Gender Gaps in the Evaluation of Research: Evidence from Submissions to Economics Conferences*

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Abstract

We study gender differences in the evaluation of submissions to economics conferences. Using data from the Annual Congress of the European Economic Association (2015-2017), the Annual Meeting of the Spanish Economic Association (2012-2017), and the Spring Meeting of Young Economists (2017), we find that all-female-authored papers are 3.2 p.p. (6.8%) less likely to be accepted than all-male-authored papers. This gap is present after controlling for (i) number of authors, (ii) referee fixed effects, (iii) field, (iv) cites of the paper at submission year, (v) previous publication record of the authors, and (vi) the quality of the affiliations of the authors. We also find that the gap is entirely driven by male referees—female referees evaluate male and female-authored papers similarly, but male referees are more favorable towards papers written by men.

Keywords: gender, economics profession, academic labor market

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1 Introduction

Improving gender equality in academia and research is at the center of public policy debate, and is therefore attracting much attention in the academic literature. Economics in particular remains a male-dominated field. Although the share of women in economics has grown, it is still lower than in STEM fields.[1] For instance, in the US, women account for 33% of new PhDs, 29% of assistant professors at Ph.D. granting departments, and only 14% of full professors (Committee on the Status of Women in the Economics Profession (2017)). Potential explanations for the low representation of women include differences in the preference for competitive environments (Niederle and Vesterlund (2007), Buser, Niederle, and Oosterbeek (2014)) or in bargaining abilities in the labor market (Blackaby, Booth, and Frank (2005)), the presence of children and differences in child-rearing responsibilities (Bertrand (2013); Bertrand, Black, Jensen, and Lleras-Muney (2018)), and gender-based discrimination (Goldin and Rouse (2000)).

In this paper, we study gender differences in the evaluation of submissions to economics conferences. Conferences are an essential part of academic life. They are useful to receive feedback, improve presentation and communication skills, get to know fellow economists in the field, hear about the latest research, gain visibility, and develop networking and future collaborations. Hence, the presence of gender gaps in the evaluation process may have substantial impact on the professional careers of economists. Furthermore, understanding whether or not there are gender differences in this context can be informative about the state of gender equality in the academic environment.[2]

Conferences submissions are evaluated through blind peer-review, which is an established component of professional practice. The fundamental principle is straightforward: experts in a given domain appraise the professional performance, creativity, or quality of scientific work produced by others in their field or area of competence (Lee, Sugimoto, Zhang, and Cronin (2013)). Peer review in economics covers a wide spectrum of activities, including the evaluation of research grant applications, review of articles submitted to journals, rating of papers and posters submitted to conferences, and promotion and tenure decisions. Threats to the impartiality of the review may be larger in the context of conferences, where referees have to evaluate a large number of papers in a short period of time.[3] While there is a growing amount of work on gender gaps at the evaluation of grants proposals, papers submitted to journals, and

[1] Lundberg and Stearns (2019), using data on the share of female faculty in top-50 departments for several science and social science disciplines from 2002 to 2012, document that economics remains within the lowest group, along with physics, math, and engineering, and far below the biological and other social sciences. Indeed, Ceci, Ginther, Kahn, and Williams (2014) find economics to be an "outlier" among academic fields because of "a persistent sex gap in promotion that cannot readily be explained by productivity differences".

[2] A recent survey (American Economic Association, 2019) describes a competitive climate in the economics profession that is hostile to women and, in particular, related to experiences of discrimination in invitations to participate in research conferences, associations, and networks.

[3] For example, in the conferences that we study, referees rate an average of 8 papers in less than two or five weeks, depending on the conference.

promotions, less is known regarding conferences.[4]

We have obtained unique data from the submissions to three general-interest academic conferences: the *Annual Congress of the European Economic Association* (EEA), the *Annual Meeting of the Spanish Economic Association* (SAEe), and the *Spring Meeting of Young Economists* (SMYE).[5] These conferences are some of the largest in the world. For example, in 2017 they hosted approximately 1,000, 350, and 150 presentations, respectively. Our dataset covers all submissions from 2015–2017 for the EEA, 2012–2017 for the SAEe, and 2017 for the SMYE, adding up to 9,342 submissions, and contains information on the gender of the authors and the referees that evaluate each paper, and on the acceptance decision. For the case of the SAEe, we also have information on whether the submissions correspond to regular sessions (typical contributed sessions) or to the so-called job-market sessions, a type of submissions intended for job-market candidates to present their job-market papers. In addition, we have complemented the data with a rich set of controls—the rank of the affiliations of the authors, their prior publications, and the field, cites, and eventual publication of the paper.

We begin by showing that a 1-p.p rise in the share of male authors is associated with a .054-p.p. rise in the probability that the paper is accepted, i.e. switching from an all-female-authored to an all-male-authored paper increases the probability of acceptance by 5.4 p.p. Given the baseline rate of acceptance for papers with all male authors (47.1%), this amounts to an 11.5% effect.

We then study whether this gap can be explained by several factors that correlate with gender and acceptance rates: (i) given that women are more likely to single-author, we include number of authors fixed effects, (ii) to account for the possible non-random assignment of papers to referees, we add referee fixed effects, (iii) to control for fields differences, we include fifteen field fixed effects, (iv) to account for possible gender differences in the quality of papers, we control for the cites of the paper, (v) to account for the prominence of the authors, we control for their previous publication record (number of publications in a set of top journals in the years before the submission), and (vi) to account for the institutions of the authors, we control for the ranking of the affiliations of the authors. After taking these factors into account, the gender gap is reduced but still sizable (3.2 p.p., or 6.8%) and statistically significant.

Next, we investigate whether the gender gap is driven by some specific conference, by male-dominated fields, by male or female referees, or by prominent authors. We find that the gap (i) is present in the three conferences, and we cannot reject that it is the same across them, (ii) is not larger in fields with a higher share of men, (iii) is entirely driven by male referees—female referees evaluate male and female-authored papers similarly, but male referees are more favorable towards papers written by men, and (iv) is driven

[4]To the best of our knowledge, gender gaps in the context of conferences have only been studied by a concurrent working paper by Chari and Goldsmith-Pinkham (2018), who study NBER Summer Institutes. However, although they provide some evidence on the evaluation of submissions, their focus is more on how women's representation has evolved over fields and time.

[5]We have also contacted the American Economic Association, the Econometric Society, and the Royal Economic Society to obtain data from their general-interest conferences, but no concrete progress has been made.

by papers written by prominent authors—those who have published in a set of top journals in the last years before the submission, i.e. the gender gap is larger (zero) when we compare papers written by male and female economists who have (have not) published in the last years before submission.

Finally, we discuss the possible mechanisms behind our results. First, we discuss the possibility of gender bias in our quality controls (cites of the paper and prior publications and affiliations of the authors). This can explain our findings if these variables are biased *in favor of women*, which we think is unlikely in light of other work (Card, DellaVigna, Funk, and Iriberri (2018), Sarsons (2017)). Second, it could be that male referees have stereotypes against female economists. However, this mechanism cannot easily explain why there is no gender gap for papers written by non-prominent authors. Third, it could be that papers' unobserved characteristics differ by gender, and conferences' referees value the characteristics of male-authored papers more. While we cannot rule out this explanation, it is also hard to reconcile with our heterogeneity results—it is not clear why those unobserved characteristics would only be valued by male referees, or would only matter for papers written by prominent authors. Finally, we study whether the results may be driven by connections. In particular, connections can create the gender gap if (i) as suggested by previous literature (e.g., Sandström and Hällsten (2007) or Zinovyeva and Bagues (2015)), connections play a role in evaluations, i.e. referees are more likely to evaluate positively a paper written by someone they have a personal bond with, and (ii) male economists are better connected than female economists, as found, for example, by Ductor, Goyal, and Prummer (2018) and Hilmer and Hilmer (2007). Consistent with this mechanism, we find that there is no gender gap in the SAEe's job-market submissions, a context in which connections between authors are referees are arguably low, as job-market candidates are entering the academic environment and have not had much time to develop networks.

Our paper contributes to two strands of the literature. First, by providing a systematic analysis of the evaluation of submissions to conferences, we contribute to the growing literature on gender differences in the evaluation of research. Our paper is most closely related to a concurrent working paper by Chari and Goldsmith-Pinkham (2018). They use data from the 2016 and 2017 editions of the NBER Summer Institute and find no difference in acceptance rates by gender. In comparison to Chari and Goldsmith-Pinkham (2018), we have information on the gender of the referees that evaluate each paper, and quality controls.[6] Other literature on the existence of gender gaps in the evaluation of research has found mixed results. Blank (1991), conducting a randomized experiment at the American Economic Review, finds no differences in the acceptance rates of female-authored papers in single-blind and double-blind submissions. Similarly, Abrevaya and Hamermesh (2012) find no evidence of gender differences at the evaluations at an anonymous journal. By contrast, Broder (1993), Wennerds and

[6]Note that, given that Chari and Goldsmith-Pinkham (2018) do not control for quality, it is not straightforward to compare our estimates of the gender gap with theirs.

Wold (1997), and Van der Lee and Ellemers (2015) find that grant proposals submitted by women are rated lower than those submitted by men. Finally, two concurrent working papers find gender gaps in the evaluation of submissions to journals: Card, DellaVigna, Funk, and Iriberri (2018), using data from four leading economics journals, find that female-authored papers receive more citations than observably similar male-authored papers, suggesting that referees set a higher bar for female-authored papers, and Hengel (2018) finds that female-authored papers are better written than equivalent papers by men, and explains this gap with tougher editorial standards for women and/or biased referee assignment.

Second, by providing evidence on the interaction between the authors' and the referees' gender, our paper also contributes to the literature on "in-group" biases, i.e. the preferential treatment of individuals of one's group. In-group biases have been found, for example, among Jewish and Arab judges in Israel (Shayo and Zussman (2011)) and among NBA referees, who tend to favor players of their own race (Price and Wolfers (2010)). Regarding in-group *gender* biases, Boring (2017) and Mengel, Sauermann, and Zölitz (2018) find that both male and female students evaluate male instructors higher, suggesting the presence of *absolute* biases against women. Similarly, Krawczyk and Smyk (2016), with a lab experiment, provide evidence that both women and men evaluate papers by women worse. De Paola and Scoppa (2015) find that female candidates are less likely to be promoted when the committee is composed exclusively of males, while the gender gap disappears with mixed-sex committees, suggesting the presence of male in-group bias. Bagues, Sylos-Labini, and Zinovyeva (2017), by contrast, find that a larger number of women in evaluation committees does not increase the number of female candidates who qualify.[7] Our findings indicate the presence of male but not female "in-group" bias, as male (female) referees are more (equally) favorable to papers written by male (female) authors.

The paper proceeds as follows. Section 2 provides some background on the conferences used in the analysis. Section 3 lays out the data. Section 4 presents the main results, robustness checks, and additional results by conference, masculinity of the field, gender of the referees, and prominence of the authors. Section 5 discusses the possible mechanisms behind our findings. Section 6 concludes.

2 Background

We have obtained submissions data from three conferences: the European Economic Association Annual Congress (EEA), the Annual Meeting of the Spanish Economic Association (SAEe), and the Spring Meeting of Young Economists (SMYE).

The European Economic Association is an international scientific body, with membership open to all persons involved or interested in economics. The Annual Congress, which takes place at the end of

[7] Perhaps an exception in this literature is Bagues and Esteve-Volart (2010), who find that female applicants to the Spanish judiciary have lower chances of being hired when they are randomly assigned to an evaluation committee including women.

August or early September, is a main event among the Association's activities. The first Annual Congress was held in Vienna in 1986. Since then, the Annual Congress has been held in many major cities in Europe. Annual congresses feature traditionally two plenary lectures in addition to the Presidential Address and consist of a number of invited paper sessions and panel debates as well as contributed papers sessions. In recent years, annual congresses have been held jointly with the Econometric Society. We have data for the 2015, 2016, and 2017 editions of the conference, which took place in Mannheim, Geneva, and Lisbon, respectively.

The main goal of the Spanish Economic Association is the promotion and dissemination of scientific knowledge in economics through the organization of conferences, publications, and any other activity that may further that aim. The annual conference brings together experts in all areas of economics every year in December since 1976. From 1976 to 2001 the conference, originally called Simposio de Análisis Económico, was organized by the Universitat Autònoma de Barcelona. Since 2001, the Simposio became the annual conference of the Spanish Association of Economics and is organized every year by a different institution. We have data for years 2012–2017, when it was organized by the Universidad de Vigo (2012), CEMFI and Universidad Internacional Menéndez Pelayo (2013), Universitat de les Illes Balears (2014), Universitat de Girona (2015), Universidad del País Vasco (2016), and Barcelona Graduate School of Economics (2017). It hosts two types of sessions: regular and job market, for which PhD candidates can send their job-market papers.[8]

The aim of the European Association of Young Economists is to facilitate the interaction between young researchers in economics working on topics within the field. Its main activity is the organization of the yearly meeting: the Spring Meeting of Young Economists (SMYE). The SMYE started in 1996 as a small-scale event for German Ph.D. Students in Essen. With driving forces Uwe Dulleck and Achim Wambach, it expanded rapidly from an initial 30 participants to over 100 participants during the third edition in Berlin. By now, the Spring Meeting of Young Economists has become an international event, which has been organized in 11 different countries, and receives over 700 applications per year. Only non-tenured researchers under the age of 35 can submit papers. Co-authors of submitted papers, however, can be of any status or age. For the SMYE, we have data from the 2017 edition, when it was organized in Mallorca.

The three conferences follow a similar evaluation procedure. A program chair or board is responsible for the selection of papers. The board assigns papers to referees, which are given a few weeks to evaluate the papers.[9] In our sample, an average of 7.7 papers per referee and 1.5 referees per paper are assigned. This assignment is mostly done on the basis of field. Referees then grade papers. Although the program

[8]The evaluation process and acceptance rates are similar for the two types of submissions.

[9]For the SMYE, referees are given approximately five weeks to submit their grades. For the SAEe and the EEA, they are given around two weeks.

chair makes the final selection, referees are influential.[10]

3 Data

In this section, we describe the variables used in the analysis. For more details on the procedure employed to build the dataset, please see the Dataset Construction Appendix.

Outcomes. Our main outcome is a dummy variable that takes the value of 1 if paper p (evaluated by referee r, submitted in year y to conference c) was accepted into the conference. Table 1 shows the summary statistics, where the unit of observation is a pair paper-referee, as will be used in the empirical analysis. We can see that the mean acceptance rate was 52%.

For the SMYE, and for the EEA in 2016 and 2017, we also have data on the grades given by any given referee to any given paper. The mean grade, on a scale of 0-10, is 5.73.

Finally, at the SMYE each referee can nominate each paper that he or she reviews to be considered for the best paper award. Hence, as an alternative outcome variable for this conference, we consider the share of referees that nominate the paper for the award.[11] The mean of this variable is .07, i.e., on average, 7% of the referees that evaluate a paper recommend it for the award.

Treatments. We capture the authors' gender in two alternative ways: (i) with the share of male authors of the paper, and (ii) to account for possible non-linearities, with three dummies indicating whether the paper has a majority of male authors, half-male and half-female authors, or a majority of female authors.[12] These categories represent 65%, 12%, and 24% of the observations, respectively.

Referees. We will consider the gender of referees in some of our empirical analyses. In Table 1, we can see that, in our sample, 76% of evaluations were done by a male referee.

Fields. We have divided the papers into fifteen fields.[13] Consistent with previous work that has documented that women are more represented in some fields than in others (e.g. Dolado, Felgueroso, and Almunia (2012)), we also find that this is the case in our sample. This can be seen in Table A1, which shows the summary statistics by the gender of the authors. For example, the share of observations on macroeconomics is .22 (.18) among papers written by a majority of male (female) authors, while this share is .11 (.21) on applied microeconomics.

[10] In particular, the rules of the SMYE stipulate that the final selection is based on the average score, i.e. no discretionary decisions made by the EAYE Board. There is no such rule in the SAEe or in the EEA, but it is standard practice to follow referees' recommendations.

[11] We only observe the number of referees that nominate each paper, not whether each individual referee nominates the paper. Hence, our measure is the number of nominations obtained divided by the number of referees that evaluated the paper.

[12] Card, DellaVigna, Funk, and Iriberri (2018) capture the gender of the authors by focusing on the gender of the author with the most publications (the so-called senior author). We cannot follow the same approach as we only have 2.1% of the observations with a senior female author.

[13] These fields are the ones used by the EEA to categorize submissions. They are applied microeconomics, behavioral, development, econometrics, history, theory, environmental, finance, industrial organization, international, labor, law and economics, macroeconomics, political economy, and public economics.

Cites of the paper. To account for the quality of the submitted paper, we have collected Google Scholar cites. Our variable Cites is defined as the asinh of the number of cites of the paper at the submission year.[14] Measuring the cites at the submission year ensures that this variable cannot be a "bad control", i.e. an outcome of having been accepted into the conference. However, one may think that, given that it takes some time for citations to be realized, an ex-post measure (i.e. some years after the conference) may capture the quality of the paper better. To take this possibility into account, in addition to the cites at submission year, we have collected an ex-post measure—the cites that the paper had in March 2019. We find that both measures of cites are highly correlated with the acceptance decision but, in fact, the ex-ante measure is a better predictor. Hence, we take the ex-ante cites as our preferred variable.[15] Finally, as an additional (ex-post) quality measure, we have collected data on whether the paper had been published by March 2019 in any of the 35 high-impact journals considered by Card, DellaVigna, Funk, and Iriberri (2018).[16]

Prominence of the authors. While the cites of the paper are predictive of the acceptance decision, they may be a noisy proxy of the quality of the paper. As an additional, indirect measure of quality, we consider the publication record of the authors in the years before the conference. Our main variable, Prominence, is the number of publications in the set of 35 high-impact journals in the five years prior to the submission year. For multiple-authored papers, we consider the number of publications of the most prolific co-author. For robustness, we also consider the number of publications *in top-5 journals* in the five years before submission, and the number of publications in the aforementioned 35 journals in the *10* years before the submission.

Institutions of the authors. We consider the quality of the affiliation of the authors at the submission year, measured through the IDEAS/Repec ranking of institutions. For multiple-authored papers, we consider the affiliation of the author in the highest-ranked institution. Our variables are four mutually-exclusive dummies indicating whether the affiliation is among the top-200 institutions (approximately, 2.5% of institutions), between the top 200 and the top 5%, between the top 5% and the top 10%, or below the top 10%.

4 Empirical Analysis

4.1 Main Results

Our research question is whether the gender of the author affects the probability that a paper is accepted into conferences. We begin by considering the following linear probability model:

[14]The asinh transformation is similar to the log but can accommodate zero citations. It is defined as follows: $asinh(x) = ln(x + (1 + x^2)^{1/2})$.

[15]In the appendix, we show the robustness of the results to taking the ex-post variable.

[16]The list of journals can be consulted on Table A2.

$$\text{Accepted}_{prcy} = \beta \text{Sh. Male Authors}_{prcy} + \alpha_{cy} + \epsilon_{prcy}, \tag{1}$$

where Accepted is a dummy variable that takes the value of 1 if paper p, evaluated by referee r, submitted in year y to conference c, was accepted into the conference, Sh. Male Authors is the proportion of male authors in the paper, α_{cy} are conference-year fixed effects, β is the parameter of interest, and ϵ_{prcy} is an error term. The unit of observation is a pair paper-referee.

The results of fitting this model are in column (1) of Table 2. We see that a 1-p.p rise in the share of male authors in the paper is associated with a .054-p.p. rise in the probability that the paper is accepted, i.e. switching from an all-female-authored to an all-male-authored paper increases the probability of acceptance by 5.4 p.p. Given the baseline rate of acceptance for papers with all male authors (47.1%), this amounts to an 11.5% effect. This effect is significant at the 1% level. Given the baseline acceptance rate for papers with all male authors (47.1%), this amounts to an 11.5% effect.

We next estimate whether this gap can be explained by several factors that may correlate with both the gender of the authors and the acceptance decision.

Number of authors. It has been documented that women single-author more than men (see, e.g., Boschini and Sjögren (2007)). We find that this is also the case in our sample: the mean share of male authors in single-authored papers is .66, while it is above .71 in multiple-authored papers.[17] If referees are harsher evaluating single-authored papers, this may make female-authored papers less likely to be accepted. To account for this possibility, we add number-of-authors fixed effects (α_n) to equation (1). The results, reported in column (2) of Table 2, reveal that controlling for the number of authors reduces but does not eliminate the gender gap, which is now 4.6 p.p.

Non-random assignment of papers to referees. The assignment of papers to referees may be non-random: it might be that female-authored papers are assigned to harsher referees, thus potentially driving the gender gap. To account for this possibility, we add referee fixed effects (α_r). The results, shown in column (3) of Table 2, do not change much: the gender gap in acceptance rates is now 4.9 p.p.

Field. As discussed in the previous section, women are relatively more represented in some fields than others. If it is relatively harder to be accepted in more feminized fields (for example, because there are relatively fewer slots at conferences), then this might explain the gender gap. To take this issue into account, we add field fixed effects (α_f). Note, however, that the referee fixed effects most likely already account for this, as papers are assigned to referees, to a large extent, by topic. In fact, the results (column (4) of Table 2) reveal that the gender gap barely changes after adding the field fixed effects.

Cites of the paper. If women submit papers of lower quality than men, this might explain why the

[17]More specifically, the mean share of male authors is .66 for papers with one author, .71 for papers with two and three authors, .74 for papers with four authors, .72 for papers with five authors, and .81 for papers with six authors.

probability of acceptance of female-authored papers is lower. To control for quality, we add the cites of the paper as a control variable. The results, shown in column (5) of Table 2, indicate that this variable is highly correlated with the acceptance decision. The gender gap after including this control is reduced to 4.4 p.p., but is still significant.

Prominence of the authors. As an additional, indirect measure, of quality, we add as a control the number of publications of the most prolific coauthor in a set of 35 leading journals in the five years before the submission. In column (6) of Table 2, we can see that one more prior publication of the author(s) increases the probability of acceptance by 4.3 p.p. The gender gap drops considerably after including this control: it is now 3.2 p.p. (significant at the 5% level).

Institutions of the authors. Finally, if women are more likely to be in lower-ranked institutions, and referees are harsher against authors in those institutions, this could explain the gender gap. To account for this possibility, we add the institution-quality dummies as controls, where lower-ranked institutions are the omitted category. We find that papers written by authors from a top 2.5% (2.5-5%, 5-10%) institution are 27.8 p.p. (16.8 p.p., 9.8 p.p.) more likely to be accepted than those written by authors from a below-10% institution. These are sizable effects, that could have two explanations. First, it may be that referees use the affiliation of the authors as an element of judgment, i.e. it is an element that they take into consideration to submit their recommendations. Second, if the two previous quality controls (cites and prominence) do not completely account for the quality of the paper, affiliations may capture some of it. After including these controls, the gender gap remains similar, at 3.2 p.p. (significant at the 5% level). This represents a 6.8% effect. To put this magnitude into perspective, note that the gender effect is comparable to the effect of an additional prior publication of the authors.

Hence, the results indicate that there is a gender gap that remains after controlling for the number of authors, assignment to referees, field, quality of the paper, prominence of the authors, and institutions of the authors. In the next subsection we lay out some additional results and robustness checks.

4.2 Additional Results

Non-linearities. To account for possible non-linearities in the effect of the share of male authors, we replace the share of male authors with dummies for having a majority of male authors and half-male and half-female authors, where papers with a majority of female authors are the omitted category. The results are shown in Table A3. In the last column, which includes all the fixed effects and controls, we can see that papers with a majority of male authors are 3.1 p.p. more likely to be accepted than those with a majority of female authors, and this effect is significant at the 5% level. Papers co-authored by a team of half men and half women are equally likely to be accepted than papers with a majority of female co-authors.

Grades and nomination outcomes. Our main outcome variable is the acceptance decision, which is potentially influenced by the referees and by the program committee. Although the fact that the gender gap remains similar when referee fixed effects are included suggests that referees drive the gap, here we provide additional evidence that reinforces this conclusion. For the SMYE and for the EEA in 2016 and 2017, we have data on the grade given by each referee to each paper. In Table A4, we consider the same specifications that we used for the acceptance decision, but with Grade as the outcome variable. The results indicate that, after including all the controls (column 7), all-male-authored papers receive, on a 0-10 scale, .14 more points than all-female-authored papers (effect significant at the 10% level). For the SMYE, we also have data on whether the paper was nominated by referees for the best paper award. The results (Table A5) indicate that all-male-authored papers are 2.8 p.p. more likely to be nominated than all-female-authored papers (significant at the 5% level).

Robustness checks. We study how the estimates change if we: (i) control for the ex-post (as opposed to ex-ante) number of cites, (ii) control for the publication of the paper, (iii) consider the number of publications in top-5 (instead of top-35) journals, (iv) consider the number of publications in the last ten (instead of five) years, (v) use a probit instead of a linear probability model. The results are shown in Table A6. The gender gap remains similar in these five specifications.

4.3 Heterogeneity Analysis

Here we investigate whether the gender gap is heterogeneous in four dimensions: conference, field, referees' gender, and authors' prominence. These results will help guide the discussion on the mechanisms in the next section.[18]

The gender gap by conference. To investigate whether the effect is driven by any particular conference, we consider the following equation:

$$\begin{aligned}\text{Accepted}_{prcy} \quad = \quad & \beta_1 \text{Sh. Male Authors}_{prcy} + \beta_2 \text{Sh. Male Authors x SAEe}_{prcy} \\ & + \beta_3 \text{Sh. Male Authors x SMYE}_{prcy} + \alpha_{cy} + \alpha_n + \alpha_r + \alpha_f + X_{prcy} + \epsilon_{prcy}, \quad (2)\end{aligned}$$

[18] In addition to the issues laid out next, we have also studied three additional questions. First, we have estimated whether the gender gap changes by year. The results suggest that the gap is quite stable over time—we cannot reject the null that the coefficient is the same over the six years in our sample. Note, however, that we only have observations from the SAEe for the early years, so the effects are quite imprecisely estimated. Second, we have estimated whether the gap differs by the gender of the chair of the admissions committee. The chair was female in the EEA in 2017, in the SAEe in 2012 and 2016, and in the SMYE. We cannot reject the null that the gap is the same with male and female chairs. Third, we have explored if the gender of the *submitter* plays a role. If program chairs or referees are more interested in having men present at the conference, they may be more likely to accept papers who are going to be presented by men, which may in turn generate the gender gap that we observe. We do not observe which author presents the paper, but we do observe the submitter, who, in most cases, ends up presenting. Note that, when all authors are of the same gender (77% of the sample), we cannot disentangle whether it is the gender of the authors or the gender of the submitter that matters. Hence, we focus on papers with mixed-gender authors, and estimate the gender gap controlling for the gender of the submitter. The results indicate that the gap is driven by the gender of the authors, while the coefficient on the gender of the submitter is close to zero. Given the small sample size, however, these results are imprecise.

where X_{prcy} contains the cites, prominence, and institutions controls, β_1 captures the gender gap at the omitted category (the EEA), and β_2 (β_3) captures the differential gender gap at the SAEe (SMYE) relative to the EEA.

The results are in Table 3. As we did for the main results, we add the fixed effects and controls sequentially. The full model corresponding to equation (2) is displayed in column 7. We can see that the effect for the omitted category (the EEA) is 3.2 p.p. (non-significant, due to the reduced number of observations when studying one subsample). The interactions terms are very close to zero and non-significant, suggesting that there is a gender gap of a similar magnitude in the three conferences.

The gender gap by masculinity of the field. Next, we study whether the gender gap is larger in fields with a relatively larger presence of men.[19] For this, we generate the variable Masculine Field, which takes the value of one (zero) if the share of male authors in the field of the paper is above (below) the median.[20] We then estimate:

$$\begin{aligned} \text{Accepted}_{prcy} \quad &= \quad \beta_1 \text{Sh. Male Authors}_{prcy} + \beta_2 \text{Sh. Male Authors x Masc. Field}_{prcy} \\ &\quad + \alpha_{cy} + \alpha_n + \alpha_r + \alpha_f + X_{prcy} + \epsilon_{prcy}, \end{aligned} \tag{3}$$

where β_1 captures the gender gap for papers in relatively less masculine fields, and β_2 captures the differential effect for papers in relatively more masculine fields.

The results are displayed in Table 4. When all controls are included (last column), there is no significant difference between the gender gap in relatively more and less masculine fields. The point estimate of the interaction effect is positive (2.1 p.p.), perhaps suggesting that the gap is somewhat larger in more masculine fields, but the coefficient is not significant.

The gender gap by the gender of the referees. Does the gender of the authors interact with the gender of the referees? In other words, is the gender gap in acceptance rates driven by male or female referees? To address this question, we consider the following equation:

$$\begin{aligned} \text{Accepted}_{prcy} \quad &= \quad \beta_1 \text{Sh. Male Authors}_{prcy} + \beta_2 \text{Sh. Male Authors x Male Referee}_{prcy} \\ &\quad + \alpha_{cy} + \alpha_n + \alpha_r + \alpha_f + X_{prcy} + \epsilon_{prcy}, \end{aligned} \tag{4}$$

where β_1 captures the gender gap when female referees evaluate papers, and β_2 the differential gap by the gender of the referee.[21]

[19] A more disaggregated analysis into specific fields yields estimates that are too imprecise to be meaningful.

[20] Fields with an above-median share of male authors (i.e. Masculine Field=1) are econometrics, theory, finance, macroeconomics, and political economy. Note that less than half of the fields are in this group. This is because some of them (e.g. macro) are relatively large fields.

[21] Note that, for this equation to make sense, we always need to include the referee fixed effects in the regression, so we only

The results (Table 5) indicate that the gender differences in the probability of acceptance are entirely driven by *male* referees. In the last column, we can see that, when papers are evaluated by female referees, there is no gender gap between male and female-authored papers, but, when papers are evaluated by male referees, there is a 4.5 p.p. gap (effect significant at the 10% level).

The gender gap by the prominence of the authors. Finally, we study whether the gender gap differs by the prominence of authors. For this, we define a variable, Prominence Dummy, that takes the value of one if Prominence>0 and zero otherwise, and consider this estimating equation:

$$\begin{aligned}\text{Accepted}_{prcy} &= \beta_1 \text{Sh. Male Authors}_{prcy} + \beta_2 \text{Sh. Male Authors x Prominence Dummy}_{prcy} \\ &\quad + \beta_3 \text{Prominence Dummy}_{prcy} + \alpha_{cy} + \alpha_n + \alpha_r + \alpha_f + X_{prcy} + \epsilon_{prcy}, \qquad (5)\end{aligned}$$

where β_1 captures the gender gap for papers in which no coauthor has published any paper in the set of 35 top journal in the last five years before submission (75% of the sample), and β_2 captures the differential effect for papers written by (at least) one author with (at least) one publication in that set of journals.

The results (Table 6) indicate that most of the gender gap is driven by prominent authors. In the last column, which includes the full set of covariates, we can see that there might be a small gap for papers written by non-prominent authors: the point estimate is 1.7 p.p., but not significant. For papers written by prominent authors, this gap is 8 p.p. larger.

5 Mechanisms

The empirical analysis presented so far indicates that there is a gender gap in acceptance rates, which is present even after taking into account the number of authors, non-random assignment of papers to referees, fields, cites of the paper, prominence of the authors, and affiliations of the authors. This gender gap is similar for the three conferences and for more and less male-dominated fields. On the contrary, the gender gap is entirely driven by male referees, and is larger for papers written by prominent authors. What drives the gender gap? Here we discuss four possible mechanisms.

Our quality measures are gender biased. One possibility is that the number of cites is gender biased. If this is the case, we may find a gender gap in the evaluation of submissions to conferences after controlling for quality, but this would not imply a gender *bias* in conferences' evaluations. Note that, under this explanation, for the evaluations of submissions to conferences to be gender neutral, it should be that the number of cites is biased *in favor of women*, i.e. female-authored papers are more cited than

consider the specifications with referee fixed effects. An alternative approach, which yields similar results, would be to drop the referee fixed effects and include a dummy for the gender of the referee. Also note that it is not possible to include paper fixed effects to identify the interaction, given that our outcome variable does not vary within paper.

male-authored papers conditional on quality. If cites are biased *against* women, then the gender bias in conferences evaluations would be larger than what we find in this paper, i.e. we would be obtaining a lower bound of the bias.

While determining biases in citations is beyond the scope of this paper, Card, DellaVigna, Funk, and Iriberri (2018) argue, based on a survey to economists, that citations are biased against women. If this is the case, we would be underestimating the gender bias in the evaluation of submissions to conferences.

Finally, note that the same argument applies to our other quality measures, namely, the prior publications of the authors, and the affiliations of the authors. Gender biases in these variables could account for the gender gap, to the extent that they are biased in favor of women, i.e. women publishing better and being affiliated with better institutions than men of the same quality.[22]

Referees have stereotypes against female economists. Another possible explanation is that referees discriminate against female-authored papers. If only male referees share these stereotypes, this could explain why the gap driven by male referees.

However, this mechanism cannot easily account for why there is no gender gap for papers written by non-prominent authors: if (male) referees are biased against women, this should also result in a gender gap when evaluating papers written by non-prominent authors. Furthermore, as argued by Bagues, Sylos-Labini, and Zinovyeva (2017), one would expect prejudices against women to be stronger in fields that are less feminized and, therefore, offer fewer chances to interact with female researchers. However, we find no significant differences in the gender gap by the masculinity of the field.

Papers' unobserved characteristics differ by gender. It may be that female-authored papers lack some characteristics that are especially valued by conferences' referees. For example, if, in comparison with male-authored papers, female-authored papers make more substantive relative to methodological contributions, and conferences' referees are especially interested in this type of papers, this could generate a gender gap in acceptance rates.[23]

Although we cannot rule out this channel, we do not believe that it is the most natural explanation to our findings, as it cannot easily account for the observed heterogeneities. First, it is not clear why we should expect that these unobserved papers' characteristics are only valued by male and not female referees. Second, and more importantly, it is not clear how this mechanism can explain why the effect appears only for the evaluation of papers written by prominent authors. One possibility would be that the gender difference in the papers' unobserved characteristics is only present for papers written by prominent authors, i.e. that papers written by male and female prominent authors differ, but papers written by

[22] However, Sarsons (2017) suggests that women are given *less* credit for papers written with men, affecting negatively their tenure prospects.

[23] We say "especially" interested because, given that we control for fields and quality, these unobserved characteristics must be things that are valued by referees beyond field and quality (as proxied by the number of cites, prominence, and institutions).

male and female non-prominent authors do not. Another possibility would be that (male) referees only value these unobservable characteristics of the papers in papers written by prominent authors.

Male economists are better connected than female economists. Finally, if connections (networks) play a role in the evaluation of papers, and male economists are better connected than female economists, this could generate the gender gap in acceptance rates. By connections, we mean that the referee and the author(s) of the evaluated paper have a personal bond.[24] While we cannot directly test this mechanism, we argue that it is a plausible explanation for our empirical findings. In particular, this mechanism can explain our results if (i) the probability of acceptance increases if the referee and the authors are connected, (ii) male referees are more likely to be connected with male than with female authors, while female referees are similarly connected with male and with female authors, and (iii) referees are equally likely to be connected with male and female *non-prominent* authors.

Regarding the first point, there is ample evidence that connections play an important role in evaluation processes, including national qualification exams, evaluations at the university level, and grant peer-review (e.g. Combes, Linnemer, and Visser (2008), De Paola and Scoppa (2015) Durante, Labartino, and Perotti (2011)) Perotti (2002), Sandström and Hällsten (2007), Zinovyeva and Bagues (2015)). It is plausible that this is also the case at conferences evaluations.[25]

Second, for this theory to explain why there is a gender gap in acceptance rates, and why the gap is driven by male referees, it should be the case male referees are more likely to be connected with male than with female authors, while female referees are similarly connected with male and with female authors. There is evidence that male economists are better connected than female economists. For example, Ductor, Goyal, and Prummer (2018) show that women have fewer collaborators than men. This hypothesis is also consistent with Hilmer and Hilmer (2007), who observe that, in the US, around half of the economics PhD students being advised by women are female, while only 18% of economics PhD students advised by men are female.

And third, for this theory to explain why there is no gap for papers written by non-prominent authors, it should be the case that referees are equally likely to be connected with male and female non-prominent authors. This will be the case if connections between referees and non-prominent authors are low.[26]

To provide some suggestive evidence on this regard, we leverage the fact that the SAEe organizes two types of sessions: regular sessions and job-market sessions, in which job-market candidates present

[24]Cases in which this is likely to happen, and that are usually the focus of the literature on networks, are that the referee and the authors are or have been co-authors, colleagues, advisors, or mentors.

[25]Given that the refereeing process for conferences submissions is comparatively fast—that is, less time is spent on deciding on each paper compared with, for example, academic promotions—we think that considerations other than the quality of the paper, including connections, may play an even larger role in our context.

[26]At the extreme, note that, if referees and non-prominent authors are never connected, then obviously referees are equally likely to be connected with male and female non-prominent authors.

their job-market papers.[27] We expect that, given that job-market candidates are entering the academic environment and have not had much time to develop networks, their connections with referees are low.[28] If our argument about connections is correct, we should see a smaller or no gender gap in the subsample of job-market sessions. In Tables A7 and A8, we show the results for the SAEe job-market and regular submissions, respectively. Once all the controls are included (last columns of the tables), there is no significant gap in job-market submissions, while in regular sessions there is a 4.8 p.p. gap (significant at the 10% level). Hence, these results are consistent with a mechanism on connections, while are harder to reconcile with alternative theories.[29]

6 Conclusion

We have found that all-female-authored papers are 3.2 p.p. (6.8%) less likely to be accepted. This gap is present after accounting for the cites of the paper, the publication record of the authors in the years before the submission, and the ranking of the affiliation of the authors. We have also found that the gap is similar for the three conferences and in more and less male-dominated fields. However, our results indicate that the gender gap is entirely driven by male referees.

These findings have direct policy implications for the design of systems to evaluate research and, more specifically, to select papers for conferences. In particular, they imply that a more gender-balanced pool of referees would lead to more gender-neutral acceptance decisions. For example, the Executive Committee of the Spanish Economic Association has recently decided that future editions of the SAEe will have a gender-balanced panel of referees. Our results suggest that this decision may enhance equality of opportunities for female economists.

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[27] We can observe regular versus job-market submissions for years 2013 to 2017. In these years, 39% of submissions were job-market.

[28] Some job-market papers may be co-authored, but this is not frequent. In our job-market subsample, 79% of papers are single-authored, compared with 46% in the rest of the sample.

[29] In particular, if the gap is driven by stereotypes, it is not clear why there is no gap in job-market sessions. Similarly, if the gap is driven by some heterogeneity in unobserved aspects of papers, it is not clear why such heterogeneity is not present (or not valued by referees) in job-market sessions.

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Tables

Table 1: Summary Statistics

	mean	min	max	sd	count
Accepted	0.52	0.00	1.00	0.50	16154
Grade	5.73	0.00	10.00	2.16	5825
Nomination	0.07	0.00	1.00	0.15	1949
Share Male Authors	0.69	0.00	1.00	0.40	16154
Half Male Authors	0.12	0.00	1.00	0.32	16154
Majority Male Authors	0.65	0.00	1.00	0.48	16154
Majority Female Authors	0.24	0.00	1.00	0.43	16154
Male Referee	0.76	0.00	1.00	0.42	16154
Applied Micro	0.14	0.00	1.00	0.35	16154
Behavioral	0.06	0.00	1.00	0.23	16154
Development	0.05	0.00	1.00	0.22	16154
Econometrics	0.04	0.00	1.00	0.19	16154
History	0.01	0.00	1.00	0.10	16154
Theory	0.06	0.00	1.00	0.24	16154
Environmental	0.01	0.00	1.00	0.11	16154
Finance	0.10	0.00	1.00	0.30	16154
IO	0.05	0.00	1.00	0.22	16154
International	0.07	0.00	1.00	0.26	16154
Labor	0.06	0.00	1.00	0.24	16154
Law and Economics	0.00	0.00	1.00	0.05	16154
Macroeconomics	0.20	0.00	1.00	0.40	16154
Political Economy	0.03	0.00	1.00	0.17	16154
Public	0.10	0.00	1.00	0.30	16154
Cites	0.13	0.00	5.43	0.46	16154
Cites Ex Post	0.99	0.00	6.68	1.35	16154
Published	0.08	0.00	1.00	0.28	16154
Prominence	0.70	0.00	20.00	1.75	16154
Prominence 10 Y	1.21	0.00	37.00	3.08	16154
Prominence Top 5	0.12	0.00	9.00	0.52	16154
Prominence Dummy	0.25	0.00	1.00	0.43	16154
Top 2.5% Institution	0.47	0.00	1.00	0.50	16154
2.5%-5% Institution	0.19	0.00	1.00	0.39	16154
5%-10% Institution	0.17	0.00	1.00	0.38	16154
Below 10% Institution	0.17	0.00	1.00	0.37	16154

The unit of observation is a pair paper-referee. The variable Grade is available only for the SMYE and for the EEA in 2016 and 2017, and the variable Nomination is available only for the SMYE.

Table 2: The Impact of the Authors' Gender on the Probability of Acceptance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sh. Male Authors	0.0536***	0.0463***	0.0491***	0.0471***	0.0441***	0.0323**	0.0316**
	(0.0148)	(0.0148)	(0.0147)	(0.0148)	(0.0148)	(0.0148)	(0.0143)
Cites					0.0921***	0.0791***	0.0634***
					(0.0127)	(0.0125)	(0.0122)
Prominence						0.0428***	0.0350***
						(0.00348)	(0.00334)
Top 2.5% Ins.							0.278***
							(0.0170)
2.5%-5% Ins.							0.168***
							(0.0193)
5%-10% Ins.							0.0977***
							(0.0185)
Constant	0.484***	0.489***	0.487***	0.478***	0.471***	0.451***	0.275***
	(0.0130)	(0.0130)	(0.0109)	(0.0231)	(0.0232)	(0.0233)	(0.0264)
Observations	16154	16154	16154	16154	16154	16154	16154
R^2	0.099	0.107	0.166	0.171	0.177	0.195	0.234
Conf.-Year FE	Y	Y	Y	Y	Y	Y	Y
# Authors FE		Y	Y	Y	Y	Y	Y
Referee FE			Y	Y	Y	Y	Y
Field FE				Y	Y	Y	Y

Results of regressing a dummy indicating whether the paper was accepted on the variables and fixed effects indicated in the first column, where Cites is the asinh of the number of cites of the paper at the submission year, Prominence is the number of publications in the set of 35 high-impact journals specified in Table A2 in the five years prior to the submission year by the most prolific co-author, and Top 2.5% Ins., 2.5%-5% Ins., and 5%-10% Ins. are dummies indicating whether the (best) affiliation of the authors is among the top-200 institutions (approximately, 2.5% of institutions), between the top 200 and the top 5%, or between the top 5% and the top 10%, respectively. Standard errors clustered by paper and referee in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: The Impact of the Authors' Gender on the Probability of Acceptance, by Conference

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sh. Male Auth.	0.0540***	0.0456**	0.0530***	0.0498**	0.0459**	0.0313	0.0318
	(0.0206)	(0.0205)	(0.0204)	(0.0205)	(0.0204)	(0.0205)	(0.0197)
Sh. Male Auth. x SAEe	-0.00161	0.00569	-0.00800	-0.00278	-0.00157	0.00257	-0.00347
	(0.0293)	(0.0293)	(0.0290)	(0.0291)	(0.0292)	(0.0291)	(0.0278)
Sh. Male Auth. x SMYE	0.0000570	-0.00487	-0.0180	-0.0176	-0.0125	0.00312	0.00549
	(0.0437)	(0.0437)	(0.0415)	(0.0417)	(0.0417)	(0.0416)	(0.0417)
Cites					0.0921***	0.0792***	0.0634***
					(0.0127)	(0.0125)	(0.0122)
Prominence						0.0428***	0.0350***
						(0.00348)	(0.00335)
Top 2.5% Ins.							0.278***
							(0.0170)
2.5%-5% Ins.							0.168***
							(0.0193)
5%-10% Ins.							0.0978***
							(0.0185)
Constant	0.484***	0.489***	0.487***	0.478***	0.471***	0.451***	0.274***
	(0.0133)	(0.0133)	(0.0112)	(0.0232)	(0.0233)	(0.0234)	(0.0265)
Observations	16154	16154	16154	16154	16154	16154	16154
R^2	0.099	0.107	0.166	0.171	0.177	0.195	0.234
Conf.-Year FE	Y	Y	Y	Y	Y	Y	Y
# Authors FE		Y	Y	Y	Y	Y	Y
Referee FE			Y	Y	Y	Y	Y
Field FE				Y	Y	Y	Y

Results of regressing a dummy indicating whether the paper was accepted on the variables and fixed effects indicated in the first column, where Cites is the asinh of the number of cites of the paper at the submission year, Prominence is the number of publications in the set of 35 high-impact journals specified in Table A2 in the five years prior to the submission year by the most prolific co-author, and Top 2.5% Ins., 2.5%-5% Ins., and 5%-10% Ins. are dummies indicating whether the (best) affiliation of the authors is among the top-200 institutions (approximately, 2.5% of institutions), between the top 200 and the top 5%, or between the top 5% and the top 10%, respectively. Standard errors clustered by paper and referee in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: The Impact of the Authors' Gender on the Probability of Acceptance, by Masculinity of Field

	(1)	(2)	(3)	(4)	(5)	(6)
Sh. Male Authors	0.0463**	0.0361*	0.0362*	0.0345*	0.0228	0.0211
	(0.0188)	(0.0187)	(0.0190)	(0.0190)	(0.0189)	(0.0182)
Sh. Male Authors x Masc. Field	0.0202	0.0233	0.0276	0.0242	0.0240	0.0264
	(0.0296)	(0.0295)	(0.0289)	(0.0287)	(0.0286)	(0.0278)
Cites				0.0920***	0.0790***	0.0632***
				(0.0127)	(0.0125)	(0.0122)
Prominence					0.0428***	0.0350***
					(0.00348)	(0.00334)
Top 2.5% Ins.						0.278***
						(0.0170)
2.5%-5% Ins.						0.168***
						(0.0193)
5%-10% Ins.						0.0984***
						(0.0185)
Constant	0.502***	0.504***	0.484***	0.476***	0.456***	0.280***
	(0.0214)	(0.0213)	(0.0239)	(0.0240)	(0.0241)	(0.0272)
Observations	16154	16154	16154	16154	16154	16154
R^2	0.106	0.115	0.171	0.177	0.195	0.234
Conf.-Year FE	Y	Y	Y	Y	Y	Y
# Authors FE		Y	Y	Y	Y	Y
Referee FE			Y	Y	Y	Y
Field FE	Y	Y	Y	Y	Y	Y

Results of regressing a dummy indicating whether the paper was accepted on the variables and fixed effects indicated in the first column, where Masc. Field takes the value of one (zero) if the share of male authors in the field of the paper is above (below) the median, Cites is the asinh of the number of cites of the paper at the submission year, Prominence is the number of publications in the set of 35 high-impact journals specified in Table A2 in the five years prior to the submission year by the most prolific co-author, and Top 2.5% Ins., 2.5%-5% Ins., and 5%-10% Ins. are dummies indicating whether the (best) affiliation of the authors is among the top-200 institutions (approximately, 2.5% of institutions), between the top 200 and the top 5%, or between the top 5% and the top 10%, respectively. Standard errors clustered by paper and referee in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: The Impact of the Authors' Gender on the Probability of Acceptance, by the Gender of Referees

	(1)	(2)	(3)	(4)	(5)	(6)
Sh. Male Authors	0.0181	0.00912	0.00752	0.00449	-0.00401	-0.00222
	(0.0210)	(0.0208)	(0.0210)	(0.0212)	(0.0213)	(0.0211)
Sh Male Authors x Male Ref.	0.0534^{**}	0.0530^{**}	0.0525^{**}	0.0525^{**}	0.0481^{**}	0.0449^{*}
	(0.0242)	(0.0239)	(0.0240)	(0.0241)	(0.0243)	(0.0238)
Cites				0.0921^{***}	0.0792^{***}	0.0634^{***}
				(0.0127)	(0.0125)	(0.0122)
Prominence					0.0427^{***}	0.0350^{***}
					(0.00348)	(0.00334)
Top 2.5% Ins.						0.278^{***}
						(0.0170)
2.5%-5% Ins.						0.168^{***}
						(0.0193)
5%-10% Ins.						0.0980^{***}
						(0.0185)
Constant	0.480^{***}	0.486^{***}	0.476^{***}	0.469^{***}	0.449^{***}	0.273^{***}
	(0.0110)	(0.0110)	(0.0231)	(0.0232)	(0.0233)	(0.0264)
Observations	16154	16154	16154	16154	16154	16154
R^2	0.157	0.166	0.171	0.178	0.195	0.234
Conf.-Year FE	Y	Y	Y	Y	Y	Y
# Authors FE		Y	Y	Y	Y	Y
Referee FE	Y	Y	Y	Y	Y	Y
Field FE			Y	Y	Y	Y

Results of regressing a dummy indicating whether the paper was accepted on the variables and fixed effects indicated in the first column, where Cites is the asinh of the number of cites of the paper at the submission year, Prominence is the number of publications in the set of 35 high-impact journals specified in Table A2 in the five years prior to the submission year by the most prolific co-author, and Top 2.5% Ins., 2.5%-5% Ins., and 5%-10% Ins. are dummies indicating whether the (best) affiliation of the authors is among the top-200 institutions (approximately, 2.5% of institutions), between the top 200 and the top 5%, or between the top 5% and the top 10%, respectively. Standard errors clustered by paper and referee in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: The Impact of the Authors' Gender on the Probability of Acceptance, by the Authors' Prominence

	(1)	(2)	(3)	(4)	(5)	(6)
Sh. Male Authors	0.0184	0.0179	0.0195	0.0180	0.0156	0.0172
	(0.0162)	(0.0162)	(0.0162)	(0.0162)	(0.0162)	(0.0155)
Sh Male Authors x Prom. Dummy	0.0771*	0.0785**	0.0890**	0.0882**	0.0914**	0.0796**
	(0.0395)	(0.0394)	(0.0390)	(0.0387)	(0.0383)	(0.0372)
Prom. Dummy	0.148***	0.138***	0.130***	0.130***	0.120***	0.0951***
	(0.0318)	(0.0324)	(0.0322)	(0.0320)	(0.0316)	(0.0309)
Cites					0.0794***	0.0637***
					(0.0125)	(0.0122)
Top 2.5% Ins.						0.276***
						(0.0170)
2.5%-5% Ins.						0.165***
						(0.0193)
5%-10% Ins.						0.0981***
						(0.0186)
Constant	0.456***	0.459***	0.457***	0.446***	0.442***	0.270***
	(0.0139)	(0.0140)	(0.0120)	(0.0240)	(0.0240)	(0.0271)
Observations	16154	16154	16154	16154	16154	16154
R^2	0.131	0.131	0.189	0.193	0.198	0.236
Conf.-Year FE	Y	Y	Y	Y	Y	Y
# Authors FE		Y	Y	Y	Y	Y
Referee FE			Y	Y	Y	Y
Field FE				Y	Y	Y

Results of regressing a dummy indicating whether the paper was accepted on the variables and fixed effects indicated in the first column, where Cites is the asinh of the number of cites of the paper at the submission year, Prominence Dummy indicates whether any co-author has published in the set of 35 high-impact journals specified in Table A2 in the five years prior to the submission year, and Top 2.5% Ins., 2.5%-5% Ins., and 5%-10% Ins. are dummies indicating whether the (best) affiliation of the authors is among the top-200 institutions (approximately, 2.5% of institutions), between the top 200 and the top 5%, or between the top 5% and the top 10%, respectively. Standard errors clustered by paper and referee in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Online Appendices

Dataset Construction

The procedure to build the database takes place in several stages. Raw data are obtained from Conference Maker. Each year, submissions are identified by a unique *paper id*. To guarantee confidentiality, different elements of the files have been processed separately in order to codify the following variables:

Gender variables. We temporarily stored authors' and referees' names in a different file in order to codify gender, and deleted names afterwards. Gender is inferred from the first names of the authors using three different packages used in previous literature: (i) the R-package gender, constructed from U.S. Social Security data, (ii) the database constructed by Tang, Ross, Saxena, and Chen (2011) from Facebook lists of names, and (iii) a list constructed by Bagues and Campa (2017) with data from the Spanish National Institute of Statistics (INE). Names that could not be identified with the previous procedures, or for which we obtained conflicting genders, were completed by hand by a research assistant, inferring gender from photos or pronouns on the webpages or CVs of the authors. Papers for which in the end we cannot identify the gender of the author or, for multiple-authored papers, of all the co-authors, are dropped from the analysis (2.1% of observations).

Fields variables. For all the SMYE submissions, and 65% of SAEe submissions, we have a variable from Conference Maker showing the field indicated by the authors at the time of submission. In these cases, we coded our fifteen field variables from this information. For the remaining cases (EEA and 35% of SAEe submissions), we temporarily stored the papers' titles on a different file and assigned the field by hand from the titles. After that, we deleted the file with the titles.

Cites variables. We temporarily stored the title of each paper in a separate file. We instructed our research assistants to look for each paper in Google Scholar, and to collect the number of cites at the time of the search (March 2019) and at one year before the paper was submitted (by restricting the search to papers dated until that year). After this procedure, we deleted the titles.

Prominence variables. We temporarily stored the names of the authors in a different file. To obtain the prior record publication of the authors, we downloaded from Econlit the names of all the authors who have published at any of the journals listed in Table A2 since 2002. We then merged those names with the names in our dataset. After this merge, we deleted names.

Institutions variables. We temporarily stored the authors' institutions (obtained from Conference Maker) in a different file, and matched those institutions with their position at the ranking of *IDEAS/RePEc*, as of 3 December 2018. After this merge, we deleted institution names.

Appendix Tables

Table A1: Summary Statistics, Mean of Variables by the Gender of the Authors

Sample	All	Maj. Male Authors	Half-Male and Half-Female	Maj. Female Authors
Accepted	0.52	0.54	0.52	0.47
Grade	5.73	5.76	5.83	5.58
Nomination	0.07	0.07	0.07	0.05
Sh. Male Authors	0.69	0.96	0.50	0.04
Male Referee	0.76	0.78	0.77	0.72
Applied Micro	0.14	0.11	0.19	0.21
Behavioral	0.06	0.05	0.06	0.06
Development	0.05	0.04	0.05	0.08
Econometrics	0.04	0.04	0.03	0.03
History	0.01	0.01	0.01	0.01
Theory	0.06	0.07	0.05	0.04
Environmental	0.01	0.01	0.02	0.02
Finance	0.10	0.11	0.10	0.08
IO	0.05	0.06	0.03	0.05
International	0.07	0.07	0.08	0.08
Labor	0.06	0.05	0.07	0.08
Law and Economics	0.00	0.00	0.00	0.00
Macroeconomics	0.20	0.22	0.18	0.15
Political Economy	0.03	0.04	0.02	0.03
Public	0.10	0.11	0.11	0.09
Cites	0.13	0.15	0.13	0.10
Cites Ex Post	0.99	1.05	1.01	0.82
Published	0.08	0.09	0.08	0.07
Prominence	0.70	0.82	0.85	0.29
Prominence 10 Y	1.21	1.41	1.53	0.50
Prominence Top 5	0.12	0.15	0.12	0.05
Prominence Dummy	0.25	0.29	0.33	0.12
Top 2.5% Institution	0.47	0.49	0.46	0.42
2.5%-5% Institution	0.19	0.18	0.21	0.21
5%-10% Institution	0.17	0.16	0.22	0.17
Below 10% Institution	0.17	0.17	0.11	0.19
Observations	16154	10428	1888	3838

The unit of observation is a pair paper-referee. The variable Grade is available only for the SMYE and for the EEA in 2016 and 2017, and the variable Nomination is available only for the SMYE.

Table A2: List of Journals Used in Publication Counts

American Economic Journal: Applied Economics	Journal of Economic Growth
American Economic Journal: Macroeconomics	Journal of Economic Theory
American Economic Journal: Microeconomics	Journal of Finance
American Economic Journal: Economic Policy	Journal of Financial Economics
American Economic Review	Journal of Health Economics
Brookings Papers on Economic Policy	Journal of International Economics
Econometrica	Journal of Labor Economics
Economic Journal	Journal of Monetary Economics
Experimental Economics	Journal of Money, Credit and Banking
Games and Economic Behavior	Journal of Political Economy
International Economic Review	Journal of Public Economics
International Journal of Industrial Organization	Journal of Urban Economics
Journal of the European Economic Association	Quarterly Journal of Economics
Journal of Accounting and Economics	The RAND Journal of Economics
Journal of American Statistical Association	Review of Economics and Statistics
Journal of Business and Economic Statistics	Review of Financial Studies
Journal of Development Economics	Review of Economic Studies
Journal of Econometrics	

This list of 35 journals is used to create the variable Prominence—the number of articles published in the five years before submission—and has been obtained from Card, DellaVigna, Funk, and Iriberri (2018).

Table A3: The Impact of the Authors' Gender on the Probability of Acceptance, Non-linear Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Half Male Authors	0.0459**	0.00169	0.00256	-0.000146	-0.00254	-0.00549	0.00395
	(0.0211)	(0.0247)	(0.0247)	(0.0246)	(0.0245)	(0.0242)	(0.0238)
Majority Male Authors	0.0608***	0.0427***	0.0453***	0.0433***	0.0406***	0.0299**	0.0309**
	(0.0144)	(0.0145)	(0.0144)	(0.0145)	(0.0144)	(0.0144)	(0.0139)
Cites					0.0923***	0.0793***	0.0635***
					(0.0127)	(0.0125)	(0.0122)
Prominence						0.0427***	0.0350***
						(0.00348)	(0.00334)
Top 2.5% Ins.							0.278***
							(0.0170)
2.5%-5% Ins.							0.168***
							(0.0193)
5%-10% Ins.							0.0980***
							(0.0185)
Constant	0.476***	0.493***	0.491***	0.482***	0.475***	0.454***	0.276***
	(0.0136)	(0.0139)	(0.0118)	(0.0238)	(0.0239)	(0.0239)	(0.0273)
Observations	16154	16154	16154	16154	16154	16154	16154
R^2	0.100	0.108	0.166	0.171	0.178	0.195	0.234
Conf.-Year FE	Y	Y	Y	Y	Y	Y	Y
# Authors FE		Y	Y	Y	Y	Y	Y
Referee FE			Y	Y	Y	Y	Y
Field FE				Y	Y	Y	Y

Results of regressing a 5%-10% Ins. indicating whether the paper was accepted on the variables and fixed effects indicated in the first column, where Cites is the asinh of the number of cites of the paper at the submission year, Prominence is the number of publications in the set of 35 high-impact journals specified in Table A2 in the five years prior to the submission year by the most prolific co-author, and Top 2.5% Ins., 2.5%-5% Ins., and 5%-10% Ins. are dummies indicating whether the (best) affiliation of the authors is among the top-200 institutions (approximately, 2.5% of institutions), between the top 200 and the top 5%, or between the top 5% and the top 10%, respectively. Standard errors clustered by paper and referee in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: The Impact of the Authors' Gender on the Grade Given by Referees

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sh. Male Authors	0.261***	0.214***	0.214***	0.201***	0.183**	0.147*	0.140*
	(0.0774)	(0.0778)	(0.0761)	(0.0763)	(0.0766)	(0.0763)	(0.0739)
Cites					0.549***	0.473***	0.429***
					(0.0716)	(0.0702)	(0.0700)
Prominence						0.260***	0.228***
						(0.0251)	(0.0232)
Top 2.5% Ins.							1.140***
							(0.0836)
2.5%-5% Ins.							0.814***
							(0.0940)
5%-10% Ins.							0.529***
							(0.0934)
Constant	5.549***	5.581***	5.580***	5.525***	5.471***	5.388***	4.663***
	(0.0702)	(0.0705)	(0.0528)	(0.176)	(0.172)	(0.167)	(0.176)
Observations	5825	5825	5825	5825	5825	5825	5825
R^2	0.072	0.081	0.229	0.235	0.245	0.272	0.304
Conf.-Year FE	Y	Y	Y	Y	Y	Y	Y
# Authors FE		Y	Y	Y	Y	Y	Y
Referee FE			Y	Y	Y	Y	Y
Field FE				Y	Y	Y	Y

Results of regressing the grade (0–10) given by each referee to each paper on the variables and fixed effects indicated in the first column, where Cites is the asinh of the number of cites of the paper at the submission year, Prominence is the number of publications in the set of 35 high-impact journals specified in Table A2 in the five years prior to the submission year by the most prolific co-author, and Top 2.5% Ins., 2.5%-5% Ins., and 5%-10% Ins. are dummies indicating whether the (best) affiliation of the authors is among the top-200 institutions (approximately, 2.5% of institutions), between the top 200 and the top 5%, or between the top 5% and the top 10%, respectively. Standard errors clustered by paper and referee in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: The Impact of the Authors' Gender on Nomination for Best-Paper Award

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sh. Male Authors	0.0220	0.0215	0.0290**	0.0285**	0.0300**	0.0297**	0.0283**
	(0.0138)	(0.0137)	(0.0143)	(0.0145)	(0.0145)	(0.0145)	(0.0143)
Cites					0.130**	0.130**	0.131***
					(0.0517)	(0.0513)	(0.0498)
Prominence						0.00586	0.00426
						(0.00511)	(0.00492)
Top 2.5% Ins.							0.0256*
							(0.0153)
2.5%-5% Ins.							0.0101
							(0.0183)
5%-10% Ins.							-0.00507
							(0.0159)
Constant	0.0524***	0.0527***	0.0481***	0.0552**	0.0471*	0.0471*	0.0390
	(0.0102)	(0.0101)	(0.00951)	(0.0246)	(0.0243)	(0.0244)	(0.0272)
Observations	1949	1949	1949	1949	1949	1949	1949
R^2	0.004	0.008	0.185	0.193	0.207	0.208	0.214
Conf.-Year FE	Y	Y	Y	Y	Y	Y	Y
# Authors FE		Y	Y	Y	Y	Y	Y
Referee FE			Y	Y	Y	Y	Y
Field FE				Y	Y	Y	Y

Results of regressing the share of referees the nominated the paper for the best paper award on the variables and fixed effects indicated in the first column, where Cites is the asinh of the number of cites of the paper at the submission year, Prominence is the number of publications in the set of 35 high-impact journals specified in Table A2 in the five years prior to the submission year by the most prolific co-author, and Top 2.5% Ins., 2.5%-5% Ins., and 5%-10% Ins. are dummies indicating whether the (best) affiliation of the authors is among the top-200 institutions (approximately, 2.5% of institutions), between the top 200 and the top 5%, or between the top 5% and the top 10%, respectively. Standard errors clustered by paper and referee in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: The Impact of the Authors' Gender on the Probability of Acceptance, Robustness Checks

	(1) Cites Ex Post	(2) Publication	(3) Prominence 10 Y	(4) Prominence Top 5	(5) Probit
Sh. Male Authors	0.0284**	0.0286**	0.0326**	0.0381***	0.0313***
	(0.0141)	(0.0141)	(0.0143)	(0.0142)	(0.0100)
Cites Ex Post	0.0526***	0.0484***			
	(0.00452)	(0.00495)			
Prominence	0.0313***	0.0310***			0.0446***
	(0.00336)	(0.00337)			(0.00333)
Top 2.5% Ins.	0.268***	0.267***	0.277***	0.286***	0.272***
	(0.0169)	(0.0169)	(0.0170)	(0.0171)	(0.0119)
2.5%-5% Ins.	0.164***	0.163***	0.167***	0.168***	0.164***
	(0.0193)	(0.0193)	(0.0193)	(0.0194)	(0.0137)
5%-10% Ins.	0.0975***	0.0967***	0.0978***	0.0993***	0.0974***
	(0.0183)	(0.0183)	(0.0186)	(0.0187)	(0.0125)
Published		0.0538***			
		(0.0199)			
Cites			0.0645***	0.0672***	0.0649***
			(0.0122)	(0.0122)	(0.00931)
Prominence 10 Y			0.0197***		
			(0.00196)		
Prominence Top 5				0.0828***	
				(0.00981)	
Constant	0.243***	0.243***	0.276***	0.281***	
	(0.0263)	(0.0262)	(0.0265)	(0.0265)	
Observations	16154	16154	16154	16154	15542
R^2	0.248	0.248	0.234	0.229	
Conf.-Year FE	Y	Y	Y	Y	Y
# Authors FE	Y	Y	Y	Y	Y
Referee FE	Y	Y	Y	Y	Y
Field FE	Y	Y	Y	Y	Y

Results of regressing a dummy indicating whether the paper was accepted on the variables and fixed effects indicated in the first column, where Cites (Cites Ex Post) is the asinh of the number of cites of the paper at the submission year (March 2019), Prominence (Prominence 10 Y) is the number of publications in the set of 35 high-impact journals specified in Table A2 in the 5 (10) years prior to the submission year by the most prolific co-author, Prominence Top 5 is the number of publications in top-5 journals in the five years prior to the submission year by the most prolific co-author, Published is a dummy that indicates if the paper has been published by March 2019 at any journal in the set of 35 high-impact journals specified in Table A2, and Top 2.5% Ins., 2.5%-5% Ins., and 5%-10% Ins. are dummies indicating whether the (best) affiliation of the authors is among the top-200 institutions (approximately, 2.5% of institutions), between the top 200 and the top 5%, or between the top 5% and the top 10%, respectively. Standard errors clustered by paper and referee in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: The Impact of the Authors' Gender on the Probability of Acceptance, SAEe Job-Market Sessions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sh. Male Authors	0.0319	0.0339	0.0241	0.0319	0.0329	0.0307	0.0213
	(0.0298)	(0.0298)	(0.0307)	(0.0306)	(0.0307)	(0.0306)	(0.0308)
Cites					-0.0497	-0.0544	-0.0511
					(0.0525)	(0.0519)	(0.0545)
Prominence						0.0193	0.0138
						(0.0153)	(0.0146)
Top 2.5% Ins.							0.182***
							(0.0475)
2.5%-5% Ins.							0.0730
							(0.0533)
5%-10% Ins.							-0.0274
							(0.0730)
Constant	0.735***	0.734***	0.742***	0.757***	0.762***	0.762***	0.636***
	(0.0238)	(0.0240)	(0.0212)	(0.0615)	(0.0623)	(0.0621)	(0.0751)
Observations	1161	1161	1150	1150	1150	1150	1150
R^2	0.124	0.127	0.240	0.254	0.255	0.257	0.288
Conf.-Year FE	Y	Y	Y	Y	Y	Y	Y
# Authors FE		Y	Y	Y	Y	Y	Y
Referee FE			Y	Y	Y	Y	Y
Field FE				Y	Y	Y	Y

Results of regressing a dummy indicating whether the paper was accepted on the variables and fixed effects indicated in the first column, where Cites is the asinh of the number of cites of the paper at the submission year, Prominence is the number of publications in the set of 35 high-impact journals specified in Table A2 in the five years prior to the submission year by the most prolific co-author, and Top 2.5% Ins., 2.5%-5% Ins., and 5%-10% Ins. are dummies indicating whether the (best) affiliation of the authors is among the top-200 institutions (approximately, 2.5% of institutions), between the top 200 and the top 5%, or between the top 5% and the top 10%, respectively. Standard errors clustered by paper and referee in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: The Impact of the Authors' Gender on the Probability of Acceptance, SAEe Regular Sessions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sh. Male Authors	0.0723***	0.0738***	0.0734***	0.0682**	0.0667**	0.0565**	0.0486*
	(0.0265)	(0.0261)	(0.0267)	(0.0270)	(0.0268)	(0.0270)	(0.0262)
Cites					0.0545**	0.0463**	0.0337*
					(0.0211)	(0.0215)	(0.0199)
Prominence						0.0291***	0.0158**
						(0.00717)	(0.00662)
Top 2.5% Ins.							0.362***
							(0.0378)
2.5%-5% Ins.							0.248***
							(0.0429)
5%-10% Ins.							0.194***
							(0.0478)
Constant	0.688***	0.687***	0.688***	0.571***	0.562***	0.542***	0.322***
	(0.0220)	(0.0221)	(0.0182)	(0.0453)	(0.0454)	(0.0470)	(0.0561)
Observations	1804	1804	1801	1801	1801	1801	1801
R^2	0.055	0.069	0.146	0.158	0.162	0.170	0.233
Conf.-Year FE	Y	Y	Y	Y	Y	Y	Y
# Authors FE		Y	Y	Y	Y	Y	Y
Referee FE			Y	Y	Y	Y	Y
Field FE				Y	Y	Y	Y

Results of regressing a dummy indicating whether the paper was accepted on the variables and fixed effects indicated in the first column, where Cites is the asinh of the number of cites of the paper at the submission year, Prominence is the number of publications in the set of 35 high-impact journals specified in Table A2 in the five years prior to the submission year by the most prolific co-author, and Top 2.5% Ins., 2.5%-5% Ins., and 5%-10% Ins. are dummies indicating whether the (best) affiliation of the authors is among the top-200 institutions (approximately, 2.5% of institutions), between the top 200 and the top 5%, or between the top 5% and the top 10%, respectively. Standard errors clustered by paper and referee in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.