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Research Similarity and Women in Academia

Abstract

We investigate the extent to which research similarity between senior and junior researchers influences promotion in academia and study its implications in terms of gender diversity among faculty. Using data on the universe of job applications for tenure-track assistant professor positions in economics in Italy and exploiting NLP techniques (i.e., document embeddings) on the abstract of each publication of the scholars in our dataset, we propose a novel measure of research similarity, which can capture closeness in research topics, methodologies or policy relevance between candidates and members of selection committees. We show that the level of similarity is strongly associated with the winning probability. Moreover, while there are no gender differences in average similarity, maximum similarity with members of the selection committee is lower for female candidates. This gender gap disappears when similarity is calculated only focusing on female members of the committee. The results suggest that similarity bias in male-dominated environments can have implications for gender and research diversity.

JEL-Codes: J160, J710, J820.

Keywords: cosine similarity, document embeddings, academia, economics, gender differences, labour force composition.

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1 Introduction

Academia is characterised by a global gender imbalance. Economics is one of the fields with lower socioeconomic diversity and female representation (Stansbury and Schultz, 2022). In Europe, the share of women working in economics in academic departments is overall 32%, and it becomes 27% in senior positions (Auriol et al., 2022). Besides fairness concerns, the evidence that a more diverse workplace increases the level of productivity (for instance, by improving creativity performance) explains the need to understand why this gap persists and, eventually, which policies can address it. According to Bayer and Rouse (2016), the under-representation of women limits the questions asked and the identification of innovative perspectives through which familiar problems can be addressed.

This paper investigates the extent to which research similarity between senior and junior researchers influences promotion in academia and studies its implications in terms of gender diversity among faculty. The key idea we explore is that of self-image bias put forward in the psychology literature: people tend to assign greater weight to traits representing their strong points as compared to those representing their shortcomings Hill et al. (1988). Recently, Siniscalchi and Veronesi (2021) have developed a theoretical model where they incorporate self-image bias, suggesting that scholars promote scholars with more similar characteristics to their own, to explain women's under-representation in academia. Self-image bias, combined with heterogeneity by gender in field of study/ field of research (Chari and Goldsmith-Pinkham, 2017; Beneito et al., 2021; Sierminska and Oaxaca, 2021; Lundberg and Stearns, 2019) and with senior academics being mainly men, may be associated with the gender imbalance observed.

To address our research question, we propose a novel measure of research similarity, which can capture closeness in research characteristics, such as topics of research, methodologies adopted, policy relevance of the questions addressed, rather than the mere field of research. We build a dataset comprising the universe of job applications to public calls for tenure-track assistant professor positions in economics in Italy in the period 2014-2021, and we collect the abstracts of papers of all candidates, members of selection committees and faculty of departments launching the calls. Using a tool from Natural Language Processing (i.e., document embeddings), we compute the abstract similarity for each possible combination of candidate and selection committee members (or department members) and aggregate these similarity scores at the candidate-call level, to examine their role in influencing the outcome of the selection.

We show that research similarity relates positively with the probability of winning the selection procedure and becoming a tenure-track assistant professor, even when controlling for a rich set of candidate characteristics. We also show that women are less likely to win the selection procedure and that research similarity partly contributes to reducing the gap in the winning probability. This can be explained by the fact that, although there is no gender gap in average similarity between candidates and members of the selection committee, women and men differ in terms of maximum similarity. Men are more likely to be strongly similar to one of the members of the committee. This gender difference disappears when we focus only on female members of the committee. These results suggest that similarity bias in male-dominated contexts can contribute to explain the persistence of female under-representation in academia. They also highlight the narrowing of heterogeneity in research characteristics, with potential losses for the profession as a whole.

Our paper contributes to different strands of the literature. First, we add to the literature examining gender differences in research characteristics. Existing evidence shows that women do research in different fields of economics than men. Women are scarce in macro, finance and mathematical and quantitative methods, and more abundant in labour and other applied microeconomics fields (Chari and Goldsmith-Pinkham, 2017; Beneito et al., 2021; Sierminska and Oaxaca, 2021). Greater disparities are found among academic economists than among graduate students (Sierminska and Oaxaca, 2021) and there is no evidence of significant changes over time (Lundberg and Stearns, 2019). We complement this literature by proposing a more granular measure of research characteristics besides fields of study, based on the application of NLP to paper abstracts. We show that research similarity has explanatory power for the winning probability, even when controlling for different measures of candidate quality, and that it can reduce the gender gap in the winning probability. Second, we contribute to the literature on gender bias and under-representation of women in academia. Several papers document the existence of gender bias in academia, for instance, in teaching evaluations (Paredes et al., 2023), in the publication process (Hengel, 2022; Sarsons, 2017), in citation patterns (Koffi, 2021), in reference letters (Baltrunaite et al., 2022; Eberhardt et al., 2023), and seminar behaviour (Dupas et al., 2021). We test the presence of a specific type of bias, i.e. self-image or similarity bias, show its importance in influencing the outcome of the selection process and document gender differences in similarity. Our paper also complements the evidence on the role played by the gender of the evaluator in national assessments for promotion to Associate and Full professor, both in the Italian and in the Spanish context (De Paola and Scoppa, 2015; Bagues et al., 2017). We show that the gender gap in similarity, which influences positively the winning probability, is driven by male members of selection committees. Finally, our paper is related to the literature using NLP to detect gender stereotypes and in-group bias (Ash et al., 2021; Chen et al., 2021). More specifically, it is close to papers using NLP and word embeddings to measure gender bias (Ash et al., 2023) and its influence on labour market performance (Baltrunaite et al., 2022). We here adopt document embeddings as state-of-the-art framework in NLP to represent text as vectors and capture high-levels of semantic complexity. The position of vectors in a multi-dimensional space can reveal closeness across publications under very many respects. We study similarity across abstracts to detect the presence of self-image bias and explore its relationship with the outcomes of selection processes, while at the same time supplying an enhanced measure of similarity/diversity in knowledge production, which can be used in other contexts, or to address different questions.

The paper is organised as follows. Section 2 and 3 describe the institutional setting and the dataset, respectively. Section 4 presents the methodology. Section 5 provides descriptive evidence and discusses selection issues. Section 6 presents and discusses the results. Finally, Section 7 concludes.

2 Institutional setting

In Italy, the selection procedure for assistant professorships starts from a publicly advertised call. A department seeking to cover a (tenure-track) assistant professor position decides the broad field of research of the call, indicates a full professor of the department who will belong to the selection committee (the internal member), together with two external members, who are randomly chosen from a restricted pool of professors from other universities that are indicated by the hiring department.[1] The selection process consists of multiple stages. In the first stage, the selection committee, whose composition is not public at the time candidates apply to the position, carries out the first screening and ranks candidates according to their CVs and publications, following pre-set criteria. These are decided upon by the committee,

[1] Note that the profile of the ideal candidate can be defined only according to macro-field of research. A finer definition of the field of research of the ideal candidate is not allowed (Law 30 December 2010, n. 240, `https://www.parlamento.it/parlam/leggi/10240l.htm`). Note also that some universities may not select members of the selection committee randomly. Since we do not exploit the random composition of the committee in our empirical strategy, this feature is not key in our setting.

before the list of candidates applying for the position is made public, and following broad rules decided at the University level (e.g., x points to be assigned to CVs and y points to be assigned to publications), in accordance with guidelines offered by the Ministry of University and Research. The selection committee writes a short evaluation report for all candidates, gives an overall assessment (e.g., excellent, very good, good, fair, below average), and drafts a shortlist with at least 6 candidates, who are invited to an interview with the selection committee. After the interview, the selection committee publishes a ranking of the candidates, the overall points assigned to each of them, and indicates the winner of the selection procedure.

3 Data

By combining web-scraping techniques and manual retrieval, we build a novel dataset containing information on all candidates, members of selection committees and faculty of the hiring department for each call opened in Italy in the period 2014-2021 in the broad area of Economics, which is divided into Economics, Economic Policy, Public Economics, Econometrics, Applied Economics following Ministerial classification. Our dataset covers 238 calls for tenure track positions, involving 714 committee members and 2244 candidates.[2] Starting from the candidate dataset, it includes information on gender, publication records, university of the PhD, PhD graduation year, current occupation, and score earned in the procedure by each candidate, with the identification of the winning candidate. We also collect the publications of the candidates, and their abstracts in particular. In total, we have information on 8845 publications of candidates. We then retrieve information on publication records and gender of each member of both the selection committees and the departments opening the call. When collecting publications, we consider only faculty members who are economists/are incardinated in the ministerial economic areas, which we listed above. In total, the dataset of members of selection committees and departments includes 1377 professors and 33111 publications.

Our data comes from three main sources. First, the CINECA website, which collects historical information on the faculty of departments. Second, the institutional websites of each Italian university have information on calls and their outcomes, which allows to construct the candidate side of the dataset. Finally, the publication data comes from the Elsevier's abstract and citation database SCOPUS.com, which

[2]During the 2014-2021 period, 248 calls were issued. However, for 10 of them, we have not been able to collect all the information we needed.

provides information on author profiles, including cover affiliations, number of publications and their bibliographic data, references, and, importantly, the abstracts of the publications.

Although our main analysis focuses only on senior (tenure-track) assistant professorships, in order to shed light on the selection process we also collect data on calls for junior (non tenure-track) assistant professorships, as we will discuss in section 5.

4 Methodology

We first describe the corpus construction and the methodology for text analysis, to then introduce the estimation equations.

4.1 Research similarity: corpus construction and text analysis

For each scholar in our dataset, i.e., candidates, members of selection committees and members of departments, we collect the abstract of all their publications. The overall number of publications and abstracts is 41956. We then consider all publications preceding the year of the call and, using text analysis, we calculate a measure of research similarity between candidate and members of the selection committee and between candidate and members of the department opening the call. The measures of research similarity are constructed by resorting to Natural Language Processing (NLP) techniques. As first step, we pre-process the texts of the abstracts of the papers by removing specific words related to copyright and editorial information, such as "Elsevier Ltd.", "Copyright", and "All rights reserved". Next, we represent each research paper using a document embedding of its abstract. A document embedding is a vector-based representation of a document, in this case, the abstract. The purpose of this representation is to capture the semantic meaning of the texts. Specifically, documents that share similar semantic characteristics will be represented by vectors that are closer to each other in a multidimensional space.

To create document embeddings, we employ a specific technique called SentenceTransformers[3] (Reimers and Gurevych, 2019), which is a state-of-the-art framework for generating high-quality vector representations of sentences and documents. SentenceTransformers uses advanced deep learning models to encode the contextual

[3] We employ `https://huggingface.co/sentence-transformers/all-mpnet-base-v2`

information of the text, enabling the creation of meaningful and semantically rich document embeddings. It maps sentences and paragraphs to a 768 dimensional dense vector space. By leveraging the power of SentenceTransformers, our research similarity measures benefit from the latest advancements in NLP and provide accurate representations for comparing research papers based on their abstracts.

The similarity between two vectors (or embeddings) is traditionally determined using the cosine distance. The cosine similarity index ranges between -1 and 1, where a smaller angle between two vectors indicates a higher degree of textual similarity. In our study, we use this metric to assess the similarity between the publication abstracts of each relevant combination of candidates and members of the committees (or departments). To summarise the results at the candidate level, we aggregate the similarity measures obtained at the publication/abstract level. Specifically, we calculate the mean (Mean Sim) and maximum (Max Sim) similarities between all the candidates and the selection committees' (or departments') publications. Figure A.1 illustrates the distribution of similarity values for these two measures. Given the texts we are considering are abstracts of economic papers, the mean and the maximum similarity are always positive. The increase in the density of maximum similarity at 1 captures instances of coauthorship.

Figure A.2 shows two examples of pairs of abstracts with different cosine similarities. The first one is an example of high similarity (the cosine similarity between abstracts 1 and 2 is 0.93), while the second one is an example of low similarity (the cosine similarity between abstracts 3 and 4 is 0.008).

4.2 Estimation equations

Our analysis proceeds in two steps. First, we test whether the similarity between candidates and members of the selection committee predicts the winning probability of the candidate. Then, we investigate how such similarity changes by the gender of the candidate.

Thus, we first estimate the following linear probability model:

$$Winner_{ijst} = \varphi_1 * DSimIndex_{ijst} + \varphi_2 X_i + Year_t + s_s + \varepsilon_{ijst} \tag{1}$$

where $Winner_{ijst}$ is a dummy equal to 1 if candidate i wins the selection of call j in the macro-field s in year t. $DSimIndex_{ijst}$ is a dummy equal to 1 if the similarity index (Mean Sim or Max Sim) between candidate i and members of the selection committee for call j in year t and macro-field s is above the 50th percentile.[4] X_i is a vector of candidate characteristics, namely, gender, years from PhD, number of publications, current position, and whether the candidate is an internal or external candidate. $Year_t$ and s_s are year and macro-field fixed effects, respectively. Finally, ε_{ijst} is the error term. In further specifications, we replace year and macro-field fixed effects with call or candidate fixed effects.

To analyse whether female and male candidates differ in terms of similarity with the members of the selection committee, we estimate the following linear probability model:

$$DSimIndex_{ijst} = \varphi_1 Female_i + \varphi_2 X_i + Year_t + s_s + \varepsilon_{ijst} \tag{2}$$

where $Female_i$ is a dummy for female candidates, which captures gender differences in similarity, measured as either Mean Sim or Max Sim, while the other variables are defined as before. Likewise, in further specifications of the model, we replace year and macro-field fixed effects with call or candidate fixed effects.

5 Descriptive evidence and selection issues

In this section, we present summary statistics and offer some stylised facts on the job market for (tenure-track) assistant professor positions in Italy. We discuss selection by gender into applying to assistant professor positions and participating in job interviews, to lay the ground to discuss the role of research similarity.

5.1 Descriptive statistics

Table 1 shows that our dataset includes 2244 candidates. The share of women among them is 35%. The probability for a candidate of winning a selection is 9.6%. On average, the share of women in committees and in departments is 31% and 33%, respectively.[5] Each call has, on average, 16 candidates.

[4]In further specifications, we use the continuous version of the similarity variable rather than the dummy variable. See Section 6.

[5]In Figure A.3, we show the dynamics of the share of women in selection committees, which displays limited variation over time.

Table 1: Summary statistics

Calls for senior assistant professorships

Variable	*Mean*	*Sd*	*N Cand.*
Female	0.350	0.477	2244
Winner	0.096	0.294	2244
PhD Abroad	0.249	0.432	2244
Currently Abroad	0.285	0.451	2244
Years from PhD	7.156	3.083	2244
N cand/call	15.948	8.784	2244
Share women in the Committee	0.311	0.226	2244
Share women in the Department	0.335	0.159	2244

Notes. The table provides summary statistics of the candidates in our sample and the average share of women in selection committees and departments launching the calls for senior assistant professorships. Years: 2014-2021.

In Table 2, we report summary statistics by gender of the candidate, focusing on observable characteristics, including the publication record, and on similarity with members of the selection committee. The results of a t-test show that, although the probability of winning the selection or being shortlisted for the interview does not differ by gender, women seem to be more qualified candidates: they have a higher number of publications in A+ journals, and they are also more senior since more years passed from the PhD defence to the time of the call. On the other hand, men have, on average, a higher total number of A publications.[6] Interestingly, women are more likely than men to be present at the interview, when shortlisted. Finally, in Panel 3 there is no evidence of significant gender differences in terms of similarity with the selection committee, although the maximum similarity for men is 0.01 larger than that for women.

In Figures A.4-A.5 in the Appendix, we show the distributions of our similarity indices by gender of the candidate and gender of the members of the committees. Interestingly, while there are no clear differences by gender in the similarity distributions when we focus on female members of the committees, the distribution of the maximum similarity with male members of the committees for female candidates appears to be left-shifted, compared to that for male candidates, suggesting that

[6] Top 6 journals are AER, QJE, JPE, REStud, Econometrica, JF; A+ journals are AEJs, EJ, JEEA, Rand, JPubE, JME, RFS, JEc, JOLE, JHR, QE, JTE, JDE, JIE; A journals are defined according to the ANVUR - National Agency for the Evaluation of University and Research - classification.

female candidates have lower values of maximum similarity with male members of the committees, compared to male candidates.[7]

Table 2: Summary statistics: Differences by gender

Candidates for senior assistant professorships

Panel 1: Characteristics					
Variable	*Men*	*Women*	*T-STAT*	*Diff*	*p-value*
Winner	0,10	0,10	-0,25	0,00	0,80
Shortlisted	0,50	0,49	0,73	0,02	0,46
Present	0,57	0,65	-2,60	0,08	**0,01**
PhD Abroad	0,24	0,27	-1,57	-0,03	0,12
Years from PhD	7,07	7,32	-1,89	-0,26	**0,06**
Panel 2: Publication Record					
Variable	*Men*	*Women*	*T-STAT*	*Diff*	*p-value*
At least one Top 6	0,01	0,02	-1,67	-0,01	0,10
N pubs in A+	0,15	0,27	-4,80	-0,12	**0,00**
N pubs in A	6,14	5,72	2,48	0,42	**0,01**
At least one in Interdisciplinary	0,03	0,02	1,51	0,01	0,13
Panel 3: Similarity					
Variable	*Men*	*Women*	*T-STAT*	*Diff*	*p-value*
Mean Sim with Committee	0,22	0,22	-0.82	0,00	0,41
Max Sim with Committee	0,59	0,58	1,31	0,01	0,19

Notes. The table reports summary statistics and t-tests by gender of the candidates for the following variables: probability of winning the selection, probability of being shortlisted, probability of being present at the interview, share of those with a PhD abroad, average number of years from PhD, share of those with at least one publication in a Top 6, average number of publications in A+ journals, average number of publications in A journals, share of those with at least one pub in Interdisciplinary journals, average and max similarity with the committee. Top 6 journals are AER, QJE, JPE, REStud, Econometrica, JF; A+ journals are AEJs, EJ, JEEA, Rand, JPubE, JME, RFS, JEc, JOLE, JHE, QE, JTE, JDE, JIE; A journals are defined according to the ANVUR classification.

5.2 The selection into the pool of candidates

According to the summary statistics reported in Tables 1 and 2, women are under-represented among candidates for senior assistant professorships. Moreover, female candidates are characterised by a higher academic quality (i.e., they have a higher

[7] In Figure A.6, we provide the distributions for similarity among candidates (instead of those between candidates and members of the committees), separately for female and male candidates. The distributions appear quite similar, which is not in line with the hypothesis that female candidates do research on a smaller group of topics compared to male ones.

number of highly ranked publications) and a higher academic age (i.e., they have a higher number of years from the PhD graduation at the time of the application) than their male counterparts. This suggests that the selection of researchers in the pool of candidates for tenure-track assistant professor positions might operate differently for women and men.

In order to investigate whether the lower female share is driven by gender differences in self-selection for tenure-track assistant professorships, or by a lower winning probability of women in a previous stage of the academic career ladder, we proceed as follows. First, we explore whether female and male researchers differ in terms of their probability of applying for a senior assistant professorship. We start by providing in Table 3 descriptive evidence on gender differences in the number of applications per candidate in our sample.

Table 3: Gender differences in application to senior assistant professorships

Overall and by geographic areas

Number of Applications per Year					
Variable	*Men*	*Women*	*T-STAT*	*Diff*	*p-value*
N applications/ year	5,47	5,67	-0,86	-0,20	0,39
Appl. in NI and in SI	0,03	0,02	0,86	0,01	0,39
Appl. NI and in CI	0,04	0,03	1,68	0,01	**0,09**
Appl. SI and in CI	0,05	0,04	1,10	0,01	0,27

Notes. The table reports means and t-tests by gender of the candidates for the following variables: Number of applications per year; probability of applying in the same year for at least one position in Northern Italy and one in Southern Italy; probability of applying in the same year for at least one position in Northern and one in Central Italy; probability of applying in the same year for at least one position in Southern Italy and one in Central Italy.

The table shows that, on average, candidates apply for 5 calls/job positions per year. There is no evidence of statistically significant differences between genders. However, female candidates seem to be less geographically mobile. The probability of applying in the same year for at least one position in Central Italy *and* at least one in Northern Italy is lower for women than for men.

To better explore these gender differences in the application probability, we then construct a pseudo dataset at the candidate/call level in which, for each candidate applying for at least one call in a given year, we add observations also for the other calls in the same or subsequent years for which the candidate has not applied, and generate a dummy equal to 1 if the candidate has applied for that specific call and 0 otherwise.[8] Using this dummy as dependent variable, we estimate an equation akin to Equation 1 (without including the similarity dummy) and investigate the role of gender in explaining our outcome of interest– the application probability.

Table 4: Application probability

Calls for senior assistant professorships

	(1)	(2)	(3)
Female	-0.00325**	-0.00604***	-0.00591***
	(0.00162)	(0.00166)	(0.00164)
PhD Abroad		0.00487**	0.00488**
		(0.00194)	(0.00192)
Abroad		-0.0367***	-0.0360***
		(0.00169)	(0.00167)
At least one Top 6		0.00931	0.00901
		(0.00610)	(0.00600)
Tot A+ pubs		0.000769	0.000852
		(0.00141)	(0.00139)
Tot A pubs		-0.000784***	-0.000726***
		(0.000187)	(0.000185)
At least one interd.		0.00560	0.00556
		(0.00409)	(0.00399)
$\overline{Y}$	0.037	0.037	0.037
Observations	57,429	57,429	57,429
Sector and Year FE	No	Yes	No
Call FE	No	No	Yes

Notes. Dependent variable: Application probability for senior (tenure-track) assistant professorships in economics. Estimates from a Linear Probability Model. Robust standard errors in parenthesis. Years: 2014-2021 *** p<0.01, ** p<0.05, * p<0.1

The results in Table 4 show that, conditional on observable characteristics such as the publication record, the application probability is 0.32 percentage points lower for female candidates compared to male candidates, which corresponds to 8.8% of the average application probability $\overline{Y}$ in the sample. The coefficient of the female dummy is even larger in size when we include sector and year fixed effect (column 2) or call fixed effect (column 3).

Finally, we investigate whether – in addition to self-selection –, the lower percentage of women among candidates for senior assistant professorships depends on the

[8] For each candidate, we add observations until the year in which the candidate wins a selection or, if the candidate never wins any selection, until 2021, the last year of our period of analysis.

lower winning probability of female candidates in the previous stage of the tenure process, i.e., the selection for junior assistant professorships. To do so, we collect information on the universe of calls and candidates for junior assistant professor positions. Descriptive statistics on this dataset are provided in the Appendix, Table A.1 and A.2. During the 2014-2021 period, we observe 169 calls and 971 candidates. As for candidates for tenure-track assistant professorships, we observe whether the candidate is the winner of the competition, the year of the PhD and whether she/he has received the PhD abroad, whether she/he is abroad at the time of the application, and his/her publication record.

Interestingly, Table A.1 shows that women represent a higher percentage of the sample compared to the pool of applicants for senior positions (40% vs 35%). Moreover, female candidates do not appear significantly different in terms of observable characteristics compared to male candidates: in particular, there is no evidence of a statistically significant difference in the number of publications (Table A.2). Yet, female candidates are less likely to win.[9]

We thus proceed to empirically investigate whether female candidates have a lower probability than male ones to win the competition. To do so, we construct a dummy equal to 1 if the candidate wins the competition, 0 otherwise. According to Table A.3, the probability of winning the selection is much lower (5.3-6.8 percentage points or 32-41%) for them than for male candidates, even conditional on their publication records.

These results suggest that the evidence that women make up a lower percentage of candidates for senior assistant professorships and that those participating in the selection are better candidates than their male counterparts is explained by two factors. First, women are less likely to apply than men, maybe because they prefer to gain more experience and publications before applying for a senior position, or because they are less mobile.[10] Second, there is a gender gap at the entry-level of the profession, which reduces the participation of women in calls for senior assistant professorship and explains why those female researchers who do participate seem to come from the upper tail of the quality distribution.

[9]Since, on average, candidates at this stage only have one publication, we cannot calculate our similarity indexes for this sample, and compare female and male candidates according to their similarity in research to the members of selection committees, since the text on which to run document embeddings is too limited.

[10]This is line with the literature on gender differences in competition, see for instance Niederle and Vesterlund (2007) and Gneezy and Rustichini (2004).

5.3 Gender gap in the winning probability and selection bias

Before turning to our main empirical analysis, we investigate whether a gender gap exists in the probability of succeeding in the competition for senior assistant professorships, discarding, for now, the role played by research similarity. To do so, we use a specification similar to Equation 1, which however does not include the similarity dummy. In particular, we use the specification that includes year and macro-field fixed effects.

The results are reported in Table A.4. While our main dependent variable is the probability of winning the competition (column 1), we also look at gender differences in the probability of being shortlisted (column 2) and in the probability of being present at the interview, if shortlisted (column 3). According to the results reported in the table, the coefficient of the female dummy is negative in the first two columns, although not statistically significant. This suggests that the probability for women to win the competition or being shortlisted is 1 and 3 percentage points (12 and 6%) lower than for men, respectively. Moreover, column 3 confirms the evidence provided in Table 2 that female candidates are more likely than male ones to participate in the interview if shortlisted (the participation probability is 6 percentage points, or 10%, higher for women than for men).

Since the probability of being present at the interview strongly influences the probability of winning the competition, we correct for this selection bias in our analysis on the gender gap in the winning probability. Specifically, similar to the Heckman selection model, we implement a two-stage procedure. In the first stage, we estimate the probability of being present at the interview by using a probit model where the dependent variable is a dummy equal to 1 if the candidate is present at the interview (if shortlisted) and as covariates all those characteristics that we observe for the candidate (which are listed in Section 4), plus a variable for the number of applications that the candidate does per year. Then, in the second stage, we estimate a linear probability model similar to Equation 1, augmented by the inclusion of our estimate of the probability of participating in the interview.

The results are shown in Table 5. Interestingly, the coefficient of the gender dummy is now statistically significant, negative, and bigger in magnitude. This provides further evidence that women are characterised by a lower probability of succeeding in the competition than men. As we expected, the coefficient of the probability of being present is positive and also highly significant.

Overall, the evidence provided in this section suggests that there exist important gender differences in the selection to assistant professor positions. Women are less likely than men to apply for senior assistant professorships. However, when they apply, they are more likely to be present at the interview, if shortlisted. Although women seem to be better candidates than men along several dimensions, their probability of winning the competition is lower than that of their male counterparts. In the next section, we investigate the role of research similarity in explaining the outcome of the selection and whether female and male candidates differ in terms of similarity with the members of the committee. We will also explore how research similarity relates to the gender gap in the winning probability we have identified.

Table 5: Gender gap in the winning probability, LPM

VARIABLES	(1) Winner	(2) Winner
Female	-0.0641***	-0.0562***
	(0.0160)	(0.0169)
PhD Abroad	0.0180	0.0197
	(0.0155)	(0.0163)
Abroad	-0.0661***	-0.0374**
	(0.0153)	(0.0168)
Years from PhD	-0.00336	-0.00494**
	(0.00216)	(0.00214)
Internal Cand.	0.0501	0.0643
	(0.0447)	(0.0452)
At least one Top 6	-0.0317	-0.0653
	(0.0671)	(0.0780)
Tot A+ pubs	0.0572***	0.0646***
	(0.0154)	(0.0155)
At least one Interd.	0.00534	0.0159
	(0.0400)	(0.0452)
Tot A pubs	0.0153***	0.0148***
	(0.00214)	(0.00218)
Pr(present)	0.833***	0.820***
	(0.124)	(0.135)
$\overline{Y}$	0.096	0.096
Observations	2,244	2,244
R-squared	0.066	0.160
Call FE	No	Yes
Year FE	Yes	No
Sector FE	Yes	No

Dependent variable: Winning probability for tenure track assistant professorships in economics. Estimates from a Linear Probability Model. Pr(present) is a probit estimate of the probability of being present at the interview, if shortlisted. Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

6 Results

We now turn to examining whether similarity predicts the winning probability, and then, whether there is evidence of gender differences in similarity, which are consistent with the observed female under-representation in academia.

6.1 The effects of research similarity on the winning probability

Table 6 reports the results of the estimation of Equation 1. While columns 1-3 use average similarity (Mean Sim) as key explanatory variable, columns 4-6 investigate the role played by the maximum similarity (Max Sim) between the candidate and the members of the selection committee. Columns 1 and 4 report the results of the specification with macro-field and year fixed effects; columns 2 and 5 those with call fixed effects. Finally, columns 3 and 6 incorporate candidate fixed effects.

The results show that similarity plays an important role in predicting the winning probability. Those candidates for which the dummy based on the mean similarity is equal to 1 have a probability of winning the competition of 7.1 percentage points higher than those for whom the dummy is equal to 0. The coefficient does not strongly vary when we include call or candidate fixed effects. An effect similar, if not larger, in magnitude and significance, is played by the dummy based on maximum similarity. It is worth pointing out that the effect of the similarity indexes is even larger than that of having an additional publication in an A+ journal. Besides the effect of publications, it is interesting to note the positive and large effect of being an internal candidate.

We replicate our analysis for the winning probability including among the controls also our estimate of the probability of the candidate of taking part in the interview if shortlisted. The results are provided in Table 7 and confirm both the important role played by research similarity, and the presence of a gender gap in the winning probability, once we control for the probability of being present at the interview. Interestingly, the gender gap in the winning probability is lower in magnitude compared to Table 5, especially in columns 4-5, where we include our maximum similarity dummy.[11] According to these results, the inclusion of the maximum similarity dummy explains 8-10% of the female gender gap reported in Table 5.

[11]This is consistent with the results discussed in the next section showing that gender differences in similarity exist only with respect to the maximum similarity with the members of the committees.

Table 6: The role of research similarity for the winning probability, LPM

VARIABLES	(1) Winner	(2) Winner	(3) Winner	(4) Winner	(5) Winner	(6) Winner
Dummy Simil.	0.0713***	0.0656***	0.0586***	0.0729***	0.0683***	0.0539***
	(0.0124)	(0.0130)	(0.0142)	(0.0128)	(0.0137)	(0.0144)
Female	-0.0114	-0.00673		-0.00726	-0.00168	
	(0.0132)	(0.0137)		(0.0132)	(0.0137)	
PhD Abroad	0.0220	0.0229		0.0225	0.0233	
	(0.0154)	(0.0163)		(0.0154)	(0.0163)	
Abroad	-0.0150	0.00996	0.00750	-0.00757	0.0181	0.0116
	(0.0133)	(0.0145)	(0.0194)	(0.0133)	(0.0144)	(0.0185)
Years from PhD	0.000962	-0.000741	-0.0118	0.00102	-0.000544	-0.00845
	(0.00203)	(0.00198)	(0.0161)	(0.00205)	(0.00198)	(0.0152)
Internal Cand.	0.202***	0.215***	0.102***	0.204***	0.217***	0.108**
	(0.0389)	(0.0385)	(0.0312)	(0.0387)	(0.0382)	(0.0429)
At least one Top 6	0.0398	0.00869	-0.0563	0.0444	0.00637	-0.0550*
	(0.0670)	(0.0755)	(0.308)	(0.0673)	(0.0764)	(0.0295)
Tot A+ pubs	0.0326**	0.0389**	0.0889*	0.0325**	0.0396***	0.0866
	(0.0155)	(0.0152)	(0.0508)	(0.0152)	(0.0152)	(0.0613)
At least one Interd.	0.0235	0.0316	-0.148	0.0225	0.0310	-0.110***
	(0.0404)	(0.0457)	(0.261)	(0.0405)	(0.0460)	(0.0415)
Tot A pubs	0.00834***	0.00804***	0.0117*	0.00657***	0.00638***	0.00946
	(0.00170)	(0.00173)	(0.00632)	(0.00173)	(0.00176)	(0.00682)
	Mean	**Mean**	**Mean**	**Max**	**Max**	**Max**
$\overline{Y}$	0.096	0.096	0.096	0.096	0.096	0.096
Observations	2,244	2,244	2,244	2,244	2,244	2,244
R-squared	0.065	0.157	0.448	0.065	0.158	0.448
Call FE	No	Yes	No	No	Yes	No
Year FE	Yes	No	No	Yes	No	No
Sector FE	Yes	No	No	Yes	No	No
Candidate FE	No	No	Yes	No	No	Yes

Dependent variables: Winning Probability for senior assistant professorships in economics. Estimates from a Linear Probability Model. Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table 7: The role of research similarity for the winning probability, LPM

Controlling for the probability of taking part to the interview

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Winner	Winner	Winner	Winner	Winner	Winner
Dummy Simil.	0.0678***	0.0621***	0.0588***	0.0697***	0.0650***	0.0546***
	(0.0122)	(0.0129)	(0.0142)	(0.0126)	(0.0136)	(0.0143)
Female	-0.0616***	-0.0562***		-0.0579***	-0.0516***	
	(0.0159)	(0.0168)		(0.0159)	(0.0168)	
Pr(present)	0.794***	0.786***	0.0346	0.799***	0.788***	0.0629
	(0.123)	(0.133)	(0.131)	(0.123)	(0.133)	(0.120)
PhD Abroad	0.0178	0.0190		0.0182	0.0194	
	(0.0154)	(0.0162)		(0.0154)	(0.0162)	
Abroad	-0.0659***	-0.0399**	0.00567	-0.0591***	-0.0323*	0.00829
	(0.0152)	(0.0168)	(0.0206)	(0.0152)	(0.0167)	(0.0195)
Years from PhD	-0.00339	-0.00502**	-0.0119	-0.00336	-0.00484**	-0.00861
	(0.00215)	(0.00213)	(0.0161)	(0.00217)	(0.00213)	(0.0152)
Internal Cand.	0.0519	0.0639	0.0958**	0.0527	0.0649	0.0974**
	(0.0442)	(0.0447)	(0.0381)	(0.0441)	(0.0446)	(0.0468)
At least one Top 6	-0.0286	-0.0602	-0.0582	-0.0246	-0.0625	-0.0584*
	(0.0677)	(0.0776)	(0.308)	(0.0679)	(0.0784)	(0.0305)
Tot A+ pubs	0.0537***	0.0609***	0.0900*	0.0538***	0.0617***	0.0887
	(0.0157)	(0.0157)	(0.0510)	(0.0154)	(0.0157)	(0.0615)
At least one Interd.	0.00979	0.0196	-0.151	0.00879	0.0190	-0.116***
	(0.0400)	(0.0450)	(0.261)	(0.0402)	(0.0454)	(0.0443)
Tot A pubs	0.0152***	0.0147***	0.0120*	0.0135***	0.0131***	0.00997
	(0.00210)	(0.00215)	(0.00642)	(0.00212)	(0.00218)	(0.00701)
	Mean	**Mean**	**Mean**	**Max**	**Max**	**Max**
$\overline{Y}$	0.096	0.096	0.096	0.096	0.096	0.096
Observations	2,244	2,244	2,244	2,244	2,244	2,244
R-squared	0.079	0.169	0.448	0.078	0.170	0.448
Call FE	No	Yes	No	No	Yes	NO
Year FE	Yes	No	No	Yes	No	NO
Sector FE	Yes	No	No	Yes	No	No
Candidate FE	No	No	Yes	No	No	Yes

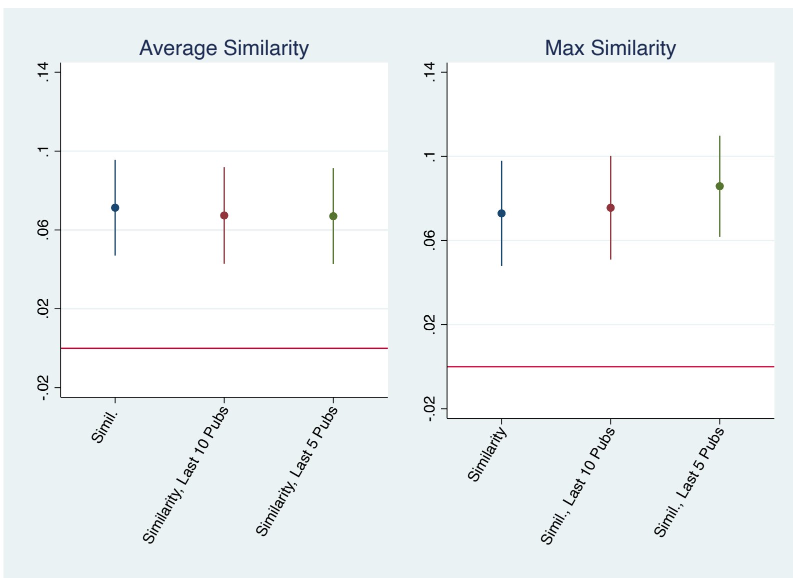
Dependent variable: Probability of winning the competition for senior assistant professorships. Estimates from a Linear Probability Model. Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

6.1.1 Robustness checks and heterogeneity analysis

We run several robustness checks. First, we analyse whether the effect of research similarity on the winning probability is robust to a change in the measure of research similarity. Specifically, we construct our two similarity indices focusing only on the most recent publications of the members of the committees. Specifically, the 10 and 5 most recent publications. We recall that a publication is included in the similarity measure only when it precedes the time of the call. Figure 1 shows the results and indicates that this change in the construction of our measures does not affect the results. If any difference exists, the effect of the maximum similarity increases when we focus on the last 5 publications.

Figure 1: The role of similarity for the winning probability

Alternative measures of similarity



The graph shows the coefficient of the two similarity dummies in the estimation of Equation 1 (mean or max similarity) for alternative measures of similarity (considering all the publications of the members of the selection committees, only the last 10 most recent publications, and only the last 5 most recent publications). A publication is included when it precedes the time of the call.

As a second robustness check, we test whether our measures of similarity are simply capturing co-authorship. To investigate this issue, we rerun our regressions including among the controls a dummy for co-authorship. The results are reported in Table 8, Panel 1, and suggest that, although co-authorship plays an important role in influencing the winning probability, the result on the effect of the research similarity indicators is robust to the inclusion of this additional control.[12]

We also investigate the role of research similarity between candidates and members of departments opening the call and study whether our results are robust to including this measure of similarity in the regression. Table 8, Panel 2, reports the results: the coefficient of the similarity dummy computed with respect to members of the department is not statistically significant and is small in size.

In a further check, we change our dependent variable and analyse the influence of research similarity between candidates and members of selection committees on the probability of being shortlisted for the interview, rather than on the winning probability.[13] The results are in Table A.5 and confirm the robustness of the effect of similarity. According to the results reported in the table, our similarity dummies are associated with an increase in the probability of being shortlisted for the interview, ranging from 16 to 8.2 percentage points.[14]

Finally, we check that our results are robust to using a continuous variable for research similarity instead of the mean and maximum similarity dummies, and to using a probit model instead of the linear probability model. The results are reported in Table A.7 Panel 1 and Panel 2, respectively, and confirm the robustness of our results.

Finally, we perform two heterogeneity analyses. First, we investigate whether the role played by the similarity between candidate and members of selection committees varies across gender. To address this question, we augment the specification in Equation 1 with an interaction term between the female dummy and the mean/max similarity dummy. The results of this new specification are included in Table 9 and show that there is no evidence supporting a differential effect of similarity on the winning probability by gender. Similarity increases the winning probability for both female and male candidates.

Note that we do not investigate how the effect varies with the share of female members in the selection committee, because there is not enough variation in the gender composition of the committee to explore. As shown in Table 1, women on

[12] In our dataset, the share of candidates who have publications coauthored with a member of the selection committee is lower than 5%.

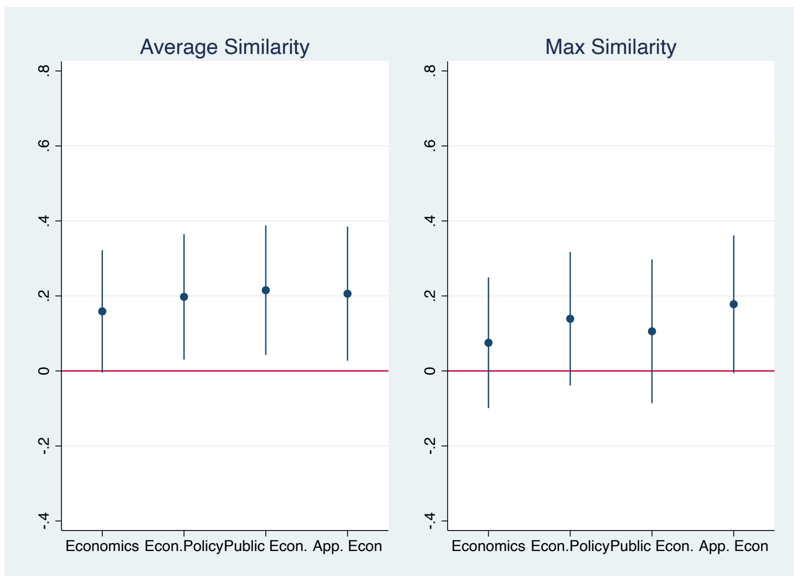
[13] This allows us to further address the concern that the winning probability can be endogenous to the decision of those candidates that have been admitted to the interview to take part in it.

[14] In Table A.6, we also replicate the same analysis for the probability of being present and show that the role of similarity does not play any role this time. We further discuss this point in Section 6.3.

average represent 31% of the members of the committee (less than 1 in 3 members) and the standard deviation is quite low. Figure A.3 shows that the change over time is also limited.

Last, we investigate whether the effect varies by macro-field (Economics, Economic Policy, Public Economics, Applied Economics, Econometrics). We include in Equation 1 interaction terms between the mean and max similarity dummies, respectively, and macro-field dummies. In Figure 2, we plot the coefficients of the interaction terms. Econometrics is the omitted category. The figure shows that there are small differences across macro-fields with respect to the role of the mean similarity, while there are no differences in the effect of the maximum similarity on the winning probability.

Figure 2: The role of similarity by Macro-Field



The graphs shows the coefficients of the interaction terms between the similarity dummies and the macro-field dummies (Equation 1). Econometrics is the omitted category

Table 8: The role of similarity for the winning probability, LPM

VARIABLES	(1) Winner	(2) Winner	(3) Winner	(4) Winner	(5) Winner	(6) Winner
Panel 1: Controlling for Co-authorship						
Coauthor	0.249***	0.224***	0.155**	0.241***	0.214***	0.150**
	(0.0610)	(0.0627)	(0.0652)	(0.0620)	(0.0634)	(0.0660)
Dummy Similarity	0.0623***	0.0579***	0.0553***	0.0593***	0.0563***	0.0499***
	(0.0123)	(0.0130)	(0.0156)	(0.0127)	(0.0137)	(0.0145)
Female	-0.0116	-0.00671		-0.00821	-0.00240	
	(0.0130)	(0.0136)		(0.0130)	(0.0136)	
	Mean	**Mean**	**Mean**	**Max**	**Max**	**Max**
Observations	2,244	2,244	2,244	2,244	2,244	2,244
R-squared	0.083	0.169	0.449	0.081	0.169	0.449
Panel 2: Controlling for the similarity with the department						
DummySimilarity	0.0752***	0.0727***	0.0593***	0.0687***	0.0602***	0.0561***
	(0.0141)	(0.0150)	(0.0159)	(0.0128)	(0.0137)	(0.0146)
DummySimDepart.	-0.0179	-0.0247	-0.0129	0.0111	0.0211	-0.0187
	(0.0141)	(0.0156)	(0.0181)	(0.0126)	(0.0148)	(0.0141)
Female	-0.0126	-0.00651		-0.00888	-0.00225	
	(0.0132)	(0.0137)		(0.0132)	(0.0137)	
Observations	2,222	2,222	2,222	2,222	2,222	2,222
R-squared	0.062	0.153	0.443	0.062	0.153	0.443
	Mean	**Mean**	**Mean**	**Max**	**Max**	**Max**
$\overline{Y}$	0.096	0.096	0.096	0.096	0.096	0.096
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Call FE	No	Yes	No	No	Yes	No
Year FE	Yes	No	No	Yes	No	No
Sector FE	Yes	No	No	Yes	No	No
Candidate FE	No	No	Yes	No	No	Yes

Dependent variable: Winning probability for senior assistant professorships in economics. Estimates from a Linear Probability Model. Coauthor is a dummy variable equal to 1 if the candidate and a member of the selection committee are coauthors. While *DummySimilarity* regards the similarity between the candidate and the recruiting committee, *DummySimDepart* measures the similarity between the candidate and the economics faculty of the department opening the call. Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table 9: The role of similarity for the winning probability, LPM

Heterogeneity by the gender of the candidate

VARIABLES	(1) Winner	(2) Winner	(3) Winner	(4) Winner	(5) Winner	(6) Winner
Dummy Similarity	0.0718***	0.0675***	0.0658***	0.0669***	0.0581***	0.0540***
	(0.0153)	(0.0159)	(0.0182)	(0.0157)	(0.0165)	(0.0172)
Dummy Similarity*Female	-0.00152	-0.00558	-0.0146	0.0239	0.0297	0.00663
	(0.0257)	(0.0276)	(0.0340)	(0.0274)	(0.0287)	(0.0316)
Female	-0.0107	-0.00395		-0.0184	-0.0145	
	(0.0158)	(0.0170)		(0.0143)	(0.0156)	
	Mean	**Mean**	**Mean**	**Max**	**Max**	**Max**
$\overline{Y}$	0.096	0.096	0.096	0.096	0.096	0.096
Observations	2,244	2,244	2,244	2,244	2,244	2,244
R-squared	0.065	0.157	0.446	0.062	0.158	0.445
Call FE	No	Yes	No	No	Yes	No
Year FE	Yes	No	No	Yes	No	No
Sector FE	Yes	No	No	Yes	No	No
Candidate FE	No	No	Yes	No	No	Yes

Dependent variables: Winning probability for senior assistant professorships in economics. Estimates from a Linear Probability Model. Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1 *** p<0.01, ** p<0.05, * p<0.1

6.2 Gender differences in research similarity

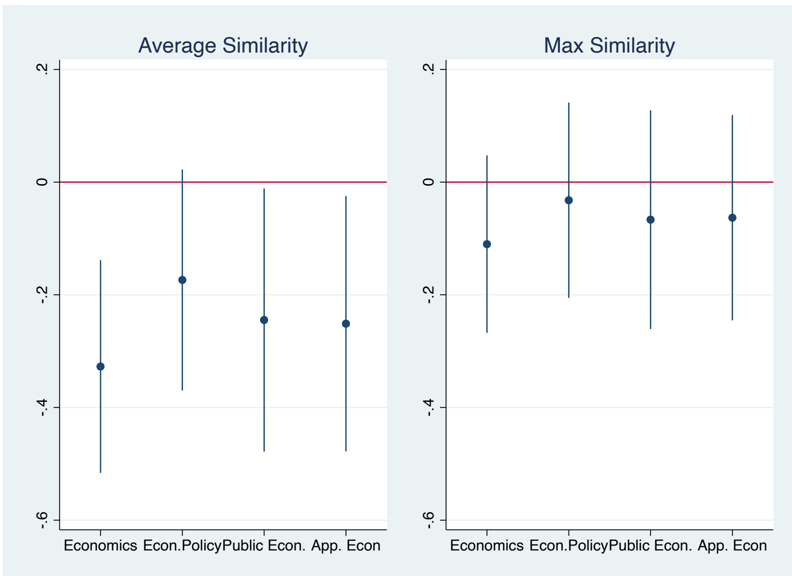
We now discuss the results of the estimation of Equation 2, to uncover whether female and male candidates differ in terms of mean and maximum similarity with the selection committee. The results are reported in Table 10. Columns 1-3 use as dependent variable the dummy for the mean similarity with the selection committee, while columns 4-6 the dummy for the maximum similarity with the selection committee. Columns 2 and 5 include year and sector fixed effects, while columns 3 and 6 include call fixed effects.

The coefficient of the female dummy is not statistically different from 0 in the first three columns, but it becomes significant and larger in size in all the last three columns. This suggests that, although female and male candidates do not differ in terms of mean similarity, male candidates are more likely than female ones to be strongly similar to a member of the selection committee(the probability that the dummy variable based on the maximum similarity is equal to 1 is 5 percentage point or 10% larger for male candidates than for female candidates). Being abroad relates negatively to maximum similarity, indicating that candidates applying from abroad are less close in terms of research to members of selection committees, in most cases based in Italian universities.

In order to shed light on the role of the gender composition of the selection committee in explaining this result, we run the same analysis focusing first only on female members, and then only on male members of the committees. The results are provided in Table 11. Interestingly, we find that the gender gap in the maximum similarity disappears when we look only at female members of the committee (Table 11, Panel 1), while it is even larger when we focus only on male members (Table 11, Panel 2). This provides supporting evidence for the hypothesis that women and men do have different research agendas, and that the fact that female candidates are less likely to be strongly similar to one of the members of the committee is driven by the fact that the committees are composed mainly by men.

Finally, we explore whether the gender gap in similarity varies across macro-fields. As before, we augment Equation 2 with an interaction term between the female dummy and the macro-field dummies. The results, reported in Figure 3, show that, while the gender gap in maximum similarity does not vary by macro-field, the gender gap in mean similarity is larger for economics and public economics, compared to econometrics, which is the omitted category, possibly indicating more heterogeneity in research interests and methodologies in the broad economics and public economics macro-fields.

Figure 3: Gender differences in similarity



Notes: The graphs show the coefficients of the interaction terms between the female dummy and the macro-field dummies of Equation 2. Econometrics is the omitted

Table 10: Gender differences in similarity, LPM

	Mean	Mean	Mean	Max	Max	Max
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.000528	-0.000419	0.0348	-0.0518**	-0.0575***	-0.0405*
	(0.0225)	(0.0222)	(0.0227)	(0.0220)	(0.0218)	(0.0226)
PhD Abroad	-0.0114	0.00609	0.0135	-0.00355	-0.00100	0.00721
	(0.0257)	(0.0255)	(0.0267)	(0.0250)	(0.0251)	(0.0258)
Abroad	0.0262	0.0330	0.0756***	-0.0696***	-0.0697***	-0.0466*
	(0.0245)	(0.0243)	(0.0265)	(0.0235)	(0.0231)	(0.0247)
Years from PhD	0.00177	0.00356	0.00417	0.00228	0.00267	0.00112
	(0.00354)	(0.00358)	(0.00359)	(0.00350)	(0.00347)	(0.00351)
Internal Cand.	0.0920**	0.0835*	0.113**	0.0622	0.0570	0.0856*
	(0.0451)	(0.0443)	(0.0462)	(0.0442)	(0.0432)	(0.0441)
At least one Top 6	-0.00927	0.00429	-0.0347	-0.0904	-0.0591	0.000644
	(0.0976)	(0.0992)	(0.0909)	(0.0909)	(0.0885)	(0.0877)
Tot A+ pubs	0.0289	0.0362*	0.0435**	0.0263	0.0365*	0.0312
	(0.0202)	(0.0201)	(0.0207)	(0.0195)	(0.0193)	(0.0212)
At least one Interd.	-0.0652	-0.0560	-0.0522	-0.0662	-0.0412	-0.0409
	(0.0693)	(0.0663)	(0.0680)	(0.0655)	(0.0661)	(0.0631)
Tot A pubs	-0.00266	-0.00241	-0.00289	0.0223***	0.0219***	0.0214***
	(0.00277)	(0.00273)	(0.00276)	(0.00259)	(0.00257)	(0.00276)
$\overline{Y}$	0.5	0.5	0.5	0.5	0.5	0.5
Observations	2,244	2,244	2,244	2,244	2,244	2,244
R-squared	0.004	0.040	0.192	0.043	0.083	0.213
Call FE	No	No	Yes	No	No	Yes
Year FE	No	Yes	No	No	Yes	No
Sector FE	No	Yes	No	No	No	No

Dependent variables: Mean/Maximum Similarity between the Candidate and Members of the committee. Estimates from a Linear Probability Model (LPM). Standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table 11: Gender differences in similarity

	Mean	Mean	Mean	Max	Max	Max
	(1)	(2)	(3)	(4)	(5)	(6)
Panel 1: With female members of the committees only						
Female	-0.00273	0.00242	0.0361	-0.00842	-0.0129	-0.00320
	(0.0259)	(0.0256)	(0.0258)	(0.0252)	(0.0251)	(0.0256)
Observations	1,674	1,674	1,674	1,674	1,674	1,674
R-squared	0.007	0.050	0.209	0.045	0.084	0.254
Panel 2: With male members of the committees only						
Female	-0.0370	-0.0403*	-0.0128	-0.0585***	-0.0568***	-0.0299
Observations	2,215	2,215	2,215	2,215	2,215	2,215
R-squared	0.007	0.039	0.175	0.040	0.071	0.254
$\overline{Y}$	0.5	0.5	0.5	0.5	0.5	0.5
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Call FE	No	No	Yes	No	No	Yes
Year FE	No	Yes	No	No	Yes	No
Sector FE	No	Yes	No	No	Yes	No

Dependent variables: Mean/Maximum Similarity between the candidate and female/male members of the selection committees. Robust Standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

6.3 Discussion

We have interpreted the premium research similarity grants to candidates in the selection process as evidence that senior academics/evaluators assess more positively junior researchers that have a research agenda similar to theirs. While there is evidence of gender homophily in Economics (Ductor and Prummer, 2023), self-image bias relates indirectly to gender through research agendas, which are the focus of this paper. In this section, we further discuss our results and alternative explanations for our findings.

One may argue that members of selection committees are not choosing the winning candidate according to their own preferences, which may be affected by self-image bias, but are rather acting upon the input of departments, which want to hire junior researchers with specific research agendas, and identify members of selection committees with that goal in mind. We note that our results hold also when we only consider the external members of the committee and exclude the internal one, who represents the direct interest of the hiring department. In addition, similarity with the department is not significant in explaining the winning probability, when we control for similarity with the selection committee. A high level of correlation in the similarity indices between the candidate and each member of the committee suggests that selection committees are homogeneous groups in terms of research interests and this is consistent with self-image bias playing a role in the recruiting process and departments anticipating it. For instance, the evidence in Table 6 indicates a stronger role of similarity compared to high-ranked publications in influencing the winning probability. While it can be in the department's interest to hire senior assistant professors with specific research interests, it holds that such research interests are likely to be already present in the department, and that female candidates are less likely to see their research agendas already represented among senior academics. We also point out that similarity plays an important role even *within* fields of research.

An alternative explanation for our findings is that candidates select into calls in which they see members of the selection committee having an agenda similar to theirs. However, candidates do not know the composition of the selection committee at the time of the application, as we discussed in Section 2. Moreover, the evidence in Table A.6 indicates that similarity does not influence the decision to participate to the interview, when shortlisted.

Overall, our evidence is consistent with the importance of similarity being driven by the demand side of the academic market, rather than the supply side, and with self-image bias playing a role in it.

7 Conclusions

There is extensive evidence supporting the (economic) advantages of having a diverse and inclusive workforce. While measuring the benefits of diversity in the academic market can be challenging, studies indicate that it impacts scholars' performance in measurable ways, like citation counts (Powell, 2018). Additionally, diversity enriches the scientific process by incorporating a broader range of perspectives and of research questions. Fostering diversity in academia is therefore not only a matter of fairness but also a matter of efficiency.

In this paper, we analyse the presence of self-image bias in academia, which may play a role in the slow changes in gender diversity among scholars and in a narrowing of the span of research agendas. We propose a novel and granular measure of similarity which, starting from the abstracts of papers, captures not only fields of research, but broader characteristics of research agendas. This new measure of similarity has the potential to better capture diversity in knowledge production than fields of research and reveal directions of research over time and space in a more accurate way. We employ it to investigate whether similarity between members of selection committees and candidates for senior assistant professorships relates to the outcome of the selection process and whether female candidates are characterised by a lower similarity index with more senior academics than their male counterparts.

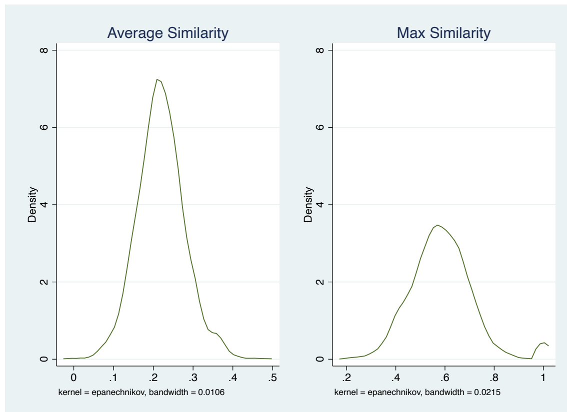
To address the research questions, we exploit data on the Italian academic job market, and collect the publications of the universe of candidates, members of recruiting committees and of faculty of departments launching calls for the period 2014-2021. By exploiting NPL techniques, we calculate an index of similarity between the publications of the members of the committees and those of the candidates, and show that candidates with a maximum similarity index larger than the median are 7 percentage points more likely to win the competition for senior assistant professor positions. Research similarity counts almost twice as much as having a top publication in influencing the outcome of a selection process; it also contributes to reducing the gender gap in the winning probability that we observe, once we take into account selection into participating to interviews. We show that women are on average less likely to be highly similar to one of the members of the committee, and that the gender gap in similarity is driven by male members of the committee, while it disappears when we focus on female members only.

The evidence presented suggests that in male-dominated contexts, similarity bias and the search for "fit" can hinder female scholars' career progress. Note that addressing similarity bias and promoting gender diversity in academia would not imply a narrowing of the topics researched in a department. The distributions of our similarity indices among candidates by gender suggest that the width of topics is the same for female and male candidates (Figure A.6). Thus, tackling self-image bias may, on the contrary, help to mitigate the tendency to conform to a standardised research profile, as observed over the last years in Economics departments (Corsi et al., 2019).

On the policy side, the identification of this source of bias provides additional justification for implementing affirmative actions that deliberately increase the representation of minorities in the profession and, consequently, in selection committees. Neglecting to address self-image bias poses a significant risk of perpetuating gender imbalance in economics and limiting innovative research.

Appendix

Figure A.1: Similarity Distributions (Mean and Max).



Notes: The figure shows the distribution of the average similarity and maximum similarity between candidates and members of selection committees.

Figure A.2: Examples of abstracts

High Similarity (0.93)

Abstract 1: Organized crime uses political violence to influence politics in a wide set of countries. This paper exploits a novel dataset of attacks directed towards Italian local politicians to study how (and why) criminal organizations use violence against them. We test two complementary theories to predict the use of violence i) before elections, to affect the electoral outcome; and ii) after elections, to influence politicians from the beginning of their term. We provide causal evidence in favor of the latter hypothesis. The probability of being a target of violence increases in the weeks right after an election in areas with a high presence of organized crime, especially when elections result in a change of local government.

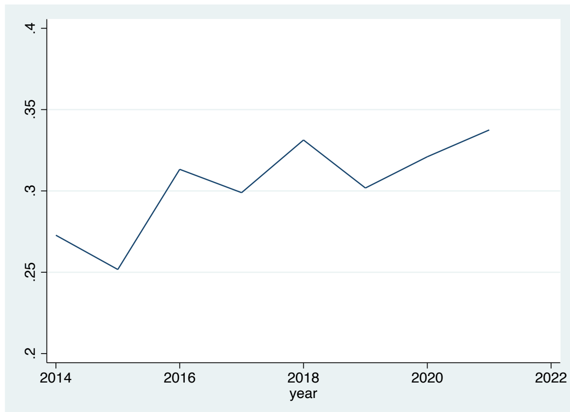
Abstract 2: We develop a model explaining how criminal organizations strategically use pre-electoral violence as a way of influencing electoral results and politicians' behaviour. We then characterize the incentives to use such violence under different levels of electoral competition and different electoral rules. Our theory is consistent with the empirical evidence within Sicily and across Italian regions. Specifically, the presence of organized crime is associated with abnormal spikes in violence against politicians before elections-particularly when the electoral outcome is more uncertain-which in turn reduces voting for parties opposed by criminal organizations. Using a very large data set of parliamentary debates, we also show that violence by the Sicilian Mafia reduces anti-Mafia efforts by members of parliament appointed in Sicily, particularly from the parties that traditionally oppose the Mafia.

Low Similarity (0.008)

Abstract 3: We explore the effects on strategic behavior of alternative representations of a centipede game that differ in terms of complexity. In a laboratory experiment, we manipulate the way in which payoffs are presented to subjects in two different ways. In both cases, information is made less accessible relative to the standard representation of the game. Results show that these manipulations shift the distribution of take nodes further away from the equilibrium prediction. The evidence is consistent with the view that failures of game-form recognition and the resulting limits to strategic reasoning are crucial for explaining non-equilibrium behavior in the centipede game.

Abstract 4: To investigate empirically the association between a direct measure of assimilation with a host culture and immigrants' subjective well-being, this study uses data from the German Socio-Economic Panel. A positive, significant association arises between cultural assimilation and immigrants' life satisfaction, even after controlling for several potential confounding factors, such as immigrants' individual (demographic and socio-economic) characteristics and regional controls that capture their external social conditions. Finally, the strength of the association varies with time since migration; it is significant for "established" and second-generation immigrants but vanishes for "recent" immigrants.

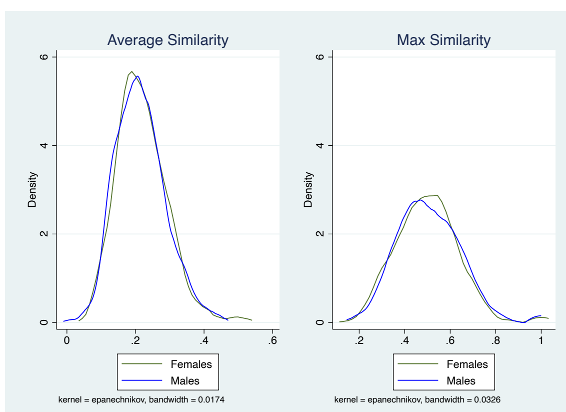
Figure A.3: Share of women in selection committees



Notes: The figure shows the share of women in selection committees for tenure track assistant professorships in economics in Italy in the period 2014-2021

Figure A.4: Similarity distributions (Mean and Max)

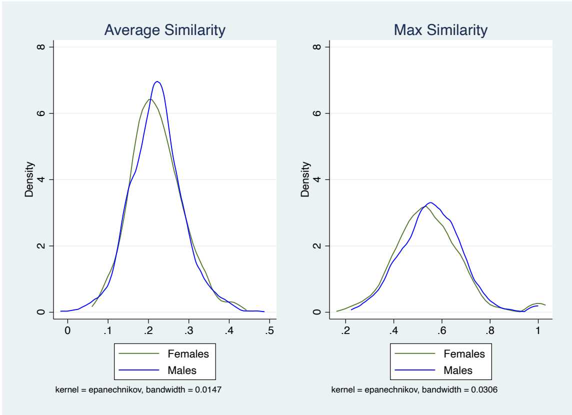
By gender of the candidates, only female members of selection committees



Notes: The figure shows the distribution of the average similarity and maximum similarity between candidates and female members of selection committees.

Figure A.5: Similarity distributions (Mean and Max)

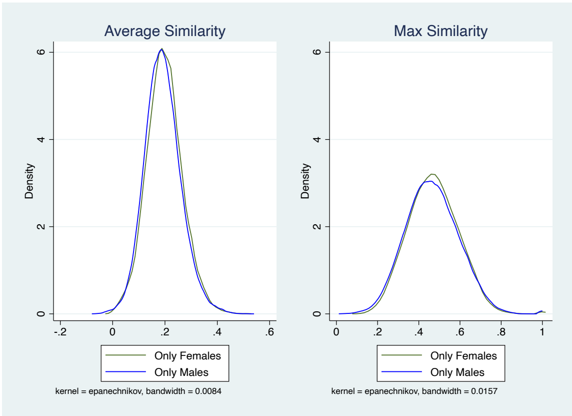
By gender of the candidates, only male members of selection committees



Notes: The figure shows the distribution of the average similarity and maximum similarity between candidates and male members of selection committees

Figure A.6: Similarity among candidates (Mean and Max)

By gender



Notes: The figure shows the distribution of the average similarity and maximum similarity among candidates

Table A.1: Summary statistics

Calls for Junior Assistant Professorships

Variable	*Mean*	*Sd*	*N Cand.*
Female	0.402	0.490	971
Winner	0.163	0.369	971
PhD Abroad	0.198	0.398	971
Currently Abroad	0.234	0.423	971
Years from PhD	4.881	3.129	971
N cand/call	11.417	9.385	971
Share women in the Committee	0.335	0.472	971

Notes. The table provides summary statistics for candidates for junior assistant professorships and reports the share of women in selection committees. Years: 2014-2021.

Table A.2: Summary statistics: Differences by gender

Candidates for Junior Assistant Professorships

Panel 1: Characteristics					
Variable	*Men*	*Women*	*T-STAT*	*Diff*	*p-value*
Winner	0,18	0,14	1,90	0,04	**0,06**
PhD Abroad	0,21	0,18	1,01	0,03	0,31
Currently Abroad	0,28	0,17	3,89	0,10	**0,00**
Years from PhD	4,79	5,02	-1,10	-0,23	0,27
Panel 2: Publication Record					
Variable	*Men*	*Women*	*T-STAT*	*Diff*	*p-value*
At least one Top 6	0,00	0,00	0,27	0,00	0,78
N pubs in A+	0,06	0,08	-1,29	-0,02	0,20
N pubs in A	1,51	1,38	1,31	0,11	0.19
At least one in Interdisciplinary	0,01	0,02	-1,21	-0,01	0,23

Notes. The table reports summary statistics and the results of a t-test by gender of the candidates for the following variables: winning probability, share of those with a PhD Abroad or currently Abroad, average number of years from PhD, share of those with at least one publication in a Top 6, average number of publications in A+ and in A journals, share of those with at least one publication in interdisciplinary journals. Top 6 journals are AER, QJE, JPE, REStud, Econometrica, JF; A+ journals are AEJs, EJ, JEEA, Rand, JPubE, JME, RFS, JEc, JOLE, JHE, QE, JTE, JDE, JIE; A journals are defined according to the ANVUR classification.

Table A.3: Winning Probability

Calls for Junior Assistant Professorships

VARIABLES	(1) Winner	(2) Winner	(3) Winner
Female	-0.0535**	-0.0574**	-0.0682***
	(0.0238)	(0.0241)	(0.0262)
PhD Abroad	-0.0271	-0.0265	-0.0456
	(0.0291)	(0.0293)	(0.0316)
Abroad	-0.0705***	-0.0659**	-0.0549*
	(0.0269)	(0.0269)	(0.0308)
Years from PhD	0.00462	0.00421	0.00259
	(0.00410)	(0.00428)	(0.00487)
At least one Top 6	-0.121**	-0.146	-0.245
	(0.0566)	(0.129)	(0.205)
Tot A+ pubs	0.00843	0.0136	0.0413
	(0.0463)	(0.0468)	(0.0487)
At least one interd.	0.0931	0.137	0.0788
	(0.119)	(0.118)	(0.132)
Tot A pubs	0.0106	0.00908	0.00939
	(0.00837)	(0.00857)	(0.00950)
$\overline{Y}$	0.163	0.163	0.163
Observations	971	971	971
R-squared	0.017	0.040	0.220
Call FE	No	No	Yes
Year FE	No	Yes	No
Sector FE	No	Yes	No

Dependent variable: Winning probability for junior (non tenure-track) assistant professorships in economics. Estimates from a Linear Probability Model. Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table A.4: Gender Gaps in outcomes

Calls for senior assistant professorships

VARIABLES	(1) Winner	(2) Shortlisted	(3) Present
Female	-0.0115	-0.0300	0.0586*
	(0.0132)	(0.0214)	(0.0306)
PhD Abroad	0.0224	0.0510**	0.00550
	(0.0155)	(0.0246)	(0.0347)
Abroad	-0.0127	-0.105***	0.0682*
	(0.0133)	(0.0234)	(0.0357)
Years from PhD	0.00122	-0.00274	0.00553
	(0.00205)	(0.00346)	(0.00526)
Internal Cand.	0.208***	0.192***	0.196***
	(0.0395)	(0.0395)	(0.0484)
At least one Top 6	0.0401	0.0399	0.0823
	(0.0664)	(0.101)	(0.107)
Tot A+ pubs	0.0352**	0.125***	-0.0279
	(0.0152)	(0.0185)	(0.0244)
At least one interd.	0.0195	0.0230	0.0170
	(0.0403)	(0.0623)	(0.0963)
Tot A pubs	0.00817***	0.0277***	-0.00882**
	(0.00173)	(0.00266)	(0.00376)
$\overline{Y}$	0.096	0.499	0.602
Observations	2,244	2,244	1,120
R-squared	0.051	0.113	0.065
Call FE	No	No	No
Year FE	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes

Dependent variables: In column (1), probability of winning; in column (2) probability of being shortlisted for the interview; in column (3), probability of being present at the interview. Estimates from a Linear Probability Model. Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table A.5: The role of research similarity for the probability of being shortlisted

VARIABLES	(1) Shortlisted	(2) Shortlisted	(3) Shortlisted	(4) Shortlisted	(5) Shortlisted	(6) Shortlisted
Dummy Simil.	0.156***	0.0961***	0.110***	0.129***	0.0978***	0.0789***
	(0.0204)	(0.0198)	(0.0254)	(0.0215)	(0.0203)	(0.0264)
Female	-0.0362*	-0.00549		-0.0290	0.00156	
	(0.0215)	(0.0201)		(0.0215)	(0.0201)	
PhD Abroad	0.0550**	0.0555**		0.0556**	0.0557**	
	(0.0247)	(0.0233)		(0.0247)	(0.0232)	
Abroad	-0.117***	-0.0180	-0.0600*	-0.102***	-0.00577	-0.0539
	(0.0232)	(0.0230)	(0.0349)	(0.0234)	(0.0230)	(0.0379)
Years from PhD	-0.00308	-0.00876***	-0.0649**	-0.00283	-0.00848***	-0.0612*
	(0.00340)	(0.00306)	(0.0310)	(0.00350)	(0.00308)	(0.0326)
Internal Cand.	0.168***	0.180***	0.106*	0.174***	0.183***	0.118**
	(0.0392)	(0.0416)	(0.0553)	(0.0384)	(0.0412)	(0.0577)
At least one Top 6	0.0715	0.00683		0.0890	0.00964	
	(0.103)	(0.107)		(0.103)	(0.108)	
Tot A+ pubs	0.122***	0.165***	0.0176	0.122***	0.165***	0.0120
	(0.0191)	(0.0206)	(0.0909)	(0.0190)	(0.0205)	(0.110)
At least one interd.	0.0316	0.0796	0.348	0.0258	0.0772	0.403***
	(0.0613)	(0.0569)	(0.460)	(0.0619)	(0.0575)	(0.141)
Tot A pubs	0.0278***	0.0253***	0.0313***	0.0247***	0.0231***	0.0280**
	(0.00260)	(0.00250)	(0.0113)	(0.00269)	(0.00254)	(0.0119)
	Mean	**Mean**	**Mean**	**Max**	**Max**	**Max**
$\overline{Y}$	0.499	0.499	0.499	0.499	0.499	0.499
Observations	2,190	2,190	2,190	2,190	2,190	2,190
R-squared	0.139	0.412	0.406	0.131	0.412	0.403
Call FE	No	Yes	No	No	Yes	No
Year FE	Yes	No	No	Yes	No	No
Sector FE	Yes	No	No	Yes	No	No
Candidate FE	No	No	Yes	No	No	Yes

Dependent variable: Probability of being shortlisted for tenure-track assistant professorships in economics. Estimates from a Linear Probability Model. Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table A.6: The role of research similarity for the probability of participating in the interview

VARIABLES	(1) Present	(2) Present	(3) Present	(4) Present	(5) Present	(6) Present
Dummy Simil.	-0.0384	-0.0283	-0.0257	0.00781	-0.0101	0.0102
	(0.0304)	(0.0339)	(0.0449)	(0.0308)	(0.0337)	(0.0434)
Female	0.0527*	0.0607*		0.0553*	0.0604*	
	(0.0313)	(0.0327)		(0.0314)	(0.0328)	
PhD Abroad	0.0170	0.00865		0.0184	0.00932	
	(0.0353)	(0.0389)		(0.0353)	(0.0390)	
Abroad	0.0416	0.0263	0.0549	0.0375	0.0223	0.0543
	(0.0366)	(0.0425)	(0.0602)	(0.0366)	(0.0424)	(0.0665)
Years from PhD	0.00758	0.00167	0.0273	0.00742	0.00153	0.0244
	(0.00541)	(0.00569)	(0.0720)	(0.00542)	(0.00569)	(0.0790)
Internal Cand.	0.198***	0.214***	0.121	0.192***	0.211***	0.117
	(0.0466)	(0.0568)	(0.0862)	(0.0465)	(0.0567)	(0.0861)
At least one Top 6	0.0303	-0.0554		0.0279	-0.0563	
	(0.107)	(0.103)		(0.108)	(0.102)	
Tot A+ pubs	-0.0238	-0.0438	-0.0664	-0.0223	-0.0432	-0.0557
	(0.0250)	(0.0280)	(0.161)	(0.0250)	(0.0279)	(0.164)
At least one interd.	-0.00815	-0.0387	0.576	-0.00623	-0.0357	0.581**
	(0.100)	(0.109)	(0.526)	(0.0993)	(0.109)	(0.292)
Tot A pubs	-0.00767**	-0.00836*	-0.00875	-0.00775**	-0.00812*	-0.00860
	(0.00390)	(0.00439)	(0.0181)	(0.00393)	(0.00444)	(0.0214)
	Mean	**Mean**	**Mean**	**Max**	**Max**	**Max**
$\overline{Y}$	0.602	0.602	0.602	0.602	0.602	0.602
Observations	1,035	1,035	1,035	1,035	1,035	1,035
R-squared	0.044	0.303	0.404	0.043	0.303	0.403
Call FE	No	Yes	No	No	Yes	No
Year FE	Yes	No	No	Yes	No	No
Sector FE	Yes	No	No	Yes	No	No
Candidate FE	No	No	Yes	No	No	Yes

Dependent variable: Probability of being present at the interview if shortlisted for tenure track assistant professorships in economics. Estimates from a Linear Probability Model. Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table A.7: The role of research similarity for the winning probability

VARIABLES	(1) Winner	(2) Winner	(3) Winner	(4) Winner
Panel 1: Similarity as a continous variables				
Similarity	0.851***	0.759***	0.427***	0.382***
	(0.112)	(0.115)	(0.0588)	(0.0603)
Female	-0.0116	-0.00747	-0.00650	-0.00194
	(0.0131)	(0.0137)	(0.0130)	(0.0136)
Observations	2,244	2,244	2,244	2,244
R-squared	0.078	0.165	0.082	0.168
Panel 2: Probit Model (Marginal Effects)				
Dummy Similarity	0.0699***	0.0682***	0.0714***	0.0675***
	(0.0119)	(0.0113)	(0.0125)	(0.0121)
Female	-0.00833	-0.00387	-0.00571	0.00146
	(0.0120)	(0.0111)	(0.0121)	(0.0114)
Observations	2,244	2,080	2,244	2,080
Pseudo R2	0.0902	0.182	0.0890	0.180
	Mean	**Mean**	**Max**	**Max**
$\overline{Y}$	0.096	0.096	0.096	0.096
Controls	Yes	Yes	Yes	Yes
Call FE	No	Yes	No	Yes
Year FE	Yes	No	Yes	No
Sector FE	Yes	No	Yes	No

Dependent variable: Winning Probability for tenure track assistant professorships in economics. OLS estimates with similarity as continuous variable in Panel 1. Marginal effect estimates from a Probit Model in Panel 2. Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

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