essential role in defining trajectories of those involved and their individual benefits may be asymmetric depending on experience or reputation (Bidault and Hildebrand, 2014; Sarsons, 2017). Thus, the selection of collaborators becomes an important decision since a personal network of high-profile co-authors can increase the number of cites (Li et al., 2013). To publish in top-ranking journals allows authors to reach a wider audience and get numerous cites (Heckman and Moktan, 2020).

Whenever an author collaborates, they create an individual collaboration network, where each node is an author, and the link represents a paper published jointly. Therefore, the collaboration network shows all direct co-author relationships and represents a social network with valuable information on direct and indirect connections of each author (Li et al., 2013). Thus, RePEc data is well suited to be used under a network science approach, where nodes represent authors and links represent a relationship between them (Newman, 2004). We create a collaboration network where two authors share a link if they have co-authored in at least one article.

An individual's collaboration network reflects, for instance, the author's ability to form and preserve ties, and could serve as a signal of quality (Ductor et al., 2014). It has been found that an author's collaboration network has explanatory power when examining that individual's citation performance. Bosquet and Combes (2013) show that a larger team size and a larger total collaboration network increases the number of total cites.

Bidault and Hildebrand (2014) observe that collaboration between asymmetric authors (academic age and publication profile) affects the cites of their work differently depending on the co-authors' characteristics and the persistence of their relationship. Thus, junior authors benefit from a partnership with senior authors since their work may be more visible and receive more cites. Another possibility of why young co-authors of SC authors benefit from this collaboration is that high-impact authors tend to cite more their co-authors than low-impact authors (Gazni and Thelwall, 2014). On the productivity side, Qi et al. (2017) show that young researchers that collaborate with an outstanding researcher tend to be more productive, but this effect weakens as time passes.

Most co-author relationships do not occur at random. It has been found that the probability of a new collaboration is greater when two authors are closer in an existing collaboration network since individuals are looking to minimize search costs with their available information to ensure a better fit in ability and quality (Fafchamps et al., 2010). Thus, the importance of controlling for network characteristics in our PSM approach.

3 Methods

3.1 Data

We start from a curated list of 445,847 published articles in economics published between 1990 and 2019 obtained from RePEc. From each article, we derived its author, journal, and year of publication.

We compute the collaboration adjacency list from this data set by considering only articles with more than one author published between 1990 and 2019, yielding a network without self-loops and parallel links. After dropping isolated nodes (authors who only appear in single-author papers), the collaboration network consists of 108,761 edges and 39,330 nodes where each node represents an author that published at least one paper in co-authorship, and an edge between two authors means that they published at least one joint paper. We identify the gender of 36,665 authors using Gender API (https://genderapi.io) through their first names. We define career length as the difference between an author's last and first publication (See Gender identification in Supplementary materials).

Consistent with the general gender imbalance in academia (Penner, 2015; Abramo et al., 2009), men are overrepresented among economic science authors. Male researchers are 76.2% of all the authors. The proportion of male authors varies from country to country (Figure 1), e.g. the U.S. has male proportion of 78.9% vs. 49.1% in Russia. The male proportion is significantly higher than the female proportion, with a mean of 80% across all countries. In terms of continents, the most balanced, gender-wise, is Europe with a male proportion of 67.6%, followed by Oceania (76.9%), Africa (77.4%), the Americas (79.2%), and Asia (79.4%).

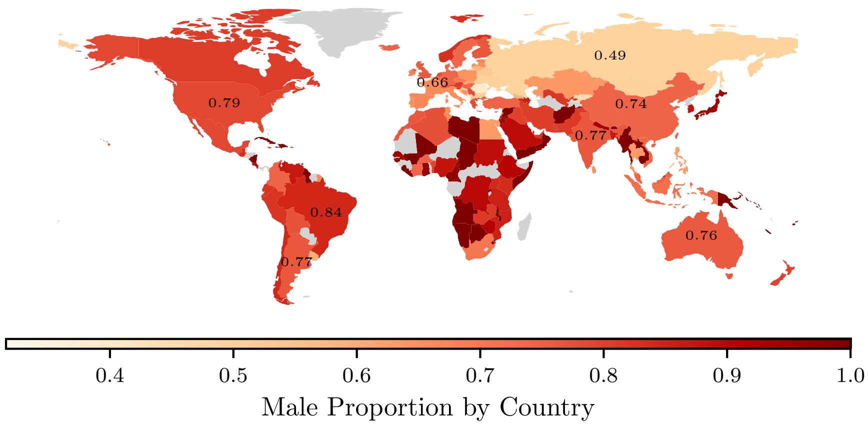


Figure 1: Male proportion within the economics field over the world: 1990-2019. Data is taken from a sample of 48,390 authors with gender and workplace institution data available.

Evidence shows that the impact of academic publications (number of cites each author receives) evolves under a preferential attachment mechanism, where, at a certain time, more cited nodes receive more cites than the rest (Jeong et al., 2003). We call the super-cited group (SCG) as the authors with a number of cites greater than 1.5 times the inter-quartile range of the citation distribution. Since we are interested in the evolution of collaboration across time, we define the SCG each year depending on the number of cites produced that year.

Table 1 shows the mean of publications, co-authors, cites, and academic age by gender and by group (SC and non SC). We observe that non-SC authors are younger and have fewer cites, publications, and co-authors. On the other hand, if we focus only on female researchers, they have lower values for all metrics than the male set, both for the SC and non SC groups.

Our data shows that the SCG receives 48% of total cites and accounts for 10% of all the authors, on average. Across all years, this group consists of 3,915 authors (10.1% of all authors) and receives 3.2 million cites (66% of all cites). Notably, the proportion of women in the SC group is only 12%, half the proportion of female economists in the overall population.

Table 1: Mean statistics by gender and group. Age is the number of years from first publication to 2019. Data was taken from a sample of 32,792 authors for which publications, cites, and gender is known.

Super Cited	Gender	Publications	Co-authors	Cites	Academic age
No	Female	7.80	3.92	39.20	11.54
No	Male	10.76	4.52	50.81	14.25
Yes	Female	35.48	13.14	760.44	24.42
Yes	Male	52.69	16.14	1007.39	29.43

Figure 2 shows for each author, at the top, the number of cites and articles five years before (Year -5) and five years after (Year 5) collaboration with a SC author (Year 0). At the bottom, we present the evolution of the mean number of cites and articles published before and after collaborating with the SC group for each gender.

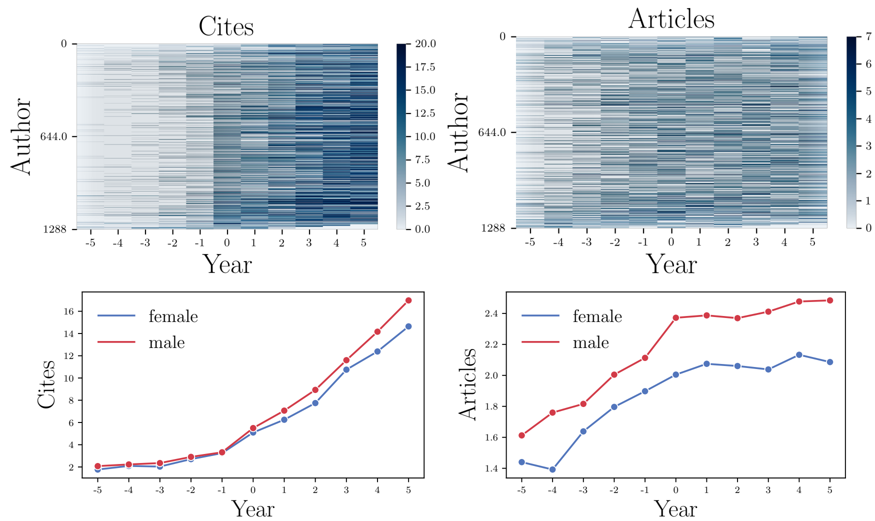


Figure 2: Effect on impact and productivity of collaboration with a SC author. Top: number of cites and articles. Bottom: mean of cites and articles.

The mean number of cites (bottom-left) is 2.8 before collaborating with the SCG and 10.3 afterward, nearly a four-fold increase. On the other hand, the mean number of articles (bottom-right) before (1.8) and after (2.3) collaboration with a SC author does not increment as much as cites. If we look at the number of cites received (top-left), where a darker color represents more cites, the collaboration with a SC author has a considerable effect on the impact of a junior author; we do not observe this change in color intensity in the number of articles (top-right).

3.2 Empirical Strategy

To investigate the effect of collaboration with SC authors in the success of male and female researchers, we consider cases where this collaboration happens at the early stage of the career. The early career stage is defined as the first five years within the first publication of an author, while the effect is taking into account the next five years after the co-authorship.

We begin our analysis by considering all researchers whose careers started between 1990 and 2009 and lasted at least ten years and who are not themselves SC authors. Since SC collaborators are not likely to be randomly assigned, we use a matching procedure to create an appropriate counterfactual. Hence, we use a propensity score matching technique using pre-treatment measures of the authors' collaboration network and the pre-treatment academic impact of researchers.

As discussed in Section 2, a collaboration network embeds information about the nodes and their social status within it. Thus, we use network measures to proxy influential authors' characteristics, in contrast to related papers that use explicit job-related or academic characteristics such as institutional ranking or Ph.D. awarding institution. We can reasonably argue that a young researcher will be more centrally located in the collaboration network when she/he works in a better-ranked institution and holds a Ph.D. from a prestigious university.

We calculate the propensity score using a probit model that includes the following pre-treatment variables:

- The average degree in the collaboration network during the first five years within the first publication of an author. Degree is the number of direct co-authors.

- The average closeness centrality in the collaboration network during the first five years within 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 takes into account all the researchers who are directly and indirectly linked to him/her. Thus, an author is more centrally located in the collaboration network when she/he is closer to every other author, either directly or indirectly.

- The fraction of times the author is in the largest component during the first five years within his first publication. The largest connected component includes the maximal subnetwork such that all authors can be connected by a path in the network.

- The number of cites and papers during the first five years within the first publication of an author.

We are aware of the existence of different centrality network measures. However, the number of 'steps' between an author and the rest, captured by closeness centrality, is more relevant in our context than the author's proximity to a path between any two other authors, captured by other measures like betweenness centrality. Therefore, a high centrality value indicates that an author has few 'degrees of separation' to collaborate with a new researcher, and this could have implications in a more diverse set of co-authors across the years than someone with a small centrality value.

The treatment variable is defined as an indicator function equal to one if a researcher collaborates with a SC author during the first five years within his/her first publication.

To calculate the Average Treatment Effect on the Treated (ATT), the matching estimator is implemented as:

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

Y_1 is the outcome variable conditional on being treated and Y_0 the outcome conditional on not being treated. I_1 denotes the set of treated units (SC collaborators during the first five years within the first publication of an author), I_0 the set of non treated (non SC collaborators), and S_P the region of common support. The weights $W(i,j)$ depend on the particular cross-sectional estimator employed. We use the Kernel, Nearest-neighbor, Radio and Stratification matching estimators.[1]

In the Kernel matching estimator, treated units are matched with a weighted average of all controls with weights given by an inversely proportional relation of

[1] See (A. Smith and E. Todd, 2005), (Becker and Ichino, 2002), (Heckman et al., 1998) and (Heckman et al., 1997)) for a detailed explanation of these estimators.

the distance between the propensity scores of treated and controls. Particularly,

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

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

In Nearest Neighbor, 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.

In Radius Matching, each treated unit is matched only with the control units whose propensity score falls into a predefined caliper of the propensity score of the treated unit. When there are multiple best controls, the average outcome of those controls is used. As recommended by (Austin, 2011), we match on the propensity score using a radio equal to 0.2 of the standard deviation of the propensity score.

The Stratification method consists of dividing the observations into a set of intervals such that within each range, treated and control units have the same propensity score on average. 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.

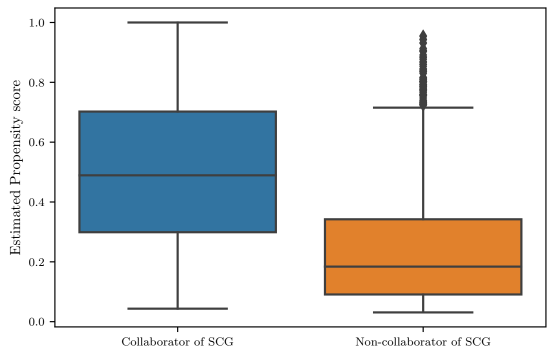
Each of the above four methods reaches different points on the frontier of the trade-off between quality and quantity of the matches. Their joint consideration offers a way to assess the robustness of the estimates (Becker and Ichino, 2002).

Finally, it is relevant to mention that identification of the ATT by the matching estimator requires that: 1) outcomes are independent of the treatment conditional on a set of observable characteristics ($Y_0 \perp\!\!\!\perp D|Z$); 2) for all observable characteristics, there should be a positive probability of being treated or not treated, that is $0 < Pr(D = 1|Z) < 1$.

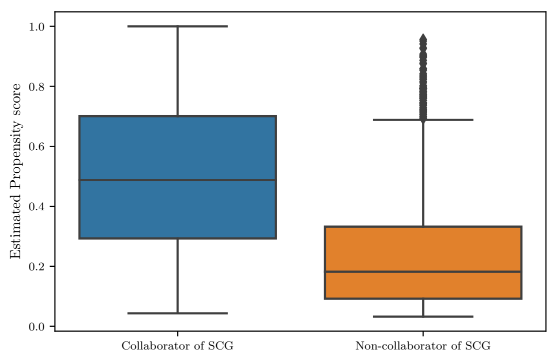
4 Results

Table A.1 in the Supplementary materials shows the results of estimating the propensity score using the variables detailed above.[2] We calculate the propensity scores using the 4,136 researchers for which there is available data on every independent and dependent variable.

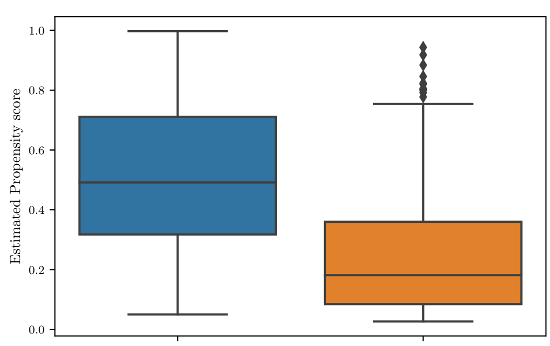
[2]The propensity score is estimated using the Stata program pscore developed by (Becker and Ichino, 2002).



(a) All



(b) Male



(c) Female

Figure 3: Non-collaborator and Collaborator of SCG

The median of the propensity score is indicated by the horizontal line near the middle of the box and is 0.18 and 0.49 for non-collaborators and collaborators of SCG, respectively (Figure 3 panel a). The height of the box (Q3 minus Q1) represents the interquartile range, and the separate points on the chart are the outliers. The quality of the matches improves by imposing the common support restriction (Becker and Ichino, 2002). We drop nineteen non-collaborator researchers that fall outside the common support region. The mean of the scores over the common support is 0.326, and its standard deviation is 0.241.

When looking separately for men and female researchers, we observe that the probability of being a SC collaborator is roughly the same at 0.33 and 0.32, respectively. The restriction of common support 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 A.2, A.3, and A.4 in the Supplementary materials, show that the balancing property is satisfied over the common support region. We report the difference in means and two-sided p-value of these t-tests among the treatment and control groups in each of the eleven and seven optimal blocks of the sample. None of these differences is statistically significant at the 99 percent level of confidence.

Table 2 reports the ATT on impact (number of cites accrued between career years 6 and 10 and the average number of cites received per paper published between career years 6 and 10), productivity (number of papers published between career years 6 and 10), and the probability of being in the SCG between career years 6 and 10. Bootstrapped standard errors are estimated for all estimators.

There are 1349 authors who co-authored a paper in the first five years of their career with a member of the SCG and are not in the SCG themselves: 1074 are men and 275 are women. In all groups (all, female and male), we find that the group of junior researchers who co-authored with a member of the SCG achieve a higher impact than the control group. Moreover, the differences with respect to the controls are statistically significant in all cases, except when using the NN estimator for the subsamples of male and female researchers and when using total cites as a measure of impact.

In general, we do not find statistically significant differences in terms of productivity. However, we find that junior researchers who co-authored with a super cited author have a higher probability of becoming a super cited author themselves between career years 6 and 10, relative to the controls.

When testing the differences in the coefficients of the effect of co-authoring with a SC author across genders, we cannot reject the null hypotheses that all of these coefficients are equal to each other. Thus, it seems that co-authorship with a SC author has the same effect on impact, productivity, and the probability of being in the SCG, independently of the gender. This is true for all estimators, except for the radius matching estimator, where we find a larger effect for men (30 more cites) than for women (20 more cites) in the number of cites.

Our results show that co-authorship with a SC author could lead to a medium-term career advantage that is not different across genders in line with the findings of Li et al. (2019).

To explore 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 during years 6 and 10 of their careers relative to their control groups.

Table 3 presents the results of this analysis. As shown, the treatment group gets more opportunities to further collaborate with a member of the SCG than the control group, which occurs both in terms of the number of co-authorships with a SC author and the number of unique SC co-authors. There are statistically significant differences between SC and non-SC collaborators independently of the matching estimator used. The number of SC collaborations in the treated group is between 1.2 and 1.9 greater relative to the control group, while the number of unique SC co-authors is between 0.6 and 0.9 more relative to the non-treated. There is no robust differential effect across genders, which is expected as we do not find a differential effect on the impact and productivity of co-authoring with a member of the SCG.

Table 2: Average Treatment on the Treated: Productivity, Impact and Probability of becoming a SC author

	Cites (years 6-10)	Papers (years 6-10)	Av. Cites pp (years 6-10)	If Supercited (years 6-10)	Observations	
					Treated	Control
Panel A: Kernel						
All	8.90	-0.53	2.08	0.08	1349	2768
	(3.24)***	(0.44)	(0.29)***	(0.02)***		
Male	9.56	-0.52	1.98	0.09	1074	2231
	(3.68)***	(0.52)	(0.37)***	(0.02)***		
Female	8.26	-0.37	2.58	0.08	275	512
	(4.3)*	(0.48)	(0.58)***	(0.04)**		
t-diff Male vs Female	0.23	-0.21	-0.88	0.26		
Panel B: Nearest Neighbor						
All	8.51	-0.04	1.70	0.07	1349	1302
	(3.94)**	(0.51)	(0.45)***	(0.03)**		
Male	5.57	-1.02	1.55	0.06	1074	950
	(4.36)	(0.64)	(0.45)***	(0.03)**		
Female	8.98	-0.12	2.62	0.08	275	199
	(5.84)	(0.61)	(0.75)***	(0.04)**		
t-diff Male vs Female	-0.47	-1.01	-1.22	-0.46		
Panel C: Radio						
All	28.35	0.77	3.87	0.16	1349	2768
	(2.1)***	(0.25)***	(0.22)***	(0.01)***		
Male	30.43	0.91	3.87	0.17	1074	2231
	(2.5)***	(0.31)***	(0.28)***	(0.02)***		
Female	20.39	0.30	3.77	0.12	274	512
	(3.6)***	(0.41)	(0.52)***	(0.03)***		
t-diff Male vs Female	2.29	1.19	0.18	1.53		
Panel D: Stratification						
All	6.937**	-0.67	1.98	0.07	1348	2769
	(3.43)	(0.44)	(0.31)***	(0.02)***		
Male	8.274**	-0.68	1.92	0.09	1073	2232
	(4.11)	(0.58)	(0.36)***	(0.02)***		
Female	8.662**	-0.47	2.72	0.09	275	512
	(4.12)	(0.45)	(0.59)***	(0.04)**		
t-diff Male vs Female	-0.07	-0.29	-1.17	-0.17		

Table 3: Average Treatment on the Treated: Number of SC co-authorships and Number of unique SC co-authors

	No. SC co-authorships (years 6-10)	No. SC co-authors (years 6-10)	Observations	
			Treated	Control
Panel A: Kernel				
All	1.24	0.66	1349	2768
	(0.22)***	(0.07)***		
Male	1.13	0.63	1074	2231
	(0.26)***	(0.08)***		
Female	1.80	0.78	275	512
	(0.27)***	(0.12)***		
t-diff Male vs Female	-1.79	-1.04		
Panel B: Nearest Neighbor				
All	1.33	0.68	1349	1302
	(0.21)***	(0.08)***		
Male	0.75	0.51	1074	950
	(0.34)***	(0.11)***		
Female	1.93	0.76	275	199
	(0.31)***	(0.16)***		
t-diff Male vs Female	-2.57	-1.25		
Panel C: Radio				
All	1.94	0.95	1349	2768
	(0.14)***	(0.05)***		
Male	1.92	0.96	1074	2231
	(0.16)***	(0.06)***		
Female	2.00	0.91	274	512
	(0.27)***	(0.11)***		
t-diff Male vs Female	-0.25	0.38		
Panel D: Stratification				
All	1.16	0.63	1348	2769
	(0.21)***	(0.07)***		
Male	1.08	0.62	1073	2232
	(0.25)***	(0.08)***		
Female	1.81	0.79	275	512
	(0.28)***	(0.12)***		
t-diff Male vs Female	-1.97	-1.20		

5 Conclusions

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

Our results show how co-authorship with a SC author derives in a medium-term career advantage that is not different across genders. When testing the differences in the coefficients of co-authoring with a super cited author across genders, we find that we cannot reject the null hypotheses that all of these coefficients are equal to each other for most estimators. Thus, it seems that co-authorship with a super-cited author has the same effect on impact, productivity, and the probability of being in the SCG, independently of gender.

To explore one possible mechanism of the advantage received of the collaboration with a SC, we explore whether there is greater collaboration with a SC after the initial one. We find that, for both genders, those who co-authored within their first five years get more opportunities to further collaborate with a member of the SCG than their counterparts who did not collaborate.

The use of the collaboration network to perform the matching between male and female authors gives a global view of each author's position in the co-authoring space and allows for a fine-grained analysis of collaboration's different effects in early career researchers across gender.

In academia, female scientists tend to leave their career more often than their male colleagues, specially during their early stage. Indeed, when we remove the control on career length, we do see a growing gap in impact between genders in the years after their first collaboration with a SC author (Supplementary Figure 4).The fact that this effect is lost when conditioning for career length could imply that this is only true for people that have secured a position in academia.

A limitation of this study could lie in the extent of its data. The RePEc data set is a voluntary one, so the incentive for an economist to sign-in and upload their information is paramount for the completeness of the dataset. Other available datasets like the Web of Science or the Microsoft Academic Graph could bypass this limitation as they capture authors' information from the publications themselves. A broader look into the effects of collaboration with super-cited authors could also be possible using a larger dataset consisting of more fields.

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Suplemmentary materials (not for publication)

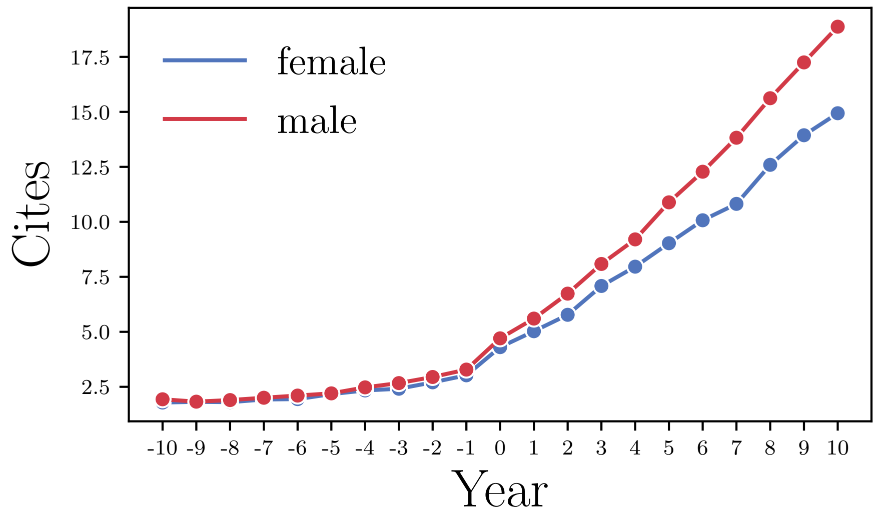

Figure 4: Mean of cites: all authors

Gender identification

The website `https://genderapi.io/` provides an application programming interface (API) to query the gender of a person given their first name and, optionally, their country. The first name is then compared to data with the same name, and a gender is returned as well as a probability. The website currently supports names from 188 countries and has more than 2 million unique names with gender assignation.

In order to test the gender identification of the website, we use a test set comprising $1,481$ female economists. From the complete list of authors in the RePEc repository, we obtain the gender of 90.32% of them. Comparing this set to the test set, we obtain a precision of 96% and recall of 91%. Limiting the comparison to genders with a probability of 90% or higher and comparing to the test set, we obtain a precision of 99% and recall of 90%. We aim to maximize precision and limit our analysis to authors with a gender likelihood of 90% or higher.

Table A.1: Propensity Score

Variables	(1) All	(2) Male	(3) Female
Average degree	0.598***	0.598***	0.652**
	(0.133)	(0.150)	(0.327)
Average degree squared	-0.109***	-0.111***	-0.110
	(0.0372)	(0.0418)	(0.0979)
Average degree cubic	0.00622**	0.00630**	0.00618
	(0.00275)	(0.00306)	(0.00802)
Average closenness centrality	-1.373***	-1.399***	-1.260***
	(0.102)	(0.115)	(0.226)
Fraction largest component	0.0336	0.0586	-0.0465
	(0.103)	(0.116)	(0.222)
No. of papers	-0.0309***	-0.0272***	-0.0479***
	(0.00719)	(0.00791)	(0.0180)
Cites	0.0842***	0.0794***	0.110***
	(0.00540)	(0.00599)	(0.0136)
Cites squared	-0.000765***	-0.000686***	-0.00124***
	(0.000102)	(0.000113)	(0.000267)
Constant	-0.825***	-0.806***	-0.993***
	(0.151)	(0.169)	(0.354)
Observations	4,136	3,321	815

Notes. Standard errors in parentheses.*** $p<0.01$, ** $p<0.05$, * $p<0.1$. The joint hypothesis that the coefficients on the linear, squared and cubic of the variable average degree are equal to zero for the female sample is rejected. Thus, these coefficients are jointly significant.

Table A.2: Balance tests. Dependent variable: Collaborator of SCG, all researchers.

		1	2	3	4	5	6	7	8	9	10	11
Average degree	Dif	0.000	-0.045	0.001	0.010	0.045	0.014	-0.085	0.003	0.073	0.042	-0.882
	p-value	n.a.	0.573	0.993	0.913	0.710	0.886	0.335	0.973	0.634	0.866	0.212
Average degree squared	Dif	0.000	-0.132	-0.051	0.169	0.072	-0.224	-0.676	0.040	0.769	1.007	-9.895
	p-value	n.a.	0.590	0.873	0.723	0.926	0.651	0.199	0.945	0.592	0.577	0.300
Average degree cubic	Dif	0.000	-0.291	-0.396	1.288	-0.816	-2.486	-4.751	0.262	7.719	10.312	-106.190
	p-value	n.a.	0.633	0.719	0.620	0.866	0.284	0.151	0.953	0.575	0.391	0.387
Average closenness centrality	Dif	-0.001	0.017	-0.011	-0.045	-0.015	-0.015	-0.008	0.019	-0.006	0.027	0.007
	p-value	0.869	0.100	0.613	0.036	0.525	0.555	0.716	0.310	0.810	0.495	0.873
Fraction largest component	Dif	0.000	0.000	-0.003	0.008	0.005	-0.011	-0.024	-0.025	-0.002	0.025	-0.022
	p-value	n.a.	n.a.	0.513	0.243	0.685	0.553	0.285	0.363	0.967	0.691	0.776
No. of papers	Dif	0.025	-0.272	0.085	0.160	-0.192	0.266	0.452	-0.261	-0.644	-0.203	-1.966
	p-value	0.968	0.514	0.839	0.681	0.593	0.499	0.122	0.429	0.315	0.853	0.276
Cites	Dif	-0.081	-0.191	-0.409	-0.799	-0.675	-0.430	0.237	0.171	-2.083	-2.242	-7.557
	p-value	0.486	0.509	0.255	0.045	0.167	0.418	0.629	0.752	0.123	0.391	0.081
Cites squared	Dif	-0.211	-1.117	-2.678	-5.903	-8.841	-1.951	9.757	21.016	-146.577	-234.848	-695.193
	p-value	0.650	0.607	0.458	0.222	0.251	0.825	0.312	0.190	0.132	0.293	0.079
Observations	Control	257	480	418	309	270	208	301	373	112	29	11
	Treated	7	26	59	74	83	91	171	350	290	110	88
	Total	264	506	477	383	353	299	472	723	402	139	99

Table A.3: Balance tests. Dependent variable: Collaborator of SCG, male researchers.

		1	2	3	4	5	6	7	8	9	10	11
Average degree	Dif	0.003	0.022	0.082	0.000	-0.016	-0.291	0.103	-0.046	0.053	-0.008	-0.440
	p-value	0.875	0.636	0.534	0.998	0.932	0.084	0.203	0.647	0.580	0.962	0.202
Average degree squared	Dif	0.006	0.057	0.249	-0.056	0.195	-1.303	0.268	-0.389	0.684	-0.360	-4.450
	p-value	0.875	0.646	0.552	0.876	0.848	0.210	0.510	0.527	0.374	0.811	0.291
Average degree cubic	Dif	0.012	0.114	0.624	-0.415	2.229	-5.122	-0.410	-3.209	7.297	-5.405	-45.849
	p-value	0.875	0.661	0.566	0.750	0.721	0.429	0.841	0.419	0.274	0.700	0.389
Average closenness centrality	Dif	0.000	0.016	0.021	-0.017	-0.048	-0.068	-0.014	-0.007	0.023	0.019	0.004
	p-value	n.a.	0.176	0.190	0.456	0.167	0.038	0.485	0.786	0.283	0.509	0.921
Fraction largest component	Dif	0.000	0.000	0.000	-0.005	0.008	0.012	-0.003	-0.023	-0.028	0.000	0.013
	p-value	n.a.	n.a.	n.a.	0.261	0.500	0.292	0.821	0.354	0.358	0.998	0.832
No. of papers	Dif	-0.290	-1.577	0.138	-0.026	1.094	-0.461	0.472	0.095	-0.261	-0.450	-1.491
	p-value	0.593	0.112	0.825	0.951	0.087	0.458	0.131	0.789	0.494	0.509	0.225
Cites	Dif	-0.145	-0.481	0.116	-0.569	-0.217	-0.664	-0.676	0.040	0.077	-0.815	-7.688
	p-value	0.211	0.239	0.837	0.155	0.748	0.326	0.101	0.945	0.903	0.583	0.011
Cites squared	Dif	-0.425	-2.996	1.361	-4.594	-0.586	-6.047	-6.775	8.026	15.976	-77.947	-694.748
	p-value	0.270	0.341	0.765	0.265	0.937	0.532	0.325	0.483	0.403	0.451	0.011
Observations	Control	200	229	159	352	146	103	396	236	286	97	27
	Treated	5	6	16	52	23	41	136	126	287	226	156
	Total	205	235	175	404	169	144	532	362	573	323	183

Table A.4: Balance tests. Dependent variable: Collaborator of SCG, female researchers.

		1	2	3	4	5	6	7
Average degree	Dif	0.034	0.311	0.218	-0.168	0.004	-0.168	0.088
	p-value	0.728	0.133	0.168	0.233	0.981	0.622	0.907
Average degree squared	Dif	0.125	1.039	0.784	-0.605	-0.443	-1.442	0.742
	p-value	0.670	0.130	0.170	0.491	0.619	0.611	0.932
Average degree cubic	Dif	0.338	2.734	2.336	-1.335	-4.175	-12.231	-7.500
	p-value	0.624	0.150	0.179	0.803	0.381	0.595	0.938
Average closenness centrality	Dif	-0.022	0.091	-0.079	0.010	0.005	-0.004	0.055
	p-value	0.406	0.148	0.115	0.787	0.910	0.939	0.440
Fraction largest component	Dif	0.000	0.000	0.009	0.051	-0.108	0.011	-0.059
	p-value	n.a.	n.a.	0.582	0.147	0.081	0.896	0.598
No. of papers	Dif	0.540	-0.701	0.770	-0.571	-0.066	-1.069	2.279
	p-value	0.546	0.291	0.196	0.143	0.931	0.349	0.122
Cites	Dif	-0.030	-0.540	-1.263	-0.042	-1.381	-0.905	-1.354
	p-value	0.951	0.489	0.089	0.937	0.309	0.711	0.734
Cites squared	Dif	-0.001	-3.510	-10.784	1.335	-91.608	7.581	-109.194
	p-value	1.000	0.566	0.192	0.859	0.278	0.954	0.677
Observations	Control	121	86	55	139	79	23	9
	Treated	7	7	17	70	73	58	43
	Total	128	93	72	209	152	81	52