Research Similarity and Women in Academia *

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Abstract

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

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

JEL classification codes: J16, J71, J82

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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 for 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 (2023) 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; Lundberg and Stearns, 2019; Belot et al., 2023; Beneito et al., 2021; Sierminska and Oaxaca, 2021) 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 based on text analysis, which can capture similarity in research characteristics such as research topics, methodologies used, policy relevance of the questions addressed, rather than mere research fields. We construct a dataset that covers the universe of job applications to public calls for tenure track assistant professorships in economics in Italy in the period 2014-2021, and we collect the abstracts of the papers of all candidates, selection committee members and faculty members of the departments issuing the calls. Using a Natural Language Processing tool (i.e., document embeddings), we compute the abstract similarity for each possible combination of candidate and selection committee member and aggregate these similarity scores at the candidate-call level, to examine their role in influencing the selection outcome. We show that research similarity is positively associated with the probability of winning the selection and becoming a tenure track assistant professor, even when controlling for a rich set of candidate characteristics and candidate or call fixed effects. We also show that, although there is no gender gap in the average similarity between candidates and selection committee members, women and men differ in maximum similarity. Men are more likely than women to be very similar to one of the committee members and this gender difference disappears when we focus only on female committee members. Last, we show that gender differences in (maximum) research similarity help explaining the gender gap in the probability of winning that we document when the probability of attending the interview in the last stage of the selection is taken into account. These results suggest that similarity bias in male-dominated contexts may help 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 probability of winning, even when controlling for a rich set of candidate characteristics and fixed effects. We also show that the gender gap in the probability of winning is smaller when we control for research similarity. 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., 2023; 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 positively influences the probability of winning, is driven by male selection committee members. 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., 2023). 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 framework

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

[1]Note that the profile of the ideal candidate can be defined only according to broad fields of research specified by Ministerial guidelines. They are Economics, Economic Policy, Public Economics, Econometrics, and Applied Economics. 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.

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, before the list of candidates applying for the position is known to them, 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 score assigned to each of them and how it is split between CVs, publications and interview, and indicates the winner of the selection process.

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 the ministerial classification. Our dataset covers 237 calls for tenure track positions, involving 714 committee members and 2364 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 8230 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. In the collection of publications, we only consider faculty members who are economists and are assigned to the ministerial economic areas, which we listed above. In total, the dataset of members of selection committees and departments includes 1381 professors and 26186 publications.

Our data come from three main sources. First, we use data from CINECA,

[2]During the 2014-2021 period, 248 calls were issued. However, for 11 of them, we could not collect all the necessary information.

which collects historical information on faculties affiliated to departments. Second, the institutional websites of each Italian university have information on calls and their results, which allows us to construct the candidate side of the dataset. Finally, the publication data come from the Elsevier's abstract and citation database SCOPUS.com, which provides information on author profiles, including 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 entire selection process we also collect the same type of data described above for calls for junior (non-tenure track) assistant professorships, as we will discuss in Section 5. Before applying for senior assistant professor positions, many candidates apply for junior assistant professor positions as a first step in the academic pipeline.

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 34416. 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 applying 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 Sentence-Transformers[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 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 the maximum (Max Sim) similarity between the publications of a candidate and those of the selection committee (or department) members. Figure A.1 illustrates the distribution of mean and maximum similarity between candidates and selection committee members. 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 main analysis consists of two steps. First, we test whether the similarity between candidates and selection committee members predicts the probability of winning of the candidate. We then examine how this similarity varies with the gender of the

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

candidate.

Thus, we first estimate the following linear probability model:

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

where $Winner_{ijst}$ is a dummy equal to 1 if candidate i wins the selection of call j in the broad 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 selection committee members for call j in year t and broad field s is above the 50th percentile.[4] X_i is a vector of candidate characteristics, namely, gender, years from PhD, whether the PhD was taken abroad, whether the candidate is employed abroad at the time of the call, number and quality of publications, whether the candidate is already working in the department launching the call *(Internal)* and whether he/she has coauthored at least a publication with a member of the selection committee. $Year_t$ and s_s are year and broad-field fixed effects, respectively. Finally, ε_{ijst} is the error term. In further specifications, we replace year and broad-field fixed effects with call or candidate fixed effects.

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

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

where $DSimIndex_{ijst}$ is defined above, $Female_i$ is a dummy for female candidates, which captures gender differences in mean or maximum similarity, and all the other variables are defined as before (with the exception of gender that enters separately and it is not included in X_i). Likewise, in further specifications of the model, we replace year and broad-field fixed effects with call or candidate fixed effects.

5 Descriptive evidence: selection issues and gender gaps

In this section, we present summary statistics and discuss selection by gender into applying to senior assistant professor positions and participating in job interviews, to examine the existence of a gender gap in the probability of winning and lay the ground to discuss the role of research similarity.

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

5.1 Descriptive statistics

Table 1 shows that our dataset includes 2364 candidates. The share of women among them is 36%. The probability for a candidate of winning a selection is 10%. On average, the share of women in committees and in departments is 32% and 33%, respectively.[5] Each call has, on average, 16 candidates.

Table 1: Summary statistics

Calls for senior assistant professorships

Variable	*Mean*	*Sd*	*N Cand.*
Female	0.356	0.479	2364
Winner	0.101	0.301	2364
PhD Abroad	0.240	0.413	2364
Currently Abroad	0.274	0.446	2364
Years from PhD	7.178	3.078	2364
N cand/call	15.825	8.793	2364
Share women in the Committee	0.316	0.229	2364
Share women in the Department	0.334	0.158	2364

Notes. The table provides summary statistics for the following variables: share of females, probability of winning, share of candidates with a PhD abroad or currently abroad, average number of years from PhD, average number of candidates per call and average share of women in selection committees and departments issuing 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 selection committee members. 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,

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

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	-0.19	0.00	0.85
Shortlisted	0.51	0.50	0.61	0.01	0.54
Present	0.57	0.65	-2.53	-0.07	**0.01**
PhD Abroad	0.23	0.26	-1.47	-0.03	0.14
Currently Abroad	0.28	0.25	-1.57	-0.03	0.12
Years from PhD	7.09	7.34	-1.94	-0.26	**0.05**
Internal Candidate	0.04	0.10	-5.10	-0.06	**0.00**
Coauthor	0.02	0.04	-1.42	-0.01	0.16
Panel 2: Publication Record					
Variable	*Men*	*Women*	*T-STAT*	*Diff*	*p-value*
At least one Top 6	0.01	0.02	-1.62	-0.01	0.11
N pubs in A+	0.15	0.25	-4.50	-0.11	**0.00**
N pubs in A	6.30	5.84	2.74	0.46	**0.01**
N pubs	9.89	8.96	3.10	0.92	**0.00**
At least one interdisciplinary	0.03	0.02	1.47	0.01	0.14
Panel 3: Similarity					
Variable	*Men*	*Women*	*T-STAT*	*Diff*	*p-value*
Mean Sim with Committee	0.220	0.223	-1.173	0.003	0,241
Max Sim with Committee	0.593	0.588	0.989	0.006	0.323

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, share of those working abroad at the time of the selection, average number of years from PhD, share of internal candidates, share of candidates with a coauthor in the selection committee, share of those with at least one Top 6 publication, average number of A+ publications, average number of A publications, share of those with at least one interdisciplinary publication, mean 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.

men have, on average, a higher number of A publications and total publications.[6] Interestingly, women are more likely than men to be present at the interview, when shortlisted, and more likely to be internal candidates. 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 slightly 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 committee members. Interestingly, while there are no clear differences by gender in the similarity distributions when we focus on female committee members, the distribution of the maximum similarity with male committee members for female candidates appears to be left-shifted, compared to that for male candidates, suggesting that female candidates have lower values of maximum similarity with male committee members, compared to male candidates.[7]

5.2 The selection into the pool of candidates

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

To investigate what might explain the lower proportion of women in the candidate pool, we examine the role of self-selection in applying for tenure track assistant professorships and gender differences in the probability of winning at an earlier stage

[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 (link).

[7]The distributions for the maximum similarity with the male members of the committee are different by gender according to the Kolmogorov- Smirnov test. In Figure A.6, we also 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.

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. To this end, we 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 research similarity dummy) and investigate the role of gender in explaining our outcome of interest, i.e., the application probability. The results in Table 3 show that, conditional on observable characteristics and on the inclusion of fixed effects, the application probability is around 0.4 percentage points lower for female candidates compared to male candidates, which corresponds to 10% of the average application probability $\overline{Y}$ in the sample.

Second, we investigate whether, in addition to self-selection, the lower proportion of women among candidates for senior assistant professorships depends on the lower probability of success of female candidates at 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 professorships. 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 the publication record. Interestingly, Table A.1 shows that women represent a higher proportion 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 publication record (Table A.2). Yet, female candidates are less likely to win.

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

Table 3: Application probability

Calls for senior assistant professorships

	(1)	(2)	(3)
Female	-0.00201	-0.00410**	-0.00402**
	(0.00156)	(0.00159)	(0.00158)
PhD Abroad		0.00749***	0.00740***
		(0.00198)	(0.00196)
Abroad		-0.0349***	-0.0342***
		(0.00159)	(0.00157)
Years from PhD		-0.00198***	-0.00191***
		(0.000222)	(0.000220)
At least one Top 6		0.00610	0.00591
		(0.00613)	(0.00603)
N pubs in A+		-5.92e-05	4.33e-05
		(0.00137)	(0.00134)
N pubs in A		-0.000579**	-0.000532**
		(0.000232)	(0.000231)
N pubs		1.41e-05	7.27e-06
		(0.000111)	(0.000110)
At least one interd.		0.00502	0.00502
		(0.00397)	(0.00388)
$\overline{Y}$	0.037	0.037	0.037
Observations	61,689	61,689	61,689
R-squared	0.000	0.020	0.042
Broad Field 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. Our controls include a dummy for candidates holding a PhD from abroad and for being currently abroad, number of years from PhD, a dummy for candidates with at least one Top 6 publication, number of A+ and A publications, number of publications, dummy for those with at least one publication in interdisciplinary journals. Robust standard errors in parentheses. Years: 2014-2021 *** p<0.01, ** p<0.05, * p<0.1

We therefore examine empirically whether female candidates have a lower probability of winning the selection than male candidates. To do this, we construct a dummy equal to 1 if the candidate wins the competition, and equal to 0 otherwise.[9] According to Table A.3, the probability of winning the selection is much lower (5.4-6.9 percentage points or 33-42%) for female than for male candidates, even conditional on their publication record.

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 consistent with two pieces of evidence. 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,[10] or because they are less mobile.[11] Second, there is a gender gap in the probability of winning 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.

5.3 Gender gap in the probability of winning and selection bias

Before turning to our main empirical analysis, we examine whether there is a gender gap in the probability of success in the competition for senior assistant professorships, ignoring for the moment the role played by research similarity. To do so, we use a specification similar to Equation 1, without including the similarity dummy.

The results are reported in Table A.5. While our main dependent variable is the probability of winning the competition (column 1), we also look at the probability of being shortlisted (column 2) and the probability of being present at the interview, if shortlisted (column 3). According to the results reported in the table, the coefficient

[9] Note that the way selection procedures for junior assistant professorships work is the same as that for senior assistant professorships that we have described in Section 2.

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

[11] In Table A.4, we also provide descriptive evidence on gender differences in the number of applications per candidate in our sample. 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 Southern Italy is lower for women than for men.

of the female dummy is negative in the first two columns, although not statistically significant, while it is positive and significant in column 3. This indicates that female candidates are more likely than male candidates to attend the interview if shortlisted (the participation probability is 6 percentage points, or 10% higher for women than for men), in line with the descriptive evidence from Table 2.

As the probability of being present at the interview, which also depends on the probability of being shortlisted, strongly influences the probability of winning the competition, we correct for this selection bias in our analysis of the gender gap in the probability of winning. Specifically, similar to the Heckman selection model, we implement a three-stage procedure. In the first stage, we estimate the probability of being shortlisted using a probit model where the dependent variable is a dummy equal to 1 if the candidate is selected for the interview and equal to 0 otherwise, and as covariates all the observable candidate characteristics listed in Section 4, plus a variable capturing the number of applications the candidate makes per year. Then, in the second stage, we regress the probability of being present at the interview on the same covariates, plus the predicted value of the probability of being shortlisted. Finally, in the last step, we estimate a linear probability model similar to Equation 1, extended to include our estimate of the probability of participating in the interview.

The results are shown in Table 4. Interestingly, the coefficient of the gender dummy is now statistically significant, negative, and bigger in magnitude compared to the one in Table A.5, column 1. This provides evidence that women are characterised by a lower probability of winning the competition for senior assistant professor positions than men. As expected, the coefficient of the probability of being present is positive and highly significant.

Overall, the evidence presented in this section suggests that there are important gender differences in selection for senior assistant professorships. Women are less likely than men to apply for senior assistant professorships. However, when they do apply, they are more likely to be present at the interview, if they are shortlisted. Although women appear to be better candidates than men on some dimensions, they are less likely to be successful than their male counterparts and win a senior assistant professorship. In the next section, we investigate the role of research similarity in explaining selection outcomes. Then, we examine whether female and male candidates differ in their similarity to committee members and whether gender differences in research similarity can explain the gender gap in the probability of winning that we have identified.

Table 4: Gender gap in the probability of winning, LPM

VARIABLES	(1) Winner	(2) Winner
Female	-0.0777***	-0.0685***
	(0.0166)	(0.0172)
PhD Abroad	0.0129	0.0109
	(0.0164)	(0.0172)
Abroad	-0.0761***	-0.0478***
	(0.0158)	(0.0172)
Years from PhD	-0.00536**	-0.00715***
	(0.00231)	(0.00229)
Internal Cand.	0.00912	0.0110
	(0.0443)	(0.0446)
Coauthor	0.0846	0.0688
	(0.0620)	(0.0634)
At least one Top 6	-0.0490	-0.0782
	(0.0675)	(0.0769)
N pubs in A+	0.0586***	0.0672***
	(0.0152)	(0.0152)
N pubs in A	0.0278***	0.0286***
	(0.00341)	(0.00362)
N pubs	-0.00723***	-0.00770***
	(0.00112)	(0.00122)
At least one interd.	-0.0255	-0.0158
	(0.0423)	(0.0477)
Pr(present)	1.027***	1.046***
	(0.147)	(0.160)
$\overline{Y}$	0.10	0.10
Observations	2,364	2,364
R-squared	0.085	0.168
Call FE	No	Yes
Year FE	Yes	No
Broad Field FE	Yes	No

Notes. Dependent variable: Probability of winning a senior assistant professorship in economics. Estimates from a Linear Probability Model. Pr(present) is a probit estimate of the probability of being present at the interview. Our controls include a dummy for candidates holding a PhD from abroad and for being currently abroad, number of years from PhD, a dummy for internal candidates and for coauthorship, a dummy for those with at least one Top 6 publication, number of A+ and A publications, number of publications, dummy for those with at least one publication in interdisciplinary journals. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

6 Results

We first consider whether similarity predicts the probability of winning and conduct a series of robustness tests and heterogeneity analyses to further explore the role of similarity in the probability of success. We then examine whether there is evidence of gender differences in research similarity that can explain the gender gap in the probability of winning we have documented in the previous section.

6.1 The effect of research similarity on the probability of winning

Table 5 reports the results of the estimation of Equation 1. While columns 1-3 use the average similarity dummy as key explanatory variable, columns 4-6 investigate the role played by the maximum similarity dummy. Columns 1 and 4 show the results of the specification with broad-field and year fixed effects; columns 2 and 5 those with call fixed effects. Finally, columns 3 and 6 incorporate year and candidate fixed effects.

The results show that similarity is positively related to the probability of winning. Candidates for whom the dummy based on average similarity is equal to 1 are 6.1 percentage points more likely to win than those for whom the dummy is equal to 0. The coefficient is also positive and significant – though slightly smaller in magnitude – when we use more demanding specifications and include call or candidate and year fixed effects. The effect of the maximum similarity dummy is similar, if not larger, in magnitude and significance in all specifications. Consistent with the results in the previous section, when we do not control for the probability of attending the interview (equation 1), the female dummy is negative but insignificant, suggesting that women and men do not differ in their chances of becoming senior assistant professors. It is also worth noting that the effect of the similarity indices is even larger than that of an additional A+ publication (in columns 1-2, 4-5). Besides the positive effect of high quality publications on the probability of winning, it is interesting to note the positive and large effect of having a coauthor on the selection committee and of being an internal candidate.

Table 5: The role of research similarity in the probability of winning, LPM

VARIABLES	(1) Winner	(2) Winner	(3) Winner	(4) Winner	(5) Winner	(6) Winner
Dummy Similarity	0.0613***	0.0559***	0.0466***	0.0662***	0.0666***	0.0500***
	(0.0122)	(0.0129)	(0.0144)	(0.0126)	(0.0135)	(0.0145)
Female	-0.0143	-0.00541	0.0117	-0.0107	-0.00116	0.0153
	(0.0129)	(0.0133)	(0.315)	(0.0129)	(0.0132)	(0.0186)
PhD Abroad	0.0262	0.0240		0.0252	0.0228	
	(0.0164)	(0.0173)		(0.0164)	(0.0172)	
Abroad	-0.0189	0.00863	0.0117	-0.0123	0.0158	0.0153
	(0.0135)	(0.0147)	(0.0195)	(0.0134)	(0.0146)	(0.0186)
Years from PhD	0.00133	-0.000384	0.0703	0.00143	-0.000215	0.0877
	(0.00201)	(0.00194)	(0.101)	(0.00203)	(0.00194)	(0.0788)
Internal Cand.	0.180***	0.187***	0.0968***	0.183***	0.190***	0.103**
	(0.0374)	(0.0369)	(0.0317)	(0.0373)	(0.0366)	(0.0408)
Coauthor	0.220***	0.211***	0.153***	0.207***	0.195***	0.143**
	(0.0571)	(0.0579)	(0.0440)	(0.0582)	(0.0586)	(0.0638)
At least one Top 6	0.0367	0.0124	-0.0699	0.0408	0.0101	-0.0691*
	(0.0672)	(0.0748)	(0.315)	(0.0674)	(0.0756)	(0.0357)
N pubs in A+	0.0334**	0.0397***	0.123**	0.0332**	0.0400***	0.123**
	(0.0153)	(0.0149)	(0.0495)	(0.0150)	(0.0149)	(0.0621)
N pubs in A	0.0113***	0.0116***	0.0137	0.0107***	0.0109***	0.0118
	(0.00223)	(0.00232)	(0.0133)	(0.00227)	(0.00238)	(0.0121)
N pubs	-0.00266***	-0.00290***	-0.00508	-0.00327***	-0.00347***	-0.00510
	(0.000922)	(0.000995)	(0.0101)	(0.000929)	(0.00101)	(0.00861)
At least one interd.	0.0397	0.0476	-0.132	0.0385	0.0470	-0.0964**
	(0.0415)	(0.0474)	(0.269)	(0.0416)	(0.0477)	(0.0480)
	Mean	**Mean**	**Mean**	**Max**	**Max**	**Max**
$\overline{Y}$	0.10	0.10	0.10	0.10	0.10	0.10
Observations	2,364	2,364	2,364	2,364	2,364	2,364
R-squared	0.079	0.160	0.450	0.080	0.163	0.451
Call FE	No	Yes	No	No	Yes	No
Year FE	Yes	No	Yes	Yes	No	Yes
Broad Field FE	Yes	No	No	Yes	No	No
Candidate FE	No	No	Yes	No	No	Yes

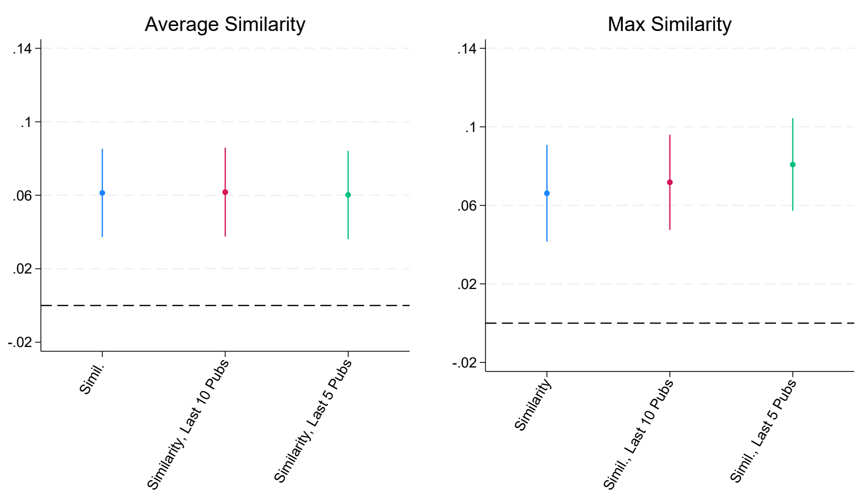
Notes. Dependent variable: Probability of winning a senior assistant professorship in economics. Estimates from a Linear Probability Model. Our controls include a dummy for candidates holding a PhD from abroad and for being currently abroad,number of years from PhD, a dummy for internal candidates and for coauthorship, a dummy for those with at least one Top 6 publication, number of A+ and A publications, number of publications, dummy for those with at least one publication in interdisciplinary journals. Robust standard errors in parentheses. *** 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 probability of winning 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 committee members. 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 in the probability of winning

Alternative measures of similarity



Notes. The figure shows the coefficients 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 selection committee members, only the last 10 most recent publications, and only the last 5 most recent publications). A publication is included if it was published before the date of the call.

As a second robustness check, we test whether our measures of similarity are simply capturing common networks. To investigate this issue, we rerun our regressions including among the controls a dummy equal to 1 if the candidate and one of the committee members have a common coauthor, and equal to 0 otherwise. The results are reported in Table 6, Panel 1, and suggest that, although common networks play an important role in influencing the probability of winning, the result on the effect of the research similarity indicators is robust to the inclusion of this additional control.[12]

In addition, we check the robustness of our results by including dummies for the candidate's main field of research among the controls, as well as a measure of the impact/quality of the candidate's publications, namely, the average number of citations per paper. The results are provided in Table 6, Panel 2 and 3, respectively. The inclusion of these new variables does not affect the results.[13]

We also examine 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 6, Panel 4, reports the results: the coefficients of our similarity dummies are still positive and statistically significant, while the similarity indices computed with respect to department members are not statistically significant, with the exception of column 6.

The results show that being an internal candidate strongly influences the probability of winning the selection. In order to address the concern that this might indicate the existence of some sort of private information received by the internal candidate from the department, we check that the effect of similarity still holds when we focus only on those calls where there were no internal candidates. The results are provided in Table 7, Panel 1. The effect of our similarity measures now appear to be even stronger.

Our results also hold when we restrict our sample to those calls with only male committee members (Table 7, Panel 2) and when we focus on the similarity between the candidate and only the external members of the committee (Table 7, Panel 3).

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

[12]In our dataset, the probability of having a coauthor in common is 8%.

[13]The main field of research of the candidate is identified using the JEL codes of the publications of the candidate and following the same procedure used in Card and DellaVigna (2013). For those publications without a JEL code, we use a topic model to predict the field of the candidate. Specifically, we use a logistic regression as classification algorithm. We do not include the citation variable in the baseline specifications because, although we only consider the articles published in the years prior to selection, the citation count includes all citations received by these publications up to the year in which we downloaded the SCOPUS data, 2023. Due to endogeneity concerns that may arise, we decided to include this control only in a robustness check.

probability.[14] The results are in Table A.6 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 14 to 8.4 percentage points.[15]

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.8 Panel 1 and Panel 2, respectively, and confirm the robustness of our results. Moreover, Figure A.9 and Figure A.10 show, respectively, the predicted probability of winning and the marginal effects estimated using a partially linear model with a restricted cubic spline (R-rsm), which confirm the non linearity of the relationship between our similarity indices and the probability of winning.[16]

We conduct two heterogeneity analyses. First, we examine whether the role played by the similarity between candidates and the selection committee members varies by gender. To address this question, we add an interaction term between the female dummy and the mean/max similarity dummy to the specification in Equation 1. The results of this new specification are included in Table 8 and show that there is no evidence of a differential effect of similarity on winning probability by gender. Similarity increases the probability of winning for both female and male candidates.[17]

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

[15]In Table A.7, we replicate the same analysis for the probability of being present and show that similarity does not play any role this time. We further discuss this point in Section 6.4.

[16]The knots are located at 0.181, 0.218, 0.255 for the regression using mean similarity and at 0.507, 0.582, and 0.658 for that including the maximum similarity dummy. The three points represent the 25th, 50th, and 75th percentiles, respectively. The restricted cubic spline provides flexibility in modelling the relationship between predictors and outcomes, enabling the exploration of nonlinear effects. In comparison to alternative models, the placement of knots, which are points where the curve transitions, is less critical, offering an additional advantage of this type of model.

[17]Note that we do not examine how the effect varies with the proportion of female members on the selection committee, as there is not enough variation in the gender composition of the committee to explore this. As shown in Table 1, women on average represent 31% of the members of the committees (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.

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

Robustness checks I

VARIABLES	(1) Winner	(2) Winner	(3) Winner	(4) Winner	(5) Winner	(6) Winner
Panel 1: Controlling for Common Network						
Dummy Similarity	0.0551***	0.0500***	0.0420***	0.0588***	0.0597***	0.0454***
	(0.0123)	(0.0130)	(0.0159)	(0.0126)	(0.0135)	(0.0147)
Common Network	0.0894***	0.0961***	0.0622**	0.0866***	0.0922***	0.0601*
	(0.0291)	(0.0307)	(0.0313)	(0.0289)	(0.0304)	(0.0312)
	Mean	**Mean**	**Mean**	**Max**	**Max**	**Max**
Observations	2,364	2,364	2,364	2,364	2,364	2,364
R-squared	0.086	0.167	0.452	0.086	0.169	0.453
Panel 2: Controlling for the main field of research of the candidate						
Dummy Similarity	0.0696***	0.0639***		0.0711***	0.0689***	
	(0.0135)	(0.0141)		(0.0131)	(0.0143)	
	Mean	**Mean**		**Max**	**Max**	
Observations	2,102	2,102		2,102	2,102	
R-squared	0.073	0.168		0.073	0.169	
Panel 3: Controlling for citations						
Dummy Similarity	0.0616***	0.0564***	0.0466***	0.0662***	0.0665***	0.0500***
	(0.0123)	(0.0130)	(0.0144)	(0.0126)	(0.0135)	(0.0145)
Average Citations	0.000188	0.000294	-0.000203	1.74e-05	0.000136	-0.000265
	(0.000431)	(0.000443)	(0.00172)	(0.000435)	(0.000443)	(0.00182)
Female	-0.0116	-0.00671		-0.00821	-0.00240	
	(0.0130)	(0.0136)		(0.0130)	(0.0136)	
	Mean	**Mean**	**Mean**	**Max**	**Max**	**Max**
Observations	2,364	2,364	2,364	2,364	2,364	2,364
R-squared	0.079	0.160	0.450	0.080	0.163	0.451
Panel 4: Controlling for similarity with the department						
Dummy Similarity	0.0593***	0.0577***	0.0439***	0.0620***	0.0578***	0.0508***
	(0.0137)	(0.0146)	(0.0160)	(0.0126)	(0.0135)	(0.0147)
Dummy Similarity Depart.	-0.00472	-0.0124	0.00159	0.00770	0.0221	-0.0288**
	(0.0138)	(0.0152)	(0.0181)	(0.0124)	(0.0146)	(0.0140)
Observations	2,340	2,340	2,340	2,340	2,340	2,340
R-squared	0.060	0.141	0.442	0.063	0.146	0.444
	Mean	**Mean**	**Mean**	**Max**	**Max**	**Max**
$\overline{Y}$	0.10	0.10	0.10	0.10	0.10	0.10
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Call FE	No	Yes	No	No	Yes	No
Year FE	Yes	No	Yes	Yes	No	Yes
Broad Field FE	Yes	No	No	Yes	No	No
Candidate FE	No	No	Yes	No	No	Yes

Notes. Dependent variable: Probability of winning a senior assistant professorship in economics. Estimates from a Linear Probability Model. *Common network* is equal to 1 if the candidate and a member of the committee have a common coauthor. *Citations* measures the average number of citation per publication of the candidate up to 2023. *Field* indicates the main field of research of the candidate. *DummySimDepart* measures the similarity between the candidate and the economics faculty of the department opening the call. In all panels our controls include a dummy for candidates holding a PhD from abroad and for being currently abroad, average number of years from PhD, a dummy for internal candidates and for coauthorship, a dummy for those with at least one Top 6 publication, number of A+ and A publications, number of publications, share of those with at least one publication in interdisciplinary journals. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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

Robustness checks II

VARIABLES	(1) Winner	(2) Winner	(3) Winner	(4) Winner	(5) Winner	(6) Winner
Panel 1: Only calls with no internal candidates						
Dummy Similarity	0.0821***	0.0772***	0.0749***	0.0827***	0.0903***	0.0627***
	(0.0180)	(0.0194)	(0.0223)	(0.0179)	(0.0190)	(0.0222)
	Mean	**Mean**	**Mean**	**Max**	**Max**	**Max**
Observations	1,302	1,302	1,302	1,302	1,302	1,302
R-squared	0.041	0.127	0.515	0.041	0.132	0.514
Panel 2: Only calls with no female members in the committee						
Dummy Similarity	0.0566**	0.0532**	0.0274	0.0657**	0.0736***	0.0674*
	(0.0252)	(0.0271)	(0.0313)	(0.0256)	(0.0277)	(0.0364)
	Mean	**Mean**	**Mean**	**Max**	**Max**	**Max**
Observations	583	583	583	583	583	583
R-squared	0.091	0.147	0.730	0.094	0.152	0.735
Panel 3: Similarity only with external committee members						
Dummy Similarity	0.0523***	0.0467***	0.0411***	0.0641***	0.0616***	0.0519***
	(0.0124)	(0.0131)	(0.0145)	(0.0131)	(0.0145)	(0.0151)
	Mean	**Mean**	**Mean**	**Max**	**Max**	**Max**
Observations	2,298	2,298	2,298	2,298	2,298	2,298
R-squared	0.078	0.160	0.456	0.081	0.163	0.458
$\overline{Y}$	0.10	0.10	0.10	0.10	0.10	0.10
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Call FE	No	Yes	No	No	Yes	No
Year FE	Yes	No	Yes	Yes	No	Yes
Broad Field FE	Yes	No	No	Yes	No	No
Candidate FE	No	No	Yes	No	No	Yes

Notes. Dependent variable: Probability of winning a senior assistant professorship in economics. Estimates from a Linear Probability Model. In all panels our controls include a dummy for candidates holding a PhD from abroad and for being currently abroad, number of years from PhD, a dummy for internal candidates and for coauthorship, a dummy for those with at least one Top 6 publication, number of A+ and A publications, number of publications, dummy for those with at least one publication in interdisciplinary journals. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

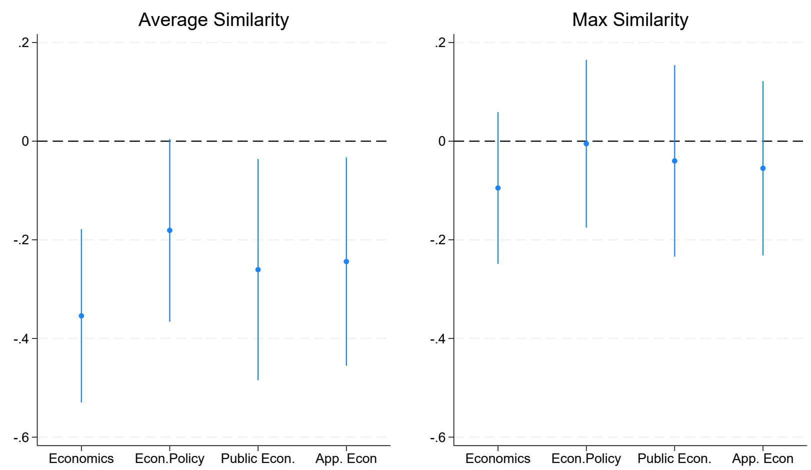
Table 8: The role of similarity in the probability of winning, LPM

Heterogeneity by candidate gender

VARIABLES	(1) Winner	(2) Winner	(3) Winner	(4) Winner	(5) Winner	(6) Winner
Dummy Similarity	0.0656***	0.0594***	0.0518***	0.0619***	0.0568***	0.0475***
	(0.0154)	(0.0157)	(0.0186)	(0.0157)	(0.0163)	(0.0174)
Dummy Similarity*Female	-0.0124	-0.0101	-0.0151	0.0176	0.0282	0.00739
	(0.0251)	(0.0266)	(0.0340)	(0.0265)	(0.0275)	(0.0311)
Female	-0.00789	-0.000205	0.0116	-0.0186	-0.0136	0.0153
	(0.0159)	(0.0169)	(0.0187)	(0.0139)	(0.0151)	(0.0185)
	Mean	**Mean**	**Mean**	**Max**	**Max**	**Max**
$\overline{Y}$	0.10	0.10	0.10	0.10	0.10	0.10
Observations	2,364	2,364	2,364	2,364	2,364	2,364
R-squared	0.079	0.160	0.450	0.078	0.163	0.451
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Call FE	No	Yes	No	No	Yes	No
Year FE	Yes	No	Yes	Yes	No	Yes
Broad Field FE	Yes	No	No	Yes	No	No
Candidate FE	No	No	Yes	No	No	Yes

Notes. Dependent variables: Probability of winning a senior assistant professorship in economics. Estimates from a Linear Probability Model. In all panels our controls include a dummy for candidates holding a PhD from abroad and for being currently abroad, number of years from PhD, a dummy for internal candidates and for coauthorship, a dummy for those with at least one Top 6 publication, number of A+ and A publications, number of publications, dummy for those with at least one publication in interdisciplinary journals. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1 *** p<0.01, ** p<0.05, * p<0.1

Figure 2: The role of similarity in the probability of winning by broad field of the call



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

Last, we investigate whether the effect varies by broad fields (Economics, Economic Policy, Public Economics, Applied Economics, Econometrics). We include in Equation 1 interaction terms between the mean and max similarity dummies, respectively, and broad-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 probability of winning.

6.2 Gender differences in research similarity

We now discuss the results of the estimation of Equation 2, to see whether female and male candidates differ in terms of mean and maximum similarity to the selection committee. The results are reported in Table 9. Columns 1-3 use as dependent variable the dummy for the mean similarity to the selection committee, while columns 4-6 the dummy for the maximum similarity to the selection committee. Columns 2 and 5 include year and broad field fixed effects, while columns 3 and 6 include call fixed effects.

Table 9: Gender differences in similarity, LPM

	Mean	Mean	Mean	Max	Max	Max
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.00196	-0.000957	0.0317	-0.0494**	-0.0543***	-0.0373*
	(0.0215)	(0.0211)	(0.0214)	(0.0210)	(0.0207)	(0.0214)
PhD Abroad	-0.0331	-0.0169	-0.0149	-2.45e-05	0.000381	0.00443
	(0.0257)	(0.0255)	(0.0265)	(0.0254)	(0.0253)	(0.0261)
Abroad	0.0279	0.0369	0.0736***	-0.0690***	-0.0651***	-0.0465*
	(0.0238)	(0.0235)	(0.0256)	(0.0231)	(0.0227)	(0.0242)
Years from PhD	0.00418	0.00623*	0.00662**	0.00351	0.00426	0.00302
	(0.00336)	(0.00337)	(0.00334)	(0.00341)	(0.00334)	(0.00337)
Internal Cand.	0.0672	0.0536	0.0635	0.00931	-0.000695	0.0190
	(0.0426)	(0.0418)	(0.0429)	(0.0410)	(0.0403)	(0.0404)
Coauthor	0.359***	0.335***	0.325***	0.530***	0.505***	0.517***
	(0.0431)	(0.0417)	(0.0464)	(0.0189)	(0.0244)	(0.0348)
At least one Top 6	-0.0161	0.00306	-0.0340	-0.0881	-0.0591	0.00597
	(0.0974)	(0.0977)	(0.0872)	(0.0908)	(0.0890)	(0.0863)
N pubs in A+	0.0208	0.0312	0.0450**	0.0219	0.0329*	0.0325
	(0.0198)	(0.0197)	(0.0201)	(0.0191)	(0.0188)	(0.0205)
N pubs in A	0.0167***	0.0196***	0.0215***	0.0243***	0.0276***	0.0284***
	(0.00370)	(0.00366)	(0.00382)	(0.00383)	(0.00371)	(0.00397)
N pubs	-0.0137***	-0.0154***	-0.0167***	-0.00241	-0.00496**	-0.00553**
	(0.00159)	(0.00163)	(0.00183)	(0.00211)	(0.00199)	(0.00220)
At least one interd.	-0.0721	-0.0506	-0.0359	-0.0573	-0.0274	-0.0206
	(0.0667)	(0.0647)	(0.0650)	(0.0642)	(0.0647)	(0.0641)
Observations	2,364	2,364	2,364	2,364	2,364	2,364
R-squared	0.035	0.078	0.226	0.074	0.115	0.236
$\overline{Y}$	0.5	0.5	0.5	0.5	0.5	0.5
Observations	2,364	2,364	2,364	2,364	2,364	2,364
R-squared	0.035	0.078	0.226	0.074	0.115	0.236
Call FE	No	No	Yes	No	No	Yes
Year FE	No	Yes	No	No	Yes	No
Broad Field FE	No	Yes	No	No	Yes	No

Notes. Dependent variables: Mean/Maximum Similarity between the Candidate and Members of the committee. Estimates from a Linear Probability Model. Our controls include a dummy for candidates holding a PhD from abroad and for being currently abroad, number of years from PhD, a dummy for internal candidates and for coauthorship, a dummy for those with at least one Top 6 publication, number of A+ and A publications, number of publications, dummy for those with at least one publication in interdisciplinary journals. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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 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 candidates to be very similar to a selection committee member. The probability that the dummy variable based on the maximum similarity is equal to 1 is 5 percentage points or 10% larger for male candidates than for female candidates. When looking at the other controls, being abroad relates negatively to maximum similarity, indicating that candidates applying from abroad are less close in terms of research to selection committee members, in most cases based in Italian universities.

We now examine if the gender composition of the selection committee matters for the gender gap in maximum similarity we have shown. We estimate again equation 2, focusing first only on the female members, and then only on the male members of the committees. The results are provided in Table 10. Interestingly, we find that the gender gap in the maximum similarity disappears when we look only at female committee members (Table 10, Panel 1), while it is even larger when we focus only on male members (Table 10, Panel 2). This supports the hypothesis that female candidates are less likely to be very similar to one of the committee members because selection committees are predominantly composed of men.

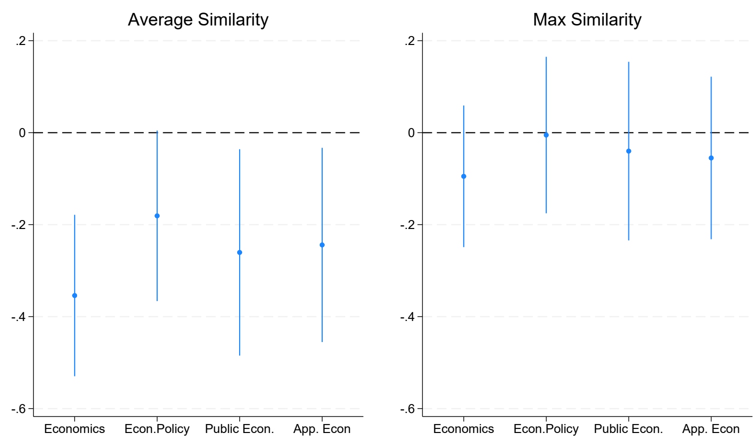
Finally, we explore whether the gender gap in similarity varies across broad fields. As before, we add to Equation 2 an interaction term between the female dummy and the broad-field dummies. The results, reported in Figure 3, show that, while the gender gap in maximum similarity does not vary by macro-field, 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 fields of economics and public economics.

Table 10: 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	-0.00828	-0.00143	0.0272	-0.0162	-0.0185	-0.00734
	(0.0248)	(0.0244)	(0.0244)	(0.0242)	(0.0241)	(0.0244)
Observations	1,781	1,781	1,781	1,781	1,781	1,781
R-squared	0.030	0.075	0.232	0.056	0.098	0.259
Panel 2: With male members of the committees only						
Female	-0.0354	-0.0370*	-0.0165	-0.0471**	-0.0447**	-0.0216
	(0.0218)	(0.0214)	(0.0219)	(0.0214)	(0.0211)	(0.0210)
Observations	2,327	2,327	2,327	2,327	2,327	2,327
R-squared	0.031	0.070	0.205	0.052	0.087	0.267
$\overline{Y}$	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
Broad Field FE	No	Yes	No	No	Yes	No

Notes. Dependent variables: Mean/Maximum Similarity between the candidate and female/male members of the selection committees. Our controls include a dummy for candidates holding a PhD from abroad and for being currently abroad, number of years from PhD, a dummy for internal candidates and for coauthorship, a dummy for those with at least one Top 6 publication, number of A+ and A publications, number of publications, dummy for those with at least one publication in interdisciplinary journals. Robust Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Figure 3: Gender differences in similarity by broad fields



Notes. The figure shows the coefficients of the interaction terms between the female dummy and the dummies for broad fields of the call (Equation 2). Econometrics is the omitted

6.3 Research similarity and the gender gap in the probability of winning

Having shown that there is a gender gap in (maximum) research similarity, we explore its role in explaining the presence of women in academia. To do this, we replicate the analysis in Table 4, which includes the probability of attending the interview in the controls, and add the mean or maximum similarity dummy to the regression. In other words, we add to equation 1 the estimate of a candidate's probability of attending the interview and explore the role of research similarity in the probability of winning.

The results are shown in Table 11 and confirm that research similarity is positively and significantly related to the probability of winning, both when we use the mean and the maximum similarity dummy and in all specifications considered. When we control for the probability of attending the interview, we observe that the coefficient of the female dummy is negative and significant in all specifications, implying a gender gap in the probability of winning. Interestingly, the gender gap in the probability of winning is smaller in magnitude compared to Table 4, especially in columns 4 and 5, where we use the maximum similarity dummy.[18] This is consistent

[18]The coefficients of the female dummy are statistically different in columns 4-5 of Table 11 from

with the result that there are gender differences in research similarity only when the latter is measured by the maximum similarity with the committee members. According to these results, the inclusion of the maximum similarity dummy explains 6-7% of the gender gap reported in Table 4.

those in columns 1-2 of Table 4. There are no statistically significant differences when we use mean similarity, instead.

Table 11: The role of research similarity in the probability of winning, LPM

Controlling for the probability of taking part to the interview

VARIABLES	(1) Winner	(2) Winner	(3) Winner	(4) Winner	(5) Winner	(6) Winner
Dummy Similarity	0.0567***	0.0506***	0.0467***	0.0629***	0.0636***	0.0504***
	(0.0121)	(0.0128)	(0.0145)	(0.0124)	(0.0134)	(0.0145)
Female	-0.0748***	-0.0674***		-0.0722***	-0.0643***	
	(0.0164)	(0.0171)		(0.0164)	(0.0171)	
Pr (Present)	0.982***	1.003***	0.00668	0.993***	1.016***	0.0353
	(0.146)	(0.158)	(0.139)	(0.146)	(0.157)	(0.128)
PhD Abroad	0.0144	0.0122		0.0133	0.0110	
	(0.0163)	(0.0172)		(0.0163)	(0.0171)	
Abroad	-0.0756***	-0.0490***	0.0114	-0.0700***	-0.0431**	0.0137
	(0.0157)	(0.0172)	(0.0207)	(0.0157)	(0.0171)	(0.0196)
Years from PhD	-0.00541**	-0.00719***	0.0704	-0.00540**	-0.00714***	0.0885
	(0.00230)	(0.00229)	(0.101)	(0.00231)	(0.00228)	(0.0788)
Internal Cand.	0.0137	0.0152	0.0958**	0.0149	0.0149	0.0980**
	(0.0440)	(0.0443)	(0.0380)	(0.0438)	(0.0442)	(0.0452)
Coauthor	0.0724	0.0589	0.152***	0.0580	0.0404	0.137**
	(0.0616)	(0.0632)	(0.0485)	(0.0627)	(0.0639)	(0.0671)
At least one Top 6	-0.0454	-0.0728	-0.0703	-0.0424	-0.0761	-0.0711*
	(0.0680)	(0.0767)	(0.316)	(0.0681)	(0.0774)	(0.0369)
N pubs in A+	0.0558***	0.0639***	0.123**	0.0558***	0.0644***	0.124**
	(0.0155)	(0.0154)	(0.0496)	(0.0152)	(0.0153)	(0.0622)
N pubs in A	0.0260***	0.0268***	0.0138	0.0256***	0.0263***	0.0122
	(0.00336)	(0.00356)	(0.0134)	(0.00337)	(0.00359)	(0.0123)
N pubs	-0.00620***	-0.00670***	-0.00509	-0.00680***	-0.00724***	-0.00515
	(0.00110)	(0.00120)	(0.0101)	(0.00111)	(0.00122)	(0.00860)
At least one interd.	-0.0199	-0.0115	-0.133	-0.0217	-0.0128	-0.101*
	(0.0421)	(0.0474)	(0.270)	(0.0422)	(0.0477)	(0.0524)
	Mean	**Mean**	**Mean**	**Max**	**Max**	**Max**
$\overline{Y}$	0.10	0.10	0.10	0.10	0.10	0.10
Observations	2,364	2,364	2,364	2,364	2,364	2,364
R-squared	0.092	0.172	0.450	0.094	0.175	0.451
Call FE	No	Yes	No	No	Yes	No
Year FE	Yes	No	Yes	Yes	No	Yes
Broad Field FE	Yes	No	No	Yes	No	No
Candidate FE	No	No	Yes	No	No	Yes

Notes. Dependent variable: Probability of winning a senior assistant professorship. Estimates from a Linear Probability Model. Our controls include a dummy for candidates holding a PhD from abroad and for being currently abroad, number of years from PhD, a dummy for internal candidates and for coauthorship, a dummy for those with at least one Top 6 publication, number of A+ and A publications, number of publications, dummy for those with at least one publication in interdisciplinary journals. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

6.4 Discussion

We have interpreted the premium that research similarity grants to candidates in the selection process as evidence that senior academics/evaluators rate junior researchers with research agendas similar to their own more positively. 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.

It can be argued that selection committee members do not choose the winning candidate according to their own preferences, which may be influenced by self-image bias, but rather act on input from departments that want to hire junior researchers with specific research characteristics and identify members of selection committees with this 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 (Table 7). In addition, similarity to the department has no positive effect on the probability of winning, when we control for similarity with the selection committee (Table 6). We also observe a high level of correlation in the similarity indices between the candidate and each member of the committee: this suggests that selection committees are homogeneous groups in terms of research interests. On the one hand, this may indicate that departments have a particular research profile in mind. On the other hand, homogeneous research characteristics in the selection committee may signal that departments expect them to act according to a self-image bias and favour a candidate similar to themselves rather than the most qualified one. For example, the evidence in Table 6 suggests that, in many specifications, similarity plays a stronger role in influencing the probability of winning than high ranked publications. We also point out that similarity plays an important role even *within* fields of research.[19]

It may also be that our results are not explained by self-image bias, but rather by a comparative advantage that committee members have in judging candidates more similar to themselves. For example, they may be better at inferring the impact of the candidate's work. However, we find no evidence that committee members with higher similarity scores are better judges of future research impact: the positive influence of similarity is also present when we control for the citations of the candidate's

[19]As discussed in Section 6.1.1, in Table 6 we show that our results are robust to the inclusion of the main field of research of the candidate among the controls. The dummies for the broad fields of the calls, are instead already included in the baseline specification.

publications (see Section 6.1.1 and Table 6). Moreover, if we test whether winning candidates with a higher similarity index are more productive after promotion, we do not find evidence confirming this hypothesis. The results are reported in Table A.9. As proxy of quality we use the publication record (i.e., average number of citations per publication, a dummy for A+ publications and a dummy for Top 6 publications) starting from the year after the call. In Panel 1, we focus only on winning candidates and look simply at the relationship between mean (or max) similarity of the winning candidate with the selection committee and their publication record after becoming senior assistant professors. In Panel 2, we extend the analysis to the entire sample of candidates and interact the dummy for the winning candidate with the variable measuring the similarity index of the winner applied to all candidates participating to the call. We find no evidence that higher similarity is associated with hiring of higher quality. Winning candidates with higher similarity index are not more productive after promotion compared to other winning candidates with a lower index. Moreover, the difference in post-productivity between the winning candidate and the other candidates participating to the same call is not larger in calls where the winning candidate has a higher similarity index.

An alternative explanation for our findings may be that candidates choose to participate in calls where they see that selection committee members have an agenda similar to their own. 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.7 indicates that similarity does not influence the decision to participate to the interview, when shortlisted.

Finally, there may be a concern that our similarity measures capture closeness in language rather than in research characteristics. Although we cannot fully exclude that language may play a role, we note that more than 90% of our sample of candidates is made up of non-native English speakers. Therefore, the variation in our index cannot be driven by language differences between native and non-native English speakers. In addition, we focus on the abstracts of scientific publications (within fields), where differences in language use across genders are likely to be more limited. Finally, when we look at the distribution of our similarity indices by field, we do not find that such distributions in a field like econometrics, where the language is likely to be more standardised, differ from the distributions in other fields (see Figure A.7, where we distinguish by broad field of the call or Figure A.8, where we distinguish by research field of the candidate).

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. Since female candidates are less likely to be very similar to male members of selection committees, and since men make up a higher proportion of selection committee members, self-image bias explains part of the gender gap in economics.

7 Conclusions

There is extensive evidence of the (economic) benefits of a diverse and inclusive workforce. While measuring the benefits of diversity in the academic market can be challenging, studies show that it does impact on scholars' performance in measurable ways, such as citation counts (Powell, 2018). Diversity also enriches the scientific process by bringing in a wider range of perspectives and research questions. Promoting diversity in academia is therefore not only a matter of fairness, but also 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 the narrowing of research agendas. We propose a novel and granular measure of similarity that captures not only research areas, but also broader characteristics of research agendas, starting from the abstracts of the papers. This new measure of similarity has the potential to capture the diversity of knowledge production better than fields of research, and to reveal research directions over time and space more accurately. We use it to investigate whether the similarity between selection committee members and candidates for senior assistant professorships is related 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, offering an explanation for the gender gap in the probability of becoming a senior assistant professor.

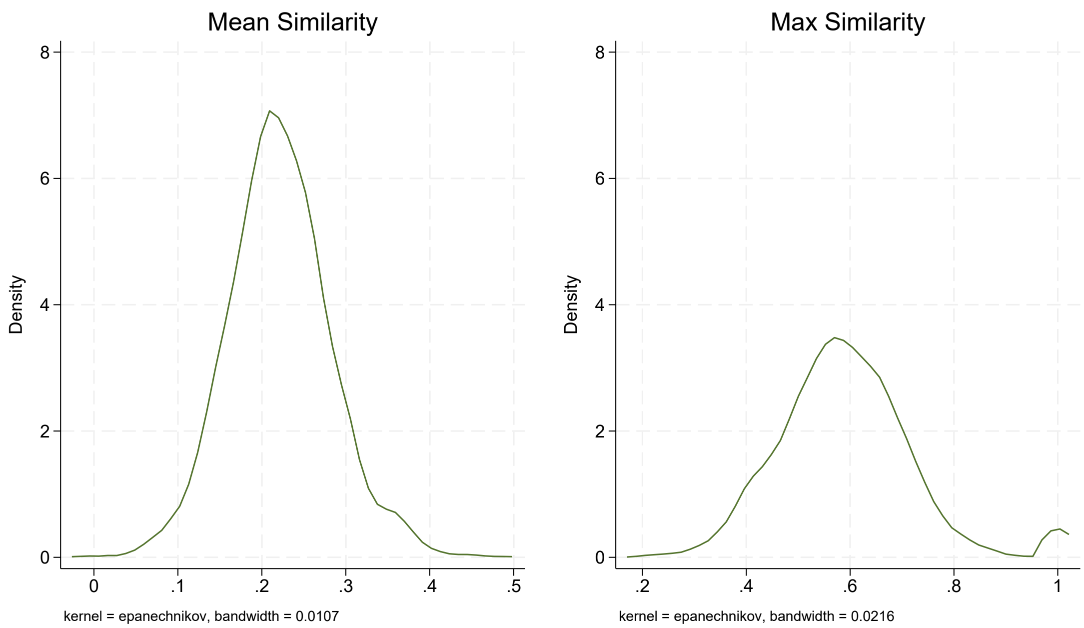
In order to answer the research questions, we use data on the Italian academic job market, and collect the publications of the universe of candidates, members of recruitment committees and of faculty of departments opening calls for the period 2014-2021. By applying NLP techniques, we calculate an index of similarity between the publications of the committee members and those of the candidates, and show that candidates with a mean or maximum similarity larger than the median are between 4.7 and 6.6 percentage points more likely to win the competition for senior assistant professorships. The role of research similarity in explaining the probability of winning is robust to a number of checks. We also find that women are, on average, less likely to be very similar to one of the committee members. This gender gap in maximum similarity is driven by male committee members, while it disappears when we focus only on female members, and it may help explain the gender gap in the probability of winning that we observe once when control for selection into the interview.

The evidence presented suggests that in male-dominated contexts, similarity bias and the search for "fit" can hinder the career progression of female academics. Note that addressing similarity bias and promoting gender diversity in academia would not imply narrowing the topics researched in a department. The distribution of our similarity indices between candidates by gender suggests that the range of topics is the same for female and male candidates (Figure A.6). Thus, addressing self-image bias may, on the contrary, help to mitigate the tendency to conform to a standardised research profile, as has been observed in economics departments in recent years (Corsi et al., 2019).

On the policy side, the identification of this source of bias provides additional justification for the implementation of affirmative action measures that deliberately increase the representation of minorities in the profession and, consequently, on selection committees. It also highlights the importance of establishing transparent and objective criteria in the evaluation process, while ensuring a degree of diversity in research interests among committee members. Failure to address self-image bias carries a significant risk of perpetuating the 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 mean similarity and maximum similarity between candidates and members of selection committees.

Figure A.2: Examples of abstracts with high and low similarity

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.

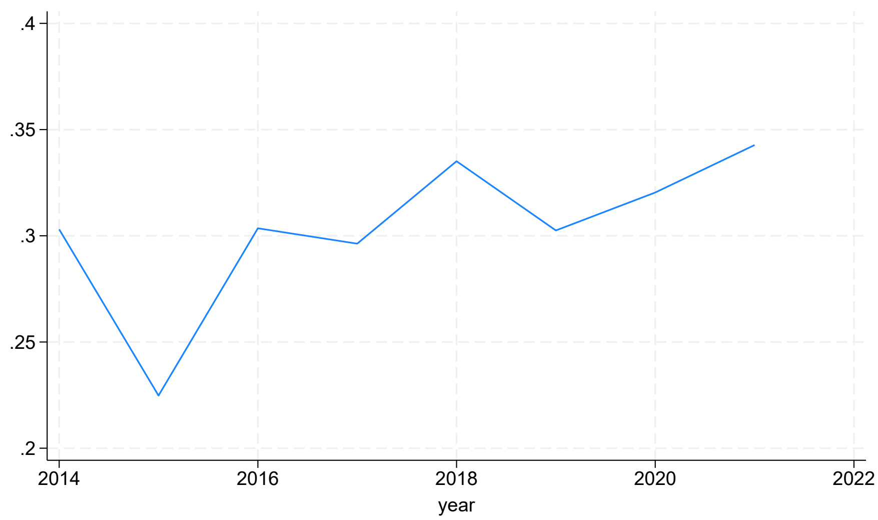
Abstract 2: We develop a model explaining how criminal organizations strategically use pre-electoral violence as a way of influencing electoral results and politicians' behaviour. We then characterize the incentives to use such violence under different levels of electoral competition and different electoral 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.

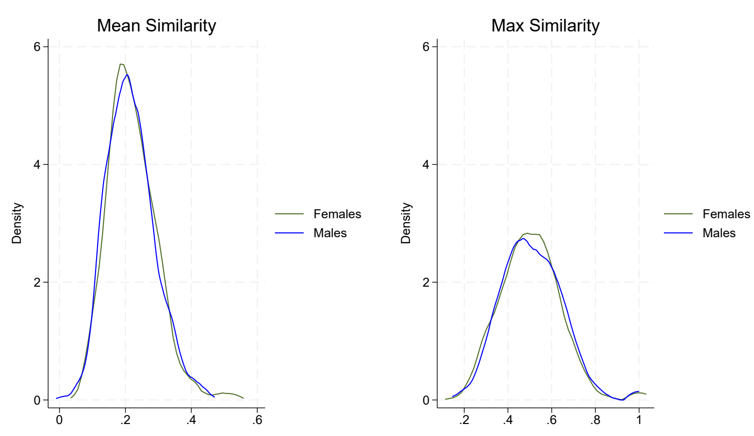
Figure A.3: Share of women in selection committees



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

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

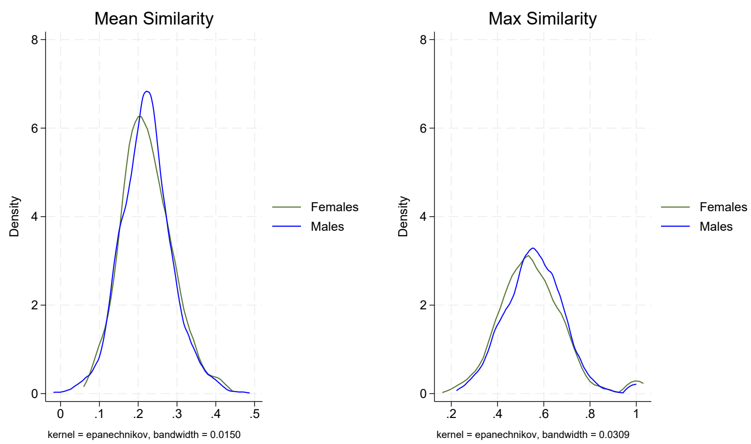
By candidate gender, female members of selection committees only



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

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

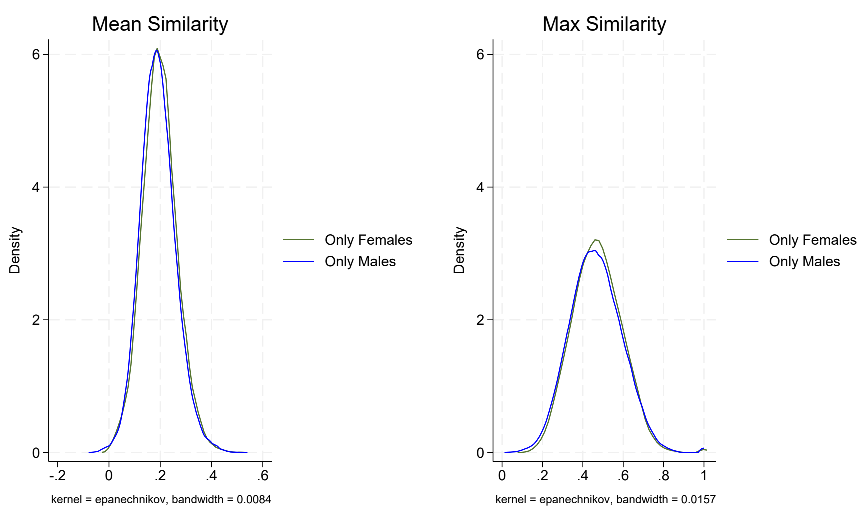
By candidate gender, male members of selection committees only



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

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

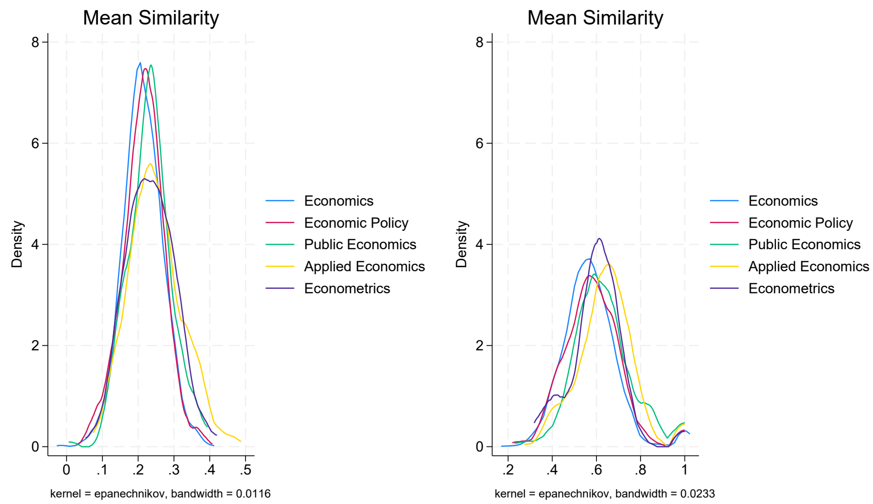
By gender



Notes. The figure shows the distribution of mean similarity and maximum similarity between candidates by gender

Figure A.7: Similarity distributions (Mean and Max)

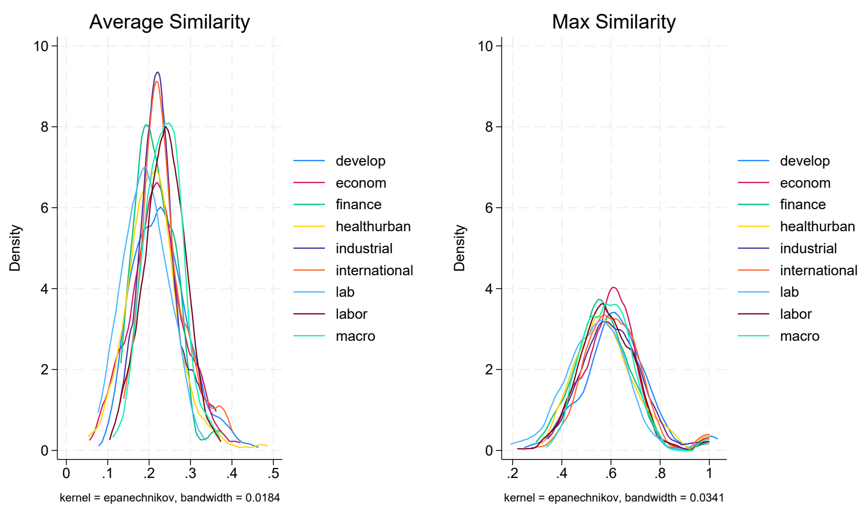
By broad field of the call



Notes. The figure shows the distribution of mean similarity and maximum similarity between candidates and members of selection committees, by broad field of the call

Figure A.8: Similarity distributions (Mean and Max)

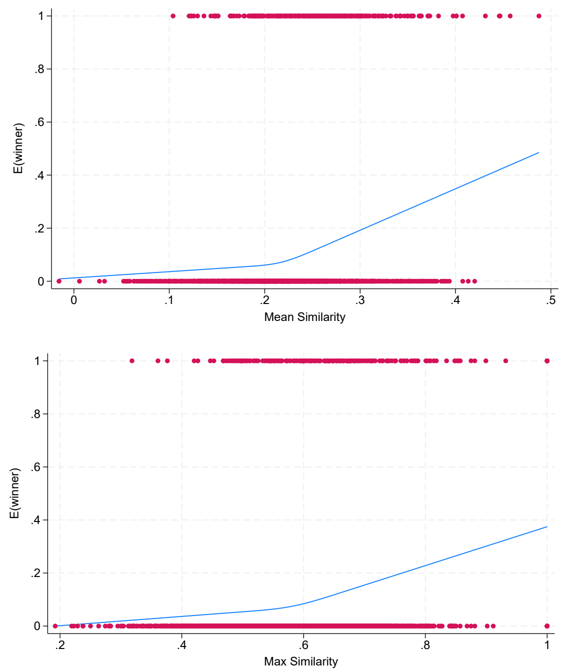
By main sub-field of the candidate



Notes. The figure shows the distribution of mean similarity and maximum similarity between candidates and members of selection committees, by main sub-field of the candidate

Figure A.9: Predicted probability of winning

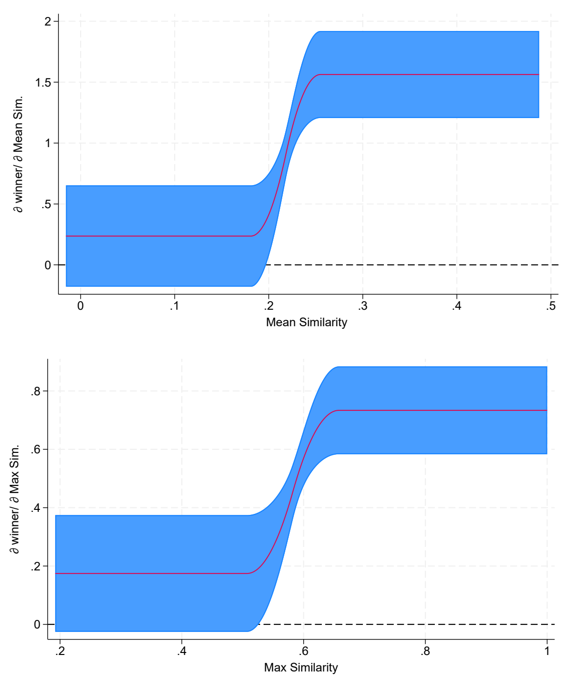
Estimates from a restricted cubic spline model



Notes. The figures show the predicted probability of winning for each value of the mean similarity index /max similarity index.

Figure A.10: Marginal Effects

Estimates from a restricted cubic spline model



Notes. The figures show the marginal effects for each value of the mean similarity index/max similarity index.

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 shows summary statistics for candidates for junior assistant professorships for the following variables: share of women, probability of winning, share of candidates with a PhD abroad or currently abroad, average number of years from PhD. It also reports the average number of candidates per call and 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
N pubs	4.62	4.71	-0.29	-0.09	0.77
At least one 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: probability of winning, share of candidates with a PhD abroad or currently abroad, average number of years from PhD, share of candidates with at least one Top 6 publication, average number of A+ and A publications, average number of publications, 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: Probability of winning

Calls for Junior Assistant Professorships

VARIABLES	(1) Winner	(2) Winner	(3) Winner
Female	-0.0542**	-0.0578**	-0.0692***
	(0.0239)	(0.0242)	(0.0262)
PhD Abroad	-0.0276	-0.0270	-0.0467
	(0.0292)	(0.0295)	(0.0317)
Abroad	-0.0709***	-0.0664**	-0.0570*
	(0.0270)	(0.0271)	(0.0313)
Years from PhD	0.00377	0.00371	0.00151
	(0.00434)	(0.00448)	(0.00517)
At least one Top 6	-0.116**	-0.143	-0.239
	(0.0561)	(0.128)	(0.202)
N pubs in A+	0.0140	0.0170	0.0489
	(0.0470)	(0.0475)	(0.0493)
N pubs in A	0.00673	0.00673	0.00461
	(0.0100)	(0.0101)	(0.0113)
N pubs	0.00256	0.00159	0.00331
	(0.00359)	(0.00363)	(0.00380)
At least one interd.	0.0957	0.139	0.0863
	(0.118)	(0.117)	(0.131)
$\overline{Y}$	0.163	0.163	0.163
Observations	971	971	971
R-squared	0.018	0.041	0.221
Call FE	No	No	Yes
Year FE	No	Yes	No
Broad Field FE	No	Yes	No

Notes. Dependent variable: Probability of winning a junior assistant professorship in economics. Estimates from a Linear Probability Model. Our controls include a dummy for candidates holding a PhD from abroad and for being currently abroad, number of years from PhD, a dummy for internal candidates and for coauthorship, a dummy for those with at least one Top 6 publication, number of A+ and A publications, number of publications, dummy for those with at least one publication in interdisciplinary journals. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.4: 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	5,33	5,49	-0,75	-0,16	0,45
Appl. in NI and in SI	0,01	0,01	0,70	0,00	0,48
Appl. NI and in CI	0,04	0,03	1,51	0,01	0,13
Appl. SI and in CI	0,05	0,04	1,72	0,02	**0,09**

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 Italy 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.

Table A.5: Gender gaps in outcomes

Calls for senior assistant professorships

VARIABLES	(1) Winner	(2) Shortlisted	(3) Present
Female	-0.0143	-0.0296	0.0566*
	(0.0129)	(0.0207)	(0.0294)
PhD Abroad	0.0252	0.0424*	0.0126
	(0.0165)	(0.0251)	(0.0353)
Abroad	-0.0166	-0.0990***	0.0599*
	(0.0135)	(0.0230)	(0.0352)
Years from PhD	0.00171	-0.000882	0.00698
	(0.00202)	(0.00334)	(0.00513)
Internal Cand.	0.183***	0.187***	0.171***
	(0.0378)	(0.0381)	(0.0479)
Coauthor	0.240***	0.194***	0.152***
	(0.0574)	(0.0498)	(0.0582)
At least one Top 6	0.0369	0.0386	0.0852
	(0.0667)	(0.102)	(0.109)
N pubs in A+	0.0353**	0.119***	-0.0234
	(0.0150)	(0.0183)	(0.0243)
N pubs in A	0.0125***	0.0396***	-0.0142**
	(0.00227)	(0.00364)	(0.00586)
N pubs	-0.00360***	-0.00894***	0.00305
	(0.000934)	(0.00188)	(0.00361)
At least one interd.	0.0366	0.00573	0.0638
	(0.0417)	(0.0618)	(0.0943)
$\overline{Y}$	0.10	0.50	0.60
Observations	2,364	2,364	1,195
R-squared	0.069	0.127	0.066
Call FE	No	No	No
Year FE	Yes	Yes	Yes
Broad Field FE	Yes	Yes	Yes

Notes. 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 if shortlisted. Estimates from a Linear Probability Model. Our controls include a dummy for candidates holding a PhD from abroad and for being currently abroad, number of years from PhD, a dummy for internal candidates and for coauthorship, a dummy for those with at least one Top 6 publication, number of A+ and A publications, number of publications, dummy for those with at least one publication in interdisciplinary journals. *** p<0.01, ** p<0.05, * p<0.1

Table A.6: The role of research similarity in the probability of being shortlisted

VARIABLES	(1) Shortlisted	(2) Shortlisted	(3) Shortlisted	(4) Shortlisted	(5) Shortlisted	(6) Shortlisted
Dummy Simil.	0.145***	0.0843***	0.125***	0.126***	0.0957***	0.0910***
	(0.0203)	(0.0198)	(0.0252)	(0.0212)	(0.0199)	(0.0262)
Female	-0.0354*	-0.00742		-0.0287	-0.00138	
	(0.0207)	(0.0194)		(0.0208)	(0.0194)	
PhD Abroad	0.0487*	0.0469**		0.0455*	0.0447*	
	(0.0252)	(0.0237)		(0.0253)	(0.0236)	
Abroad	-0.111***	-0.0127	-0.0473	-0.0968***	-0.00170	-0.0402
	(0.0230)	(0.0228)	(0.0342)	(0.0231)	(0.0227)	(0.0373)
Years from PhD	-0.00182	-0.00694**	-0.317*	-0.00143	-0.00668**	-0.274***
	(0.00330)	(0.00294)	(0.174)	(0.00337)	(0.00294)	(0.104)
Internal Cand.	0.170***	0.181***	0.113**	0.178***	0.184***	0.128**
	(0.0380)	(0.0408)	(0.0548)	(0.0373)	(0.0404)	(0.0565)
Coauthor	0.134***	0.0825	0.0830	0.119**	0.0603	0.0795
	(0.0494)	(0.0538)	(0.0763)	(0.0503)	(0.0543)	(0.0763)
At least one Top 6	0.0710	0.0106		0.0876	0.0126	
	(0.103)	(0.106)		(0.103)	(0.107)	
N pubs in A+	0.116***	0.160***	0.0204	0.116***	0.160***	0.0200
	(0.0189)	(0.0201)	(0.0862)	(0.0188)	(0.0199)	(0.102)
N pubs in A	0.0363***	0.0358***	0.0575**	0.0358***	0.0349***	0.0535**
	(0.00368)	(0.00336)	(0.0230)	(0.00372)	(0.00337)	(0.0218)
N pubs	-0.00659***	-0.00835***	-0.0229	-0.00817***	-0.00920***	-0.0229
	(0.00195)	(0.00155)	(0.0175)	(0.00190)	(0.00150)	(0.0146)
At least one interd.	0.0185	0.0697	0.448	0.0130	0.0677	0.513***
	(0.0613)	(0.0577)	(0.464)	(0.0623)	(0.0582)	(0.156)
	Mean	**Mean**	**Mean**	**Max**	**Max**	**Max**
$\overline{Y}$	0.499	0.499	0.499	0.499	0.499	0.499
Observations	2,308	2,308	2,308	2,308	2,308	2,308
R-squared	0.148	0.418	0.410	0.142	0.420	0.407
Call FE	No	Yes	No	No	Yes	No
Year FE	Yes	No	Yes	Yes	No	Yes
Broad Field FE	Yes	No	No	Yes	No	No
Candidate FE	No	No	Yes	No	No	Yes

Notes. Dependent variable: Probability of being shortlisted for senior assistant professorships in economics. Estimates from a Linear Probability Model. Our controls include a dummy for candidates holding a PhD from abroad and for being currently abroad, number of years from PhD, a dummy for internal candidates and for coauthorship, a dummy for those with at least one Top 6 publication, number of A+ and A publications, number of publications, dummy for those with at least one publication in interdisciplinary journals. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.7: The role of research similarity in the probability of attending the interview

VARIABLES	(1) Present	(2) Present	(3) Present	(4) Present	(5) Present	(6) Present
Dummy Similarity	-0.0470	-0.0398	-0.0383	-0.00740	-0.0249	-0.0149
	(0.0301)	(0.0338)	(0.0450)	(0.0307)	(0.0334)	(0.0434)
Female	0.0531*	0.0593*		0.0546*	0.0581*	
	(0.0299)	(0.0316)		(0.0300)	(0.0317)	
PhD Abroad	0.0224	0.0142		0.0247	0.0162	
	(0.0358)	(0.0393)		(0.0359)	(0.0393)	
Abroad	0.0311	0.0325	0.0580	0.0275	0.0281	0.0590
	(0.0360)	(0.0417)	(0.0592)	(0.0360)	(0.0416)	(0.0645)
Years from PhD	0.00963*	0.00143	0.640***	0.00944*	0.00124	0.636***
	(0.00529)	(0.00558)	(0.239)	(0.00530)	(0.00557)	(0.133)
Internal Cand.	0.166***	0.169***	0.101	0.162***	0.167***	0.0950
	(0.0460)	(0.0549)	(0.0849)	(0.0459)	(0.0549)	(0.0878)
Coauthor	0.163***	0.193***	0.161	0.152***	0.191***	0.155
	(0.0572)	(0.0662)	(0.104)	(0.0580)	(0.0669)	(0.118)
At least one Top 6	0.0333	-0.0589		0.0280	-0.0614	
	(0.109)	(0.103)		(0.110)	(0.102)	
N pubs in A+	-0.0216	-0.0402	-0.0784	-0.0198	-0.0396	-0.0721
	(0.0248)	(0.0277)	(0.147)	(0.0249)	(0.0276)	(0.152)
N pubs in A	-0.00974*	-0.0135**	-0.0466	-0.0104*	-0.0139**	-0.0478
	(0.00586)	(0.00656)	(0.0481)	(0.00590)	(0.00659)	(0.0576)
N pubs	0.000465	0.00198	0.0187	0.00115	0.00263	0.0206
	(0.00358)	(0.00352)	(0.0390)	(0.00357)	(0.00349)	(0.0506)
At least one interd.	0.0417	0.0235	0.549	0.0411	0.0247	0.530
	(0.0962)	(0.113)	(0.540)	(0.0954)	(0.113)	(0.327)
	Mean	**Mean**	**Mean**	**Max**	**Max**	**Max**
$\overline{Y}$	0.602	0.602	0.602	0.602	0.602	0.602
Observations	1,102	1,102	1,102	1,102	1,102	1,102
R-squared	0.050	0.289	0.404	0.047	0.288	0.404
Call FE	No	Yes	No	No	Yes	No
Year FE	Yes	No	Yes	Yes	No	Yes
Broad Field FE	Yes	No	No	Yes	No	No
Candidate FE	No	No	Yes	No	No	Yes

Notes. Dependent variable: Probability of being present at the interview if shortlisted for senior assistant professorships in economics. Estimates from a Linear Probability Model. Our controls include a dummy for candidates holding a PhD from abroad and for being currently abroad, number of years from PhD, a dummy for internal candidates and for coauthorship, a dummy for those with at least one Top 6 publication, number of A+ and A publications, number of publications, dummy for those with at least one publication in interdisciplinary journals. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.8: The role of research similarity in the probability of winning

VARIABLES	(1) Winner	(2) Winner	(3) Winner	(4) Winner	(5) Winner	(6) Winner
	Panel 1: Similarity as a continuous variables					
Similarity	0.924***	0.847***	0.823***	0.437***	0.417***	0.326***
	(0.112)	(0.116)	(0.163)	(0.0570)	(0.0586)	(0.0632)
Female	-0.0136	-0.00591	-0.0256	-0.00877	-0.000158	-0.0439*
	(0.0129)	(0.0133)	(0.0232)	(0.0128)	(0.0132)	(0.0259)
Observations	2,364	2,364	2,364	2,364	2,364	2,364
R-squared	0.081	0.159	0.453	0.081	0.161	0.452
	Panel 2: Probit Model (Marginal Effects)					
Dummy Similarity	0.0606***	0.0538***		0.0675***	0.0654***	
	(0.0119)	(0.0104)		(0.0124)	(0.0112)	
Observations	2,364	2,358		2,364	2,358	
Pseudo R2	0.101	0.190		0.104	0.196	
	Mean	**Mean**	**Mean**	**Max**	**Max**	**Max**
$\overline{Y}$	0.10	0.10	0.10	0.10	0.10	0.10
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Call FE	No	Yes	No	No	Yes	No
Year FE	Yes	No	Yes	Yes	No	Yes
Broad Field FE	Yes	No	No	Yes	No	No
Candidate FE	No	No	Yes	No	No	Yes

Notes. Dependent variable: Probability of winning a senior assistant professorship in economics. OLS estimates with similarity as continuous variable in Panel 1. Marginal effect estimates from a Probit Model in Panel 2. Our controls include a dummy for candidates holding a PhD from abroad and for being currently abroad, number of years from PhD, a dummy for internal candidates and for coauthorship, a dummy for those with at least one Top 6 publication, number of A+ and A publications, number of publications, dummy for those with at least one publication in interdisciplinary journals. Robust standard errors in parentheses. *** p<0.01, ** p<0.0

Table A.9: Similarity and publication record after evaluation

VARIABLES	(1) Citations	(2) Citations	(3) A+ pub.	(4) A+ pub.	(5) Top 6 pub.	(6) Top 6 pub.
			Panel 1: Only winning candidates			
Similarity Winner	0.353	3.393	0.338	0.377*	-0.0557	0.0161
	(16.22)	(13.25)	(0.338)	(0.201)	(0.0581)	(0.0355)
Female	-4.540	-4.510	0.00188	0.000318	-0.00639	-0.00544
	(3.397)	(3.422)	(0.0461)	(0.0450)	(0.00655)	(0.00603)
Observations	232	232	238	238	238	238
R-squared	0.196	0.196	0.407	0.414	0.246	0.245
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Broad Field FE	Yes	Yes	Yes	Yes	Yes	Yes
			Panel 1: All candidates			
Winner	2.667	3.417	0.0690	0.0714	0.000112	-0.0118
	(3.918)	(4.737)	(0.0971)	(0.112)	(0.0255)	(0.0276)
Similarity Winner*Winner	-6.325	-3.550	-0.170	-0.0686	-0.0194	0.0106
	(11.60)	(5.420)	(0.355)	(0.155)	(0.0892)	(0.0394)
Female	-1.753***	-1.746***	0.0162	0.0163	-0.00655***	-0.00656***
	(0.461)	(0.459)	(0.0131)	(0.0131)	(0.00246)	(0.00244)
Observations	2,324	2,324	2,364	2,364	2,364	2,364
R-squared	0.136	0.136	0.303	0.303	0.168	0.168
Call FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
	Mean	**Max**	**Mean**	**Max**	**Mean**	**Max**

Notes. Dependent variables: Average citations per publication(columns 1-2); dummy if at least one publication is in A+ journals (columns 3-4); dummy if at least one publication is in Top 6 journals (columns 5-6). Data on citations until 2023. Data on publications are from the call a candidate won and until 2023. *Similarity winner* measures the (mean or max) similarity between the winning candidate and the members of the selection committee. Our controls include a dummy for candidates holding a PhD from abroad and for being currently abroad, number of years from PhD, a dummy for internal candidates and for coauthorship, a dummy for those with at least one Top 6 publication, number of A+ and A publications, number of publications, dummy for those with at least one publication in interdisciplinary journals, all measured at the time of the call. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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