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# Demographic Differences in Letters of Recommendation for Economics Ph.D. Students

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## **Demographic Differences in Letters of Recommendation for Economics Ph.D. Students**

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### **Abstract**

We analyze letters of recommendation for more than 2,200 economics and finance Ph.D. graduates and document that letters for female and Black or Hispanic job candidates are weaker in some dimensions, while letters for Asian candidates are notably less positive overall. Female and Asian candidates are less likely to be recommended to top academic departments. Letter characteristics, especially a top recommendation, have meaningful effects on initial job placements and journal publications. The effect appears to be causal—we instrument for better letters and still estimate a meaningful impact of letter quality on outcomes.

JEL classification: A11, A23, J15, J16

Key words: recommendation letters, gender in economics, race and ethnicity in economics, research institutions, professional labor markets

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Letters of recommendation from faculty advisors play a critical role in the job market for Ph.D. economists. These letters assess the quality and potential of the candidate’s research and their capacity to generate impactful research in the future. At their best, letters can effectively convey qualitative (“soft”) information about a candidate. But these letters can also have shortcomings. They offer a subjective view of the candidate, requiring readers to extract the assessment from the text, which can be particularly challenging if there is limited information about the letter writer or their assessment of past candidates. Most concerningly, letters of recommendation can be subject to conscious/explicit or unconscious bias, resulting in assessments that do not accurately reflect candidates’ research quality and scholarly potential. Similarity bias could particularly affect candidates with demographic characteristics underrepresented among economics faculty.<sup>2</sup>

We analyze the text of 6,362 recommendation letters received by a large U.S.-based research institution for 2,227 new Ph.D. job candidates during four recent annual recruiting cycles (2018 to 2021). About 80 percent of the applicants are from U.S. Ph.D. programs. We pair the recommendation letters with information supplied by the candidates about their primary field of research interest, their Ph.D. granting institution, and confidential information about their self-identified gender, race, and ethnicity. From analysis of the letter writers, we identify the letter writer’s gender and whether the writer is Asian<sup>3</sup> based on name-matching supplemented by hand searches. We identify key characteristics of the text of each letter, including overall word count and, following much of the previous literature, the number of words associated with “standout” and “grindstone” characteristics, respectively. We also create a binary measure that places more importance on identifying students at the far-right tail of potential, based on the letter writer’s recommendation for the caliber of hiring institution appropriate for the candidate – in particular, whether the letter writer recommends the candidate to a top department. Finally, we name-match the sample of candidates to faculty lists at top 20 economics and finance departments following their Ph.D. graduation year and to authors of journal publications from EconLit, the American Economic Association’s bibliographic database, in the three year-period following graduation to assess early career outcomes.

We find meaningful differences in letter characteristics associated with gender, race, and ethnicity. Letters for candidates who self-identify as Asian are significantly shorter, contain fewer standout words and more grindstone words. Letters for Asian candidates are also less likely to contain a top recommendation. These differences are quite large, with letters for Asian candidates being 30 to 40 percent less likely to contain a top recommendation. We also find some systematic differences for letters written for candidates

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<sup>2</sup> According to a 2019 Brookings report, 23 percent of economics faculty in academia are women and 21 percent are minorities (Black, Hispanic, Asian, and other minorities). See Akee (2020) and Wessel et al. (2019).

<sup>3</sup> Current name-based identification techniques yield low-certainty outcomes except for Asian names.

who self-identify as Hispanic or Black.<sup>4</sup> Letters for female candidates have higher shares of grindstone words and are less likely to contain a recommendation to a top department. These results are consistent with those in some other fields where, for instance, standout words are more likely to be used for white surgical residents (Powers et al. 2020, Chapman et al. 2022).

We also find significant differences in the length and substance of letters by discipline within economics. This matters to confirm that our results are not driven by demographic differences in interest in economics subfields and may also be an independently interesting result for economists considering how to interpret letters from different subfields. Letters written for candidates who identify “Finance” or “Macroeconomics” as their primary field of interest are shorter and use fewer grindstone words. Letters for candidates focusing on Macroeconomics also use fewer standout words.

Our results are robust to controlling for the characteristics of the letter writer. Both female and Asian letters writers are less likely to make top recommendations. In contrast, senior (full professor) letter writers are more likely to make such recommendations. We also examine the interactive impact of both the candidate and the letter writer being female or Asian. We find that female letter writers are more likely to make top recommendations for female candidates but that this interaction is insufficient to overcome the lower rates of such recommendations by female letter writers and for female candidates in general – that is, female candidates are still less likely to receive a top recommendation as compared to other candidates even when the letter writer is female. In fact, because female letter writers are less likely to make top recommendations overall, the gap for female candidates is actually larger when the letter writer is also a woman. In contrast to the results for gender, letters for Asian job candidates are less likely to contain a top recommendation when the letter writer is also Asian, though the numerical impact is small. We confirm that this non-result holds when we use a name-matching technique to distinguish between South Asian and East Asian candidates and letter writers, in case we are mismeasuring the potential similarity between letter writers and candidates. Overall, our results do not support the idea that demographic differences in letter quality arise solely from similarity bias.

In the final section of the paper, we examine the relationship between letter characteristics and early career outcomes. In particular, we examine initial job placements and publications. Controlling for candidate characteristics, field of interest, Ph.D.-granting institution characteristics, and letter writer characteristics, we find that stronger letters are indeed associated with better early career outcomes, especially letters

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<sup>4</sup> Because the sample contains relatively few applicants who self-identify as Black or African American and due to privacy concerns given the small sample, we combine these candidates with those who self-identify as Hispanic. In results not reported here, estimated coefficients for Black candidates are more negative on some outcome variables such as letter length.

that contain a top recommendation. We confirm a causal interpretation of relationship between letters and outcomes by instrumenting for letter quality with letter writer fixed effects and finding similar results.

Letters do not capture all the variation in early career outcomes and we document significant roles for candidate characteristics in addition to letter quality. Interestingly, female candidates are more likely to be in a top 20 job after controlling for letter characteristics, suggesting that the negative impact of being less likely to have a letter with a top recommendation is offset through other channels. This is not the case for Asian candidates, whose letters are less likely to contain a top recommendation and who are less likely to be in a top 20 job over and above the impact of letter characteristics. Finally, we find that publication outcomes are weaker for female, Asian, and Black or Hispanic candidates, even after controlling for letter characteristics.

Our work adds to the growing body of literature studying outcomes for different demographics in the economics field (see, for instance, Baltrunaite et al. (2022), Card et al. (2020), Dupas et al. (2025), Eberhardt et al. (2023), Hengel (2022), Sherman and Tookes (2022), Wessel et al. (2019)), much of which has focused on gender. It also builds on a literature outside of economics looking at letters of recommendation, many of which also document worse recommendation letters for underrepresented job candidates, especially women (Berstein et al. (2022), Chapman et al. (2022), Dutt et al. (2016), French et al. (2019), Hauser and Lemmons (2018), Heath et al. (2019), Isaac et al. (2011), Kobayashi et al. (2020), Lin et al. (2019), Madera (2018), Powers et al. (2020), Schmader et al. (2007), Trix and Psenka (2003), and Zhao et al. (2023)). This paper is the first to analyze a large dataset of letters from candidates receiving Ph.D.’s in economics or finance predominantly from U.S.-based research universities, in contrast to earlier studies of economists, which analyzed samples of candidates applying to European institutions. While we build on the study of gender in letters of recommendation in economics, we have novel access to self-identified information on race and ethnicity as well as field of study within economics. To the best of our knowledge, our paper is the first to examine these factors in economics recommendation letters.

The remainder of this paper is organized as follows. The next section (Section 2) contains a brief literature review. Section 3 describes how we constructed the core data set of recommendation letters and provides an overview of the key characteristics of the pool of applicants and letters. We also assess the representativeness of our sample by comparing it to available information on the characteristics of the broader pool of U.S. economics Ph.D. graduates. Section 4 discusses the techniques we used to characterize the content and tone of the letters and presents our primary results, including analysis of how letter characteristics are associated with early career outcomes. The section also contains a series of robustness checks of the key findings. Section 5 is a summary and conclusion.

## 2. Literature Review

Previous research has explored differences in recommendation letters for underrepresented populations. This work includes evidence of gender-based differences in recommendation letters submitted for positions across a variety of academic fields, including faculty positions in chemistry and biochemistry (Schmader et al. 2007), geoscience (Dutt et al. 2016), at medical schools or residency programs (Trix and Psenka 2003, Heath et al. 2019, Isaac et al. 2011, Lin et al. 2019), for assistant professor positions (Madera 2018), and for undergraduates applying for international research programs (Hauser and Lemmons 2018). However, some papers using more recent data have found no or only minor gender-based differences in letters for medical residency programs (Chapman et al. 2022, French et al. 2019, Kobayashi et al. 2020, Powers et al. 2020) and some studies have found more positive letters for female candidates, including longer, more specific, more positive in tone letters for applicants to masters programs in data and computer science (Zhao et al. 2023) and few gender differences, or more positive letters for women in experimental particle physics (Bernstein et al 2022). Two of the more recent studies (Chapman et al. 2022 and Powers et al. 2020) also examine differences by race, finding that letters written for under-represented minorities were less likely to include “standout” descriptors such as “outstanding” or “exceptional” and/or more likely to include “grindstone” words such as “diligent” or “hard-working.”

In a study closely related to our own, Eberhardt et al. (2023) examine letters of recommendation for economics faculty positions at a large U.K. research university and find widespread differences in the attributes emphasized for male versus female candidates. In particular, they find that letters for female candidates are more likely to use “grindstone” terms and, in some cases, are less likely to use terms citing ability. Similarly, Baltrunaite et al. (2022) find differences in language in letters written for male and female economics Ph.D. candidates at two large Italian research institutions and that these differences negatively affect subsequent career outcomes. Our work extends these studies by examining a sample of candidates coming predominantly from U.S. Ph.D. programs and by examining differences in letters by field of study within economics and by the race and ethnicity of the candidates, as well as by gender.<sup>5</sup>

Our work also contributes to a growing literature on the impact of demographic differences such as gender, race, and ethnicity in the economics profession with a focus on underrepresented populations. Much of the work studying this issue has focused on gender. Women are under-represented in economics at all levels of the profession, including undergraduate economics majors (Avilova and Goldin (2024), Bayer and Wilcox (2019)) and in Ph.D. programs (Bayer and Rouse (2016), Boustan and Langan (2019)). This underrepresentation in the pipeline grows larger for economics faculty (Wessel et al. (2019)) and the

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<sup>5</sup> Eberhardt et al. (2023) controls for ethnicity/race but does not discuss the estimated coefficients, while Baltrunaite et al. (2022) does not study race and ethnicity. Both papers control for field of study in their key regressions, but do not discuss the results.

faculty gender gap grows with seniority and is larger at higher-ranked institutions (Auriol et al. (2022)) including in finance programs (Sherman and Tookes (2022)). While female representation on economics faculty has improved since the 1990s, that improvement has leveled off since the early 2000s (Lundberg and Stearns (2019)).

A number of papers find that female economists have worse career outcomes in terms of receiving tenure and publishing in academic journals. Compared with other disciplines, female economics faculty members are less likely to get tenure and took longer to do so (Ginther and Kahn (2004), Ginther et al. (2025)). While there is no relationship between co-authoring and tenure for male economics faculty, women with more co-authored papers are less likely to receive tenure, suggesting that women are given less credit for contributing to group work (Sarsons et al. (2021)). Women are under-represented at some conferences, especially in sessions focused on Finance and Macroeconomics (Chari and Goldsmith-Pinkham (2017)) and are subject to more frequent and more hostile questions during seminars (Dupas et al. (2021)). In one online forum, posts about female economists were more likely to discuss appearance and personal issues, while posts about male economists emphasized academic and professional achievement (Wu (2018)).

In terms of publications, women are under-represented in top economics and finance journals (Hengel (2022), Su et al. (2024), Brooks et al. (2025), Sherman and Tookes (2022)), with some evidence suggesting that the barriers to publication are higher. Female-authored papers in top journals receive significantly more citations (Card et al. (2019), Hengel and Moon (2020)), suggesting that they are of higher quality than comparable male-authored papers.<sup>6</sup> Female-authored papers are better written and writing quality improves during the review process, consistent with the idea that female authors feel subject to higher writing standards (Hengel (2022)). Similarly, following a rejection, female assistant professors report a significantly lower perceived likelihood of publication in a leading journal relative to male assistant professors (Shastry and Shurchkov (2024)).

Although the literature examining the relationship between race and ethnicity and economists' career outcomes is smaller than the literature focusing on gender, the findings are generally similar. Black, Hispanic, and Asian economists are underrepresented at all levels of the economics profession, starting with undergraduate majors (Bayer and Wilcox (2019)), in Ph.D. programs (Bayer and Rouse (2016)), and on academic faculty (Wessel et al. (2019)). While representation has increased over time, papers written by Black, Hispanic, and Asian economists continue to be underrepresented in economics journals (Koffi et al. (2024)), though at least one paper finds few statistically significant differences in publication outcomes associated with race or ethnicity, possibly owing to the limited sample size (Ginther et al. (2025)). Based

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<sup>6</sup> In contrast, Koffi (2025) finds that female-authored papers are more likely to be overlooked than comparable male-authored papers in lists of cited papers and Su et al. (2024) finds that female-authored papers in finance journals are less likely to be cited.

on experimental data, follow-back rates on #EconTwitter are lower for Black Ph.D. students than white students, suggesting that Black economists may have more difficulty forming networks to promote their research (Ajzenman et al. (2025)).

A related theme in the research on gender, race, and ethnicity in economics is the role of mentoring and the impact of similarity between faculty advisors and students. While early work suggests little impact of having female faculty members on initial job placements of female Ph.D. candidates (Neumark and Gardecki (1996)), more recent work demonstrates that female Ph.D. candidates are less likely to take academic jobs and have weaker subsequent publication records when female faculty take leaves (Kjelsrud and Parsa (2025)). Similarly, departments with better career outcomes for female Ph.D. candidates tend to have more female faculty and senior faculty with better awareness of gender issues (Boustan and Langan (2019)).

### 3. Data

Our dataset comes from applications for economist positions at a large U.S. policy institution focused on economic research. Applications were received in the falls of 2017 to 2020 and we limit the sample to candidates expected to receive their Ph.D.'s in the following year. Applications were solicited in each year in any field of economics. Upon completion of an initial indication of interest in the position, candidates were asked to submit up to three letters of recommendation.

The resulting sample includes 2,227 candidates. Letters were generally made available in PDF format and converted to text, resulting in a sample of 6,362 letters, an average of 2.86 letters per candidate (see Table 1). This number is slightly below the expected number of three as in some cases, we were unable to convert some letters submitted as PDFs into text files or because candidates submitted fewer than three letters. The average letter has about 1,150 words (see Table 3), with a significant amount of variability.

We also know the Ph.D. granting institution of the candidates. The vast majority (approximately 80 percent) of candidates come from U.S. institutions. A significant minority come from business schools, at approximately 11 percent of the sample. We categorize institutions as "Top 10 U.S. institutions" using the US News and World Report rankings for economics departments and the W.P. Carey Business Intelligence rankings of business school finance departments. Candidates from these institutions are overrepresented, constituting 24 percent of the sample.

#### A. Demographics

In addition to submitting letters of recommendation, job candidates filled in additional demographic information, which is summarized in Table 1. Candidates were asked to indicate, on a voluntary basis, their race and ethnicity using demographic groupings based on the U.S. Office of Management and Budget (OMB) categories for race and ethnicity: White, Black or African American, American Indian or Alaska

Native, Asian, and Native Hawaiian or Other Pacific Islander. Candidates could also select “Two or More Races,” or “Some Other Race,” for people who do not identify with any of the OMB race categories. For ethnicity, candidates may select one of two OMB categories: “Hispanic or Latino” or “Not Hispanic or Latino.” Candidates may also select “I do not wish to provide this information”; fewer than 1 percent of candidates chose not to provide this information. We did not attribute race or ethnicity to candidates who did not self-identify – these candidates, along with those who selected “Two or More Races” or “Some Other Race” were dropped from the sample; approximately 2 percent of the original pool dropped for these reasons. Almost 40 percent of the resulting set of Ph.D. candidates identify as Asian and 13 percent as Hispanic. Very few candidates in our sample, approximately 1 percent, identify as Black or African American.

Candidates were also asked on a voluntary basis to identify their gender, which could be “Male”, “Female” or “I do not wish to provide this information.” For candidates who chose not to provide that information we made use of pronouns used in the letters to assign the candidates to genders.<sup>7</sup> Thirty percent of the candidates in our sample are women.

Information on gender and race/ethnicity was collected for statistical purposes on a voluntary basis from all job applicants to the organization, not just for economists. This information candidates submitted was not used in the hiring process and was not provided to hiring managers or those reviewing or interviewing job candidates.

## **B. Fields of Interest**

Candidates selected primary and secondary fields of interest from a drop-down menu of choices. We aggregate candidates’ primary field of interest to: Finance, Macroeconomics, International Economics, Labor/Microeconomics, and Other. Online Appendix Table A1 shows the mapping of candidate fields of interest to the full set of these categories. The most common primary interest fields are Finance (20%) and Macroeconomics (26%).<sup>8</sup>

## **C. Selection**

Our sample is composed of candidates who chose to apply for an entry-level economist position at a single U.S. research institution. This construction could raise concerns that the sample might not be representative of the universe of Ph.D. candidates and thus that our results could reflect sample selection bias

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<sup>7</sup> At least one of the letters for each of the candidates who selected “I do not wish to provide this information” included gendered pronouns that allowed for this assignment.

<sup>8</sup> “Other” is actually the most common response in the sample, at 32%, but contains a mix of underlying primary fields of interest.

rather than true differences in the letter characteristics for different categories of candidates. These differences or omitted variables would have to arise from candidates of different quality being differently likely to apply to the institution in ways that vary with candidate characteristics. For example, if only the most talented women apply to this institution we would misattribute the positive selection of women candidates to the institution as a positive effect for women. *A priori* we have no reason to believe that there is differential selection by talent by candidate characteristics.

Ideally, we would address this concern by comparing characteristics of the candidates in our sample with information about the universe of candidates, including data on demographic characteristics and field of study. We are not aware of a comprehensive database of economics Ph.D. graduates with information on gender, race, ethnicity, and/or field of study. Instead, we make use of data from the American Economic Association (AEA) committees that publish information on graduates of U.S. Ph.D. programs to understand the representativeness of our sample. Table 2 tabulates statistics on gender, race, ethnicity, and institution type (Top 10) for the subset of 1,564 candidates in our sample who receive Ph.D.’s from U.S. economics (non-business school) programs. We compare the share of candidates who are female and who attend top 10 economics programs (first two rows of the tables) to data from the Committee on the Status of Women in the Economics Profession (CSWEP) for all U.S. economics programs. We compare those who self-identify as Asian, Black, or Hispanic (bottom 3 rows of the table) to U.S. citizens and permanent residents receiving Ph.D.’s from U.S. economics programs based on data from the Committee on the Status of Minority Groups in the Economics Profession (CSMGE). We do not have information on citizenship or immigration status in our data, so our comparisons of race and ethnicity will include a broader set of candidates than in the CSMGE data.

In demographic terms, the subset of our sample for which we can compare demographic information is generally comparable to the universe of Ph.D. candidates graduating from U.S. economics programs. Our sample has a similar share of female candidates (31 percent versus 33 percent overall), so is representative in that dimension, but has a higher share of candidates who self-identify as Hispanic or Asian. The share identifying as Asian is notably higher than in the CSMGE data (41 percent versus 14 percent), which likely reflects that our sample includes non-U.S. citizens and permanent residents. At least one study (Bayer and Rouse 2016) finds that half of Ph.D.’s granted by U.S. economics programs to temporary visa holders – candidates who would be in our sample but not in the CSMGE data – go to Asian candidates, which would be consistent with our sample demographics. Finally, the very low share of Black candidates is a documented feature of the economics profession at all levels from undergraduate majors to senior faculty (see, for instance, Committee on the Status of Minority Groups in the Economics Profession 2023) that applies to our sample as well.

A potentially important way in which our sample differs from the universe of candidates is that it has a higher portion of graduates from top 10 U.S. economics programs. This over-sampling from the strongest Ph.D. programs could affect our results if the demographic characteristics of these graduates differ significantly from the overall pool of candidates – if candidates from top programs are stronger, on average, than from other programs, we could misattribute these underlying quality differences to differences in demographic characteristics, if the demographics of top programs are different.

To provide some insight into this issue, we created a “universe” of top 10 program candidates by scraping lists of Ph.D. graduates from archived department websites.<sup>9</sup> We use name-matching techniques to identify whether these candidates are female or Asian and then compare the shares of such candidates in the universe to those in our sample. We cannot reject the hypotheses the shares of female and Asian candidates, respectively, are the same in our sample as in all of the job market candidates from top 10 programs, giving further support to the idea that our sample is representative in these dimensions.

#### **4. Results**

This section presents the main results of our analysis, focusing first on the core characteristics of the letters and then describing a new measure of letter quality based on whether the candidate is recommended to a top economics or finance department. In both cases, we examine how these quality indicators vary by the demographic characteristics of the candidate, controlling for characteristics of the Ph.D.-granting institution and the letter writer.

##### **A. Letter Characteristics**

We begin our analysis by examining the characteristics of the letters commonly used in the literature: letter length and letter quality, as measured by the share of words reflecting positive attributes of the candidate. Summary statistics for letters are presented in Table 3. We begin with a simple count of the number of words in the letter, since longer letters potentially provide more detailed and in-depth discussion of the candidate. Letter length has also been used as an outcome variable associated with letter quality in other research. Letters have 1,154 words on average, but there is a significant amount of variation, with an interquartile range of 650 words (from 780 to 1,430 words per letter).

We then examine the content of the letter. Following the literature on letters of recommendation in other fields, we code words into those characterized as “standout” and those describing “grindstone”. Previous research (Baltrunaite et al. 2022; Eberhardt et al. 2023) has found systematic differences in the language used in letters for male and female candidates in economics, finding that female candidates are

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<sup>9</sup> We were able to find historical website information for all but five program-years of the top 10 programs.

more likely to be described using words stressing hard work, diligence, and personality, as compared to words stressing talent, skills, and accomplishments, which are more frequently used for male candidates. We take a similar approach to this earlier work, using a standardized dictionary of words associated with “standout” and with “grindstone”. In particular, we use a dictionary of words drawn from the Linguistic Inquiry and Word Count (LIWC) database, based on a word list from Bernstein et al. (2022), modified for economics.<sup>10</sup>

“Grindstone” words, sometimes known as “effort” words, are positive words related to a candidate’s efforts or willingness to work hard. While seemingly positive, research suggests that words such as “hard working”, “methodical”, and “diligent” may be backhanded compliments, faint praise, or even “doubt raisers” to the extent that they emphasize the amount of work more than describing a candidate’s intellect or potential (for example in physics, Zhao et al. 2023). Baltrunaite et al. (2021) suggest that these words are more likely be used to describe women, due to an association with women as communal. The average letter has approximately 2.4 grindstone words, or 0.22 percent of the words in the letter.

“Standout Words”, sometimes known as “accomplishment” words, in contrast, tend to illustrate achievement or excellence. Examples include “excellent”, “superb”, “outstanding”, and “innovation”. Standout words are more common in recommendation letters than are grindstone words, with an average of just under 13 words per letter, or 1.1 percent of the overall number of words per letter.

We also identify some demographic characteristics of the letter writers. Specifically, we identify whether the letter writer is female or Asian using name-based algorithms, supplemented by hand-coding for names that are not conclusively assigned to a gender by the algorithm.<sup>11</sup> Ideally, we would identify the race/ethnicity for the full set of letter writers, but the currently available name-based algorithms do not assign race/ethnicity with a sufficiently high degree of confidence other than for Asian names. Similar to Baltrunaite et al. (2021), letter writers are mostly male, with 17 percent of letters from female professors. Female candidates are more likely to have letters written by female faculty than male candidates – overall, 22 percent of letters written for female candidates are written by female faculty, as compared to 15 percent for male candidates. Fifteen percent of the letters are from Asian letter writers, a much smaller share than the overall set of Asian candidates in the sample (40 percent). Asian candidates are more likely than white candidates to have letters written by Asian faculty, with 19 percent of letters for Asian candidates written by Asian faculty, as compared to 12 percent for white candidates.

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<sup>10</sup> The full list of words can be found in Online Appendix Table A2. We remove from grindstone words “persist\*” and “work\*” as these words are frequently used in economics research and words related to top (covered in the Top variable). The analysis is sensitive to the selection of the word list.

<sup>11</sup> We ran the list of author names through the gender-guesser algorithms (available at [gender-guesser · PyPI](https://pypi.org/project/gender-guesser/) and [Spreadsheet processing tool - Gender Guessing \(gender-guesser.com\)](https://pypi.org/project/gender-guesser/)), which assign probability scores based on an international database. For probability scores of 60 percent or lower, we confirmed or changed the match by hand.

Finally, we identify whether the letter writer is a senior faculty member, defined as full professors at U.S. research universities. We name-match letter writers to faculty lists at U.S. Ph.D.-granting institutions from the Academic Analytics Research Center (AARC). We also developed an expanded measure of senior letter writers including full professors at non-Ph.D.-granting U.S. colleges and universities and at non-U.S. universities via a hand-coded name-matching process based on academic CVs. The results using the expanded definition of full professor are not meaningfully altered when using the expanded definition of senior letter writer.

## B. Regression Results: Letter Characteristics

This section presents the results of regressions of various letter characteristics on information about the candidate, letter writer, and institution awarding the Ph.D. The regressions have a similar format:

$$Y_{cw} = \beta_1 \text{Candidate Characteristics}_c + \beta_2 \text{Candidate Field}_c + \beta_3 \text{Institution Characteristics}_c + \beta_4 \text{Letter Writer Characteristics}_w + \varepsilon_{cw}$$

Where  $Y_{cw}$  is a feature of the letter written for candidate  $c$  by letter writer  $w$ ; *Candidate Characteristics* include the gender and race/ethnicity of the candidate; *Candidate Field* are controls for the candidate's primary field of interest (Macroeconomics or Finance); *Institution Characteristics* include controls for whether the Ph.D.-granting institution is in the United States, whether it is a business school, and whether it is a top 10 finance or economics department. Finally, in some specifications, we include controls for female and Asian letter writers and for senior letter writers (*Letter Writer Characteristics*).

Table 4 presents the results for letter length, where letter length (*Word Count*) is regressed against a series of controls.<sup>12</sup> The first column contains dummy variables for the candidate's demographic characteristics, including gender (*Female*) and whether the candidate self-identifies as Asian or Black or Hispanic. We combine Black and Hispanic candidates into a single category since there are so few Black candidates in our sample, just 1 percent overall, and we were concerned about both the empirical stability of the resulting estimates and the potential for revealing information about individual candidates. This approach is not optimal, as Black and Hispanic candidates are distinct and could have differential letter characteristics and outcomes. In results not reported here, we have repeated our analysis using separate controls for Hispanic and Black candidates, respectively. The resulting coefficients are generally similar in size and statistical significance to those reported when the two sets of candidates are combined, though letters for Black candidates are less positive than those for Hispanic candidates in some dimensions. The second column

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<sup>12</sup> We also estimate these regressions using the log of letter length instead of letter length (number of words). The results are qualitatively identical to those presented in Table 4.

includes controls for the two sub-specialty fields most frequently represented among the candidates, Finance and Macroeconomics.<sup>13</sup> Column (3) contains our main specification, including controls for demographic characteristics, sub-specialty field and Ph.D.-granting institution.

We find that letters for Asian candidates and candidates focusing on Finance and Macroeconomics are systematically shorter than letters for other candidates. The results suggest that letters for Asian candidates are approximately 100 words shorter than letters for other candidates – about 9 percent shorter, given an average letter length of 1,154 words. Including controls for the field of interest is important, as we see systematic differences in candidate characteristics by field of interest and significant differences in letter length by field. Candidates specializing in Finance and Macroeconomics also have shorter letters, with letters for Finance candidates having more than 150 (13 percent) fewer words. We do not find differences in letter length for female or for Black or Hispanic candidates; while generally negative, indicating shorter letters, the coefficients on these variables are small and imprecisely estimated.

These results hold when we control for characteristics of the Ph.D.-granting institution, when we cluster residuals by candidate or by letter writer (columns (4) and (5)), and when we control for letter writer characteristics (column (6)). These controls suggest that letters for candidates from U.S. schools are shorter but that letters from top 10 economics and finance programs are about 145 words (13 percent) longer than letters for candidates from other programs. To the extent that top 10 programs have stronger students than other programs on average, this difference is consistent with the idea that letter length is a signal of higher candidate quality. We also validate that the results are robust to institution fixed effects, confirming that the results are similar within Ph.D. programs (see Online Appendix Table A3).

There is no difference in letter length between male and female letter writers, while letters by Asian letter writers are 50 words shorter than letters by non-Asian writers (column (6)). Letters by senior letter writers are also shorter, but the result is not statistically significant.

Tables 5 and 6 report results for regressions examining the percentage of standout and grindstone words in the letters. The tables have the same format as Table 4, with column (3) containing our primary specification. The results show that letters describing female candidates have a higher share of grindstone words (Table 6) and the same share of standout words (Table 5) as male candidates. To the extent that grindstone words are viewed as less positive, these results are consistent with previous findings in economics and some other disciplines, which have generally found recommendation letters for women are less positive than those for men. On average, the share of grindstone words in letters for female candidates was about 7 percent higher than for male candidates, a result that holds after clustering errors by candidate or

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<sup>13</sup> The omitted field of specialization includes all other areas of economics, including labor, international and “other”. Together, these represent just over half of the letters in the sample.

by letter writer (columns (4) and (5)) and when controlling for the characteristics, including gender, of the letter writer (column (6)).

Letters for candidates from top 10 economics and finance programs both have lower shares of grindstone words; to the extent that candidates from these programs are stronger on average than the rest of population, this finding is consistent with the idea that grindstone words are associated with weaker letters.

The results also suggest systematic differences in letter content by sub-specialty field. Letters for candidates focusing on Finance have smaller shares of grindstone words, while letters for candidates focusing on Macroeconomics have smaller percentages of both grindstone and standout words.

We document that the share of standout words is smaller for Asian and Black or Hispanic candidates, even after including all controls. The shares of standout words in letters for Asian and Black or Hispanic candidates are about 6 to 8 percent lower than the share for white candidates. While overall grindstone and standout words are positively correlated, letters for Asian candidates include higher shares of grindstone words (0.013 percent more grindstone words, or about 6 percent higher than letters for white candidates). However, there is no statistically significant difference in grindstone words for Black and Hispanic candidates.

The analysis thus far relies on standardized classifications of letter content and sentiment. To supplement this analysis, we develop a measure of letter quality based on whether a candidate is recommended for a job at the very top economics or finance departments. Most recommendation letters contain a summary sentence – typically at the beginning or at the end of the letter – indicating the economics or finance department most suitable for the candidate. These sentences take a variety of forms, with a wide range of wording. However, the strongest recommendations indicate that the candidate would be appropriate for the “top 10”, “very top”, “very best”, or “leading” departments. We develop an indicator variable for each letter that indicates whether the letter contains such a recommendation. Developing a measure specific to the economic research profession is consistent with the suggestions of Trix and Penska (2003) who highlight the importance of knowledge of what is “high status” in a field.

We used a two-step process to create the indicator variable. First, using the text file version of each letter, we identified all sentences containing the word “department” and then sorted those sentences according to whether the words top, “best”, “leading”, “top tier”, or “highest ranked” were also in the sentence. The algorithm then screened out sentences containing the words “outside”, “other than”, “except”, “exception”, and “apart from” to eliminate cases where the letter recommended the candidate to “all but the very best” or “all departments, except the very best”. The algorithm also drops sentences with irrelevant words suggesting the sentence is not about the candidate, such as “department chair”, “in the department”, or

“police department”. We then hand-reviewed the algorithm results, making adjustments as necessary.<sup>14</sup> Overall, about 12 percent of the letters include a top recommendation and 23 percent of candidates in our sample received at least one letter with a top recommendation. Thus, at least in percentage terms, the top recommendation is limited to a meaningful, but small, portion of the sample.<sup>15</sup>

Table 7 contains the results of regressions of our top recommendation variable on candidate, institution, letter, and letter writer characteristics. The results are consistent with the idea that a top recommendation is a signal of candidate quality. Letters for candidates getting Ph.D.’s from top 10 economics and finance programs are more likely to include a top recommendation. Letters for candidates specializing in Finance are more likely to contain a top recommendation, though this result weakens when we include controls for the characteristics of the Ph.D.-granting institution (column (3)). Female and Asian letter writers are less likely to include a top recommendation in their letters (column (4)). Letters written by senior letter writers are more likely to include a top recommendation.

Letters written for female and Asian candidates are less likely to contain a recommendation to a top economics or finance department. These differences are both statistically and empirically important. The probability that a letter written for a female candidate contains a top recommendation is about 1.5 percentage points lower than for a male candidate, for whom 13 percent of letters contain this recommendation (a 10 percent lower incidence). To the extent that a top recommendation endorses research potential, this finding echoes Benson et al. (2024), who find that women managers receive substantially lower “potential” ratings despite receiving higher performance ratings. The coefficient on female candidate drops when we include controls for letter writer characteristics (columns (4) to (6)), suggesting that some part of the impact for female candidates may be coming through pairings with female letter writers, a relationship we explore further below.

The differences in top recommendations are even starker for Asian candidate letters, where the probabilities of containing a top recommendation are 4.5 to 6 percentage points lower than letters for white candidates. Since nearly 15 percent of letters for white candidates contain a top recommendation, these coefficients imply a 30 to 40 percent lower incidence of top recommendations for Asian candidates. These differences persist after clustering residuals at the candidate and letter writer levels (columns (5) and (6))

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<sup>14</sup> On the basis of the hand review, we changed 268 cases that the algorithm had identified as top to not top and 32 cases the algorithm had identified as not top to top. A typical instance of the former is when the recommendation referred to the Ph.D.-granting department rather than the candidate (“we did not [place] any students at top departments”) or if “very top” refers to a non-academic or non-Ph.D.-granting institution (“top teaching college”). We limited the top indicator to recommendations to top 20 departments (e.g., a recommendation to a top 50 department would not be coded as top).

<sup>15</sup> Eberhardt et al. (2023) also develop an indicator based on letter language describing candidate quality, including signals that the candidate should be of interest to “very top” departments. However, their measure is broader than ours, as it reflects other types of positive language (“great hire” or “a star candidate”). Twenty-four percent of their letters contain these positive signals, as compared to 12 percent of our sample containing a top recommendation.

and controlling for other letter characteristics such as letter length and the percentage of grindstone and standout words (column (7)).

Column (7) also adds insight to our interpretation of the analysis of words in the letters. Consistent with the literature, letters that are strong in other dimensions are more likely to contain a top recommendation. Specifically, longer letters and letters with higher percentages of standout words and lower percentages of grindstone words are more likely to also include a top recommendation sentence.

As noted above, female candidates are significantly more likely than male candidates to have at least one letter written by a female letter writer and Asian candidates are more likely to have at least one letter written by an Asian letter writer. One question is whether there are differences in the content of letters when female or Asian candidates pair with a female or Asian letter writers (presumably, a faculty advisor or mentor) than when they pair with male or non-Asian letter writers, respectively. This might be the case if there are similarity preferences, and advisers write better letters for people who are more similar to themselves. Another explanation is that letter writers could have more accurate beliefs about the quality of candidates with whom they share a common group identity (Bohren et al. (2025b)).<sup>16</sup> Since characteristics differ for candidates and letter writers, with senior faculty letter writers less likely to be women or Asian, this could explain some of the result, if letter writers have preferences for people who are like them.

To explore this question, we cross the variables for female candidate (*Female*) and female letter writer (*Female Writer*) and Asian candidate (*Asian*) and Asian letter writer (*Asian Writer*). These results are presented in Table 8. The table presents the top recommendation regression specification controlling for candidate characteristics, institution characteristics, letter writer characteristics (columns (1) and (2)) and also including other letter characteristics (columns (3) and (4)). The results do not change meaningfully when the additional letter characteristics are included.

The coefficient estimates suggest that letters written by female faculty are more likely to include a top recommendation when the candidate is also female, though the coefficient is imprecisely estimated (columns (2) and (4)). However, this differential (positive 1 percent) is not sufficient to overcome the lower overall rate of top recommendations by female letter writers (negative 3.4 percent) and the lower overall probability that letters for female candidates contains a top recommendation (negative 1.5 percent). In fact, the estimates suggest that while letters for female candidates are less likely to contain a top recommendation whether the letter writer is male or female, this gap is actually *larger* when the letter writer is female. Letters written for female candidates by female letter writers are roughly 4 percent less likely to contain a top

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<sup>16</sup> Bohren et al. (2025b) argue that distinguishing between statistical discrimination based on accurate versus inaccurate beliefs is important in developing appropriate policy responses to address discriminatory outcomes. Further, discrimination based on inaccurate beliefs can propagate if others learn from the views of those with inaccurate beliefs but do not know that the beliefs are inaccurate (Bohren et al. (2025a)).

recommendation than are letters for male candidates written by male letter writers (the sum of the coefficients on *Female*, *Female Writer*, and *Female x Female Writer*) versus 1.5 percent less likely when the letter writer is male (the coefficient on *Female*).<sup>17</sup>

Conversely, the results do not indicate that Asian letter writers are more or less likely to make a top recommendation for Asian candidates than for other candidates -- the coefficient is imprecisely estimated and flips sign once letter characteristics are included. Summing the coefficients in the specification, we estimate that Asian candidates are 6 to 8 percent less likely to receive a top recommendation when the letter writer is also Asian (the sum of coefficients on *Asian*, *Asian Writer*, and *Asian x Asian Writer*), as compared to 4.5 to 6 percent less likely when the letter writer is not Asian (the coefficient on *Asian*). Asian combines South Asian and East Asian candidates into a single demographic category. This could potentially result in measurement error, as candidates we record as similar to their letter writers may not have a high amount of similarity. Therefore, we algorithmically separate Asian candidates and letter writers between South and East Asian and estimate interactions for each of these subsets (i.e., East Asian candidates X East Asian letter writers and South Asian candidates X South Asian letter writers). We continue not to find statistically significant coefficients for this type of similarity. It is, of course, inherently challenging to measure similarity, as even within this finer definition, we are unable to use name algorithms to separate candidates of Indian vs Pakistani origin within South Asian names, or candidates of Chinese, Korean, Japanese or Vietnamese origin within East Asian names.

As a final exploration of the role of letter writers on letter characteristics, we estimate regressions including letter writer fixed effects. By including letter writer fixed effects, we control for writer-specific tendencies to produce stronger or weaker letters in general (that is, not related to candidate characteristics or potential). These results are reported in Table 9. We lose about 30 percent of the letters in this specification, as more than half of letter writers have only one letter in our sample. Still, the results continue to indicate that letters for Asian candidates are weaker in nearly every dimension and that letters for Black or Hispanic candidates are weaker in some dimensions (shorter letters with a smaller share of standout words). The fixed effects results do not show significant differences in letter strength for female candidates, consistent with the idea that a significant portion of the weaker letters for female candidates comes from the greater rate of pairing with female letter writers, who tend to make fewer top recommendations.

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<sup>17</sup> One potential explanation for the lower rate of top recommendations by female letter writers is that female faculty members could be more junior on average than male faculty members (Baltrunaite et al. 2022). We control for the seniority of the letter writer in our main specifications. In results not reported here, we also estimated specifications interacting letter writer seniority with female letter writer. Those results did not suggest a meaningful interaction. Finally, our results finding a net negative impact of having a female letter writer on the probability that a letter for a female candidate contains a top recommendation stand somewhat in contrast to those in Kjelsrud and Parsa (2025), who find that the unexpected absence of female advisors who go on sabbatical is associated with worse early career outcomes for female graduate students.

### C. Regression Results: Early Career Outcomes

In this section, we explore an important follow-on question, which is whether weaker letters for female, Asian and Black or Hispanic candidates are correlated with early career outcomes for these candidates. Do candidates with stronger letters experience better career outcomes? Are there residual associations between candidate characteristics related to gender and race/ethnicity after controlling for letter content? We note that it is hard to draw normative conclusions from these results since outcomes may themselves both be dependent on letters of recommendation and be affected by demographic differences. While it may be tempting to view these outcomes as measures of unobserved ability, in addition to being affected directly by letters, there may be significant differences in outcomes that related to demographic characteristics. For example, Hengel (2022) finds that female authored papers have higher writing standards and spend longer in peer review and Card et al. (2019) find that female authored papers receive 25 percent more citations than similar male authored papers.

To understand outcomes, we create variables intended to capture early career outcomes for the candidates in our sample. The first variable captures initial job placements, a binary measure indicating whether the candidate's initial job placement was in a top 20 economics or finance department (*Top 20 Academic Job*). The other variables capture the number of publications and a binary variable for any publications in top 8 and top 100 journals, capturing in net a four-year window starting with the year the candidate applied and expected to receive their Ph.D. and ending three years later because this is the longest period we observe for candidates in the 2021 job market cycle.

To construct the initial job placement variable, we name match the candidates in our sample with lists of faculty at top 20 economics and finance departments, where ranking is based on the US News and World Report and W.P. Carey Business Intelligence rankings of economics departments and business school finance departments, respectively. In particular, we name-matched our candidates to economics and finance department faculty lists from the AARC database for the academic year following the year the candidate is on the market, supplemented by a hand-search of CVs and resumes for candidates who did not match in the AARC dataset. The non-AARC-matched candidates took academic jobs at non-Ph.D.-granting institutions or at non-U.S. universities (neither of which are included in the AARC data), took policy sector jobs such as at the Federal Reserve or World Bank, or took private sector positions. Only a small fraction (6 percent) of candidates have initial jobs at top 20 departments (see Table 10). The share among candidates coming from top 10 Ph.D. programs is higher at 17 percent, consistent with higher shares of those candidates with more positive letters.

Table 11 contains results for initial job placements. As in earlier tables, column (3) contains our core specification including candidate, Ph.D.-granting institution, and field of interest characteristics, while column (4) extends this specification to include letter writer and letter characteristics. The results in Table

11 are based on letter-level regressions to focus on the association between letter characteristics and job outcomes; the results of candidate-level regressions in which we average letter characteristics for each candidate are essentially identical.

Consistent with department rankings, candidates from top 10 economics and finance departments are significantly more likely to join a top 20 department. These results are qualitatively unchanged when we include letter writer and letter characteristics (column (4)). The results suggest that stronger letters are associated with higher probabilities of finding an initial job at a top 20 academic department. Both letter length and a top recommendation are strongly associated with higher probabilities of finding a top 20 academic job. These results are economically as well as statistically significant – a top recommendation is associated with a 17 percentage point higher probability of a candidate finding a top 20 academic job, a very large increment given the overall average probability in the sample of 6 percent.

Consistently across the specifications, the results indicate that female job candidates are more likely to be in a top 20 job, with the coefficient rising in both size and statistical significance as we include more controls, including letter characteristics (column (4)). For these candidates, it appears that the negative impacts of having letters that are less likely to contain a top recommendation and more likely to contain grindstone words are offset through other channels. This is not the case for Asian job candidates, who are both less likely to have an initial job placement at a top 20 academic department controlling for letter and other characteristics and whose letters are weaker across all dimensions we examine. We do not find meaningful differences in top 20 jobs for Black or Hispanic candidates.

We count the number of publications for each candidate in top 100 (*No. Top 100 Pubs*) based on RePEC rankings and top 8 journals (*No. Top 8 Pubs.*), including the top 5 economics journals (Heckman and Moktan 2020) and the top 3 finance journals (Currie and Pandher 2020).<sup>18</sup> To identify publications, we name-match the candidates in our sample to a listing of journal publications from EconLit within three years from the Ph.D. date. We supplemented algorithmic first and last name matching with hand checks based on middle initials where available. In doing the hand-checks, we relied on information about the Ph.D.-granting institution to help identify papers written by candidates in our sample.<sup>19</sup>

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<sup>18</sup> Top 5 economics journals are the American Economic Review, Econometrica, the Journal of Political Economy, the Review of Economic Studies, and the Quarterly Journal of Economics (Heckman and Moktan 2020). Top 3 finance journals are the Journal of Finance, the Journal of Financial Economics, and the Review of Financial Studies (Currie and Pandher 2020).

<sup>19</sup> We also compared the results of the Econlit publication measure to the AARC data for the 438 candidates in both data sets. We found a close correspondence, especially for the top 8 publications (98 percent). We also found a high degree of agreement (93 percent) between the two versions of the binary variable for top 100 publications. However, the number of top 100 publications variables agree at a somewhat lower rate (just over 80 percent), with disagreements roughly evenly split between cases where the Econlit variable identifies more or fewer publications than the AARC version.

More than 40 percent of candidates have at least one top 100 journal publication within three years of finishing their Ph.D.; the average number of such publications per candidate is 0.79 across the full sample. Not surprisingly, the share of candidates and number of publications in top 8 journals is considerably lower, with just 11 percent of candidates having any publications in a top 8 journal within the first three years (the average number of top 8 publications per candidate is just 0.16). In the results presented below, we focus on the number of early career top journal publications; our results are not sensitive to the way the publications variables are defined (binary vs. counts).

Table 12 presents results related to early career publications. The first four columns present results for the number of top 100 journal publications while the fifth through eighth columns narrow in on the top 8 journals with highest impact. The results are quite similar for both publication measures and across specifications. In particular, female, Asian, and Black or Hispanic candidates have significantly fewer top journal publications than male and white candidates. These results are material – female candidates, for instance, have about a third fewer top 100 journal publications and 24 to 30 percent fewer top 8 journal publications, even after controlling for letter characteristics.<sup>20</sup> Letter characteristics are in fact strongly associated with early career publication outcomes. Longer letters, letters with higher shares of standout words and lower shares of grindstone words, and most significantly, containing a top recommendation are all positively associated with the number of early career journal publications. Letters with a top recommendation are associated with a two-thirds increase in the average number of top 100 journal publications (an increment of 0.53 to the average number of 0.79) and nearly 3.5 times the average number of top 8 journal publications (an increment of 0.39 to the average of 0.16).

Letters written by senior letter writers are associated with better early career outcomes. Candidates with senior letter writers are four percent more likely to take an initial job at a top 20 academic department and have more top 100 and top 8 journal publications in the first three years of their careers. Our results do not provide insight into the source of this association. It could be that full professors (our definition of senior letter writer) could attract higher caliber graduate students or that senior tenured faculty members are more skilled and experienced at mentoring graduate students and thus produce stronger job candidates, whose subsequent early career outcomes reflect that higher quality. It is also possible that more senior faculty are better known to others in the profession and thus that their letters are more influential in generating opportunities for their advisees. These explanations are not mutually exclusive, of course.

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<sup>20</sup> These findings are consistent with the results in Card et al. (2020), which finds that female-authored papers in top journals receive about 25 percent more citations than male-authored papers, suggesting that female-authored papers receive less favorable treatment at these journals than would be the case under a strategy that attempted to maximize citations to the journals. Our findings also echo those in Ge and Wu (2024), who find that economics Ph.D. job candidates with difficult-to-pronounce names are less likely to find tenure-track jobs and are more likely to find jobs at institutions with lower research productivity.

#### D. Instrumental Variables

The strong relationship between letters and outcomes could be causal evidence of the importance of these letters for early career success. Better letters may lead to first round interviews with more and higher ranked departments and exposure to economics journal editors. More job market interviews mean more opportunities to land a high-quality position. Academic publications benefit from additional interviews with more and higher ranked departments, particularly if interviews are converted to job talks. Interview conversations about candidate's research and job talks may result in improved paper quality. This result is also consistent with a less direct channel whereby letters measure the extent of advisor support. Faculty advisor support may lead to better early career outcomes as advisors who advocate for their students to get interviews could also recommend their students' work to editors and referees. In either case, if letters causally lead to early career success, and letters are systematically related to candidate characteristics, then this pattern suggests a channel through which underrepresented candidates may be disadvantaged in establishing careers in economics.

However, another explanation for the relationship between letters and outcomes is that the letters accurately capture the talent of Ph.D. candidates. To the extent that early career success is a function of economics aptitude and research ideas, better candidates should receive better letters, get better jobs and have better publications outcomes. The omitted variable is the candidate talent and, regardless of letter quality, better candidates would have better early career success.

To explore this question, we need an instrument that is related to letter characteristics but not to candidate outcomes, except through the letter. We take advantage of the fact that different letter writers have different propensities to write more positive (or more negative) letters, which we measure through letter writer fixed effects. For this strategy to be valid, letter writers must have a range of candidates across the quality spectrum, such that there is not strong clustering of higher or lower quality candidates across letter writers. This seems a reasonable assumption. For instance, even though some letter writers may have more prestige than others, letter writer fixed effects are not necessarily related to the letter writer's status in the economics profession after controlling for the quality of the Ph.D. program. Even if we are concerned that the best students match with the best professors, the best professors are not necessarily more positive about their students. In any case, in most programs the advisor match is determined by field of economics, with even very well-known faculty typically advising a range of the Ph.D. students in their field of expertise.

We implement two stage least squares (2SLS) using writer fixed effects from the specification in Table 9 for each of our key letter characteristics. Consistent with the high explanatory power of writer fixed effects, the instrument has ample predictive power. We then use these writer fixed effects to instrument for our measures of letter quality (letter length, share of standout words, share of grindstone words, and top recommendation) in regressions of each of our early career outcome variables. These results are reported

in Table 13. Overall, the results are remarkably similar to the un-instrumented results in Tables 11 and 12, suggesting that there is likely a direct causal link between letter quality and outcomes unassociated with candidate quality. While the basic specifications already address potential relationships between writer fixed effects and candidate quality by controlling for the quality of the Ph.D. program, we also estimated specifications with institution fixed effects and find similarly strong results as when instrumenting for letter quality with writer fixed effects.

#### **E. Interpretation**

The instrumental variables results suggest that there is a direct causal link between letter quality and early career outcomes. If this is the case, then understanding demographic differences in letter quality becomes even more important, since it would appear that these differences are creating differential opportunities for economics Ph.D. candidates. Even if letters simply reflect ability to succeed in the economics profession, then the next research question would be to explain why that ability would be associated with personal characteristics in the population of economics graduate students.

While this paper does not shed light on the reasons for these results, we outline some possible explanations for future research to explore: For example, this association could arise if admissions standards for economics graduate school vary systematically with race and gender, resulting in differences in the distribution of women, Asian, and Black or Hispanic students. Such differences could arise if admissions committees are less able to forecast aptitude for candidates with whom they have less experience, although that should lead to greater variability in outcomes by demographics, not necessarily to lower mean outcomes. Demographic differences could also arise if graduate schools are less able to train and educate students whose characteristics differ from faculty. Finally, this could arise if candidates are equal in ability when admitted to graduate schools, but the profession in terms of publications and jobs does not value research and research interests of women, Asian and Black and Hispanic students, or if the most talented of these students choose not to pursue academic positions.<sup>21</sup>

While we have combined in this paper some discussion of these characteristics as populations that are underrepresented in economics, the same forces may not be at play for different characteristics. For example, while female writers are more likely to write positive letters for women, we do not find similar results for Asian writers and Asian candidates. After we control for letter quality, we find that Black or Hispanic candidates are no less likely and women, indeed, are more likely to obtain top 20 academic jobs.

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<sup>21</sup> For example, scholars such as Lisa Cook have said they were discouraged from some topics, saying “nobody wants to hear about women, and they sure don’t want to hear about Black people” (Khang 2020). Antman et al. (2024) find that while female Ph.D. candidates are more likely to write a dissertation focused on topics related to inequality, minority Ph.D. candidates are not more likely to do so.

But they are significantly less likely to publish papers in either top 8 or top 100 journals. However, even incorporating the negative effect from having worse letters, Asian candidates are both less likely to get a top academic position and less likely to publish papers in either top 8 or top 100 journals, although the latter effect is not statistically significant. These lower rates of publication in top journals for female, Asian, and Black or Hispanic candidates continue to hold if we include a control for whether the candidate accepts a top 20 job, suggesting that some additional factors beyond initial job placement are affecting early career publications.

## F. Robustness

We explored a number of dimensions of robustness. First, since we are uncertain about the type of selection we may have across Ph.D. granting programs, we limit the sample to candidates receiving Ph.D.'s from U.S. economics departments and business schools. It is possible that the content and impact of recommendation letters differs systematically between U.S. and non-U.S. graduate programs. There could also be letter differences if letter writers from non-U.S. programs do not use English as their primary language of communication. Finally, candidates coming from non-U.S. programs could differ in unobserved ways from candidates applying for such job who are already located in the United States.

Not surprisingly, since candidates from U.S. programs make up 80 percent of our overall sample, the results are quite similar to those from the full sample (see Online Appendix Table A4). The most notable differences are that letters for female candidates have statistically higher shares of standout words in the U.S.-only sample – while the coefficient was positive for the full sample, it was not estimated precisely. Additionally, Black or Hispanic candidates do not have statistically fewer top 100 and top 8 journal publications in the U.S. only sample. While the coefficients are negative and similar in magnitude to those of the whole sample, they are less precisely estimated.

Another approach is to limit the sample to subsamples of candidates that are more similar. First, we limit the sample candidates from the top 10 economics and finance departments. This may reduce selection bias and also control for nonlinearities in selection into those schools and the properties of subspecialty fields within those schools. The results are qualitatively consistent with those in the broader sample (see Online Appendix Table A5). We also estimate specifications with institution-specific fixed effects to more fully control for differences in Ph.D. program quality. The results are not meaningfully different in this specification (see Online Appendix Table A3).

Another approach to unobserved variation in the candidates is to consider only candidates in a particular subspecialty. Since we have the most applicants with an interest in Macroeconomics and Finance, one concern could be that the depth of the candidate pools with these specialties differs from other fields of interest and that these differences could account for some of our findings. To explore this possibility, we

run our analysis only for candidates whose primary subspecialty is Macroeconomics (see Online Appendix Table A6) and only for candidates whose primary subspecialty is Finance (Online Appendix Table A7). By looking across candidates within a field of interest, we allow the effect of the control variables such as the type of university to be different within subfields of economics. Results are similar for Macroeconomics candidates as they are for the sample as a whole – letters for Asian students are shorter, contain fewer standout words and more grindstone words than letters for other candidates. Letters for female and Asian candidates are less likely to contain a recommendation to a top economics or finance department. Results for candidates specializing in Finance also mirror those for the broader sample.

## 5. Conclusion

We document consistent patterns in letters of recommendation for new Ph.D. economics and finance job candidates. Asian candidates have weaker letters of recommendation across almost all dimensions. Consistent with other studies, we find differences by gender, with letters for female candidates containing higher shares of grindstone words, though no meaningful differences in letter length or in the share of standout words. When we turn to a binary measure which places more importance on identifying students at the far-right tail of ability, the results are quite stark. Female and Asian Ph.D. candidates, both minorities in the economics profession, are less likely to be described as candidates who should be placed in the very top departments, a finding that holds when we control for other letter characteristics, for field of specialization, and for the caliber of the Ph.D.-granting institution. Finally, we find that stronger letters, especially longer letters and letters containing a top recommendation, are strongly correlated with better early career outcomes, including having an initial job at a top 20 academic department and having more publications in top academic journals. We further find that female, Asian, and Black or Hispanic candidates have weaker early career outcomes in some dimensions, even after controlling for letter characteristics.

In addition to documenting important patterns in economics Ph.D. letters of recommendation that relate to candidates' personal characteristics, an additional important takeaway is the result that letters are different across fields. Presumably this does not matter much within a field, for example, if Finance candidates are always compared with other Finance candidates. However, for departments that are considering candidates across fields, having an understanding that there are differences based on field of interest is helpful information when comparing recommendation letters.

While this paper documents important patterns in letters of recommendation, we do not speculate as to why we find these differences. Since differences do not arise from innate ability associated with these characteristics, there may be a host of potential explanations including differences in unobserved quality, conscious or unconscious bias, or the match between letter writers and students. Results on similarity bias are mixed, with women letter writers writing more positive letters for women, but no differences in the

letters written by Asian letter writers for Asian candidates. Since these letters are associated with outcomes, it is also important to understand if differences arise from the candidate pool admitted to graduate schools, the ability of graduate schools to educate candidates with different characteristics equally, differential faculty evaluations of candidates, or a lack of early career success for the types of methods and research questions that interest candidates with these characteristics. Finally, we are not able to measure other types of underrepresentation, such as sexual orientation or socioeconomic background, and the extent to which these characteristics have similar implications for the quality of recommendation letters and early career outcomes.

## References

Ajzenman, Nicolás, Bruno Furman, and Pedro C. Sant'Anna. 2025. "Discrimination in the Formation of Academic Networks: A Field Experiment on #EconTwitter." *American Economic Review: Insights* 7(3): 357–375. <https://doi.org/10.1257/aeri.20240298>

Akee, Randall. 2020. "The Race Problem in Economics." *Brookings Commentary*. January 22, 2020. <https://www.brookings.edu/articles/the-race-problem-in-economics/>.

Antman, Francesca M., Kirk B. Doran, Xuechao Qian, and Bruce A. Weinberg. 2024. "Demographic Diversity and Economic Research: Fields of Specialization and Research on Race, Ethnicity, and Inequality." *AEA Papers and Proceedings* 114: 528–534. <https://doi.org/10.1257/pandp.20241129>.

Auriol, Emmanuelle, Guido Friebel, Alisa Weinberger, and Sascha Wilhelm. 2022. "Underrepresentation of Women in the Economics Profession More Pronounced in the United States Compared to Heterogeneous Europe." *Proceedings of the National Academy of Sciences* 119(16). <https://doi.org/10.1073/pnas.2118853119>.

Avilova, Tatyana, and Claudia Goldin. 2024. "Seeking the 'Missing Women' of Economics with the Undergraduate Women in Economics Challenge." *Journal of Economic Perspectives* 38(3): 137–162. <https://doi.org/10.1257/jep.38.3.137>.

Baltrunaite, Audinga, Alessandra Casarico, and Lucia Rizzica. 2022. "Women in Economics: The Role of Gendered References at Entry in the Profession." *Centre for Economic Policy Research Discussion Paper* DP17474, July 2022. <https://cepr.org/publications/dp17474>.

Bayer, Amanda, and Cecilia Elena Rouse. 2016. "Diversity in the Economics Profession: A New Attack on an Old Problem." *Journal of Economic Perspectives* 30(4): 221–242. <https://doi.org/10.1257/jep.30.4.221>.

Bayer, Amanda, and David W. Wilcox. 2019. "The Unequal Distribution of Economic Education: A Report on the Race, Ethnicity, and Gender of Economics Majors at U.S. Colleges and Universities." *Journal of Economic Education* 50(3): 299–320. <https://doi.org/10.1080/00220485.2019.1618766>.

Benson, Alan, Danielle Li, and Kelly Shue. 2024. "Potential and the Gender Promotions Gap." SSRN Working Paper (March 4, 2024). <http://dx.doi.org/10.2139/ssrn.4747175>.

Bernstein, Robert H., Michael W. Macy, Wendy M. Williams, Christopher J. Cameron, Sterling Chance Williams-Ceci, and Stephen J. Ceci. 2022. "Assessing Gender Bias in Particle Physics and Social Science Recommendations for Academic Jobs." *Social Sciences* 11(2): article 74. <https://doi.org/10.3390/socsci11020074>.

Bohren, J. Aislinn, Peter Hull, and Alex Imas. 2025a. "Systemic Discrimination: Theory and Measurement." *Quarterly Journal of Economics*. 140(3): 1743–1799. <https://academic.oup.com/qje/article/140/3/1743/8123617>

Bohren, J. Aislinn, Kareem Haggag, Alex Imas, and Devin G. Pope. 2025b. "Inaccurate Statistical Discrimination: An Identification Problem." *Review of Economics and Statistics*. 107(3): 605–620. <https://ideas.repec.org/a/tpr/restat/v107y2025i3p605-620.html>

Boustan, Leah, and Andrew Langan. 2019. "Variation in Women's Success across PhD Programs in Economics." *Journal of Economic Perspectives* 33(1): 23–42. <https://doi.org/10.1257/jep.33.1.23>.

Brooks, Chris, Linda Schopohl, Rui Tao, Jessica Walker, and Meng Zhu. 2025. “The Female Finance Penalty: Why Are Women Less Successful in Academic Finance than Related Fields?” *Research Policy* 54(4): 105207. <https://doi.org/10.1016/j.respol.2025.105207>.

Card, David, Stefano DellaVigna, Patricia Funk, and Nagore Iribarri. 2020. “Are Referees and Editors in Economics Gender Neutral?” *The Quarterly Journal of Economics* 135(1): 269–327. <https://doi.org/10.1093/qje/qjz035>.

Chapman, Bhavana V., Michael K. Rooney, Ethan B. Ludmir, Denise De La Cruz, Abigail Salcedo, Chelsea C. Pinnix, Prajnan Das, Reshma Jaggi, Charles R. Thomas Jr., and Emma B. Holliday. 2022. “Linguistic Biases in Letters of Recommendation for Radiation Oncology Residency Applicants from 2015 to 2019.” *Journal of Cancer Education* 37(4): 965–972. <https://pubmed.ncbi.nlm.nih.gov/33111188/>.

Chari, Anusha, and Paul Goldsmith-Pinkham. 2017. “Gender Representation in Economics across Topics and Time: Evidence from the NBER Summer Institute (No. w23953).” *National Bureau of Economic Research Working Paper* w23953. <https://doi.org/10.3386/w23953>.

Committee on the Status of Minority Groups in the Economics Profession. 2023. “Report of the Committee on the Status of Minority Groups in the Economics Profession (CSMGE).” December 2023. *American Economic Association*. <https://www.aeaweb.org/content/file?id=20038>.

Currie, Russell R., and Gurupadesh S. Pandher. 2020. “Finance Journal Rankings: Active Scholar Assessment Revisited.” *Journal of Banking and Finance* 111: 105–117. <https://doi.org/10.1016/j.jbankfin.2019.105717>

Dupas, Pascaline, Alicia Sasser Modestino, Muriel Niederle, Justin Wolfers, and The Seminar Dynamics Collective. 2021. “Gender and the Dynamics of Seminars.” *NBER Working Paper* w28494. <https://doi.org/10.3386/w28494>.

Dutt, Kuheli, Danielle L. Pfaff, Ariel F. Bernstein, Joseph S. Dillard, and Caryn J. Block. 2016. “Gender Differences in Recommendation Letters for Postdoctoral Fellowships in Geoscience.” *Nature Geoscience* 9: 805–808. <https://doi.org/10.1038/ngeo2819>.

Eberhardt, Markus, Giovanni Facchini, and Valeria Rueda. 2023. “Gender Differences in Reference Letters: Evidence from the Economics Job Market.” *Economic Journal* 133(655, October): 2676–2708. <https://doi.org/10.1093/ej/uead045>.

French, Judith C., Samuel J. Zolin, Erika Lampert, Alexandra Aiello, Kalman P. Bencsath, Kaitlin A. Ritter, Andrew T. Strong, Jeremy M. Lipman, Michael A. Valente, and Ajita S. Prabhu. 2019. “Gender and Letters of Recommendation: A Linguistic Comparison of the Impact of Gender on Surgical Residency Applicants.” *Journal of Surgical Education* 76(4): 899–905. <https://pubmed.ncbi.nlm.nih.gov/30598383/>.

Ge, Qi, and Stephen Wu. 2024. “How Do You Say Your Name? Difficult-to-Pronounce Names and Labor Market Outcomes.” *American Economic Journal: Economic Policy* 16(4): 254–279. <https://doi.org/10.1257/pol.20220611>.

Ginther, Donna K., and Shulamit Kahn. 2004. “Women in Economics: Moving Up or Falling Off the Academic Career Ladder?” *Journal of Economic Perspectives* 18(3): 193–214. <https://doi.org/10.1257/0895330042162386>.

Ginther, Donna K., Shulamit Kahn, and Diana Milakhina. 2025. “Same as It Ever Was: Gender, Race, and Ethnicity Differences in Promotion for Academic Economists.” *AEA Papers and Proceedings* 115: 195–201. <https://doi.org/10.1257/pandp.20251049>.

Houser, Chris, and Kelly Lemmons. 2018. “Implicit Bias in Letters of Recommendation for an Undergraduate Research Internship.” *Journal of Further and Higher Education* 42(5): 585–595. <https://doi.org/10.1080/0309877X.2017.1301410>.

Heath, Janae K., Gary E. Weissman, Caitlin B. Clancy, Haochang Shou, John T. Farrar, and C. Jessica Dine. 2019. “Gender-based Linguistic Differences in Physician Trainee Evaluations of Medical Faculty Using Automated Text Mining.” *JAMA Network Open* (May 2019). <https://doi.org/10.1001/jamanetworkopen.2019.3520>.

Heckman, James J., and Sidharth Moktan. 2020. “Publishing and Promotion in Economics: The Tyranny of the Top Five.” *Journal of Economic Literature* 58(2): 419–470. <https://doi.org/10.1257/jel.20191574>.

Hengel, Erin, and Eun Mi Moon. 2020. “Gender and Equality at Top Economics Journals.” (unpublished report). <https://livrepository.liverpool.ac.uk/3111517/1/quality-summary.pdf>.

Hengel, Erin. 2022. “Publishing While Female: Are Women Held to Higher Standards? Evidence from Peer Review.” *Economic Journal* 132(648, November): 2951–2991. <https://doi.org/10.1093/ej/ueac032>.

Isaac, Carol, Jocelyn Chertoff, Barbara Lee, and Molly Carnes. 2011. “Do Students’ and Authors’ Gender Affect Evaluations? A Linguistic Analysis of Medical School Performance Evaluations.” *Academic Medicine* 86(1): 59–66. <https://doi.org/10.1097/ACM.0b013e318200561d>.

Khang, Hyun-Sund. 2020. “The Accidental Economist.” *Finance & Development Magazine*, December 2020. International Monetary Fund. <https://www.imf.org/en/Publications/fandd/issues/2020/12/profile-of-economist-lisa-cook-michigan-state-university>.

Kjelsrud, Anders, and Sahar Parsa. 2025. “Mentorship and the Gender Gap in Academia.” SSRN Working Paper. <http://dx.doi.org/10.2139/ssrn.5193388>.

Kobayashi, Audrey N., Robert S. Sterling, Sean A. Tackett, Brant W. Chee, Dawn M. Laporte, and Casey Jo Humbyrd. 2020. “Are There Gender-based Differences in Language in Letters of Recommendation to an Orthopaedic Surgery Residency Program?” *Clinical Orthopaedics and Related Research* 478(7): 1400–1408. <https://doi.org/10.1097/CORR.0000000000001053>.

Koffi, Marlène, Roland Pongou, and Leonard Wantchekon. 2024. “Racial Inequality and Publication in Economics.” *AEA Papers and Proceedings* 114: 300–304. <https://doi.org/10.1257/pandp.20241030>.

Koffi, Marlène. 2025. “Innovative Ideas and Gender (In)Equality.” *American Economic Review* 115(7): 2207–2236. <https://doi.org/10.1257/aer.20211811>.

Lin, Fei, Soo Kyung Oh, Lynn K. Gordon, Stacy L. Pineles, Jamie B. Rosenberg, and Irena Tsui. 2019. “Gender-based Differences in Letters of Recommendation Written for Ophthalmology Residency Applications.” *BMC Medical Education* 19: 476. <https://doi.org/10.1186/s12909-019-1910-6>.

Lundberg, Shelley, and Jenna Stearns. 2019. “Women in Economics: Stalled Progress.” *Journal of Economic Perspectives* 33(1): 3–22. <https://doi.org/10.1257/jep.33.1.3>.

Madera, Juan M., Michelle R. Hebl, Heather Dial, Randi Martin, and Virginia Valian. 2018. “Raising Doubt in Letters of Recommendation for Academia.” *Journal of Business Psychology* 34: 287–303. <https://doi.org/10.1007/s10869-018-9541-1>.

Neumark, David, and Rosella Gardecki. 1996. “Women Helping Women? Role-model and Mentoring Effects on Female Ph.D. Students in Economics.” NBER Working Paper w5733. <https://doi.org/10.3386/w5733>.

Powers, Alexa, Katherine M. Gerull, Rachel Rothman, Sandra A. Klein, Rick W. Wright, and Christopher J. Dy. 2020. “Race- and Gender-based Differences in Descriptions of Applicants in the Letters of Recommendation for Orthopaedic Surgery Residency.” *Journal of Bone and Joint Surgery Open Access* (June 2020). <https://doi.org/10.2106/JBJS.OA.20.00023>.

Sarsons, Heather, Klarita Gérxhani, Ernesto Reuben, and Arthur Schram. 2021. “Gender Differences in Recognition for Group Work.” *Journal of Political Economy* 129(1): 101–147. <https://doi.org/10.1086/711401>.

Schmader, Toni, Jessica Whitehead, and Vicki H. Wysocki. 2007. “A Linguistic Comparison of Letters of Recommendation for Male and Female Chemistry and Biochemistry Job Applicants.” *Sex Roles* 57: 509–514. <https://doi.org/10.1007/s11199-007-9291-4>.

Shastry, Gauri K., and Olga Shurchkov. 2024. “Reject or Revise: Gender Differences in Persistence and Publishing in Economics.” *Economic Inquiry* 62(3): 933–956. <https://doi.org/10.1111/ecin.13218>.

Sherman, Mila Getmansky, and Heather E. Tookes. 2022. “Female Representation in the Academic Finance Profession.” *The Journal of Finance* 77: 317–365. <https://doi.org/10.1111/jofi.13094>.

Su, Yang, Brian M. Lucey, and Ashish Jha. 2024. “Gender Dynamics and Academic Recognition in Finance: Evidence from Citation Patterns and Journal Rankings.” SSRN Working Paper. <https://doi.org/10.2139/ssrn.5114345>.

Trix, Frances, and Carolyn Psenka. 2003. “Exploring the Color of Glass: Letters of Recommendation for Female and Male Medical Faculty.” *Discourse & Society* 14(2): 191–220. <https://doi.org/10.1177/0957926503014002277>.

Wessel, David, Louise Sheiner, and Michael Ng. 2019. “Gender and Racial Diversity of Federal Government Economists.” Working paper. *Hutchins Center on Fiscal and Monetary Policy, Brookings Institution*. [Diversity-report\\_updated-3.pdf](https://www.hks.harvard.edu/files/hks/working-papers/2019/2019-010.pdf)

Wu, Alice H. 2018. “Gendered Language on the Economics Job Market Rumors Forum.” *AEA Papers and Proceedings* 108: 175–179. <https://doi.org/10.1257/pandp.20181101>.

Zhao, Yijun, Zhengxin Qi, John Grossi, and Gary M. Weiss. 2023. “Gender and Culture Bias in Letters of Recommendation for Computer Science and Data Science Masters Programs.” *Scientific Reports* 13: 14367. <https://doi.org/10.1038/s41598-023-41564-w>.

## Tables

**Table 1: Summary Statistics for Applicants**

	Mean	St. Dev.
<i>Candidate Characteristics</i>		
Female	0.30	0.46
Asian	0.37	0.48
Black	0.01	0.12
Hispanic	0.13	0.33
<i>Primary Field of Interest</i>		
Finance	0.20	0.40
Macro	0.26	0.44
<i>Institution Characteristics</i>		
Top 10 U.S. Inst.	0.24	0.43
U.S. Inst.	0.79	0.41
B-School	0.11	0.31
<i>Number of Letters</i>		
No. Letters	2.86	0.70
N	2227	

Notes: Table presents summary statistics for the full sample of 2,227 applicants from 2018-2021. *Female*, *Asian*, *Black*, and *Hispanic* are binary variables equal to 1 for candidates self-identifying with those characteristics. *Finance* and *Macro* are binary variables equal to 1 for candidates indicating a primary interest in those fields. *Top 10 U.S. Inst.* is a binary variable equal to 1 for candidates matriculating at a top 10 economics or finance Ph.D. program. *U.S. Inst.* and *B-School* are binary variables equal to 1 for candidates matriculating at institutions in the United States or business schools, respectively. *No. Letters* is the number of letters of recommendation candidates submitted for their application.

**Table 2:** Sample Selection in Applicant Pool

	US Economics Department Sample		AEA Sample	
	N	Mean	N	Mean
Female	1564	0.31	4415	0.33
Top 10 U.S. Inst.	1564	0.27	4415	0.19
Asian	1564	0.41	1807	0.14
Black	1564	0.02	1807	0.03
Hispanic	1564	0.14	1807	0.06

Notes: Table presents summary statistics for the subsample of 1,564 applicants receiving Ph.D.'s from U.S. economics departments and are thus comparable to the pool of Ph.D. recipients for which there is data available from the American Economic Association (AEA). The AEA sample is based on information from the Committee on the Status of Women in the Economics Profession (CSWEP, first two rows) and the Committee on the Status of Minority Groups in the Economics Profession (CSMGP, last three rows). The CSWEP sample includes all Ph.D. graduates from U.S. economics departments, while the CSMGP sample includes U.S. citizens and permanent residents receiving a Ph.D. from a U.S. economics department.

**Table 3:** Summary Statistics for Letters

	Mean	Median	St. Dev.	P25	P75
Word Count	1153.68	1070.00	541.26	780.00	1430.00
Standout %	1.12	1.06	0.51	0.77	1.40
Grindstone %	0.22	0.18	0.21	0.08	0.31
No. Standout Words	12.79	11.00	7.83	7.00	17.00
No. Grindstone Words	2.42	2.00	2.31	1.00	3.00
Top Rec	0.12	0.00	0.33	0.00	0.00
Female Writer	0.17	0.00	0.38	0.00	0.00
Asian Writer	0.15	0.00	0.36	0.00	0.00
Full Prof Writer	0.51	1.00	0.50	0.00	1.00
N	6362				

Notes: Table presents summary statistics for full sample of 6,362 letters for 2,227 applicants from 2018-2021. *Word Count* is the number of words in each letter. *Standout %* and *Grindstone %* are the number of standout and grindstone words as a percentage of the total number of words in the letter. *No. Standout Words* and *No. Grindstone Words* are the number of standout and grindstone words in each letter, respectively. *Top Rec* is a binary variable equal to 1 for letters that indicate that a candidate is suitable to be placed at the very top economics or business school departments. *Female Writer*, *Asian Writer*, and *Full Prof Writer* are binary variables equal to 1 if the letter writer is female, Asian, or a full professor, respectively.

**Table 4:** Candidate and Institution Characteristics and Letter Word Count

	(1) Word Count	(2) Word Count	(3) Word Count	(4) Word Count	(5) Word Count	(6) Word Count
Female	-5.76 (14.52)	-20.33 (14.78)	-16.50 (14.72)	-16.50 (17.14)	-16.50 (15.16)	-16.86 (14.76)
Asian	-111.05 *** (14.81)	-108.29 *** (14.76)	-99.14 *** (15.06)	-99.14 *** (17.54)	-99.14 *** (16.07)	-96.44 *** (15.08)
Black or Hispanic	14.07 (20.00)	1.40 (20.04)	-4.12 (20.04)	-4.12 (23.55)	-4.12 (20.55)	-3.47 (20.06)
Finance		-138.11 *** (16.39)	-156.64 *** (18.97)	-156.64 *** (22.16)	-156.64 *** (21.67)	-153.79 *** (19.15)
Macro		-42.22 ** (16.41)	-46.35 *** (16.49)	-46.35 ** (19.12)	-46.35 ** (21.97)	-45.97 *** (16.56)
Top 10 Econ			148.79 *** (17.74)	148.79 *** (20.92)	148.79 *** (27.08)	148.42 *** (18.06)
Top 10 B-School			142.17 *** (33.00)	142.17 *** (37.97)	142.17 *** (37.80)	141.89 *** (33.06)
U.S. Inst.			-64.46 *** (18.44)	-64.46 *** (21.28)	-64.46 *** (23.15)	-53.77 *** (19.52)
B-School			-5.29 (26.51)	-5.29 (30.82)	-5.29 (28.64)	-4.76 (26.49)
Female Writer						1.56 (17.21)
Asian Writer						-51.01 *** (17.43)
Full Prof Writer						-12.91 (14.66)
Sample	Full	Full	Full	Full	Full	Full
FE	No	No	No	No	No	No
Err Cluster	No	No	No	Cand	Writer	No
N	6362	6362	6362	6362	6362	6362
R-squared	0.01	0.02	0.03	0.03	0.03	0.03

Notes: Table presents results of an OLS regression on the letter word count based on the sample of 6,362 letters for 2,227 applicants from 2018-2021. Explanatory variables include binary variables indicating candidate characteristics (*Female*, *Asian*, and *Black or Hispanic*), field of interest (*Finance* and *Macro*), institution characteristics (*Top 10 Econ*, *Top 10 B-School*, *U.S. Inst.*, and *B-School*), and letter writer characteristics (*Female Writer*, *Asian Writer*, and *Full Prof Writer*). Standard errors are robust and clustered at the candidate level in specification (4) and the writer level in specification (5). The omitted race is white. The symbols \*\*\*, \*\*, and \* indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

**Table 5:** Candidate and Institution Characteristics and Percent of Standout Words

	(1) Standout %	(2) Standout %	(3) Standout %	(4) Standout %	(5) Standout %	(6) Standout %
Female	0.022 (0.014)	0.021 (0.014)	0.021 (0.014)	0.021 (0.017)	0.021 (0.014)	0.020 (0.014)
Asian	-0.082*** (0.014)	-0.085*** (0.014)	-0.086*** (0.015)	-0.086*** (0.017)	-0.086*** (0.016)	-0.087*** (0.015)
Black or Hispanic	-0.074*** (0.018)	-0.067*** (0.018)	-0.068*** (0.018)	-0.068*** (0.021)	-0.068*** (0.018)	-0.069*** (0.018)
Finance	0.035** (0.017)	0.028 (0.020)	0.028 (0.023)	0.028 (0.023)	0.028 (0.023)	0.028 (0.020)
Macro	-0.060*** (0.015)	-0.059*** (0.016)	-0.059*** (0.019)	-0.059*** (0.020)	-0.059*** (0.020)	-0.059*** (0.016)
Top 10 Econ		0.005 (0.016)	0.005 (0.019)	0.005 (0.022)	0.005 (0.022)	0.008 (0.016)
Top 10 B-School		-0.034 (0.039)	-0.034 (0.046)	-0.034 (0.041)	-0.034 (0.041)	-0.033 (0.039)
U.S. Inst.		0.006 (0.018)	0.006 (0.021)	0.006 (0.020)	0.006 (0.020)	0.009 (0.019)
B-School		0.036 (0.030)	0.036 (0.035)	0.036 (0.032)	0.036 (0.032)	0.036 (0.030)
Female Writer						-0.002 (0.017)
Asian Writer						0.023 (0.019)
Full Prof Writer						-0.010 (0.014)
Sample	Full	Full	Full	Full	Full	Full
FE	No	No	No	No	No	No
Err Cluster	No	No	No	Cand	Writer	No
N	6362	6362	6362	6362	6362	6362
R-squared	0.01	0.01	0.01	0.01	0.01	0.01

Notes: Table presents results of an OLS regression on the percentage of standout words based on the sample of 6,362 letters for 2,227 applicants from 2018-2021. Explanatory variables include binary variables indicating candidate characteristics (*Female*, *Asian*, and *Black or Hispanic*), field of interest (*Finance* and *Macro*), institution characteristics (*Top 10 Econ*, *Top 10 B-School*, *U.S. Inst.*, and *B-School*), and letter writer characteristics (*Female Writer*, *Asian Writer*, and *Full Prof Writer*). Standard errors are robust and clustered at the candidate level in specification (4) and the writer level in specification (5). The omitted race is white. The symbols \*\*\*, \*\*, and \* indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

**Table 6:** Candidate and Institution Characteristics and Percent of Grindstone Words

	(1) Grind- stone %	(2) Grind- stone %	(3) Grind- stone %	(4) Grind- stone %	(5) Grind- stone %	(6) Grind- stone %
Female	0.025*** (0.006)	0.017*** (0.006)	0.016*** (0.006)	0.016** (0.007)	0.016*** (0.006)	0.014** (0.006)
Asian	0.012** (0.006)	0.011* (0.006)	0.013** (0.006)	0.013* (0.007)	0.013** (0.006)	0.013** (0.006)
Black or Hispanic	0.003 (0.008)	0.002 (0.008)	0.006 (0.008)	0.006 (0.009)	0.006 (0.008)	0.006 (0.008)
Finance		-0.042*** (0.007)	-0.035*** (0.008)	-0.035*** (0.009)	-0.035*** (0.008)	-0.034*** (0.008)
Macro		-0.059*** (0.006)	-0.061*** (0.006)	-0.061*** (0.007)	-0.061*** (0.006)	-0.059*** (0.006)
Top 10 Econ			-0.038*** (0.007)	-0.038*** (0.008)	-0.038*** (0.007)	-0.034*** (0.007)
Top 10 B-School			-0.046*** (0.014)	-0.046*** (0.017)	-0.046*** (0.015)	-0.044*** (0.014)
U.S. Inst.			-0.004 (0.007)	-0.004 (0.009)	-0.004 (0.008)	0.005 (0.008)
B-School			-0.011 (0.012)	-0.011 (0.013)	-0.011 (0.012)	-0.010 (0.012)
Female Writer						0.012 (0.007)
Asian Writer						0.006 (0.007)
Full Prof Writer						-0.020*** (0.006)
Sample	Full	Full	Full	Full	Full	Full
FE	No	No	No	No	No	No
Err Cluster	No	No	No	Cand	Writer	No
N	6362	6362	6362	6362	6362	6362
R-squared	0.00	0.02	0.03	0.03	0.03	0.03

Notes: Table presents results of an OLS regression on the percentage of grindstone words based on the sample of 6,362 letters for 2,227 applicants from 2018-2021. Explanatory variables include binary variables indicating candidate characteristics (*Female*, *Asian*, and *Black or Hispanic*), field of interest (*Finance* and *Macro*), institution characteristics (*Top 10 Econ*, *Top 10 B-School*, *U.S. Inst.*, and *B-School*), and letter writer characteristics (*Female Writer*, *Asian Writer*, and *Full Prof Writer*). Standard errors are robust and clustered at the candidate level in specification (4) and the writer level in specification (5). The omitted race is white. The symbols \*\*\*, \*\*, and \* indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

**Table 7:** Candidate and Institution Characteristics and Top Recommendation

	(1) Top Rec	(2) Top Rec	(3) Top Rec	(4) Top Rec	(5) Top Rec	(6) Top Rec	(7) Top Rec
Female	-0.027*** (0.009)	-0.022** (0.009)	-0.016* (0.008)	-0.013 (0.008)	-0.013 (0.010)	-0.013 (0.008)	-0.012 (0.008)
Asian	-0.064*** (0.008)	-0.065*** (0.008)	-0.062*** (0.009)	-0.061*** (0.009)	-0.061*** (0.010)	-0.061*** (0.009)	-0.044*** (0.008)
Black or Hispanic	0.009 (0.014)	0.013 (0.014)	0.000 (0.014)	0.001 (0.014)	0.001 (0.017)	0.001 (0.014)	0.006 (0.013)
Finance		0.045*** (0.011)	0.015 (0.013)	0.012 (0.013)	0.012 (0.016)	0.012 (0.014)	0.027** (0.013)
Macro		0.008 (0.010)	0.008 (0.010)	0.005 (0.010)	0.005 (0.012)	0.005 (0.011)	0.012 (0.010)
Top 10 Econ			0.199*** (0.013)	0.193*** (0.013)	0.193*** (0.016)	0.193*** (0.017)	0.174*** (0.013)
Top 10 B-School			0.158*** (0.030)	0.154*** (0.030)	0.154*** (0.035)	0.154*** (0.033)	0.138*** (0.029)
U.S. Inst.			-0.041*** (0.011)	-0.050*** (0.012)	-0.050*** (0.014)	-0.050*** (0.014)	-0.044*** (0.011)
B-School			0.045** (0.019)	0.044** (0.019)	0.044** (0.021)	0.044** (0.022)	0.042** (0.018)
Female Writer				-0.031*** (0.009)	-0.031*** (0.009)	-0.031** (0.012)	-0.031*** (0.009)
Asian Writer				-0.023** (0.010)	-0.023** (0.010)	-0.023* (0.013)	-0.018* (0.010)
Full Prof Writer				0.025*** (0.009)	0.025*** (0.008)	0.025** (0.011)	0.027*** (0.008)
Word Count (hundreds)							0.012** (0.001)
Standout %							0.062*** (0.007)
Grindstone %							-0.031** (0.016)
Sample	Full						
FE	No						
Err Cluster	No	No	No	No	Cand	Writer	No
N	6362	6362	6362	6362	6362	6362	6362
R-squared	0.01	0.01	0.08	0.08	0.08	0.08	0.12

Notes: Table presents results of an OLS regression on a binary variable indicating whether a letter recommends the candidate to a top program based on the sample of 6,362 letters for 2,227 applicants from 2018-2021. Explanatory variables include binary variables indicating candidate characteristics (*Female*, *Asian*, and *Black or Hispanic*), field of interest (*Finance* and *Macro*), institution characteristics (*Top 10 Econ*, *Top 10 B-School*, *U.S. Inst.*, and *B-School*), and letter writer characteristics (*Female Writer*, *Asian Writer*, and *Full Prof Writer*), as well as continuous variables for letter length and content (*Word Count*, *Standout %*, and *Grindstone %*). Standard errors are robust and clustered at the candidate level in specification (5) and the writer level in specification (6). The omitted race is white. The symbols \*\*\*, \*\*, and \* indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

**Table 8:** Impact of Female/Asian Letter Writers for Female/Asian Candidates

	(1) Top Rec	(2) Top Rec	(3) Top Rec	(4) Top Rec
Female	-0.013 (0.008)	-0.015 (0.010)	-0.012 (0.008)	-0.014 (0.009)
Asian	-0.061*** (0.009)	-0.062*** (0.009)	-0.044*** (0.008)	-0.044*** (0.009)
Black or Hispanic	0.001 (0.014)	0.002 (0.014)	0.006 (0.013)	0.006 (0.013)
Finance	0.012 (0.013)	0.012 (0.013)	0.027** (0.013)	0.027** (0.013)
Macro	0.005 (0.010)	0.005 (0.010)	0.012 (0.010)	0.012 (0.010)
Top 10 Econ	0.193*** (0.013)	0.193*** (0.013)	0.174*** (0.013)	0.174*** (0.013)
Top 10 B-School	0.154*** (0.030)	0.154*** (0.030)	0.138*** (0.029)	0.138*** (0.029)
U.S. Inst.	-0.050*** (0.012)	-0.050*** (0.012)	-0.044*** (0.011)	-0.045*** (0.011)
B-School	0.044** (0.019)	0.044** (0.019)	0.042** (0.018)	0.042** (0.018)
Female Writer	-0.031*** (0.009)	-0.034*** (0.012)	-0.031*** (0.009)	-0.035*** (0.012)
Female Cand. x Female Writer		0.009 (0.019)		0.012 (0.019)
Asian Writer	-0.023** (0.010)	-0.025 (0.016)	-0.018* (0.010)	-0.017 (0.015)
Asian Cand. x Asian Writer		0.005 (0.020)		-0.002 (0.019)
Full Prof Writer	0.025*** (0.009)	0.025*** (0.009)	0.027*** (0.008)	0.027*** (0.008)
Word Count (hundreds)			0.012*** (0.001)	0.012*** (0.001)
Standout %			0.062*** (0.007)	0.062*** (0.007)
Grindstone %			-0.031** (0.016)	-0.032** (0.016)
Sample	Full	Full	Full	Full
FE	No	No	No	No
Err Cluster	No	No	No	No
N	6362	6362	6362	6362
R-squared	0.08	0.08	0.12	0.12

Notes: Table presents results of an OLS regression on a binary variable indicating whether a letter recommends the candidate to a top program based on the sample of 6,362 letters for 2,227 applicants from 2018-2021. Explanatory variables include binary variables indicating candidate characteristics (*Female*, *Asian*, and *Black or Hispanic*), field of interest (*Finance* and *Macro*), institution characteristics (*Top 10 Econ*, *Top 10 B-School*, *U.S. Inst.*, and *B-School*), and letter writer characteristics (*Female Writer*, *Asian Writer*, and *Full Prof Writer*), as well as continuous variables for letter length and content (*Word Count*, *Standout %*, and *Grindstone %*). Standard errors are robust. The omitted race is white. The symbols \*\*\*, \*\*, and \* indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

**Table 9:** Letter Characteristics with Writer Fixed Effects

	(1) Word Count	(2) Standout %	(3) Grindstone %	(4) Top Rec
Female	-3.789 (16.646)	0.026 (0.018)	0.005 (0.008)	-0.008 (0.013)
Asian	-55.113*** (17.649)	-0.058*** (0.019)	0.001 (0.008)	-0.076*** (0.015)
Black or Hispanic	-50.544** (23.723)	-0.042* (0.024)	0.008 (0.013)	-0.012 (0.021)
Finance	-14.119 (33.460)	0.043 (0.036)	-0.007 (0.014)	0.044 (0.034)
Macro	-1.254 (24.632)	0.016 (0.028)	-0.013 (0.011)	0.009 (0.020)
Top 10 Econ	98.188* (53.081)	-0.015 (0.053)	0.018 (0.026)	0.038 (0.058)
Top 10 B-School	12.314 (65.099)	0.021 (0.073)	-0.018 (0.032)	-0.029 (0.069)
U.S. Inst.	29.211 (47.109)	0.052 (0.049)	0.009 (0.022)	0.056 (0.048)
B-School	69.137 (44.806)	0.018 (0.052)	0.019 (0.029)	0.026 (0.041)
Sample	Full	Full	Full	Full
FE	Writer	Writer	Writer	Writer
Err Cluster	Candidate	Candidate	Candidate	Candidate
N	4509	4509	4509	4509
R-squared	0.63	0.53	0.45	0.47
F-Test	125787.43	31192.59	1228.26	1865.20
F-Test p-value	0.00	0.00	0.00	0.00

Notes: Table presents results of an OLS regression with writer fixed effects on letter characteristics (*Word Count*, *Standout %*, *Grindstone %*, and *Top Rec*) based on the sample of 4,509 letters for 1,961 applicants whose writers each have more than one letter in our sample from 2018-2021. Explanatory variables include binary variables indicating candidate characteristics (*Female*, *Asian*, and *Black or Hispanic*), field of interest (*Finance* and *Macro*), and institution characteristics (*Top 10 Econ*, *Top 10 B-School*, *U.S. Inst.*, and *B-School*). The reported F-statistic and corresponding p-value are based on a joint significance test of the writer fixed effects. Standard errors are robust and clustered at the candidate level. The omitted race is white. The symbols \*\*\*, \*\*, and \* indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

**Table 10:** Summary Statistics for Early Career Outcomes

	N	Mean	St. Dev.
<i>Panel A: Full Sample</i>			
Top 20 Academic Job	2227	0.06	0.24
No. Top 100 Pubs	2227	0.79	1.23
No. Top 8 Pubs	2227	0.16	0.53
Has Top 100 Pub	2227	0.44	0.50
Has Top 8 Pub	2227	0.11	0.31
<i>Panel B: Top 10 Economics and Finance Department Sample</i>			
Top 20 Academic Job	530	0.17	0.38
No. Top 100 Pubs	530	1.00	1.40
No. Top 8 Pubs	530	0.39	0.84
Has Top 100 Pub	530	0.50	0.50
Has Top 8 Pub	530	0.25	0.44

Notes: Table presents summary statistics on early career outcomes for the full sample of 2,227 applicants from 2018-2021. *Top 20 Academic Job* is a binary variable equal to 1 for candidates that took a job at a top 20 academic department. *No. Top 100 Pubs* and *No. Top 8 Pubs* are the number of publications in the three years after receiving a Ph.D. in top 100 journals and in top 8 journals, respectively. *Has Top 100 Pub* and *Has Top 8 Pub* are binary variables equal to 1 for candidates that published in the three years after receiving a Ph.D. in a top 100 journal and in a top 8 journal, respectively. Panel A reports statistics for the full applicant sample and Panel B reports statistics for the subsample of applicants from top 10 economics and finance departments.

**Table 11:** Early Career Outcomes: Initial Job Placement

	(1) Top 20 Academic Job	(2) Top 20 Academic Job	(3) Top 20 Academic Job	(4) Top 20 Academic Job
Female	0.020 (0.013)	0.022* (0.013)	0.028** (0.012)	0.033*** (0.012)
Asian	-0.057*** (0.011)	-0.059*** (0.011)	-0.062*** (0.012)	-0.048*** (0.011)
Black or Hispanic	0.009 (0.020)	0.014 (0.020)	-0.002 (0.019)	-0.002 (0.018)
Finance		0.035** (0.017)	0.034* (0.019)	0.034* (0.018)
Macro		-0.013 (0.012)	-0.009 (0.012)	-0.010 (0.011)
Top 10 Econ			0.170*** (0.020)	0.126*** (0.018)
Top 10 B-School			0.084** (0.040)	0.052 (0.039)
U.S. Inst.			0.000 (0.013)	-0.009 (0.013)
B-School			0.015 (0.024)	0.005 (0.023)
Female Writer				0.006 (0.007)
Asian Writer				0.018** (0.008)
Full Prof Writer				0.035*** (0.006)
Word Count (hundreds)				0.004*** (0.001)
Standout %				0.008 (0.006)
Grindstone %				-0.004 (0.022)
Top Rec				0.167*** (0.019)
Sample	Full	Full	Full	Full
FE	No	No	No	No
Err Cluster	Cand	Cand	Cand	Cand
N	6362	6362	6362	6362
R-squared	0.01	0.02	0.09	0.16

Notes: Table presents results of an OLS regression on a binary variable indicating that the candidate took a job at a top 20 academic department based on the sample of 6,362 letters for 2,227 applicants from 2018-2021. Explanatory variables include binary variables indicating candidate characteristics (*Female*, *Asian*, and *Black or Hispanic*), field of interest (*Finance* and *Macro*), institution characteristics (*Top 10 Econ*, *Top 10 B-School*, *U.S. Inst.*, and *B-School*), and letter writer characteristics (*Female Writer*, *Asian Writer*, *Full Prof Writer*, and *Top Rec*), as well as continuous variables for letter length and content (*Word Count (hundreds of words)*, *Standout %*, and *Grindstone %*). Standard errors are robust and clustered at the candidate level. The omitted race is white. The symbols \*\*\*, \*\*, and \* indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

**Table 12:** Early Career Outcomes: Journal Publications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
	No. Top 100 Pubs	No. Top 100 Pubs	No. Top 100 Pubs	No. Top 100 Pubs	No. Top 8 Pubs	No. Top 8 Pubs	No. Top 8 Pubs	No. Top 8 Pubs	
Female	-0.295*** (0.051)	-0.308*** (0.052)	-0.302*** (0.052)	-0.286*** (0.051)	-0.083*** (0.023)	-0.067*** (0.022)	-0.056*** (0.021)	-0.045** (0.020)	
Asian	-0.215*** (0.058)	-0.209*** (0.058)	-0.158*** (0.058)	-0.085 (0.056)	-0.100*** (0.026)	-0.105*** (0.025)	-0.108*** (0.025)	-0.073*** (0.023)	
Black or Hispanic	-0.147* (0.084)	-0.167** (0.084)	-0.164** (0.083)	-0.152* (0.080)	-0.060 (0.037)	-0.041 (0.037)	-0.069* (0.037)	-0.066* (0.036)	
Finance		-0.168** (0.071)	-0.180** (0.086)	-0.163** (0.083)		0.179*** (0.040)	0.159*** (0.048)	0.160*** (0.045)	
Macro		0.019 (0.066)	-0.009 (0.067)	-0.012 (0.065)		0.019 (0.029)	0.025 (0.028)	0.020 (0.027)	
Top 10 Econ			0.360*** (0.081)	0.194** (0.078)			0.324*** (0.044)	0.224*** (0.037)	
Top 10 B-School				0.411*** (0.138)	0.287** (0.133)		0.259*** (0.097)	0.182* (0.093)	
U.S. Inst.					-0.288*** (0.074)	-0.288*** (0.073)		-0.022 (0.028)	-0.023 (0.028)
B-School					-0.196* (0.101)	-0.231** (0.099)		0.021 (0.060)	-0.001 (0.057)
Female Writer					0.015 (0.041)			0.005 (0.014)	
Asian Writer					-0.093** (0.039)			-0.005 (0.017)	
Full Prof Writer					0.090*** (0.032)			0.046*** (0.014)	
Word Count (hundreds)					0.022*** (0.004)			0.008*** (0.002)	
Standout %					0.117*** (0.036)			0.022* (0.012)	
Grindstone %					-0.193** (0.076)			-0.076*** (0.029)	
Top Rec					0.525*** (0.082)			0.392*** (0.047)	
Sample	Full								
FE	No								
Err Cluster	Cand								
N	6362	6362	6362	6362	6362	6362	6362	6362	
R-squared	0.02	0.02	0.04	0.08	0.01	0.03	0.09	0.15	

Notes: Table presents results of OLS regressions on the number of publications in the three years after receiving a Ph.D. in top 100 journals (*No. Top 100 Pubs*) and in top 8 journals (*No. Top 8 Pubs*) based on the sample of 6,362 letters for 2,227 applicants from 2018-2021. Explanatory variables include binary variables indicating candidate characteristics (*Female*, *Asian*, and *Black or Hispanic*), field of interest (*Finance* and *Macro*), institution characteristics (*Top 10 Econ*, *Top 10 B-School*, *U.S. Inst.*, and *B-School*), and letter writer characteristics (*Female Writer*, *Asian Writer*, *Full Prof Writer*, and *Top Rec*), as well as continuous variables for letter length and content (*Word Count (hundreds of words)*, *Standout %*, and *Grindstone %*). Standard errors are robust and clustered at the candidate level. The omitted race is white. The symbols \*\*\*, \*\*, and \* indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

**Table 13:** Early Career Outcomes: Instrumental Variable Specification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Top 20 Academic Job				No. Top 100 Pubs				No. Top 8 Pubs			
Word Count (hundreds)	0.003*** (0.001)				0.025*** (0.005)				0.010*** (0.003)			
Standout		0.016 (0.010)				0.033 (0.051)				0.035* (0.020)		
Grindstone			-0.039 (0.035)				-0.448*** (0.140)				-0.174*** (0.059)	
Top Rec				0.166*** (0.027)				0.585*** (0.107)				0.391*** (0.068)
Female	0.034** (0.015)	0.034** (0.015)	0.035** (0.015)	0.036** (0.015)	-0.274*** (0.058)	-0.275*** (0.058)	-0.271*** (0.058)	-0.268*** (0.057)	-0.057** (0.026)	-0.058** (0.026)	-0.056** (0.026)	-0.053** (0.025)
Asian	-0.073*** (0.014)	-0.075*** (0.014)	-0.076*** (0.014)	-0.064*** (0.013)	-0.161** (0.065)	-0.185*** (0.065)	-0.186*** (0.066)	-0.144** (0.064)	-0.120*** (0.030)	-0.128*** (0.030)	-0.130*** (0.030)	-0.102*** (0.028)
Black or Hispanic	-0.005 (0.022)	-0.005 (0.023)	-0.006 (0.022)	-0.006 (0.022)	-0.159* (0.094)	-0.167* (0.095)	-0.166* (0.094)	-0.169* (0.093)	-0.065 (0.042)	-0.067 (0.043)	-0.068 (0.043)	-0.069* (0.042)
Finance	0.044* (0.025)	0.038 (0.025)	0.038 (0.025)	0.036 (0.024)	-0.106 (0.098)	-0.152 (0.098)	-0.162 (0.098)	-0.160* (0.095)	0.211*** (0.066)	0.190*** (0.065)	0.188*** (0.065)	0.186*** (0.061)
Macro	-0.012 (0.015)	-0.012 (0.015)	-0.015 (0.015)	-0.014 (0.014)	-0.005 (0.071)	-0.013 (0.072)	-0.040 (0.074)	-0.019 (0.071)	0.024 (0.032)	0.022 (0.032)	0.010 (0.032)	0.017 (0.030)
Top 10 Econ	0.170*** (0.021)	0.174*** (0.021)	0.173*** (0.021)	0.141*** (0.020)	0.349*** (0.086)	0.380*** (0.087)	0.366*** (0.087)	0.264*** (0.086)	0.335*** (0.045)	0.347*** (0.046)	0.342*** (0.046)	0.270*** (0.040)
Top 10 B-School	0.067 (0.041)	0.071* (0.042)	0.069* (0.042)	0.049 (0.041)	0.401*** (0.139)	0.428*** (0.140)	0.407*** (0.141)	0.351** (0.137)	0.203** (0.099)	0.216** (0.100)	0.207** (0.100)	0.164* (0.096)
U.S. Inst.	0.001 (0.017)	-0.003 (0.017)	-0.002 (0.017)	0.007 (0.016)	-0.201** (0.078)	-0.224*** (0.078)	-0.225*** (0.078)	-0.192** (0.077)	-0.027 (0.037)	-0.038 (0.037)	-0.037 (0.037)	-0.015 (0.035)
B-School	0.011 (0.030)	0.010 (0.030)	0.010 (0.030)	-0.003 (0.029)	-0.270** (0.106)	-0.271** (0.107)	-0.274*** (0.106)	-0.318*** (0.105)	0.008 (0.074)	0.006 (0.075)	0.006 (0.074)	-0.024 (0.072)
Specification	IV											
Sample	Full											
FE	No											
Err Cluster	Cand											
N	4509	4509	4509	4509	4509	4509	4509	4509	4509	4509	4509	4509
R-squared	0.11	0.10	0.10	0.16	0.06	0.04	0.04	0.07	0.11	0.10	0.10	0.15

Notes: Table presents results of instrumental variable regressions of early career outcomes (*Top 20 Academic*, *No. Top 100 Pubs*, and *No. Top 8 Pubs*), where letter characteristics are instrumented by writer fixed effects. The sample consists of 4,509 letters for 1,961 applicants whose writers each have more than one letter in our sample from 2018-2021. Explanatory variables include binary variables indicating candidate characteristics (*Female*, *Asian*, and *Black or Hispanic*), field of interest (*Finance* and *Macro*), and institution characteristics (*Top 10 Econ*, *Top 10 B-School*, *U.S. Inst.*, and *B-School*). Standard errors are robust. The omitted race is white. The symbols \*\*\*, \*\*, and \* indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

## Online Appendix

**Table A1:** Candidate Primary Field of Interest

	Mean	St. Dev.
Finance	0.20	0.40
International	0.08	0.27
Labor	0.14	0.34
Macro	0.26	0.44
Other Fields	0.32	0.47
Micro	0.05	0.22
Health, Education, and Welfare	0.03	0.18
Industrial Organization	0.06	0.24
Urban, Rural, and Regional	0.03	0.16
Applied	0.10	0.29
Public Finance	0.05	0.21
N/A	0.01	0.08
<b>N</b>	<b>2227</b>	

Notes: Table presents summary statistics for candidates by self-reported primary field of interest for the full sample of 2,227 applicants from 2018-2021.

**Table A2:** Standout and Grindstone Word List

Panel A: Standout Words			
achieve*	amazing	award*	best
challeng*	compelling	competitive	complete package
decisive	essential	excel*	exceptional
extremely	extraordinar*	fabulous	first-rate
full package	fundamental	highest possible	high quality
important*	impress*	innovat*	leader of the field
led	make our short list	magnificent	master*
most	natural*	novel	original
outstanding*	passion*	phenomenal	prestig*
remarkable	significant*	star	strong*
substantial	superb	supreme*	surpass
terrific*	tour de force	transforma*	unique
unmatched	unparalleled	wonderful	world class
single-author	single author	upper 5	upper 10
upper tier	first tier	top student	trailblazer
role model	academic star	rising star	superstar
star of the field	compares well with	would hire	best I've worked with
shortlist	top few students	the best student	one of the top
would be happy to hire	without any reservation	best postdoctoral fellow	best I have worked with
future leader of the field	compares favorably with	one of the best I have worked with	one of the two best I have worked with
head and shoulders above	strongest recommendation	strongest possible recommendation	
Panel B: Grindstone Words			
assiduous	busy	careful	conscientious
dedicate*	depend*	diligen*	disciplined
effective	effort*	hard-working	hardworking
hardest working	hard working	hard worker	industrious
methodical	meticulous	multitask	multi-task
organiz*	reliab*	responsib*	thorough*
trust*			

Notes: Words followed by a \* denote word stems.

**Table A3:** Letter Characteristics with Institution Fixed Effects

	(1) Word Count	(2) Standout %	(3) Grindstone %	(4) Top Rec
Female	-25.394 (17.256)	0.022 (0.017)	0.013* (0.007)	-0.011 (0.011)
Asian	-71.005*** (18.460)	-0.092*** (0.018)	0.012 (0.008)	-0.055*** (0.011)
Black or Hispanic	-7.798 (24.008)	-0.044** (0.021)	0.013 (0.010)	0.002 (0.018)
Finance	-134.936*** (24.227)	0.002 (0.025)	-0.032*** (0.011)	0.021 (0.020)
Macro	-28.298 (19.843)	-0.065*** (0.020)	-0.058*** (0.008)	0.005 (0.013)
Female Writer	1.371 (16.678)	-0.022 (0.017)	0.017** (0.008)	-0.035*** (0.010)
Asian Writer	-49.654*** (18.291)	0.029 (0.019)	0.008 (0.008)	-0.022** (0.011)
Full Prof Writer	-25.783 (15.925)	-0.017 (0.014)	-0.014** (0.006)	0.014 (0.009)
Sample	Full	Full	Full	Full
FE	Inst.	Inst.	Inst.	Inst.
Err Cluster	Candidate	Candidate	Candidate	Candidate
N	6348	6348	6348	6348
R-squared	0.14	0.11	0.11	0.15
F-Test	43838.31	3.41e+09	572640.91	4.05
F-Test p-value	0.00	0.00	0.00	0.00

Notes: Table presents results of an OLS regression with institution fixed effects on letter characteristics (*Word Count*, *Standout %*, *Grindstone %*, and *Top Rec*) based on the sample of 6,348 letters for 2,213 applicants from 2018-2021. Explanatory variables include binary variables indicating candidate characteristics (*Female*, *Asian*, and *Black or Hispanic*), field of interest (*Finance* and *Macro*), and letter writer characteristics (*Female Writer*, *Asian Writer*, *Full Prof Writer*). The reported F-statistic and corresponding p-value are based on a joint significance test of the institution fixed effects. Standard errors are robust and clustered at the candidate level. The omitted race is white. The symbols \*\*\*, \*\*, and \* indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

**Table A4: Robustness: Letter Characteristics and Early Career Outcomes:  
U.S. Economics and Finance Departments**

	(1) Word Count	(2) Standout %	(3) Grind- stone %	(4) Top Rec	(5) Top 20 Academic	(6) No. Top 100 Pubs	(7) No. Top 8 Pubs
Female	-11.534 (16.509)	0.029* (0.016)	0.012* (0.007)	-0.013 (0.009)	0.028** (0.013)	-0.269*** (0.056)	-0.040* (0.023)
Asian	-98.032*** (16.561)	-0.094*** (0.016)	0.008 (0.006)	-0.069*** (0.009)	-0.056*** (0.012)	-0.061 (0.062)	-0.072*** (0.027)
Black or Hispanic	-11.892 (21.685)	-0.072*** (0.020)	0.004 (0.009)	-0.010 (0.015)	-0.005 (0.021)	-0.132 (0.090)	-0.056 (0.042)
Finance	-170.647*** (22.728)	0.045* (0.025)	-0.030*** (0.009)	0.031* (0.017)	0.048* (0.025)	-0.144 (0.093)	0.183*** (0.063)
Macro	-45.600** (18.522)	-0.046*** (0.018)	-0.063*** (0.007)	0.022** (0.011)	-0.009 (0.013)	-0.010 (0.072)	0.016 (0.032)
Top 10 Econ	149.848*** (18.213)	0.007 (0.016)	-0.035*** (0.007)	0.193*** (0.013)	0.120*** (0.018)	0.195** (0.078)	0.227*** (0.036)
Top 10 B-School	116.440*** (36.643)	-0.046 (0.044)	-0.040** (0.016)	0.150*** (0.031)	0.055 (0.041)	0.262* (0.141)	0.176* (0.102)
B-School	31.772 (33.969)	0.042 (0.040)	-0.018 (0.015)	0.041* (0.024)	-0.011 (0.030)	-0.212* (0.120)	-0.006 (0.080)
Female Writer	10.305 (19.424)	0.010 (0.019)	0.010 (0.008)	-0.021* (0.011)	0.006 (0.008)	0.048 (0.046)	0.009 (0.016)
Asian Writer	-41.485** (18.760)	0.021 (0.021)	0.008 (0.008)	-0.026** (0.011)	0.019** (0.009)	-0.100** (0.042)	-0.007 (0.018)
Full Prof Writer	2.303 (15.671)	0.001 (0.015)	-0.020*** (0.006)	0.025*** (0.009)	0.034*** (0.006)	0.093*** (0.034)	0.038*** (0.013)
Word Count (hundreds)					0.004*** (0.001)	0.026*** (0.005)	0.007*** (0.002)
Standout %					0.005 (0.006)	0.073** (0.035)	0.007 (0.012)
Grindstone %					-0.020 (0.013)	-0.205** (0.089)	-0.066** (0.033)
Top Rec					0.183*** (0.023)	0.514*** (0.085)	0.386*** (0.055)
Sample	U.S.	U.S.	U.S.	U.S.	U.S.	U.S.	U.S.
FE	No	No	No	No	No	No	No
Err Cluster	No	No	No	No	Cand	Cand	Cand
N	5024	5024	5024	5024	5024	5024	5024
R-squared	0.04	0.01	0.03	0.10	0.17	0.08	0.16

Notes: Table presents results of OLS regressions on letter characteristics (*Word Count*, *Standout %*, *Grindstone %*, and *Top Rec*) and early career outcomes (*Top 20 Academic*, *No. Top 100 Pubs*, and *No. Top 8 Pubs*) based on the sample of 5,024 letters for 1,757 applicants from U.S. economics and finance departments between 2018-2021. Explanatory variables include binary variables indicating candidate characteristics (*Female*, *Asian*, and *Black or Hispanic*), field of interest (*Finance* and *Macro*), institution characteristics (*B-School*), and letter writer characteristics (*Female Writer*, *Asian Writer*, *Full Prof Writer*, and *Top Rec*), as well as continuous variables for letter length and content (*Word Count (hundreds of words)*, *Standout %*, and *Grindstone %*). Standard errors are robust. The omitted race is white. The symbols \*\*\*, \*\*, and \* indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

**Table A5:** Robustness: Letter Characteristics and Early Career Outcomes:  
Top 10 Economics and Finance Department Sample

	(1) Word Count	(2) Standout %	(3) Grind- stone %	(4) Top Rec	(5) Top 20 Ac- ademic	(6) No. Top 100 Pubs	(7) No. Top 8 Pubs
Female	-18.879 (28.312)	0.001 (0.028)	0.001 (0.011)	-0.027 (0.025)	0.065* (0.037)	-0.279** (0.115)	-0.138** (0.062)
Asian	-109.170*** (28.208)	-0.131*** (0.027)	0.004 (0.010)	-0.153*** (0.024)	-0.127*** (0.033)	-0.229* (0.127)	-0.217*** (0.073)
Black or Hispanic	6.474 (38.610)	-0.036 (0.033)	0.015 (0.016)	-0.033 (0.033)	-0.006 (0.049)	-0.093 (0.193)	-0.144 (0.105)
Finance	-170.127*** (33.944)	0.043 (0.036)	-0.030** (0.012)	0.038 (0.033)	0.056 (0.051)	-0.185 (0.160)	0.190 (0.124)
Macro	-48.453 (34.565)	-0.032 (0.030)	-0.047*** (0.011)	-0.009 (0.027)	-0.038 (0.038)	-0.034 (0.165)	0.068 (0.096)
B-School	-3.136 (33.742)	0.007 (0.038)	-0.016 (0.012)	0.002 (0.033)	-0.070 (0.048)	-0.082 (0.154)	-0.024 (0.122)
Female Writer	-35.890 (34.910)	-0.023 (0.034)	0.006 (0.013)	-0.041 (0.029)	0.001 (0.024)	0.027 (0.089)	-0.007 (0.048)
Asian Writer	27.627 (36.125)	-0.018 (0.035)	-0.000 (0.013)	-0.064** (0.030)	0.067** (0.029)	-0.072 (0.089)	-0.033 (0.057)
Full Prof Writer	-65.862** (29.202)	0.044 (0.027)	-0.019* (0.011)	0.055** (0.024)	0.105*** (0.019)	0.315*** (0.072)	0.164*** (0.039)
Word Count (hundreds)					0.010*** (0.002)	0.035*** (0.009)	0.018*** (0.006)
Standout %					0.031 (0.020)	0.001 (0.081)	0.018 (0.038)
Grindstone %					-0.035 (0.040)	-0.403** (0.194)	-0.178* (0.098)
Top Rec					0.189*** (0.031)	0.493*** (0.110)	0.478*** (0.077)
Sample	Top 10	Top 10	Top 10	Top 10	Top 10	Top 10	Top 10
FE	No	No	No	No	No	No	No
Err Cluster	No	No	No	No	Cand	Cand	Cand
N	1597	1597	1597	1597	1597	1597	1597
R-squared	0.04	0.02	0.02	0.04	0.14	0.09	0.14

Notes: Table presents results of OLS regressions on letter characteristics (*Word Count*, *Standout %*, *Grindstone %*, and *Top Rec*) and early career outcomes (*Top 20 Academic*, *No. Top 100 Pubs*, and *No. Top 8 Pubs*) based on the sample of 1,597 letters for 530 applicants from top 10 economics and finance departments between 2018-2021. Explanatory variables include binary variables indicating candidate characteristics (*Female*, *Asian*, and *Black or Hispanic*), field of interest (*Finance* and *Macro*), institution characteristics (*B-School*), and letter writer characteristics (*Female Writer*, *Asian Writer*, *Full Prof Writer*, and *Top Rec*), as well as continuous variables for letter length and content (*Word Count (hundreds of words)*, *Standout %*, and *Grindstone %*). Standard errors are robust. The omitted race is white. The symbols \*\*\*, \*\*, and \* indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

**Table A6:** Robustness: Letter Characteristics and Early Career Outcomes:  
Macroeconomics as Primary Field Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Word Count	Standout %	Grind-stone %	Top Rec	Top 20 Academic	No. Top 100 Pubs	No. Top 8 Pubs
Female	-7.963 (30.437)	-0.019 (0.030)	0.005 (0.010)	-0.035** (0.017)	0.010 (0.020)	-0.352*** (0.095)	-0.087** (0.037)
Asian	-70.667** (29.593)	-0.061** (0.030)	0.030*** (0.010)	-0.058*** (0.017)	-0.047*** (0.016)	-0.187* (0.106)	-0.089** (0.044)
Black or Hispanic	-11.103 (35.929)	-0.084*** (0.032)	-0.005 (0.011)	-0.011 (0.024)	0.006 (0.030)	-0.207 (0.154)	-0.060 (0.062)
Top 10 Econ	159.682*** (34.849)	0.046 (0.031)	-0.012 (0.010)	0.168*** (0.025)	0.098*** (0.032)	0.189 (0.153)	0.293*** (0.080)
Top 10 B-School	-8.262 (160.122)	0.219 (0.146)	0.031 (0.040)	0.138 (0.138)	-0.057* (0.034)	-0.677 (0.688)	0.346 (0.358)
U.S. Inst.	-42.812 (34.701)	-0.000 (0.034)	-0.009 (0.012)	-0.015 (0.019)	0.005 (0.015)	-0.298** (0.116)	-0.077 (0.049)
B-School	-47.933 (127.254)	-0.195** (0.094)	-0.060** (0.028)	0.095 (0.083)	-0.020 (0.026)	0.368 (0.611)	-0.071 (0.065)
Female Writer	-19.261 (34.688)	-0.013 (0.037)	-0.003 (0.013)	-0.047*** (0.018)	0.022 (0.014)	-0.005 (0.077)	-0.005 (0.028)
Asian Writer	-48.978 (37.239)	0.114*** (0.044)	0.007 (0.013)	0.010 (0.022)	0.014 (0.015)	-0.147** (0.073)	0.024 (0.033)
Full Prof Writer	-38.397 (28.641)	-0.010 (0.031)	-0.032*** (0.010)	0.037** (0.018)	0.029** (0.011)	0.163** (0.063)	0.056* (0.029)
Word Count (hundreds)					0.003** (0.001)	0.030*** (0.007)	0.015*** (0.004)
Standout %					0.005 (0.010)	0.111* (0.066)	0.023 (0.024)
Grindstone %					-0.037 (0.023)	0.052 (0.185)	-0.068 (0.058)
Top Rec					0.172*** (0.037)	0.638*** (0.149)	0.410*** (0.100)
Sample	Macro	Macro	Macro	Macro	Macro	Macro	Macro
FE	No	No	No	No	No	No	No
Err Cluster	No	No	No	No	Cand	Cand	Cand
N	1692	1692	1692	1692	1692	1692	1692
R-squared	0.02	0.01	0.02	0.07	0.17	0.11	0.18

Notes: Table presents results of OLS regressions on letter characteristics (*Word Count*, *Standout %*, *Grindstone %*, and *Top Rec*) and early career outcomes (*Top 20 Academic*, *No. Top 100 Pubs*, and *No. Top 8 Pubs*) based on the sample of 1,692 letters for 590 applicants from 2018-2021 who specified Macroeconomics as their primary field of interest. Explanatory variables include binary variables indicating candidate characteristics (*Female*, *Asian*, and *Black or Hispanic*), institution characteristics (*Top 10 Econ*, *Top 10 B-School*, *U.S. Inst.*, and *B-School*), and letter writer characteristics (*Female Writer*, *Asian Writer*, *Full Prof Writer*, and *Top Rec*), as well as continuous variables for letter length and content (*Word Count (hundreds of words)*, *Standout %*, and *Grindstone %*). Standard errors are robust. The omitted race is white. The symbols \*\*\*, \*\*, and \* indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

**Table A7:** Robustness: Letter Characteristics and Early Career Outcomes:  
Finance as Primary Field Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Word Count	Standout %	Grindstone %	Top Rec	Top 20 Academic	No. Top 100 Pubs	No. Top 8 Pubs
Female	-22.713 (31.224)	-0.009 (0.035)	0.031** (0.014)	0.002 (0.023)	0.093** (0.037)	-0.177* (0.107)	-0.052 (0.068)
Asian	-52.773* (28.257)	-0.015 (0.033)	0.015 (0.012)	-0.039* (0.022)	-0.086*** (0.030)	0.046 (0.109)	-0.057 (0.070)
Black or Hispanic	-10.606 (55.404)	0.032 (0.049)	-0.008 (0.022)	0.052 (0.042)	-0.026 (0.058)	0.135 (0.232)	-0.046 (0.156)
Top 10 Econ	135.909*** (44.387)	0.036 (0.052)	-0.044** (0.018)	0.255*** (0.039)	0.187*** (0.062)	0.036 (0.201)	0.160 (0.150)
Top 10 B-School	155.864*** (37.626)	-0.056 (0.046)	-0.046*** (0.018)	0.146*** (0.034)	0.032 (0.046)	0.258 (0.157)	0.096 (0.113)
U.S. Inst.	-84.038** (36.985)	0.019 (0.042)	0.013 (0.017)	-0.005 (0.026)	0.012 (0.031)	-0.306** (0.125)	0.014 (0.077)
B-School	36.364 (31.697)	0.082** (0.038)	-0.005 (0.015)	0.066*** (0.023)	0.021 (0.030)	-0.290** (0.117)	-0.029 (0.072)
Female Writer	51.882 (39.587)	-0.035 (0.042)	0.002 (0.018)	-0.027 (0.030)	0.007 (0.023)	-0.042 (0.093)	0.019 (0.058)
Asian Writer	-20.235 (30.229)	0.059 (0.043)	-0.010 (0.013)	-0.105*** (0.022)	0.028 (0.022)	-0.034 (0.079)	-0.022 (0.050)
Full Prof Writer	-32.050 (29.423)	-0.060* (0.033)	-0.019 (0.013)	-0.038* (0.022)	0.050*** (0.017)	0.141** (0.067)	0.113** (0.047)
Word Count (hundreds)					0.010*** (0.002)	0.022*** (0.008)	0.021*** (0.005)
Standout %					0.017 (0.016)	0.094 (0.061)	0.066* (0.035)
Grindstone %					-0.000 (0.035)	-0.053 (0.167)	-0.095 (0.096)
Top Rec					0.110*** (0.034)	0.741*** (0.154)	0.565*** (0.109)
Sample	Finance	Finance	Finance	Finance	Finance	Finance	Finance
FE	No	No	No	No	No	No	No
Err Cluster	No	No	No	No	Cand	Cand	Cand
N	1324	1324	1324	1324	1324	1324	1324
R-squared	0.03	0.01	0.02	0.08	0.17	0.10	0.15

Notes: Table presents results of OLS regressions on letter characteristics (*Word Count*, *Standout %*, *Grindstone %*, and *Top Rec*) and early career outcomes (*Top 20 Academic*, *No. Top 100 Pubs*, and *No. Top 8 Pubs*) based on the sample of 1,324 letters for 439 applicants from 2018-2021 who specified Finance as their primary field of interest. Explanatory variables include binary variables indicating candidate characteristics (*Female*, *Asian*, and *Black or Hispanic*), institution characteristics (*Top 10 Econ*, *Top 10 B-School*, *U.S. Inst.*, and *B-School*), and letter writer characteristics (*Female Writer*, *Asian Writer*, *Full Prof Writer*, and *Top Rec*), as well as continuous variables for letter length and content (*Word Count (hundreds of words)*, *Standout %*, and *Grindstone %*). Standard errors are robust. The omitted race is white. The symbols \*\*\*, \*\*, and \* indicate statistical significance at the 1, 5, and 10 percent levels, respectively.