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Does information affect homophily?[☆]

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ABSTRACT

It is common for mentorship programs to use race, gender, and nationality to match mentors and mentees. Despite the popularity of these programs, there is little evidence on whether mentees value mentors with shared traits. Using novel administrative data from an online college mentoring platform connecting students and alumni, we document that female students indeed disproportionately reach out to female mentors. We investigate whether female students make costly trade-offs in order to access a female mentor. By eliciting students' preferences over mentor attributes, we find that female students are willing to trade off occupational match in order to access a female mentor. This willingness to pay for female mentors declines to zero when information on mentor quality is provided. The evidence suggests that female students use mentor gender to alleviate information problems, but do not derive direct utility from it. We discuss the implications of these results for the design of initiatives that match on shared traits.

1. Introduction

Homophily—the tendency to associate with those who have traits similar to oneself—is a ubiquitous social phenomenon but its determinants are not well understood. In many settings, we may observe individuals making costly trade-offs in order to match on shared characteristics. For example, there is evidence that female patients prefer to stay on a long waitlist to see a female doctor even when male doctors are readily available (Reyes, 2008; McDevitt and Roberts, 2014). It may be natural to assume that the demand for shared characteristics reflects utility derived from interacting with someone similar to oneself. Indeed, homophily can arise because individuals obtain utility *directly* from interacting with someone like themselves (taste- or preference-based discrimination, as in Becker (1971)). However, it could also be the case that, in the absence of information on other characteristics, individuals rely on easily observed traits as signals (statistical discrimination based on various moments of the quality distribution, as in Aigner and Cain (1977), or inaccurate statistical discrimination, as in Bohren et al. (2019)).

We study whether homophily by gender is driven by preferences for shared traits. A main prediction of Becker's model of taste-based discrimination is that people should be willing to pay to interact with members of their own group (Becker, 1971; Bertrand and Duflo, 2017; Charles and Guryan, 2018). We test this prediction in the context of mentorship. Mentorship is a setting where—unlike hiring or lending or renting—explicitly using race, gender, and nationality to determine matches is common, encouraged, and even considered best practice. Among the top 50 U.S. News colleges/universities, all but two host a mentorship program designed specifically for women in STEM fields, and 80% of the programs match students with a same-gender mentor.[1] Despite the popularity of these programs, as of yet, there is little evidence on whether mentees value same-gender mentors or whether demand

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[1] Of the 24 programs that provide information on the nature of matching, 19 match female students with a female mentor.

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for same-gender mentors arises due to a lack of information on mentor quality.

Using novel administrative data from an online college student/alumni mentoring platform serving eight colleges and universities, we document substantial homophily by gender in student-alumni interactions. Female students are 36% more likely to reach out to female mentors relative to male students, conditional on various observable characteristics including student major, alumni major, and alumni occupation. This propensity to reach out to female mentors may come at a cost: female mentors are 13% less likely than male mentors to respond to messages sent by female students.

Although these patterns are consistent with taste-based discrimination, that is, female students incurring a cost in order to access a female mentor, it is also possible that we as researchers are unable to control for all mentor attributes used in students' decisions; students could use information outside of the mentoring platform to decide whom to contact, leading to omitted variable bias. To causally identify students' preferences for mentor characteristics, we implement a hypothetical choice preference elicitation survey that incentivizes truthful responses. In the survey, students are shown pairs of hypothetical mentors' profiles and asked to select which mentor they prefer (Wiswall and Zafar, 2018). Students are informed that their answers to the survey will be used to provide personalized information on how to find mentors based on their preferences.

We find that female students strongly prefer female mentors, while male students exhibit a weak preference for male mentors. Furthermore, using the trade-offs students make between mentor gender and other mentor attributes, we estimate that female students are willing to give up access to a mentor with their preferred occupation in order to match with a mentor of the same gender.

Next we investigate whether female students' preference for female mentors reflects taste-based discrimination. Taste-based discrimination could arise from female students' affinity for interacting with women. Alternatively, it could arise from female students valuing an attribute that only female mentors possess, for example, first-hand knowledge of being a woman in STEM. We conduct a within-survey experiment to determine whether female students' willingness to pay for female mentors is only present in information-poor environments. The survey uses hypothetical choice preference elicitation with incentives for truthful reporting and randomizes students into (1) a basic profile condition, in which mentor profiles contain basic information about the mentor (name, job, graduation year, etc.) or (2) a ratings condition, in which profiles contain all basic information plus ratings from a past mentee. The ratings contain the past mentee's perception of the mentor's knowledge about job opportunities, friendliness/approachability, and the extent to which the mentor gave personalized advice. These attributes are often difficult to observe about mentors prior to contacting them. In addition to randomizing each of the ratings, the mentee's gender is randomized.

Female students are willing to pay for female mentors only when there is no information on mentor quality. In the basic profile condition, as discussed above, female students are willing to trade off a mentor with their preferred occupation in order to access a female mentor. In the ratings condition, we find that this willingness to pay declines to zero. Furthermore, the estimates imply that when information on mentor quality is available female students are unwilling to trade off *any* dimension of mentor quality in order to access a female mentor. We also find no evidence that female students' preferences for mentor quality differ from that of male students. All students—male and female—value the attributes described in the ratings, particularly a mentor's knowledge of job opportunities.

If female students' preference for female mentors is *not* due to taste-based discrimination, several alternative explanations are possible. Our survey reveals that female students believe that female mentors are more friendly/approachable than male mentors. In the absence of information on mentor approachability, female students' beliefs, whether they are accurate (Aigner and Cain, 1977) or inaccurate (Bohren et al., 2019), may lead them to gravitate to female mentors. Specifically, female students may rely on the perception that women are more approachable than men, on average, which could stem from stereotypes that contain some truth but are often exaggerated (Bordalo et al., 2016). For example, Eyal and Epley (2017) find that though women are somewhat more socially sensitive than men, people believe that the average difference is larger than it actually is. Homophily could also arise from differences in other moments of the mentor quality distribution.[2] All of these explanations have in common that gender is valued for its information content and direct provision of that information would reduce students' valuations of mentor gender.

Our experimental design also allows us to investigate whether female students perceive gender-specific benefits (or costs) of same-gender pairings. Using the randomization of past mentee gender to ratings, we find that female students similarly value ratings from male and female mentees and both types of ratings similarly attenuate female students' willingness to pay (WTP) for female mentors. These results suggest that female-specific experiences with mentors do not explain homophily by gender in our setting.

Our results have implications for initiatives that match on shared traits, such as mentorship programs that match on race/ethnicity, nationality, gender, and sexual orientation, or firms' efforts to increase diversity by asking underrepresented minority (URM) employees to conduct interviews with or otherwise help recruit URM applicants (Rivera, 2015). If shared traits are used as a signal of match quality, these initiatives—while well intentioned—could lead to efficiency losses relative to a scenario in which information on valued traits is used. As an example of this, ride-sharing platforms have opted to inform riders that their driver has been background checked rather than offer same-gender matching (Tang et al., 2021). In addition, since matching on shared traits often occurs in settings where individuals with the trait are scarce and the task has low promotability, shifting to matching based on quality metrics would alleviate the time burden of these initiatives on already underrepresented groups (Babcock et al., 2017).

Our paper contributes to the literature that examines the determinants of discriminatory behavior—particularly focused on isolating the role of statistical discrimination—including papers that study coworker choice (Hedegaard and Tyran, 2018), manager choice (Alam, 2020), hiring (Agan and Starr, 2017; Kaas and Manger, 2012; Abel et al., 2020), and the take-up of advice (Ayalew et al., 2021).[3,4] Our paper specifically relates to the literature that uses information provision to distinguish between taste-based and statistical discrimination. In the context of hiring,

[2] If students use a threshold crossing model of mentor quality to choose a mentor, then differences in the perceived variance of mentor quality (or match quality) by gender could lead to homophily (Heckman and Siegelman, 1993). For example, students could think that the variance of mentor quality differs by gender and female students could be more risk averse than male students, yielding different choices (Aigner and Cain, 1977).

[3] Many papers additionally document differential effects by in-group status, e.g., in advising (Canaan and Mouganie, 2021; Porter and Serra, 2020), teaching (Carrell et al., 2010), social work (Behncke et al., 2010), and physician choice (Alsan et al., 2019; Cabral and Dillender, 2021; Zeltzer et al., 2020)

[4] Our paper contributes to the narrower literature that investigates the roots of homophily. There is a large literature on social networks documenting homophily (Currarini et al., 2009; Bertrand and Duflo, 2017).

correspondence studies vary the information available to employers in order to disentangle these two types of discrimination. For example, Oreopoulos (2011) uses a correspondence study to estimate discrimination against immigrants in the Canadian labor market and finds that providing information on language skills, educational background, and firm experience does not attenuate differences in callback rates, suggesting a strong role for taste-based discrimination. Similarly, Hedegaard and Tyran (2018) find that Danish students discriminate against immigrants even when information on productivity is provided. In contrast, Agan and Starr (2017) find that removing information about criminal convictions from men's resumes increases racial discrimination in the U.S. In contemporaneous work on patients' selection of physicians, Chan (2021) uses a survey-based preference elicitation and finds that homophily by gender is somewhat attenuated when information on physician quality is provided. These information issues are the root of the Heckman and Siegelman (1993) critique. Neumark and Rich (2019) find a role for these biases in estimates of average discrimination in audit/correspondence studies, but the change in the implied degree of discrimination is sometimes positive and sometimes negative.

Our paper similarly estimates students' propensity to choose a same-gender mentor with and without additional information on mentor quality. In addition, we disentangle taste-based from statistical discrimination using a key prediction from Becker's model: in the presence of taste-based discrimination, individuals should be willing to pay to access a mentor of the same gender. Specifically, we compute how much students are willing to trade off in order to access a mentor of the same gender, with and without additional information on mentor quality.

Unlike hiring, we investigate a setting in which discrimination—in the form of same-gender preference—is encouraged and even considered best practice, but as of yet, there is little evidence on its roots and the trade-offs involved. It is often presumed that there is an additional benefit associated with matching on shared traits. In the healthcare context with doctor-patient matching and in the employee recruitment context through interviewer-interviewee matching, it may also be important to know what drives observed preferences for same-gender matches.

The remainder of this paper proceeds as follows. In Section 2, we analyze administrative data from an online mentorship platform for college students. In Section 3, we discuss the design of a survey experiment to estimate students' preferences over mentor attributes. In Section 4, we present the results of the experiment. In Section 5, we discuss the implications of our results. Section 6 concludes.

2. Observational evidence: homophily by gender on an online mentoring platform

Using administrative data from an online student-alumni mentoring platform, we provide descriptive evidence that college students tend to choose same-gender mentors.

2.1. Data

The online student-alumni mentoring website is designed to connect current undergraduates with alumni of their college/university in order to give students access to mentorship, career guidance, and professional connections as they search for jobs and internships. The site has more than 50,000 users across dozens of institutions ranging from small liberal arts colleges to large public universities. Students and alumni sign up for the site and create a profile with information about their academic background and their professional background. Users within the same university (students and alumni) can directly message one another on the platform. Our data include all messages sent between students and alumni, de-identified and linked to message sender and message recipient by a unique profile ID. Gender is assigned based on the first name of users. Our data also include information on the self-reported job title, degree, and graduation year of each alumna/alumnus user, as well as the intended degree of each student user. We manually classify college majors according to ACS 2016 general degree codes.[5] Occupations are derived from job titles using O*NET-SOC AutoCoder.[6]

We observe 13,038 conversations on the site between July 2017 through October 2019, where a conversation is defined as a series of messages between two people.[7] In order to study the preferences of undergraduate students for contacting alumni for mentoring and advice, we restrict our analysis to the 6,325 conversations initiated by students and sent to alumni recipients, keeping the eight schools that had at least 100 student-initiated conversations. We also drop the 99th percentile most prolific student senders and restrict to conversations that pertain to the students' future careers. Dropped conversation topics include inquiries regarding interviews for a class project, invitations to speak to a class, thank you messages from prior interactions, and inquiries regarding housing/re-location. These restrictions yield a sample of 3,349 student-alumni interactions, which we analyze in the next subsection.[8]

Appendix Table A1 provides summary statistics on the population, separately for students and for alumni. The student population is 50% female while the alumni users are 46% female. Users are primarily from research universities. Restricting to messages as described above, 12% of student users send at least one message on the site, and 11% of alumni respond to at least one such message on the site. As documented in Appendix Figs. A1, A2, and A3, the modal student major for both male and female students as well as female alumni is social sciences, while the modal major of male alumni is business. In addition, we note that more than a third of both male and female alumni work in either a management occupation or in business and financial operations occupations. Many also work in education, training, and library occupations, and these occupations make up a larger share of female relative to male alumni.

2.2. Who contacts whom? Homophily by gender

Fig. 1 Panel A characterizes homophily by gender by plotting the fraction of interactions that occur among same-gender members, against the availability of same-gender members on the platform (*inbreeding homophily*). Specifically, each dot represents the fraction of messages sent by female (male) students that are sent to female (male) alumni, on the y-axis, plotted against the fraction of alumni from that university who are female (male), on the x-axis, for each of the eight universities/colleges in the sample. The solid 45 degree line depicts the composition of student-alumni interactions that we would expect if students messaged alumni at random on the platform. The fraction of same-gender interactions on the site is higher than what would be expected by chance at almost all of the universities.

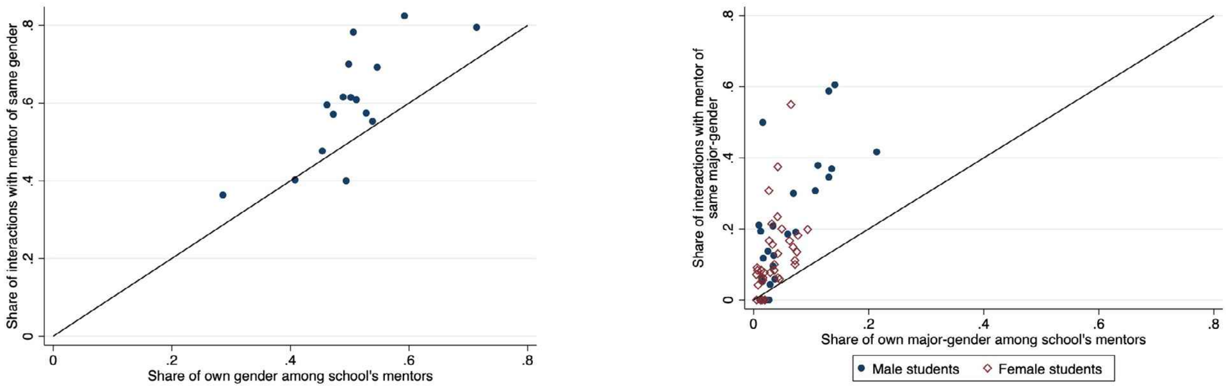
In Fig. 1 Panel B, we further divide the students and alumni by their college major, and plot whether students tend to contact

[5] There are 39 codes, available at: https://usa.ipums.org/usa-action/variables/DEGFIELD#codes_section

[6] See Online Appendix B for more details on data preparation.

[7] One might be concerned that the response time is censored, but the median time to respond to a message is one day, the 75th percentile of response time is four days and the 95th percentile is 56 days. Excluding the five percent of responses that arrive after 56 days, there are no gender differences in response time.

[8] See Gallen and Wasserman (2021), Fig. 1, for a complete description of initial message topics in this subset of student-alumni interactions on the site.



(a) Homophily by Gender (b) Homophily by Gender and College Major

Fig. 1. Homophily on an online mentoring platform. Note: This figure uses data from eight universities/colleges to plot the share of messages initiated by students that were sent to an alumni with a shared trait. The left panel analyzes the fraction of conversations with a same-gender alumni and the right panel examines the fraction of conversations with a same-gender and same-major alumni.

alumni of their same gender and major more than they would due to chance. The solid circles plot the fraction of male students in a given major who sent messages sent to alumni with the same gender and major against the fraction of alumni who are the same gender-major. The hollow diamonds plot the analogous data for female students. We again observe a strongly positive relationship and substantial deviation from the 45 degree line.

To probe whether the sorting patterns in Fig. 1 are driven by other characteristics of alumni that are correlated with alumni gender, we estimate the following regression specification:

$$RecipientFemale_{ij} = \alpha + \beta StudentFemale_i + X'_{ij}\gamma + \epsilon_{ij} \quad (1)$$

where $RecipientFemale_{ij}$ is an indicator variable for whether the alumni recipient j is female and $StudentFemale_i$ is an indicator variable for whether the student sender i of the message is female. X_{ij} includes controls for sender and recipient characteristics. This specification tests whether students exhibit *relative homophily*: the difference in the rates at which female and male students to reach out to female mentors. The baseline results are reported in Table 1: without controls, the coefficient β is 0.210, indicating that female students are 21 percentage points more likely to contact female mentors than male students. The differential pairing of female students and female alumni attenuates but remains significant when we add controls for school, student major, student graduation year, recipient major, and recipient occupation fixed effects, as well as a linear term for recipient graduation year. We note that the coefficient on $StudentFemale_i$ falls when we add student and alumni controls. This suggests that in our dataset, and perhaps more broadly in observational measures of homophily, unobservable differences between male and female mentors are important in explaining sorting patterns.[9]

One reason that female students could be more likely to reach out to female mentors is that they expect in-group bias, that is, female mentors are more responsive or give better responses to female students than male mentors. However, we see little evidence for this explanation in our data. In Table 2, we test whether the propensity of mentors to respond to initial messages, the length of these responses, and the sentiment of these responses differs by student and mentor gender. Female mentors are 8.6 percentage points, or 13%, less likely than male mentors to respond to initial messages from female students. We also document that male students receive slightly lower rates of response from female mentors but we cannot reject that the effect is different from zero

Table 1
Relative homophily by gender.

	(1)	(2)	(3)
Student Female	0.210***	0.150***	0.134***
	(0.021)	(0.018)	(0.018)
Mean among male students	0.306		
Mentor Controls	No	Yes	Yes
Student Controls	No	No	Yes
Observations	3349	3349	3349
R-squared	0.046	0.150	0.175

Note: This table displays coefficients β from a regression of the form $RecipientFemale_{ij} = \alpha + \beta StudentFemale_i + X'_{ij}\gamma + \epsilon_{ij}$. Controls include school, student major, student graduation year, recipient major, and recipient occupation fixed effects, as well as a linear term for recipient graduation year. Robust standard errors in parentheses, clustered at the student sender level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2
Responses to students, by mentor gender.

	(1) Response Received	(2) Length of Response	(3) Log Length of Response
	Panel A: Female Student Sample		
Mentor is female	−0.086***	−40.790	−0.068
	(0.025)	(51.711)	(0.063)
Male mentor mean	0.666	539.888	5.766
Observations	1611	1035	1035
R-squared	0.120	0.133	0.172
	Panel B: Male Student Sample		
Mentor is female	−0.032	29.826	0.078
	(0.027)	(50.717)	(0.075)
Male mentor mean	0.570	438.032	5.579
Observations	1738	999	999
R-squared	0.109	0.140	0.177

Note: This table presents the results of a regression of the outcomes of messages sent by students (labeled in each regression in columns 1–3) on an indicator for whether the message was sent to a female mentor. All regressions include controls for school, student major, student graduation year, recipient major, and recipient occupation fixed effects, as well as a linear term for recipient graduation year. The analysis in Panel A restricts to only female students who send messages, while the analysis in Panel B restricts to only male students who send messages. Robust standard errors clustered at the student level are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

9 In Section 3 we formally elicit students' preferences for mentor characteristics in part to address this concern.

or different from the effect for female students.[10] In this setting, female mentors' lower response rate is not explained by excess requests: they do not receive more messages from students overall than male mentors. The average male alumnus registered on the platform receives 0.29 messages, while the average female alumnus receives 0.26 messages.[11] Furthermore, the initial responses that female students receive from female mentors are shorter than those received from male mentors, but these contrasts are not statistically significant (see Appendix Table A2). When we examine the sentiment of the responses, there is also no indication that female mentors are more encouraging to female students than male mentors (see Appendix Table A3).

While female mentors do not exhibit in-group bias in initial responses, it is possible they are more willing to provide long-term mentorship to female students. In Appendix Table A4 we analyze whether mentors offer to continue the interaction and whether mentors respond to subsequent messages from the same student. Although imprecisely estimated, there is little evidence that female mentors are more invested in long-term mentorship than male mentors, with female or male students. Based on these patterns, female students appear to be trading off responsiveness or response quality when messaging a female alumnus.[12]

Another possibility is that female students gravitate to female mentors in order to obtain information on gender-specific topics, such as sexism, safety in the workplace, and work-life balance. Do we see any evidence of this on the mentoring platform? We search for the following terms in the initial messages sent by students: female, woman, women, sexual harassment, empowerment, sexism, sexist, sexually, culture, family, safety, safe, parental, maternity, work-life, work life, work/life. After eliminating false positives (for example, *culture* arising from *agriculture*, or *family* indicating that a person enjoyed a trip with their *family*), only 47 or 1.4% of messages relate to gender-specific topics. It is extremely uncommon for students to approach mentors on this platform with such questions. General questions about careers, jobs or majors are much more common, and are equally likely to be asked by male and female students. When we examine all of the questions that students ask, we find that female students do not differentiate the questions they ask by mentor gender (see Appendix Table A5). Of course, it is possible that more sensitive topics come up in unobserved future interactions.

Even if female students do not ask directly about gender-specific topics, they may be more likely to value female mentors' perspectives in settings where women are scarce. We investigate whether the strength of homophily by gender varies based on (1) the extent of female representation in a student's major (2) the extent of female representation in the occupation of contacted mentors and (3) whether the student is in a STEM major. Consistent with this hypothesis, we find that homophily is slightly (but insignificantly) stronger in low female representation settings (see Appendix Table A6).

Overall, the observational data are consistent with homophily being driven by taste-based discrimination: female students appear willing to pay (e.g. in response rates, response length) in order to access female mentors. However, there are several important caveats to keep in mind when interpreting these results. First, many interactions transition off of the mentoring platform after the first response (about 40% of alumni offer to have a phone call when they respond). Second, many of our results are imprecisely estimated and do not rule out small benefits to female students who contact female mentors. Third, there is a gap between what students observe about alumni when deciding whom to contact and what the researcher observes. For example, students can potentially glean additional information about alumni from an online search. Since alumni are bundles of characteristics, it is also difficult to ascertain which are valued by the students based on their choices. Fourth, these data do not allow us to rule out other sources of homophily, in particular, that it arises from beliefs about the quality of mentoring by women relative to men. To address these issues, in the next section we implement a preference elicitation survey that isolates and quantifies students' willingness to pay to access a mentor of the same gender.

3. Estimating willingness to pay for mentor gender: methodology

3.1. Preference elicitation survey

As discussed in the Introduction, a main prediction of Becker's taste-based discrimination model is that individuals should be willing to pay to access members of their own group. Are students willing to pay to access a mentor of the same gender by trading off other mentor characteristics (e.g. job market experience, availability, industry/occupation proximity)? Using a survey methodology to elicit willingness to pay for non-pecuniary job attributes developed by Wiswall and Zafar (2018) and used by Maestas et al. (2018), we estimate students' WTP for mentors of the same gender.

We recruited 834 UCLA students to participate in a survey experiment.[13] Students taking the survey are shown 30 pairs of hypothetical mentors and asked to choose which professional they prefer within each pair. Students were informed that "In the first section of the survey, you will be shown 30 profiles of hypothetical mentors. You should think of mentors as alumni of UCLA who have volunteered to help current students navigate their major choice, career choice, and to provide advice and answer questions related to these decisions." Each mentor in the pair has a randomly assigned occupation, availability for mentoring (30 min or 60 min), first-generation college student status, graduation year (2015 or 2005), and name that unambiguously conveys gender. The characteristics of mentor profiles are sampled randomly and independently with equal probability across all possibilities both within and across profile pairs. By observing the choices of students in each mentor pair, we are able to estimate their preferences for each of the mentor attributes and use these estimates to compute their WTP for a mentor of the same gender.

Our recruitment and compensation procedures are designed to elicit students' true preferences over mentor characteristics (Becker et al., 1964). From November 2021 to January 2022, the study was advertised at UCLA using email lists from every undergraduate major, a handful of large undergraduate classes, and the

[10] Appendix Table A2 pools male and female students to test whether the interaction effect of student and mentor gender is statistically significant. If we saw that female mentors have significantly more negative responses to male students, then we might conclude that female students do gain disproportionately from these interactions, but perhaps female mentors have worse unobservables. This does not seem to be the case. Instead, all point estimates for interaction terms are negative and we can reject even modest positive effects of female mentors on female students relative to male students.

[11] Appendix Fig. A4 plots the average differences in the number of requests by alumni gender across question types. Among all question types, female mentors only receive significantly more questions than male mentors on housing advice. Male mentors receive significantly more questions than female mentors in six of the question types, all pertaining to career and job advice.

[12] In a field experiment that controls for all observable student characteristics and the wording of student messages, we also show that female professionals are less responsive and give shorter replies to female students than male professionals (Gallen and Wasserman, 2021).

[13] We note that UCLA is not one of the schools in the observational data sample. UCLA does use an online mentoring platform to connect students and alumni, but it uses a different platform than the one we have data from.

career center newsletter. Study recruitment was targeted to students interested in career advice. Since the survey was advertised via email lists and accessed via a Qualtrics link, students were able to take the survey completely on their own without the supervision of a researcher. We think this setting guards against social desirability bias and social image concerns.

Once students began the study, they were informed: "We will use your responses in this section to give you personalized suggestions on how to find mentors. If you decide to receive these suggestions, you will receive these suggestions via email (which you will enter at the end of the survey). We will not contact any mentors on your behalf, we will only provide you with recommendations consistent with the choices you make in the next portion of this questionnaire." An example of the mentor targeting advice email is available in Appendix Fig. A5. Students also received a $5 payment to their UCLA flexible spending card. A similar methodology is used by Kessler et al. (2019) to elicit employers' true preferences over employee characteristics. As an indication that students thoughtfully considered profiles, the median time to complete the survey was 11 min and 99.6 percent of students passed our attention check.

Because we recruited undergraduate students from all majors, the survey adapts to each student's preferences by only showing mentors with occupations of interest to the student. Before being shown the mentor pairs, each student is asked to select their preferred career path from a comprehensive set of 24 broad career paths.[14] To aid in the student's selection, we provided four examples of occupations associated with each career path. For example, if the student selected the broad career path "Marketing," then the student would see the following text: "Examples include: VP of Marketing, Business Analytics Lead, Brand Manager, and Sales Representative." In the preference elicitation, the mentor profiles are randomly assigned occupations from the set of these same four occupations within the student's chosen broad career path. For example, if the student chose the broad career path "Marketing" then the hypothetical mentors viewed by the student were randomly assigned occupations from the following list: VP of Marketing, Business Analytics Lead, Brand Manager, and Sales Representative. This customization ensures that students are only shown mentor profiles relevant to their interests. Appendix Table A7 lists the broad career paths and their associated occupations.

3.2. Testing the effect of mentor quality information on willingness to pay

In order to test the effect of information provision on student WTP for same-gender mentors, before starting the survey, students are randomized to see one of two survey templates. Students randomized into the 'no ratings' template are shown only the information about mentors described above—gender, occupation, availability, first-generation status, and graduation year. Students randomized into the 'ratings' template received all of the information above, and additionally received ratings from a (hypothetical) past mentee. Fig. 2 provides a screenshot of the mentor pairs shown to students during the survey in the 'ratings' template.[15] The 'no ratings' template is identical except the bottom box featuring ratings is omitted. We randomized the gender of the past mentee and the ratings. Ratings were either one star, three stars, or five stars (each with equal probability) in each of three evaluation categories: knowledgeable about job opportunities, easy to talk to/friendly, gave personalized advice. To select these attributes, in a pilot survey of the same population, we asked students why mentor gender is important. Two characteristics were by far the most cited by female students: female mentors were more comfortable to interact with and better able to give advice "specifically for me." In the ratings, we also include a proxy for a mentor's general knowledge.

3.3. Econometric framework

In order to estimate students' preferences for mentor attributes, we assume student i of gender g has preferences over mentor j which can be approximated with a linear indirect utility function in mentor characteristics characteristics $\mathbf{x}$ in choice pair c:

$$V_{ijc} = \gamma^g + \mathbf{x}'_{ijc}\beta^g + \varepsilon_{ijc} \tag{2}$$

The probability that a student selects mentor a over mentor b in choice c is:

$$P^g(V_{iac} > V_{ibc}) = \alpha^g + (\mathbf{x}_{iac} - \mathbf{x}_{ibc})\prime\beta^g + \epsilon_{ic} \tag{3}$$

We estimate the following specification using a linear probability model (LPM):

$$C_{ic} = \alpha^g + (\mathbf{x}_{iac} - \mathbf{x}_{ibc})\prime\beta^g + \epsilon_{ic} \tag{4}$$

where the dependent variable C_{ic} is an indicator for whether the student chose mentor a over mentor b in a given mentor pair. The independent variables are the differences in the characteristics of mentor a, $\mathbf{x}_{iac}$, and mentor b, $\mathbf{x}_{ibc}$, in choice pair c. The characteristics we control for are those observable to students: mentor gender, graduation year, availability, occupation, first-generation college student status, and when available, ratings and past mentee gender. α^g captures the propensity to select the left profile (profile a) in a way that is unexplained by characteristics. In addition to the LPM, as robustness, we estimate a logit model.[16] This empirical specification is similar to those used by Maestas et al. (2018), Wiswall and Zafar (2018), and Mas and Pallais (2017). We do not adjust our results for inattention as in Mas and Pallais (2017) because in practice we find that 99.6 percent of students passed our attention check.

We use the estimates of students' preferences for mentor attributes to compute students' willingness to pay to access a mentor of the same gender. Willingness to pay metrics are traditionally denominated in monetary terms, for instance, the willingness to pay in hourly wages for a job with a higher fraction of coworkers who are female. Informal interactions for the purpose of information gathering seldom involve a monetary exchange.[17] For this reason, we use whether the student is willing to trade off a mentor with their preferred occupation in order to access a same-gender mentor, by computing the ratio of the two coefficients.

Note that, due to our survey design, mentor gender is randomly assigned to each profile and is, by construction, not correlated with other mentor characteristics. An additional benefit of the survey design is that we as researchers observe and control for all mentor attributes observed by students.

3.4. Summary statistics

Appendix Table A8 reports summary statistics for the 834 students who took the preference elicitation survey between November 2021 and January 2022. The survey respondents represent a diverse cross-section of UCLA undergraduates: 63% are female, 28% are first-generation college students, 54% are Asian American/Pacific Islander, and 14% are Hispanic/Latino. Students, on average, are sophomores, but freshmen through seniors are repre-

[14] These coincide with the 24 broad career groups used by the UCLA online alumni-student mentoring platform, *UCLAOne*.

[15] Note that the location of the mentor was always Los Angeles.

[16] The logit estimates the coefficients from $P^g(V_{iac} > V_{ibc}) = \frac{\exp\{(\mathbf{x}_{iac} - \mathbf{x}_{ibc})\prime\beta^g\}}{1+\exp\{(\mathbf{x}_{iac} - \mathbf{x}_{ibc})\prime\beta^g)\}}$.

[17] This stands in contrast to formal information gathering interactions, such as soliciting financial advice from a professional.

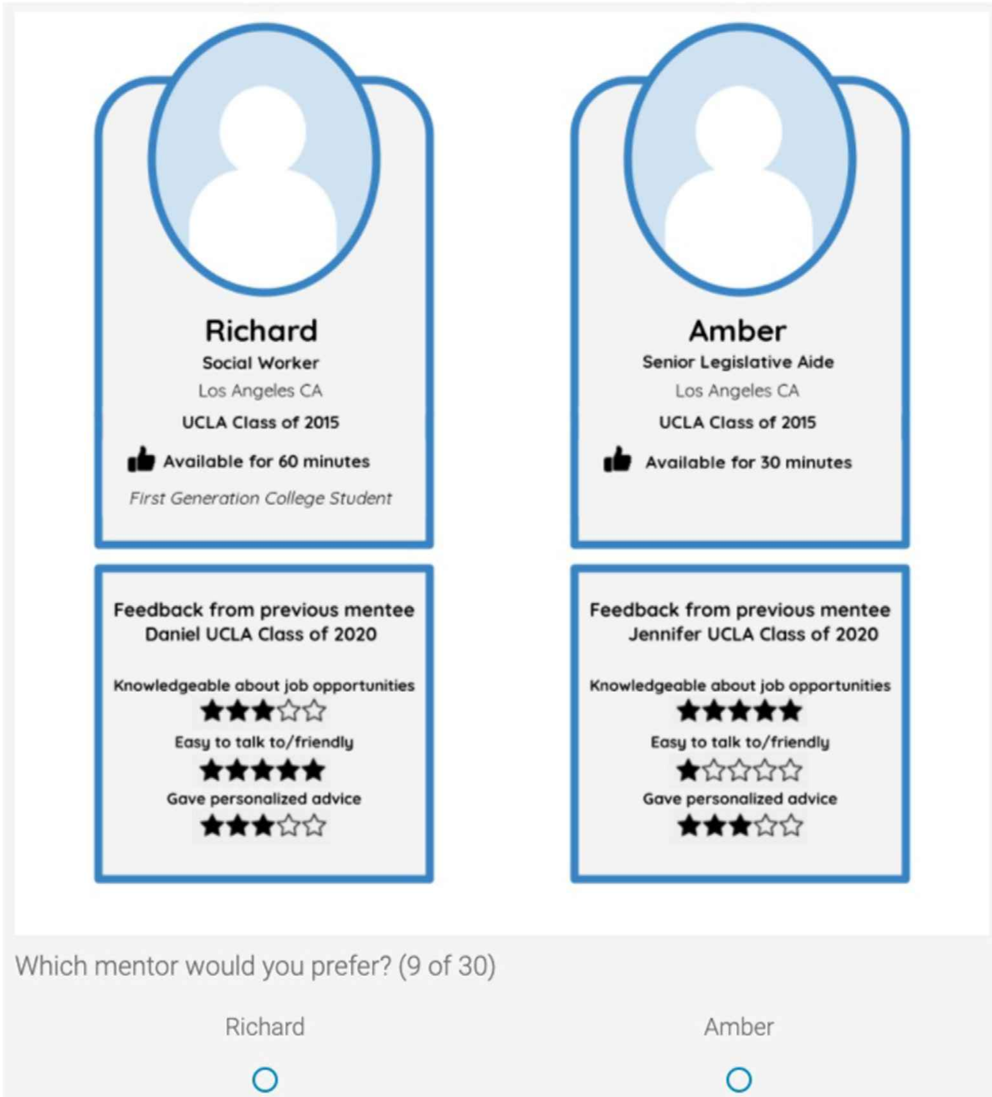


Fig. 2. Example of mentor profiles. Note: This figure is a screenshot of a pair of profiles shown in the hypothetical choice preference elicitation survey administered among UCLA undergraduate students. The profiles are from the survey version with mentor ratings. The survey version without ratings omits the box below each profile. The profiles correspond to the career path, Community and Social Services. The full set of career paths is: Accounting; Administrative/Support; Arts and Design; Business Development; Community and Social Services; Consulting; Education; Engineering; Entrepreneurship; Finance; Healthcare Services; Human Resources; Information Technology; Legal; Marketing; Media and Communications; Military and Protective Services; Operations; Program and Product Management; Quality Assurance; Real Estate; Research; Sales; Purchasing.

sented in the sample.[18] We confirm that student demographics are balanced across the two survey templates, overall and by gender in Appendix Tables A9 and A10.[19]

4. Estimating willingness to pay for mentor gender: results

In this section we use an incentive compatible preference elicitation survey to estimate students' preferences over mentor attributes. We find that female students have a strong preference for female mentors and are willing to trade off valuable mentor attributes in order to access a female mentor. In contrast, male students have a weak preference for male mentors. Female students' preference for female mentors is not driven by taste-based discrimination: when we provide students with information on mentor quality through ratings of mentors given by past mentees, female students are no longer willing to trade off valuable mentor characteristics in order to access a mentor of the same gender.

4.1. Female students are willing to pay for female mentors

We start off by estimating students' preferences for mentor characteristics in the 'no ratings' survey condition, separately for male and female students.[20] In Table 3 columns 1 and 2, we find that, all else equal, both male and female students value mentors whose occupation matches the student's preferred occupation (within the student's chosen broad career path).[21] In fact, students

[18] Among currently enrolled UCLA undergraduates, 58% of students are female, 31% are first-generation students, 33% are Asian/Pacific Islander, and 21% are Hispanic/Latino.

[19] We also find that students' college majors and preferred broad occupations are balanced across the ratings and no ratings conditions.

[20] We cannot separately analyze non-binary students due to their small sample size.

[21] After the preference elicitation, we ask students which of the four occupations in their chosen career path is their most preferred.

Table 3
Student preferences for mentor attributes: by student gender.

	(1)	(2)	(3)	(4)
	No Ratings		Ratings	
	Female	Male	Female	Male
Mentor is female	0.093***	−0.016*	0.007	−0.002
	(0.008)	(0.009)	(0.006)	(0.009)
Mentor has preferred occ	0.335***	0.324***	0.130***	0.129***
	(0.012)	(0.016)	(0.011)	(0.016)
Mentor graduation year	0.007***	0.005***	0.001*	0.002**
	(0.001)	(0.002)	(0.001)	(0.001)
Availability (in 10 min increments)	0.031***	0.039***	0.003	0.010***
	(0.003)	(0.004)	(0.002)	(0.003)
Mentor first gen	0.070***	0.037***	0.024***	0.018**
	(0.011)	(0.012)	(0.007)	(0.009)
Knowledgeable about job opportunities			0.091***	0.092***
			(0.003)	(0.004)
Easy to talk to/friendly			0.065***	0.067***
			(0.003)	(0.003)
Gave personalized advice			0.071***	0.067***
			(0.003)	(0.004)
Mentee is female			−0.008	0.010
			(0.007)	(0.009)
WTP for female mentor	0.278***	−0.051*	0.054	−0.012
	(0.027)	(0.029)	(0.049)	(0.068)
p-value $\text{WTP}_{noratings}$ = $\text{WTP}_{ratings}$	0.000	0.601		
p-value WTP_{female} = WTP_{male}	0.000		0.436	
Observations	8100	4620	7710	3900
Number of students	270	154	257	130

Note: This table displays coefficients β from estimating the following linear probability model: $C_{ic} = \alpha^g + (\mathbf{x}_{iac} - \mathbf{x}_{ibc})\prime\beta^g + \epsilon_{ic}$. Willingness to pay is calculated as the ratio of the coefficients on female mentor and preferred occupation. Standard errors, clustered at the student level, are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

are 32–34 percentage points more likely to choose a mentor when the mentor's occupation switches from non-preferred to preferred.

We also find evidence of homophily: female students strongly and significantly prefer female mentors. Female students are 9.3 percentage points more likely to choose a mentor profile when the profile switches from male to female. In contrast, male students have a much weaker (and marginally significant) preference for male mentors. While mentor occupation and gender are both independently valued by female students, note that female students' preference for mentor occupation is substantially stronger than their preference for mentor gender.

Next we compute students' willingness to pay (WTP) to access a mentor of the same gender. While WTP metrics are traditionally denominated in monetary terms, informal interactions for the purpose of information gathering seldom charge a fee but often involve trade-offs. We calculate WTP for a female mentor as the ratio of the coefficients on female mentor and preferred occupation. The estimates indicate that female students are willing to give up a mentor with their preferred occupation 28 percent of the time in order to access a female mentor.[22] In contrast, the corresponding willingness to pay of male students for male mentors is just 5 percent. The results are nearly identical when using a logit specification (see Appendix Table A11).[23]

4.2. Information on mentor quality eliminates willingness to pay

When additional information on mentor quality is available, are female students still willing to trade off valuable mentor attributes in order to access a female mentor? We investigate this question with use of the 'ratings' survey condition, in which we include information on mentor quality based on ratings from a past mentee. Specifically, in Table 3 columns 3 and 4, we estimate students' preferences for mentor characteristics in the 'ratings' survey condition, again by student gender. The inclusion of mentor ratings attenuates students' preferences for all original mentor attributes, but the attenuation is most pronounced for mentor gender. For both male and female students, the coefficients on mentor gender are now precisely estimated zeroes. Female students' willingness to pay for a female mentor—as measured by the trade-off of mentor gender relative to occupation match—declines by an order of magnitude and is now indistinguishable from zero. This means that when additional information on mentor quality is provided, students are no longer willing to trade off important mentor attributes such as occupation match in order to access a mentor of the same gender. Moreover, we can reject equality of female students' WTP estimates in the 'ratings' and 'no ratings' survey conditions. The complete attenuation of WTP is consistent with Bayesian updating in a setting where female students have disperse priors over the gender difference in mentor quality, the mentee ratings are credible and precise signals of quality, and female students value mentor gender due to beliefs regarding gender differences in exactly the attributes for which we provide quality ratings.

We note that the attenuation of willingness to pay in the 'ratings' condition is not mechanically driven by the fact that profiles with ratings are longer, have more mentor attributes, or are in some other way distracting from the original attributes. When we analyze a pre-registered secondary outcome—the willingness to pay of first-generation college students for first-generation mentors—we find that including ratings *does not* attenuate their willingness to pay (Appendix Table A13).

When we examine students' valuation of mentor ratings, we find that students value all three categories, with knowledge about job opportunities valued a bit more than whether the mentor is easy to talk to/friendly and whether the mentor gives personalized advice. Furthermore, female students are not more sensitive to mentor quality than are male students: their respective coefficients on mentor quality are nearly identical.

[22] This calculation depends on the linearity assumption in our econometric framework. If we limit our analysis to choice pairs in which female students are directly trading off their preferred occupation and whether the mentor is female, we find that female students make this trade off 21 percent of the time.

[23] Note that the observational data shows much stronger homophily among male students than the preference elicitation survey, suggesting an important role for omitted variable bias in observational measures of homophily.

4.3. Roots of homophily by gender

In the presence of information on mentor quality, female students are no longer willing to trade off valuable mentor characteristics in order to access a female mentor. This result implies that homophily is not driven by taste-based discrimination. Why does information provision affect female students' WTP for female mentors? Female students could be using mentor gender as a proxy for mentor quality. To shed light on female students' perceptions of how mentors gender shapes mentor quality, we asked students after the preference elicitation whether mentor gender was important to them and why. Fifty percent of female students and just 10% of male students reported that mentor gender is important.[24] Among the female students who stated that they valued a female mentor, 85% reported that it is because female mentors are friendlier/easier to talk to and 53% reported that it is because female mentors are better at giving personalized advice. In contrast, only 9% reported that female mentors are more knowledgeable about job opportunities. Female students' perceptions that male and female mentors differ, on average, is consistent with statistical discrimination based on (accurate or inaccurate) beliefs. Student's beliefs could arise due to stereotypes that are partially accurate but exaggerated (Bordalo et al., 2016; Eyal and Epley, 2017).

We also explore whether the WTP for female mentors depends on the perception of gender-specific benefits (or costs). Using the randomization of the gender of the past mentee who rates the mentor, we test whether (1) students value ratings from a same-gender mentee more and (2) whether the preference for female mentors is equally attenuated by male and female mentee ratings. In Table 4 we find that ratings from male and female mentees are equally valued by female students (as well as by male students). In addition, by limiting the analysis to pairs of profiles with only male or only female past mentees, we find that both are equally effective in attenuating female students' WTP for female mentors. These results suggest that female students do not require information on the benefits that female mentees derived from female mentors, such as discussions of personal experiences being a woman in finance. Furthermore, female students do not require another woman to vouch for a mentor prior to mentor selection.

Female students' WTP for female mentors may also vary with the extent of female representation in their major. In settings where women are scarce, do female students have a higher WTP? We divide female students into those whose major is high female representation (>50% female) and those whose major is low female representation (<=50% female). We replicate the main analysis with these two groups of students in Table 5. In the no ratings condition, these two groups of female students exhibit nearly identical willingness to pay for a female mentor. This evidence suggests that female students do not disproportionately value female mentors in settings where women are underrepresented. It is interesting to note, however, that for women in low female representation majors, the WTP for a female mentor attenuates but does not decline to zero with the inclusion of the ratings.[25] This pattern indicates that female students could value a mentor's gender per se or information that is exclusively provided by women (e.g. gender-specific information).[26]

[24] Students' stated preferences were strongly predictive of their revealed preferences from the preference elicitation.

[25] We cannot reject that the high and low female representation coefficients are the same, however.

[26] In Appendix Table A12 we split female students based on whether they are in a STEM major. Here we see no heterogeneity in WTP by STEM major status in either the ratings or no ratings conditions. For both groups of students, WTP declines to close to zero with the inclusion of ratings.

Table 4
Student preferences for mentor attributes: role of mentee gender.

	(1) Female	(2) Male
Mentor is female	0.007	−0.002
	(0.006)	(0.009)
Mentor has preferred occupation	0.130***	0.129***
	(0.011)	(0.016)
Mentor graduation year	0.001*	0.002**
	(0.001)	(0.001)
Availability (in 10 min. increments)	0.003	0.010***
	(0.002)	(0.003)
Mentor first generation	0.024***	0.018**
	(0.007)	(0.009)
Knowledgeable about job opportunities	0.091***	0.092***
	(0.003)	(0.005)
Easy to talk to/friendly	0.065***	0.068***
	(0.003)	(0.004)
Gave personalized advice	0.072***	0.065***
	(0.003)	(0.005)
Mentee is female × Knowledgeable about job opportunities	−0.000	0.000
	(0.004)	(0.006)
Mentee is female × Easy to talk to/friendly	0.000	−0.003
	(0.004)	(0.005)
Mentee is female × Gave personalized advice	−0.002	0.004
	(0.004)	(0.006)
WTP for female mentor	0.053	−0.013
	(0.049)	(0.068)
Observations	7710	3900
R-squared	0.399	0.394
Number of students	257	130

Note: This table displays coefficients β from estimating the following linear probability model: $C_{ic} = \alpha^g + (\mathbf{x}_{iac} - \mathbf{x}_{ibc})'\beta^g + \epsilon_{ic}$. Willingness to pay is calculated as the ratio of the coefficients on female mentor and preferred occupation. Standard errors, clustered at the student level, are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5. Implications for program design

Our results have implications for mentorship programs that match on race/ethnicity, nationality, gender, and sexual orientation. Optimal program design depends on the source of homophily. In some cases, matching based on shared traits may be optimal because students directly value that trait or get unique information from mentors with that trait. For example, as a pre-registered secondary outcome in our preference elicitation survey, we estimate that homophily by first-generation college student status is substantial and invariant to providing information on mentor quality (see Appendix Table A13).

If homophily is driven by lack of information on mentor quality, then resources could be better invested recruiting mentors based on quality rather than shared traits. For example, if recruiting female mentors requires sacrificing some dimension of mentor quality and female students are aware of the quality trade-off, then female students are unwilling to make that trade-off. Female students would rather have a mentor of a different gender than sacrifice mentor quality.

How should mentorship programs incorporate participant preferences into their design? Given a matching rule, let $f(x)$ be the distribution of mentorship quality for a given student when there is no screening of mentors. If the program restricts mentors to share traits with students (for example, by offering female students only female mentors), then it shifts the distribution of mentorship quality to $f^g(x)$. For example, if mentorship quality is on average higher in the population of female mentors, then $f^g(x) = f(x + a)$. An alternative policy is quality screening, which we can model as truncating the distribution $f(x)$ below some threshold, $f(x|x > q)$. Assuming that truncating based on quality is costly, and perhaps

Table 5
Female student preferences for mentor attributes: by female representation in major.

	(1)	(2)	(3)	(4)
	No Ratings		Ratings	
	High Rep.	Low Rep.	High Rep.	Low Rep.
Mentor is female	0.094***	0.092***	0.001	0.018
	(0.010)	(0.014)	(0.008)	(0.012)
Mentor has preferred occupation	0.345***	0.323***	0.124***	0.143***
	(0.015)	(0.019)	(0.014)	(0.020)
Mentor graduation year	0.006***	0.008***	0.002**	−0.000
	(0.001)	(0.002)	(0.001)	(0.001)
Availability (in 10 min. increments)	0.032***	0.030***	0.000	0.011***
	(0.004)	(0.004)	(0.003)	(0.004)
Mentor first generation	0.089***	0.036**	0.029***	0.013
	(0.014)	(0.018)	(0.009)	(0.013)
Knowledgeable about job opportunities			0.090***	0.094***
			(0.003)	(0.005)
Easy to talk to/friendly			0.065***	0.066***
			(0.004)	(0.005)
Gave personalized advice			0.073***	0.065***
			(0.003)	(0.004)
Mentee is female			−0.003	−0.020*
			(0.008)	(0.012)
WTP for female mentor	0.273***	0.286***	0.009	0.127*
	(0.034)	(0.048)	(0.062)	(0.077)
p-value $WTP_{noratings} = WTP_{ratings}$	0.000	0.080		
Observations	5040	2970	5100	2580
Number of students	168	99	170	86

Note: This table displays coefficients β from estimating the following linear probability model: $C_{ic} = \alpha^g + (\mathbf{x}_{iac} - \mathbf{x}_{ibc})\prime\beta^g + \epsilon_{ic}$. Willingness to pay is calculated as the ratio of the coefficients on female mentor and preferred occupation. The sample is limited to female students. Student majors are crosswalked to IPUMS field of degrees categories. A major is classified as high female representation if over 50 percent of 22–29 year old individuals with the college degree are female, based on the ACS 2019 5-year file. Four students who have not yet declared a major are excluded. Standard errors, clustered at the student level, are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

increasingly costly as the quality truncation threshold increases, programs may be better off restricting matches to shared traits.[27] If obtaining information on quality is straightforward, then the optimal policy would screen mentors on quality. See Appendix Fig. A6 for a graphical example of mentorship quality under the these policies.

There are several ways to obtain information on mentor quality. For established mentorship programs, organizers can survey mentees about their experiences and invite mentors in the future in part based on the feedback. For new mentorship programs, organizers can use their networks and informal channels to glean information on mentor quality. In addition, quality signals are often publicly available through advising/mentoring awards, which potential mentors may advertise on their resumes.

More broadly, many initiatives in employee recruitment, service-provider matching, and doctor-patient matching commonly match on shared traits. On the one hand, this matching could be efficient. For example, simply asking patients whether they prefer a female gynecologist could be optimal if some female patients are uncomfortable being treated by male doctors. On the other hand, such matching could lead to efficiency losses relative to those that incorporate information on valued traits into the matching process. As an example of this, ride-sharing platforms have opted to inform riders that their driver has been background checked rather than offer same-gender matching. Finally, since matching on shared traits often occurs in settings where individuals with the trait are scarce, an additional benefit of shifting to matching based on quality metrics is it would alleviate the time burden of these initiatives on already underrepresented groups.

[27] We think of this cost abstractly. For example, in settings where there is selection of mentors into mentoring roles, the cost of truncating on quality may be that fewer mentors volunteer and the overall pool is worse or is scarce.

6. Conclusion

This paper studies whether homophily by gender is driven by preferences for shared traits. Using administrative data from a mentoring platform for college students, we document that students have a strong tendency to contact alumni of their own gender. Based on the metrics available our data, female students appear to be trading off mentor quality in order to access female mentors. Using a hypothetical choice preference elicitation, we confirm that female students are willing to trade off valuable mentors characteristics in order to access a female mentor—but only when there is a dearth of information on mentor quality. This pattern is consistent with belief-based explanations for homophily: in settings where information on quality is scarce, female students gravitate to female mentors because they believe that female mentors are on average higher quality than male mentors.

A natural next question is whether the beliefs that female students have about female mentors are correct. While this question is difficult to answer using our observational data, future work could investigate the origin and accuracy of these beliefs. We also readily acknowledge that sources of homophily may depend on the setting. Our paper highlights the importance of understanding the roots of homophily when considering optimal policy design.

Data availability

The data from the experiment will be available through an online repository. Mentorship platform data are proprietary and not available for public disclosure. We will assist researchers with access.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Appendix Figures and Tables

see Figs. A1,A2,A3,A4,A5,A6 and Tables A1,A2, A3, A4, A5, A6, A7, A8, A9,A10, A11, A12, A13.

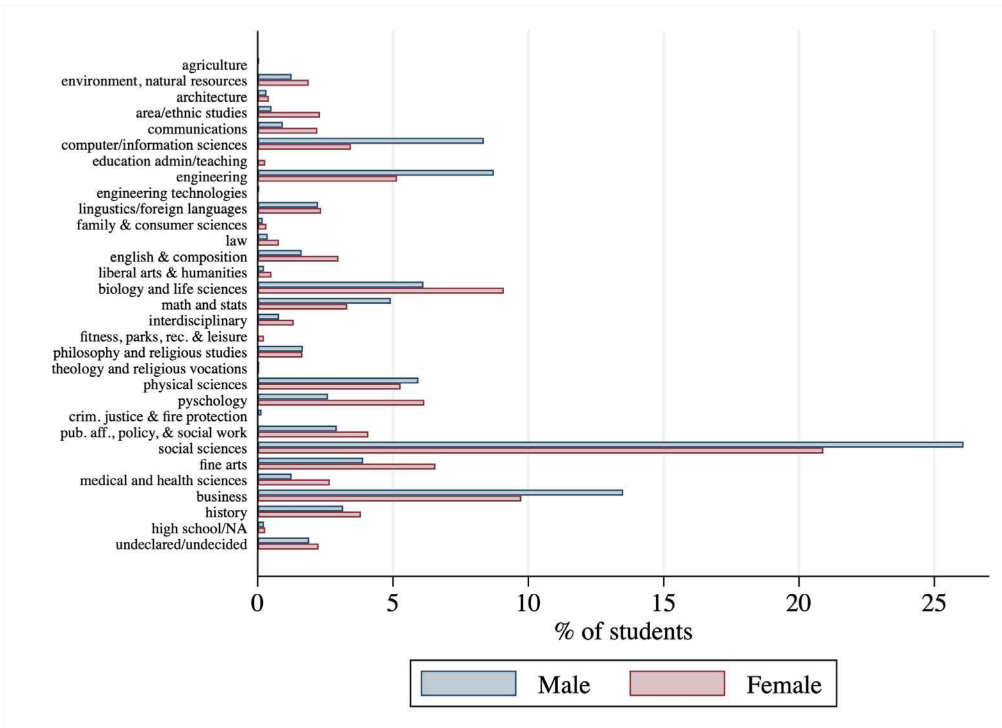


Fig. A1. Distribution of student majors. Note: This figure depicts the majors of students, by student gender, on the mentoring platform. The data include all students with profiles on the platform.

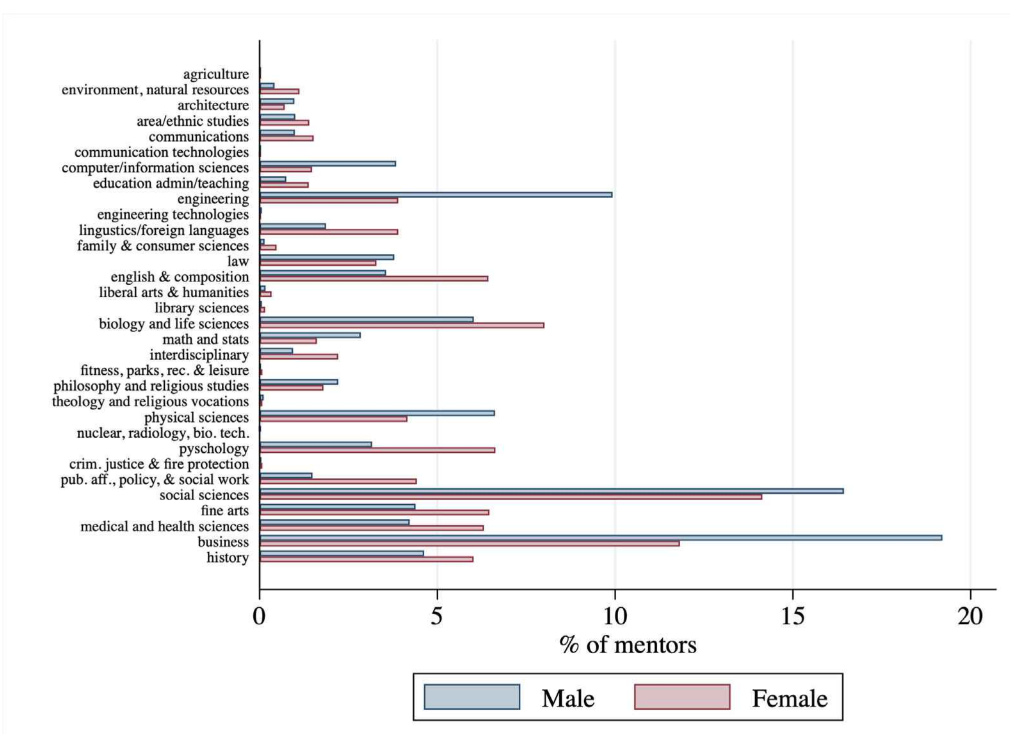


Fig. A2. Distribution of alumni majors. Note: This figure depicts the majors of alumni, by gender, on the platform. The data include all alumni with profiles on the platform.

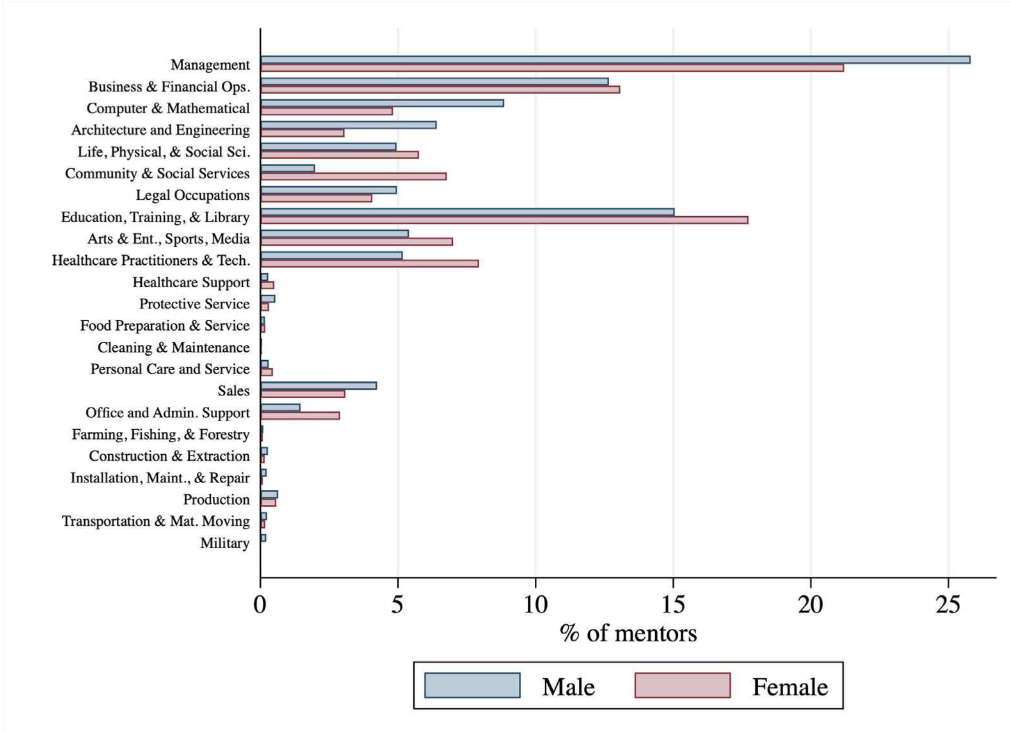


Fig. A3. Distribution of alumni occupations. Note: This figure depicts the occupations of alumni, by gender, on the platform. The data include all alumni with profiles on the platform.

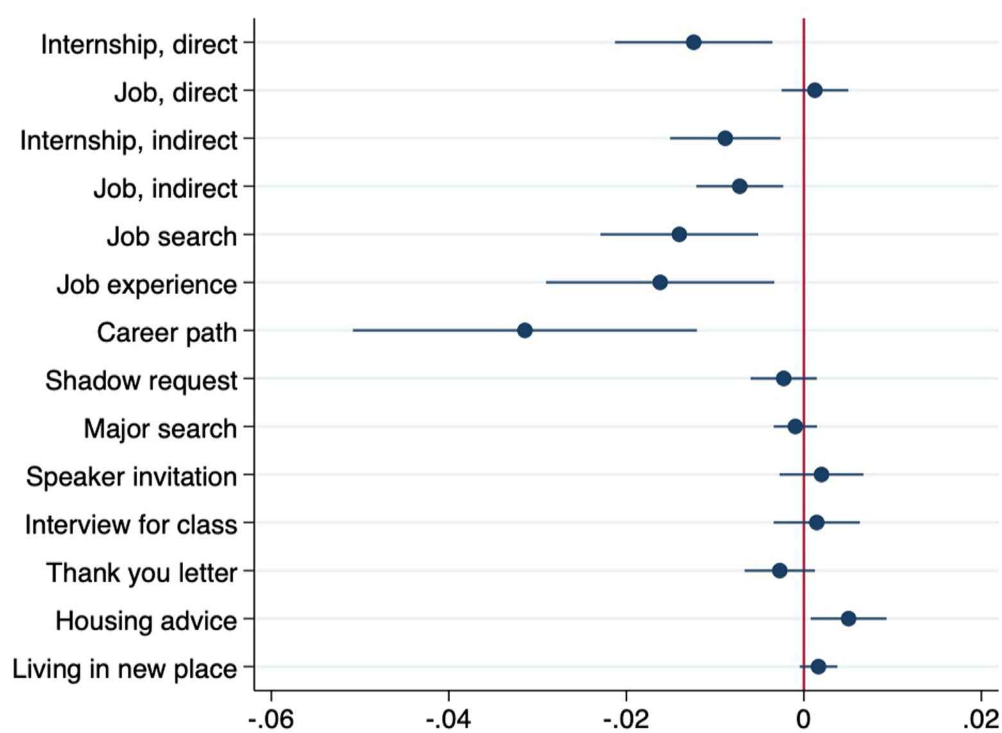


Fig. A4. Questions asked, by alumni gender. Note: This figure plots the coefficient from a regression in which the outcome variable is total number of messages of a particular type received by an alumni registered on the platform (including zeroes), and the independent variable is an indicator of mentor gender. Additional controls are graduation year, as well as fixed effects for major, school, and occupation of the alumni. Point estimates of the coefficient for each question type are dots and robust standard errors are represented in the bars. A given message can be coded as asking more than one potential type of question (for example, a message can ask about both job search and for advice about living in a new place).

UCLA

Hello,

Thank you for taking the career advice survey. Please find below your personalized advice.

Did you know that you can search and review Alumni Mentor profiles on UCLAOne using the Directory tab: https://uclaone.com/ Alumni who are willing to provide mentorship have a "willing to help" banner.

Using the type of mentor you consistently chose in the mentor comparison portion of the survey, we evaluated whether you valued (1) the job title of a mentor (2) whether the mentor was a first-generation college goer and (3) the experience of a mentor (years since graduation).

Based on your choices, you seem to be interested in mentors who are first generation college students and are recent college graduates. Your choices did not suggest a strong preference for the other mentor characteristics.

To find mentors with these characteristics, on the directory page of UCLAOne, filter your search using one or more of the following categories:

- UCLA: field of study, major, graduation year, communities (e.g. First-Generation)
- Keyword search (e.g. Senior Legislative Aide)
- Location: city, state, country

We hope this information was helpful to you!

Fig. A5. Example of advice Email. Note: This figure is a screenshot of an advice email that students received, based on their survey responses.

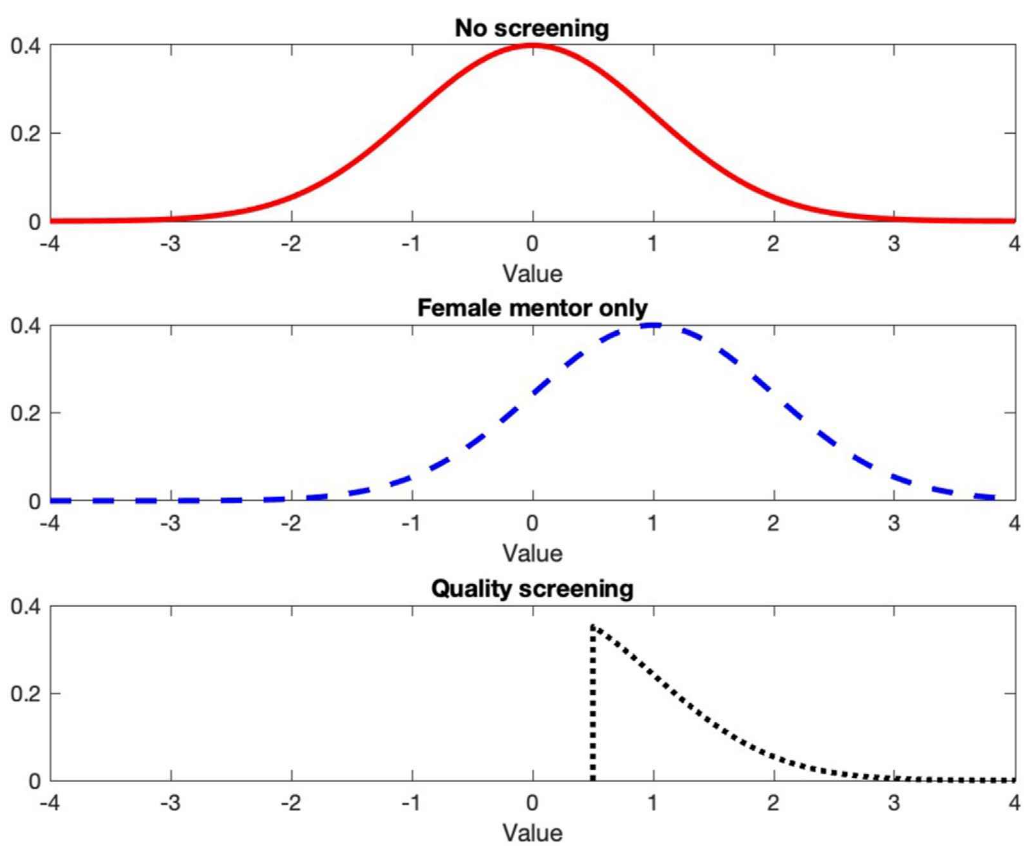


Fig. A6. Mentorship quality under various policies. Note: This figure depicts the distribution of mentorship quality for a given mentor-female student pair when there is no screening of mentors (top panel), when only female mentors are available to female students (middle panel), and when mentors are screened on quality (bottom panel). The distribution of mentorship quality in these examples is normal. The distribution of mentorship quality when only female mentors are available is assumed to have the same variance but a higher mean than the distribution of mentorship quality when there is no screening.

Table A1
Mentoring platform summary statistics: student and alumni users.

	(1)	(2)	(3)	(4)
	Students		Alumni	
	Mean	SD	Mean	SD
Female	0.500	0.500	0.460	0.498
Graduation Year	2019	2.719	2005	14.130
Major unknown	0.532	0.499	0.106	0.308
Any Message Sent	0.116	0.321	0.093	0.29
Total Messages Sent	0.364	1.705	0.127	2.744
Liberal Arts College	0.337	0.473	0.463	0.499
Research University	0.663	0.473	0.537	0.499
Observations	9257		16113	

Note: This table displays summary statistics for student and alumni users of the mentoring platform among schools with substantial messaging between students and alumni in our data. The variable Any Message Sent is an indicator for whether a message was sent (or responded to, in the case of alumni) restricting to the set of conversations between students and alumni in which students initiated the conversation the topic of the conversation was job- or major- related.

Table A2
Responses by mentor and student gender.

	(1) Response Received	(2) Length of Response	(3) Log Length of Response
Mentor is female	−0.026	14.089	0.082
	(0.026)	(48.313)	(0.072)
Student is female	0.050*	70.209	0.130**
	(0.026)	(45.875)	(0.065)
Mentor is female × Student is female	−0.049	−26.439	−0.130
	(0.035)	(67.125)	(0.090)
Sample	All Students	All Students	All Students
Male mentor mean	0.570	438.032	5.579
Observations	3349	2034	2034
R-squared	0.088	0.101	0.132

Note: This table presents the results of a regression of the outcomes of messages sent by students (labeled in each regression in columns 1–3) on an indicator for whether the message was sent to a female mentor, and indicator of whether the message was sent by a female student, and the interaction of these indicators. The mean outcome among messages sent to male mentors is listed in the bottom panel. All regressions include controls for school, student major, student graduation year, recipient major, and recipient occupation fixed effects, as well as a linear term for recipient graduation year. Robust standard errors clustered at the student level are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3
Response sentiment, by student and alumni gender.

	(1) Anger	(2) Anticipation	(3) Disgust	(4) Fear	(5) Joy	(6) Negative	(7) Positive	(8) Sadness	(9) Surprise	(10) Trust
Panel A: Female Student Sample										
Mentor is Female	−0.047	0.170	−0.017	−0.011	0.146	−0.046	−0.052	0.047	−0.006	0.035
	(0.051)	(0.210)	(0.047)	(0.070)	(0.161)	(0.088)	(0.290)	(0.075)	(0.084)	(0.188)
Male Mentor Mean	0.303	4.067	0.280	0.493	2.774	0.799	6.300	0.544	0.659	3.679
Observations	1035	1035	1035	1035	1035	1035	1035	1035	1035	1035
Panel B: Male Student Sample										
Mentor is Female	−0.148**	−0.391	0.069	−0.151*	−0.224	−0.147	−0.000	0.013	0.062	−0.218
	(0.070)	(0.270)	(0.069)	(0.089)	(0.221)	(0.118)	(0.292)	(0.096)	(0.114)	(0.246)
Male Mentor Mean	0.385	4.160	0.289	0.530	2.794	0.797	5.659	0.583	0.675	3.597
Observations	999	999	999	999	999	999	999	999	999	999

Note: This table presents the results of a regression of the sentiment of responses received by students on an indicator for whether the message was sent to a female mentor. The sentiment of the message is defined as percentage of words in the response with listed sentiment, using the NRC Emotion lexicon. All regressions include controls for school, student major, student graduation year, recipient major, and recipient occupation fixed effects, as well as a linear term for recipient graduation year. Robust standard errors clustered at the student level are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4
Future interactions, by student and alumni gender.

	(1) Total Responses | Responded	(2) Total Responses Including 0	(3) Total Response Length	(4) Offer Followup	(5) 2nd Response	(6) 3rd Response
			Panel A: Female Student Sample			
Mentor is female	0.156	−0.064	−281.049	0.033	0.025	0.101
	(0.111)	(0.081)	(210.783)	(0.022)	(0.043)	(0.067)
Male mentor mean	1.898	1.264	1125.667	0.854	0.673	0.610
Observations	1035	1611	1035	1035	669	322
			Panel B: Male Student Sample			
Mentor is female	−0.113	−0.117	−22.537	−0.019	−0.019	0.004
	(0.104)	(0.076)	(78.394)	(0.032)	(0.043)	(0.075)
Male mentor mean	1.983	1.131	712.196	0.849	0.698	0.631
Observations	999	1738	999	999	681	334

Note: This table presents results of a regression of the outcomes of messages sent by female students (Panel A) and male students (Panel B) on an indicator of whether the message was sent to a female mentor. The mean outcomes for male mentors are also reported below the regression coefficients. All regressions include controls for school, student major, student graduation year, recipient major, and recipient occupation fixed effects, as well as a linear term for recipient graduation year. Standard errors, clustered at the student level, are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5
Questions asked, by student and alumni gender.

	(1) Career path	(2) Job search	(3) Job experience	(4) Job, direct	(5) Job, indirect	(6) Internship direct	(7) Internship indirect	(8) Shadow request	(9) Major search	(10) Course selection	(11) Phone call	(12) Meet in person
						Panel A: Female Students						
Mentor is female	0.026	−0.023	−0.031	0.006	−0.006	−0.004	−0.028**	0.001	-0.005	-0.005	-0.029	0.010
	(0.024)	(0.019)	(0.020)	(0.010)	(0.010)	(0.019)	(0.013)	(0.009)	(0.005)	(0.008)	(0.025)	(0.015)
Male mentor mean	0.622	0.201	0.243	0.027	0.064	0.172	0.130	0.037	0.015	0.028	0.434	0.057
Observations	1617	1617	1617	1617	1617	1617	1617	1617	1617	1617	1617	1617
						Panel B: Male Students						
Mentor is female	−0.018	−0.022	0.006	0.027*	−0.016	0.001	−0.018	-0.008	-0.005	-0.002	-0.030	0.004
	(0.027)	(0.024)	(0.025)	(0.014)	(0.016)	(0.020)	(0.015)	(0.010)	(0.004)	(0.009)	(0.028)	(0.012)
Male mentor mean	0.647	0.245	0.237	0.048	0.084	0.221	0.100	0.022	0.017	0.017	0.437	0.069
Observations	1738	1738	1738	1738	1738	1738	1738	1738	1738	1738	1738	1738

Note: This table presents results of a regression of the outcomes of messages sent by female students (Panel A) and male students (Panel B) on an indicator of whether the message was sent to a female mentor. The mean outcomes for male mentors are also reported below the regression coefficients. All regressions include controls for school, student major, student graduation year, recipient major, and recipient occupation fixed effects, as well as a linear term for recipient graduation year. Standard errors, clustered at the student level, are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6
Relative homophily by gender by female representation in major and occupation.

Female Rep. Indicator:	(1) Student's Major > 50% Female (ACS)	(2) > 50% of Mentors in Occ × School are Female	(3) Student is in STEM Major
Student Female	0.152***	0.143***	0.130***
	(0.036)	(0.021)	(0.021)
Student Female × Female Rep. Indicator	-0.024	-0.024	0.017
	(0.041)	(0.037)	(0.040)

Note: This table presents results of a regression of whether a message was sent to a female mentor on an indicator of whether the message was sent by a female student, fully interacted with an indicator of whether the students major was more than 50% female (in column (1)), or the mentors within the occupation × school of the mentor receiving the message are more than 50% female (in column (2)), or whether the student has a STEM major (in column (3)). The mean outcomes for male mentors are also reported below the regression coefficients.All regressions include controls for school, student major, student graduation year, recipient major, and recipient occupation fixed effects, as well as a linear term for recipient graduation year. Robust standard errors clustered at the student level are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7
Broad career paths and associated job titles.

Broad Career Path	Job title 1	Job title 2	Job title 3	Job title 4
Accounting	Director of Finance	Risk Management Strategist	Investment Banker	Accountant
Administrative/Support	Executive Assistant	Human Resources Specialist	Events Coordinator	Compliance Manager
Arts and Design	Freelance Writer	Architect	Filmmaker	Creative Director
Business Development	Director of Partnerships	Strategy Professional	Head of Corporate Development	Business Development Data Analyst
Community and Social Services	Program Manager	Social Worker	Community Organizer	Senior Legislative Aide
Consulting	Managment Consultant	Pharmaceutical Strategy Consultant	Business Development Data Analyst	Vice President of Strategy
Education	Teacher	School Counselor	University Relations Director	Principal
Engineering	Data Scientist	Software Engineer	Mechanical Engineer	Systems Analyst
Entrepreneurship	Co-founder and CEO	Venture Capitalist	Director of Business Development	Strategy Professional
Finance	Chief Financial Officer (CFO)	Investment Banker	Venture Capitalist	Private Equity Associate
Healthcare Services	Healthcare Consultant	Dentist	Physician	Pharmacist
Human Resources	Director of Human Resources	Recruiting Coordinator	Executive Coach	Talent Agent
Information Technology	IT Technician	Software Engineer	Data Scientist	Head of Information Security
Legal	Compliance Manager	Attorney	Senior Paralegal	Non-profit Director
Marketing	VP Marketing	Business Analytics Lead	Brand Manager	Sales Representative
Media and Communications	Creative Director	Journalist	Social Media Strategist	Senior Copywriter
Military and Protective Services	Private Investigator	Military Officer	Chief Security Architect	Police Officer
Operations	Supply Chain Manager	Chief Operating Officer (COO)	Management Consultant	Packaging and Distribution Consultant
Program and Product Management	Digital Product Manager	Business Analyst	Strategy Lead	Director of Supply
Quality Assurance	Software Quality Assurance	Compliance Manager	Research Lab Coordinator	Pharmaceutical Quality Control Manager
Real Estate	Realtor	Real Estate Developer	Commercial Finance Executive	Mortgage Loan Officer
Research	Senior Policy Analyst	Professor	Scientist	VP Clinical Development
Sales	Sales Representative	Director of Customer Services	Regional Sales Manager	Real Estate Agent
Purchasing	Fashion Buyer	Purchasing Analyst	Supply Chain Manager	Sales Representative

Note: This table lists each broad career path and its associated job titles. Students are asked the broad occupation they are most interested in. In the preference elicitation, the four associated job titles are randomly assigned to hypothetical mentors.

Table A8
Survey summary statistics.

	(1) All Students	(2) Female	(3) Male	(4) Non-binary	(5) First Generation	(6) Non First Generation
Female	0.63				0.68	0.61
	(0.48)				(0.47)	(0.49)
Non-binary	0.03				0.02	0.03
	(0.16)				(0.13)	(0.18)
First-generation college goer	0.28	0.30	0.25	0.17		
	(0.45)	(0.46)	(0.44)	(0.39)		
Asian/Pacific Islander	0.54	0.54	0.55	0.43	0.43	0.59
	(0.50)	(0.50)	(0.50)	(0.51)	(0.50)	(0.49)
Hispanic/Latino	0.14	0.13	0.14	0.17	0.38	0.04
	(0.34)	(0.34)	(0.35)	(0.39)	(0.49)	(0.20)
White/Caucasian	0.22	0.21	0.22	0.30	0.11	0.26
	(0.41)	(0.41)	(0.42)	(0.47)	(0.31)	(0.44)
Expected graduation year	2024	2024	2024	2024	2024	2024
	(1.11)	(1.12)	(1.06)	(1.31)	(1.11)	(1.11)
Observations	834	527	284	23	235	599

Note: This table reports summary statistics for the preference elicitation survey respondents. Students chose between three gender identities: male, female, and non-binary. Statistics are reported for all students, and separately by gender category and first-generation college student status. Standard deviations are in parentheses.

Table A9
Balance table for ratings vs. no ratings.

	(1) No Ratings	(2) Ratings	(3) Difference	(4) P-value
Fraction Female	0.619	0.646	0.026	0.429
Fraction First Generation College Students	0.280	0.284	0.004	0.895
Fraction Asian/Pacific Islander	0.537	0.548	0.011	0.750
Fraction Hispanic/Latino	0.144	0.131	−0.014	0.563
Fraction White	0.218	0.221	0.003	0.911
Expected Graduation Year	2023.7	2023.7	0.058	0.448
Fraction High Female Rep. Major	0.533	0.538	0.005	0.895
Fraction STEM Major	0.501	0.447	−0.054	0.118
Number of students	436	398		

Note: This table displays mean student characteristics for students who were randomized into the ‘no ratings’ preference elicitation template, the ‘ratings’ template, and provides the p-value for a t-test of the difference between the two groups.

Table A10
Balance table for ratings vs. no ratings, by student gender.

	(1)	(2)	(3)	(4)	(5)	(6)
	Female Students			Male Students		
	No Ratings	Ratings	P-value	No Ratings	Ratings	P-value
Fraction First Generation College Students	0.311	0.292	0.631	0.229	0.270	0.413
Fraction Asian/Pacific Islander	0.548	0.533	0.729	0.518	0.574	0.324
Fraction Hispanic/Latino	0.148	0.121	0.356	0.139	0.149	0.797
Fraction White	0.196	0.233	0.300	0.253	0.199	0.259
Expected Graduation Year	2023.7	2023.8	0.426	2023.6	2023.6	0.899
Fraction High Female Rep. Major	0.629	0.664	0.406	0.380	0.304	0.171
Fraction STEM Major	0.449	0.363	0.045	0.584	0.601	0.763
Number of students	270	257		166	141	

Note: This table displays mean student characteristics for students who were randomized into the ‘no ratings’ preference elicitation template, the ‘ratings’ template, by gender, and provides the p-value for a t-test of the difference between the two groups.

Table A11
Student preferences for mentor attributes estimated with logit: by student gender.

	(1)	(2)	(3)	(4)
	No Ratings		Ratings	
	Female	Male	Female	Male
Mentor is female	0.480***	−0.081*	0.059	−0.030
	(0.043)	(0.046)	(0.043)	(0.059)
Mentor has preferred occupation	1.738***	1.617***	0.909***	0.937***
	(0.087)	(0.118)	(0.078)	(0.105)
Mentor graduation year	0.038***	0.024***	0.008*	0.016**
	(0.005)	(0.008)	(0.005)	(0.007)
Availability (in 10 min. increments)	0.159***	0.191***	0.031**	0.071***
	(0.015)	(0.021)	(0.015)	(0.021)
Mentor first generation	0.359***	0.182***	0.167***	0.112**
	(0.056)	(0.058)	(0.047)	(0.056)
Knowledgeable about job opportunities			0.611***	0.629***
			(0.026)	(0.042)
Easy to talk to/friendly			0.446***	0.465***
			(0.024)	(0.031)
Gave personalized advice			0.489***	0.468***
			(0.025)	(0.035)
Mentee is female			−0.047	0.097
			(0.045)	(0.061)
WTP for female mentor	0.276***	−0.050*	0.065	−0.032
	(0.027)	(0.028)	(0.047)	(0.063)
p-value $\text{WTP}_{noratings}$ = $\text{WTP}_{ratings}$	0.000	0.799		
p-value WTP_{female} = WTP_{male}	0.000		0.215	
Observations	8100	4620	7710	3900
Number of students	270	154	257	130

Note: This table displays coefficients β from estimating the following logit model: $C_{ic} = \alpha^g + (\mathbf{x}_{iac} - \mathbf{x}_{ibc})'\beta^g + \epsilon_{ic}$. Willingness to pay is calculated as the ratio of the coefficients on female mentor and preferred occupation. Standard errors, clustered at the student level, are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A12
Female student preferences for mentor attributes: by STEM major.

	(1)	(2)	(3)	(4)
	No Ratings		Ratings	
	STEM	Non-STEM	STEM	Non-STEM
Mentor is female	0.102***	0.087***	0.008	0.006
	(0.011)	(0.012)	(0.011)	(0.008)
Mentor has preferred occupation	0.371***	0.307***	0.165***	0.112***
	(0.015)	(0.017)	(0.020)	(0.014)
Mentor graduation year	0.008***	0.007***	−0.000	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
Availability (in 10 min. increments)	0.034***	0.029***	−0.001	0.006**
	(0.004)	(0.004)	(0.004)	(0.003)
Mentor first generation	0.053***	0.083***	0.025**	0.023**
	(0.015)	(0.015)	(0.012)	(0.009)
Knowledgeable about job opportunities			0.082***	0.097***
			(0.004)	(0.003)
Easy to talk to/friendly			0.061***	0.067***
			(0.005)	(0.004)
Gave personalized advice			0.069***	0.071***
			(0.004)	(0.003)
Mentee is female			−0.025**	0.001
			(0.011)	(0.008)
WTP for female mentor	0.276***	0.284***	0.046	0.049
	(0.035)	(0.043)	(0.065)	(0.071)
p-value $WTP_{noratings}$ = $WTP_{ratings}$	0.002	0.005		
Observations	3600	4410	2790	4890
Number of students	120	147	93	163

Note: This table displays coefficients β from estimating the following linear probability model: $C_{ic} = \alpha^g + (\mathbf{x}_{iac} - \mathbf{x}_{ibc})\prime\beta^g + \epsilon_{ic}$. Willingness to pay is calculated as the ratio of the coefficients on female mentor and preferred occupation. The sample is limited to female students. STEM majors include the following IPUMS field of degrees: Environment and Natural Resources; Computer and Information Sciences; Engineering; Engineering Technologies; Biology and Life Sciences; Mathematics and Statistics; Physical Sciences; Nuclear, Industrial Radiology, and Biological Technologies; and Medical and Health Sciences and Services. Four students who have not yet declared a major are excluded. Standard errors, clustered at the student level, are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A13
Student preferences for mentor attributes: by first-generation status.

	(1)	(2)	(3)	(4)
	No Ratings		Ratings	
	First Generation	Non First Generation	First Generation	Non First Generation
Mentor first generation	0.159***	0.017**	0.070***	0.002
	(0.016)	(0.008)	(0.011)	(0.006)
Mentor is female	0.048***	0.053***	0.017*	0.001
	(0.012)	(0.008)	(0.010)	(0.006)
Mentor has preferred occupation	0.306***	0.340***	0.090***	0.146***
	(0.018)	(0.011)	(0.014)	(0.011)
Mentor graduation year	0.006***	0.006***	0.001	0.002**
	(0.002)	(0.001)	(0.001)	(0.001)
Availability (in 10 min. increments)	0.034***	0.033***	0.007**	0.005**
	(0.004)	(0.003)	(0.004)	(0.002)
Knowledgeable about job opportunities			0.094***	0.090***
			(0.004)	(0.003)
Easy to talk to/friendly			0.065***	0.066***
			(0.004)	(0.003)
Gave personalized advice			0.071***	0.069***
			(0.004)	(0.003)
Mentee is female			0.001	−0.003
			(0.011)	(0.006)
WTP for first gen mentor	0.518***	0.051**	0.778***	0.017
	(0.065)	(0.025)	(0.170)	(0.042)
p-value $WTP_{noratings}$ = $WTP_{ratings}$	0.153	0.483		
p-value $WTP_{firstgen}$ = WTP_{non}	0.000		0.000	
Observations	3660	9420	3390	8550
Number of students	122	314	113	285

Note: This table displays coefficients β from estimating the following linear probability model: $C_{ic} = \alpha^g + (\mathbf{x}_{iac} - \mathbf{x}_{ibc})\prime\beta^g + \epsilon_{ic}$. Willingness to pay is calculated as the ratio of the coefficients on first-generation mentor and preferred occupation. Standard errors, clustered at the student level, are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix B. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.jpubeco.2023.104876.

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