

Gender Differences in Reference Letters: Evidence from the Economics Job Market*

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Abstract

Academia, and economics in particular, faces increased scrutiny because of gender imbalance. This paper studies the job market for entry-level faculty positions. We employ machine learning methods to analyze gendered patterns in the text of 12,000 reference letters written in support of over 3,700 candidates. Using both supervised and unsupervised techniques, we document widespread differences in the attributes emphasized. Women are systematically more likely to be described using ‘grindstone’ terms and at times less likely to be praised for their ability. Using information on initial placement we highlight the implications of gender stereotyping for the quality of academic placement.

JEL Codes: J16, A11.

Keywords: Gender, Natural Language Processing, Stereotyping, Diversity.

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1 Introduction

Gender disparities in the workplace have received significant attention in public debate. Academia is facing increased scrutiny due to its low female representation, especially in the field of economics (Valian, 1999; Lundberg, 2020, Part I). Recent empirical work has documented that the economics career pipeline for women is ‘leaky’, meaning that women tend to drop out of the profession at critical transitions, such as the jump from earning a Ph.D. to an assistant professorship, or from assistant to associate professor (for a broad review, see Lundberg and Stearns, 2019). This paper studies the first step of the academic career of an economist, the junior ‘job market’ —the stage at which the leak has grown the most in the past decade (Lundberg and Stearns, 2019)— and which so far has not received much systematic attention (Lundberg, 2020).

The academic job market in economics is unique in that it is a highly structured institution. It starts every year in late Fall, with universities posting their job advertisements and potential applicants preparing a ‘job market package’. The latter consists of one or more academic papers, a CV and a set of recommendation letters written by scholars familiar with the candidate. All the parties involved, i.e. the candidates, the letter writers and the hiring committees, interact via centralized platforms. Typically, the same package is used for the vast majority of jobs, making the marginal cost of an additional application low. Reference letters are not tailored to a particular institution and the same letter is usually used for *all* job applications (for more details see Coles et al., 2010).

In this paper, we investigate the presence of differences in the language used in reference letters, depending on the gender of the candidate being recommended. We use a unique dataset encompassing all applications for entry-level positions received by a research-intensive university in the U.K. over the 2017-2021 period. Deploying Natural Language Processing tools, we analyze the text of almost 12,000 reference letters written in support of 3,700 candidates. A standard letter covers a lengthy discussion of the candidate’s job market paper, some reference to their additional research, and to their teaching and citizenship skills. Importantly, the final section of the letter provides a summary assessment of the candidate’s academic abilities and recruitment prospects. Since we are primarily interested in the way candidates are described, we focus much of our attention on this final section.

This corpus is then transformed into a term-frequency-inverse-document-frequency (tf-idf) representation. Borrowing from methods developed in cognitive psychology and linguistics, we quantify whether letters written in support of female candidates emphasize systematically different attributes. We use three complementary approaches. First, we employ an unsupervised method to ascertain the terms in the letters that are the best predictors of a candidate’s gender. We adopt a LASSO technique that selects the strongest predictors. Among these, we frequently observe terms related to research interests, but also to personality (‘nice’, ‘pleasant’) and ‘grindstone’ attributes (‘determined’, ‘hardworking’, etc.). Second, we rely on a supervised method, building dictionaries of words for common attributes emphasized

in reference letters. These dictionaries are informed by existing research on the topic (Trix and Psenka, 2003; Schmader et al., 2007). We validate our dictionaries through an original comprehensive survey of academic economists based in U.K. research-intensive universities. Corroborating the exploratory results from the LASSO, we observe that descriptions of female candidates tend to emphasize significantly more ‘grindstone’ attributes. In further specifications, we also uncover a tendency to use fewer terms related to ability and research. Third, we also qualify the strength of support received by a candidate by analysing the type of placement recommendation received (e.g. “I recommend this person to any institution, including the very best”). We observe that women receive fewer positive signals, but no difference in negative ones. They are also more likely to be compared to other candidates.

This paper thus documents differences in the language chosen for female and male candidates. In line with previous research, we observe that women are described with more ‘grindstone’ attributes and at times fewer ‘ability’ ones (Bourdieu and Passeron, 1977; Trix and Psenka, 2003; Schmader et al., 2007). A natural question following on from these findings is whether the differences uncovered matter. Diligence and working hard are positive attributes (see Alan et al., 2019, on ‘grit’). However, given the overwhelmingly positive tone of recommendation letters in the job market, it may be misleading to interpret our findings as suggesting that women receive ‘better’ recommendations. The opposite may well be true. In fact, as noted by Valian (1999, p. 170) “[a]lthough working hard is a virtue, labeling a woman a hard worker can be damning with faint praise. If someone is not considered able to begin with, working hard can be seen as confirmation of his or her inability.” More generally, sociologists have pointed out that minorities are more often praised for their diligence than for their innate ability and that the signal of diligence is often interpreted as a lack of innate talent (Bourdieu and Passeron, 1977, p.201).

To illustrate the importance of language in reference letters, we study the correlation between the attributes emphasized in letters and job market placement. We manually collected information from personal websites, academic departments’ placement records, and LinkedIn profiles, to establish whether the candidate placed in academia or elsewhere. For academic placements, we also link the hiring institution to its RePEc (Research Papers in Economics) rankings. To the best of our knowledge, we are the first to collect such information.¹ The results indicate that language matters differentially for women and men. In particular, male candidates benefit from ‘standout’ terminology while females do not. For academic placements, letters emphasizing ‘grindstone’ are associated with obtaining a job in a less prestigious institution, but only so for women.

In studying gendered patterns in the language of reference letters, we address several empirical challenges. More specifically, the attributes emphasized in reference letters may be influenced by many factors, such as the institution the candidate graduated from or their research

¹In a related paper, Baltrunaite et al. (2022) study placement in the same year for all candidates, i.e. between one and up to ten years after their initial placement, and focus on attainment of the associate professor rank.

field. Some of these determinants may differ systematically for male and female candidates. We tackle this problem in a variety of ways. In our baseline specifications, we control for the observable candidate and writer characteristics obtained from the application platform and from additional information we collected manually. On the writer's side, we control for their gender, the number of letters they provide in our sample, and the RePEc ranking of their institution. On the candidate side, we control for ethnicity, years since Ph.D. completion, broad field of specialization, publication record, and the ranking of their Ph.D.-awarding institution. The baseline results are not sensitive to these controls, nor to alternative definitions of the reference letter ends. We also check that the results are not driven by alternative explanations that could correlate with the gender of the letterwriter such as the location of the Ph.D.-granting institution, the gender or the cultural background of the letterwriter, the academic field of the candidate, or the extent of networking conducted before the market, among others.

Still, we may worry that unobservable determinants could affect our findings. Therefore, we run more restrictive models that allow us to account for unobserved, time-invariant institutional and letterwriter characteristics. A first set of models, which include fixed effects for the Ph.D.-granting institution, confirm the gendered patterns observed even for candidates of the same cohort at the same institution. In further analysis, we restrict the sample to referees who have written letters for both male and female candidates and employ writer fixed effects. These more demanding specifications confirm that differences in describing male and female candidates are detectable even when we focus on individual writers. Further probing indicates that more experience in writing for female candidates attenuates some of these differences.

This article is related to the literature on gender representation in academia. Several papers have shown that women are under-represented in math-intensive fields (for a detailed review of the literature see [Ceci and Williams, 2009](#), p.3-16; [Kahn and Ginther, 2017](#)). Investigations of different aspects of academic life have uncovered significant barriers. For example, [Nittrouer et al. \(2018\)](#) and [Hospido and Sanz \(2021\)](#), among others, observe that female academics are less likely to be accepted to present their work at academic conferences. Many researchers have emphasized systematic gender biases in student evaluations of teachers, which are frequently-used indicators of performance in promotion and tenure packages ([MacNell et al., 2015](#); [Boring, 2017](#); [Fan et al., 2019](#); [Mengel et al., 2019](#); [Boring and Philippe, 2021](#)). These patterns are persistent, despite evidence of a demand for diversity ([Funk et al., 2019](#)).

While other math-intensive fields have shown some improvement, economics has been in the spotlight for its persistently low representation of women ([Bayer and Rouse, 2016](#); [Lundberg and Stearns, 2019](#)). Not only is there low female representation at the earliest stages of the profession, but the career pipeline is also 'leaky'. In trying to understand barriers to women's advancement in economics, researchers have looked at different stages of an academic career.

Focusing on the first one, [Boustan and Langan \(2019\)](#) document the wide variation of gender representation across Ph.D. programs, and that this representation tends to be a persistent attribute of a department. Turning to the next steps as academic professionals, other limitations to the advancement of women have been observed. In particular, there is evidence that females face barriers to promotion ([Ginther and Kahn, 2004](#); [Sarsons, 2017](#); [Bosquet et al., 2019](#)), higher standards to judge the quality of their research ([Card et al., 2020](#); [Dupas et al., 2021](#); [Grossbard et al., 2021](#); [Hengel, 2022](#)), and that their work gets cited less ([Koffi, 2021](#)). Taken together, all these factors are likely to hamper the progression of women in their academic careers. We contribute to this burgeoning literature by focusing on a major and to date unexplored stepping stone: the junior job market. At this stage, beyond institutional credentials, little information about the candidate’s research or teaching is observed. Therefore, reference letters play a crucial role in supporting the applicant.

The professional culture in economics may also be problematic for women’s advancement. [Wu \(2018\)](#) reports evidence of gender biases in posts about women in a well-known and widely used anonymous forum in the profession. Similarly, [Dupas et al. \(2021\)](#) study the seminar culture and present evidence that female speakers face more hostile audiences. By analyzing recommendation letters, we are investigating a different aspect of the professional culture, namely mentorship. As opposed to these previous studies, our focus is on a setting in which economists fulfil a supportive and nurturing role.

Existing literature has uncovered gendered patterns in academic reference letters in other disciplines. For example, [Trix and Psenka \(2003\)](#) show that letters written in support of female applicants to medical faculty positions are shorter and emphasize more ‘grindstone’ and ‘teaching characteristics’. Looking at job applicants in chemistry and biochemistry, [Schmader et al. \(2007\)](#) observe similar patterns. [Madera et al. \(2009\)](#) documents that letters for female applicants in psychology emphasize their ‘communal’ attributes (‘nice’, ‘collegial’, etc.). This line of research has also uncovered systematic differences in the presence of doubt raisers in geosciences ([Dutt et al., 2016](#)), and psychology ([Hebl et al., 2018](#); [Madera et al., 2019](#)).

We contribute to this literature in three main ways. First, we validate the ‘sentiment’ classification previously used by carrying out an original survey of academic economists.

Second, by focusing on economics, we can leverage a substantially larger sample of letters that are broadly representative of a highly structured and globalized academic job market. This allows us to rely on unsupervised techniques to describe gendered patterns in the language used when writing references. More specifically, fitting a LASSO, we show that many of the words that best predict letters written for women relate to ‘grindstone’ or ‘teaching and citizenship’ traits, whereas many ‘ability’ terms are more predictive of letters written for men. In other words, gendered differences in language used are already salient when describing the data with an unsupervised approach. This suggests in turn that the patterns uncovered in this literature with supervised techniques are unlikely to be driven by biases in the selection of the relevant terms.

Third, we also further advance the literature by analysing gendered differences in the quality of placement recommendations (e.g. whether people are explicitly recommended to a top institution). More importantly, we also analyse the implications of gendered language on the initial placement *outcomes* of candidates. Ongoing work on reference letters by [Baltrunaite et al. \(2022\)](#) confirms these patterns for two Italian institutions and when focusing on longer-term career outcomes.

The remainder of the paper is organized as follows. In Section 2 we discuss our sample as well as the general approach of our main textual analysis. Section 3 explains the process of data cleaning and preparation, followed by the exploratory analysis using unsupervised methods in Section 4. Section 5 outlines the supervised approach and presents the baseline results, with extensions and additional robustness checks. Section 6 discusses the analysis of job market placement, followed by concluding remarks.

2 Data

We collected and cleaned the text of almost 12,000 reference letters written in support of over 3,700 candidates who applied for entry-level positions between 2017 and 2021 at a research-intensive economics department in the U.K.² In each year in our sample the department advertised multiple positions open to all fields.

The department is one of the largest in the U.K., with over 55 regular faculty members and was ranked in the top-5 in the most recent public evaluation of scientific research carried out in U.K. universities (Research Excellence Framework, 2021). It has been consistently ranked in the top-75 worldwide according to the RePEc rankings. The majority of the faculty has an international background, with 53% having earned a Ph.D. outside the U.K. (half of them in the U.S., the other half in other European countries). The department has a large Ph.D. program, with over 50 students in residence in a given year. 23% of staff is female.³

The applications were collected from the *EconJobMarket* (EJM) platform. Access to and handling of these confidential data were in accordance with the data processing agreement signed between the researchers and EJM, which obtained appropriate ethical approval.

For each letter, we know a number of characteristics of the candidate and the letter writer. For candidates, we know characteristics they entered on *EconJobMarket*, such as gender, ethnicity, and the institution granting their Ph.D.⁴ We also manually collect data from the candidates' CVs: we add information on their publication record at the time of application and their graduation date. The institutional ranking of both letter writers and candidates are taken from RePEc.⁵ Information on the main advisor is also collected. Finally, we manually searched on-

²All applications were filed exclusively through EJM, without any additional paperwork required.

³A figure slightly below the average for U.K. research-intensive institutions in the so-called Russell Group. For more details see [De Fraja et al. \(2019\)](#).

⁴If the gender was withheld in the EJM application, it was determined using a manual internet search.

⁵See Appendix A for more details on how the ranking is constructed.

line for each individual candidate to establish their first professional placement in the year following their first appearance in our sample. Combining information from personal websites, academic departments' placement records, and LinkedIn profiles, we establish whether the candidate placed in academia or elsewhere. For academic placements, we also collect the name of the institution, which we link to RePEc rankings.

For each letterwriter, we have information on the institution where they were based at the time the letter was written. Using the R library 'GenderizeR', we also infer their gender from their first names. For this procedure, we adopt a conservative approach and manually search for cases in which the gender probability reported by the algorithm is below 0.75.⁶ We also manually collected information on their academic rank, their seniority (year of Ph.D. completion), and their country of birth.⁷

Summary statistics of these characteristics are presented in Tables 1 and 2. The majority of applicants and reference letter writers are based in the top-100 ranked institutions, with slightly more letter writers concentrated at the very top, as also shown in Figure 1. We have 5,655 writers (female share 17.4%) in our sample, and on average each writer has written slightly more than two letters. Overall, approximately 30% of the candidates in our sample are women. This statistic is consistent with the figures reported by Lundberg and Stearns (2019) and has remained stable over time as shown in Figure 2. Table 3 shows the share of applicants by country. Approximately 50% of the candidates are based at U.S. institutions and 14% in the U.K. (see also Appendix Table 3 for a detailed breakdown).

Reference letters for the economics job market have a mean length of 1,089 words, which corresponds to around three pages A4, with a standard deviation of 554 words (around 1.5 pages). A standard letter covers a lengthy discussion of the candidate's job market paper, some reference to their additional research, and to their teaching and citizenship attributes. Importantly, the final section of the letter provides a summary assessment of the candidate's academic abilities and recruitment prospects.

⁶The names of only 284 individuals fall below this threshold (5.9% of all letterwriters) and their gender has been determined using a manual search.

⁷If the country of birth was unknown, we have attributed it based on the location of the location of the institution that granted their undergraduate degree.

Table 1: Descriptive Statistics — candidate characteristics

Variable	Full Sample					Males		Females		Difference (M - F)		
	N	Mean	SD	Min	Max	N	Mean	N	Mean	Estimate	p-value	sig.
Panel (A) Characteristics of the candidates												
<i>Gender</i>												
Female	3721	0.291	0.454	0	1	2639	0	1082	1	-1		
<i>Ethnicity</i>												
Asian	3721	0.316	0.465	0	1	2639	0.286	1082	0.389	-0.103	0.000	***
Black	3721	0.018	0.132	0	1	2639	0.022	1082	0.008	0.013	0.005	***
American Indian	3721	0.005	0.067	0	1	2639	0.006	1082	0.002	0.004	0.115	
Hispanic	3721	0.091	0.287	0	1	2639	0.100	1082	0.068	0.031	0.003	***
Hispanic Withheld	3721	0.133	0.340	0	1	2639	0.143	1082	0.109	0.034	0.006	***
White	3721	0.435	0.496	0	1	2639	0.454	1082	0.389	0.065	0.000	***
<i>PhD location</i>												
US-based Institution	3721	0.504	0.500	0	1	2639	0.501	1082	0.510	-0.009	0.610	
<i>Research field</i>												
Theory	3721	0.237	0.425	0	1	2639	0.240	1082	0.228	0.012	0.436	
Macro	3721	0.262	0.440	0	1	2639	0.269	1082	0.247	0.022	0.168	
Applied	3721	0.243	0.429	0	1	2639	0.216	1082	0.310	-0.094	0.000	***
Residual	3721	0.020	0.141	0	1	2639	0.023	1082	0.013	0.011	0.039	**
<i>PhD institution</i>												
RePEc Rank top-25	3721	0.183	0.387	0	1	2639	0.189	1082	0.166	0.023	0.098	*
Rank 26-50	3721	0.133	0.339	0	1	2639	0.135	1082	0.127	0.009	0.480	
Rank 51-100	3721	0.147	0.354	0	1	2639	0.143	1082	0.157	-0.014	0.265	
Rank 101-200	3721	0.192	0.394	0	1	2639	0.199	1082	0.175	0.025	0.083	*
Rank 201-500	3721	0.222	0.416	0	1	2639	0.208	1082	0.256	-0.048	0.002	***
Rank 500+	3721	0.123	0.329	0	1	2639	0.125	1082	0.119	0.005	0.646	
Years since PhD	3721	1.073	2.201	0	22	2639	1.144	1082	0.899	0.244	0.002	***
<i>Publications (counts)</i>												
Total	3721	1.156	2.057	0	18	2639	1.223	1082	0.991	0.232	0.002	***
Top-Five	3721	0.048	0.236	0	3	2639	0.016	1082	0.007	0.008	0.062	*
Top General Interest	3721	0.013	0.121	0	2	2639	0.020	1082	0.018	0.002	0.765	
Top Field	3721	0.020	0.148	0	2	2639	0.055	1082	0.033	0.021	0.012	**

Notes: Top-Field journals are JIE, JET, JoE, JME, JPubE, JLE, JDE, JEH, JFE, JF, Rand. Top-General Interest are the JEEA, REStat, EJ, IER, and all AEJs. See data section for additional information.

Table 2: Descriptive Statistics — letter and letter writer characteristics

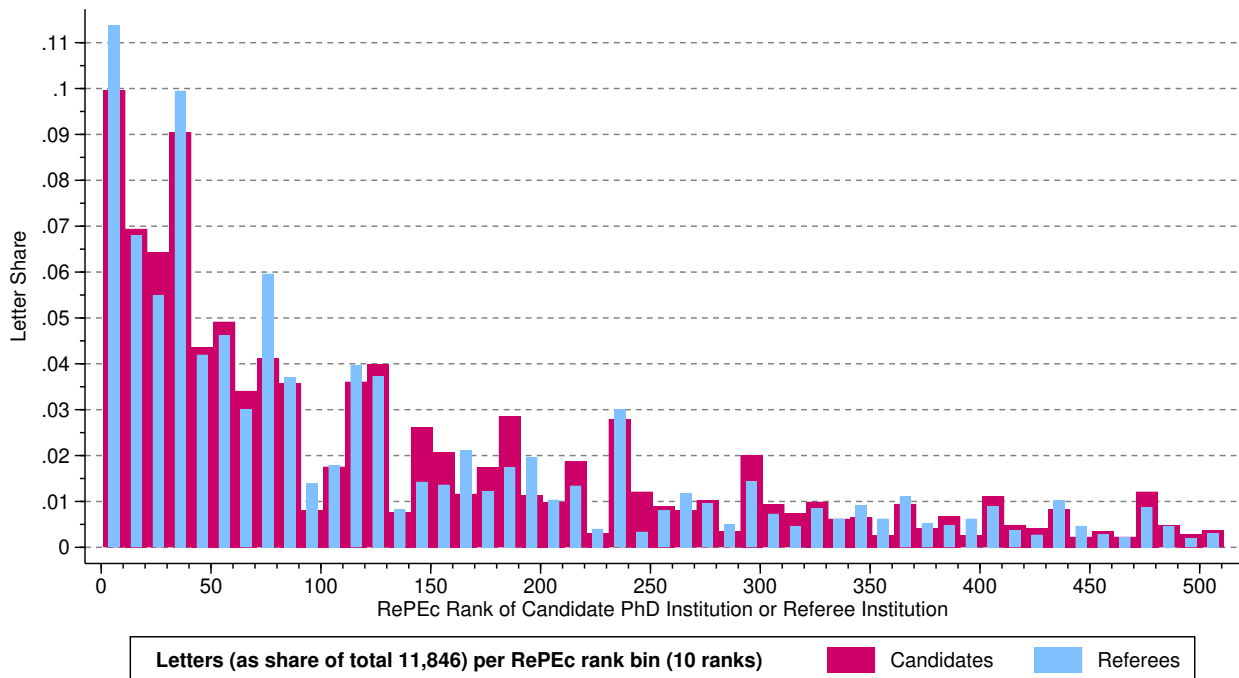
Variable	Full Sample				Males		Females		Difference (M - F)		
	N	Mean	SD	Min	Max	N	Mean	N	Mean	Estimate	p-value sig.
Panel (A) Characteristics of the letters											
Total Word count	11846	1089	554	197	5000	8486	1092	3360	1081	11.820	0.295
Word bags											
Ability	11846	0.257	0.203	0	1.396	8486	0.258	3360	0.255	0.003	0.513
Grindstone	11846	0.075	0.101	0	0.787	8486	0.073	3360	0.080	-0.007	0.001 ***
Recruitment	11846	0.337	0.269	0	2.004	8486	0.340	3360	0.330	0.009	0.087 *
Research	11846	0.914	0.484	0	2.996	8486	0.921	3360	0.896	0.025	0.011 **
Standout	11846	0.349	0.216	0	1.578	8486	0.350	3360	0.347	0.003	0.567
Teaching and Citizenship	11846	0.368	0.333	0	1.949	8486	0.365	3360	0.376	-0.012	0.086 *
Letter writers											
Female	11846	0.148	0.355	0	1	8486	0.132	3360	0.188	-0.056	0.000 ***
RePEc Rank top-25	11846	0.188	0.391	0	1	8486	0.189	3360	0.183	0.006	0.439
Rank 26-50	11846	0.114	0.318	0	1	8486	0.116	3360	0.109	0.007	0.262
Rank 51-100	11846	0.149	0.356	0	1	8486	0.146	3360	0.157	-0.010	0.161
Rank 101-200	11846	0.161	0.368	0	1	8486	0.168	3360	0.143	0.026	0.001 ***
Rank 201-500	11846	0.186	0.389	0	1	8486	0.179	3360	0.205	-0.026	0.001 ***
Rank 500+	11846	0.202	0.401	0	1	8486	0.201	3360	0.204	-0.003	0.746
Panel (B) Characteristics of the letterwriter											
Variable	Full Sample				Male Writer		Female Writer		Difference (M - F)		
	N	Mean	SD	Min	Max	N	Mean	N	Mean	Estimate	p-value sig.
Female Writer	5655	0.174	0.379	0	1	4670	0	985	1	-1	
Letters in the sample	5655	2.140	1.951	1	23	4670	2.210	985	1.810	0.400	0.000 ***
RePEc Rank top-25	5655	0.163	0.370	0	1	4670	0.166	985	0.153	0.012	0.346
Rank 26-50	5655	0.092	0.289	0	1	4670	0.090	985	0.098	-0.008	0.423
Rank 51-100	5655	0.131	0.337	0	1	4670	0.132	985	0.125	0.007	0.540
Rank 101-200	5655	0.162	0.369	0	1	4670	0.162	985	0.163	-0.002	0.903
Rank 201-500	5655	0.218	0.413	0	1	4670	0.219	985	0.210	0.009	0.519
Rank 500+	5655	0.234	0.423	0	1	4670	0.231	985	0.250	-0.019	0.198
Assistant Professor	5526	0.155	0.362	0	1	4568	0.143	957	0.215	-0.072	0.000 ***
Associate Professor	5526	0.208	0.406	0	1	4568	0.195	957	0.271	-0.076	0.000 ***
Full Professor/Chair	5526	0.637	0.481	0	1	4568	0.662	957	0.514	0.148	0.000 ***
PhD Year	5095	2000	11.430	1953	2021	4210	1999	885	2003	-3.543	0.000 ***
Prior to 2000	5095	0.420	0.494	0	1	4210	0.442	885	0.318	0.125	0.000 ***
After (incl) 2000	5095	0.580	0.494	0	1	4210	0.558	885	0.682	-0.125	0.000 ***

Notes: Institutional rankings are based on RePEc. See data section for additional information.

Since we are primarily interested in the way candidates are described, we focus our analysis on this end section. Section 3.1 explains how this section is extracted. A typical example of the information provided is given by the following quotation. Identifiable and sensitive characteristics have been redacted to protect privacy.

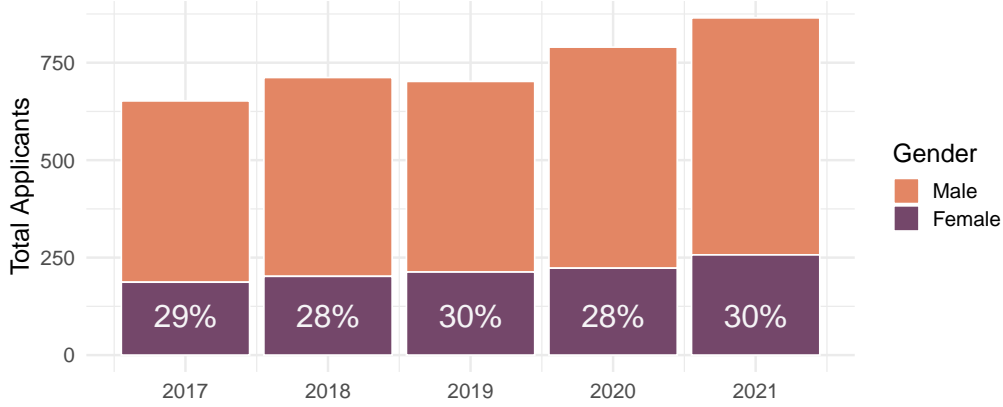
“...working in this area. In terms of recent students coming out of [Institution X] that I have worked with, [Candidate α] would be on a par of with a number of excellent recent placements such as [Candidate β] who went to [Institution Y], [Candidate γ], who went to [Institution Z] and [Candidate δ] who went to [Institution W]. These economists are carving out excellent, innovative careers and I can see [Candidate α] joining their ranks. What makes [Candidate α] stand out from recent cohorts is [Candidate α]'s ability to work with governments. [Candidate α] has been central to the work that [Institution X] does in [Country A]. Precisely, [Candidate α] has done such a good job starting up projects with the government and delivering answers to big, difficult to tackle questions. You can see this hallmark in all [Candidate α]'s papers and I have a sense [Candidate α] is going to be highly productive in [his/her] career for this reason. I therefore recommend that all top economics departments, business schools and public policy schools interested in hiring someone in [Field ϕ] take a careful look at this application.”

Figure 1: RePEc Rank of Candidate and Letter Writer Institution



Notes: The figure presents the frequency distribution of candidate and letter writer institutional rank (in bins of 10 institutions).

Figure 2: Gender distribution of applicants in the sample



Notes: The figure shows the total number of applicants per year and the share of female applicants each year

Table 3: Descriptive Statistics: Candidate Country

ISO3	Candidates	Percent	Cum	ISO3	Candidates	Percent	Cum
USA	1,874	50.5	51	CHN	8	0.2	99
GBR	503	13.6	64	IRL	8	0.2	99
CAN	191	5.2	69	HUN	7	0.2	99
FRA	190	5.1	74	GRC	6	0.2	99
DEU	164	4.4	79	IND	6	0.2	99
ESP	157	4.2	83	BRA	5	0.1	100
ITA	132	3.6	87	RUS	5	0.1	100
NLD	106	2.9	89	PSE	4	0.1	100
SWE	62	1.7	91	TUR	4	0.1	100
AUS	49	1.3	92	IRN	3	0.1	100
CHE	49	1.3	94	ISR	3	0.1	100
BEL	41	1.1	95	JPN	3	0.1	100
HKG	26	0.7	96	MEX	3	0.1	100
DNK	18	0.5	96	CHL	2	0.1	100
NOR	16	0.4	96	BGR	1	0.0	100
SGP	15	0.4	97	CYP	1	0.0	100
n/a	13	0.4	97	GEO	1	0.0	100
PRT	12	0.3	98	KOR	1	0.0	100
AUT	11	0.3	98	MYS	1	0.0	100
CZE	10	0.3	98	NZL	1	0.0	100
FIN	9	0.2	98				
Total					3,721		

Notes: 3-digit iso code for geographic location of the applicant (PhD institution, not nationality), in order of magnitude. Cum – cumulative sum (rounded).

3 Methods

3.1 Data processing

In this section, we explain the methods employed to transform our collection of letters into data.

Following standard procedure, we pre-process the text. First, we clean all punctuation and

clearly separate out the words. Next, we remove all common stop words such as articles or pronouns. Furthermore, we stem the words, i.e. we reduce the words to their common stem (or root). For instance, the words “published”, “publishing”, or “publishes”, will all be collapsed to the stem “publish”. Following these steps, we have converted each reference letter into a collection of (stemmed) words.

We then need to establish a measure of the importance of each word per letter. We compute the term-frequency-inverse-document-frequency (tf-idf) of each word using Python’s Sklearn library.

We now define a few concepts to explain how we transform our collection of letters into data. Each letter is a *document*. Denote each document $d \in \{1, \dots, D\}$. The corpus D is the set of documents. Each document d contains N_d words $w_i(d)$, $i \in \{1, \dots, N_d\}$. Words are drawn from a set of terms $t \in \{1, \dots, T\}$. The set of terms is the entire vocabulary present in the corpus.

We represent the corpus of letters with a matrix of dimension $D \times T$. Each row of this matrix represents a document, and each column represents a term. For each document, each cell refers to the term-frequency-inverse-document-frequency (tf-idf) of the term. The tf-idf is a common measure used to quantify the importance of a term in each document, compared to its prevalence in the corpus. The tf-idf is the product of the term frequency and the inverse-document frequency. The term frequency $\text{tf}(t, d)$ is the number of times term t appears in document d :

$$\text{tf}(t, d) = \sum_i^{N_d} \mathbf{1}\{w_i = t\}. \quad (1)$$

The inverse-document frequency is the logarithmically scaled inverse fraction of the document frequency of t , $\text{df}(t)$, which is the number of documents that contain the term t :

$$\text{idf}(t) = \log \frac{1 + D}{1 + \text{df}(t)} \quad (2)$$

$$\text{with } \text{df}(t) = \sum_d \mathbf{1}\{\text{tf}(t, d) > 0\}. \quad (3)$$

The term-frequency-inverse-document-frequency (tf-idf) is then:⁸

⁸By default, Python’s Sklearn uses an L-2 normalization, which means that it normalises the final tf-idf with the vector’s Euclidian norm. This is aimed at correcting for long versus short documents. Following standard procedure, we also drop terms that are either too common (i.e. that appear in more than 70% of documents) or too rare (less than 1% of documents).

$$\text{tfidf}(t, d) = \text{tf}(t, d) \times \text{idf}(t) = \log \frac{1 + D}{1 + \text{df}(t)} \sum_i^{N_d} \mathbf{1}\{w_i = t\}. \quad (4)$$

This approach is considered standard for text vectorization in natural language processing, and researchers have shown that this simple representation is sufficient to infer interesting properties from texts ([Grimmer and Stewart, 2013](#)). This approach has many advantages. First, it is easy to implement. Second, the tf-idf for each word has the simple interpretation of capturing the importance of each word in the document, relative to its frequency in the corpus. We can also measure the importance of specific attributes in each letter by summing the tf-idf for the groups of words in the attribute category for each letter.

This approach has two main shortcomings. First, the vector space grows linearly with the vocabulary, which can cause significant computational challenges. In our case, our sample size is not large enough for this to become an issue. The second shortcoming is that the relationships *between* words are not taken into account. More recent deep-learning techniques use word embedding representations resulting in a vector-space of low dimension. With word embeddings, terms represented with vectors that are close in space are semantically similar. Recent literature in law and economics has pioneered the implementation of word embeddings, for instance, to compare the similarity of different semantic fields inside a given corpus ([Ash et al., 2022, 2021](#), among others). Many of these papers are interested in exploring whether different semantic fields are correlated in different corpora (e.g. whether ‘female’ words tend to be associated with ‘career’ words or ‘family’ words). Unfortunately, word embeddings may perform disappointingly compared to traditional methods in smaller samples ([Shao et al., 2018](#); [Ash et al., 2021](#)), and our sample is much smaller than the those used in the new economics literature applying word embeddings.⁹

3.2 Separating ends

In most of our analysis, we concentrate on the end of the letter. The rationale behind this choice is that reference letters in economics follow a fairly rigid structure, and the end of the letter is where the referees summarize their opinion about the candidate, including their job market prospects.

We use a two-step procedure to separate the letter ends. First, we create a dictionary of commonly used closing phrases (e.g. “Yours sincerely”). These phrases flag the end of the letter, and permit cleaning out long signatures (with multiple affiliations, addresses, etc.). We then take the 200 words *before* the first closing phrase flagged, which roughly corresponds to the length of one large paragraph. With this approach, we cover more than 89% of the

⁹For instance, [Ash et al.’s \(2021\)](#) analysis of judge-specific corpora falls in the category of a “small” sample for word embeddings. Their analysis relies on corpora with at least 1.5 million tokens (pre-processed words). For comparison, our main sample of interest, which consists of the universe of end of letters, contains approximately 852,000 tokens.

letters. For letters without any identifiable closing phrase, we use the last 200 words of the document. We also consider 150 and 250 words cuts for the letter ends in the robustness section.

3.3 Language Categorisation

Reference letters for the economics job market tend to have an overwhelmingly positive tone. Therefore, a standard computational text analysis that aims at weighting positive terms against negative ones is not appropriate in this context. We build instead on the categorization proposed by [Schmader et al. \(2007\)](#) in their analysis of a smaller sample of applicants in chemistry ($n = 277$) for a large U.S. research university, which in turn builds on earlier qualitative work by [Trix and Psenka \(2003\)](#).

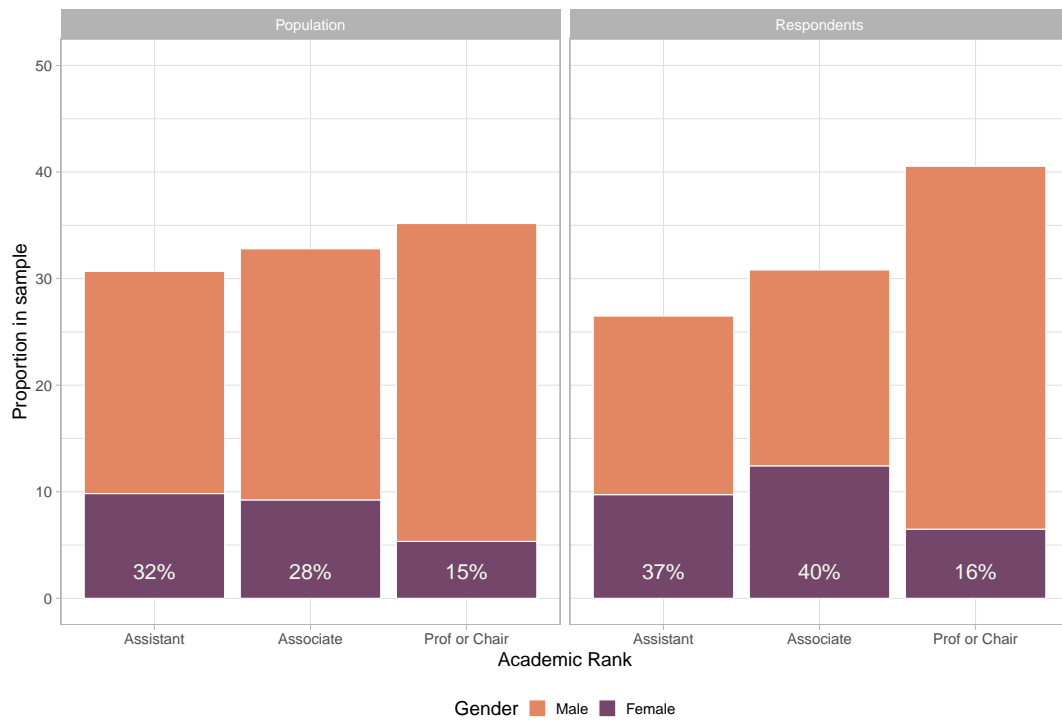
[Schmader et al. \(2007\)](#) propose five language categories that can be used to describe relevant features of an applicant, including *ability traits*, *grindstone traits*, *research terms*, *standout adjectives*, and *teaching and citizenship terms*. We add a category that refers to the *recruitment prospects* of the candidate. Ability traits involve language aimed at highlighting the applicant's suitability for the advertised position and include words such as *talent*, *intellectual*, *creative*, etc. Grindstone traits refer to language that, in the words of [Trix and Psenka \(2003, 207\)](#), resemble "putting one's shoulder to the grindstone". Words in this category include *hardworking*, *conscientious*, *diligent*, etc. Research terms are descriptors of the type of research carried out by the candidate and related matters e.g. *applied economics*, *game theory*, *public economics*, etc. Standout terms highlight especially desirable attributes of the applicant, like *excellent*, *top*, *strongest* etc. Teaching and citizenship is a broad category that refers both to the candidate's skills in the classroom, as well as their behavior with colleagues. Language in this group includes *good teacher*, *excellent colleague*, *friendly*, etc. The last category, recruitment prospects, has been added to identify words that, in the highly competitive and globalized labor market for fresh economics Ph.D.s, are widely used to describe the expected placement of the candidate. Words in this group include *highly recommended*, *top department*, *tenure track* etc. Appendix Figure [B.2](#) shows word clouds for each of our language categories.

To corroborate our word classification, we carried out a survey of all faculty employed at U.K. economics departments which were submitted to the 2014 Research Excellence Framework (REF).¹⁰ Each participant was shown a sample of 20 words and asked to classify them in one of the six categories listed above. The survey was run between the end of March and the beginning of April 2021, and a total of 1,205 individuals were contacted. Participants were incentivized with a lottery of Amazon vouchers worth £20 each. 195 took part in the survey, corresponding to 16 percent of the underlying population.

Figure [3](#) provides a breakdown of the population and of the survey respondents by level of seniority and gender. As can be seen, about one-third of the population (left panel) are as-

¹⁰The REF is a periodic, comprehensive assessment of the research carried out by UK universities. For more information, see [De Fraja et al. \(2019\)](#).

Figure 3: Population of academic surveyed compared to respondents



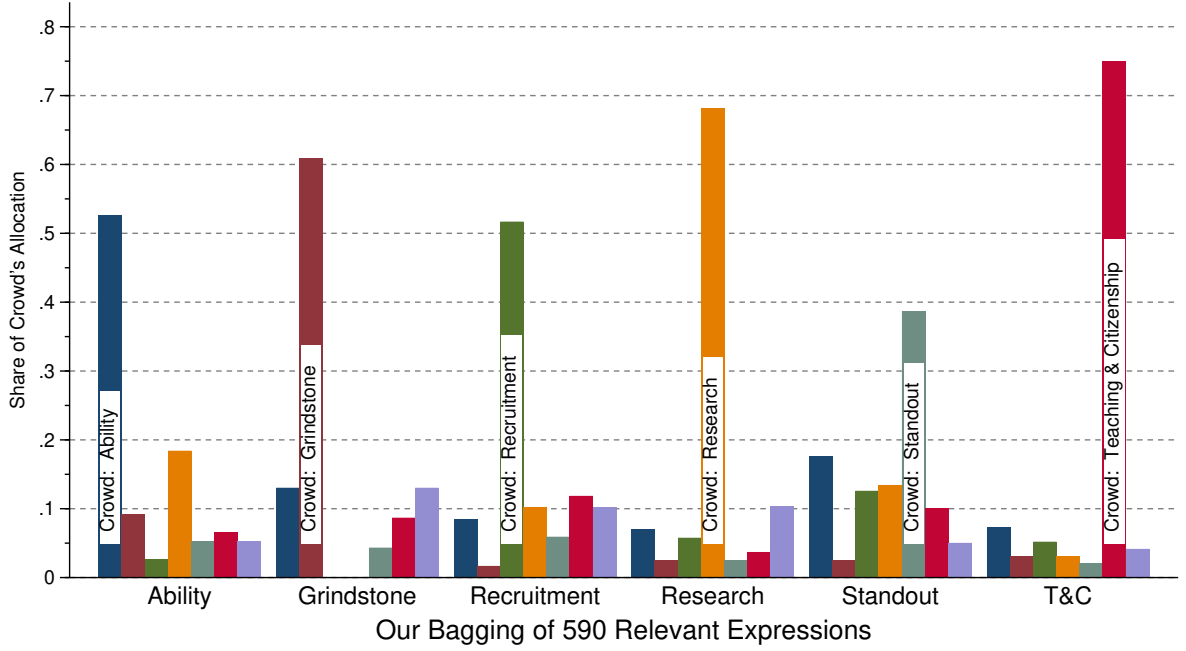
Notes: The figure compares the representation of women per academic rank between the total population surveyed and the respondents of the validation exercise. The percentages at the top of each bar are the share of women inside the category. The category ‘others’, is accounted for in the calculations, but excluded from the graphs because of its low representation (<2% of the sample in both the population and the validation sample).

sociate professors, with a slightly higher share represented by full professors, and a slightly smaller one by assistant professors. The share of females declines with seniority, representing 32% of staff at the assistant professor level, and only 15% at the most senior level. Turning to our sample (right panel), respondents are slightly more likely to be full professors, and slightly less likely to be assistant professors than in the underlying population. Not surprisingly, females are over-represented among respondents, especially at the intermediate level of seniority.

Figure 4 illustrates the extent to which our own assessment of an expression is shared by the academics who took part in our survey. For all expressions classified into a language category by the authors, we show the distribution of classifications chosen by the plurality of validators.¹¹ While there is variation across language categories, there is broad consensus between our categorization and that of the profession.

¹¹See Appendix A for more details on how the figure is constructed.

Figure 4: Correspondence between authors’ sentiment categories and the ‘wisdom of the crowd’



Notes: This figure shows the correspondence between the authors’ chosen classification for each expression and the classification chosen by validators. For any word validated, it is attributed to the category that was chosen by the plurality of validators who were shown that word. See more details in Appendix A.

4 Unsupervised Analysis

4.1 Methodology

As an initial unsupervised analysis, we ask whether specific terms used are more predictive of the gender of the candidate. To this end, we employ a least absolute shrinkage and selection operator (LASSO) to select the relevant set of terms. The LASSO estimator $\hat{\beta}$ solves the following problem:

$$\hat{\beta} = \arg \min_{\beta} \left\{ \frac{1}{2D} \sum_{d=1}^D (y_d - \mathbf{x}'_d \beta)^2 + \lambda \sum_{j=1}^p \omega_j |\beta_j| \right\}, \quad (5)$$

where d is the letter. The gender of the candidate is the binary variable y_d . Vector x_d is the collection of $\text{tfidf}(t, d)$ for the corpus. The second, penalty, term in equation (5) contains the ‘tuning’ parameters λ and ω which are selected to reduce the number of non-zero but small coefficients. p is the total number of terms.

We implement different LASSO estimators which vary in their treatment of the penalty function: for a 75% training sample, we consider a cross-validation (CV) LASSO, an adaptive LASSO, as well as an elastic net (enet) LASSO. These approaches differ in the way the optimal tuning parameters (λ, ω) are estimated or, in the case of the enet, by the specific form

the penalty function takes. Since female candidates make up only 30% of our sample, we also experiment with ‘oversampling’ females in the training sample. The final set of selected terms is not sensitive to the choice of LASSO method nor to the oversampling choice.

We only present results from the adaptive LASSO because across all specifications, it has higher predictive power than the enet and the CV.¹²

4.2 LASSO Results

A visualization of the results is presented in Figure 5. The Figure records the 289 predictors selected by the LASSO. We present the standardized beta coefficients of the linear probability model of candidate gender on tf-idf. Each line groups up to 6 predictors with similar coefficient magnitudes. The bars represent the range of the coefficient of the predictors listed in the line. Positive predictors are associated with female candidates, whereas negative ones are associated with males.

First, the figure reflects that women select across different research fields. Research on ‘women’, ‘health’, or ‘environment(al)’ tends to be disproportionately carried out by female candidates, whereas ‘theory’, ‘history’, or ‘finance’ appear to be associated with male candidates. This ‘self-selection’ mechanism is one that we also consider carefully in the remainder of the paper.

Second, qualitatively, it appears that certain personality traits are gender specific. While women are disproportionately more likely to be described as ‘driven’, ‘determined’, or ‘hard-working’, men are disproportionately seen as ‘thinkers’ or ‘creative’. This is a pattern that will be confirmed in the next section. Also aligning with gender stereotyping, descriptives related to ‘communal attributes’ (‘nice’, ‘pleasant person’) are associated with women.

Finally, it is worth noting that traits such as youth (‘young researcher’) and shyness are reserved to women. This finding conforms to the stereotyping of women as naïve or child-like that has been documented in sociology (see for instance [Goffman, 1979](#), pp. 5 and 50-51, and [Gornick, 1979](#)), and for which there is suggestive evidence that it may harm women’s credibility in the workplace (for a review see [MacArthur et al., 2020](#)).

This exploratory analysis shows that even using an unsupervised method such as the LASSO, a portrait of women as ‘determined’ and ‘hardworking’ is drawn. This observation is consistent with the previous findings highlighting that female candidates are mostly praised on their ‘grindstone’ attributes ([Trix and Psenka, 2003](#); [Valian, 2005](#)).

¹²We compare the areas under the receiving operator curve (AUROC). The ROC is a measure of predictive fit employed in the binary dependent variable literature, quantifying the correctly predicted 0s and correctly predicted 1s.

Figure 5: LASSO Visualization



Notes: This figure shows the terms selected in the LASSO exercise. In each line, the vertical bars illustrate the range of the standardized beta coefficient for all the words listed. The beta coefficient is the change in propensity that the candidate is female associated with a one standard deviation increase in the tf-idf of the term. This LASSO exercise is conducted with stemmed words. In this figure, we have attributed to each stem its most frequent corresponding word. 289 stems out of 1,425 are selected by the adaptive LASSO. $N = 11,846$, AUROC = 0.739.

5 Supervised Analysis with Dictionaries

In our supervised analysis, we employ the dictionaries related to ‘ability’, ‘grindstone’, ‘research’, ‘recruitment’, ‘standout’, and ‘teaching & citizenship’ discussed in Section 3.3—we refer to these as ‘sentiments’ for ease of discussion.

5.1 Specification and implementation

We run regressions defined in equation (6) using ordinary least squares.

$$\text{Sentiment}_{diwt} = \alpha + \beta \text{Female}_i + \mathbf{X}_i' \gamma + \mathbf{W}_w' \lambda + \nu_t + \varepsilon_{diwt} \quad (6)$$

Sentiment_{diwt} is the importance of each sentiment in letter d , written for candidate i by letter writer w in year t . For each sentiment (‘ability’, ‘grindstone’, etc.), Sentiment_{diwt} is the sum of $\text{tfidf}(t, d)$ of all the terms in letter d associated with that sentiment in our dictionaries. Female_i is an indicator equal to 1 if the candidate is female, and β is our coefficient of interest. \mathbf{X}_i is a vector of candidate-level controls, \mathbf{W}_w is a vector of letter-writer controls; both are described in more detail below. We further include recruitment cohort fixed effects ν_t .

It is possible that attributes of candidates or letter writers that influence how a recommendation is written differ systematically between men and women. For instance, publication records may vary by gender, which in turn might affect the recommendation’s strength (Hengel, 2022). Similarly, female candidates may not be represented in highly ranked institutions in the same way as males, etc. The variables included in the regression aim at accounting for these differences.

First, with regards to candidate attributes, all specifications include controls for their ethnicity, race, and the year they entered the job market. We sequentially add indicator variables accounting for the RePEc ranking band of the candidate’s Ph.D.-awarding institution.¹³ Finally, we control for the years since Ph.D. completion, for the broad field of specialization¹⁴ and for the publication record. For the latter, we include the total number of publications and the number of articles published in top-field, top-5, and top general interest journals.¹⁵

Next, turning to the letterwriters’ characteristics, we control for their gender, the RePEc ranking band of their institution, and the number of reference letters they provide in our sample. These controls proxy for the quality and prestige of the letter writer. Finally, we also account for the length of the letter (total word count).

Each empirical model is estimated using four different sets of standard errors: robust, clus-

¹³In particular we distinguish: top-25, top-26-50, top-51-100, top-101-200, top-201-500, and an indicator for institutions not included in our top-5% RePEc ranking in January 2021 (12% of the sample).

¹⁴Section 5.3 describes in greater detail how we define fields and the robustness of our results to alternative definitions.

¹⁵We define the following journals as top field: JDE, JEH, JET, JF, JFE, JIE, JME, JoE, JPubE, and RAND. Top general interest journals are: the four AEJs, EJ, IER, JEEA, and REStat.

tered by letterwriter, clustered by letter writer institution, and clustered by candidate Ph.D.-awarding institution.¹⁶

5.2 Main Results

Baseline Table 4 presents baseline results for the six outcomes using standard errors clustered by letter writer. In Figure 6 we visualize these results along those from a similar analysis carried out by further splitting the sample by letterwriter institutional ranking. Heterogeneity by institutional quality is a natural concern: familiarity with the job market might vary across institutions and in turn this might lead to different reference writing practices. Similarly, institutional culture, which may vary across the hierarchy of economic departments, can also shape language in references. For instance, [Lundberg and Stearns \(2019\)](#) highlight the hierarchical nature of the economics profession, in which a high fraction of potential letterwriters come from the most prestigious institutions. We address this here by focusing on top-25 or top-100 institutions and then probe this issue further in our analysis using institutional fixed effects below.

The standard errors are computed using the four types of clustering described at the end of section 5.1. The total number of outcomes, specifications and clusterings combine into a total of 504 regressions. To visualize all these results in Figure 6, a darker shading of the marker indicates more specifications yielding statistically significant estimates for $\hat{\beta}$ (see the figure’s notes for more details). Fully filled symbols are significant at the 1% level across all possible standard error clusterings. Hollow symbols do not reach significance for any type of clustering. The coefficient magnitudes are the estimates from equation (6) normalized by the standard deviation of the respective dependent variable.

Figure 6 shows that no matter the institutional ranking, and across all specifications, female candidates are significantly more likely to be associated with ‘grindstone’ terms (from 5 to 12% of a standard deviation). These results confirm our interpretation of the unsupervised analysis (see section 4). We also observe that fewer terms related to research are used in letters supporting female candidates. Both of these results echo findings from other disciplines ([Trix and Psenka, 2003](#); [Valian, 2005](#)).

Furthermore, in all subsamples, female candidates are on average associated weakly and insignificantly so with more ‘teaching and citizenship’ terms. We also find no statistically significant differences between female and male candidates for ‘standout’ terms—in contrast with [Trix and Psenka \(2003\)](#) and [Schmader et al. \(2007\)](#), who observe a higher frequency of these adjectives in letters supporting male applicants for academic positions in medicine, and chemistry and biochemistry, respectively.¹⁷

Finally, we find fewer terms related to ‘ability’ or ‘recruitment’ for female candidates, but the

¹⁶Exceptions here are naturally the candidate institution FE and writer FE specifications.

¹⁷We also experiment with separating the teaching and citizenship ‘sentiments’. The coefficients remain insignificant and small in magnitude. Results are available in Appendix Figure E.1.

estimates are not statistically significant.

The magnitude of the estimates of interest does not differ greatly across specifications, even after controlling for proxies capturing determinants of language that correlate with gender. This stability provides some reassurance that other unobserved confounding determinants of language used in references are unlikely to explain away the results.

Table 4: Sentiments — End of Letters

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ability	-0.0147 (0.70)	-0.0124 (0.59)	-0.0142 (0.68)	-0.0172 (0.82)	-0.0172 (0.82)	-0.0219 (1.04)	-0.0212 (1.00)
Grindstone	0.0637 (3.02)***	0.0615 (2.91)***	0.0636 (3.01)***	0.0599 (2.83)***	0.0596 (2.81)***	0.0534 (2.52)**	0.0532 (2.52)**
Recruitment	-0.0236 (1.11)	-0.0237 (1.13)	-0.0227 (1.08)	-0.0344 (1.63)	-0.0313 (1.49)	-0.0275 (1.30)	-0.0240 (1.16)
Research	-0.0548 (2.66)***	-0.0520 (2.52)**	-0.0520 (2.52)**	-0.0484 (2.35)**	-0.0477 (2.31)**	-0.0437 (2.11)**	-0.0456 (2.22)**
Standout	-0.0035 (0.17)	-0.0013 (0.06)	-0.0036 (0.17)	-0.0115 (0.55)	-0.0087 (0.42)	-0.0106 (0.51)	-0.0078 (0.37)
Teaching & Citizenship	0.0343 (1.60)	0.0250 (1.18)	0.0240 (1.13)	0.0163 (0.76)	0.0136 (0.64)	0.0059 (0.28)	0.0070 (0.34)
FE/Variables absorbed	10	15	15	19	19	25	25
Additional covariates			1	1	5	6	7
Number of Letters	11846	11846	11846	11846	11846	11846	11846
dto for females	3360	3360	3360	3360	3360	3360	3360
Number of candidates	3721	3721	3721	3721	3721	3721	3721
dto female	1082	1082	1082	1082	1082	1082	1082
Number of writers	5655	5655	5655	5655	5655	5655	5655
dto female	985	985	985	985	985	985	985
Letters by fem writers	1751	1751	1751	1751	1751	1751	1751
Year FE	yes	yes	yes	yes	yes	yes	yes
Ethnicity/Race FE	yes	yes	yes	yes	yes	yes	yes
Institution Rank FE	no	yes	yes	yes	yes	yes	yes
Years since PhD	no	no	yes	yes	yes	yes	yes
Research Field FE	no	no	no	yes	yes	yes	yes
Publications	no	no	no	no	yes	yes	yes
Writer characteristics	no	no	no	no	no	yes	yes
Letter length	no	no	no	no	no	no	yes

Notes: The table shows results of the OLS regression of each ‘sentiment’ (e.g. ‘ability’, ‘grindstone’, etc) on a female candidate indicator as well as controls mentioned in the text (letter ends with 200 words). The table reports the estimate for the female indicator. Each row reports a different outcome, whereas each column reports a different specification. Standard errors are clustered at the letter writer level, we report the absolute t -statistics in parentheses. The coefficients are reported in terms of standard deviations of the dependent variable. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Male and Female Writers Figure 7 compares results by letterwriter gender.¹⁸ The pattern uncovered for ‘grindstone’ words continues to hold when we separately consider male and

¹⁸There are 985 female letter writers (who have written 1,751 letters) in total, of whom only 156 are in the top-25 group (with 314 letters), and 382 in the top-100 group (735).

Figure 6: Regression results, all letter writers combined



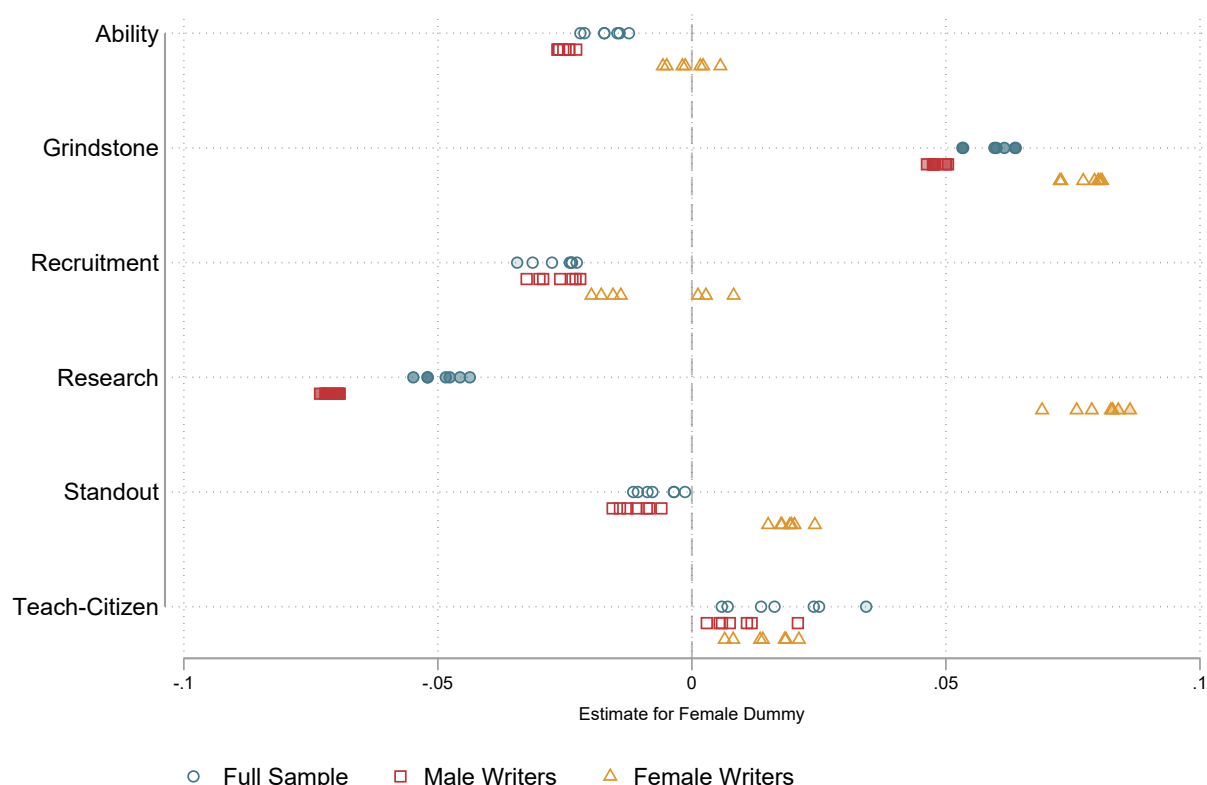
Notes: This figure shows the coefficient estimates for the regressions specified in 6. We compare all seven specifications described in Table 4. The symbol's filling permits visualizing significance. Using four levels of possible standard error clustering (none, candidate's institution, letter-writer's institution, or letter writer), we flag significance at 3 different levels (10%, 5%, and 1%). We thus flag 12 possible significance indicators. For each level of clustering, the symbol in the graph is thus shaded with a 9% ($\approx 100/12$) opacity when it reaches significance at each possible level. The darker the symbol, the more often it is significant. Fully filled symbols are significant at 1% level across all possible clustering. Hollow symbols do not reach significance for any type of standard error.

female referees. When it comes to research, it appears instead that the negative effect we have documented above is entirely driven by male writers. Female referees are actually *more* likely to use research terms for female candidates than for males.

In comparing male and female writers, we may worry that female referees cluster in departments with specific characteristics or that female writers attract different candidate types. We address these concerns later in this section by adding institution, writer or candidate fixed effects.

Cultural Background Gender norms differ across cultures and are highly persistent over time (see e.g. [Alesina et al., 2013](#)). Academic economists come from all over the world, and thus we can explore whether the effects we have uncovered so far are driven by writers born in countries with more traditional gender norms. To carry out this analysis we start by manually collecting, for each referee in our sample, information on their country of birth.¹⁹

¹⁹When this information was unavailable, we use the country of the institution granting their undergraduate degree as a proxy.



Notes: This figure shows the coefficient estimates for the regressions specified in 6, estimated separately for male and female letterwriters. We compare all seven specifications described in Table 4. The symbol’s filling permits visualizing significance. Using 4 levels of possible standard error clustering (none, candidate’s institution, letter-writer’s institution, or letter writer), we flag significance at 3 different levels (10%, 5%, and 1%). We thus flag 12 possible significance indicators. Then, for each level of clustering, the symbol in the graph is shadowed with a 9% ($\approx 100/12$) opacity when it reaches significance at each possible level. The darker the symbol, the more often it is significant. Fully filled symbols are significant at 1% level across all possible clustering. Hollow symbols do not reach significance for any level of standard error.

To measure gender norms, we then follow the literature and use data from the World Value Survey (WVS, Wave 7, 2017-2020).²⁰ In particular, we rely on whether the respondent agrees with the following statements: ‘A pre-school child suffers with a working mother’, ‘University is more important for a boy than for a girl’, and ‘Men make better business executives than women do’. We consider a writer’s country of birth as having more ‘traditional’ gender norms if the share of individuals agreeing/strongly agreeing with each statement is above the median for our sample.²¹

The results are reported in Figure 8. We observe that for all measures of gender norms, writers from all origins still tend to use more ‘grindstone’ terms for female candidates. Therefore, our results are not driven uniquely by referees born in countries with ‘traditional’ gender norms. However, we notice that the estimates are qualitatively larger for these writers, al-

²⁰Due to lack of later data we use WVS results from 2010-14 for India.

²¹We average the shares by country across the three responses, akin to a first principal component, and take the median cut-off for this average response. Regression results for each of the three statements as well as the average are provided in Appendix Table C.4.

though the difference is not significant.²²

Figure 8: Regression results, by gender norms of writer



Notes: This figure shows the coefficient estimates for the regressions specified in 6, estimated separately for letterwriters from countries with traditional versus liberal gender norms. We compare all seven specifications described in Table 4. The symbol’s filling permits visualizing significance. Using four levels of possible standard error clustering (none, candidate’s institution, letter-writer’s institution, or letter writer), we flag significance at 3 different levels (10%, 5%, and 1%). We thus flag 12 possible significance indicators. Then, for each level of clustering, the symbol in the graph is shaded with a 9% ($\approx 100/12$) opacity when it reaches significance at each possible level. The darker the symbol, the more often it is significant. Fully filled symbols are significant at 1% level across all possible clustering. Hollow symbols do not reach significance for any level of standard error.

Specifications with Fixed Effects We have uncovered systematic differences in the attributes highlighted for female and male candidates. Here we explore whether these differences are driven by the sorting of female candidates across institutions and/or letterwriters.

Boustan and Langan (2019) document that female representation is a persistent attribute of economics departments, and that it matters to promote women’s careers. Hence, it is important to study whether institutional sorting drives our results. We run regressions including fixed effects for the candidate’s institution. The results are reported in Figure 9. They suggest that among students from the same cohort, graduating from the same institution—who, for example, were admitted to PhD programs arguably applying the same entry requirements—women are still significantly more likely to be described with ‘grindstone’ terms.

We are still concerned that, even within the same graduate program, sorting across letter-

²²The results for a fully interacted model are presented in Appendix Table C.4.

Figure 9: Regression results with candidate institution or writer fixed effects



Notes: This figure shows the coefficient estimates for the regressions specified in 6, estimated separately with candidate institution or letter-writer fixed effects. The symbol's filling permit visualizing significance. Using two levels of possible standard error clustering for each fixed effect: none or candidate's institution (resp. letter writer) for candidate's fixed effects (resp. letter-writers' fixed effects). We flag significance at three different levels (10%, 5%, and 1%). We thus flag six possible significance indicators. Then, for each level of clustering, the symbol in the graph is shaded with a 17% ($\approx 100/6$) opacity when it reaches significance at each possible level. The darker the symbol the more often they are significant. The darker the symbol, the more often it is significant. Fully filled symbols are significant at 1% level across all possible clustering. Hollow symbols do not reach significance for any level of standard error clustering. Additional information on the sample and results for the unclustered, robust standard errors are contained in Appendix Section C.

writers could explain our findings. To address this concern, in Figure 9 we plot also the estimates of a set of specifications including writer fixed effects.²³ Note that these models are identified from referees who have written two or more letters across all five sample years, with at least one for a female and one for a male candidate. This significantly reduces our sample (we can include only 18% of the letterwriters).

In the same figure we also separately consider the sample of referees who have less (more) experience with female candidates.²⁴ This analysis permits unveiling significant heterogeneity. The 'less experienced' group appears to have a significantly higher likelihood of using 'grindstone' terms for women *and* a lower likelihood of using 'ability' ones. These estimates

²³In our analysis we drop the top-1% most prolific referees ($n = 12$), namely those with a dozen or more letters in the sample, since fixed effects estimates are sensitive to outliers. Leaving these referees in the sample leads to qualitatively similar results.

²⁴Less (more) experience is defined as to balance the sample of letters across both groups. Writers who have written less (more) than a third of letters for women are considered less experienced. The 'less experienced' group accounts for 42% of referees in the subsample with two or more letters and at least one female candidate.

are also larger in magnitude compared to the baseline shown in Figure 6. Experience may matter for two main reasons. On the one hand, referees may vary in their perception of women, and female candidates could sort accordingly to avoid stereotyping. On the other hand, it could be that referees do not differ initially, but that their exposure to female candidates leads them to update prior stereotyping (a learning effect also observed for example by Beaman et al., 2009). Further research is needed to disentangle these two mechanisms.

Furthermore, it is worth pointing out that writers with more experience put less emphasis on ‘teaching and citizenship’ qualities for women compared to men, although not robustly significantly so.

Finally, fixed effects also allow a more subtle comparison of female and male *writers*. In particular we can contrast the language chosen by male and female writers for the same candidate by adding *candidate* fixed effects. For job applicants who have both male and female referees, we test whether female writers use different language in general and for female candidates in particular. Our results are presented in Appendix Table C.9. They suggest that, for the same candidate, female *writers* use different language. They rely more on ‘grindstone’ and ‘teaching and citizenship’ language, and less on ‘recruitment’. Importantly, there is no difference in these patterns depending on the gender of the *candidate*, pointing towards the absence of ‘same-sex preferences’ of letterwriters.

5.3 Robustness Checks

Alternative letter lengths In our baseline analysis, we have defined the end of letter using the last 200 words before the ‘polite’ end phrase. In Appendix Figure E.2 we explore the sensitivity of the baseline results to this choice by experimenting with two alternative cutoffs, using 150 and 250 words. We also study the full reference letters (see Appendix Figure E.2).²⁵ Our findings are unaffected.

Fields We explore heterogeneity of the results according to the candidate’s research field to assess possible sub-cultural differences in the profession. Grouping applicants into meaningful research areas is challenging. On the EJM platform, they typically choose a field, loosely based on JEL codes. Unfortunately, the EJM fields pool diverse subgroups of the profession, i.e. scholars that are unlikely to publish in the same journals or participate in the same events (conferences, seminars, etc.). For instance, the EJM field ‘Development and Growth’ includes both macroeconomists working on long-run growth and microeconomists carrying out field experiments in developing countries. Given these shortcomings, we employ an unsupervised data-driven approach to classify candidates into three broad research groups, namely Applied Economics, Theory, and Macroeconomics, and a residual category. Appendix sec-

²⁵ Appendix figures are accompanied by corresponding tables providing further details on specification and sample. For ease of presentation, we do not refer to these tables in the maintext.

tion [D](#) describes the procedure.²⁶

One possible explanation for the association of women to ‘grindstone’ expressions is that they sort into research fields that require more industriousness than ability. This set of skills is often associated with empirical work. However, the results reported in Appendix Figure [D.3](#) show that this association remains strong and significant within Applied Micro, casting doubt on such a hypothesis. We also uncover a strong negative effect for ‘ability’ and ‘research’ within Theory. This finding is worth highlighting as in this field raw talent is arguably valued very highly. This observation sheds new light on earlier findings by [Leslie et al. \(2015\)](#), according to whom academic fields that particularly emphasize the role of raw talent are characterized by lower female representation.

Main Advisors So far we have used all the letters that were submitted for each applicant, i.e. those which were written by the main advisor and those written by other faculty members familiar with the candidate’s research. As the main advisor might have better knowledge of the applicant, it is important to investigate whether there are differences in the language he/she used compared to that of the other referees. We collect data on the identity of the letter writers for candidates who were in the job market up to three years after completing their Ph.D.²⁷ The results of our analysis are illustrated in Appendix Figure [E.4](#), where we report our baseline estimates for the collected sample and those obtained focusing separately on the letters written by the main advisor and the other reviewers.

The findings indicate that the patterns for ‘grindstone’ terms are generally comparable, but accentuated for letterwriters who are *not* the main advisors. Moreover, there is notable divergence in case of ‘ability’ and ‘standout’. Compared to main advisors, other referees use significantly fewer ‘ability’ and ‘standout’ terms. Overall, this analysis presents suggestive evidence that main advisors are writing more favorable letters for women compared to other referees. Main advisors arguably know the candidates much better and spend more time writing and polishing the letters²⁸ and through these lengthy processes some of the unconscious stereotyping may be toned down.

Location of PhD granting institution The job market for economists is historically a U.S. institution, and faculty members based there may be better acquainted with the standards of reference writing. We investigate whether our results are driven by letterwriters outside the U.S., in which case our findings might result from lower levels of experience in the process. Figure [E.5](#) presents the results. Overall, we do not uncover significant differences between the two groups, with the exception of ‘research’ terms. Referees based outside the U.S. use sig-

²⁶The baseline analysis reported in Figure [6](#) employs research field fixed effects using these four clusters. In Figure [E.3](#) we repeat the same exercise using instead the more detailed 145 field definitions from EJM. The findings are robust.

²⁷This represents around 50% of the sample of candidates. Candidates who defended earlier were less likely to have a letter from their Ph.D. advisor and were also less likely to report that information on their CV.

²⁸Letters from main advisors are on average 33% longer.

nificantly fewer research-related words for female candidates compared to their U.S.-based counterparts.

Candidate’s visibility So far our analysis has accounted for the underlying potential of the candidate by controlling for the number and quality of their publications and the ranking of their institution. Additionally, we have shown that our results continue to hold when we compare candidates within the same institution. As a further robustness check, we also account for the circulation of the candidate’s job market paper at the time they are on the market. This proxies for the candidate’s visibility and/or the extent of networking carried out in this period. We do so by manually collecting information from the job market paper acknowledgements. Using the Stanford Name Entity Recognition Tagger, we separate out *people* thanked and *institutions* mentioned. We also compute the length of this note and flag whether the job market paper is single-authored. Appendix Figure E.3 shows that results with these controls remain unchanged compared to the baseline.

Postdocs Female candidates — who may be conscious of gender stereotyping — may change their behavior during their career to make stereotypical traits less salient (e.g. Hengel, 2022, highlights that women improve their writing throughout their careers, whereas men do not). To assess this possibility, we contrast the estimates for candidates fresh out of Ph.D. programs and those who have been out for 1-3 years (‘post-docs’). Results are reported in Appendix Figure E.6. Overall, the estimates for the postdoc sample are noisier, as expected due to smaller sample sizes. For ‘grindstone’ language, the effects remain generally stable. We do however observe an increase in the language related to ‘ability’ for female postdocs compared to their male counterparts. Further research is needed to establish whether this effect is driven by learning, as found by Hengel (2022), or by differential selection into postdocs.

Letterwriter Seniority/Rank Results with fixed effects in Figure 9 indicate that writers with less experience with female candidates use more stereotypical language. One alternative explanation for this finding could be that stereotyping reduces with academic experience *per se*. Using manually collected information on the year the letterwriter graduated from their Ph.D. or their academic rank (assistant, associate, full professor), we illustrate that this is not the case. In Appendix Figures E.7 and E.8, we observe that the most senior letterwriters use gender stereotypical language much more often and that they drive the ‘grindstone’ results.²⁹

5.4 Additional Results

In this section, we shift our attention away from the analysis of the ‘sentiments’ expressed in letters (‘ability’, ‘grindstone’, etc.) and consider alternative attributes that speak to the

²⁹We conduct additional analysis (not reported) splitting the Ph.D. cohorts into five rather than two groups and obtain qualitatively identical findings.

quality of the candidate or how the letter is written.

Placement Qualifiers Many letter ends carry explicit signals about the candidate, which can be positive or negative, as well as comparisons with placements of recent graduates —see our earlier discussion in Section 2. To analyse potentially gendered patterns in the prevalence of these signals, we compile a dictionary of over 1,000 placement qualifiers. Examples include (for negatives) “except maybe from those in the top 10/20/30” or “apart from the very best”; (for positives) “great hire”, “a star candidate”, “including institutions at the very top”; (for comparatives) “compared to” or “on par.” 24% of letters in our sample include at least one positive signal, 13% a negative one and 6% of all letters include a comparative term.

In the baseline specification, we replace the dependent variable with outcomes related to these qualifiers. The first three lines in Figure 10 show that letters written in support of women tend to have significantly fewer positive signals, no significant difference in terms of negative ones, and a net negative signal.³⁰ These results also hold when we consider instead binary variables flagging the presence of either positive or negative signals, or the sign of the net signal.³¹ The effects are sizeable. For instance, a letter in support of a female candidate has a 3 percentage point lower probability of containing a positive signal, to be compared with the fact that only 24% of letters contain one.

Finally, we study comparative terms using total counts or an indicator for their presence. This analysis suggests that letters written in support of female candidates have a 1 percentage point higher likelihood of carrying a comparison, a sizeable effect given that only 6% of letters contain one.

Overall, this analysis suggests that women are not shown in a more negative light (in contrast to findings in the literature about ‘doubt raisers’, e.g. [Trix and Psenka, 2003](#); [Madera et al., 2009](#)). However, they obtain less outright praise, which is consistent with the work of [Dutt et al. \(2016\)](#), who find that women in geosciences are less likely to receive ‘excellent’ letters. The higher prevalence of comparative terms suggests though that the information provided for female candidates might be more ‘precise’.

Letter Length and Readability A standard finding in the literature suggests that letters for female candidates are shorter ([Trix and Psenka, 2003](#)). We also investigate proxies for letterwriter effort by looking at letter length and writing clarity in the full reference letter as well as on the discussion of the candidate’s Job Market Paper.³² Our results, reported in Appendix Figure F.1 show that female candidates in economics do not receive shorter letters than their male peers. However, the analysis of readability, using the Flesch Reading Ease score suggests that letters for female candidates are harder to read.³³ The same pattern holds

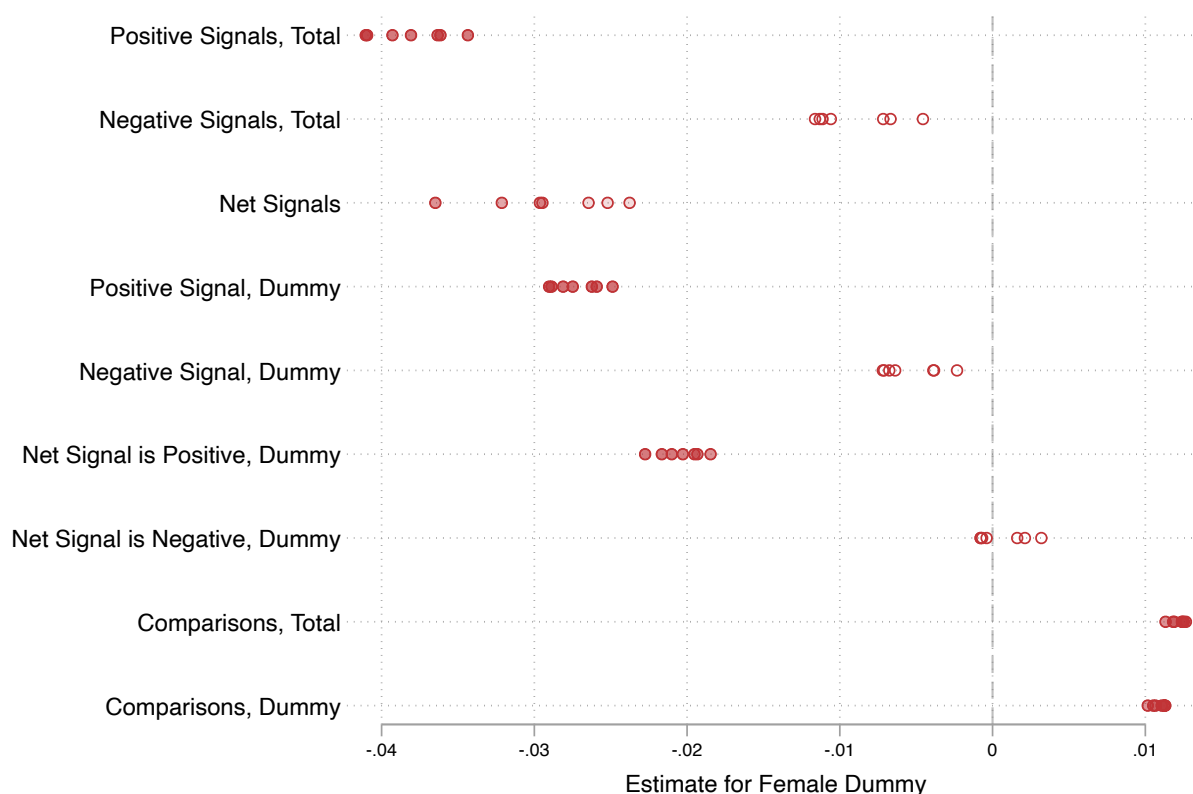
³⁰The net signal simply subtracts the count of negative from that of the positive signals.

³¹The dummy for net negative (positive) signal is 1 if the net signal is negative (positive) and 0 otherwise.

³²This corresponds to the ‘research slice’ — see Appendix section D for more details.

³³See [Hengel \(2022, Table 1\)](#) for exact definitions. For the Flesch index a higher score means the text is easier to read, for the Dale-Chall the reverse is the case.

Figure 10: Regression results, placement signals as outcomes



Notes: This figure shows the coefficient estimates for the regressions specified in 6 when outcomes are proxies for academic placement. Rows 1-3 are for counts of positive, negative and net signals; rows 4-7 adopt binary variables for the same outcomes; the final two rows are counts and dummy for comparative statements in the letter end. The symbol's filling permit visualizing significance. Using four levels of possible standard error clustering (none, candidate's institution, letter-writer's institution, or letter writer), we flag significance at three different levels (10%, 5%, and 1%). We thus flag twelve possible significance indicators. Then, for each level of clustering, the symbol in the graph is shaded with a 9% ($\approx 100/12$) opacity when it reaches significance at each possible level. The darker the symbol the more often they are significant. The darker the symbol, the more often it is significant. Fully filled symbols are significant at 1% level across all possible clustering. Hollow symbols do not reach significance for any level of standard error clustering.

true for the Dale-Chall Readability score, even if the results are not statistically significant. Finally, our investigation of the 'research slice' provides no clear evidence of a bias in the discussion of the candidate's JMP.

Timing of the Reference Letter Work by [Baltrunaite et al. \(2022\)](#) finds that, for their sample of references submitted to two Italian institutions, letterwriters are significantly less likely to send references for female candidates by the deadline stated on the EJM platform.

We test whether this finding also holds in our sample, using two alternative measures of timeliness. First, we construct a binary variable equal to 1 if the application package contains strictly fewer than 3 letters, the required number in our application process. The results, shown in Appendix Figure [F.1](#), confirm that female candidates are significantly more likely to have an incomplete set of references.

Second, we exploit information on the date stated on the reference letter, which is a proxy for

the timeliness of the referee given that by default the same letter is automatically submitted by the EJM platform to all institutions.³⁴ Our results, shown in the same figure, indicate that letters for female candidates tend to be written earlier (between 5 to 10 days earlier, depending on the specification), but this effect is imprecisely estimated and not robust to the inclusion of a full set of controls.

6 Placement

So far our analysis has focused on gendered patterns in the reference letters. We have documented differences in the language chosen for female and male candidates. In line with previous literature, we observe that women are described with more ‘grindstone’ attributes and at times fewer ‘ability’ and ‘research’ ones (Bourdieu and Passeron, 1977; Trix and Psenka, 2003; Schmader et al., 2007). The obvious corollary question is whether these differences matter for job market outcomes.

To answer this question, we have carried out a systematic collection of the first professional placement of each candidate in the year following their appearance in our sample. Combining information from personal websites, academic departments’ placement records, and LinkedIn profiles, we establish whether the candidate placed in academia or elsewhere. For academic placements, we also link the name of the institution to its RePEc rankings to proxy for the prestige of the job.

It is important to be mindful that reference letters are only one input in the recruitment process. They typically play an important role in enabling candidates to secure interviews at the job market meetings. Many other factors such as presentation skills, research agenda, or departmental politics determine whether a candidate actually receives a job offer. Therefore any result linking letters to actual placement needs to be interpreted with caution.

To study the relation between letter sentiment and placement, we estimate the following regression model:

$$\begin{aligned} \text{Placement}_{diwt} = & \alpha + \beta \text{Female}_i \\ & + \sum_{k=1}^6 (\theta_k \text{Sentiment}_{diwt} + \kappa_k \text{Sentiment}_{diwt} \times \text{Female}_i) \\ & + \mathbf{X}'_i \gamma + \mathbf{W}'_w \lambda + \nu_t + \varepsilon_{diwt}, \end{aligned} \tag{7}$$

where Placement_{diwt} is the job market outcome of individual i , for whom letter d was written by writer w in year t . For each sentiment k — ‘ability’, ‘grindstone’, etc. — we are interested in its impact on placement and whether this impact varies with the gender of the candidate.

³⁴We focus only on recent Ph.D.s for whom letters are presumably written for the first time. We rely on the package `ctparse` to detect and parse dates in the beginning of the letters, which we also double-check manually.

Controls are the same as defined in section 5.

Our results are reported in Table 5. We consider three measures of placement.³⁵ The first is a binary variable flagging whether a candidate obtained an academic job and takes into consideration all candidates for whom we found job market outcomes. The second and third measures focus on those who embarked on an academic career, and study the ‘quality’ of the academic placement. Our first proxy is the RePEc institution score (in logs), a continuous variable, which we rescale for ease of interpretation so that a positive coefficient indicates a more prestigious institution. The other is a binary variable indicating whether the candidate placed among the top-100 institutions in RePEc. Odd columns report a parsimonious model, with only the sentiments and cohort fixed effects as controls, whereas even ones report estimates accounting for the full set of controls.

Overall, we observe that women are more likely to place in academia (columns 1, 2), and conditional on embarking on an academic career, they land jobs in more prestigious institutions (columns 3-6). These results are compatible with both positive selection of women in academia and ‘positive discrimination’. Evidence of both phenomena has been uncovered by recent literature (for positive selection, see [Iaria et al., 2022](#), for ‘positive discrimination’ see [Card et al., 2022](#)).

We turn now to the analysis of the effect of ‘sentiment’ on placement. ‘Standout’ and ‘teaching and citizenship’ terms are the only ones to significantly affect the probability of placing in academia. Columns 1 and 2 show that a one standard deviation increase in the usage of ‘standout’ terms is associated with a 2 percentage point higher likelihood of an academic placement. For female candidates the aggregate effect is effectively nil instead. For ‘teaching and citizenship’ we find no effect for male candidates, but a positive one for women (amounting to a 1.7 percentage point increase in the likelihood of academic placement).

In columns 3 and 4 two ‘sentiments’ stand out: ‘grindstone’ and ‘teaching and citizenship’. The results for ‘grindstone’ indicate no statistically significant effect for men, whereas for women a one standard deviation increase in this ‘sentiment’ is associated with a significant and large (7.5%) decrease in the ranking of the institutions where they place. Moreover, men who receive letters emphasizing ‘teaching and citizenship’ get jobs in higher-ranked institutions (2-5% increase in ranking), whereas the effect is reversed for women (3.5-4% decrease in ranking).

When considering the likelihood of placing in a top-100 institution (columns 5 and 6), it is again the ‘grindstone’ sentiment that plays an important role, especially for women. A one

³⁵Models 1 and 2 contain letters for all 2,588 candidates for whom placement information was found, the dependent variable is 1 for an academic placement (AP position or postdoc) and 0 otherwise (international organisations, central banks, or private sector). Models 3 and 4 contain letters for 957 candidates who placed among the top-500 institutions in RePEc, the only ones for which a RePEc score is computed. The RePEc score is a continuous variable (e.g. third-placed UC Berkeley has a score of 7.12, first-placed Harvard of 1.96). Models 5 and 6 include letters for 1,865 candidates who placed in academia as either AP or postdocs. In this sample we can include all academic institutions (we are not constrained by the availability of a RePEc score). Teaching fellows are included in academic placements in 1 and 2, but results remain identical if we exclude them.

standard deviation increase in ‘grindstone’ terms is associated with a negligible effect for male candidates but a large negative effect for women, in the order of a 2.5-2.7 percentage points decrease in the probability of obtaining a job in a higher-ranked institution. Letters with more ‘standout’ and ‘recruitment’ terms are associated with better placement for both men and women, although significance and magnitudes drop when adding controls. Results for other sentiments are not statistically significant.

In this analysis, we do not account for the presence of placement qualifiers, which also exhibit gendered patterns as shown in Figure 10. The reason is that many placement terms are already included in the ‘standout’, ‘ability’, or ‘recruitment’ sentiments, although without differentiating between positives and negatives. As a robustness check, we present in Appendix Table F.3 the results when including the binary variables for placement qualifiers. The results for sentiments commented above remain unchanged. The analysis also suggests that positive signals only improve placement for men, and comparatives mostly worsen outcomes for women.

This discussion indicates that the gendered sentiments expressed in job market reference letters are associated with initial placement patterns. Investigating the determinants of placement in academia suggests that male candidates benefit from ‘standout’ terminology while females do not. Furthermore, our RePEc score/ranking analysis indicates that ‘grindstone’ terminology hurts female placement, whether we consider a continuous measure of institutional quality or a binary identifier. Although further research is needed to establish causality, our results indicate that the language in reference letters can play an important role in the first step of the academic career. These results are consistent with findings by [Baltrunaite et al. \(2022\)](#) on longer-term career outcomes.

Table 5: Letter Sentiment and Placement

Dependent Variable Sample	(1)	(2)	(3)	(4)	(5)	(6)
	Academia (dummy) All Placements		Inst. RePEc Score (log) Academic Placements		Top-100 RePEc Inst. AP & Postdoc	
	Controls	Sentiment	All	Sentiment	All	Sentiment
Female Candidate	8.9056 (2.37)**	7.7799 (2.10)**	9.3252 (0.58)	16.1753 (1.05)	7.5799 (1.91)*	11.0226 (2.88)***
Ability	0.1695 (0.28)	0.0250 (0.04)	1.6531 (0.61)	1.6181 (0.60)	0.5855 (0.97)	0.5340 (0.91)
Ability × Female Candidate	-0.0861 (0.08)	-0.1182 (0.11)	2.7112 (0.58)	1.6501 (0.36)	-0.1985 (0.18)	-0.3874 (0.35)
Grindstone	-0.4843 (0.82)	-0.6444 (1.10)	-2.9895 (1.28)	2.2784 (1.00)	-0.1255 (0.20)	0.2417 (0.41)
Grindstone × Female Candidate	0.1153 (0.11)	0.4257 (0.43)	-7.5681 (1.71)*	-7.3065 (1.67)*	-2.4693 (2.31)**	-2.6931 (2.61)***
Recruitment	0.7008 (1.14)	0.8262 (1.34)	2.9000 (1.15)	1.2626 (0.50)	1.7340 (2.84)***	0.6485 (1.07)
Recruitment × Female Candidate	0.4961 (0.48)	0.2396 (0.23)	-1.5203 (0.34)	-1.1223 (0.26)	-1.5329 (1.44)	-1.4431 (1.37)
Research	-0.4928 (0.80)	-0.1069 (0.18)	0.5148 (0.21)	2.1020 (0.88)	0.4740 (0.79)	0.8660 (1.51)
Research × Female Candidate	-1.7432 (1.63)	-1.5594 (1.47)	1.4390 (0.32)	-0.4129 (0.10)	-0.6586 (0.58)	-0.9651 (0.87)
Standout	1.9208 (3.28)***	1.9660 (3.39)***	0.9753 (0.37)	-0.5659 (0.22)	1.0028 (1.72)*	-0.0134 (0.02)
Standout × Female Candidate	-1.9979 (1.85)*	-1.8693 (1.76)*	5.7513 (1.25)	5.6810 (1.29)	1.0984 (0.96)	0.7742 (0.70)
Teaching and Citizenship	0.1599 (0.26)	-0.2112 (0.35)	2.1171 (0.84)	4.6536 (1.87)*	-0.8781 (1.45)	0.3622 (0.62)
T&C × Female Candidate	1.6494 (1.61)	1.7722 (1.75)*	-6.0157 (1.42)	-7.1823 (1.73)*	-1.1095 (1.05)	-1.4229 (1.39)
FE absorbed	5	25	5	25	5	25
Add. covariates	0	6	0	6	0	6
Number of Letters dto for females	8760 2588	8760 2588	3119 991	3119 991	6008 1872	6008 1872
Number of candidates dto female	2738 830	2738 830	957 313	957 313	1865 596	1865 596
Number of writers dto female	4461 774	4461 774	2091 324	2091 324	3453 586	3453 586
Letters by fem writers	1339	1339	445	445	910	910
Year FE	yes	yes	yes	yes	yes	yes
Letter Sentiments	yes	yes	yes	yes	yes	yes
Ethnicity/Race FE	no	yes	no	yes	no	yes
Institution Rank FE	no	yes	no	yes	no	yes
Years since PhD	no	yes	no	yes	no	yes
Research Field FE	no	yes	no	yes	no	yes
Publications	no	yes	no	yes	no	yes
Writer Chars	no	yes	no	yes	no	yes
Letter length	no	yes	no	yes	no	yes

Notes: The table shows OLS regression results of placement outcomes on the letter-specific sum of tf-idf statistics related to the bag of expressions mentioned in the row label and its interaction with a female candidate dummy as well as the additional controls as indicated. We report the absolute t -statistics in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. Results are in percentage points except in (3) and (4) where they are in percent. Further, signs in (3) and (4) are reversed for consistency with the other two placement outcomes.

7 Concluding Remarks

In this paper, we carried out what is to the best of our knowledge the first systematic analysis of recommendation letters in the junior academic job market in economics. Using both supervised and unsupervised methods, we have documented the presence of important differences in the language used to describe female applicants. Women are more often described with terms praising their ‘hard work’ or ‘dedication’ than men. This pattern is robust to alternative specifications and holds across many subsamples of the data. Similarly, we uncover evidence of a lower emphasis on ‘ability’, especially when comparing individuals within the same institution or for those sharing the same referee. Sociologists have characterised these language patterns as a form of stereotyping, and highlighted their potential negative connotations as a strong emphasis on diligence may imply a lack of ‘brilliance’ ([Bourdieu and Passeron, 1977](#); [Valian, 1999](#)). We illustrate the salience of language in reference letters for job market placement by documenting that men benefit from standout terminology while women do not; and that women receiving letters emphasizing that they ‘work hard’ obtain less prestigious academic positions, while the same is not true for men.

As academics, we know how much time is spent writing and polishing reference letters for job market candidates. This is an occasion where we try our best to promote our students. Therefore, it is unlikely that, on average, we are willingly undermining female students by emphasizing less desirable attributes. On a positive note, recent research has shown that unconscious biases can be addressed by providing the actors involved with evidence of the existence of such biases ([Boring and Philippe, 2021](#)). By documenting instances of gendered language patterns, we hope this research will be a first step towards increasing awareness of our biases and thereby reducing stereotyping in the job markets.

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A Variable and methods description

Validation exercise

To construct Figure 4 we assess the correspondence between the validators' chosen categories and ours as follows. Within each of the authors' chosen categories, for each word, we identify the category chosen by a plurality of validators. In the case of ties (e.g. "diligent", which the authors classified as "grindstone", was classified by 28.5% of validators as "ability", and 28.5% as "grindstone"), we attribute that word to both categories ("diligent" is attributed both to "ability" and "grindstone"). For each of our chosen categories, Figure 4 presents the distribution of winning categories. Words for which there are two winning categories count twice in the total, so that the sum of the bars is equal to 1.

Table A.1: Summary Statistics of words in each category

Category	Av. Doc Freq	Av. TF-IDF (x 1000)	N Words	Av. Validators per Word
Ability	8896.56	5.77	57	6.98
Grindstone	8991.60	4.99	20	6.56
Recruitment	9011.69	4.32	118	6.72
Research	9038.12	4.77	210	6.46
Standout	8958.87	5.02	106	6.70
Teach-Citizen	8971.88	5.06	94	6.81

Notes: This table shows summary statistics of words in each category. The First column gives the categories. The second (third) columns give the average TF-IDF (document frequency) of words in each category. The fourth column gives the number of words in each category. The fifth column gives the average number of validators who cross-validated our categorisation for each word.

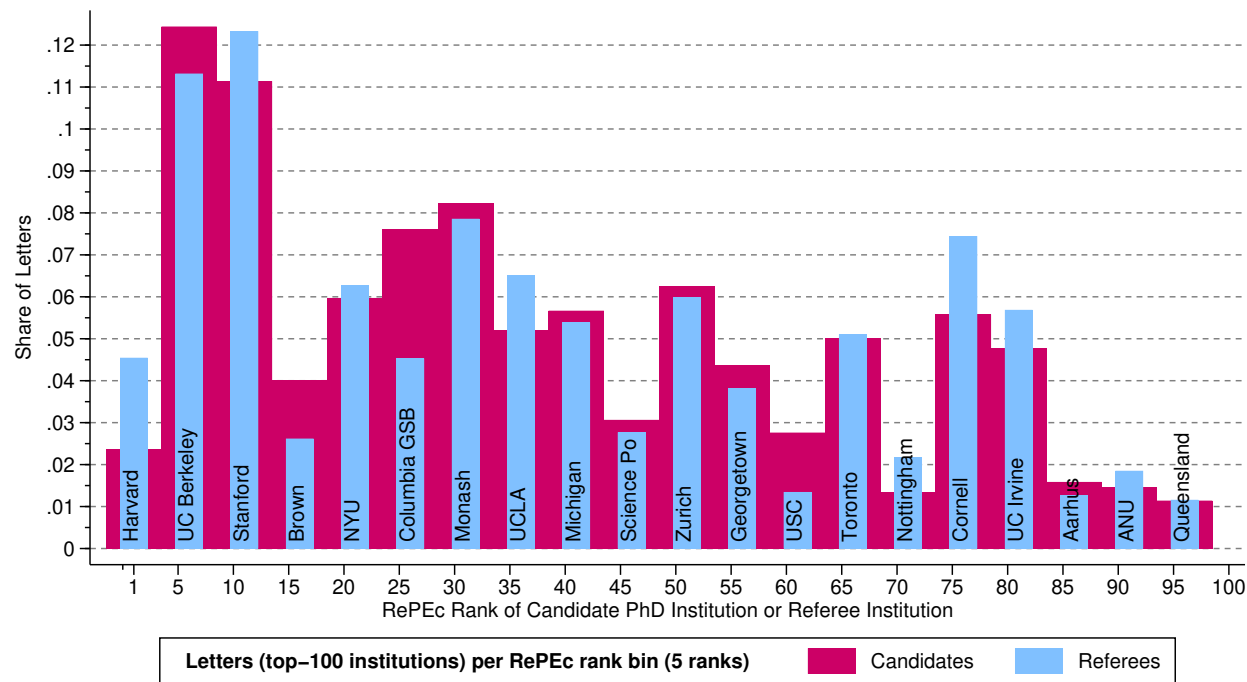
Institutional Ranking

We used the Research Papers in Economics (RePEc) ranking for the top 5% of economic institutions as our guide to rank writer and candidate institutions.³⁶ We drop three research organisations (NBER, IZA, CEPR) but keep international institutions like the IMF as well as the Federal Reserve Banks in the rankings since referees from these institutions are not uncommon. Writer institutional affiliation is collected from their CV via manual internet search and manually matched to the RePEc institutions. We categorise writers into bands on the basis of their institutional ranking: 1-25, 26-50, 51-100, 101-200, 201-500, and higher (omitted category in our regressions). We are missing RePEc-listed affiliation and hence rankings for around 16% of writers, but these only account for 12% of our sample of reference letters. The rank of candidate PhD-institutions has been similarly constructed.

³⁶Version January 2021, see <https://ideas.repec.org/top/top.inst.all.html> for the current version. The RePEc ranking refers to the top 10% but only the top 5% are ranked, the remainder are unranked within the percentile (all those within the 6th percentile, all those within the 7th percentile, etc).

B Additional Descriptive Statistics

Figure B.1: RePEc Rank of Candidate and Letter Writer Institution, Zooming into Top-100 institutions



Notes: The figure presents the frequency distribution of candidate and letter writer institution rank, zooming in on the top-100 (bin width 5 ranks), highlighting one institutions for each bin.

Figure B.2: Word clouds for each sentiment



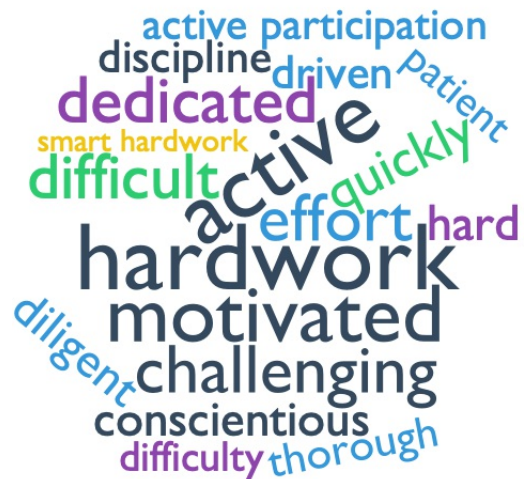
(a) Ability



(c) Recruitment



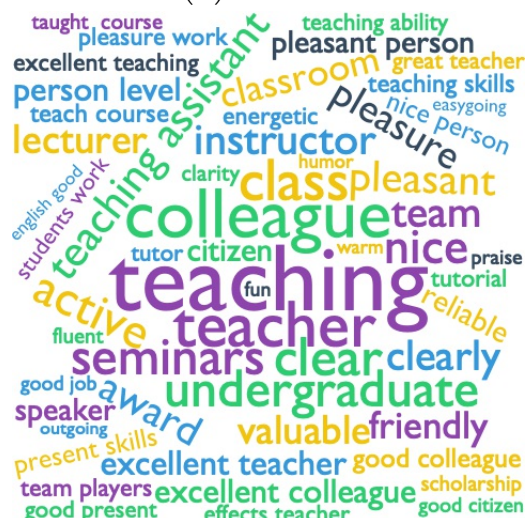
(e) Standout



(b) Grindstone



(d) Research



(f) Teach and Citizen

Notes: The word clouds depict the expressions attributed to each sentiment. The size of the word is illustrative of its document frequency. Within each cloud, larger words are more common in the corpus. The size of the words should not be compared across wordclouds, as the font sizes are adjusted to improve legibility.

C Results Tables

Baseline results

Table C.1: Baseline Results by Writer Institutional Rank

	(1)	(2)	(3)
Writer RePEc Rank	All	Top-25	Top-100
Ability	-0.0212 (1.00)	-0.0370 (0.75)	-0.0326 (1.02)
Grindstone	0.0532 (2.52)**	0.0836 (1.72)*	0.0509 (1.62)
Recruitment	-0.0240 (1.16)	-0.0425 (0.87)	-0.0269 (0.86)
Research	-0.0456 (2.22)**	-0.0376 (0.77)	-0.0503 (1.64)
Standout	-0.0078 (0.37)	-0.0547 (1.11)	0.0134 (0.43)
Teaching & Citizenship	0.0070 (0.34)	0.0071 (0.14)	0.0260 (0.83)
FE/Variables absorbed	25	20	23
Additional covariates	7	7	7
Number of Letters dto for females	11846 3360	2224 616	5344 1508
Number of candidates dto female	3721 1082	1111 318	2301 664
Number of writers dto female	5655 985	969 156	2285 382
Letters by fem writers	1751	314	735
Year FE	yes	yes	yes
Ethnicity/Race FE	yes	yes	yes
Institution Rank FE	yes	yes	yes
Years since PhD	yes	yes	yes
Research Field FE	yes	yes	yes
Publications	yes	yes	yes
Writer characteristics	yes	yes	yes
Letter length	yes	yes	yes

Notes: The table shows results of the OLS regression of each ‘sentiment’ (e.g. ability, grindstone, etc) on a female candidate indicator as well as controls mentioned in the text. The table reports the estimate for the female indicator in the full sample, column 1, and for writer institutions in the top-25 and top-100 in columns 2 and 3, respectively. Each row reports a different outcome, whereas each column reports a different specification. Standard errors are clustered at the letter writer level, we report the absolute *t*-statistics in parentheses. The coefficients are reported in terms of standard deviations of the dependent variable. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. Return to Figure 6 in the maintext.

Male and Female Writers

Table C.2: Male Writers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ability	-0.0241 (1.04)	-0.0228 (0.98)	-0.0242 (1.05)	-0.0265 (1.14)	-0.0263 (1.13)	-0.0261 (1.12)	-0.0253 (1.09)
Grindstone	0.0504 (2.20)**	0.0477 (2.08)**	0.0500 (2.18)**	0.0475 (2.06)**	0.0463 (2.00)**	0.0476 (2.06)**	0.0475 (2.05)**
Recruitment	-0.0235 (1.00)	-0.0229 (0.98)	-0.0220 (0.94)	-0.0325 (1.40)	-0.0293 (1.25)	-0.0300 (1.29)	-0.0259 (1.14)
Research	-0.0732 (3.25)***	-0.0718 (3.19)***	-0.0715 (3.17)***	-0.0696 (3.09)***	-0.0693 (3.07)***	-0.0696 (3.08)***	-0.0721 (3.21)***
Standout	-0.0089 (0.38)	-0.0060 (0.26)	-0.0084 (0.36)	-0.0156 (0.67)	-0.0127 (0.54)	-0.0142 (0.61)	-0.0109 (0.47)
Teaching & Citizenship	0.0209 (0.89)	0.0118 (0.51)	0.0108 (0.47)	0.0055 (0.23)	0.0029 (0.13)	0.0059 (0.26)	0.0075 (0.32)
FE/Variables absorbed	10	15	15	19	19	24	24
Additional covariates			1	1	5	6	7
Number of Letters	10095	10095	10095	10095	10095	10095	10095
dto for females	2729	2729	2729	2729	2729	2729	2729
Number of candidates	3683	3683	3683	3683	3683	3683	3683
dto female	1057	1057	1057	1057	1057	1057	1057
Number of writers	4670	4670	4670	4670	4670	4670	4670
dto female	0	0	0	0	0	0	0
Letters by fem writers	0	0	0	0	0	0	0
Year FE	yes	yes	yes	yes	yes	yes	yes
Ethnicity/Race FE	yes	yes	yes	yes	yes	yes	yes
Institution Rank FE	no	yes	yes	yes	yes	yes	yes
Years since PhD	no	no	yes	yes	yes	yes	yes
Research Field FE	no	no	no	yes	yes	yes	yes
Publications	no	no	no	no	yes	yes	yes
Writer characteristics	no	no	no	no	no	yes	yes
Letter length	no	no	no	no	no	no	yes

Notes: The sample is restricted to male letter writers. The table shows results of the OLS regression of each 'sentiment' (e.g. ability, grindstone, etc) on a female candidate indicator as well as controls mentioned in the text. The table reports the estimate for the female indicator. Each row reports a different outcome, whereas each column reports a different specification. Standard errors are clustered at the letter writer level, we report the absolute t-statistics in parentheses. The coefficients are reported in terms of standard deviations of the dependent variable. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. Return to Figure 7 in the maintext.

Table C.3: Female Writers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ability	0.0022 (0.04)	0.0056 (0.11)	0.0017 (0.03)	-0.0013 (0.02)	-0.0019 (0.04)	-0.0057 (0.11)	-0.0050 (0.10)
Grindstone	0.0804 (1.52)	0.0793 (1.52)	0.0807 (1.54)	0.0770 (1.47)	0.0800 (1.52)	0.0727 (1.39)	0.0724 (1.39)
Recruitment	0.0082 (0.16)	0.0012 (0.02)	0.0028 (0.06)	-0.0155 (0.31)	-0.0140 (0.28)	-0.0198 (0.39)	-0.0178 (0.35)
Research	0.0689 (1.33)	0.0787 (1.53)	0.0757 (1.47)	0.0862 (1.66)*	0.0839 (1.62)	0.0828 (1.60)	0.0825 (1.60)
Standout	0.0242 (0.49)	0.0202 (0.41)	0.0193 (0.39)	0.0150 (0.30)	0.0175 (0.36)	0.0177 (0.36)	0.0196 (0.41)
Teaching & Citizenship	0.0211 (0.40)	0.0140 (0.27)	0.0134 (0.26)	0.0065 (0.12)	0.0081 (0.16)	0.0183 (0.36)	0.0185 (0.36)
FE/Variables absorbed	10	15	15	19	19	24	24
Additional covariates			1	1	5	6	7
Number of Letters dto for females	1751 631	1751 631	1751 631	1751 631	1751 631	1751 631	1751 631
Number of candidates dto female	1414 482	1414 482	1414 482	1414 482	1414 482	1414 482	1414 482
Number of writers dto female	985 985	985 985	985 985	985 985	985 985	985 985	985 985
Letters by fem writers	1751	1751	1751	1751	1751	1751	1751
Year FE	yes	yes	yes	yes	yes	yes	yes
Ethnicity/Race FE	yes	yes	yes	yes	yes	yes	yes
Institution Rank FE	no	yes	yes	yes	yes	yes	yes
Years since PhD	no	no	yes	yes	yes	yes	yes
Research Field FE	no	no	no	yes	yes	yes	yes
Publications	no	no	no	no	yes	yes	yes
Writer characteristics	no	no	no	no	no	yes	yes
Letter length	no	no	no	no	no	no	yes

Notes: The sample is restricted to female letter writers. The table shows results of the OLS regression of each 'sentiment' (e.g. ability, grindstone, etc) on a female candidate indicator as well as controls mentioned in the text. The table reports the estimate for the female indicator. Each row reports a different outcome, whereas each column reports a different specification. Standard errors are clustered at the letter writer level, we report the absolute t-statistics in parentheses. The coefficients are reported in terms of standard deviations of the dependent variable. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. Return to Figure 7 in the maintext.

Cultural Background

Table C.4: Cultural Background

	(1)	(2)	(3)	(4)	(5)
‘Traditional Norms’		Pre-Schooler	Uni Boys	Male Execs	Average
Ability	-0.0197 (0.88)	-0.0095 (0.32)	0.0009 (0.03)	-0.0113 (0.42)	-0.0124 (0.43)
Interaction: Traditional Norms		-0.0120 (0.27)	-0.0335 (0.73)	-0.0163 (0.34)	-0.0110 (0.24)
Grindstone	0.0573 (2.56)**	0.0634 (2.10)**	0.0364 (1.06)	0.0479 (1.80)*	0.0482 (1.66)*
Interaction: Traditional Norms		-0.0062 (0.14)	0.0359 (0.79)	0.0358 (0.72)	0.0240 (0.53)
Recruitment	-0.0333 (1.52)	-0.0448 (1.49)	-0.0407 (1.14)	-0.0431 (1.65)*	-0.0476 (1.64)
Interaction: Traditional Norms		0.0303 (0.69)	0.0082 (0.18)	0.0344 (0.72)	0.0373 (0.84)
Research	-0.0377 (1.74)*	-0.0015 (0.05)	-0.0499 (1.49)	-0.0256 (0.99)	-0.0080 (0.28)
Interaction: Traditional Norms		-0.0739 (1.71)*	0.0175 (0.40)	-0.0328 (0.70)	-0.0643 (1.47)
Standout	0.0129 (0.59)	0.0029 (0.10)	0.0261 (0.73)	0.0029 (0.11)	-0.0016 (0.06)
Interaction: Traditional Norms		0.0230 (0.52)	-0.0198 (0.44)	0.0317 (0.67)	0.0342 (0.76)
Teaching & Citizenship	0.0118 (0.53)	0.0075 (0.25)	-0.0271 (0.81)	0.0020 (0.07)	0.0027 (0.09)
Interaction: Traditional Norms		0.0091 (0.20)	0.0681 (1.52)	0.0245 (0.50)	0.0208 (0.46)
FE/Variables absorbed	25	25+	25+	25+	25+
Additional covariates	6	6	6	6	6
Number of Letters	10542	10542	10542	10542	10542
dto for females	3004	3004	3004	3004	3004
Number of candidates	3674	3674	3674	3674	3674
dto female	1066	1066	1066	1066	1066
Number of writers	4907	4907	4907	4907	4907
dto female	828	828	828	828	828
Letters by fem writers	1506	1506	1506	1506	1506
Year FE	yes	yes	yes	yes	yes
Ethnicity/Race FE	yes	yes	yes	yes	yes
Institution Rank FE	yes	yes	yes	yes	yes
Years since PhD	yes	yes	yes	yes	yes
Research Field FE	yes	yes	yes	yes	yes
Publications	yes	yes	yes	yes	yes
Writer characteristics	yes	yes	yes	yes	yes
Letter length	yes	yes	yes	yes	yes

Notes: The table shows results of the OLS regression of each ‘sentiment’ (e.g. ability, grindstone, etc) on a female candidate indicator interacted with a binary variable indicating whether the writer’s country of birth has traditional gender norms and the full set of controls. Column (5) reports estimates when the average of the 3 WVS questions is used to construct the ‘gender norms’ indicator, whereas columns (2)-(4) use each question separately. The questions are stated fully in the main text. Column (1) reports the benchmark result for this reduced sample (birth or UG countries could be identified for 87% of referees). The table reports the estimate for the female indicator and the interaction term. Each row reports a different outcome, whereas each column reports a different specification. Standard errors are clustered at the letter writer level, we report the absolute t-statistics in parentheses. The coefficients are reported in terms of standard deviations of the dependent variable. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. Return to Figure 8 in the main text.

Specifications with Fixed Effects

Table C.5: Candidate Institution FE

	(1)	(2)	(3)	(4)	(5)	(6)
Ability	-0.0147 (0.66)	-0.0183 (0.82)	-0.0233 (1.04)	-0.0228 (1.02)	-0.0280 (1.25)	-0.0265 (1.18)
Grindstone	0.0526 (2.35)**	0.0537 (2.39)**	0.0494 (2.19)**	0.0494 (2.19)**	0.0443 (1.96)*	0.0443 (1.96)*
Recruitment	-0.0213 (0.98)	-0.0214 (0.98)	-0.0321 (1.46)	-0.0308 (1.40)	-0.0284 (1.29)	-0.0237 (1.10)
Research	-0.0330 (1.50)	-0.0335 (1.52)	-0.0316 (1.43)	-0.0304 (1.37)	-0.0276 (1.24)	-0.0299 (1.35)
Standout	0.0015 (0.07)	-0.0007 (0.03)	-0.0098 (0.44)	-0.0080 (0.36)	-0.0103 (0.47)	-0.0064 (0.29)
Teaching & Citizenship	0.0065 (0.30)	0.0074 (0.34)	0.0044 (0.20)	0.0027 (0.13)	-0.0044 (0.20)	-0.0028 (0.13)
FE/Variables absorbed	237	237	241	241	247	247
Additional covariates		1	1	5	6	7
Number of Letters	10604	10604	10604	10604	10604	10604
dto for females	3158	3158	3158	3158	3158	3158
Number of candidates	3309	3309	3309	3309	3309	3309
dto female	1010	1010	1010	1010	1010	1010
Number of writers	4918	4918	4918	4918	4918	4918
dto female	853	853	853	853	853	853
Letters by fem writers	1553	1553	1553	1553	1553	1553
Year FE	yes	yes	yes	yes	yes	yes
Ethnicity/Race FE	yes	yes	yes	yes	yes	yes
Institution FE	yes	yes	yes	yes	yes	yes
Years since PhD	no	yes	yes	yes	yes	yes
Research Field FE	no	no	yes	yes	yes	yes
Publications	no	no	no	yes	yes	yes
Writer Characteristics	yes	yes	yes	no	yes	yes
Letter length	no	no	no	no	no	yes

Notes: The table shows results of the OLS regression of each ‘sentiment’ (e.g. ability, grindstone, etc) on a female candidate indicator as well as controls mentioned in the text. These specifications include FE for the candidate’s institution. The table reports the estimate for the female indicator. Each row reports a different outcome, whereas each column reports a different specification. Standard errors are clustered at the letter writer level, we report the absolute *t*-statistics in parentheses. The coefficients are reported in terms of standard deviations of the dependent variable. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Return to Figure 9 in the maintext.

Table C.6: Writer FE

	(1)	(2)	(3)	(4)	(5)	(6)
Ability	-0.0391 (1.39)	-0.0367 (1.30)	-0.0381 (1.35)	-0.0375 (1.33)	-0.0381 (1.35)	-0.0358 (1.27)
Grindstone	0.0209 (0.73)	0.0191 (0.66)	0.0179 (0.62)	0.0174 (0.60)	0.0181 (0.63)	0.0195 (0.67)
Recruitment	-0.0056 (0.22)	-0.0049 (0.19)	-0.0044 (0.18)	-0.0057 (0.23)	-0.0029 (0.12)	0.0003 (0.01)
Research	-0.0273 (1.00)	-0.0248 (0.91)	-0.0236 (0.86)	-0.0226 (0.82)	-0.0231 (0.84)	-0.0265 (0.97)
Standout	-0.0181 (0.65)	-0.0187 (0.67)	-0.0208 (0.74)	-0.0206 (0.73)	-0.0173 (0.61)	-0.0114 (0.41)
Teaching & Citizenship	-0.0244 (0.93)	-0.0254 (0.97)	-0.0279 (1.06)	-0.0280 (1.06)	-0.0309 (1.17)	-0.0286 (1.09)
FE/Variables absorbed	1319	1324	1324	1328	1328	1328
Additional covariates			1	1	5	6
Number of Letters	5226	5226	5226	5226	5226	5226
dto for females	1997	1997	1997	1997	1997	1997
Number of candidates	2774	2774	2774	2774	2774	2774
dto female	924	924	924	924	924	924
Number of writers	1314	1314	1314	1314	1314	1314
dto female	197	197	197	197	197	197
Letters by fem writers	699	699	699	699	699	699
Writer FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
Ethnicity/Race FE	yes	yes	yes	yes	yes	yes
Institution Rank FE	no	yes	yes	yes	yes	yes
Years since PhD	no	no	yes	yes	yes	yes
Research Field FE	no	no	no	yes	yes	yes
Publications	no	no	no	no	yes	yes
Letter length	no	no	no	no	no	yes

Notes: The table shows results of the OLS regression of each ‘sentiment’ (e.g. ability, grindstone, etc) on a female candidate indicator as well as controls mentioned in the text. These specifications include letterwriter fixed effects. The table reports the estimate for the female indicator. Each row reports a different outcome, whereas each column reports a different specification. Standard errors are clustered at the letter writer level, we report the absolute *t*-statistics in parentheses. The coefficients are reported in terms of standard deviations of the dependent variable. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

The sample includes only those letters from writers with two or more references for at least one male and one female candidate (gender mix). Return to Figure 9 in the maintext.

Table C.7: Writer FE, writers ‘more familiar’ with female candidates

	(1)	(2)	(3)	(4)	(5)	(6)
Ability	0.0057 (0.15)	0.0085 (0.22)	0.0075 (0.19)	0.0083 (0.21)	0.0059 (0.15)	0.0074 (0.19)
Grindstone	-0.0278 (0.70)	-0.0313 (0.79)	-0.0311 (0.79)	-0.0306 (0.77)	-0.0277 (0.69)	-0.0274 (0.69)
Recruitment	-0.0134 (0.38)	-0.0118 (0.33)	-0.0121 (0.34)	-0.0130 (0.37)	-0.0056 (0.16)	-0.0034 (0.10)
Research	-0.0408 (1.09)	-0.0344 (0.92)	-0.0328 (0.87)	-0.0325 (0.86)	-0.0337 (0.89)	-0.0357 (0.95)
Standout	-0.0558 (1.42)	-0.0548 (1.40)	-0.0564 (1.44)	-0.0558 (1.42)	-0.0524 (1.32)	-0.0485 (1.24)
Teaching & Citizenship	-0.0488 (1.35)	-0.0497 (1.38)	-0.0513 (1.42)	-0.0513 (1.41)	-0.0585 (1.61)	-0.0568 (1.57)
FE/Variables absorbed	754	759	759	763	763	763
Additional covariates			1	1	5	6
Number of Letters	2512	2512	2512	2512	2512	2512
dto for females	1334	1334	1334	1334	1334	1334
Number of candidates	1682	1682	1682	1682	1682	1682
dto female	793	793	793	793	793	793
Number of writers	749	749	749	749	749	749
dto female	129	129	129	129	129	129
Letters by fem writers	408	408	408	408	408	408
Writer FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
Ethnicity/Race FE	yes	yes	yes	yes	yes	yes
Institution Rank FE	no	yes	yes	yes	yes	yes
Years since PhD	no	no	yes	yes	yes	yes
Research Field FE	no	no	no	yes	yes	yes
Publications	no	no	no	no	yes	yes
Letter length	no	no	no	no	no	yes

Notes: The table shows results of the OLS regression of each ‘sentiment’ (e.g. ability, grindstone, etc) on a female candidate indicator as well as controls mentioned in the text. The table reports the estimate for the female indicator. These specifications include letterwriter FE. Each row reports a different outcome, whereas each column reports a different specification. Standard errors are clustered at the letter writer level, we report the absolute *t*-statistics in parentheses. The coefficients are reported in terms of standard deviations of the dependent variable. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. Sample includes only those letters from writers with two or more references for at least one male and one female candidate (gender mix), and who have had more than 1/3 of female Ph.D. students. Return to Figure 9 in the main text.

Table C.8: Writer FE, writers ‘less familiar’ with female candidates

	(1)	(2)	(3)	(4)	(5)	(6)
Ability	-0.0961 (2.35)**	-0.0953 (2.33)**	-0.0973 (2.38)**	-0.0973 (2.37)**	-0.0961 (2.34)**	-0.0931 (2.27)**
Grindstone	0.0840 (1.98)**	0.0842 (1.98)**	0.0817 (1.92)*	0.0815 (1.90)*	0.0843 (1.97)**	0.0875 (2.05)**
Recruitment	0.0033 (0.09)	0.0009 (0.02)	0.0024 (0.06)	0.0006 (0.02)	0.0005 (0.01)	0.0051 (0.14)
Research	-0.0135 (0.33)	-0.0129 (0.32)	-0.0121 (0.30)	-0.0099 (0.24)	-0.0122 (0.30)	-0.0174 (0.43)
Standout	0.0342 (0.84)	0.0331 (0.81)	0.0303 (0.74)	0.0282 (0.69)	0.0298 (0.73)	0.0379 (0.94)
Teaching & Citizenship	0.0014 (0.03)	-0.0015 (0.04)	-0.0046 (0.12)	-0.0038 (0.10)	-0.0025 (0.06)	0.0001 (0.00)
FE/Variables absorbed	570	575	575	579	579	579
Additional covariates			1	1	5	6
Number of Letters	2714	2714	2714	2714	2714	2714
dto for females	663	663	663	663	663	663
Number of candidates	1905	1905	1905	1905	1905	1905
dto female	478	478	478	478	478	478
Number of writers	565	565	565	565	565	565
dto female	68	68	68	68	68	68
Letters by fem writers	291	291	291	291	291	291
Writer FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
Ethnicity/Race FE	yes	yes	yes	yes	yes	yes
Institution Rank FE	no	yes	yes	yes	yes	yes
Years since PhD	no	no	yes	yes	yes	yes
Research Field FE	no	no	no	yes	yes	yes
Publications	no	no	no	no	yes	yes
Letter length	no	no	no	no	no	yes

Notes: The table shows results of the OLS regression of each ‘sentiment’ (e.g. ability, grindstone, etc) on a female candidate indicator as well as controls mentioned in the text. The table reports the estimate for the female indicator. These specifications include letterwriter FE. Each row reports a different outcome, whereas each column reports a different specification. Standard errors are clustered at the letter writer level, we report the absolute *t*-statistics in parentheses. The coefficients are reported in terms of standard deviations of the dependent variable. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. Sample includes only those letters from writers with two or more references for at least one male and one female candidate (gender mix), and who have had less than 1/3 of female Ph.D. students. Return to Figure 9 in the main text.

Table C.9: Candidate Fixed Effects

	(1)	(2)	(3)
Ability: Female writer	0.0789 (1.48)	0.0790 (1.46)	0.0814 (1.51)
Female writer × Female candidate	0.0265 (0.29)	0.0279 (0.31)	0.0272 (0.30)
Grindstone: Female writer	0.1724 (3.32)***	0.1513 (2.88)***	0.1535 (2.92)***
Female writer × Female candidate	-0.0708 (0.76)	-0.0788 (0.84)	-0.0794 (0.85)
Recruitment: Female writer	-0.1167 (2.28)**	-0.1130 (2.19)**	-0.1025 (2.00)**
Female writer × Female candidate	-0.0145 (0.16)	-0.0259 (0.29)	-0.0288 (0.33)
Research: Female writer	-0.0594 (1.18)	-0.0524 (1.03)	-0.0542 (1.07)
Female writer × Female candidate	0.0536 (0.62)	0.0563 (0.65)	0.0567 (0.66)
Standout: Female writer	-0.0851 (1.65)*	-0.0793 (1.52)	-0.0731 (1.41)
Female writer × Female candidate	0.1089 (1.28)	0.1078 (1.27)	0.1061 (1.26)
T&C: Female Writer	0.1081 (2.26)**	0.1074 (2.22)**	0.1104 (2.29)**
Female writer × Female candidate	0.0667 (0.78)	0.0673 (0.78)	0.0665 (0.77)
FE/Variables absorbed	822	827	827
Additional covariates		1	2
Number of Letters	2335	2335	2335
dto for females	778	778	778
Number of candidates	822	822	822
dto female	274	274	274
Number of writers	1204	1204	1204
dto female	348	348	348
Letters by fem writers	930	930	930
Year FE	no	no	no
Candidate FE	yes	yes	yes
Writer Characteristics	no	yes	yes
Letter length	no	no	yes

Notes: The table shows results of the OLS regression of each ‘sentiment’ (e.g. ability, grindstone, etc) on a female candidate indicator as well as controls mentioned in the text. These specifications include candidate FE interacted with the gender of the letterwriter. The table reports the estimate for the female indicator. Each row reports a different outcome, whereas each column reports a different specification. Standard errors are clustered at the letter writer level, we report the absolute t-statistics in parentheses. The coefficients are reported in terms of standard deviations of the dependent variable. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. Return to Figure 7 in the maintext.

D Candidate Research Fields

In this section, we describe the procedure to establish candidates' fields using an unsupervised approach.

From the recommendation letters we extract the text slice that is most likely to discuss the candidates' job market paper. To do so we flag the first instance of the term 'job market paper' or 'dissertation'. We then slice the subsequent 400 words and assemble the research slices from all the recommendation letters written for the same candidate into a single text.³⁷ We process these texts as described in section 3.1 and cluster them into four groups using an unsupervised k-means clustering approach.

Given that the objective of this procedure is to group texts that use similar terms, we deploy a different approach when transforming the text into a database. Instead of computing the tfidf, which would give more weight to terms that are more frequently used in a document compared to the rest of the corpus, we just use a binary representation in which a term is given a value equal to one if it appears in the text. This approach allows us to more easily identify the research texts that contain broad terms that could characterise a field (e.g. 'macro', 'Nash equilibrium', 'causality'), rather than singling out terms used multiple times to describe the job market paper, but that could be very specific to a particular piece of research (e.g. 'assortative matching', 'babbling equilibria'). Finally, following common recommendations for k-means clustering, we reduce the dimensionality of the problem by carrying out a PCA.

Figure D.1 shows the SSE of the k-means clustering procedure as a function of the number of clusters chosen. We identify a kink at four clusters, hence, using the 'elbow method', that is the final number of clusters we select in our analysis.

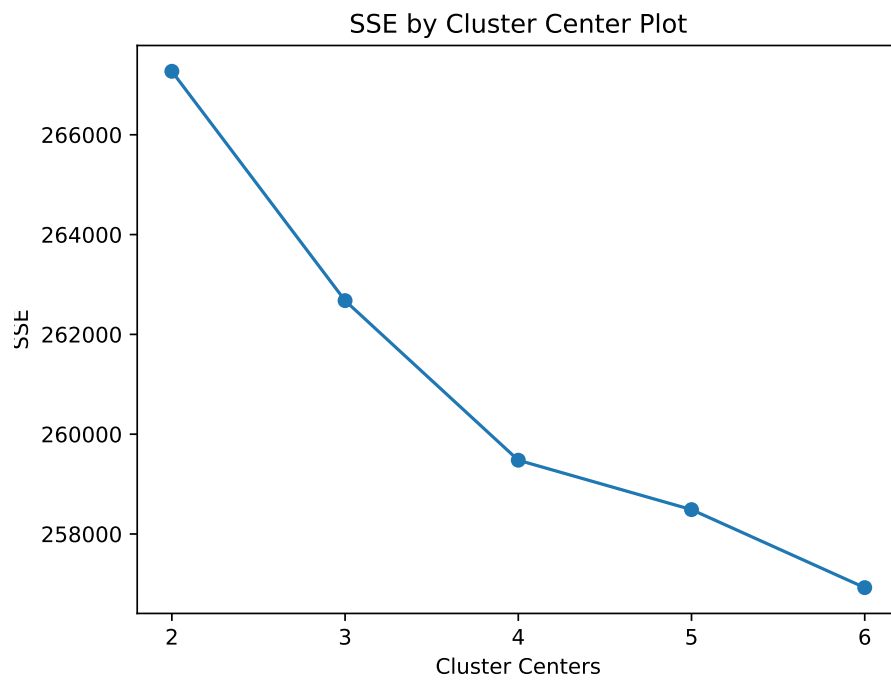
We validate these groupings by highlighting the mapping between them and the self-reported, unstructured primary research field that candidates add to their CV.³⁸ The word clouds in Figure D.2 show the frequency of the reported main fields for each of the candidates in each broad category. Three clearly identified broad groups emerge: macro, applied, and theory. 47% of candidates report 'Macro' as their main field in panel (a). Similarly, applicants listing 'Labor', 'Development', 'Public' or 'Applied Micro' make up 45% of those in panel (b); and those indicating 'Micro Theory', 'Industrial Organization', 'Econometrics', 'Behavioral', 'Applied Theory', 'Game Theory' or 'Economic Theory' represent 44% of the individuals in panel (c). The clustering procedure also creates a fourth category which we cannot credibly assign to a specific broad area and which as a result has been treated as residual.³⁹

³⁷84% are sliced based on the word 'job market paper' and 16% on 'dissertation'.

³⁸222 distinct fields are reported. While these fields do not necessarily map precisely into an existing JEL code, they are typically highly informative when it comes to the actual content of research pursued by the candidates. Moreover, not all candidates report a main field of specialization.

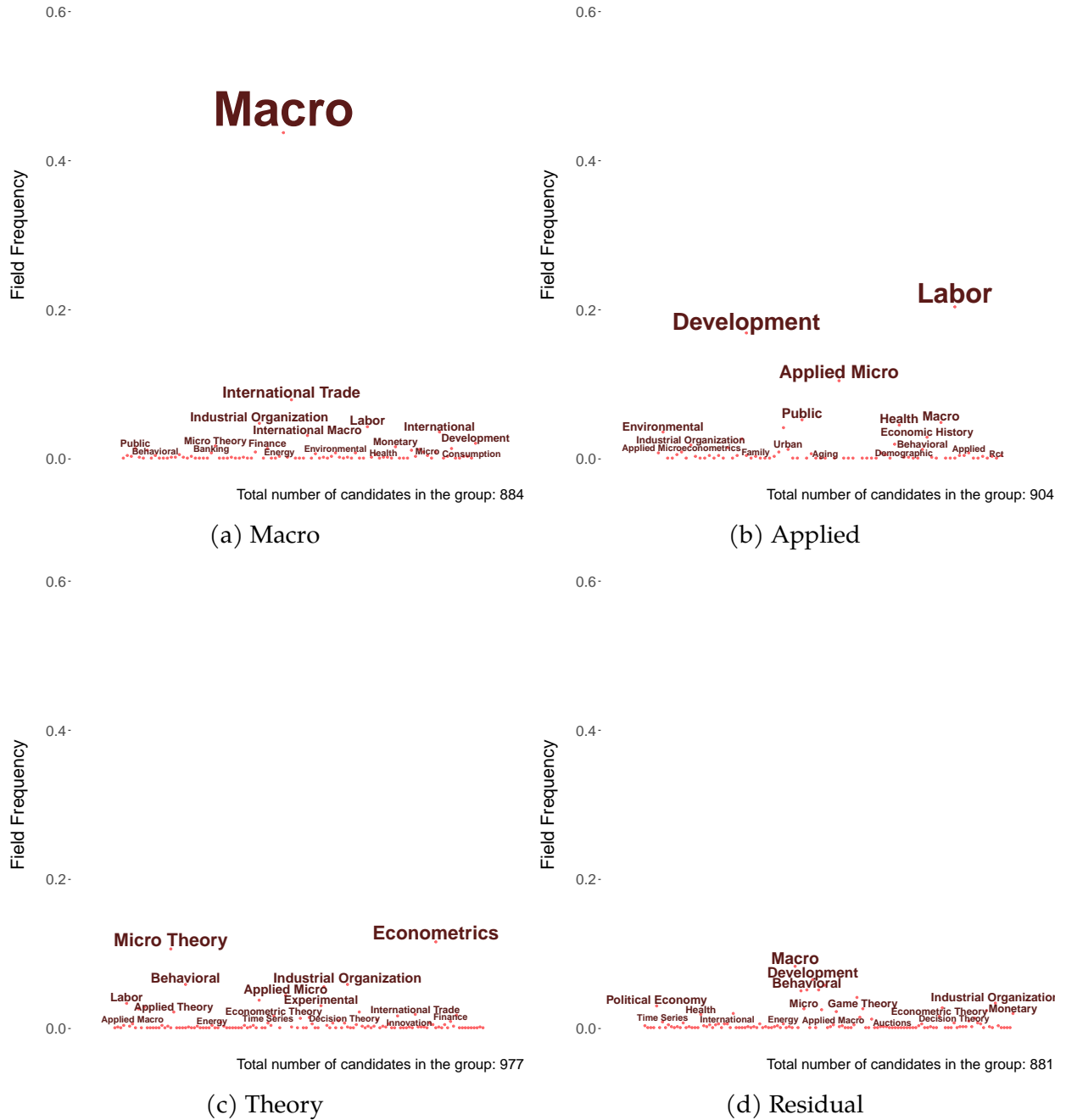
³⁹We experiment with alternative definitions of research fields as controls in the baseline regressions in Section 5.3.

Figure D.1: SSE per cluster number



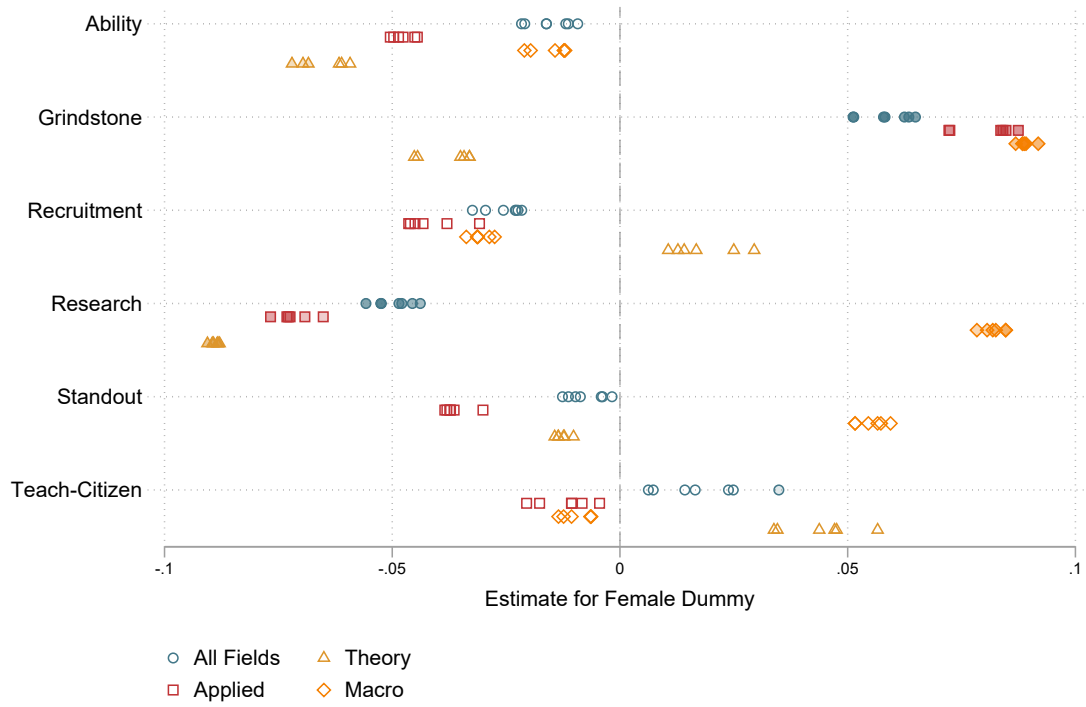
Notes: This figure presents the SSE of the k-means clustering procedure as a function of the number of clusters used to group candidates into research fields.

Figure D.2: Word clouds for Fields



Notes: The word clouds depict the research fields freely written by candidates for each of the categories. For each category, the y -axis and the font size of the fields reflects its frequency as a primary field in the CVs of candidates that reported them. The fields are randomly distributed across the x -axis.

Figure D.3: Regression results, different candidate research fields



Notes: This figure shows the coefficient estimates for the regressions specified in 6, estimated separately for different (aggregated) research field clusters. We show the three most demanding specifications. The symbol's filling permit visualizing significance. The symbol's filling permits visualizing significance. Using 4 levels of possible standard error clustering (none, candidate's institution, letter-writer's institution, or letter writer), we flag significance at 3 different levels (10%, 5%, and 1%). We thus flag 12 possible significance indicators. Then, for each level of clustering, the symbol in the graph is shadowed with a 9% ($\approx 100/12$) opacity when it reaches significance at each possible level. The darker the symbol, the more often it is significant. Fully filled symbols are significant at 1% level across all possible clustering. Hollow symbols do not reach significance for any level of standard error clustering. Additional information on the sample and results for the clustered standard errors by letter-writer are contained in Appendix Section D.

Table D.1: By Candidate Research Field

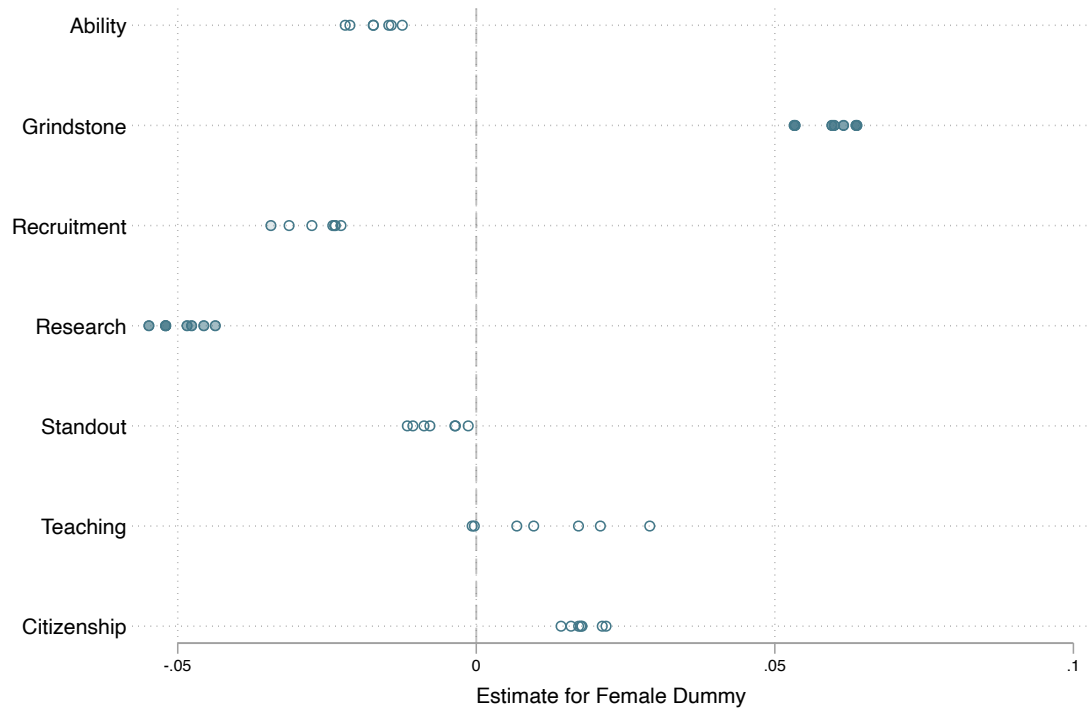
	(1)	(2)	(3)	(4)
Broad Research Fields	All Fields	Macro	Theory	Applied Micro
Ability	-0.0209 (0.98)	-0.0210 (0.46)	-0.0684 (1.65)*	-0.0497 (1.31)
Grindstone	0.0512 (2.41)**	0.0888 (1.91)*	-0.0452 (1.11)	0.0722 (1.84)*
Recruitment	-0.0425 (0.87)	-0.0946 (2.43)**	-0.0269 (0.86)	-0.0253 (0.63)
Research	-0.0376 (0.77)	-0.0301 (0.80)	-0.0503 (1.64)	-0.0633 (1.60)
Standout	-0.0547 (1.11)	-0.0299 (0.77)	0.0134 (0.43)	0.0588 (1.49)
Teaching & Citizenship	0.0071 (0.14)	0.0245 (0.63)	0.0260 (0.83)	0.0441 (1.09)
FE/Variables absorbed	24	21	21	21
Additional covariates	7	7	7	7
Number of Letters dto for females	11638 3328	2832 699	3188 838	3007 1089
Number of candidates dto female	3645 1068	884 219	976 267	904 335
Number of writers dto female	5523 965	1492 215	2135 284	1905 412
Letters by fem writers	1723	360	386	633
Year FE	yes	yes	yes	yes
Ethnicity/Race FE	yes	yes	yes	yes
Institution Rank FE	yes	yes	yes	yes
Years since PhD	yes	yes	yes	yes
Research Field FE	yes	n/a	n/a	n/a
Publications	yes	yes	yes	yes
Writer characteristics	yes	yes	yes	yes
Letter length	yes	yes	yes	yes

Notes: The table shows results of the OLS regression of each ‘sentiment’ (e.g. ability, grindstone, etc) on a female candidate indicator as well as controls mentioned in the text. The table reports the estimate for the female indicator. Each row reports a different outcome, whereas each column reports a different specification. Standard errors are clustered at the letter writer level, we report the absolute t -statistics in parentheses. The coefficients are reported in terms of standard deviations of the dependent variable. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. The regressions are run separately for candidates in each research field. See Section D for details on how the fields are constructed. Return to Section 5.3 in the maintext.

E Robustness checks

Splitting the Teaching and Citizenship ‘Sentiment’

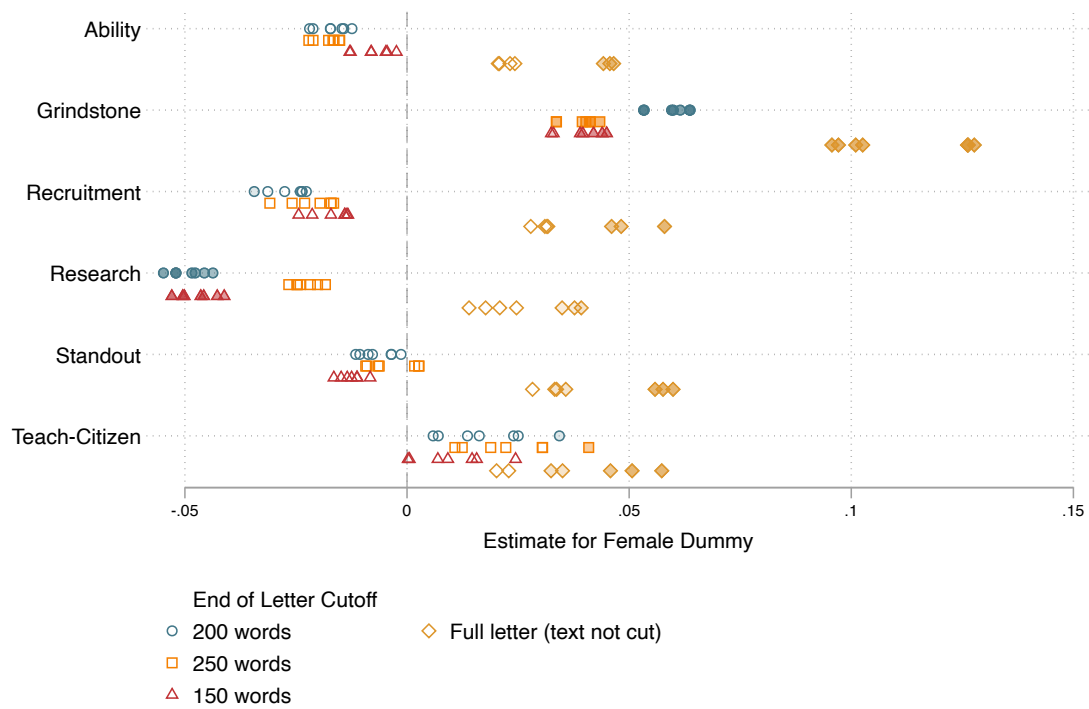
Figure E.1: Regression results, separating teaching and citizenship



Notes: The table shows results of the OLS regression of each ‘sentiment’ (e.g. ability, grindstone, etc) on a female candidate indicator as well as controls mentioned in the text. The table reports the estimate for the female indicator. Each row reports a different outcome, whereas each column reports a different specification. Standard errors are clustered at the letter writer level, we report the absolute *t*-statistics in parentheses. The coefficients are reported in terms of standard deviations of the dependent variable. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. Return to [Section 5.3](#) in the maintext.

Different letter end lengths

Figure E.2: Regression results, different end of letter lengths and full letter



Notes: The table shows results of the OLS regression of each ‘sentiment’ (e.g. ability, grindstone, etc) on a female candidate indicator as well as controls mentioned in the text. The table reports the estimate for the female indicator. Each row reports a different outcome, whereas each column reports a different specification. Standard errors are clustered at the letter writer level, we report the absolute *t*-statistics in parentheses. The coefficients are reported in terms of standard deviations of the dependent variable. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. Regressions are estimated separately for the full letter and samples where the end letter is defined using 150, 200, or 250 words. Return to [Section 5.3](#) in the maintext.

Table E.1: Different end of letter lengths and full letter

	(1)	(2)	(3)	(4)	(5)	(6)
	150 words		200 words		250 words	
Ability	-0.0048 (0.23)	-0.0127 (0.60)	-0.0147 (0.70)	-0.0212 (1.00)	-0.0164 (0.79)	-0.0212 (1.00)
Grindstone	0.0449 (2.10)**	0.0325 (1.52)	0.0637 (3.02)***	0.0532 (2.52)**	0.0434 (2.08)**	0.0336 (1.61)
Recruitment	-0.0140 (0.65)	-0.0140 (0.67)	-0.0236 (1.11)	-0.0240 (1.16)	-0.0165 (0.77)	-0.0196 (0.94)
Research	-0.0530 (2.56)**	-0.0427 (2.05)**	-0.0548 (2.66)***	-0.0456 (2.22)**	-0.0266 (1.28)	-0.0201 (0.97)
Standout	-0.0112 (0.53)	-0.0125 (0.59)	-0.0035 (0.17)	-0.0078 (0.37)	0.0017 (0.08)	-0.0063 (0.30)
Teaching & Citizenship	0.0244 (1.15)	0.0005 (0.03)	0.0343 (1.60)	0.0070 (0.34)	0.0409 (1.90)*	0.0124 (0.59)
FE/Variables absorbed	10	25	10	25	10	25
Additional covariates	1	7	1	7	1	7
Number of Letters	11814	11814	11846	11846	11794	11794
dto for females	3355	3355	3360	3360	3344	3344
Number of candidates	3722	3722	3721	3721	3718	3718
dto female	1082	1082	1082	1082	1079	1079
Number of writers	5652	5652	5655	5655	5617	5617
dto female	981	981	985	985	981	981
Letters by fem writers	1746	1746	1751	1751	1745	1745
Year FE	yes	yes	yes	yes	yes	yes
Ethnicity/Race FE	yes	yes	yes	yes	yes	yes
Institution Rank FE	no	yes	no	yes	no	yes
Years since PhD	no	yes	no	yes	no	yes
Research Field FE	no	yes	no	yes	no	yes
Publications	no	yes	no	yes	no	yes
Writer characteristics	no	yes	no	yes	no	yes
Letter length	no	yes	no	yes	no	yes

Notes: This table presents results for the analysis of three different letter end cut-offs: 150 words, 200 words or 250 words. For each category, we present the most parsimonious and the most elaborate regression model. Return to Section 5.3 in the maintext.

Full Letter

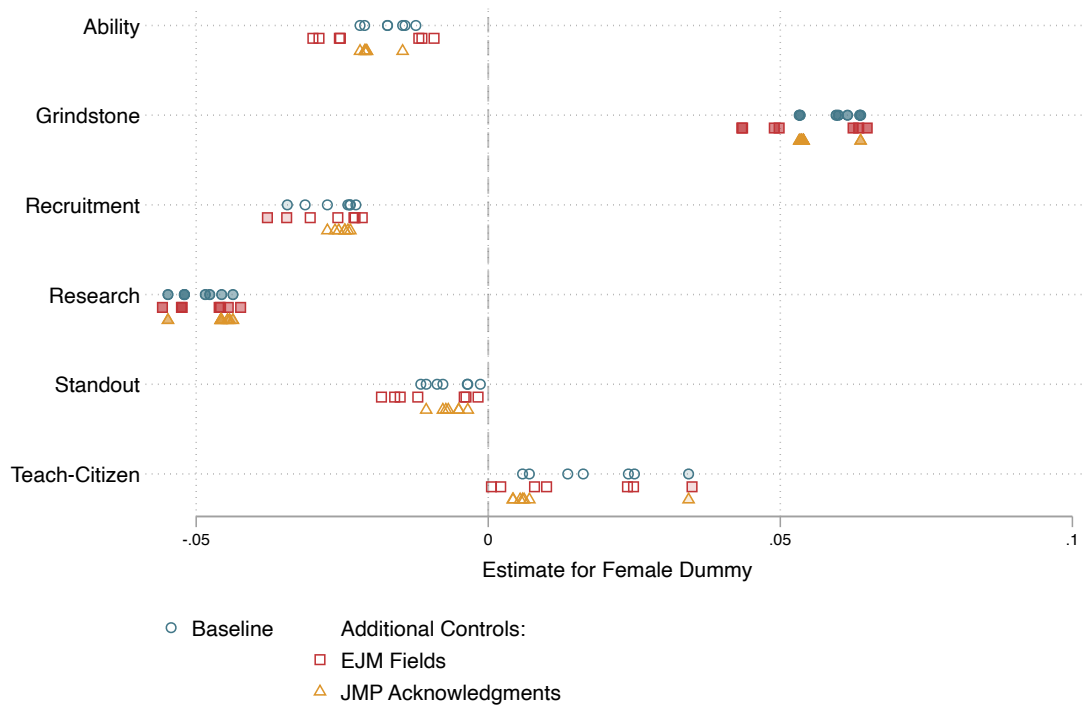
Table E.2: Full Letters — By Writer Institutional Rank

	(1)	(2)	(3)
Writer RePEc Rank	All	Top-25	Top-100
Ability	0.0205 (0.97)	0.0410 (0.85)	0.0177 (0.55)
Grindstone	0.0971 (4.64)***	0.1462 (2.98)***	0.0880 (2.87)***
Recruitment	0.0310 (1.48)	0.1094 (2.16)**	0.0760 (2.42)**
Research	0.0246 (1.19)	0.0832 (1.64)	0.0454 (1.45)
Standout	0.0357 (1.69)*	0.0590 (1.20)	0.0500 (1.60)
Teaching & Citizenship	0.0202 (1.02)	0.0578 (1.17)	0.0520 (1.72)*
FE/Variables absorbed	25	20	23
Additional covariates	7	7	7
Number of Letters	11898	2228	5371
dto for females	3367	616	1513
Number of candidates	3721	1111	2304
dto female	1082	318	667
Number of writers	5670	971	2292
dto female	986	156	382
Letters by fem writers	1756	314	737
Year FE	yes	yes	yes
Ethnicity/Race FE	yes	yes	yes
Institution Rank FE	yes	yes	yes
Years since PhD	yes	yes	yes
Research Field FE	yes	yes	yes
Publications	yes	yes	yes
Writer characteristics	yes	yes	yes
Letter length	yes	yes	yes

Notes: The table shows results of the OLS regression of each ‘sentiment’ (e.g. ability, grindstone, etc) on a female candidate indicator as well as controls mentioned in the text. The table reports the estimate for the female indicator. Each row reports a different outcome, whereas each column reports a different specification. Standard errors are clustered at the letter writer level, we report the absolute t -statistics in parentheses. The coefficients are reported in terms of standard deviations of the dependent variable. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. The regressions are run for the full letter. Return to [Section 5.3](#) in the maintext.

Additional Controls

Figure E.3: Regression results, EJM fields and JMP acknowledgements as controls



Notes: The table shows results of the OLS regression of each ‘sentiment’ (e.g. ability, grindstone, etc) on a female candidate indicator as well as controls mentioned in the text. These specifications also include two sets of additional controls, either proxies of candidate’s visibility using JMP acknowledgements, or alternative definitions of research fields using EJM Fields. The table reports the estimate for the female indicator. Each row reports a different outcome, whereas each column reports a different specification. Standard errors are clustered at the letter writer level, we report the absolute t -statistics in parentheses. The coefficients are reported in terms of standard deviations of the dependent variable. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. Return to Section 5.3 in the maintext.

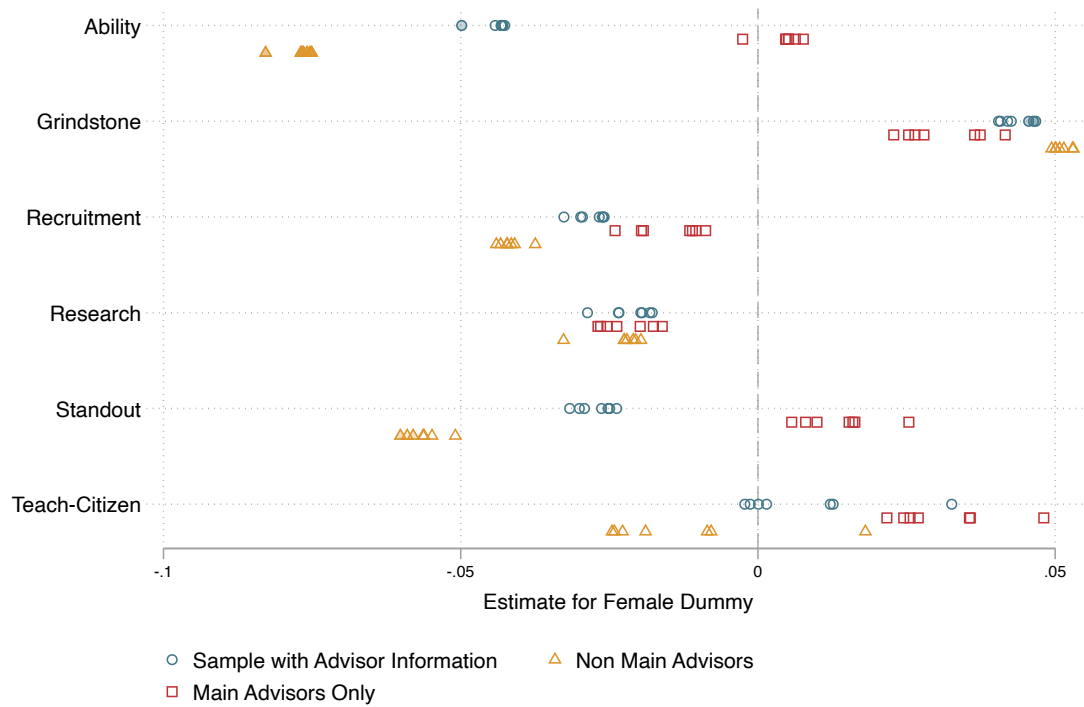
Table E.3: EJM Fields as Controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ability	-0.0119 (0.56)	-0.0093 (0.44)	-0.0113 (0.54)	-0.0253 (1.16)	-0.0255 (1.17)	-0.0300 (1.38)	-0.0290 (1.33)
Grindstone	0.0649 (3.05)***	0.0625 (2.94)***	0.0634 (2.99)***	0.0498 (2.25)**	0.0490 (2.21)**	0.0435 (1.97)**	0.0434 (1.97)**
Recruitment	-0.0230 (1.08)	-0.0228 (1.08)	-0.0216 (1.02)	-0.0378 (1.75)*	-0.0345 (1.59)	-0.0305 (1.40)	-0.0257 (1.21)
Research	-0.0558 (2.69)***	-0.0525 (2.53)**	-0.0524 (2.53)**	-0.0461 (2.15)**	-0.0458 (2.14)**	-0.0424 (1.97)**	-0.0445 (2.08)**
Standout	-0.0041 (0.19)	-0.0017 (0.08)	-0.0038 (0.18)	-0.0183 (0.84)	-0.0151 (0.69)	-0.0160 (0.74)	-0.0121 (0.56)
Teaching & Citizenship	0.0349 (1.62)	0.0249 (1.16)	0.0238 (1.11)	0.0100 (0.45)	0.0079 (0.35)	0.0006 (0.02)	0.0021 (0.10)
FE/Variables absorbed	10	15	15	159	159	165	165
Additional covariates			1	1	5	6	7
Number of Letters	11638	11638	11638	11482	11482	11482	11482
dto for females	3328	3328	3328	3268	3268	3268	3268
Number of candidates	3645	3645	3645	3591	3591	3591	3591
dto female	1068	1068	1068	1048	1048	1048	1048
Number of writers	5523	5523	5523	5466	5466	5466	5466
dto female	965	965	965	956	956	956	956
Letters by fem writers	1723	1723	1723	1704	1704	1704	1704
Year FE	yes	yes	yes	yes	yes	yes	yes
Ethnicity/Race FE	yes	yes	yes	yes	yes	yes	yes
Institution Rank FE	no	yes	yes	yes	yes	yes	yes
Years since PhD	no	no	yes	yes	yes	yes	yes
EJM Research Field FE	no	no	no	yes	yes	yes	yes
Publications	no	no	no	no	yes	yes	yes
Writer characteristics	no	no	no	no	no	yes	yes
Letter length	no	no	no	no	no	no	yes

Notes: The table shows results of the OLS regression of each ‘sentiment’ (e.g. ability, grindstone, etc) on a female candidate indicator as well as controls mentioned in the text. These specifications also include as controls alternative definitions of research fields using EJM Fields. The table reports the estimate for the female indicator. Each row reports a different outcome, whereas each column reports a different specification. Standard errors are clustered at the letter writer level, we report the absolute t -statistics in parentheses. The coefficients are reported in terms of standard deviations of the dependent variable. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. Return to Section 5.3 in the maintext.

Main Advisor vs Other Letter Writers

Figure E.4: Regression results, main advisor vs other letter writers



Notes: This figure shows the coefficient estimates for the regressions specified in 6, estimated separately for letters written by the main advisor and by others. We show the three most demanding specifications. The symbol's filling permit visualizing significance. Using 4 levels of possible standard error clustering (none, candidate's institution, letter-writer's institutions, and field), we flag significance at 3 different levels (10%, 5%, and 1%). We thus flag 12 possible significance indicators. Then, for each level of clustering, the symbol in the graph is shadowed with a 9% ($\approx 100/12$) opacity when it reaches significance at each possible level. The darker the symbol the more often they are significant. The darker the symbol, the more often it is significant. Fully filled symbols are significant at 1% level across all possible clustering. Hollow symbols do not reach significance for any level of standard error clustering. See overleaf for information on sample and results tables for clustering by letter writer. Return to Section 5.3 in the maintext.

Table E.4: Main Advisors Only

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ability	-0.0026 (0.05)	0.0052 (0.11)	0.0051 (0.11)	0.0048 (0.10)	0.0063 (0.13)	0.0046 (0.10)	0.0076 (0.16)
Grindstone	0.0416 (0.91)	0.0364 (0.80)	0.0374 (0.82)	0.0228 (0.51)	0.0279 (0.62)	0.0264 (0.59)	0.0253 (0.56)
Recruitment	-0.0088 (0.19)	-0.0105 (0.22)	-0.0115 (0.25)	-0.0240 (0.51)	-0.0193 (0.41)	-0.0196 (0.42)	-0.0110 (0.24)
Research	-0.0254 (0.57)	-0.0265 (0.59)	-0.0269 (0.60)	-0.0198 (0.44)	-0.0176 (0.39)	-0.0161 (0.36)	-0.0237 (0.53)
Standout	0.0254 (0.54)	0.0163 (0.35)	0.0160 (0.34)	0.0057 (0.12)	0.0080 (0.17)	0.0099 (0.21)	0.0153 (0.33)
Teaching & Citizenship	0.0481 (1.03)	0.0356 (0.77)	0.0357 (0.77)	0.0245 (0.53)	0.0270 (0.58)	0.0217 (0.47)	0.0256 (0.55)
FE/Variables absorbed	10	15	15	19	19	24	24
Additional covariates			1	1	5	6	7
Number of Letters	2348	2348	2348	2348	2348	2348	2348
dto for females	683	683	683	683	683	683	683
Number of candidates	1875	1875	1875	1875	1875	1875	1875
dto female	536	536	536	536	536	536	536
Number of writers	1523	1523	1523	1523	1523	1523	1523
dto female	217	217	217	217	217	217	217
Letters by fem writers	298	298	298	298	298	298	298
Year FE	yes	yes	yes	yes	yes	yes	yes
Ethnicity/Race FE	yes	yes	yes	yes	yes	yes	yes
Institution Rank FE	no	yes	yes	yes	yes	yes	yes
Years since PhD	no	no	yes	yes	yes	yes	yes
Research Field FE	no	no	no	yes	yes	yes	yes
Publications	no	no	no	no	yes	yes	yes
Writer characteristics	no	no	no	no	no	yes	yes
Letter length	no	no	no	no	no	no	yes

Notes: The table shows results of the OLS regression of each ‘sentiment’ (e.g. ability, grindstone, etc) on a female candidate indicator as well as controls mentioned in the text. The table reports the estimate for the female indicator. Each row reports a different outcome, whereas each column reports a different specification. Standard errors are clustered at the letter writer level, we report the absolute *t*-statistics in parentheses. The coefficients are reported in terms of standard deviations of the dependent variable. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. The sample includes letters written by the main advisors, for candidates for whom that information was available and who obtained their Ph.D. 0-3 years before they enter our sample. Return to Section 5.3 in the maintext.

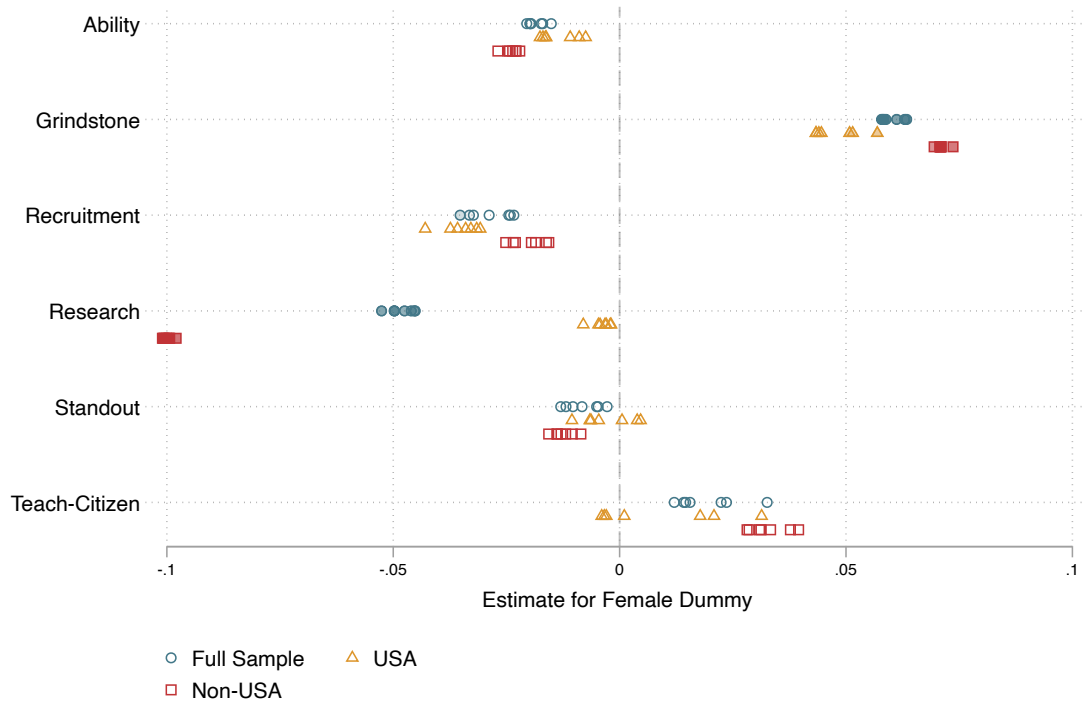
Table E.5: Exclude Main Advisors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ability	-0.0828 (2.23)**	-0.0769 (2.07)**	-0.0767 (2.06)**	-0.0764 (2.04)**	-0.0754 (2.01)**	-0.0758 (2.02)**	-0.0751 (1.99)**
Grindstone	0.0501 (1.32)	0.0507 (1.33)	0.0515 (1.35)	0.0529 (1.38)	0.0531 (1.38)	0.0500 (1.30)	0.0494 (1.29)
Recruitment	-0.0433 (1.11)	-0.0415 (1.07)	-0.0409 (1.06)	-0.0440 (1.14)	-0.0421 (1.09)	-0.0422 (1.09)	-0.0374 (0.99)
Research	-0.0327 (0.86)	-0.0225 (0.59)	-0.0225 (0.59)	-0.0210 (0.55)	-0.0197 (0.51)	-0.0206 (0.54)	-0.0220 (0.58)
Standout	-0.0590 (1.60)	-0.0562 (1.52)	-0.0563 (1.52)	-0.0601 (1.61)	-0.0580 (1.56)	-0.0548 (1.48)	-0.0509 (1.40)
Teaching & Citizenship	0.0181 (0.47)	-0.0079 (0.21)	-0.0085 (0.23)	-0.0189 (0.50)	-0.0228 (0.61)	-0.0241 (0.65)	-0.0245 (0.66)
FE/Variables absorbed	10	15	15	19	19	24	24
Additional covariates			1	1	5	6	7
Number of Letters	3733	3733	3733	3733	3733	3733	3733
dto for females	1030	1030	1030	1030	1030	1030	1030
Number of candidates	1850	1850	1850	1850	1850	1850	1850
dto female	524	524	524	524	524	524	524
Number of writers	2522	2522	2522	2522	2522	2522	2522
dto female	434	434	434	434	434	434	434
Letters by fem writers	628	628	628	628	628	628	628
Year FE	yes	yes	yes	yes	yes	yes	yes
Ethnicity/Race FE	yes	yes	yes	yes	yes	yes	yes
Institution Rank FE	no	yes	yes	yes	yes	yes	yes
Years since PhD	no	no	yes	yes	yes	yes	yes
Research Field FE	no	no	no	yes	yes	yes	yes
Publications	no	no	no	no	yes	yes	yes
Writer characteristics	no	no	no	no	no	yes	yes
Letter length	no	no	no	no	no	no	yes

Notes: The table shows results of the OLS regression of each ‘sentiment’ (e.g. ability, grindstone, etc) on a female candidate indicator as well as controls mentioned in the text. The table reports the estimate for the female indicator. Each row reports a different outcome, whereas each column reports a different specification. Standard errors are clustered at the letter writer level, we report the absolute t -statistics in parentheses. The coefficients are reported in terms of standard deviations of the dependent variable. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. The sample includes the letters written by referees who are not the main advisor, for candidates for whom this information was available and who obtained their Ph.D. 0-3 years before they appear in our data. Return to Section 5.3 in the maintext.

Location of PhD-granting institution

Figure E.5: Regression results, by location of letter writer institution



Notes: This figure shows the coefficient estimates for the regressions specified in 6, estimated separately for letter writers based in the US and in all other countries. We show the three most demanding specifications. The symbol's filling permit visualizing significance. Using 4 levels of possible standard error clustering (none, candidate's institution, letter-writer's institutions, and field), we flag significance at 3 different levels (10%, 5%, and 1%). We thus flag 12 possible significance indicators. Then, for each level of clustering, the symbol in the graph is shadowed with a 9% ($\approx 100/12$) opacity when it reaches significance at each possible level. The darker the symbol the more often they are significant. The darker the symbol, the more often it is significant. Fully filled symbols are significant at 1% level across all possible clustering. Hollow symbols do not reach significance for any level of standard error clustering. Return to Section 5.3 in the maintext.

Table E.6: US-based candidates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ability	-0.0089 (0.31)	-0.0075 (0.26)	-0.0109 (0.38)	-0.0176 (0.61)	-0.0162 (0.56)	-0.0169 (0.59)	-0.0164 (0.57)
Grindstone	0.0569 (1.91)*	0.0515 (1.73)*	0.0508 (1.70)*	0.0446 (1.47)	0.0440 (1.45)	0.0434 (1.43)	0.0434 (1.43)
Recruitment	-0.0308 (1.04)	-0.0329 (1.12)	-0.0316 (1.08)	-0.0429 (1.46)	-0.0374 (1.27)	-0.0358 (1.22)	-0.0340 (1.18)
Research	-0.0080 (0.28)	-0.0032 (0.11)	-0.0047 (0.16)	-0.0043 (0.15)	-0.0019 (0.07)	-0.0021 (0.07)	-0.0030 (0.10)
Standout	0.0046 (0.16)	0.0039 (0.13)	0.0005 (0.02)	-0.0105 (0.37)	-0.0066 (0.23)	-0.0063 (0.22)	-0.0046 (0.16)
Teaching & Citizenship	0.0314 (1.05)	0.0209 (0.71)	0.0178 (0.60)	0.0010 (0.04)	-0.0029 (0.10)	-0.0040 (0.14)	-0.0034 (0.12)
FE/Variables absorbed	10	15	15	19	19	24	24
Additional covariates			1	1	5	6	7
Number of Letters	5969	5969	5969	5969	5969	5969	5969
dto for females	1716	1716	1716	1716	1716	1716	1716
Number of candidates	1874	1874	1874	1874	1874	1874	1874
dto female	552	552	552	552	552	552	552
Number of writers	2749	2749	2749	2749	2749	2749	2749
dto female	521	521	521	521	521	521	521
Letters by fem writers	981	981	981	981	981	981	981
Year FE	yes	yes	yes	yes	yes	yes	yes
Ethnicity/Race FE	yes	yes	yes	yes	yes	yes	yes
Institution Rank FE	no	yes	yes	yes	yes	yes	yes
Years since PhD	no	no	yes	yes	yes	yes	yes
Research Field FE	no	no	no	yes	yes	yes	yes
Publications	no	no	no	no	yes	yes	yes
Writer characteristics	no	no	no	no	no	yes	yes
Letter length	no	no	no	no	no	no	yes

Notes: The table shows results of the OLS regression of each ‘sentiment’ (e.g. ability, grindstone, etc) on a female candidate indicator as well as controls mentioned in the text. The table reports the estimate for the female indicator. Each row reports a different outcome, whereas each column reports a different specification. Standard errors are clustered at the letter writer level, we report the absolute *t*-statistics in parentheses. The coefficients are reported in terms of standard deviations of the dependent variable. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. The sample includes letters in support of candidates who obtained their Ph.D. in institutions in the U.S.. Return to Section 5.3 in the maintext.

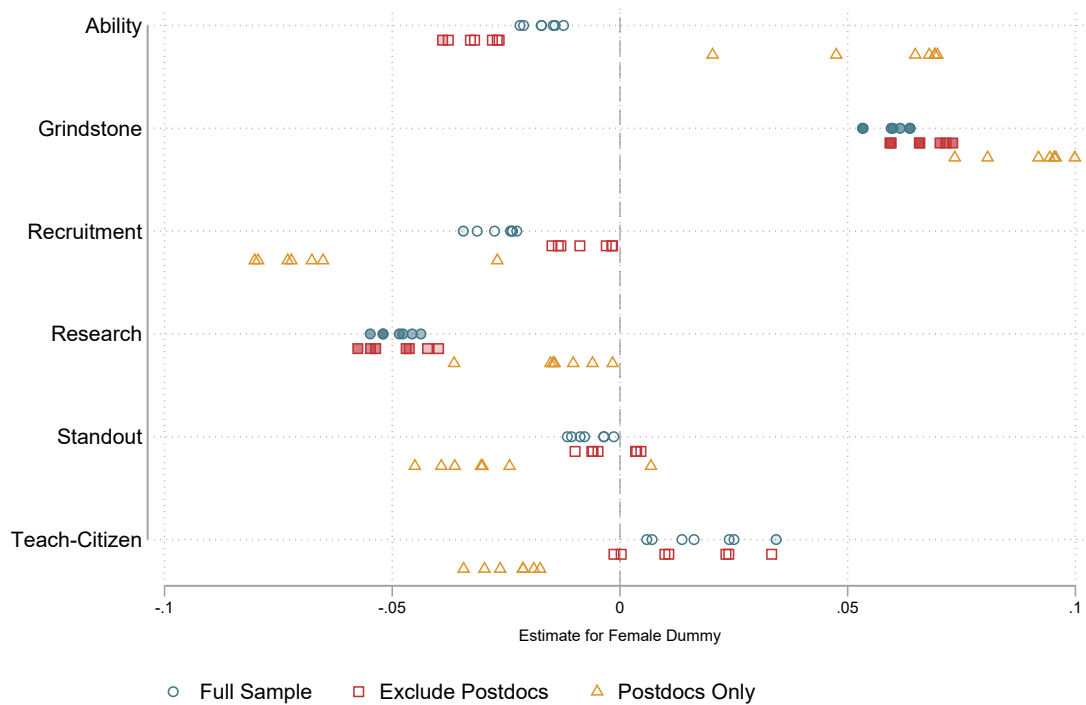
Table E.7: Non US-based candidates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ability	-0.0269 (0.88)	-0.0229 (0.75)	-0.0243 (0.80)	-0.0247 (0.80)	-0.0236 (0.77)	-0.0230 (0.75)	-0.0221 (0.72)
Grindstone	0.0695 (2.32)**	0.0710 (2.38)**	0.0736 (2.47)**	0.0709 (2.38)**	0.0709 (2.38)**	0.0710 (2.38)**	0.0707 (2.37)**
Recruitment	-0.0186 (0.61)	-0.0156 (0.52)	-0.0162 (0.53)	-0.0235 (0.78)	-0.0230 (0.76)	-0.0251 (0.83)	-0.0195 (0.65)
Research	-0.1008 (3.43)***	-0.1005 (3.40)***	-0.0994 (3.36)***	-0.0996 (3.35)***	-0.1001 (3.36)***	-0.0980 (3.29)***	-0.1010 (3.41)***
Standout	-0.0129 (0.42)	-0.0086 (0.28)	-0.0105 (0.34)	-0.0137 (0.44)	-0.0139 (0.45)	-0.0157 (0.51)	-0.0119 (0.39)
Teaching & Citizenship	0.0333 (1.10)	0.0282 (0.93)	0.0286 (0.94)	0.0309 (1.01)	0.0312 (1.02)	0.0377 (1.24)	0.0395 (1.30)
FE/Variables absorbed	10	15	15	19	19	24	24
Additional covariates			1	1	5	6	7
Number of Letters	5836	5836	5836	5836	5836	5836	5836
dto for females	1630	1630	1630	1630	1630	1630	1630
Number of candidates	1834	1834	1834	1834	1834	1834	1834
dto female	526	526	526	526	526	526	526
Number of writers	3269	3269	3269	3269	3269	3269	3269
dto female	497	497	497	497	497	497	497
Letters by fem writers	759	759	759	759	759	759	759
Year FE	yes	yes	yes	yes	yes	yes	yes
Ethnicity/Race FE	yes	yes	yes	yes	yes	yes	yes
Institution Rank FE	no	yes	yes	yes	yes	yes	yes
Years since PhD	no	no	yes	yes	yes	yes	yes
Research Field FE	no	no	no	yes	yes	yes	yes
Publications	no	no	no	no	yes	yes	yes
Writer characteristics	no	no	no	no	no	yes	yes
Letter length	no	no	no	no	no	no	yes

Notes: The table shows results of the OLS regression of each ‘sentiment’ (e.g. ability, grindstone, etc) on a female candidate indicator as well as controls mentioned in the text. The table reports the estimate for the female indicator. Each row reports a different outcome, whereas each column reports a different specification. Standard errors are clustered at the letter writer level, we report the absolute *t*-statistics in parentheses. The coefficients are reported in terms of standard deviations of the dependent variable. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. The sample includes letters in support of candidates who obtained their Ph.D. in institutions outside the U.S.. Return to Section 5.3 in the maintext.

Postdocs vs Others

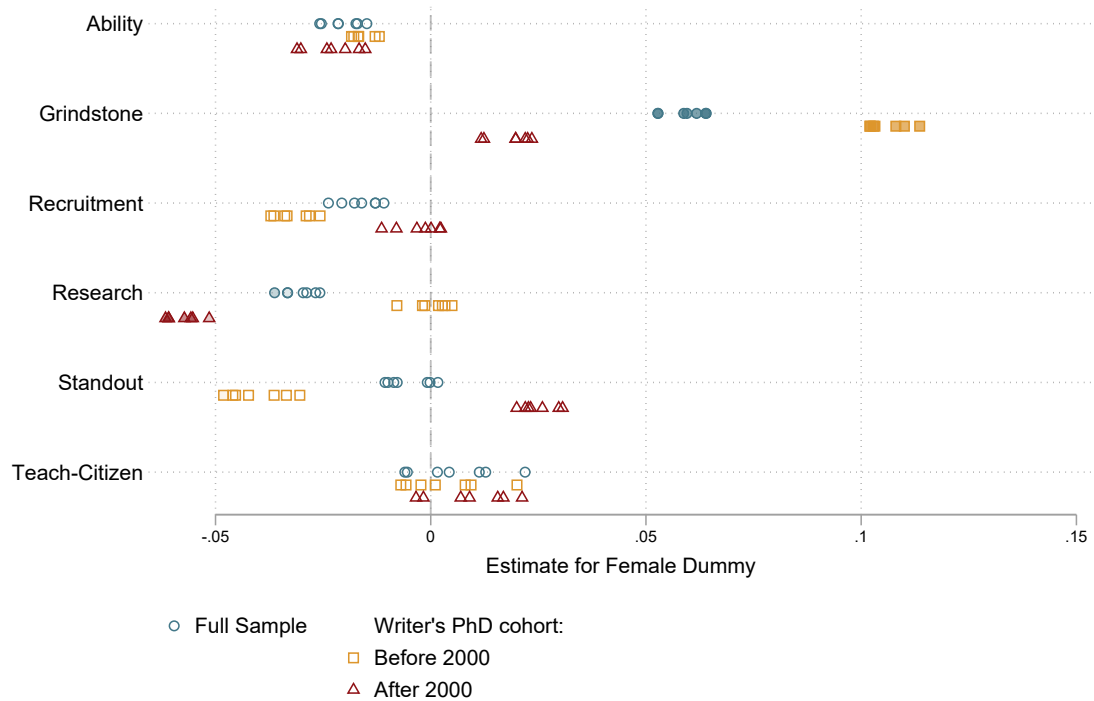
Figure E.6: Regression results, Postdocs and Candidates Freshly out of Ph.D.



Notes: This figure shows the coefficient estimates for the regressions specified in 6, estimated separately for postdocs and those who are freshly out of PhD programs. We show the three most demanding specifications. The symbol's filling permit visualizing significance. Using 4 levels of possible standard error clustering (none, candidate's institution, letter-writer's institutions, and field), we flag significance at 3 different levels (10%, 5%, and 1%). We thus flag 12 possible significance indicators. Then, for each level of clustering, the symbol in the graph is shadowed with a 9% ($\approx 100/12$) opacity when it reaches significance at each possible level. The darker the symbol the more often they are significant. The darker the symbol, the more often it is significant. Fully filled symbols are significant at 1% level across all possible clustering. Hollow symbols do not reach significance for any level of standard error clustering. See overleaf for information on sample and results tables for clustering by letter writer. Return to Section 5.3 in the maintext.

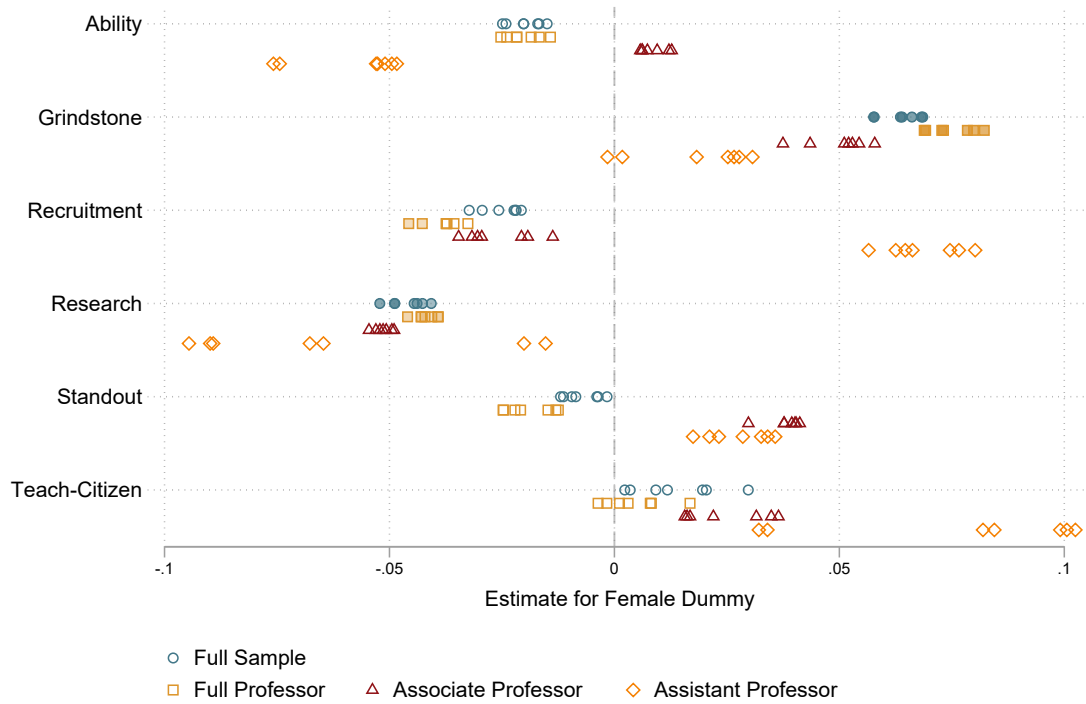
Seniority of Letterwriter

Figure E.7: Regression results, by year of PhD for letterwriter



Notes: This figure shows the coefficient estimates for the regressions specified in 6, estimated separately for letters written by the advisors who obtained their PhDs before or after 2000. We show the three most demanding specifications. The symbol's filling permit visualizing significance. Using 4 levels of possible standard error clustering (none, candidate's institution, letter-writer's institutions, and field), we flag significance at 3 different levels (10%, 5%, and 1%). We thus flag 12 possible significance indicators. Then, for each level of clustering, the symbol in the graph is shadowed with a 9% ($\approx 100/12$) opacity when it reaches significance at each possible level. The darker the symbol the more often they are significant. The darker the symbol, the more often it is significant. Fully filled symbols are significant at 1% level across all possible clustering. Hollow symbols do not reach significance for any level of standard error clustering. See overleaf for information on sample and results tables for clustering by letter writer. Return to Section 5.3 in the maintext.

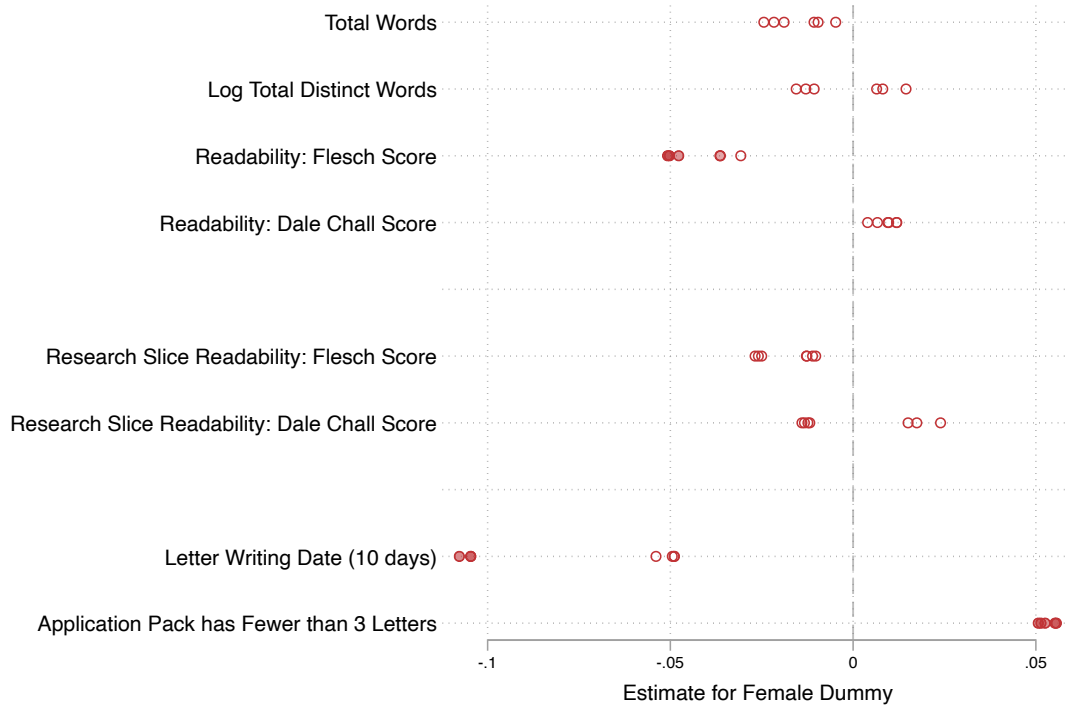
Figure E.8: Regression results, by Academic Rank of Letterwriter



Notes: This figure shows the coefficient estimates for the regressions specified in 6, estimated separately for letters written by the advisors who obtained their PhDs before or after 2000. We show the three most demanding specifications. The symbol's filling permit visualizing significance. Using 4 levels of possible standard error clustering (none, candidate's institution, letter-writer's institutions, and field), we flag significance at 3 different levels (10%, 5%, and 1%). We thus flag 12 possible significance indicators. Then, for each level of clustering, the symbol in the graph is shadowed with a 9% ($\approx 100/12$) opacity when it reaches significance at each possible level. The darker the symbol the more often they are significant. The darker the symbol, the more often it is significant. Fully filled symbols are significant at 1% level across all possible clustering. Hollow symbols do not reach significance for any level of standard error clustering. See overleaf for information on sample and results tables for clustering by letter writer. Return to Section 5.3 in the maintext.

F Additional Results

Figure F.1: Regression Results Length, Readability and Timeliness



Notes: This figure shows the coefficient estimates for the regressions specified in 6 when outcomes are proxies for length and readability of the letter (first four rows), readability of the research slice (next two rows), and the letter date (final row). The symbol's filling permit visualizing significance. In the first to seventh line, we use four levels of possible standard error clustering (none, candidate's institution, letter-writer's institution, or letter writer), flag significance at three different levels (10%, 5%, and 1%). Then, for each level of clustering, the symbol in the graph is shaded with a 9% ($\approx 100/12$) opacity when it reaches significance at each possible level. The regression reported in the eighth line is conducted at the *candidate* level, hence only two clustering levels are used (none, and letter writer institution). The symbols are then shaded accordingly. The darker the symbol the more often they are significant. The darker the symbol, the more often it is significant. Fully filled symbols are significant at 1% level across all possible clustering. Hollow symbols do not reach significance for any level of standard error clustering. Return to Section 5.4 in the maintext.

Table F.1: Readability

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Full Letter						
<i>(a) Word Counts as Dependent Variable</i>						
Number of words	-0.0096 (0.44)	-0.0048 (0.22)	-0.0107 (0.51)	-0.0244 (1.18)	-0.0217 (1.05)	-0.0189 (0.91)
Log (Number of words)	0.0081 (0.38)	0.0145 (0.70)	0.0064 (0.31)	-0.0156 (0.78)	-0.0129 (0.65)	-0.0107 (0.54)
<i>(b) Writing Quality Measures as Dependent Variable</i>						
Flesch Readability (higher=easier)	-0.0477 (2.28)**	-0.0502 (2.39)**	-0.0507 (2.41)**	-0.0363 (1.74)*	-0.0364 (1.74)*	-0.0307 (1.47)
Dale-Chall Readability (higher=harder)	0.0095 (0.45)	0.0040 (0.19)	0.0119 (0.57)	0.0119 (0.58)	0.0097 (0.47)	0.0067 (0.33)
FE/Variables absorbed	10	15	15	19	19	25
Additional covariates			1	1	5	6
Number of Letters	11846	11846	11846	11846	11846	11846
dto for females	3360	3360	3360	3360	3360	3360
Number of candidates	3721	3721	3721	3721	3721	3721
dto female	1082	1082	1082	1082	1082	1082
Number of writers	5655	5655	5655	5655	5655	5655
dto female	985	985	985	985	985	985
Letters by fem writers	1751	1751	1751	1751	1751	1751
Panel B: Research 'Slice'						
<i>Writing Quality Measures as Dependent Variable</i>						
Flesch Readability (higher = easier)	-0.0268 (1.03)	-0.0259 (0.99)	-0.0250 (0.96)	-0.0128 (0.49)	-0.0127 (0.49)	-0.0102 (0.40)
Dale-Chall Readability (higher = harder)	-0.0268 (1.03)	-0.0259 (0.99)	-0.0250 (0.96)	-0.0128 (0.49)	-0.0127 (0.49)	-0.0102 (0.40)
FE/Variables absorbed	10	15	15	18	18	24
Additional covariates			1	1	5	6
Number of Letters	8010	8010	8010	8010	8010	8010
dto for females	2348	2348	2348	2348	2348	2348
Number of candidates	3203	3203	3203	3203	3203	3203
dto female	934	934	934	934	934	934
Number of writers	3834	3834	3834	3834	3834	3834
dto female	659	659	659	659	659	659
Letters by fem writers	1199	1199	1199	1199	1199	1199
Year FE	yes	yes	yes	yes	yes	yes
Ethnicity/Race FE	yes	yes	yes	yes	yes	yes
Institution Rank FE	no	yes	yes	yes	yes	yes
Years since PhD	no	no	yes	yes	yes	yes
Research Field FE	no	no	no	yes	yes	yes
Publications	no	no	no	no	yes	yes
Writer	no	no	no	no	no	yes

Notes: The table shows results of the OLS regression of proxies of length and readability of the letter (Panel A), readability of the research slice (Panel B), and the letter date (Panel C), on a female candidate indicator as well as controls mentioned in the text. The table reports the estimate for the female indicator. Each row reports a different outcome, whereas each column reports a different specification. Standard errors are clustered at the letter writer level, we report the absolute t -statistics in parentheses. The coefficients are reported in terms of standard deviations of the dependent variable. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. The sample includes letters in support of candidates who obtained their Ph.D. in institutions outside the U.S. Return to Section 5.4 in the maintext.

Table F.2: Timing of the Reference Letter; Incomplete Set of References

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Letter dates							
Female candidate	-1.0772 (2.47)**	-1.0461 (2.39)**	-1.0461 (2.39)**	-0.4947 (1.14)	-0.5393 (1.24)	-0.4889 (1.13)	-0.4894 (1.13)
FE/Variables absorbed	10	15	15	19	19	25	25
Additional covariates			1	1	5	6	7
Number of Letters	6335	6335	6335	6335	6335	6335	6335
dto for females	1921	1921	1921	1921	1921	1921	1921
Number of candidates	2518	2518	2518	2518	2518	2518	2518
dto female	766	766	766	766	766	766	766
Number of writers	3362	3362	3362	3362	3362	3362	3362
dto female	571	571	571	571	571	571	571
Letters by fem writers	962	962	962	962	962	962	962
Year FE	yes	yes	yes	yes	yes	yes	yes
Ethnicity/Race FE	yes	yes	yes	yes	yes	yes	yes
Institution Rank FE	no	yes	yes	yes	yes	yes	yes
Years since PhD	no	no	yes	yes	yes	yes	yes
Research Field FE	no	no	no	yes	yes	yes	yes
Publications	no	no	no	no	yes	yes	yes
Writer	no	no	no	no	no	yes	yes
Letter length	no	no	no	no	no	no	yes
Panel B: Missing Letters							
Female candidate	0.0514 (4.75)***	0.0507 (4.74)***	0.0525 (4.93)***	0.0556 (5.27)***	0.0552 (5.23)***		
FE/Variables absorbed	10	15	15	19	19		
Additional covariates			1	1	5		
Number of candidates	3599	3599	3599	3599	3599		
dto female	1014	1014	1014	1014	1014		
Year FE	yes	yes	yes	yes	yes		
Ethnicity/Race FE	yes	yes	yes	yes	yes		
Institution Rank FE	no	yes	yes	yes	yes		
Years since PhD	no	no	yes	yes	yes		
Research Field FE	no	no	no	yes	yes		
Publications	no	no	no	no	yes		

Notes: The table shows two sets of OLS regression results: in Panel (A), we provide results for the date of creation mentioned in reference letter (analysis at the *letter* level; not all letters carry a date); in Panel (B), we provide results for a dummy variables indicating candidates which received fewer than three reference letters (analysis at the *candidate* level). In both cases the dependent variable is regressed on a female candidate indicator as well as controls as indicated. Standard errors are clustered at the letterwriter level in Panel (A) and at the candidate institution level in Panel (B), we report the absolute *t*-statistics in parentheses. Results can be interpreted as follows: in Panel (A) in days relative to letters for male candidates; in Panel (B) as percentage differences in the propensity of having fewer than 3 letters for women relative to men (unconditional propensity: 4%). The coefficients are reported in terms of standard deviations of the dependent variable. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. Return to Section 5.4 in the maintext.

Table F.3: Letter Sentiment and Placement

Dependent Variable Sample	(1)	(2)	(3)	(4)	(5)	(6)
	Academia (dummy)		Inst. RePEc Score (log)		Top-100 RePEc Inst.	
	All Placements		Academic Placements		AP & Postdoc	
Controls	Sentiment	All	Sentiment	All	Sentiment	All
Female Candidate	8.6237 (2.29)**	7.3242 (1.96)**	13.5673 (0.86)	19.2009 (1.25)	8.0915 (2.04)**	11.3528 (2.96)***
Ability	0.1386 (0.23)	-0.0015 (0.00)	1.8337 (0.68)	1.8195 (0.68)	0.5361 (0.89)	0.5153 (0.88)
Ability × Female Candidate	0.0067 (0.01)	-0.0159 (0.02)	2.0719 (0.44)	1.2415 (0.27)	-0.2352 (0.21)	-0.4080 (0.37)
Grindstone	-0.4505 (0.76)	-0.6308 (1.08)	-2.7406 (1.19)	-2.1999 (0.97)	-0.0600 (0.10)	0.2714 (0.46)
Grindstone × Female Candidate	0.1612 (0.16)	0.4785 (0.48)	-7.6686 (1.75)*	-7.3006 (1.68)*	-2.4453 (2.30)**	-2.7419 (2.65)***
Recruitment	0.5132 (0.75)	0.6416 (0.95)	0.5064 (0.19)	-1.0649 (0.39)	0.8722 (1.31)	0.1283 (0.20)
Recruitment × Female Candidate	-0.4642 (0.40)	-0.7090 (0.61)	0.7830 (0.16)	1.6173 (0.34)	-0.7414 (0.63)	-0.4654 (0.40)
Research	-0.5320 (0.86)	-0.1616 (0.27)	0.3078 (0.12)	1.8870 (0.79)	0.3769 (0.63)	0.7916 (1.37)
Research × Female Candidate	-1.7531 (1.64)	-1.5503 (1.46)	1.0005 (0.23)	-0.6343 (0.15)	-0.6251 (0.55)	-0.8927 (0.80)
Standout	1.7139 (2.90)***	1.8050 (3.09)***	-0.6941 (0.26)	-1.7479 (0.67)	0.4490 (0.77)	-0.3147 (0.57)
Standout × Female Candidate	-1.9051 (1.75)*	-1.7516 (1.64)	6.7010 (1.47)	6.4885 (1.48)	1.3573 (1.18)	1.0416 (0.94)
Teaching and Citizenship	0.2128 (0.35)	-0.1942 (0.32)	2.8987 (1.16)	5.1939 (2.10)**	-0.6894 (1.15)	0.4341 (0.75)
T&C × Female Candidate	1.7578 (1.71)*	1.9019 (1.87)*	-7.3107 (1.73)*	-8.2490 (2.00)**	-1.3796 (1.30)	-1.6397 (1.60)
Positive Signal	3.6735 (2.66)***	3.7462 (2.74)***	22.1738 (3.99)***	17.8880 (3.25)***	9.4404 (6.20)***	5.8958 (3.97)***
Positive Signal × Female Candidate	0.2141 (0.09)	0.1637 (0.07)	-7.1513 (0.72)	-7.3371 (0.76)	-4.5116 (1.61)	-5.0426 (1.86)*
Negative Signal	-3.9254 (2.13)**	-3.5149 (1.94)*	-13.2643 (1.68)*	-5.9041 (0.77)	-6.5720 (3.77)***	-3.9489 (2.33)**
Negative Signal × Female Candidate	8.1602 (2.57)**	7.8531 (2.47)**	-5.9269 (0.42)	-10.5593 (0.75)	2.1373 (0.66)	0.4949 (0.15)
Comparison	2.0270 (0.84)	1.7199 (0.71)	11.7534 (1.20)	13.0135 (1.35)	3.4319 (1.28)	3.0623 (1.17)
Comparison × Female Candidate	1.1538 (0.28)	2.2788 (0.57)	-22.8642 (1.35)	-21.3498 (1.31)	-6.9926 (1.64)	-6.8605 (1.67)*
FE absorbed	5	25	5	25	5	25
Add. covariates	0	6	0	6	0	6
Number of Letters dto for females	8760 2588	8760 2588	3119 991	3119 991	6008 1872	6008 1872
Number of candidates dto female	2738 830	2738 830	957 313	957 313	1865 596	1865 596
Number of writers dto female	4461 774	4461 774	2091 324	2091 324	3453 586	3453 586
Letters by fem writers	1339	1339	445	445	910	910
Year FE	yes	yes	yes	yes	yes	yes
Letter Sentiments	yes	yes	yes	yes	yes	yes
Ethnicity/Race FE	no	yes	no	yes	no	yes
Institution Rank FE	no	yes	no	yes	no	yes
Years since PhD	no	yes	no	yes	no	yes
Research Field FE	no	yes	no	yes	no	yes
Publications	no	yes	no	yes	no	yes
Writer Chars	no	yes	no	yes	no	yes
Letter length	no	yes	no	yes	no	yes