The effect of trainee career intentions on mentor's interest in the trainee: Experimental evidence from academia

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Abstract

In many industries trainees often seek careers different from their mentors. For example, many PhD students seek non-academic careers. Anecdotally, mentors invest less into different-career trainees, but it is unclear whether the relationship is causal and what moderates it. To explore this phenomenon we conducted an audit experiment in academia, where a fictional prospective PhD student emailed immunology and microbiology principal investigators (PIs) about mentorship. The student's career intention was randomly described as "applied research in industry" (n = 1,000), "basic research in academia" (n = 1,000) or with no description (control, n = 442). To mitigate concerns about skills and motivation, all emails highlighted the student's great academic record. Contrary to expectations, PIs responded similarly across all conditions. Treatment effects showed little variation based on the PIs' institution prestige, industry connections, and career length. These null findings challenge the assumption that mismatched career intentions cause less mentorship, and suggest that the benefit for mentors of trainees remaining in the mentor's career long-term is seen as small and not determinative of their interest in the trainee. If mentors do discriminate on career intentions, it likely occurs later in the training period.

Keywords: mentorship, labor market discrimination, academia, audit experiment.

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1. Introduction

Many industries rely on an apprenticeship model in which a mentor helps a trainee master skills over time (Lerman & Rauner, 2012). The model has been used in industries ranging from construction and manufacturing, to entrepreneurship and medicine, and to doctoral education and the arts (Anderson & Gold, 2019; Slavich & Castellucci, 2016; Smyth & Zimba, 2019). The satisfaction and attrition rates of trainees in apprenticeship vary substantially (Gambin & Hogarth, 2016; Ragins et al., 2000; Smyth & Zimba, 2019; Snell & Hart, 2008; Ullrich et al., 2021; Zimmerman, 2018). Factors linked to attrition include poor working conditions, insufficient training, personal circumstances, and external labor market conditions (Gambin & Hogarth, 2016; Ysseldyk et al., 2019). Combining these factors with the high levels of competition in industries like the arts and academia (Clauset et al., 2015; Slavich & Castellucci, 2016), it is not surprising that trainees often prefer not to (Fuhrmann et al., 2011; Mason et al., 2009; Roach & Sauermann, 2010) or are unable to pursue the same career as their mentor (Check Hayden, 2016; Cyranoski et al., 2011; De Janasz et al., 2003; Ganguli et al., 2022).

What are the consequences of such mismatches between mentors' careers and their trainees' career intentions? First, mismatches may lower the quality of life for trainees who decide not to do what their mentor does or if the openings simply do not exist (Chatterjee et al., 2023), but still need to complete the training for career advancement. For instance, in domains like the life sciences, a PhD and postdoctoral training are often required for advancement not only in academia but even to senior roles in the private sector and government labs. Anecdotally, trainees with mismatched intentions often report experiencing psychological distress. For example, some graduate students report feeling "afraid of being judged—or worse, ostracized—by faculty who are not supportive of exploring alternative careers during PhD training" (Schillebeeckx et al., 2013).

Second, mismatches may affect selection into apprenticeship-focused industries like academia. If mentors provide less or lower-quality mentorship to trainees with non-matching career intentions and this is well known, then only those sufficiently confident that they will place into the mentor's career will select into the track. In academic fields with few openings, this may lead to the selection of trainees on [over]confidence in their skills (Ganguli et al., 2022) or self-reliance.

Such self-selection may ultimately hurt the trainee's satisfaction and cause the field to lose out on "Einsteins" (Bell et al., 2019) who never even applied[1].

Despite the abundance of such mismatches across industries (e.g., Eby et al., 2004) and their potential consequences, the phenomenon is poorly understood theoretically or empirically. The voluminous literature on discrimination in the labor market focuses largely on the demographic or class/cultural characteristics of applicants for full-time work (Neumark, 2018; Riach & Rich, 2002; Rivera, 2017), but gives less attention to apprenticeship and stays silent on applicants' explicit career intentions. A separate literature explores how mentor-trainee concordance on intellectual and demographic dimensions relate to trainee success, although the mechanisms are usually opaque. For example, several studies investigate how intellectual (e.g., Liénard et al., 2018) and demographic similarity between mentor and trainee (Gaule & Piacentini, 2018; Hofstra et al., 2022; Rocha & Praag, 2020) predict trainee advancement. Qualitative work from this literature suggests that mentors tend to provide more career development and psychosocial support to trainees more similar to themselves in background and ambition (Burke et al., 1993; Limeri et al., 2019). In academia, a U.S. National Institutes of Health (NIH) survey of graduate and postdoctoral trainees found that matching career interests between a trainee and a principal investigator (PI) are associated with higher levels of trainee career self-efficacy (Chatterjee et al., 2023). Similarly, a survey of U.S. postdocs by Gibbs et al. (2015) reported that only half of the participants mentioned that their graduate advisors supported non-academic career paths, while fewer than one-third agreed that their departments were supportive of students interested in other career paths. Taken together, these literatures raise the possibility that trainee career intentions causally affect the availability and quality of mentorship.

This paper begins to fill the gap in understanding of career mismatches by developing theory and empirical evidence on how a trainee's career intention causally affects mentors' behavior, in particular their selection of trainees. We focus on entry into a profession—the steps *before* an individual formally applies to an opening, such as informal interactions (Lane et al., 2023; Milkman et al., 2012, 2015; Posselt, 2016; Rivera & Tilcsik, 2023)—because these early steps

[1] We thank an anonymous reviewer for pointing out that the social welfare implications of discrimination against trainees with mismatched career intentions are not straightforward. For example, it may be socially optimal for the costs of PhD training of trainees who go into industry to be borne by the hiring firm, and without a mechanism for such payments for the mismatches to be discouraged.

can be determinative for an individual's career. The existing organizational literature on employer decision-making (e.g., Rivera, 2020) suggests that mentors in competitive industries will be less responsive to prospective trainees with non-matching than matching career intentions due to concerns about trainee quality and commitment. Quality and commitment are typical considerations for employers across industries (Botelho & Chang, 2023). Yet the apprenticeship model entails an additional mechanism that may affect employer (mentor) behavior but has remained understudied—the trainee's career choice may affect the employer's own career even long after the apprenticeship period. Consequently, we argue that mentors may prefer trainees with same-career intentions for that long-term improvement on their own career. Additionally, we explore the heterogeneity across mentors' characteristics and how it moderates the selection decisions, and hypothesize that selection against trainees with non-matching career aspirations would be largest by mentors affiliated with more prestigious organizations, with fewer non-matching-career connections, and of greater seniority.

We focus on the empirical setting of graduate training in academic life sciences, given the prominence of the apprenticeship model and the substantial and consequential discretion exercised by mentors (Anderson & Gold, 2019; Milkman et al., 2015). Moreover, entry into academia is highly competitive (Clauset et al., 2015; Milojević et al., 2018; Van Bavel, 2019), with a large number of doctorate recipients working in the private sector (Opsomer et al., 2021). An analysis of the U.S. PhD's career prospects found that fewer than 20% of PhD recipients in the biological sciences were in tenure-track positions within 5-6 years after degree completion (Stephan, 2015). Figures like these suggest that for academic trainees non-academic careers are far from "nontraditional" or "alternative" but are arguably the default (Fuhrmann et al., 2011), resulting in copious career mismatches between mentors and trainees.

To test our predictions, we performed an audit experiment with 2,442 researchers (PIs) in the fields of microbiology and immunology who received emails from a fictional prospective PhD student requesting to discuss mentorship opportunities before applying to a PhD program. PIs were randomly assigned to an email that described the prospective student's career interest as either "*applied research in industry*" or "*basic research in academia*" or no description (control group). Prior work has found that even small changes to email text, such as the name and affiliation of the email sender (Ajzenman et al., 2023; Buzard et al., 2023; Milkman et al., 2015;

Rivera & Tilcsik, 2023) or whether a meeting is requested for "today" or "next Monday" (Milkman et al., 2012), can have substantial effects on recipients' behavior.

Contrary to the hypotheses, we found that PIs were similarly responsive to students in all conditions and the responses were similar in content. Treatment effects were also similar across PI's institution prestige, whether they had industry connections, and career length. These null effects are consistent with a trainee's academic quality being the primary concern driving mentors' selection decisions, and the long-term consequences of career match being of minor importance. It is also possible that mentors do weigh trainees' career intentions heavily but do not find intentions at such an early stage informative.

This study contributes to the understanding of labor market discrimination by going beyond the demographic characteristics of applicants to their stated career intentions. The results paint a surprisingly positive picture—at least in the life sciences, mentors do not discriminate against talented prospective students, and if trainees' career interests do causally affect mentorship, it is likely later in the apprenticeship process.

2. Theory Development

Understanding how employers evaluate candidates and possible discrimination against them has been a key topic for organizational scholars (Rivera, 2020). Extensive literatures examine discrimination based on applicant characteristics such as gender and race, often using the method of audit experiments (Buzard et al., 2023; Fernandez-Mateo et al., 2022; Neumark, 2018; Pager & Shepherd, 2008; Riach & Rich, 2002; Rivera & Tilcsik, 2023). Discrimination in such contexts is typically seen as emerging from employers' desire to select high performers based on imperfect information about quality (Bordalo et al., 2016; Coffman et al., 2021), as well as tastes (Rivera, 2012), the information environment (Rivera & Tilcsik, 2019), and procedures and laws governing selections (Small & Pager, 2020). What has received less attention are additional objectives employers may have that arise from the interdependencies between candidates' careers and their own, such as the objective of having the candidate stay in the same industry for a long time. We draw on the existing research on discrimination and combine it with the relatively undertheorized aspect of career interdependencies to develop hypotheses about

evaluation in a setting where candidates may have career interests that match or do not match those of employers or mentors.

We use the setting of academic life sciences for several reasons. Empirically, as noted above, the life sciences are characterized by an increasing tendency of PhD holders to transition to non-academic careers, often involving research in the private sector. Recent work has emphasized the importance of close interest overlap between the protégé and their faculty mentor in predicting the odds of mentees' continuing in academia (Liénard et al., 2018; Ullrich et al., 2021). Academia is also a setting with accumulating qualitative evidence that trainees' career choices affect mentors' advising, investments, and longer-term career outcomes (Boeder et al., 2021; Malmgren et al., 2010). Furthermore, the life sciences and academia more generally are an attractive site because academic mentors have a strong "taste for science" (Roach & Sauermann, 2010) and thus may care about trainee's *commitment to the field of academia* since trainee's career and research output affect their own reputation.

2.1. Main effect: Career interest as a signal of future returns

Organizations typically evaluate candidates for quality and commitment to the organization in order to make use of their general and organization-specific skills (Rivera, 2020). The evaluation usually entails significant uncertainty and time constraints, so employers often rely on observable signals of skills such as education and work experience (Bidwell et al., 2015; Leung, 2014). Employers also pay attention to signals in a candidate's profile to infer their fit, i.e., cultural, and long-term commitment to an organization (Botelho & Chang, 2023; Galperin et al., 2020; Rivera, 2012; Weisshaar, 2018). These considerations should also apply to the selection of trainees by mentors, since mentors are likely to prefer highly skilled and committed trainees.

Translating these arguments to the signal of career interest match or mismatch, both quality and commitment considerations would predict that, in the context of graduate programs, students with industry (*vs*. academia) career interests will be selected against. First, trainee's industry *vs*. academia interest may be correlated with quality, or hiring committees and PIs may falsely believe so. Industry career interest may indicate lower academic quality and payoff for the department's academic environment (Roach & Sauermann, 2010). Second, existing evidence shows that when evaluating quality, committees do not only privilege objective quantifiable

achievements like high test scores but also value more subjective factors such as research fit (Green & Bauer, 1995; Posselt, 2016). As industrial research is different from academic research, both in terms of process and output, student's demonstrated career interest in industry may signal poor research fit (Sauermann & Roach, 2014), making choosing their candidacy a suboptimal decision. Consequently, PIs may feel that industry-oriented trainees are more challenging to advise for PIs without knowledge of the trainee's non-matching industry (Agarwal & Ohyama, 2013). Relatedly, PhD training is costly for universities, and a student's industry orientation signals lower overall commitment to the field and potential risks of a student leaving the program prematurely. Such a concern about premature exit has been observed in the entrepreneurship context (Botelho & Chang, 2023). As a result, prospective mentors may favor academia-oriented trainees.

Lastly, there is an additional mechanism that may affect mentor's choice—the trainees's career choice may affect the mentor's own career. Potential interdependencies between mentor-trainee careers and how they might affect mentor's choices have received little attention, despite being a conceptually distinct mechanism. In the context of science and technology, it has been long recognized that researchers do not have full awareness of all relevant works, and certainly no time to read them all (Simcoe & Waguespack, 2010). Consequently, scientific impact requires not only high quality work but a "sales force" to promote that work, and in practice that sales force is often composed of former trainees or other associates (Azoulay et al., 2019). Hence, the more a PI's trainees stay in academia and publish, the larger the PI's sales force. Furthermore, some mentors might see an industry interest as a challenge to their own positive self-concept (Bailey, 2003). Specifically, a trainee's different-industry career interest may undermine the mentor's view that their choice of academia is highly desirable and uniquely prestigious.

Taken together, we hypothesize:

Hypothesis 1 (H1). *Prospective trainees with industry career aspirations will receive less attention than academia-oriented trainees.*

2.2. The moderating effects of mentor's industry connections, seniority, and prestige

We focus on three mentor characteristics that may moderate their responses to industry- *vs*. academia-oriented trainees.

Industry connections. There are substantial efforts across the globe to encourage universities to commercialize the research of their faculty through patent licensing and similar means (Ambos et al., 2008; Argyres & Liebeskind, 1998; Larsen, 2011), with the biomedical field being of primary focus. It has become common to see scientists have industry connections via being affiliated with firms directly or having collaborations with industrial scientists (Azoulay et al., 2007; Bikard et al., 2019; Lacetera, 2009; Perkmann et al., 2019). Having industry connections should make PIs more accepting of industry-interested trainees due to closer knowledge of industry, and thus perhaps better ability to mentor such trainees and help them find work, as well as personally benefiting more from mentees working in industry. Industry connections may also reflect a selection effect: PIs with industry connections might simply be more positive in accepting industry careers as a new norm. Taken together, we hypothesize:

Hypothesis 2 (H2). *Prospective trainees with industry career aspirations will be favored more by mentors with industry connections than those without.*

Seniority. Career length of a mentor may also affect their interest in industry-interested trainees. Studies have repeatedly demonstrated that mentors with experience differ from the inexperienced mentors with regards to their anticipated costs and benefits of mentorship (Ragins & Scandura, 1999). Consequently, more junior mentors might be more familiar with the changing academic labor market (Larson et al., 2014; Sauermann & Roach, 2016) and might view career outcomes as decreasingly informative about trainee competence. Complementary to this view, Bercovitz & Feldman (2008) find that the longer the elapsed time since a faculty member's graduation, the less likely they are to support research commercialization activities. We thus hypothesize:

Hypothesis 3 (H3). *Prospective trainees with industry career aspirations will be favored more by more junior mentors.*

Institutional prestige. Lastly, we argue that the prestige of a mentor's institution will also predict how they respond to industry-oriented students. Prestigious institutions usually expect their faculty to focus primarily on research, enabling high publication rates and citation counts (Long, 1978; Way et al., 2019). As a result, scientists working at elite institutions rarely exit university research careers compared to their colleagues at less-prestigious universities (Geuna & Shibayama, 2015). Prestigious-institution scientists publish at higher rates than others and depend on graduate and postdoctoral labor to do so, particularly in lab-based fields like the life sciences (Zhang et al., 2022). We expect such scientists to value research especially highly and have less exposure to non-academic work, and seek trainees with the same goals. We thus suggest:

Hypothesis 4 (H4). *Prospective trainees with industry career aspirations will be favored less by mentors from more prestigious institutions.*

3. Research Design, Data, and Methods

We use the audit study design to test how signaling one's interest in a future career in industry *vs*. academia affects the likelihood that a prospective PhD student will receive a response from a PI regarding their work and possible mentorship. The experiment was approved by the University of X's Institutional Review Board (IRB) protocol number N (university name and IRB identification number are disclosed for the revision process). The audit method includes several advantages such as its ability to provide more direct causal evidence than archival studies and its realism compared to surveys and laboratory experiments (Couture, 2008; Rivera & Tilcsik, 2023). Our research design builds on several existing audit experiments with academics (Ajzenman et al., 2023; Angeli et al., 2023; Milkman et al., 2012, 2015), and uses a between-subjects design with three arms, where the emails presented a diligent student on the cusp of graduation with research experience and specific interest in the work of the email recipient. The singular difference in each of these emails was the stated future career interests. The control condition (email) had no stated future career interest, while the other two either indicated interest in academia or industry. Sending one rather than multiple emails to each participant helped mitigate ethical concerns and inconvenience to our subjects, as well as minimize the likelihood of spillovers and suspicion. The fictitious student nor the experimenters did not respond to any replies to the initial email. We screened the replies received for any sign

of a researcher recognizing that the email was sent from a fictitious student and that the participant might be part of an audit experiment. None of the screened replies and systematic searches of all replies with keywords like "experiment" or "audit" indicated such concern.

In consultation with the IRB and in line with prior similar experiments, the subjects in the experiment were not debriefed, given that such emails are very common in researchers' everyday work and debriefing would likely pose a larger burden than benefit. A potential concern with audit studies similar to our paper is that if the fictitious student does not reply or behave untactfully in another way, and if their name or other characteristic are associated with a larger group, e.g., racial or ethnic group, subjects in the experiment may become more likely to discriminate against future *real* candidates who are members of the group. We do not believe our study poses such a threat given that we used a racially and gender-neutral name (see below). Overall, the benefits of illuminating potential discrimination on career intentions that many individuals report being a source of substantial distress were judged important enough to conduct a study involving deception.

3.1. Participants

Emails and names of PIs were obtained from the Web of Science database accessed through the Collaborative Archive & Data Research Environment (CADRE) platform of Indiana University in November of 2022. We used the database to identify all articles published[2] between 2016 and 2021 in several prominent journals in the fields of microbiology and immunology (e.g., *Immunity* and *Nature Immunology*, see Table S1 for the complete list). We collected the emails of the corresponding authors who were assumed to be the principal investigators as per field's norms. To narrow the scope of the experiment to U.S. institutions, we excluded email addresses that did not contain ".edu" at the end. Duplicates and University of X emails were removed.

We conducted a power analysis to estimate the number of participants needed for each treatment condition. We hypothesized a response rate of 20% for the industry condition and 25% for the academia condition. For a two-sided test of proportions to have 0.8 power to detect such a difference at α=0.05, each condition needs 1094 observations, and the number needed falls to

[2] The database at the time had incomplete coverage of 2021 publications.

862 for a one-sided test. Consequently we aimed for 1000 per treatment condition, and assigned any additional available emails to the Control group.

The final list contained 2,442 unique email addresses. These emails were randomized into *control* (T0) with 442 participants, *industry* (T1) with 1,000 participants, and *academia* (T2) with 1,000 participants. The email was sent by a (fictional) prospective student applying to PhD programs and interested in the work and potential mentorship of the PI. The student was identified as Jamie Anderson, a name chosen to be ambiguous on gender and race. The 2,442 emails were sent from a University of X email account linked to the fictitious student using the software "Yet Another Mail Merger" (YAMM) on December 13 and 14 of 2022.

3.2. Experimental conditions

We compare three different conditions, where we varied student's indicating their future career interests. We provide an illustration of the email that was distributed in the *industry* condition T1 in Figure 1. Condition T2 used the identical email except using "*For my future career plans, I am currently drawn to conducting basic research in academia.*" instead of the industry career goals. The control condition T0 did not include the sentence about future career plans at all. The subject line "*Prospective PhD student interested in your work*" was identical for each condition.

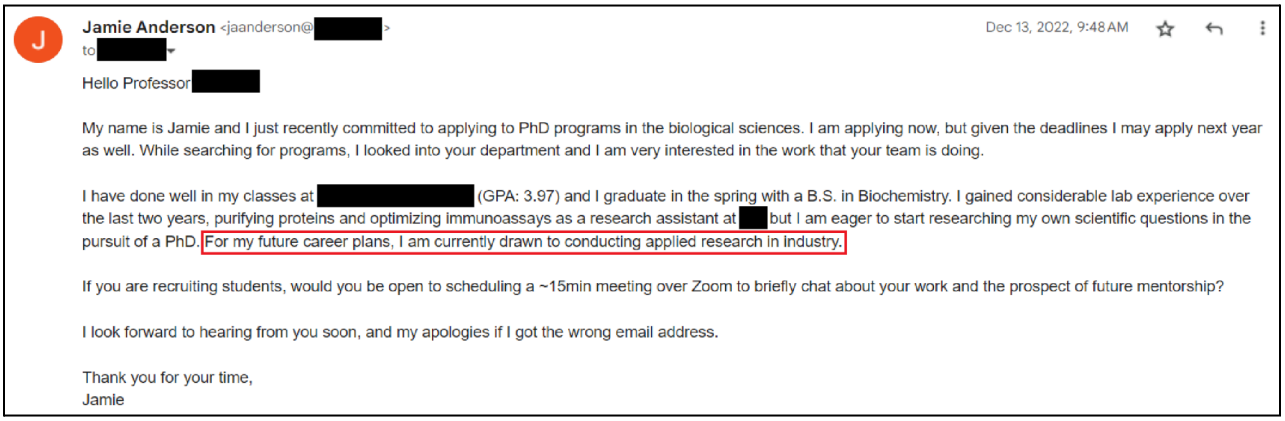


Figure 1. The email that was sent to experiment's participants in the *industry* condition T1.

We finished data collection on February 20, 2023 (approximately two months after the email send-out). The YAMM software allowed us to track whether emails were successfully sent and opened. Of the 2,442 emails that were sent, 1,398 emails were opened, 240 emails were bounced and returned with an error message, and 804 emails remained unopened. For our analyses, we

focused on the emails that were opened by the participants (corresponds to 57% of the original sample) as our experimental manipulation was situated inside the email's text.

To ensure that the recipients of the excluded emails are not systematically different from the participants we focus on, in Table S4 we report summary statistics for participants' characteristics for the emails that were excluded from our main analysis. Performing pairwise *t*-test mean comparisons between the included and excluded emails, we found that our group of included respondents had the same level of industry connections as the recipients of the excluded emails, had longer careers (1.8 years difference in career length, *p*-value = 0.000; *t*-statistic = 3.787), and were affiliated with institutions of a slightly lower rank (3.2 points difference in score, *p*-value = 0.011; *t*-statistic = -2.562). The differences, however, are only marginal, and we believe they do not bias our results. For robustness, we also repeat our main analysis on the full sample of all sent-out and non-bounced emails (see Table S5 in the Supplementary Appendix). The covariate comparisons and regression results corroborate our findings for the opened emails.

3.3. Variables

3.3.1. Focal variables

Response. Our main outcome variable is the indicator *Response*, set to 1 if the participant replied to the email and 0 otherwise. Among the 1,398 opened emails in our data, 805 participants (58%) responded.

Condition. We used a categorical variable *Group* that was coded as Control (n = 285), Industry (n = 568), or Academia (n = 545) for our three experimental conditions.

3.3.2. Moderators

To test moderation hypotheses H2-H4, we supplemented the data on authors from Web of Science with data from two other databases. First, we used DOIs to match papers in our sample to *OpenAlex* (accessed in May 2023)—one of the largest and widely used bibliometric databases (Singh Chawla, 2022). We were able to link 1,395 (99.8%) papers to *OpenAlex* and obtain author IDs. For each author we retrieved information about their current and previously recorded affiliations, their publication list, and co-author list.

To test H2, we computed an indicator *Industry connections* for each corresponding author based on the type of their affiliation as categorized by *OpenAlex*. We set the variable to 1 if an individual had an affiliation whose type was "company" ("education" was the most common affiliation type) currently or in the previous years. When accounting for current and all previous affiliations, 662 (47%) researchers are currently or were at some point in their career affiliated with a company. Among those, 17 participants had a current affiliation with a company along other affiliations they possess (9 of these individuals responded to our email). For robustness, in Table S6 we excluded these individuals and repeated our analyses—our findings hold.

To test H3, we computed the variable *Seniority* measured as the number of years passed since the PI's first publication year. We were able to gather this information for 1,260 participants (90%) in our sample. We excluded from analysis the 10% of records where *Seniority* was over 50 years on the assumption that these records were wrongly recorded by *OpenAlex*.

To test H4, for each PI, we measured the prestige of their institutions by linking their current affiliation to the *QS World University Rankings* report for the year of 2023. The QS ranking system captures an institution's reputation and research performance (Selten et al., 2020). The report contained an overall score for almost 1,500 institutions worldwide that was based on a set of criteria from academic reputation to the number of international students enrolled with a maximum score of 100. For matching, we used the Research Organization Registry (ROR) API with a required similarity score of at least 90%[3]. We first matched all institutions from the QS ranking table to their corresponding ROR IDs, then matched all affiliations of PIs in our sample to their ROR IDs, and finally joined the two datasets on ROR ID. We were able to compute the *Institutional prestige* for 733 PIs (52.4%). Some affiliations were not matched to a QS record because either the ROR API call returned a null result or the record was not among the QS records matched to ROR IDs .

Table S2 provides summary statistics for the variables and their correlations. 47% of the participants had industry connections. The participants were mostly senior, with an average of 28 years since their first publication. The participants' institutions vary greatly in rank, with an average QS Institutional prestige score of 60. A researcher's seniority and industry connections

[3] See https://ror.org/blog/2019-11-25-untangling-affiliation-strings/ and https://ror.readme.io/docs/match-organization-names-to-ror-ids for more details. Accessed on July 25, 2023.

are moderately correlated ($r = 0.32$).

Table S3 provides summary statistics for the variables by experimental condition. We also performed pairwise *t*-test mean comparisons for our key variables across conditions. We found that participants in our *industry vs*. *academia* groups do not statistically differ from each other in terms of *industry connections* and *seniority* (*p*-value > 0.1 in both cases). The participants in the *industry* group seem to be affiliated with slightly more prestigious institutions compared to the PIs in the *academia* condition, but the difference is marginal (3.6 points difference in score) and only weakly significant (*p*-value = 0.051; *t*-statistic = 1.952). We thus conclude that our two key experimental groups are balanced in terms of participants' observable characteristics. For robustness, we control for these observables in our regression models presented below.

4. Results

4.1. Content of replies

First, we performed a qualitative analysis of a sample of replies. We selected at random 10% of replies from each experimental condition, which corresponded to 29 replies from the *control* group, 57 replies from *industry*, and 55 from *academia*. We then hand-coded each response as being 1) positive, 2) negative, 3) requesting more information from the student (i.e., their resume or research publications), or 4) other. In the *control* condition, 38% of the responses were positive, i.e., a PI agreed to talk to the student. Whereas within both *industry* and *academia* groups, this rate was even higher: more than half of all replies were positive. In *industry*, 32 replies (56%) were positive while only 12 PIs (21%) declined the chat request often stating that they were not currently recruiting students. Within *academia*, 30 replies (55%) were positive and 12 (22%) were negative. This qualitative coding suggests that responses had similar composition of content across the treatment conditions, supporting the use of *Response* as a binary variable.

4.2. Main effect

Next, we conducted mean comparisons between the experimental conditions, displayed in Figure 2. The results of the *t*-test for the key comparison for H1 of *industry vs*. *academia* shows the difference was small (-0.054) and only marginally significant (*p*-value = 0.068; *t*-statistic = -1.829). These first results suggest that H1 is only weakly supported.

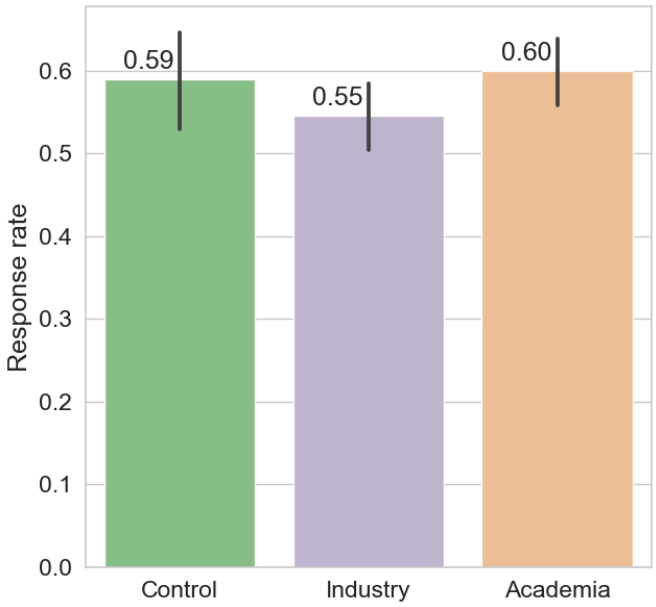


Figure 2. Response rate by treatment condition. Error bars represent 95% CIs.

To test H1 further, we estimated a linear probability model of *Response* regressed on the focal variable *Group* and controls for journal and publication year. The results are displayed in Table 1, with Model 1 including *Group* only and Model 2 including covariates. Models 3-5 add each of the three moderator variables (focal researcher's industry connections, seniority, and institution prestige) separately, and Model 6 combines all controls and moderators together in one specification. Across all models, we found no robust support for H1, in line with the simple comparison of response ratios above.

Table 1. Regression analysis for H1.

Dependent variable: Responded yes/no						
	(1)	(2)	(3)	(4)	(5)	(6)
Group = Industry	-0.054*	-0.056*	-0.053*	-0.044	-0.067	-0.033
	(0.030)	(0.030)	(0.030)	(0.031)	(0.041)	(0.043)
Group = Control	-0.011	-0.012	-0.010	-0.003	0.041	0.052
	(0.036)	(0.036)	(0.036)	(0.038)	(0.051)	(0.054)
Industry connections			0.036			-0.020
			(0.027)			(0.042)
Seniority				0.004***		0.004*
				(0.001)		(0.002)
Institutional prestige					-0.002*	-0.002**
					(0.001)	(0.001)
Intercept	0.600***	0.536***	0.514***	0.439***	0.635***	0.565***
	(0.021)	(0.056)	(0.059)	(0.069)	(0.099)	(0.115)
Publication year controls	NO	YES	YES	YES	YES	YES
Journal controls	NO	YES	YES	YES	YES	YES
N	1,398	1,398	1,395	1,260	733	660
Adjusted R^2	0.001	0.003	0.004	0.013	0.012	0.020

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are in parentheses. *Academia* group is the reference point for experimental group comparisons.

4.3. Moderator: Industry connections

Next, we test H2. Examining the raw data, we found that our two treatment conditions are pretty similar in the average number of industry-affiliated researchers (see Table S3). Interestingly, the share of industry-connected individuals was 4% higher in the academia (*vs*. industry) condition.

We then compared mean response rates across combinations of the *Industry connections* indicator and experimental conditions. Among PIs who have never had an explicit industry affiliation, replies favor academia-condition students but the difference is not statistically significant (coefficient = -0.036, *p*-value = 0.398; *t*-statistic = -0.847). Similarly, among PIs with industry connections, replies favor academia-condition students but the difference is not statistically significant (6.7% higher response rate, *p*-value = 0.109; *t*-statistic = -1.607).

Table 2 reports regression analysis for our H2. We estimated a series of linear probability models that linked the *Response* indicator to experimental condition indicators, industry connections and

its interaction with condition, experience, institutional prestige, journal, and publication year. We expected the interaction term between the *Industry* treatment and *Industry connections* to be positive. Contrary to expectations, the point estimate coefficient for the interaction term in Model 2 was actually negative (-0.038) and not statistically significant (p-value = 0.527). Model 3 adds other moderators as control variables and further supports this result. Overall, both regression and t-test analyses show no evidence that having industry connections is associated with higher response rates to industry- *vs*. academia-oriented students.

Table 2. Regression analysis for H2.

Dependent variable: Responded yes/no			
	(1)	(2)	(3)
Industry connections	0.037	0.084**	0.058
	(0.027)	(0.043)	(0.063)
Group = Industry		-0.034	-0.000
		(0.042)	(0.058)
Group = Control		0.061	0.152**
		(0.049)	(0.069)
Industry X Industry connections		-0.038	-0.072
		(0.060)	(0.086)
Control X Industry connections		-0.162**	-0.253**
		(0.073)	(0.109)
Seniority			0.004*
			(0.002)
Institutional prestige			-0.002**
			(0.001)
Intercept	0.492***	0.483***	0.515***
	(0.057)	(0.062)	(0.118)
Publication year controls	YES	YES	YES
Journal controls	YES	YES	YES
N	1,395	1,395	660
Adjusted R^2	0.003	0.006	0.025

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are in parentheses. *Academia* group is the reference point for experimental group comparisons.

While *Industry connections* captures the PI's direct connections to companies, they might also have some indirect industry connections through their co-authors. Accordingly, for each PI we computed the fraction of all-time co-authors who currently have industry affiliation. The Pearson correlation coefficient between *Industry connections* variable and this alternative measure is 0.21. Both industry and academia treatment groups had a small average share of company-connected co-authors, 3.5% and 3.3% respectively. Regressions using this alternative

measure of proximity to industry are reported in Table S7. Results corroborate those from the main measure—we found no evidence that industry proximity was associated with response rates (p-value > 0.1).

4.4. Moderator: Seniority

We now turn to testing how PI's level of seniority is associated with replies. Table S3 shows that the PI's average career length since first publication is similar across experimental conditions in the raw data.

Table 3 reports results for our regression analysis where we test the interaction effect between the *Industry* treatment and a researcher's *Seniority*. In all specifications the effect of *Industry* was not statistically different from the reference group *Academia* and the main effect was not statistically significantly changed by *Seniority.* We thus cannot reject the null hypothesis that there is no association between a researcher's *Seniority* and their response rates to students depending on their career interests.

Table 3. Regression analysis for H3.

Dependent variable: Responded yes/no			
	(1)	(2)	(3)
Seniority	0.004***	0.003	0.003
	(0.001)	(0.002)	(0.003)
Group = Industry		-0.099	-0.066
		(0.087)	(0.123)
Group = Control		-0.045	0.029
		(0.106)	(0.151)
Industry X Seniority		0.002	0.001
		(0.003)	(0.004)
Control X Seniority		0.001	0.001
		(0.003)	(0.005)
Industry connections			-0.020
			(0.042)
Institutional prestige			-0.002**
			(0.001)
Intercept	0.421***	0.468***	0.584***
	(0.067)	(0.081)	(0.132)
Publication year controls	YES	YES	YES
Journal controls	YES	YES	YES
N	1,260	1,260	660
Adjusted R^2	0.012	0.011	0.017

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are in parentheses. *Academia* group is a reference point for experimental group comparisons.

4.5. Moderator: Institutional prestige

Next, we test whether PIs affiliated with more prestigious institutions respond at different rates across experimental conditions. Table S3 shows that the means of participants' QS institution scores across experimental conditions are similar, although PIs assigned to *Industry* come from slightly more prestigious institutions on average.

Table 4 shows the regression analysis for H4. The main effect of *Institutional prestige* was negative and weakly significant (p-value = 0.058 in Model 3 of Table 4), which is in line with our baseline expectation that PIs from higher-prestige institutions generally show lower response rates to chat requests regardless of the condition. Similar to other moderation effects, we found no support for our hypothesis regarding institutional prestige. In Model 2 of Table 4, the interaction coefficient was essentially zero and highly insignificant (p-value = 0.984). We thus cannot reject the null that prestige is not associated with response rates across conditions.

Table 4. Regression analysis for H4.

Dependent variable: Responded yes/no			
	(1)	(2)	(3)
Institutional prestige	-0.002**	-0.002	-0.003*
	(0.001)	(0.001)	(0.001)
Group = Industry		-0.068	-0.086
		(0.117)	(0.124)
Group = Control		-0.031	-0.089
		(0.147)	(0.155)
Industry X Institutional prestige		0.000	0.001
		(0.002)	(0.002)
Control X Institutional prestige		0.001	0.002
		(0.002)	(0.002)
Industry connections			-0.019
			(0.042)
Seniority			0.004*
			(0.002)
Intercept	0.624***	0.648***	0.613***
	(0.098)	(0.114)	(0.131)
Publication year controls	YES	YES	YES
Journal controls	YES	YES	YES
N	733	733	660
Adjusted R^2	0.008	0.010	0.018

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are in parentheses. *Academia* group is the reference point for experimental group comparisons.

5. Discussion

In this paper, we examined the connection between a trainee's career interests and mentorship availability using the setting of academic life sciences. This connection is important theoretically and practically but has not been systematically studied. Theoretically, the literatures most relevant to this topic—on employers' decision-making and innovation labor force—have

considered a mentor's concerns about a trainee's quality and commitment/fit but not taken into account how a trainee's long-term choice of industry, i.e., beyond the period of mentorship, can still affect a mentor's own career and thus determine their interest in that trainee. Practically, many mentees report significant trouble securing mentorship when their career interests diverge from the mentors', resulting in (possibly severe) stress and even hiding their career interests from mentors. Synthesizing the limited existing theory and empirical evidence on this topic, in this paper we argued that mentors can be expected to systematically favor same-industry trainees.

To test our predictions, we performed the audit experiment examining if signaling interest in a career in industry (*vs.* academia) decreases the likelihood that a prospective PhD student will receive a response from a PI regarding their PhD programs and possible mentorship. The experiment was highly powered at n = 2,442. The fictional prospective student used a gender- and race-neutral name and was described as having a very strong academic record. Contrary to the theoretical arguments and anecdotal evidence, PIs responded at about equal rates across all three conditions (industry, academia, and control). This is contrary to the expectation of Hypothesis 1. Exploring heterogeneity across the PI's characteristics, we found no significant differences in the response rates across PI's institution prestige, industry connections, and career length. These are contrary to Hypotheses 2-4. We conclude that, at least in the life sciences, mentors do not appear to discriminate against talented prospective students intending to pursue careers in industry (*vs.* academia).

What might explain this surprising null result? We consider several possibilities, some to do with the research choices in the experiment and others suggesting a refinement of the theory. The original theory posited that 1) there is an empirical association between a trainee's career intentions and mentor's interest in the trainee, and this association is causal because career intentions signal to the mentor: 2) trainee skills/quality, 3) trainee commitment/fit, and 4) trainee's long-term benefits to PI's career. Our research minimizes the impact of trainee skills/quality (2) because the prospective student was described as highly skilled in all conditions. Consequently, one interpretation of the null treatment effect is that trainee commitment/fit (3) and long-term benefits to PI's career (4) are much smaller concerns for PIs than assumed, despite suggestive evidence of their importance in related contexts (Azoulay et al., 2019). Instead, if the theorized empirical association (1) is indeed true, the null effect is

consistent with PIs' selecting trainees primarily on skills and taking career intentions as a signal of those skills. Once the skills are unambiguous, noisy proxies of them stop being predictive of PIs' selections.

The null result may also illuminate our assumption that the theorized association may not be as valid as widely assumed or it may be valid but a consequence of reverse causation. Specifically, if PIs provide less mentorship to particular trainees, those trainees may choose to pursue different careers, not the other way around. Additionally, the null result might be due to low treatment intensity—it is possible that the faculty did not pay enough attention to the specific wording in the text, making it hard for our study to observe an effect we hypothesized about. Although this possibility remains, similar audit experiments also administered via emails reported substantial treatment effects (Ajzenman et al., 2023; Buzard et al., 2023; Milkman et al., 2015; Rivera & Tilcsik, 2023). Lastly, PIs may view career intentions at the early, prior-to-application stage as not informative of future choices and not discriminate based on them. Future work should further assess each of these possibilities because of the high stakes for trainees, mentors, and possibly even society.

6. Conclusion

This is to our knowledge the first work to systematically explore whether a trainee's career intentions causally affect mentor's interest in the trainee. It challenges the widespread assumption that there is a causal relationship, at least in the early selection stages and when skills are relatively clear. It is consistent with trainee skills being the primary concern for mentors, and post-mentorship period career intentions as being important only as a signal of those skills. This result contributes to the rich literature on the discrimination of candidates in labor market (e.g., Bikard & Fernandez-Mateo, 2022; Botelho & Chang, 2023; Galperin et al., 2020; Leung, 2014) by extending it to the domain of mentorship, where empirical evidence is limited. Second, it contributes to understanding of how organizations evaluate candidates (Rivera, 2020) by going beyond demographic characteristics and investigating the more fluid applicant characteristic of long-term career intentions. Further, it studies discrimination at the very early career stages, before an individual formally applies to an organization and matches are made. These early stages have received very little scholarly attention despite their tremendous impact on the composition of professions and organizations (Lane et al., 2023; Milkman et al., 2015).

Last, our inquiry is among the very first ones to contribute to the recent policy calls to transform the PhD training model to meet the changing labor market demands (Editorial, 2023; Ganguli et al., 2022; Sauermann & Roach, 2016). In recent decades there has been a steady increase in the number of PhDs created by U.S. institutions, with an average annual growth of about 3% (Cyranoski et al., 2011; Ghaffarzadegan et al., 2015). This growth is outpacing academic job availability and forcing many qualified individuals to either put increasingly more time into lower-wage postdoc or adjunct faculty positions or to find work outside the academy (Ashenfelter & Card, 2002; Ghaffarzadegan et al., 2015; Opsomer et al., 2021). Given these trends are becoming more of an industry norm, future work should continue to explore whether faculty account for the reality of students' career prospects and adjust their mentorship to set them for the path to success. The failure to do so might contribute to a system that sets a significant number of trainees up for psychological distress and does not acknowledge the realities of the mentors' labor market and attractive options outside of it (Marin & Vona, 2023).

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Supplementary Appendix

Table S1. Journals used for selection of study participants (n = 2,442).

Journal Name	Journal Impact Factor (2021)	Number of Emails Collected
Immunity	31.75	266
Nature Immunology	31.25	187
Lancet Infectious Diseases	21.37	186
Trends in Immunology	16.68	128
Trends in Microbiology	11.16	106
PLoS Pathogens	7.01	791
mBio	6.78	778

Table S2. Descriptive statistics and correlations for the sample of opened emails that were used for our main analysis (n = 1,398).

Variable	*N*	Mean	S.D.	Min	Max	1	2	3
1 Response (yes/no)	1,398	0.58	0.49	0				
2 Industry connections	1,395	0.47	0.5	0	1	-0.01		
3 Seniority	1,260	28.3	10.91	3	50	0.09	0.32	
4 Institutional prestige	733	60.07	22.38	24.3	100	-0.09	0.13	0.07

Table S3. Summary statistics for the sample of opened emails that were used for our main analysis (n = 1,398) broken down by experimental condition.

Variable	*N*	Mean	S.D.	Min	Max
Group = *Industry*					
Response (yes/no)	568	0.55	0.5	0	1
Industry connections	568	0.47	0.5	0	1
Seniority	508	28.1	10.69	3	50
Institutional prestige	297	61.41	22.31	24.4	100
Group = *Academia*					
Response (yes/no)	545	0.6	0.49	0	1
Industry connections	544	0.51	0.5	0	1
Seniority	493	28.01	11.07	3	50
Institutional prestige	295	57.84	22.12	24.3	100
Group = *Control*					
Response (yes/no)	285	0.59	0.49	0	1
Industry connections	283	0.41	0.49	0	1
Seniority	259	29.26	11	3	50
Institutional prestige	141	61.89	22.82	26.1	100

Table S4. Summary statistics for participants' characteristics for the emails that were excluded from our main analysis.

Variable	*N*	Mean	S.D.	Min	Max
All emails that were excluded					
Industry connections	1,038	0.47	0.5	0	1
Seniority	958	26.53***	10.99	3	50
Institutional prestige	529	63.3**	21.77	24.3	100
Broken down by the reason of exclusion:					
1. Bounced emails with a returned error message					
Industry connections	239	0.41*	0.49	0	1
Seniority	219	23.38***	11.12	3	50
Institutional prestige	103	60.21	22.93	25.2	100
2. Unopened emails					
Industry connections	799	0.49	0.5	0	1
Seniority	739	27.46*	10.79	3	50
Institutional prestige	426	64.05***	21.44	24.3	100

Note: We performed *t*-tests to compare the emails that were excluded from the analysis with the main sample of the emails that were analyzed. We performed pairwise comparisons for all excluded emails, as well as each of the subsamples within them (bounced and unopened emails). $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$ indicate whether differences between means were statistically significant.

Table S5. Regression analysis for H1—robustness test on the sample of all sent-out (including both opened and unopened) and non-bounced emails.

Dependent variable: Responded yes/no			
	(1)	(2)	(3)
Group = Industry	-0.019	-0.023	-0.029
	(0.023)	(0.023)	(0.032)
Group = Control	0.063**	0.057*	0.063
	(0.029)	(0.029)	(0.042)
Industry connections			-0.030
			(0.031)
Seniority			0.003**
			(0.001)
Institutional prestige			-0.002***
			(0.001)
Intercept	0.362***	0.307***	0.374***
	(0.016)	(0.042)	(0.086)
Publication year controls	NO	YES	YES
Journal controls	NO	YES	YES
N	2,202	2,202	1,056
Adjusted R^2	0.003	0.009	0.028

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are in parentheses. *Academia* group is a reference point for experimental group comparisons.

Table S6. Regression analysis for H1-H4—robustness test on the sample of opened emails excluding 17 participants with current company affiliation.

Dependent variable: Responded yes/no						
	(1)	(2)	(3)	(4)	(5)	(6)
Group = Industry	-0.053*	-0.054*	-0.033	-0.000	-0.066	-0.086
	(0.030)	(0.030)	(0.043)	(0.058)	(0.123)	(0.124)
Group = Control	-0.002	-0.003	0.052	0.152**	0.029	-0.089
	(0.036)	(0.036)	(0.054)	(0.069)	(0.151)	(0.155)
Industry connections			-0.020	0.058	-0.020	-0.019
			(0.042)	(0.063)	(0.042)	(0.042)
Seniority			0.004*	0.004*	0.003	0.004*
			(0.002)	(0.002)	(0.003)	(0.002)
Institutional prestige			-0.002**	-0.002**	-0.002**	-0.003*
			(0.001)	(0.001)	(0.001)	(0.001)
Industry X Industry connections				-0.072		
				(0.086)		
Control X Industry connections				-0.253**		
				(0.109)		
Industry X Seniority					0.001	
					(0.004)	
Control X Seniority					0.001	
					(0.005)	
Industry X Institutional prestige						0.001
						(0.002)
Control X Institutional prestige						0.002
						(0.002)
Intercept	0.598***	0.541***	0.565***	0.515***	0.584***	0.613***
	(0.021)	(0.057)	(0.115)	(0.118)	(0.132)	(0.131)
Publication year controls	NO	YES	YES	YES	YES	YES
Journal controls	NO	YES	YES	YES	YES	YES
N	1,381	1,381	660	660	660	660
Adjusted R^2	0.001	0.003	0.020	0.025	0.017	0.018

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are in parentheses. *Academia* group is a reference point for experimental group comparisons. Models 1-3 test our H1, Model 4 tests H2, Model 5 tests H3, and Model 6 tests H4.

Table S7. Regression analysis for H2—robustness test using *fraction of industry-affiliated co-authors* as an alternative operationalization for the *industry connections* variable.

Dependent variable: Responded yes/no			
	(1)	(2)	(3)
Fraction of industry-affiliated co-authors (%)	0.002	0.000	0.009
	(0.005)	(0.009)	(0.014)
Group = Industry		-0.071	-0.016
		(0.049)	(0.070)
Group = Control		-0.001	0.070
		(0.062)	(0.092)
Industry X Fraction of industry-affiliated co-authors (%)		0.005	-0.005
		(0.012)	(0.017)
Control X Fraction of industry-affiliated co-authors (%)		-0.004	-0.005
		(0.016)	(0.024)
Industry connections			-0.023
			(0.043)
Seniority			0.004*
			(0.002)
Institutional prestige			-0.002**
			(0.001)
Intercept	0.509***	0.538***	0.546***
	(0.058)	(0.065)	(0.122)
Publication year controls	YES	YES	YES
Journal controls	YES	YES	YES
N	1,395	1,395	660
Adjusted R^2	0.001	0.001	0.016

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are in parentheses. *Academia* group is a reference point for experimental group comparisons.