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# DOES GENDER PLAY A ROLE IN PEOPLE'S PREFERENCES FOR COLLABORATION? Evidence from the gender-neutral model of team-formation among academic researchers

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## Abstract

This paper studies the gendered patterns in academic collaboration, using researchers' probability of coauthoring with a woman, and their probability of single authoring. These two probabilities are the main components of the gender-neutral team-formation model created by Boschini and Sjögren (2007). The dataset consists of all articles published between 2016 and 2018 in the Top 2 economic academic journals. Results show that team-formation among academic scientists is not gender-neutral, since the gender gap in the propensity to coauthor with a woman grows bigger when the share of female authors increases in the field. When speculating on the other possible causes for this lack of gender-neutrality, the hypothesis that women might perceive collaboration more negatively than their male peers was suggested. To test for this hypothesis, a survey was distributed among academic researchers, measuring their beliefs and perceptions about coauthorship and its benefits. Results from this complementary survey were inconclusive, and thus could not determine the existence of a difference in perceptions between men and women.

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# I - Introduction

It is often observed in academia that women publish on average fewer articles than men (Sarsons et al., 2020; Boschini and Sjögren, 2007; Aiston and Jung, 2015). This gender gap in productivity has been a puzzling topic for multiple researchers, and many ideas have been put forward to try to explain it.

Economic academia, an overall masculine field, is riddled with gender beliefs, which have sometimes transformed into discrimination (Ridgeway, 2009). These perceptions exist as a result of the prevalence of men in the domain, but also because economics were created around value-systems and qualities that are typically seen as masculine (Nelson, 1995). Gender beliefs in academia act as biases against women in multiple ways: they are perceived as less competent (Krawczyk and Smyk, 2016), their articles are seen as less influential (Sarsons et al., 2020).

All these negative beliefs about women could affect their opportunities of collaboration (Schneider et al., 2011). Moreover, gender affects the type of relations that subjects have both in academia and in the industry. In particular, women do not create the same quality or quantity of ties as men (Clark and Corcoran, 1986; Brass, 1985; Bozeman and Corley, 2004; Ductor et al., 2018). Furthermore, women are a minority in most fields of academia, especially in economics (SED, 2018). This makes it more difficult for them to find researchers to coauthor with. And even when they do collaborate, they do not necessarily benefit from it as much as their male counterparts do (Teele and Thelen, 2017, Djupe et al., 2018, Sarsons et al., 2020).

Without these opportunities of collaboration, women miss out on all its benefits, notably the boost in productivity that it offers (Hollis, 2001; Ductor, 2014; Meng, 2016). This loss of productivity could be a reason explaining the gender gap in publication rates.

Previous studies investigating collaboration patterns in academia, in Economics and other domains, such as psychology, political science, natural sciences, and engineering, have indeed found that there were inequalities in coauthorship between men and women (Sarsons, 2016; Boschini and Sjögren, 2007; Fell and König, 2016; Teele and Thelen, 2017; Djupe et al. 2018; Sarsons et al., 2020).

This paper acts as a follow-up to Boschini and Sjögren's (2007) research; which investigated the collaboration patterns of academic scientists in the field of economics, and found that team formation in coauthorship was not gender-neutral; and will be based on a more recent period, between 2016 and 2018.

On the one hand, Teele and Thelen's (2017), Djupe et al.'s (2018), Fell and König (2016), as well as Boschini and Sjögren's (2007) works all offer great insights of gendered collaboration patterns, all using a similar methodology. They look at all publications in the top academic journals of their respective disciplines over specific periods of time, to observe collaboration, as well as gender patterns, among these publications.

On the other hand, the field of economics is interesting to examine, as it contained the lowest percentage of women among all social sciences disciplines all the way from 1980 to 2011, according to the Survey of Earned Doctorates (SED, 2018). Additionally, compared to other academic disciplines, women in economics suffer the most from inequalities in getting tenure track jobs (Ginther and Kahn, 2004). Boschini and Sjögren (2007) examined more closely women's representation, through the coauthorship patterns of economic scientists between 1991 and 2002, to find that women solo author more than their male counterparts, and that team formation in academia is not gender-neutral. A follow-up study on these coauthorship patterns during more recent years would be relevant, as the portion of women in economic academia is growing each year (SED, 2018).

Moreover, after many research articles have underlined the gender inequalities in academia (Sarsons et al., 2020; Teele and Thelen, 2017; Aiston and Jung, 2014; Boschini and Sjögren, 2007), and have given recommendations to alleviate these inequalities (Schneider et al., 2011; Mandleco 2010), universities in multiple countries put in place equal opportunity policies. These policies manifest themselves in budgets that can be used for training of hiring and selection board or general awareness training, or in quotas of female researchers that have to be reached at the higher levels of academia. (Bagilhole, 2002; Bergman and Rustad, 2013; Erasmus Magazine, 2017). With these rising efforts to reach gender parity in academia, one could expect that collaboration patterns could have become gender-neutral.

This research emerged from the following research question:

Does gender play a role in people's preferences for collaboration?

It focuses on the investigation of gendered patterns in collaboration, by studying whether gender affects researchers' probabilities of coauthoring with a woman, and their probability of single authoring. These two measures are adapted from Boschini and Sjögren's (2007) model of gender-neutral team formation.

Collaboration was studied through coauthorship in papers extracted from the top academic journals, American Economics Review and the Quarterly Journal of Economics. Results show that women have a higher propensity to coauthor with other women, as well as a higher probability of single authoring, making the gender-neutral team formation model not applicable to this sample. Other plausible causes for the lack of collaboration, and the gender gap in productivity on a larger sense, are then mentioned.

The article proceeds as follows. In Section II, the theoretical framework will be showcased, to define the important concepts of collaboration and the collaborative patterns of women in academia, as well as the hypotheses of this research, which are based on previous findings. Section III will consist of an overview of the methods used to gather the data, and descriptive statistics of the obtained data. Section IV will include a more detailed look into the results, their implications towards each hypothesis established in Section II, and their robustness. In Section V, a discussion regarding the results of this research and their implications will be outlined, including the limitations that have emerged throughout the project, and the relevant future research needed on the topic. Out of this analysis of future research emerges a supplementary analysis on the possible effect of negative perceptions about coauthorship on women's rate of coauthoring. Finally, Section VI concludes.

# II – Theoretical Framework

This theoretical framework will first expose the essential concepts and theories of gender and collaboration, before showing how these concepts impact women in economics, and their opportunities in collaboration. Finally, the previous findings on the topic will be outlined, and the resultant hypotheses for this research will be listed.

## 1. The theory of gender frame

As Ridgeway (2009) explains in one of her sociological researches, humans need a shared way of categorizing their own and others' identities, to better understand the world, especially when it comes to understanding and reacting to social interactions. Considering the massive and consistent amount of information to be treated, 'cultural-category systems' were created in the brain, as framing devices to simplify and quicken these thought processes. Gender is one of the main cultural-category systems used as a framing device.

Gender works as a 'cultural frame', and coordinates behavior by associating itself to common conception and ideas, otherwise known as stereotypes. Most stereotypes focus on presumed differences, and, unfortunately, differences can easily be transformed into inequalities through a variety of social processes (Ridgeway, 2009).

Both genders have gender beliefs associated with them, which can either put them at an advantage, or prejudice them. For example, in settings that are culturally typed as masculine, stereotypes will strongly influence judgments in their favor (Ridgeway, 2009).

It has been argued that Economics is a masculine field, not only because of the prevalence of male researchers, but also because it is "built around the distinctly masculine-biased notion of what is valuable", such as a preconception of autonomy and detachment, qualities that are intrinsically seen as masculine, over dependence and connection, perceived as more feminine. (Nelson, 1995). The idea that economics that are based on these masculine qualities, of individual accomplishment, abstraction, lack of emotion, are the only right theories follows the dualism that masculinity is seen as superior, while femininity is inferior (Nelson, 1995). This dualism results from the sociological transformation of gender differences in inequalities (Ridgeway, 2009), which were then established and accepted as a general truth, or common sense (Nelson, 1995).

The impact that these biases will have within an institution depends on two main factors: the gender composition, and a lack of constraints on individual actions within that institution (Ridgeway, 2009). In the case of economic academia, where women have always been strongly underrepresented, and where researchers can freely decide who to collaborate with, the biases prejudicing women can act very strongly, and could affect their opportunity for collaboration (Schneider et al., 2011).

## 2. Background on Collaboration

The academic field relies substantially on collaborative efforts, from discussions aimed at defining the research question, generating ideas, to getting timely feedback. In this research, collaboration will be defined as a joint work between two or more authors in a network.

Research collaboration falls under the term of "Scientific and technical human capital", which represents the sum of researchers' professional network ties and their technical skills and resources (Bozeman and Corley, 2004). Moreover, each social relationship created by a researcher through collaborative efforts becomes embedded in a network which will in turn influence him or her (Meng, 2016). These phenomena can be explained through the concepts of the Social Capital theory, and network analysis (Meng, 2016).

### a. Social capital theory

The Social Capital Theory is based on a fundamental concept in sociology: the Human Capital theory, coined for the first time by Becker (1962), and defined as "individual workers [having] a set of skills or abilities which they can improve or accumulate through training and education". The Social Capital theory was studied intensively by Bourdieu (1986), who established it later on as "the sum of the resources, actual or virtual, that accrue to an individual or a group by virtue of possessing a durable network of more or less institutionalized relationships of mutual acquaintance and recognition." (Camic et al., 1992). In more general terms, social capital theory is derived from the concept of human capital, stating that individuals develop qualities and competencies, and encompasses the idea that individuals can benefit from each other's skills in a social structure facilitating actions, whether individual or collective.

To tie this to publication records, academic scientists can access accrued knowledge, technical skills, and competencies through collaboration with their peers (Katz and Martin, 1997, Thorsteinsdottir, 2000; Melin, 2000; Beaver, 2001). When it comes to scientific publication, collaboration plays even a bigger part, as in addition to the benefits stated above, working with another qualified researcher provides advantages in time, which increases productivity (Hollis, 2001; Ductor, 2014; Meng, 2016), access to additional equipment or resources (Melin, 2000; Thorsteinsdottir, 2000), funds (Heffner, 1981; Beaver, 2001), and grants access to an additional network of other professional, which can lead to a better credibility and visibility (Katz and Martin, 1997; Beaver, 2001).

### b. Network analysis

The social network theory states that individuals are tied to each other through varied types of relations, which all have different patterns and implications (Wasserman and Faust, 1994). The total of these relations creates a network, that influences the individual (Meng, 2016). Multiple researchers argue that most collaborative work start as informal discussions (Hagstrom, 1965; Edge, 1979). The role of the network is thus primordial in the development of academic collaboration, as not only the size, but also the quality of authors' networks helps with their productivity (Besancenot et al., 2017). And, since gender affects the type of relations that the subjects have, with women usually having a denser and less influential network, with less access to authority (Brass, 1985); network analysis is relevant to this research.

## 3. Women in Economics

As aforementioned, women face implicit biases resulting from the theory of gender frame. In economics academia, they are translated in multiple ways. Women appear less competent, according to Krawczyk and Smyk (2016), who showed that when judging papers and their likeliness of being published, subjects less often believed that papers written by women were published; and women's work is judged as less influential (Sarsons et al., 2020). But these biases also negatively affect their "self-efficacy expectations", which is their beliefs that they can be successful in their careers (Ancis and Phillips, 1996)

Social Capital Theory and Network Analysis showed that not only the quantity of professional relationships matter, but also their quality. Through their 'socialization framework', Clark and Corcoran (1986) showed that, because of the small proportion of female academic scientists, women are also at a disadvantage when trying to find a mentor to guide them through their education, so they lack this academic relationship shaping the beginning of a successful career. Moreover, a lot of coauthorship projects start with informal communication, so the closer the two potential collaborators are geographically, the more likely they will be to engage in a coauthored research. (Hagstrom, 1965). As women represent a minority in the economic academic field (AAUP, 2010; NSF, 2018), they have fewer chances to share the informal communication that could spark collaborative efforts between them.

Additionally, some forms of collaboration are not seen as such, that is the case with collaboration between unequal ranks, such as teacher-student partnerships (Hagstrom, 1965). Since women are gradually less represented the higher ranks of economics academia, with PhD graduates being up to 30% women, but full-tenured professors less than 15% (Lundberg and Stearns, 2019), they might be at a disadvantage in their representativeness in collaboration.

In academia, benefiting from an influential network, or creating ties with higher-ranked researchers can lead to access to more funds, better resources, or more visibility; the structure of an academic scientist's social network is thus important.

Because of all these obstacles, women in economic academia miss out on all the aforementioned advantages, but most of all, they miss out on the boost in publication productivity that collaboration offers. Various studies defining the relationship between productivity and collaboration have indeed shown that high productivity is correlated with high levels of collaboration (Hollis, 2001; Ductor, 2014; Meng, 2016). It is thus not surprising to see that most researchers investigating publication productivity based on gender found that women have a much lower publication productivity than their male peers (Teele and Thelen, 2017; Boschini and Sjögren, 2007; Aiston and Jung, 2014; Meng, 2016)

And even if they do exert collaborative efforts, women do not benefit from it as much as their male counterparts. Bozeman and Corley (2004) found a great variance in the positive impact of collaboration on the creation of human capital. In political science, male academic scientists who coauthor are expected to acquire roughly two or more submissions, and two or more publications in journals, while for women, the predisposition to coauthor has no impact (Teele and Thelen, 2018; Djupe and al., 2018). In economics academia, women get less recognition for group work than their male counterparts when they coauthor papers, and they become less likely to receive tenure the more they coauthor, whereas men academics' tenure rate is not impacted by whether they choose to coauthor or solo-author. (Sarsons, 2017; Sarsons et al., 2020).

Based on all the aforementioned reasons, in the higher levels of academia where women are still a minority (AAUP, 2010; NSF, 2018), one of the main factors rationalizing the gender gap in publication productivity could be the lack of research collaboration with women scientists and their peers, of either gender (Kyvik and Teigen, 1996), with Boschini and Sjögren (2007) finding that women single author significantly more than their male counterparts in the field of economics. These inequalities in coauthorship benefits could also explain these discrepancies in collaboration patterns based on gender.

Academia is an ideal field to study the effects of gender on collaboration, as cooperative work is completely voluntary, researchers will only decide to work with peers if they see a clear benefit to it. It is a clear catalyzer to analyzing collaborative behaviors based on gender. As Bozeman and Corley (2004) note, although other external factors come into play, the decisions leading to academic collaboration remain "very much within the control of the individual, especially when the researcher works in an academic institution."

## 4. Collaboration Patterns in Academia

### a. Previous findings

When it comes to collaboration between genders in the social sciences, recent studies have covered this topic in the major fields of the discipline, for example Teele and Thelen (2017), and Djupe et al.'s (2018) extensive works in the gendered trends of co-authorship and submission rates in political science, or Fell and König (2016), who attempted to answer the same questions regarding psychology academic scientists.

In economics, this topic has also been studied by various researchers. Sarsons (2017) focused on the allocation of credit for group work. By using economists' CVs, she tested whether single authored and coauthored papers had a different impact on men and women's chances of obtaining tenure. The results showed that co authorship had a positive impact on men, but a negative one on female researchers.

A few years later, Sarsons dived back into the topic, this time with other researchers, to elaborate on her 2017 paper, by adding experiments (Sarsons et al., 2020). The goal of the experiment was to see if there are biases in credit attribution in settings without confounds; and the results showed that they indeed exist.

Boschini and Sjögren (2007) also published a paper on gendered collaboration in economic academia. Their research focuses on a model created to define team formation as gender-neutral. The model is based on two main components: the probability of having a female coauthor, and the probability of single authoring. They then tested this model on a sample of economics researchers. The results showed that women were more likely to coauthor with other women, but also to single author papers. The theory of a gender-neutral team formation was rejected; determining that there are gender differences in the collaboration among academic scientists.

## b. Hypotheses

This research will adopt Boschini and Sjögren's (2007) method, and will thus aim to determine whether gender influences the collaboration patterns of academic scientists in the field of economics. Multiple hypotheses can be drawn from this research question, as well as from the literature review.

*H1: Female authors will have a lower publication rate than male authors*

Multiple papers in the literature review have shown samples where women have a lower publication rate than their male counterparts (Teele and Thelen 2017; Boschini and Sjögren, 2007; Djupe et al., 2018). Sarsons et al. (2020), however, found that there were not that many differences in the number of articles published by men and the one published by female researchers. This hypothesis follows the majority of findings showing that women published less.

*H2: More papers will be coauthored than single authored*

Literature on the topic has proven that coauthorship has been on the rise in academia. Hamermesh and Oster (2002) first reported in the 1970s that only 30% of articles in the 1970s were written in collaboration. In Boschini and Sjögren's sample (2007), 56,4% of publications had multiple authors between 1991 and 2002. The other recent studies also found coauthorship as a majority (Sarsons et al., 2020; Djupe et al., 2018). Thus it would not be a surprise to see that most articles of this sample will be coauthored.

*H3: Female academic scientists will have a higher rate of single authorship*

The gendered rate of single authorship creates more mitigated results. Some studies find that women single author more (Boschini and Sjögren, 2007; Bozeman and Corley, 2004), while others find the opposite (Sarsons et al., 2020; Teele and Thelen, 2017; Djupe et al., 2018); although, both papers by Djupe et al. (2018) and Teele and Thelen (2017) only look at the last published paper to determine the rate of authorship.

*H4: Women are more likely than men to have a female coauthor.*

This hypothesis comes from an analysis of the previous literature as well. Not all of the observed articles tackle this, but the ones that do unanimously exhibit a larger propensity to coauthor with women by women than by men (Boschini and Sjögren, 2007; Bozeman and Corley, 2004; Teele and Thelen 2017)

*H5: As the share of women increases in the subfield of economics, women's probability of coauthoring with another woman increases more than men's*

This last hypothesis has been observed in the paper written by Boschini and Sjögren (2007), as it was the only one considering the effect of the proportion of women in the economic subfield on the propensity to coauthor with them. This element was a key part of the model created in their research (detailed below), and will thus be central to this research as well.

When combined, the aforementioned hypotheses form the main model tested in this research: the gender-neutral team-formation model. It was created by Boschini and Sjögren (2007), as a predictive model showing the characteristics that authors in their sample should have for their team formation patterns to be gender-neutral. According to their research, two important characteristics define the model: the gendered propensity to collaborate with a female author, and the preference for team-size formation, seen here as the preference for single authorship. This model also states the importance of the presence of women within the subfield of potential collaborators on the gender-neutrality of team formation.

Two concepts are described: gender irrelevance, and gender neutrality. Gender irrelevance implies that researchers form "one population of gender-neutral agents who are drawn from the same distribution of team-sized preferences" (Boschini and Sjögren, 2007), thus, they do not have consistent differences in their propensity to coauthor with women; as well as in their preferences regarding team-sizes. Gender neutrality is less strict, as it allows for systematic gender differences in preferences for team sizes. As a result, it heavily relies on which gender has a preference for single authorship

Boschini and Sjögren (2007) found that gender-neutrality of team-formation was not attained in their sample. The goal of this research is to see whether collaboration patterns among economics academic scientists have changed enough, through time and gender-equality measures, to now reach gender-neutral trends of team-formation.

# III – Methodology

This part will highlight the methods and tools used to gather the necessary data. As mentioned previously, the dataset consists of academic articles extracted from 2 of the highest-ranked academic journals in economics. From these articles, 3 central components create the body of this analysis: the gender of the authors, the proportion of women in the economic subfield the article was published in; and, for each author, their records of publications in the Top 5 journals of economics academia. These data collection methods are similar to the ones used by Boschini and Sjögren (2007).

## 1. Data Collection

The data will consist of all articles published between 2016 and 2018, in the *American Economic Review (AER)*, and the *Quarterly Journal of Economics (QJE)*. Multiple factors came into play when deciding which journals to focus on in this research. Firstly, they had to be ranked highly on the main academic journal ranking platforms, such as Ideas/Repec (Ideas, 2020) or the Scimago journal ranking (Scimagojr, 2020). Secondly, they had to cover various subfields of economics, and not be focused on some specific ones. Finally, their information had to be extractable through web-scraping. As a result, the American Economic Review (AER) and the Quarterly Journal of Economics (QJE) were used, which coincide with Boschini and Sjögren's (2007) choices[1], allowing for more comparable results with their research.

The data was collected with the help of web-scraping tools, from both the Econlit web page, which is a domain of the American Economic Association (AEA), and the Oxford Academic web page. The data of the American Economic Association members directory was also scraped, as well as the list of Doctoral Dissertation in Economics granted between 2016 and 2017. The trends of coauthorship patterns are studied in relation to findings in previous literature, and, in particular, with respect to the work of Boschini and Sjögren (2007). The data extracted comprised each article's publisher, title, year of publication, and authors' names.

[1] Although they also use the articles published in the Journal of Political Economy (JPE), which wasn't available for web-scraping for this research.

### a. Gender

The gender of each author was determined algorithmically, using the Genderize.io package. This Application Programming Interface (API) relies on a database of over 250,000 first names, originating from more than 79 countries and 89 languages, to make predictions about the gender of an individual, based on his or her first name. Along with the gender, it supplies the probability of certainty that the gender prediction is correct (Genderize.io, 2020). Firstly, the names of the multiple co-authors had to be separated in different excel cells, then all first names had to be pasted in an adjacent cell, in order to run the API. Once it was run, all the names resulting in a gender attribution of "null", and all blank cells, were checked. Any special symbol, such as commas and dots, had to be removed; all double names were reduced to a single name, as the API solely determines the gender of a single name. After that, any blank or "null" inference left was manually checked through an online search.

### b. JEL Codes

As the domain of economics is vast and contains various subfields, academic journals have put in place a system of classification, with JEL Codes. JEL Codes consist of a letter and one or two numbers, each letter referring to a particular subfield, and number referring to a subsection of that subfield (see Appendix A). This classification allows to conveniently divide the dataset into various subfields of economics, each containing a different proportion of women, which is of interest in this research.

#### *Relative field size*

The data was first divided based on each article's JEL code, in order to find the relative size of each subfield, as well as the proportion of women in each category. The 9 major subfields: Microeconomics (D), Macroeconomics and Monetary Economics (E), International Economics (F), Financial Economics (G), Public Economics (H), Health, Education, and Welfare (I), Labor and Demographic Economics (J), Industrial Organization (L), and Economic Development, Technological Change, and Growth (O), were examined more in detail, as they account for the biggest proportions of articles in the sample. Moreover, observing these 9 subfields allows for comparison points with the research of Boschini and Sjögren (2007).

To create a reference point of the entire population of articles, Boschini and Sjögren (2007) also extracted the data of all of the articles published in Econlit during the time period of their interest. Econlit is an extensive academic literature database service, including publications from over 1000 journals, and with nearly 65,000 entries added yearly (American Economic Association, 2020). Had there been less strict time and resources constraints, Econlit would have been web scraped and analyzed in this research, the way it was in Boschini and Sjögren's paper (2007); and would probably have provided a more representative reference point. Instead, the data from the Doctoral Dissertation in Economics List of 2016-2017 was used, which shows all PhDs granted in American and Canadian universities during these years. Additionally, the membership directory of the American Economic Association provided numbers for the relative field sized of each category, through the number of researchers self-registered under each JEL Code.

### *Female share*

The proportion of women was calculated in each one of these subfields, to assess whether the inter-gender collaboration patterns are influenced by the fraction of women present in the relevant pool of prospective collaborators. In order to use this data, an assumption had to be made, that authors who have written under a certain JEL code belong to the same subpopulation, and are thus prospective collaborators.

Unfortunately, the American Economic Association's membership directory, used in Boschini and Sjögren's (2007) paper, and listing over 17 000 economics academic researchers, prevented any sort of data extraction through web-scraping, probably to protect member's personal information. The only information available was the number of researchers who self-registered under every JEL Code. Thus, this source could be used to see the relative field size of each JEL category, but not its share of female researchers. The Doctoral Dissertations list, however, could provide these numbers.

### c. Publications in the Top 5 journals

The Top 5 journals selected in this research are, in random order, The American Economic Review, The Quarterly Journal of Economics, The Journal of Political Economics, Econometrica, and the Review of Economic studies. This is based on an aggregate ranking done by Ideas/Repec (Ideas, 2020), the Scimago journal ranking (Scimagojr, 2020), as well as the journal selection made in previous literature (Boschini and Sjögren, 2007). For each author of the sample, two pieces of information were extracted independently: the total articles published in the Top 5 journals, and the date of their first publication in one of these academic journals. The data extraction was done independently, through the platform JSTOR, and all missing variables were then searched and inserted manually. These two elements of data: the total publications in the Top 5, and the year of first publication in the Top 5, serve as control variables, to examine the authors' publication productivity, as well as their seniority. The assumption has to be made that a researcher with an earlier year of first publication has been involved in academic research activities for a longer period of time.

Once all the data was extracted and added manually, the articles previously divided by JEL Codes were brought together to form the final dataset, in order to perform descriptive statistics, before being transformed into the dependent and independent variables.

## 2. The Data

This subsection will present mostly descriptive statistics of the data obtained, in its main aspects, which are the relative field sizes of the JEL categories, the share of female authors, the authorship patterns among researchers of a subfield, and the trends of seniority and publication productivity. All this preliminary knowledge will allow to then clearly formulate the regression variables used in this research.

### a. Sample

The data was collected on a range of 737 articles published in the American Economic Review and the Quarterly Journal of Economics, with a total of 1833 co-author names. Due to authors appearing multiple times in the sample, the duplicates were calculated and subtracted, resulting in a number of individual researchers of 1521. Out of these 1521 authors, 320 are women, and 1201 are men. Women thus represent 21% of the total population of authors. The table underneath portrays the rate of multiple appearances of authors in the sample, detailing for the differences in gender.

***Table 2**: Duplicates of authors, divided by gender*

| | Female Authors | | Male Authors | | |
|---|---|---|---|---|---|
| Duplicates | Amount | (%) | Amount | (%) | Total |
| Twice | 26 | 16 | 137 | 84 | 163 |
| Three times | 4 | 10,5 | 34 | 89,5 | 38 |
| Four times | 0 | 0 | 14 | 100 | 14 |
| Five times | 1 | 20 | 4 | 80 | 5 |
| Six times | 0 | 0 | 1 | 100 | 1 |
| Seven times | 0 | 0 | 1 | 100 | 1 |
| Total | 31 | 14 | 191 | 86 | 222 |

Overall, male authors had a higher appearance rate than female authors in all categories. This table also shows that; since less than 15% of authors appear more than once, and less than 1% of the authors have more than 5 publications in the sample; the publication patterns observed are not driven by a few extremely successful authors, but rather by a large group of researchers appearing at most two times.

### b. JEL Codes

As the effect of representation of women on coauthorship patterns is also part of this research, all articles of the sample were first divided based on their JEL Codes, which link them to specific subfields of economics. As the average number of JEL Codes per article is 2,6, most articles fall under multiple categories. To offset this, articles with multiple codes were counted in each subfield. For every subfield, three main pieces of information were computed: the relative field size, the share of female researchers, and the rate of single authorship. The results of the List of Doctoral Dissertation recipients, the AEA membership directory, and Boschini and Sjögren's (2007) results, were also included in a joined table, to compare the sample and independent measures of academic scientists.

***Table 3**: Descriptive Statistics for the Major JEL Codes (%)*

| | Relative field size | | | | Female share of researchers | | | Single authorship | |
|---|---|---|---|---|---|---|---|---|---|
| JEL Code | Sample | Doctoral Dissert. | AEA members | Boschini & Sjogren (2007) | Sample | Doctoral Dissert. | Boschini & Sjogren (2007) | Sample | Boschini & Sjogren (2007) |
| D - Microeconomics | 18,6 | 16,7 | 6,3 | 19,4 | 16,9 | 23,5 | 9,6 | 21,4 | 41,0 |
| E - Macroeconomics and Monetary Economics | 9,5 | 10,1 | 10,4 | 11,2 | 11,9 | 22,9 | 7,5 | 20,0 | 42,4 |
| F- International Economics | 3,9 | 6,7 | 8,1 | 7,5 | 20,4 | 26,6 | 11,6 | 21,6 | 47,2 |
| G - Financial Economics | 7,5 | 7,4 | 8,2 | 7,4 | 11,2 | 18,4 | 9,5 | 19,0 | 27,4 |
| H - Public Economics | 5,8 | 4,3 | 4,6 | 6,7 | 16,4 | 14,0 | 10,0 | 17,3 | 42,7 |
| I - Health. Education. and Welfare | 9,0 | 10,4 | 6,3 | 5,8 | 31,1 | 43,4 | 21,4 | 16,4 | 44,2 |
| J - Labor and Demographics | 13,0 | 10,3 | 6,1 | 15,7 | 27,9 | 38,8 | 19,4 | 15,9 | 41,3 |
| L - Industrial Organization | 6,8 | 6,1 | 6,4 | 8,3 | 20,0 | 23,9 | 14,1 | 18,6 | 36,8 |
| O - Eco. Development. Technological Change. and Growth | 7,9 | 3,2 | 7,8 | 10,1 | 23,7 | 23,7 | 12,0 | 19,5 | 41,2 |
| Other | 18,0 | 24,6 | 35,8 | 8,0 | 19,8 | 28,5 | 12,8 | 18,2 | 54,2 |
| All | 100 | 100 | 100 | 100 | 21,0 | 27,8 | 12,6 | 18,8 | 41,7 |

At first glance, the results from the three different sources show a certain degree of difference. They will also be compared to the ones reported in Boschini and Sjögren's paper (2007), to observe whether variations in the relative subfield sizes, and the share of female researchers exist between the time period studied by Boschini and Sjögren (from 1991 to 2002), and the one studied in this period (from 2016 to 2018). Although this research only uses articles from the American Economic Review and the Quarterly Journal of Economics, while Boschini and Sjögren (2007) also exploited the articles from the Journal of Political Economy.

### *Relative field size*

*Sample vs. measure from Boschini and Sjögren (2007):* Regarding the relative field sizes, all outcomes are similar to the previous literature (Boschini and Sjögren, 2007), except for the fields of International Economics (F), Health, Education and Welfare (I), Labor and Demographics (J), Economic Development, Technological Change and Growth (O), and

mainly, the combination of fields comprised in the category Other, which only represented 8% in Boschini and Sjögren's work (2007), but represents 18% in this sample.
It is hard to tell whether these differences are caused by a possible unrepresentativeness of the sample, or by evolving trends of publications. Similarly to Boschini and Sjögren (2007), the field of microeconomics remains the most important one.

*Sample vs. measure from the AEA members:* Although the AEA memberships could be a comparable independent measure of the relative field size of JEL codes, since most academic scientists who have published in the Top 2 are members of the AEA; the numbers obtained from the AEA membership directory are very different from the ones of the sample. Where the absolute differences between the sample and the Doctoral Dissertation list average at 2.3%, the absolute differences between the sample and the AEA members amount to 4.7%, which is more than the double. This could be due to the fact that the primary JEL field of publication is self-reported in the AEA directory. Another explanation could be that articles from the more specialized subfields of economics (such as Economic History, or Agricultural and Natural Resources Economics for example) are published in specific journals dedicated to them, and the publications observed in this research are extracted from the 2 Top journals, which aren't specific to any fields. This is why the division of the JEL categories seems more balanced among the AEA membership directory. Because of these consequent differences, the AEA membership directory will not be used in the analysis to create a source of the mean female shares of researchers.

*Sample vs. measure from the Doctoral Dissertation list:* The outcomes of the Doctoral Dissertation list are more similar to the ones of the sample. However, they present consequent differences with Boschini and Sjögren's EconLit results (2007), which were their independent measure of academic scientists. The latter results seem more inclined to give correct estimations, since they are based on the publications of every single journal listed in the American Economic Association, between 1991 and 2002. Some of the sample results are similar to the EconLit ones from previous literature[2], but these resemblances are clearly offset by the strong differences from the other subfields.

***Female share of researchers***

Secondly, for the female share of researchers, the information from the sample and the Doctoral Dissertation list are compared. Most of the variations between the sample and the Doctoral dissertations are in the same direction as the variations between the sample of Boschini and Sjögren (2007) and their data extraction from the AEA membership. Most of the subfields in the Doctoral Dissertation have higher rates of female authorship than the sample; just like most of the fields of the AEA membership have more female researchers than Boschini and Sjögren's (2007) sample. However, for all subfields of economics, the share of female researchers is much higher in the sample than in previous literature (Boschini and Sjögren, 2007), and is even higher in the Doctoral Dissertation List. This advocates for a trend of increase in female economic researchers through time, between 1991, the time frame of Boschini and Sjögren's work (2007), to 2018, the final year of observation of this research. The results of the Doctoral Dissertation List could either show that an even more important population of women are currently joining the field, as it shows all PhDs granted to women during the time of this research; or these results could be higher because all women who received their PhD in economics don't necessarily follow with a career in academia.

In the same fashion as Boschini and Sjögren (2007) have demonstrated, women are still more prevalent in the subcategory of Health, Education and Welfare, and will probably continue to be, as the most PhDs were granted to them in this subfield between 2016 and 2017. The fields of Macroeconomics (E) and Financial Economics (F) contain the smallest portion of women in both sources.

[2] Mainly the results from the fields of International Economics (F), Financial Economics (G), Public Economics (H), and Industrial Economics (L).

### c. Authorship patterns

*Women authorship*: In this sample, women contributed to an average of 20% of publications. This is calculated as an average of the different sources of information extracted: of the 737 articles, 135 have female first authors (18,3%), if all 1833 coauthors are considered, 358 are women (19,5%); and from the female share of researchers based on JEL Codes computed in Table 2, women authors account for 21% of all publications. This number is comparable to Boschini and Sjögren's result (2007); however, it is significantly smaller than the outcome of the Doctoral Dissertation List of 2016-2017 (see Appendix B).

*Single authorship vs coauthorship*: The rates of single authorship present the highest level of difference between the sample and previous literature (Boschini and Sjögren, 2007). While these results fall in the range between 15% and 22% in this sample, they average around 41% in the previous literature (see Table 3). The overall rate of single authorship is only 18,8% over the entire sample, meaning that coauthorship represents a vast majority (81,2% of the sample). This supports the second hypothesis of this research; more papers were coauthored than single authored in this sample (*H2*).

These numbers coincide with earlier findings as well, showing that the rates of coauthorship have been expanding through the years. Hamermesh and Oster (2002) reported that only 30% of articles in the 1970s were coauthored, while in Boschini and Sjögren's work (2007), 56,4% of publications had multiple authors between 1991 and 2002.

### d. Seniority and publication productivity based on gender

In this research, the number of publications in the Top 5 journals, along with the year of the first publication in those journals, will be used as an indicator of seniority. The idea behind it, relying on a few assumptions, is that authors who have published earlier in these journals are more likely to be further along in their careers compared to the other researchers in the sample, and thus, older. To control whether team formation depends on authors' level of seniority, the year of their first publications in one of the Top 5 economics journals[3] was extracted, and listed in Table 4 below, in four different time cohorts. The time period starts in 1949, as the earliest publication in the Top 5 by all authors of the sample was in 1949; and ends in 2018, which is the final year of observation for this research. Any later publication in the Top 5 is not taken into account, as it wouldn't affect the coauthorship patterns in this study.

***Table 4**: Share of Female and Male authors in different time periods between 1949 and 2018*

| Trend in share of publication between 1949 and 2018 | | |
|---|---|---|
| Year of First Publication | Female Share (%) | Male Share (%) |
| 1949 - 1965 | 0 | 100 |
| 1965-1985 | 4 | 96 |
| 1985-2005 | 10 | 90 |
| 2005-2018 | 16 | 84 |

In this sample, women are underrepresented in every cohort, but to an even greater extent between 1949 and 1985. Not a single observed female author had a publication before 1965; and out of all authors who had published their first Top 5 article between 1965 and 1985, only 4% were women.

This table, however, shows that women gradually gained in representation in economic academia, as the female share increases from one cohort to the other, to finally reach 16% of first Top 5 publications between 2005 and 2018.

Another control variable that might affect team formation and coauthorship patterns is the publication record of researchers. This is observed as the authors' number of total publications in all Top 5 journals, from 1949 to 2018. Table 5 indicates these total publication numbers, for both men and women researchers, as well as the gender gap between these numbers.

[3] Econometrica, The American Economic Review, The Quarterly Journal of Economics, the Journal of Political Economics, and the Review of Economics studies

***Table 5****: Publication productivity of Female and Male authors as seen as the total number of articles published in the Top 5 Journals*

| | Female | Male | Gender Gap (Female Pub./Male Pub.) |
|---|---|---|---|
| Total | 1095 | 9469 | 0,48 |
| Per individual | 3,1 | 6,4 | |

There is a clear distinction in the publication record of male and female academic researcher's careers in this sample, with men having published almost two times more articles in the Top 5 journals on average throughout their careers, averaging up to 3 more articles published by men than women. This validates the first hypothesis of this research, women in this sample indeed have a lower publication rate than their male counterparts (*H1*).

The observed gendered distinction in coauthorship could thus result from the differences between male and female authors in publication productivity or seniority level. Both of these elements of information are added as control variables to the model of this research, similar to Boschini and Sjögren's (2007) research.

## 3. Data analysis

This research will be based on two models, with the same independent variables, but different dependent variables. The first model will be used to test for the fourth hypothesis, stating that women are more likely than men to have a female coauthor; and the fifth hypothesis, stating that as the share of women in the subfield increases, women's probability of coauthoring with a women will increase more than men's. The second model will focus on the trend of single authoring, and will thus test for the third hypothesis, which speculates that female academics have a higher rate of single authorship. And, combined, these models allow to apply the gender-neutral team formation model, probed by Boschini and Sjögren (2007), to this sample.

### ***Observations***

Every article is seen as an independent observation (N = 737). The characteristics of every first author are seen as the "author-specific" control variables. The random sampling is ensured by the fact that in economics academe, when multiple researchers work together on a paper, they are cited by their last names in alphabetical order. Thus, the alphabet, and the authors' last names are used as the randomizing tool.

### ***Dependent variables***

The first model will be seen as having a woman in the team, so not as a first author, but as any coauthor in the team. This will be represented as the dummy variable *FTM*, taking the value 1 if there is a woman in the team, and 0 otherwise. So, if the first author is a woman, there needs to be another woman in that team for the variable to take the value 1.

The dependent variable for the second model will regard the patterns of single authorship. This will also be a binary variable, taking the value 1 if the article is single authored, and 0 if the article is written by multiple authors.

### ***Explanatory variables***

The independent variables now presented are used for the equations of both models. They are divided into different categories: author-specific, field-specific, team-specific, and article-specific indicator variables.

Firstly, the author-specific category comprises the variables *female*, Publication in the Top 5 (*NbPub*), and the Year of the first publication in the Top 5 (*1stPub*). *Female* is a dummy indicating the gender of the first author, taking the value 1 if that author is a woman, and 0 otherwise. *NbPub* is the number of all articles published in the Top 5 by the first author; and *1stPub* is the year of the first article published in those 5 economic journals by the first author.

Secondly, the field-specific category includes the main explanatory variables, which is the representation of women in the different subfields of Economics. This explanatory variable results from the JEL categories aforementioned. Each category, or subfield, has its own relative size, and its own share of female researchers (see Table 3). As most articles are registered under multiple JEL codes, they have different relative field sizes and female share associated with them. To take this into account, weighted averages were calculated, based on the female share of publication in each JEL field, and the relative size of each of these JEL fields as the weights.

Moreover, other sources[4] were exploited to create independent measures of both the relative JEL field sizes, and their share of female researchers (see Table 3). This is why, in addition to the mean female share constructed with the data of this sample, *Fshare(SpSp)*, three other variables emerged from the independent sources of data.

The first variable for the mean share of female authors, *Fshare (SpSp)*, uses the numbers extracted from the sample used in this study, both for the female share and the relative size of the subfield. The three other measures of female share of publication are: *Fshare (SpDoct),* based on the female share of the sample and the relative size extracted from the Doctoral Dissertation List, *Fshare (DoctSp)*, based on the female share from the Doctoral Dissertation List and the relative field size from the sample, and *Fshare (DoctDoct),* with both elements of data gathered from the Doctoral Dissertation List.

Thirdly, one variable, *senior*, falls under the team-specific category. Senior is a dummy variable, taking the value 1 if the first author of the team has more publications than all other teammates, and 0 if at least one of the teammates has a better publication record than the first author.

Finally, the article-specific category comprises two variables. The first one is *publisher,* a binary variable equal to 0 if the article was published by the American Economic Journal, or 1 if it was published by the Quarterly Journal of Economics. The second variable, *Print Year* refers to the year the article appeared in one of the two journals, between 2016 and 2018.

[4] The AEA membership directory, and the 2016-2017 The Doctoral Dissertation List

# IV - Results

## 1. Probability of coauthoring with a woman

The first probit model used in this analysis part focuses on the probability of having a female teammate; only the observations with two authors are selected. This had to be done in order to represent the dependent variable FTM truly as a binary variable, taking the value of 1 if the second author is female, and 0 otherwise. This selection in observations left a sample of 273 entries, so it doesn't represent too big of a loss of observations. As *Table 4* indicated in the Data section, articles with 2 authors represent 37% of the total sample.

Multiple regressions have been run with this sample, using a probit model (see Table 6). Each regression saw a variable added to eventually form the complete model. The last 3 regressions used the different *mean female share* obtained based on the different data sources. The same set of regressions was calculated using a logit model, and yielded similar results (see Appendix C).

***Table 6**: Probit Estimation Results with Female Teammate as the Dependent Variable*

| | Probit Estimation with Female Teammate as the Dependent Variable | | | | | | |
|---|---|---|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| **Characteristics of the author:** | | | | | | | |
| *Female* | 0.519** | -3.209** | -3.107** | -2.900* | -2.540* | -2.472 | -2.607 |
| | (0.214) | (1.495) | (1.537) | (1.572) | (1.477) | (1.598) | (1.590) |
| *Publications in the Top 5* | | | -0.003 | -0.018 | -0.018 | -0.019 | -0.019 |
| | | | (0.011) | (0.015) | (0.015) | (0.015) | (0.015) |
| *Female x Publications in the Top 5* | | | -0.027 | 0.078 | 0.056 | 0.053 | 0.042 |
| | | | (0.100) | (0.132) | (0.130) | (0.117) | (0.123) |
| **Characteristics of the field(s):** | | | | | | | |
| *Mean Female Share (SpSp)* | 0.132*** | 0.092*** | 0.092*** | 0.098*** | | | |
| | (0.024) | (0.028) | (0.028) | (0.029) | | | |
| *Female x Mean Female Share (SpSp)* | | 0.169** | 0.166** | 0.162** | | | |
| | | (0.066) | (0.067) | (0.067) | | | |
| *Mean Female Share (SpDoct)* | | | | | 0.099*** | | |
| | | | | | (0.029) | | |
| *Female x Mean Female Share (SpDoct)* | | | | | 0.147** | | |
| | | | | | (0.064) | | |
| *Mean Female Share (DoctSp)* | | | | | | 0.077*** | |
| | | | | | | (0.021) | |
| *Female x Mean Female Share (DoctSp)* | | | | | | 0.107** | |
| | | | | | | (0.050) | |
| *Mean Female Share (DoctDoct)* | | | | | | | 0.078*** |
| | | | | | | | (0.022) |
| *Female x Mean Female Share (DoctDoct)* | | | | | | | 0.110** |
| | | | | | | | (0.050) |
| **Characteristics of the team:** | | | | | | | |
| *Senior* | | | | 0.593** | 0.589** | 0.593** | 0.595** |
| | | | | (0.254) | (0.255) | (0.255) | (0.256) |
| *Female x Senior* | | | | -1.305* | -1.254* | -1.281* | -1.226* |
| | | | | (0.727) | (0.728) | (0.693) | (0.711) |
| *Constant* | -3.718*** | -2.886*** | -2.875*** | -3.175*** | -3.180*** | -3.357*** | -3.376*** |
| | (0.516) | (0.584) | (0.585) | (0.614) | (0.613) | (0.636) | (0.650) |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The first regression only has 2 independent variables: *female*, and the *mean female share* extracted from the sample. Their coefficients show that, when keeping the *mean female share* of researchers in the subfield fixed, and the first author is a woman, compared to being a man, the probability of having a female teammate increases. The second coefficient shows that, when gender is kept fixed, an increase in the mean female share of researchers augments the probability of having a female collaborator. Although both coefficients are statistically significant at least at the 95% level, they are observed exempted from any interaction terms and control variables, and as a result, are not really representative of reality.

In the second regression, an interaction term is added, which changes the results seen before. The impact of the variable *Female* is now negative; but a computation of the average marginal effects shows that being a woman increases the probability of having a female teammate, compared to being a man. This result is statistically significant at the 95% level, and validates the fourth hypothesis, which states that women are more likely to coauthor with other women (*H4*). In addition, the interaction term between *female* and *mean female share* is statistically significant, which means that the effect of the prevalence of women in a subfield on the probability of having a female teammate indeed depends on whether the first author is a woman or a man.

***Figure 1***: *Interaction plot of Female and Mean Female share (SpSp) for the probability of having a Female Teammate, Predictive Margins with 95% CIs*

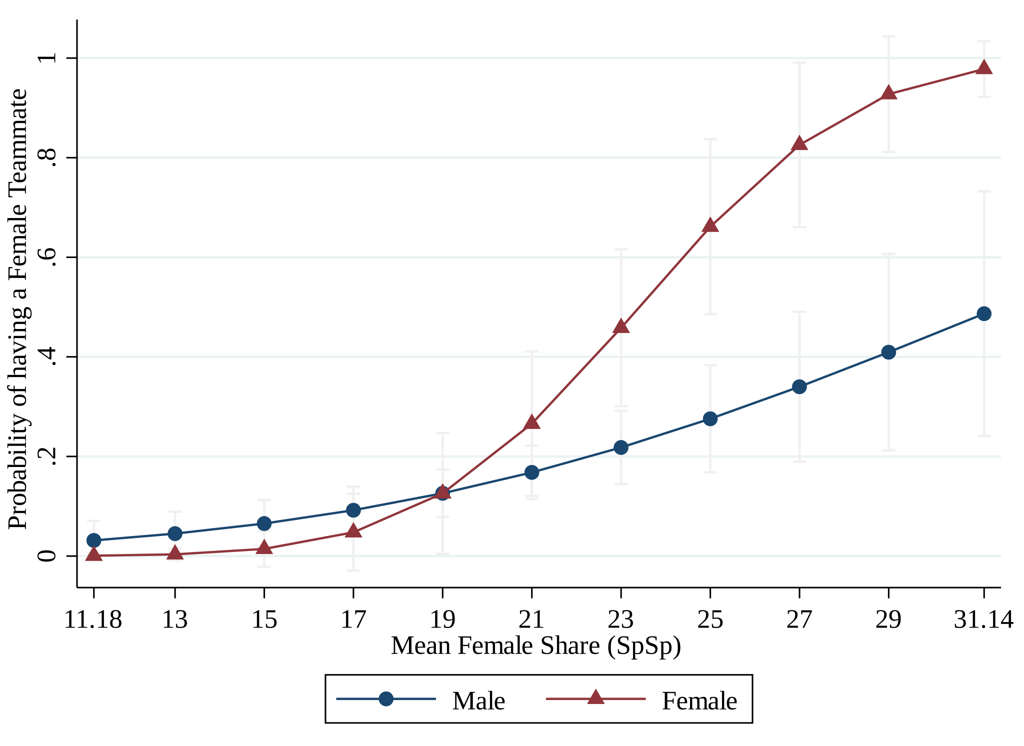



Figure 1 shows an interaction plot between the variable *Female* and *Mean female share (SpSp)*. *Mean female share* ranges between 11.18 and 31.14, which are respectively the minimum and maximum values of this variable. The difference between the two slopes shows that when the mean female share of researchers is between 11.18% and 19%, men and women have a pretty similar probability of having a female coauthor, ranging around 0% and going up to around 13%, which is pretty low. When the mean female share is greater than 19%, a dichotomy appears between the probability of having a female teammate for men versus women. In particular, women's probability of coauthoring with another woman increases at almost twice the rate of men.

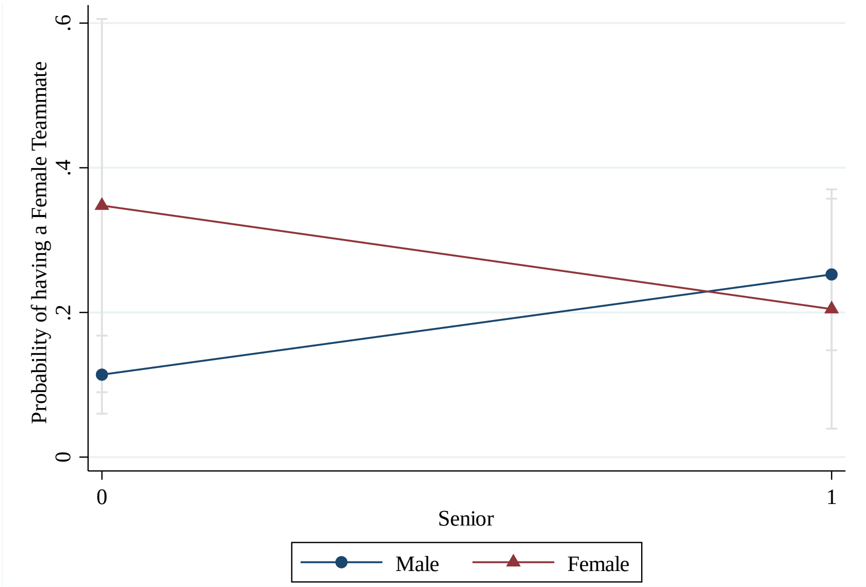
When the mean female share is equal to 31.14%, there is only one article with a woman as a first author, and she coauthored with another woman, which is why the women's slope reaches a 100% probability of having a female coauthor. Since this number is based on only one observation, it cannot reasonably be seen as representative.

However, from this graph, it can be concluded that women's propensity to coauthor with other women increases much more than men's as the mean female share in the subfield increases, which validates the fifth hypothesis of the research (*H5*).

In the third regression, additional characteristics of the first author are controlled for. The number of publications in the Top 5 economic journals, as well as an interaction term between *Publications in the top 5* and the variable *Female*, are now part of the observation. The interaction graph (see Appendix D), shows that publications in the Top 5 do not have much of an impact on the probability of having a female teammate, and that both men's and women's curves seem to be slightly decreasing. However, both of these variables' coefficients are statistically insignificant; meaning that there is no evidence supporting that researchers who have written a bigger amount of successful papers have any preference for collaborating with a woman.

The next regression includes the team members' level of seniority, along with its interaction term with the variable *Female*. The *Senior* coefficient is positive, which suggests that, if the first author has more publications than the rest of the team; he or she will be more likely to have a female teammate. Thus, having a higher level of seniority seems to affect researchers' choices for collaboration. Figure 2 depicts the interaction term between the team members' level of seniority, and the variable *female*.

***Figure 2****: Interaction plot of Female and Senior for the probability of having a Female Teammate, Predictive Margins with 95% CIs*




The variable *senior* is equal to 1 when the first author has more publications in the Top 5 than all of his or her teammates, and 0 otherwise. The two slopes show that when it comes to first authors who do not have more publications in the Top 5 than their teammates, women have a much higher probability of coauthoring with a female teammate (35%) than men (11%).

For researchers with more seniority, seen as having more publications in the Top 5 than all of their coauthors, on the contrary, men have a slightly bigger propensity to coauthor with women than female researchers.

Finally, the last 3 regressions are similar to the previous ones, except for the source used to calculate the explanatory variable *mean female share*. The sign of the coefficients of these variables, and their significance levels are similar to the *mean female share* of the sample of the study, which was analyzed above; but some make the results of the *female* variable insignificant. Both *Mean female share* variables computed from the Doctoral Dissertation list (*Mean female share (DoctSp) and Mean female share (DoctDoct)*) render the coefficient of *Gender* statistically significant, making the use of this independent source questionable.

2. Probability of Single authoring

Table 11 lists the results of all the probit regressions with *Single author* as the dependent variable. These results are based on the complete sample, consisting of 738 observations. In all regressions, being a female has a positive effect on the probability of being a single author, even though none of these coefficients are statistically significant. A logit model was also used, yielding similar results (see Appendix E).

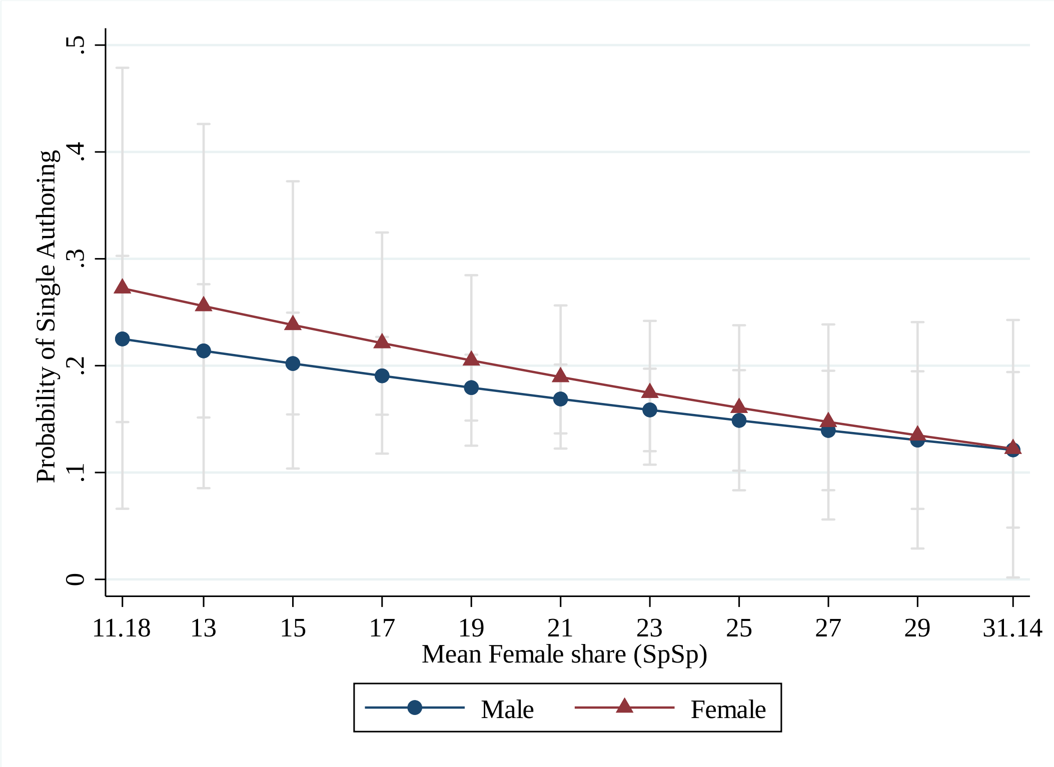
***Table 7**: Probit Estimation Results with Single Author as the Dependent Variable*

| | Probit Estimation with Single Author as the Dependent Variable | | | | | |
|---|---|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) |
| **Characteristics of the author:** | | | | | | |
| *Female* | 0.079 | 0.231 | 0.289 | 0.351 | 0.363 | 0.522 |
| | (0.142) | (0.685) | (0.700) | (0.679) | (0.733) | (0.724) |
| *Publications in the Top 5* | | | 0.008 | 0.008 | 0.008* | 0.008* |
| | | | (0.005) | (0.005) | (0.005) | (0.005) |
| *Female x Publications in the Top 5* | | | -0.003 | -0.003 | -0.002 | -0.001 |
| | | | (0.029) | (0.029) | (0.028) | (0.028) |
| **Characteristics of the field(s):** | | | | | | |
| *Mean Female Share (SpSp)* | -0.022* | -0.021 | -0.020 | | | |
| | (0.013) | (0.015) | (0.015) | | | |
| *Female x Mean Female Share (SpSp)* | | -0.007 | -0.008 | | | |
| | | (0.032) | (0.032) | | | |
| *Mean Female Share (SpDoct)* | | | | -0.021 | | |
| | | | | (0.015) | | |
| *Female x Mean Female Share (SpDoct)* | | | | -0.011 | | |
| | | | | (0.031) | | |
| *Mean Female Share (DoctSp)* | | | | | -0.013 | |
| | | | | | (0.012) | |
| *Female x Mean Female Share (DoctSp)* | | | | | -0.009 | |
| | | | | | (0.025) | |
| *Mean Female Share (DoctDoct)* | | | | | | -0.012 |
| | | | | | | (0.012) |
| *Female x Mean Female Share (DoctDo* | | | | | | -0.014 |
| | | | | | | (0.024) |
| *Constant* | -0.494* | -0.524* | -0.604** | -0.576** | -0.644* | -0.646* |
| | (0.257) | (0.288) | (0.293) | (0.292) | (0.337) | (0.337) |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The interaction term between *Female* and the *Mean female share (SpSp)* shows that women are more likely to single author papers, as the third hypothesis had speculated (*H3*), and that this probability decreases as the share of female collaborators increases in the subfield. However, this coefficient is not significant. This decrease in the probability of being a single author is similar for the population of male authors (see Figure 3).

***Figure 3**: Interaction plot of Female and Mean Female Share (SpSp) for the probability of having a Female Teammate, Predictive Margins with 95% CIs*




The graph of the interaction term between *Female* and *Publications in the Top 5* allows to see that male and female researchers have extremely similar rates of single authoring, which tend to stay the same, even as they publish more articles in the Top 5 journals (Appendix F).

Finally, the last three regressions use the *Mean female shares* computed from the Doctoral Dissertation list alternative source. The results obtained are very close to the ones yielded with the *Mean female share* from our sample. The probability of single authoring decreases as the share of female researchers in the subfield increases. They are also all insignificant.

## 3. Robustness of the results

To test the robustness and stability of the main results, the first probit model, regarding the probability of having a female author, is estimated again, but this time using all observations in the sample (n=738 observations) (see Appendix G). This implies that the effect of having multiple female coauthors cannot be caught by the FTM binary variable. Hence, the probability of having a female coauthor should be higher, as with the more coauthors a researcher has, the more chances that at least. one of these coauthors will be a woman.

The results obtained are comparable to the previous ones based on only 273 entries. Being a woman increases the probability of authoring with a woman in the first regression, but decreases it in all others. An increase in the mean female share also increases the probability of having a female coauthor. And, as the interaction graph of the variables *Female* and *Mean female share (SpSp)* shows (see Appendix H), the progression of both curves is similar, although women's propensity to coauthor with each other does not hike up as high. As it was already mentioned in the results section, this is because the curve of women's probability to coauthor with another woman is based on only one observation, so it reaches 100%; while in the robustness test, more entries are used to calculate these probabilities.

One notable difference with this robustness test is that the effect of the number of publications in the Top 5 is significant when using all articles as observations. Authors who have published more articles in the Top 5 academic journals are more likely to coauthor with women. This time a clear distinction is noticeable, the more publications female researchers have, the more likely they will be to couthor with a woman; while the opposite happens for men. Among senior-level authors, men tend to collaborate with fewer women (Appendix I).

The rest of the results, the ones regarding the variables *Senior*, and the ones from the *Mean female share* based on the different sources, are very similar to the ones obtained before, proving the stability of the earlier results.

# V - Discussion

## 1. Is team formation gender-neutral?

Among the results coming from this sample, it is clear that Boschini and Sjögren's model of gender irrelevance is not validated, as male and female researchers have a different propensity to work with a female peer. As to the concept of gender neutrality, Boschini and Sjögren (2007) explained that gender neutrality can still be reached if there is a difference in the probability of having a female teammate, as long as there is a gender difference in the probability of single authoring to counter-balance it.
So if women tend to coauthor more with female researchers, men will have to single author more in order to validate gender neutrality.

The results of this research show that women coauthor more with women, and have a higher probability of coauthoring with them as the share of women in the field increases. Moreover, they tend to single author more. These results are similar to Boschini and Sjogren's (2007). As a result, it is not possible to validate the concept of gender neutrality within this sample.

## 2. Limitations

With more time and resources, other variables could have been added to study the elements impacting coauthorship rates.

It could have been interesting to include the university of affiliation, as Boschini and Sjögren (2007) did, especially as they found a statistically significant negative effect of being affiliated with a Top 3 university on the probability of having a female teammate.
Moreover, geographic trends could have an impact on collaboration. Previous literature found that female collaboration tends to be less local, mostly due to the fact that women represent a smaller percentage of researchers, so the probability of meeting a potential female collaborator is smaller. (Boschini and Sjögren, 2007; Bozeman and Corley, 2004)

This research did not include the status of researchers, whether they were assistants, associate professor, full professor, full tenure track or non-tenure track, which is a shame, as the professional level has an impact on collaboration (Hagstrom, 1965). Although the level of seniority was analyzed through the number of publications in the Top 5, this measure cannot compare to obtaining the professional status of each researcher. Another professional element that could have been relevant to this study is whether researchers are into the field of academia, or working in the industry, since types of ties that would trickle from these different domains of work affect the productivity of researchers (Meng, 2016).

As Bozeman and Corley (2004) noted, researchers who receive more grants have more collaborators, so it could be interesting to factor in the obtention of grants based on gender.

As it was aforementioned in the methodology section, extracting other sources to create the *Mean female share* might have impacted the outcome of the regressions. Being able to extract the entirety of Econlit for the period of the study would have offered great insights, both on the relative field sizes of economics, but also for the share of female researchers. In Boschini and Sjögren's (2007) work, the different sources of *Mean female share* do provide different magnitude in outcomes.

## 3. Alternative Stories

The initial thought behind this research was that the lower productivity of women could have been the consequence of a lack of collaboration with them, since collaboration offers so many benefits in researchers' careers. This theory was fully supported by previous literature (Boschini and Sjögren, 2007), and seems to be the case here as well, since their model of gender-neutral team-formation was not validated in this sample.

But this lack of collaboration with women is not the only cause of the productivity gap of academic researchers.

So what could be the possible reasons explaining this gender gap in publication productivity?

The effect of putting names in alphabetical order could be an explanation. Sarsons et al. (2020) show the disadvantages that women face in fields of research, such as economics, where coauthors are listed alphabetically. They mention that when the contribution is clearly stated, from the most important researcher to the least impactful one, the negative effects on women's chances of obtaining tenure are less strong.
Another plausible explanation for the unequal success of men and women is that women could be advertising their papers less than men, but this was disproved by Sarsons et al. (2020). Although they do find evidence showing that women advertise their own work less than men; women who only single author are not found to be less likely to receive tenure; debunking this theory.

Additionally, this difference could find its roots deeper into the ramification of collaboration itself, and into the different types of collaboration and their influence on researchers' productivity and publication impact. Meng (2016) discovered that, in engineering academia, women created fewer collaborative ties within the industry of their research, and that put them at a disadvantage in their probability to patent.

This echoes with one of the questions raised by Sarsons et al. (2020). They wondered whether the gender gap in coauthorship could be due to the fact that women prefer to collaborate with male senior-level researchers, but then disprove this theory in their sample. The results of this research, however, seem to support this idea.

A common conception explaining women's comparatively poorer publication productivity is the effect that family has on their career. One the one hand, marriage has been thought to diminish their chances of coauthorship, on the other hand, having children have been thought of negatively impacting their work productivity in general.
Both points have been disproved on an international basis, by Aiston and Jung's (2015) work. They found that on average, married women tended to be more productive, than non-married ones. Unsurprisingly, women were more likely to take a break in their career in order to take care of their children, but the ones who did take a break ended up being

more productive than the ones who did not. This goes against the popular belief that leads to bringing forward family life as the main factor responsible for the gender gap in publication productivity in academia. Aiston and Jung (2005) also urge to stop blaming family life, and instead turn to the discriminations at the root of these inequalities. Female researchers are being asked to spend more time on administrative tasks than their male counterparts (Aiston and Jung, 2005; Barrett and Barrett, 2011, Schneider et al., 2011), and face gender biases in research-based peer-review, since they are a minority (Morley, 2014)

The more debated explanation on the productivity gap of economics researchers is, following the theory of gender frame in the literature review, that women face discrimination, based on no other than their gender. This ties in with Aiston and Jung's (2015) argument pointing out that the peer-reviewing was not at women's advantage, since they are already perceived as less competent, according to Krawczyk and Smyk (2016).

Or finally, maybe coauthorship simply is not the right way to measure collaboration (Katz and Martin, 1997). Although it has been profusely used in research, thanks to its simplicity and measurability, it might not be able to catch the intricate effects that collaborative work; which includes exchanges of ideas, brainstorming about a research question, or even just giving one's opinion about the research; has on academic scientists' careers.

## 4. Future Research

From a more behavioral standpoint, it could be interesting to approach these collaboration patterns from the angle of perceptions. Maybe women in academia have become aware of these systematic inequalities, and of the persisting minority that they form; and these negative beliefs about their opportunities of collaboration and acquiring its benefits are impacting their decision to coauthor. That is, maybe they now know that there is a chance they will not access the same benefits as their male collaborators when they coauthor. They expect to receive less credit (Sarsons et al., 2020), no improvement

in their chances to receive tenure (Sarsons et al., 2020), no gain in submissions or publications in journals (Teele and Thelen, 2018; Djupe and al., 2018).
These negative expectations and perceptions of coauthoring and its benefits could manifest themselves into behaviors, and turn women away from coauthoring altogether.

This is an interesting topic to study, as it has not been previously examined. Sarsons et al. (2020) considered it at the end of their paper, but only the obtention of a tenure track aspect, as this was the main topic of their research.

To investigate the possible existence of a difference in the perception of collaboration and its benefits between men and women, a secondary analysis was conducted. The full analysis can be found in the appendix section (see Appendix J).
The data extraction part of this research is based on a survey. The survey was distributed to 515 researchers, from both the Erasmus School of Economics, and the Rotterdam School of Management, wit 91 final observations used in the analysis.
To measure this, 7 Likert-scale statements[5] used, from the second to seventh of the total 9 statement. (see Appendix K).
For each Statement, an ordered logit model was created, with the Statement as a dependent variable; and the Gender, Professional Status, Single Authorship rate, and the Number of Publication between 2015 and 2020 as independent variables. The outcomes are available in Appendix L.

The results are quite mitigated, out of the seven statements, three of them have a negative coefficient for the Gender variable, and four of them have a positive one. However, none of these coefficients are statistically significant.
On the one hand, being a woman, compared to being a man, creates an expected 0.408 decreases in the log odds of choosing a high ranking answer, and thus getting closer to

[5] Statement 2: I believe that having written a paper with coauthors allows me to submit it to higher ranked journals
Statement 3: I believe that publishing coauthored papers has helped me/is helping me get a tenure track job
Statement 4: I believe that publishing co-authored papers brings me more citations
Statement 5: I believe that publishing co-authored papers brings me more credibility
Statement 6: I believe that I receive an adequate amount of credit when I coauthor a paper
Statement 7: Coauthoring allows me to be more productive
Statement 8: I believe collaboration offers more benefits than constraints

agreeing with the third statement; which states that the author believes that coauthoring helps with getting a tenure track job. Following that same logic, women are less likely to agree with the fourth (*Gender* $\text{coefficient}_4$ = -0.496) and the sixth statement (*Gender* $\text{coefficient}_6$ = -0.668). Hence, they have a more negative perception regarding coauthorship benefits in the obtention of more citations, and their chances of receiving an adequate amount of credit when they coauthor.

On the other hand, women are more likely to agree with the statements that coauthoring allows them to publish in higher-ranked journals (*Gender* $\text{coefficient}_2$ = 0.066), to gain in credibility (*Gender* $\text{coefficient}_5$ = 0.404) and productivity (*Gender* $\text{coefficient}_7$ = 0.333); and that collaboration on average offers more benefits than constraints (*Gender* $\text{coefficient}_8$ = 0.282).

Unfortunately, this quick research did not allow the collection of a large sample, and this could explain the lack of statistical significance of most of the obtained coefficients. None of the coefficients of the Gender variable ended up being statistically significant, the only significant results report to the Professional Status variables, when compared to PhD students' perceptions on coauthorship, or the variables of Number of Publications and Rate of Single Authorship.

Overall, these results cannot provide a conclusive answer to the hypothesis that women have a more negative perception of coauthorship and its benefits, which could result in them consciously deciding to coauthor less. It is difficult to tell whether this is caused by the limited size of the sample, or if there are no gender differences in the perception of coauthorship and its benefits among economics researchers. It could be interesting to reiterate this research with a larger sample group, to figure it out.

# VI - Conclusion

This empirical research studied the effect of gender on the collaboration patterns of academic scientists in the field of economics, using all articles published between 2016 and 2018 in the Top 2 economics academic journals as observations. Multiple hypotheses were created, based on the findings of previous literature. All of them were validated. Results showed that women researchers in this sample had a lower publication rate than their male peers, a higher rate of single authorship, but also a higher probability of working with other women; moreover, more papers were coauthored than single authored.

These conclusions, when inserted in Boschini and Sjögren's (2007) model of gender-neutral team-formation, allowed to show that team formation is not gender-neutral in economic academia.

However, this model relies heavily on the share of female researchers present in the field, and women still represent a minority in economic academia. As coauthorship with women increases along with the increase in the mean female share, it is a possibility that team formation becomes gender-neutral if women were not a minority anymore. Moreover, the data extracted for this research comes solely from the best academic journals, where women are even less represented in the higher levels of academia (AAUP, 2010; NSF, 2018). There is a possibility that team formation is gender-neutral at the lower levels, where there are more women.

In either case, this research shows that coauthorship still lacks gender neutrality, and this could come from a deeper-rooted gender belief issue. Nelson, in 1995, was already urging the need for "a richer conception of human understanding and human identity", in order to combat the biases against women in the field of economics; and it seems to still be relevant to this day.

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# Appendix

***Appendix A:*** *Economic Subfields and their respective JEL Codes*

| JEL Code subfields | |
|---|---|
| *A - General Economics and Teaching* | *K - Law and Economics* |
| *B - History of Economic Thought* | *L - Industrial Organization* |
| *C - Mathematical and Quantitative Methods* | *M - Business Administration* |
| *D - Microeconomics* | *N - Economic History* |
| *E - Macroeconomics and monetary* | *O - Economic Development* |
| *F - International Economics* | *P - Economic Systems* |
| *G - Financial Economics* | *Q - Agricultural and Natural Resource Economics* |
| *H - Public Economics* | *R - Urban, Rural, Regional, Real Estate, and Transportation* |
| *I - Health, Education and Welfare* | *Y - Miscellaneous Categories* |
| *J - Labor and Demographic Economics* | *Z - Other Special Topics* |

***Appendix B:*** *distribution of articles by team size and gender of the first author*

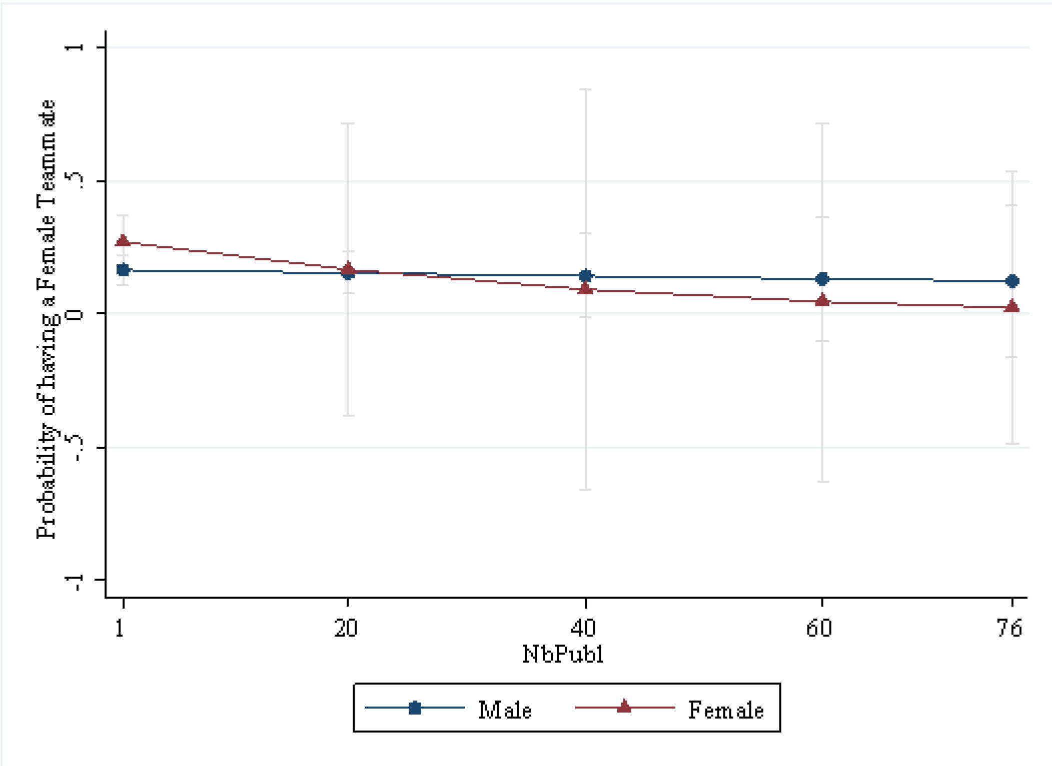
| | Gender of First author | | |
|---|---|---|---|
| Team Size | Female | Male | All |
| Single author | 25 | 107 | 132 |
| | (18,9%) | (81,1) | (17,9%) |
| Two authors | 60 | 213 | 273 |
| | (22%) | (78%) | (37%) |
| Multiple authors | 50 | 282 | 332 |
| | (15,1%) | (84,9%) | (45%) |
| All | 135 | 602 | 737 |
| | (18,3%) | (81,7%) | (100%) |

***Appendix C:*** *Logit Estimation Results with Female Teammate as the Dependent Variable*

| | Logit Estimation with Female Teammate as the Dependent Variable | | | | | | |
|---|---|---|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| **Characteristics of the author:** | | | | | | | |
| *Female* | 0.932*** | -5.369* | -5.180* | -4.770 | -4.165 | -3.920 | -4.285 |
| | (0.361) | (2.776) | (2.829) | (2.935) | (2.748) | (2.935) | (2.977) |
| *Publications in the Top 5* | | | -0.003 | -0.030 | -0.030 | -0.032 | -0.032 |
| | | | (0.019) | (0.026) | (0.026) | (0.026) | (0.026) |
| *Female x Publications in the Top 5* | | | -0.051 | 0.133 | 0.093 | 0.093 | 0.076 |
| | | | (0.174) | (0.234) | (0.231) | (0.202) | (0.218) |
| **Characteristics of the field(s):** | | | | | | | |
| *Mean Female Share (SpSp)* | 0.227*** | 0.158*** | 0.159*** | 0.173*** | | | |
| | (0.043) | (0.049) | (0.049) | (0.050) | | | |
| *Female x Mean Female Share (SpSp)* | | 0.282** | 0.278** | 0.272** | | | |
| | | (0.122) | (0.122) | (0.125) | | | |
| *Mean Female Share (SpDoct)* | | | | | 0.173*** | | |
| | | | | | (0.050) | | |
| *Female x Mean Female Share (SpDoct)* | | | | | 0.248** | | |
| | | | | | (0.119) | | |
| *Mean Female Share (DoctSp)* | | | | | | 0.135*** | |
| | | | | | | (0.038) | |
| *Female x Mean Female Share (DoctSp)* | | | | | | 0.174* | |
| | | | | | | (0.092) | |
| *Mean Female Share (DoctDoct)* | | | | | | | 0.136*** |
| | | | | | | | (0.038) |
| *Female x Mean Female Share (DoctDo* | | | | | | | 0.184** |
| | | | | | | | (0.093) |
| **Characteristics of the team:** | | | | | | | |
| *Senior* | | | | 1.105** | 1.104** | 1.118** | 1.125** |
| | | | | (0.461) | (0.462) | (0.463) | (0.463) |
| *Female x Senior* | | | | -2.348* | -2.299* | -2.292* | -2.254* |
| | | | | (1.262) | (1.272) | (1.187) | (1.237) |
| *Constant* | -6.409*** | -4.948*** | -4.934*** | -5.574*** | -5.559*** | -5.874*** | -5.905*** |
| | (0.941) | (1.051) | (1.055) | (1.128) | (1.118) | (1.164) | (1.185) |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

***Appendix D**: Interaction plot of Female and Publications in the Top 5 for the probability of having a Female Teammate, Predictive Margins with 95% CIs*

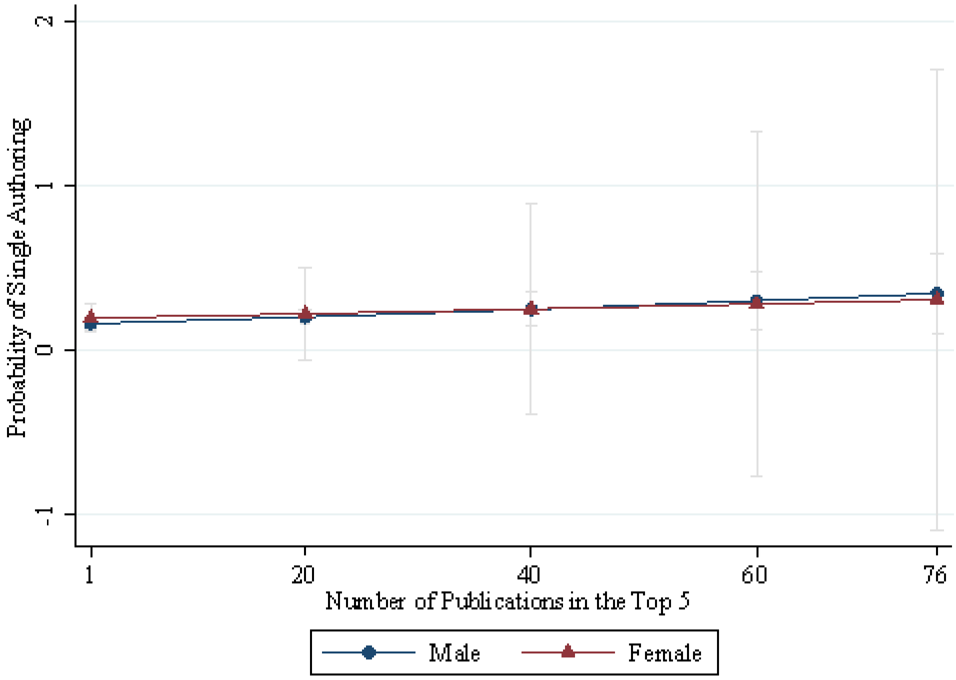


***Appendix E**: Logit Estimation Results with Single Author as the Dependent Variable*

| | Logit Estimation with Single Author as the Dependent Variable | | | | | |
|---|---|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) |
| **Characteristics of the author:** | | | | | | |
| *Female* | 0.142 | 0.389 | 0.477 | 0.587 | 0.650 | 0.935 |
| | (0.252) | (1.209) | (1.240) | (1.207) | (1.315) | (1.299) |
| *Publications in the Top 5* | | | 0.014* | 0.014* | 0.014* | 0.014* |
| | | | (0.008) | (0.008) | (0.008) | (0.008) |
| *Female x Publications in the Top 5* | | | -0.006 | -0.005 | -0.003 | -0.003 |
| | | | (0.051) | (0.051) | (0.050) | (0.051) |
| **Characteristics of the field(s):** | | | | | | |
| *Mean Female Share (SpSp)* | -0.040* | -0.037 | -0.036 | | | |
| | (0.023) | (0.026) | (0.027) | | | |
| *Female x Mean Female Share (SpSp)* | | -0.012 | -0.012 | | | |
| | | (0.057) | (0.057) | | | |
| *Mean Female Share (SpDoct)* | | | | -0.039 | | |
| | | | | (0.027) | | |
| *Female x Mean Female Share (SpDoct)* | | | | -0.017 | | |
| | | | | (0.056) | | |
| *Mean Female Share (DoctSp)* | | | | | -0.023 | |
| | | | | | (0.022) | |
| *Female x Mean Female Share (DoctSp)* | | | | | -0.016 | |
| | | | | | (0.045) | |
| *Mean Female Share (DoctDoct)* | | | | | | -0.023 |
| | | | | | | (0.022) |
| *Female x Mean Female Share (DoctDoct)* | | | | | | -0.025 |
| | | | | | | (0.044) |
| *Constant* | -0.761* | -0.810 | -0.938* | -0.885* | -1.021* | -1.022* |
| | (0.458) | (0.515) | (0.523) | (0.523) | (0.603) | (0.604) |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

***Appendix F**: Interaction plot of Female and Publications in the Top 5 for the probability of Single Authoring, Predictive Margins with 95% CIs*

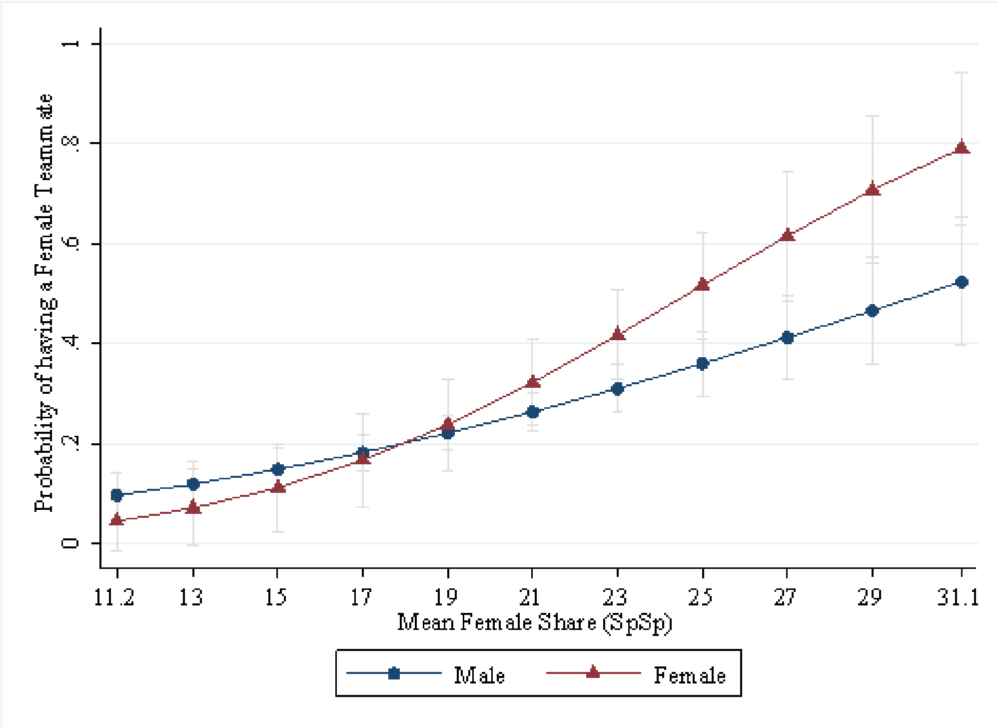


***Appendix G**: Robustness test: Probit model with Female Teammate as the dependent variable, using all observations (n = 737)*

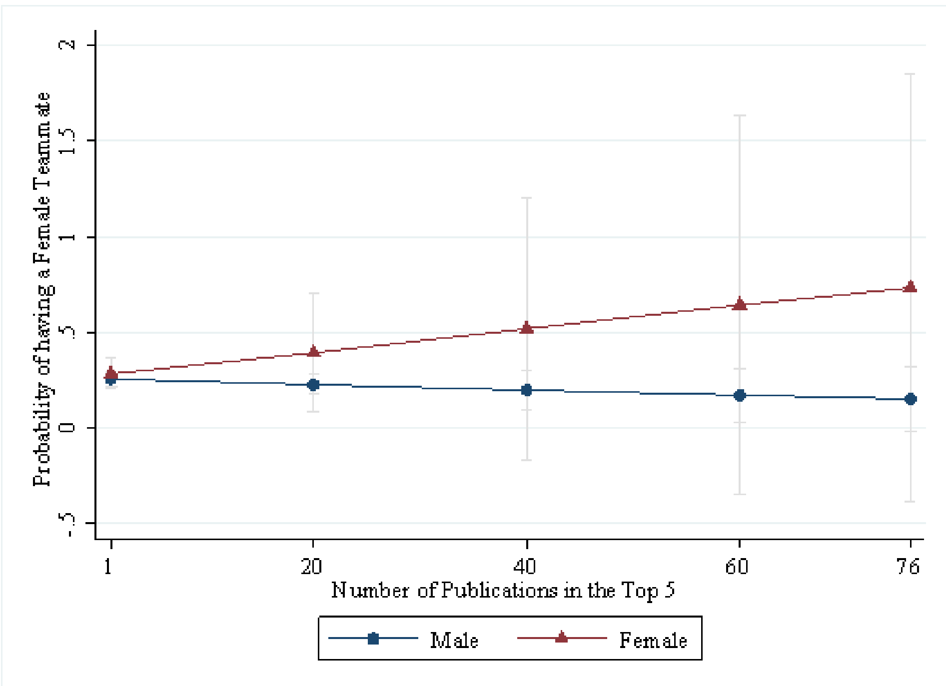
| | Robustness test: Probit model with Female Teammate as the Dependent Variable | | | | | | |
|---|---|---|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| **Characteristics of the author:** | | | | | | | |
| *Female* | 0.220* | -1.036 | -1.172 | -1.115 | -0.807 | -0.677 | -0.665 |
| | (0.130) | (0.700) | (0.716) | (0.746) | (0.703) | (0.752) | (0.739) |
| *Publications in the Top 5* | | | -0.005 | -0.020*** | -0.020*** | -0.021*** | -0.020*** |
| | | | (0.005) | (0.007) | (0.007) | (0.007) | (0.007) |
| *Female x Publications in the Top 5* | | | 0.023 | -0.002 | -0.004 | -0.008 | -0.008 |
| | | | (0.028) | (0.033) | (0.033) | (0.033) | (0.033) |
| **Characteristics of the field(s):** | | | | | | | |
| *Mean Female Share (SpSp)* | 0.081*** | 0.069*** | 0.068*** | 0.069*** | | | |
| | (0.012) | (0.014) | (0.014) | (0.014) | | | |
| *Female x Mean Female Share (SpSp)* | | 0.057* | 0.059* | 0.066** | | | |
| | | (0.031) | (0.031) | (0.032) | | | |
| *Mean Female Share (SpDoct)* | | | | | 0.069*** | | |
| | | | | | (0.014) | | |
| *Female x Mean Female Share (SpDoct)* | | | | | 0.052* | | |
| | | | | | (0.031) | | |
| *Mean Female Share (DoctSp)* | | | | | | 0.053*** | |
| | | | | | | (0.012) | |
| *Female x Mean Female Share (DoctSp)* | | | | | | 0.035 | |
| | | | | | | (0.024) | |
| *Mean Female Share (DoctDoct)* | | | | | | | 0.053*** |
| | | | | | | | (0.012) |
| *Female x Mean Female Share (DoctDoct)* | | | | | | | 0.034 |
| | | | | | | | (0.023) |
| **Characteristics of the team:** | | | | | | | |
| *Senior* | | | | 0.813*** | 0.814*** | 0.809*** | 0.812*** |
| | | | | (0.128) | (0.128) | (0.127) | (0.128) |
| *Female x Senior* | | | | -0.020 | -0.031 | -0.025 | -0.037 |
| | | | | (0.331) | (0.329) | (0.328) | (0.327) |
| *Constant* | -2.317*** | -2.072*** | -2.029*** | -2.341*** | -2.347*** | -2.420*** | -2.455*** |
| | (0.258) | (0.287) | (0.290) | (0.306) | (0.303) | (0.334) | (0.336) |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

***Appendix H****: Robustness test: Interaction plot of Female and Mean Female Share (SpSp) for the probability of having a Female Teammate, Predictive Margins with 95% CIs*




***Appendix I****: Robustness test: Interaction plot of Female and Publications in the Top 5 for the probability of having a Female Teammate, Predictive Margins with 95% CIs*



***Appendix J**: Secondary analysis on the difference in perceptions of collaboration and its benefits between men and women*

The survey was distributed to 515 researchers, from both the Erasmus School of Economics, and the Rotterdam School of Management. From these 515 researchers, 100 filled in the survey completely, averaging to a 19.4% response rate. Among those 100 economics academic researchers, 30 were women, 66 were men, and 4 counted as missing variables, so they were removed from the sample, along with other observations missing some information, amounting to a final number of 91 observations.

The survey consisted of 9 questions, and was divided into 3 sections. The first section served both as an observation of academic productivity, seen as the number of publications in the past 5 years; and as an observation of collaboration patterns, seen as the rate of single authorship, and the number of male and female coauthors. Section 2 aims to determine the main reasons researchers decide to coauthor, and question their beliefs on collaboration and its benefits. Finally, the third section consists of the control variables, the year of PhD obtention, the gender, and the professional status of each researcher.

**Primary Results**

In this sample, the main reason for coauthorship is the gain of knowledge, followed by the gain in quality, and the gain of time. The boost in visibility and credibility was given less emphasis by researchers, along with the access to more resources, whether financial or in the shape of technical equipment. Another interesting remark about researchers' main reason for coauthoring is that many of them mentioned that collaborating is fun, and sometimes just emerged from an interesting discussion they had with a peer, as was shown in earlier research by Hagstrom (1965).

Among the hypotheses from Section 1, the first one, stating that female authors published less than their male counterparts is validated. In this sample, female researchers combined a total of 84 publications, averaging to 2,8 publications per researcher, while their male colleagues amounted to 514, averaging to over 7,8 publications per researcher. Some numbers appear as outliers, as they seem abnormally high for the number of publications between 2015 and 2020. There is a possibility that the question was not

perfectly understood, and that these totals are a bit overstated. However, it should not change the overall outcome that men have published more than their female peers.
The second hypothesis, about women having a higher rate of single authorship, is not validated, as almost no female researcher has single authored paper among these survey respondents, resulting in a single authoring rate of only 0,13; while the male researchers total a single authoring rate of 0,35.
The third hypothesis is validated, more papers were coauthored; only 27 out of the 598 papers published were single authored.
Finally, the fourth hypothesis, stating that women coauthor more with other female researchers seems to also be verified in this sample. On average, 29.2% of women's coauthors are women, while 24.4% of their male counterparts' coauthors are women.

**Secondary Results**

After showing that gender has an effect on researchers' coauthoring patterns, the main body of this secondary analysis focuses on whether women have a more negative perception of collaboration and its benefit than their male peers, which could be a partial explanation to these gendered team-formation patterns. This is what this next subsection focuses on. To measure this, 7 Likert-scale statements were listed, from 2 to 7 (See Appendix K), with answers ranging from Disagree, Somewhat Disagree, Neutral, Somewhat Agree, and Agree.

For each Statement, an ordered logit model was created, with the Statement as a dependent variable; and the Gender, Professional Status, Single Authorship rate, and the Number of Publication between 2015 and 2020 as independent variables. The outcomes are available in Appendix L.

The results are quite mitigated, out of the seven statements, three of them have a negative coefficient for the Gender variable, and four of them have a positive one. However, none of these coefficients are statistically significant.
On the one hand, being a woman, compared to being a man, creates an expected 0.408 decreases in the log odds of choosing a high ranking answer, and thus getting closer to agreeing with the third statement; which states that the author believes that coauthoring helps with getting a tenure track job. Following that same logic, women are less likely to

agree with the fourth (*Gender* coefficient$_4$ = -0.496) and the sixth statement (*Gender* coefficient$_6$ = -0.668). Hence, they have a more negative perception regarding coauthorship's benefits in the obtention of more citations, and their chances of receiving an adequate amount of credit when they coauthor.

On the other hand, women are more likely to agree with the statements that coauthoring allows them to publish in higher-ranked journals (*Gender* coefficient$_2$ = 0.066), to gain in credibility (*Gender* coefficient$_5$ = 0.404) and productivity (*Gender* coefficient$_7$ = 0.333); and that collaboration on average offers more benefits than constraints (*Gender* coefficient$_8$ = 0.282).
Unfortunately, this quick research did not allow the collection of a large sample, and this could explain the lack of statistical significance of most of the obtained coefficients. None of the coefficients of the Gender variable ended up being statistically significant, the only significant results report to the Professional Status variables, when compared to PhD students' perceptions on coauthorship, or the variables of Number of Publications and Rate of Single Authorship.

Overall, these results cannot provide a conclusive answer to the hypothesis that women have a more negative perception of coauthorship and its benefits, which could result in them consciously deciding to coauthor less. It is difficult to tell whether this is caused by the limited size of the sample, or if there are no gender differences in the perception of coauthorship and its benefits among economics researchers. It could be interesting to reiterate this research with a larger sample group, to figure it out.

## ***Appendix K:*** *List of Likert-Scale Statements on perceptions*

Statement 1: I take part in many networking events to find potential collaborators

Statement 2: I believe that having written a paper with coauthors allows me to submit it to higher ranked journals

Statement 3: I believe that publishing coauthored papers has helped me/is helping me get a tenure track job

Statement 4: I believe that publishing co-authored papers brings me more citations

Statement 5: I believe that publishing co-authored papers brings me more credibility

Statement 6: I believe that I receive an adequate amount of credit when I coauthor a paper

Statement 7: Coauthoring allows me to be more productive

Statement 8: I believe collaboration offers more benefits than constraints

Statement 9: I find it easy to find potential coauthors

***Appendix L:*** *Ordered Logit Estimation Results with each Perception Statements as the Dependent Variable*

| | Ordered logit with each Perception Statement as Dependent Variable | | | | | | |
|---|---|---|---|---|---|---|---|
| VARIABLES | Statement 2 | Statement 3 | Statement 4 | Statement 5 | Statement 6 | Statement 7 | Statement 8 |
| ***Gender*** | 0.066 | -0.408 | -0.496 | 0.404 | -0.668 | 0.333 | 0.282 |
| | (0.442) | (0.429) | (0.436) | (0.444) | (0.443) | (0.468) | (0.467) |
| ***Professional Status:*** | | | | | | | |
| *(Reference category: PhD)* | | | | | | | |
| *Assistant Professor* | -0.301 | 0.775 | -0.399 | -0.607 | 0.259 | -0.193 | -0.126 |
| | (0.535) | (0.519) | (0.523) | (0.547) | (0.528) | (0.551) | (0.571) |
| *Associate Professor* | -0.517 | 0.933 | -0.276 | -1.045* | -0.264 | 0.941 | 0.851 |
| | (0.619) | (0.583) | (0.605) | (0.631) | (0.607) | (0.676) | (0.681) |
| *Full professor* | -0.082 | 0.343 | -1.343* | -1.744** | 0.387 | -0.503 | -0.000 |
| | (0.689) | (0.735) | (0.701) | (0.725) | (0.686) | (0.779) | (0.756) |
| ***Number of Publications*** | 0.016 | -0.068* | 0.033* | 0.018 | 0.005 | 0.097** | 0.025 |
| | (0.020) | (0.040) | (0.020) | (0.019) | (0.020) | (0.048) | (0.025) |
| ***Single authorship rate*** | -1.939 | -2.124 | -0.009 | 1.867 | 0.064 | 0.095 | -2.330 |
| | (1.967) | (1.993) | (1.946) | (1.964) | (1.890) | (2.081) | (2.079) |

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Statement 2: I believe that having written a paper with coauthors allows me to submit it to higher ranked journals
Statement 3: I believe that publishing coauthored papers has helped me/is helping me get a tenure track job
Statement 4: I believe that publishing co-authored papers brings me more citations
Statement 5: I believe that publishing co-authored papers brings me more credibility
Statement 6: I believe that I receive an adequate amount of credit when I coauthor a paper
Statement 7: Coauthoring allows me to be more productive
Statement 8: I believe collaboration offers more benefits than constraints