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DISCUSSION PAPER SERIES

IZA DP No. 15362

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ISSN: 2365-9793

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ABSTRACT

Does Information Affect Homophily?*

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.

JEL Classification: J16, J24, J71

Keywords: homophily, mentorship, preference elicitation, gender

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* Funding is gratefully acknowledged from the Upjohn Institute Early Career Research Grant, UCLA Faculty Senate Grant, and the Initiative for the Study of Gender in the Economy at the Becker Friedman Institute at the University of Chicago. We thank Jack Landry, Neta Grossfeld, Mikaela Hassenzahl, Reigne Dadey, and Yash Srivastav for excellent research assistance, and Jacob Model for superb technical assistance. We have benefited from comments from Danny Yagan, Heather Royer, Corinne Low, Paola Giuliano, Trevor Gallen, Romain Wacziarg, and Steven Durlauf. This experiment was pre-registered on the AEA Registry under AEARCTR-0008674.

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 match quality, individuals rely on easily observed traits as signals of match quality (statistical discrimination based on various moments of the match 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 college/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 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 percent 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 12 percent 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 plat-

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

form 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 only willing to pay for female mentors 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. 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 sheds light on another rationale for same-gender pairings and preferences: minimizing gender-specific costs, e.g. female mentees' risk of sexual harassment by male mentors. Using the randomization of 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' WTP for female mentors. These results suggest that female-specific experiences with mentors do not explain homophily by gender.

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.[3] 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 a small literature that investigates the roots of homophily.[4] 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. Our paper examines homophily in a setting where matching on shared traits is considered best practice and considerable resources are devoted to initiatives that prioritize such matching. We also contribute to a broader 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

[2]As discussed in Heckman and Siegelman (1993), 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. 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]In the absence of information on driver safety, we might observe female riders gravitating toward female drivers, who are perceived as less risky, on average. Tang et al. (2021) describes how, instead of matching passengers to drivers based on gender, ride-sharing platforms have invested in performing background checks on drivers and providing additional in-app safety features to customers. Given the scarcity of female drivers, it is straightforward to see that matching riders to drivers on gender would lead to long wait times (or higher prices) for female riders and less efficient matching overall.

[4]There is a large literature on social networks documenting homophily (Currarini et al., 2009; Bertrand and Duflo, 2017).

the take-up of advice (Ayalew et al., 2021).[5]

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 or 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 universities and colleges 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 (college major) 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.[6] Occupations are derived from job title using O*NET-SOC AutoCoder.[7]

We observe 13,038 conversations on the site, where a conversation is defined as a series of messages between two people. 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 only schools that had at least 100 student-initiated conversations. We also drop the 99th percentile most prolific student senders in terms of messages to unique alumni, yielding a sample of 4,250 messages. We further restrict the sample 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. We also

[5] 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, 2020)

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

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

drop 51 messages that cannot be classified into the above categories. These final restrictions yield a sample of 3,374 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.

2.2 Who contacts whom? Homophily by gender

Figure 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. For example, if 30 percent of alumni on the platform are female (male), then under random pairings, we would expect 30 percent of the conversations that female (male) students have on this website should be with female (male) alumni. 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 Figure 1 Panel B, we further divide the students and alumni by their college major, and plot whether students tend to contact 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 Figure 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

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

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 0.193, indicating that female students are nearly 20 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.[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 fact, on the margins which we can directly measure in the data—the propensity of mentors to respond to messages from students, as well as the length on these responses—female students appear to be trading off responsiveness or response quality when messaging a female alumnus (Table 2).[10,11]

While female students' willingness to pay for same-gender mentors on this platform is consistent with taste-based discrimination, there is still 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. 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

[9]Note that the attenuation of the coefficient on $StudentFemale_i$ when we add student and alumni controls suggests that observational measures of homophily may be driven by omitted variable bias. In Section 3 we formally elicit students' preferences for mentor characteristics in part to address this concern.

[10]In Appendix Table A2 we document that male students also receive slightly lower rates of response from female mentors and we cannot reject that the effect is different from zero or different from the effect for female students. The point estimates suggest that, if anything, female mentors respond relatively more to male students than female students. We also note that female mentors' lower response rate is not explained by excess requests: they do not receive more messages from students than male mentors.

[11]In this setting, we cannot easily quantify all of the potential differences in messages sent to female vs. male professionals. In a field experiment that controls for all observable student characteristics and the wording of student messages, we show that female professionals are less responsive and give shorter replies to female students than male professionals (Gallen and Wasserman, 2021b).

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.

Students taking the survey are shown 30 pairs of hypothetical mentors and asked to choose which professional they prefer within each pair.[12] Each mentor in the pair has a randomly assigned occupation, availability for mentoring (30 minutes or 60 minutes), 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 career center newsletter. Study recruitment was targeted to students interested in career advice. 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 Figure A2. 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 minutes 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.[13] To aid in the student's selection, we provided four examples of occupations associated with each

[12] Students were informed that "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."

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

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 career path. This customization ensures that students are only shown mentor profiles relevant to their interests.

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. Appendix Figure A1 provides a screenshot of the mentor pairs shown to students during the survey in the 'ratings' template.[14] 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: 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 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 x in choice pair c:

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

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

$$P^g\left(V_{iac} > V_{ibc}\right) = \alpha^g + (\mathbf{x}_{iac} - \mathbf{x}_{ibc})'\beta^g + \epsilon_{ic} \tag{2}$$

[14]Note that the location of the mentor was fixed; it was always Los Angeles.

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

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

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 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.[15] This empirical specification is similar to that 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.[16] 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 A3 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 represented in the sample.[17] There are few differences between male and female students, aside from female students being slightly more likely to be first-generation college goers. We confirm that student

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

[16] This stands in contrast to formal interactions for the purpose of information gathering, such as soliciting financial advice from a certified professional.

[17] 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.

demographics are balanced across the two survey templates in Appendix Table A4.

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.[18] 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).[19] In fact, students 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 to access a mentor of the same gender. 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.[20] 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 A5).[21]

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

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

[20]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.

[21]Note that the observational data shows much stronger homophily among male students than the preference elicitation

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.

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.

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.[22] 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 and 53% reported that is it 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

survey, suggesting an important role for omitted variable bias in observational measures of homophily.

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

based on (accurate or inaccurate) beliefs.

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 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 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, as would be the case if female students preferred female mentors due to the fear of sexual harassment by male mentors.

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 preregistered 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 A6).

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 match 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 match quality to $f^g(x)$. For example, if match 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 increasingly costly as the quality truncation threshold increases, programs may be better off restricting matches to shared traits. If obtaining information on quality is straightforward, for example, through the use of existing surveys of mentee experiences, then the optimal policy would screen mentors on quality. See Appendix Figure A3 for a graphical example of match quality under the these policies.

More broadly, initiatives in employee recruitment, service-provider matching, and doctor-patient matching that commonly use shared traits as a coarse proxy for match quality—while well intentioned—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.

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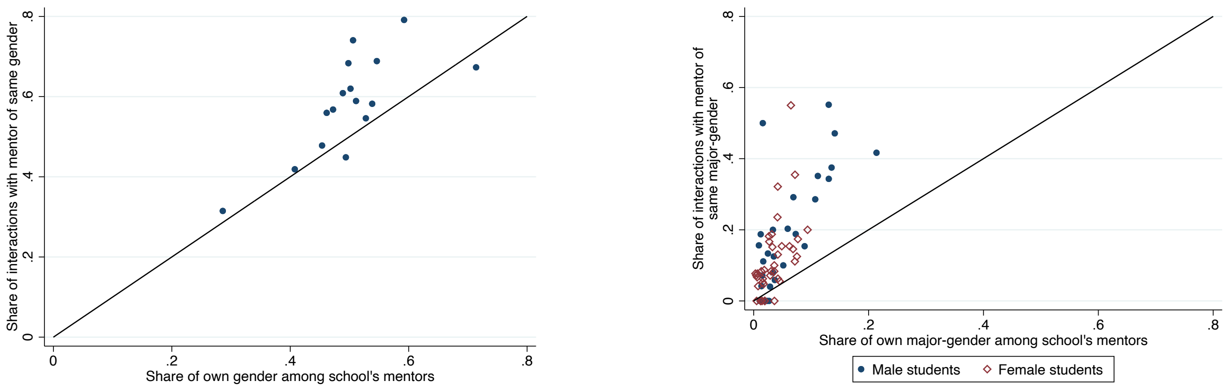
Figures and Tables

Figure 1: Homophily on an Online Mentoring Platform



(a) Homophily by Gender

(b) Homophily by Gender and College Major

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.

Table 1: Relative Homophily by Gender

	(1)	(2)	(3)
Student Female	0.193***	0.136***	0.124***
	(0.020)	(0.018)	(0.018)
Mean among male students	0.333		
Mentor Controls	No	Yes	Yes
Student Controls	No	No	Yes
Observations	4144	4139	4139
R-squared	0.038	0.139	0.150

Note: This table displays coefficients β from a regression of the form $RecipientFemale_{imj} = \alpha + \beta StudentFemale_i + X'_{ij}\gamma + \epsilon_{imj}$ 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 Female Students, by Mentor Gender

	(1) Response Received	(2) Length of Response	(3) Log Length of Response
Mentor is female	-0.083***	-38.820	-0.067
	(0.025)	(51.676)	(0.063)
Sample	Female Students	Female Students	Female Students
Mean among male mentors	0.667	539.566	5.767
Observations	1617	1039	1039
R-squared	0.119	0.133	0.174

Note: This table presents the results of a regression of the outcomes of messages sent by female students (labeled in each regression in columns 1-3) on an indicator for whether the message was sent to a female mentor. 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 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		
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: $C_{ic} = \alpha^g + (\mathbf{x}_{iac} - \mathbf{x}_{ibc})'\beta^g + \epsilon_{ic}$. Standard errors, clustered at the student level, are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

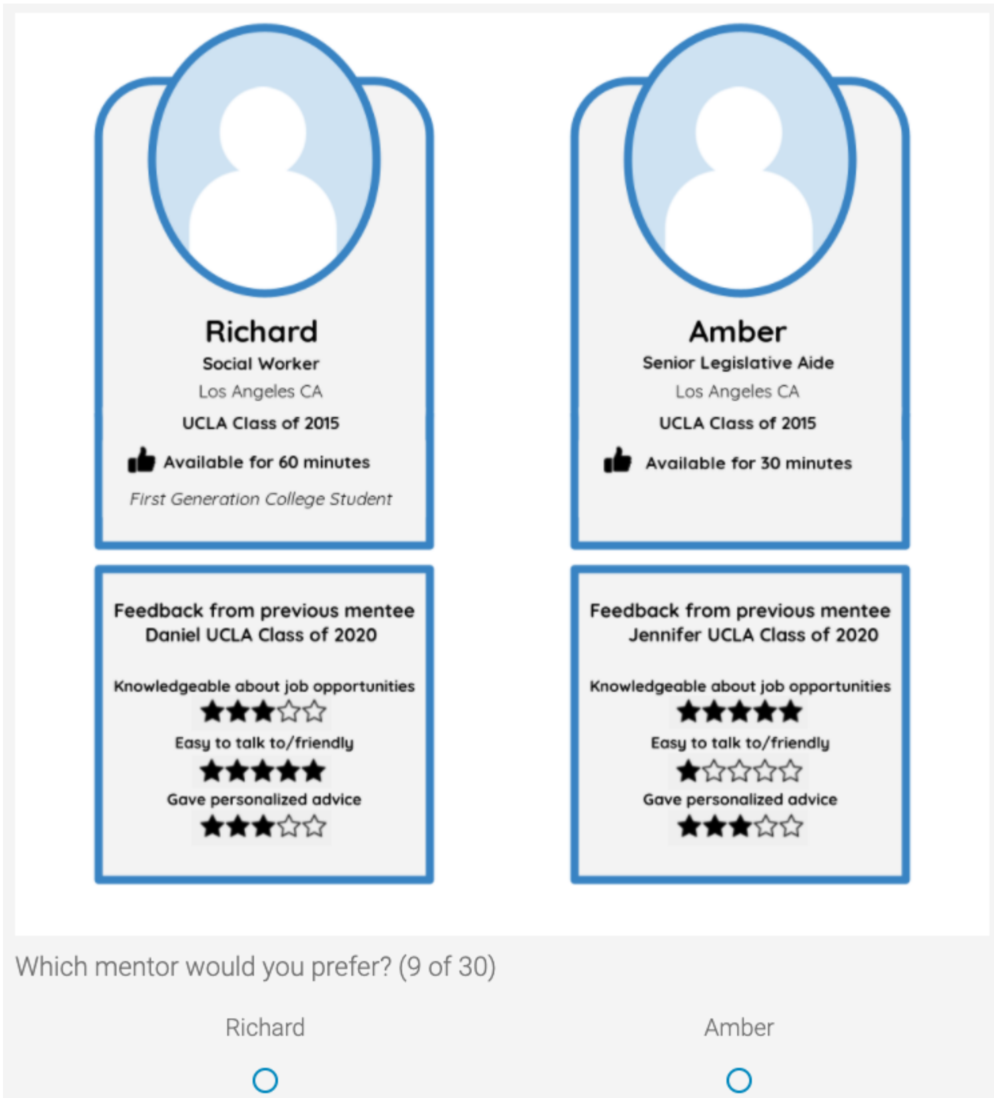
Table 4: Student Preferences for Mentor Attributes: Role of Mentee Gender

	(1) Female	(2) Male
Mentor is female	0.007	-0.002
	(0.006)	(0.009)
Mentor has preferred occ	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-gen	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: Note: This table displays coefficients β from estimating the following linear probability model: $C_{ic} = \alpha^g + (\mathbf{x}_{iac} - \mathbf{x}_{ibc})'\beta^g + \epsilon_{ic}$. Standard errors, clustered at the student level, are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A Appendix Figures and Tables

Figure A1: 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.

Figure A2: Example of Advice Email

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.

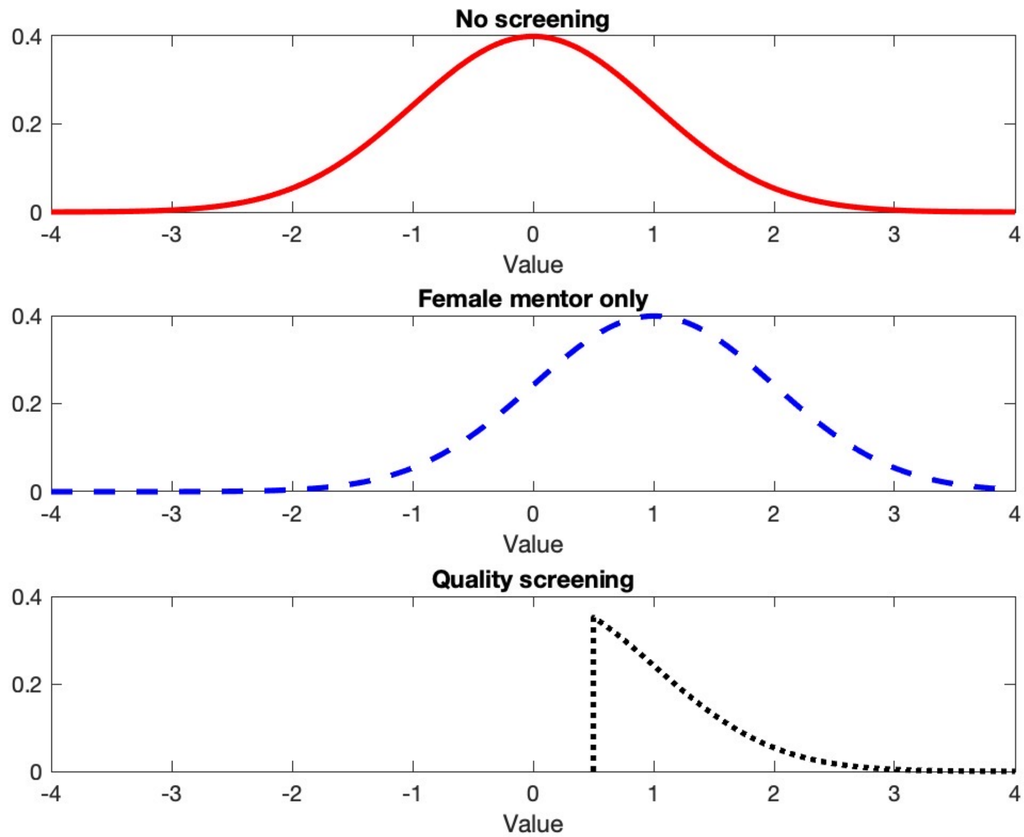
To find mentors with these characteristics, on the directory page of UCLAOne, filter your search using one or more of the following categories:

- 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!

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

Figure A3: Match quality under various policies



Note: This figure depicts the distribution of match 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 match quality in these examples is normal. The distribution of match quality when only female mentors are available is assumed to have the same variance but a higher mean than the distribution of match quality when there is no screening.

Table A1: Mentoring Platform Summary Statistics: Student and Alumni Users

	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 to Male Students by Mentor Gender

	(1) Response Received	(2) Length of Response	(3) Log Length of Response
Mentor is female	-0.032	29.826	0.078
	(0.027)	(50.717)	(0.075)
Sample	Male Students	Male Students	Male Students
Mean among male mentors	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 male students (labeled in each regression in columns 1-3) on an indicator for whether the message was sent to a female mentor. 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: Survey Summary Statistics

	All Students	Female	Male	Non-binary	First-Gen	Non First-Gen
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 A4: Balance Table for Ratings vs. No Ratings

	No Ratings	Ratings	Difference	P-value
Fraction Female	0.619	0.646	0.027	0.416
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	2023.663	2023.721	0.058	0.448
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 A5: 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 occ	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-gen	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 $WTP_{noratings} = WTP_{ratings}$	0.000	0.799		
Observations	8100	4620	7710	3900
Number of students	270	154	257	130

Note: This table displays coefficients β from estimating the following logit model: $C_{ic} = \alpha^g + (\mathbf{x}_{iac} - \mathbf{x}_{ibc})'\beta^g + \epsilon_{ic}$. Standard errors, clustered at the student level, are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Student Preferences for Mentor Attributes: By First-Generation Status

	(1)	(2)	(3)	(4)
	No Ratings		Ratings	
	First-Gen	Non First-Gen	First-Gen	Non First-Gen
Mentor first-gen	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 occ	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 $\text{WTP}_{noratings} = \text{WTP}_{ratings}$	0.153	0.483		
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: $C_{ic} = \alpha^g + (\mathbf{x}_{iac} - \mathbf{x}_{ibc})'\beta^g + \epsilon_{ic}$. Standard errors, clustered at the student level, are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B Online Appendix - Preparation of Mentoring Platform Data

Assignment of mentor job titles to occupation codes

O*NET-SOC AutoCoder was created by R.M. Wilson Consulting, Inc. for the US Department of Labor for the purpose of assigning occupation codes to resumes, job descriptions, and job titles (O*NET-SOC AutoCoder, 2020). The AutoCoder, for example, returns SOC-2010 code 13-1111, "Management Analysts," for the job title "Analyst at Y Consulting." Because the job titles in our data are user-supplied, we cannot confidently assign occupation in some cases. O*NET-SOC AutoCoder provides a confidence estimate for every occupation-job title match. We accept any matches provided with confidence scores above 70 percent (on the advice of the developer) and then manually attempt to match occupation for all remaining job titles. In case after this process our data do not include information sufficient to assign occupation, we code that as missing.

Assignment of mentor and student gender

We first assign gender using the 1990 Census and 1940-1970 Social Security Administration (SSA) name files. For a given name, if 90 percent of individuals with this name are classified as either male or female, then the name is designated as such. The remaining names are left as unclassified. In cases where there is conflict between the Census and SSA assigned gender, a name is unclassified. Because our sample includes names uncommon in the US, we use the API genderize.io (available here `https://genderize.io`) to classify any names which are uncommon or unknown in the Census and SSA files, using the same 90 percent criteria for assigning names.