Biased Beliefs and Entry into Scientific Careers*

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ABSTRACT

We investigate whether biased beliefs play a role in the persistent demand for postdoctoral training in science. We elicit the beliefs and career preferences of doctoral students at 54 U.S. chemistry departments through a survey combined with a field experiment, in which we randomize the provision of information to a subset of respondents on historical academic placements by department. We first show that respondents have excessively optimistic beliefs about their own and their peers' chances of obtaining a tenure track faculty position. Respondents who received the historical placement information treatment updated their beliefs about their own likelihood of obtaining a faculty position in a follow-up survey one year later, particularly those who had the most biased initial beliefs. However, we do not find an effect on likelihood of doing a post-doc post-graduation or other career outcomes at four years post-intervention.

Keywords: information, biased beliefs, career preferences, science, higher education

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INTRODUCTION

Pursuing a PhD and postdoctoral training are significant human capital investments involving several years of effort and substantial foregone earnings. As with earlier human capital investments, the benefits of these postgraduate investments lie in subsequent career opportunities. One such opportunity is the prospect of obtaining a tenure-track faculty position—a job that comes with considerable nonmonetary attributes in terms of prestige, autonomy, and flexibility, if not with greater pay.

However, becoming a tenure-track faculty member, particularly in the natural sciences in the United States, has become incredibly difficult. The share of PhDs that become faculty is only around 10 percent or lower in chemistry and in the life and biological sciences (Gaulé and Piacentini 2018; Sauermann and Roach 2016). Yet, despite the low likelihood of ever becoming faculty and low postdoc salaries, many graduate students pursue one or multiple postdoctoral positions, often with the hopes that it will increase their chances to obtain academic employment (Hayter and Parker 2019).

The fact that the number of PhD graduates vastly exceeds the number of faculty openings in many STEM fields has not escaped the attention of the science policy community and has been the subject of recurring debates (e.g., Alberts et al. 2014; Cyranoski et al. 2011; Freeman et al. 2001; Romer 2000; Sauermann and Roach 2016; Schillebeeckx, Maricque, and Lewis 2013).

Why do young scientists keep choosing to pursue PhD and postdoctoral training despite the dwindling academic career prospects? One possibility is that postdoctoral training improves nonacademic career prospects enough to be worthwhile even in the absence of academic career options.[1] However, evidence suggests that nonacademic careers vary substantially in the extent that they require doctoral training (Hayter and Parker 2019). Alternatively, the experience of training itself may be appealing to graduate students, as scientists are drawn to the puzzle-solving nature of doing science (Dasgupta and David 1994; Merton 1973; Sauermann and Roach 2012; Stern 2004;). Meanwhile, for foreigners, visa considerations may steer individuals not just towards graduate study, but also towards postdoctoral training, as universities are not to subject to the same H1-B restrictions as private sector firms, which would allow them to more easily remain in the U.S. (Amuedo-Dorantes and Furtado 2019; Ganguli and Gaulé 2020; Stephan and Ma 2005).

In this paper, we consider another factor that may contribute to observed human capital investment decisions: perhaps graduate students are not well informed about the state of the academic job market, and these incorrect beliefs play a role in their career decisions, particularly decisions to pursue postdoctoral training.[2] Prior studies suggest through qualitative and survey evidence that individuals already in postdoc positions were indeed overly optimistic about the likelihood of getting an academic job, and that junior scientists who had already advanced beyond the PhD reported lacking information about nonacademic career options (Hayter and Parker 2019; Sauermann and Roach 2016). Yet, it is unclear whether providing information about the academic market to PhD students prior to this would have a causal impact on their beliefs and subsequent career choices and preferences.

[1] For example, having completed postdoctoral training may have signaling or certification value in the labor market. Further, the knowledge gained through training may be applicable—and indeed highly valued—for working in industry (Aghion, Dewatripont, and Stein 2008; Dasgupta and David 1994; Sauermann and Roach 2016; Sauermann and Stephan 2010).

[2] Entering science involves a series of choices—from choosing a major in college to deciding to embark on a PhD and post-PhD career choices. Ideally, we would like to know how beliefs and information on the scientific labor market shape decisions to pursue a scientific career at an early stage.

In very different contexts, the economics literature has established that biased beliefs can drive human capital investment decisions and that providing information can causally impact subsequent educational choices (e.g., Dinkelman and Martinez 2014; Jensen 2010; Oreopoulos and Dunn 2013; Wiswall and Zafar 2015). In these studies, individuals typically underestimate the returns to education and thus underinvest in education or make suboptimal education choices.

We study postgraduate human capital decisions and ask whether beliefs are biased and whether providing information about the academic labor market can have a causal impact on subsequent education investments and career aspirations, in particular, preferences to pursue a postdoc and an academic career. Our sample consists of doctoral students at the top 54 U.S. chemistry departments using an original survey combined with a field experiment. We focus on chemistry because we are able to observe academic placements consistently, while comparable data does not exist for fields like biology or physics. However, tight academic labor markets and long postdoctoral training are prevalent across the life and hard sciences.

In the baseline survey, we first elicit beliefs about the academic market and publishing in top journals, as well as career preferences for different types of postgraduation jobs, such as postdocs, industry, government, or teaching positions. We asked respondents two types of beliefs: the beliefs about *peers* (e.g. the share of students in their program that become faculty) and the *self*-beliefs (e.g. own chance of becoming faculty). By asking about others in their program, we focus on information regarding the state of market. By contrast, the beliefs about the own chance to become faculty also incorporates beliefs about one's own ability as well as preferences for the academic career.

Upon completing the survey, a random subsample of respondents received a message with a link to a custom-built website providing information on actual historical placement records by institution in a tabular format (historical information treatment). This treatment provides structured information about the academic labor market.[3]

The control group did not receive any message. One year after the baseline survey, we conducted a follow-up survey with the respondents of the baseline survey. In order to track how beliefs changed over time and whether the information interventions caused differential adjustments in beliefs, we asked respondents the same questions about their expectations about the academic job market.

Our first result is that at baseline, doctoral students in our sample are excessively optimistic, both about the state of the academic market in their field and about publishing in top journals. When we ask respondents to state their beliefs about the share of peers from their program eventually obtaining a tenure-track position in a U.S. research-intensive university (based on the Carnegie classification as either a R1 or R2), only a third of respondents have beliefs in the correct range, with the rest being either mildly or widely overoptimistic. Being overly optimistic in turn correlates with stated preferences for doing a postdoc and academic careers more generally.

Interestingly, respondents were more optimistic about their peers' chances of obtaining a tenure-track position in a research-intensive university than about their own chances. Similar to

[3] As a pilot for a future study, another random subsample received a message with a link to a webpage from the American Chemical Society (ACS), the main professional society for chemists, listing profiles with photos and career information about professional scientists in academic, industry, and government positions (role model treatment). This treatment provides less-structured information about both the academic and nonacademic labor markets, particularly through role models who work in nonacademic sectors, with whom students would have little exposure to during their studies. Such role model interventions through various media types have been shown to impact behavior in a variety of settings, including among STEM students (e.g., La Ferrara 2016; Porter and Serra 2020).

Sauermann and Roach (2016), who show that graduate students in older cohorts are less likely to plan on doing a postdoc and are less interested in academic careers, we find that students further along in their programs are less likely to hold overoptimistic beliefs about their chances on the academic job market. Foreign students were more likely to hold overoptimistic beliefs. Female students were more optimistic than male students about the prospects of their peers, but not about their own chances of becoming faculty.

Turning to the experiment, we estimate the causal impact of the information intervention on beliefs and preferences for different careers one year later. We find that the historical information treatment led to a downward adjustment in beliefs about respondents' own chances of becoming faculty, particularly among those who had more optimistic initial beliefs. Yet, we observe no significant impact of the information on beliefs about the share of graduates from their program eventually becoming faculty.

For other outcomes, we do not observe an effect of the historical information treatment on satisfaction with pursuing a PhD, but we find that it did lead to an increase in the perceived attractiveness of an academic career. To the extent that the historical placement information made respondents realize that becoming a faculty member is more difficult than they expected, this may have reinforced the perceived attractiveness of academic careers.

We also examine longer-run outcomes by collecting data on actual placements for the subsample of chemistry students who completed their PhDs after the baseline survey four years later. For this sample, we do not see any significant effects in their actual career choices, including doing a postdoc after the PhD.

In sum, we find that the beliefs of chemistry PhD students are often biased, and providing historically accurate information leads to an adjustment in beliefs, especially among those who initially had higher beliefs. Yet, these changes in beliefs lead to limited changes in career aspirations in the longer run, and we do not detect impacts on actual career outcomes. Taken together, these results provide further questions about the role of information in postgraduate human capital investments.

There are several possible reasons for the limited estimated effects on stated career aspirations and actual outcomes. First, it could be that other preferences known to drive scientists' behavior (e.g., puzzle-solving nature of doing science or prestige) are already quite strong at this point in training, so that there was minimal impact of the information on actual career preferences and choices. Second, given the sequential nature of educational choices, and that these are individuals who are already far along in their training trajectory with little option value, switching costs may be high (Stange 2012). Third, the experience of going through postdoctoral training may be enjoyable in itself or may be desirable for visa or dual-career considerations. Finally, postdoctoral training is still valued in many industry and government positions.

While we cannot differentiate between these explanations in the current study, our findings nonetheless suggest that there is a strong rationale for departments to provide better career information, about both academic and nonacademic careers, to prospective and actual students, and there seems to be demand for such information (Sauermann and Roach 2016). Providing better information would ensure that the choices are made with full knowledge of what they imply, and the costs of collecting and sharing information on placements are low.

In addition to these implications for the postgraduate labor market, this paper contributes to the growing literature on biased beliefs and overconfidence. The prevalence and implications of biased beliefs and overconfidence has been documented across many domains (Malmendier and Taylor 2015), such as labor supply (Mueller, Spinnewijn, and Topa 2018), the housing market

(Armona, Fuster, and Zafar 2019), risky behavior (Dupas 2011) and returns to schooling (Bleemer and Zafar 2018; Loyalka et al. 2013; Wiswall and Zafar 2015). Notably, ours is the first study that investigates the existence of biased beliefs in the educational choice to pursue postgraduate studies, postdoctoral studies in particular, and estimates how these beliefs are impacted by the provision of objective information about the labor market.

The paper proceeds as follows. The following section explains the institutional context. The third section describes the data and experimental design. The fourth section presents the results, and we end with the discussion in the final section.

INSTITUTIONAL CONTEXT

In this section, we discuss entry into scientific careers with a specific focus on chemistry and academic careers in the United States. The entry into scientific careers is characterized by long periods of training. A PhD degree typically takes six years and is often followed by one or several postdocs.[4] The chemical and pharmaceutical industries, as well as the government, are major employers of chemistry PhD graduates, and graduates can enter into industry positions before or after postdoctoral training. Despite these human capital investments into becoming a professional researcher, many doctoral degree holders employed in industry do not actually conduct research in their jobs (Lautz et al. 2018).

A necessary condition for becoming a tenure-track professor in chemistry at a research-intensive U.S. university is earning a doctoral degree. However, in chemistry and other natural sciences, postdoctoral training has become de facto an additional prerequisite, with direct

[4] In the extreme case, a small but significant proportion of postdocs end up as “permadocs,” doing several subsequent postdoctoral trainings without ever advancing to another level (Powell 2015).

transitions from obtaining a PhD degree to a tenure-track position essentially unheard of. In other words, postdoctoral training is crucial for being competitive for faculty positions. As a postdoc, junior scientists build their publication portfolios, apply for grants, and gain additional scientific and professional skills. Yet, the vast majority of postdocs do not become tenure-track faculty members. Around a third of chemistry graduate students pursue postdocs, but less than 10 percent of graduating students are in a tenure-track position in a research-intensive U.S university five years after graduation (Gaulé and Piacentini 2018). Such low odds have been documented in other disciplines and countries (Stephan 2012b). Apart from doing a postdoc, alternative career options for chemistry PhD graduates include various types of industry careers or becoming a teaching-track faculty, which do not require a postdoc. Teaching-track positions may be tenure-track at teaching-focused colleges or non-tenure track at research universities.

Postdocs receive comparatively low levels of compensation during their postdoctoral training. For example, postdocs receive on average a 31 percent lower hourly wage than an average U.S. worker regardless of the education level (Stephan 2013). The opportunity cost of choosing a three-year postdoc instead of working in industry was estimated to be around $60,000 in 2012 (Stephan 2012a). Kahn and Ginther (2017) find that in biomedicine, compared with peers who started working outside academia immediately after finishing their graduate studies, those who finish a postdoc earn less when they actually start to work. They also find that postdocs forgo about one-fifth of their earnings potential in the first 15 years after finishing their doctorates, which amounts to more than $200,000.

While information on career prospects for scientists is often available from professional associations and other sources, departments generally provide relatively little career information to prospective and current graduate students. Prior to the launch of this study, we visited the websites of 56 chemistry departments in our sampling frame (see Appendix B) looking for their graduate degree holders' placement information. For 70 percent of departments, we could find no placement information at all. The remainder typically provided examples of institutions that have hired their graduates or aggregate data on placement by broad industry categories. One notable exception was the Princeton chemistry department, which provided lists of graduates and their placements at the conclusion of PhD. See Appendix C for more details on placement information available from departmental websites.

DATA AND EXPERIMENTAL DESIGN

We combine two surveys of chemistry graduate students with a field experiment, linked to the data on individual publications and career choices. The surveys provide rich descriptive data on respondents' beliefs and aspirations and how they evolve over time. To overcome potential hypothetical bias, we combine the data on hypothetical job preferences with real job preferences from hand-collected placement data of the survey respondents who finished their PhDs after the baseline survey. We also leverage data from faculty directories, PhD theses, and publications from an ongoing project on the production of knowledge in chemistry (see Catalini, Fons-Rosen, and Gaulé, 2020; Gaulé 2014; Gaulé and Piacentini 2018). Our research design and data collection approach is summarized in Figure 1.

(Insert Figure 1 about here)

Our analysis and intervention is based primarily on a survey we conducted in fall 2017 (hereafter *baseline survey*) and a follow-up survey one-year later. To construct the sampling frame, we first identified the set of 54 research-intensive U.S. universities that rank highest in the Academic Ranking of World Universities (Shanghai Ranking) in its chemistry subject ranking.

These schools have large PhD programs, and their students are presumably comparatively better placed for the academic job market. We gathered the names and emails of all individuals (n=9,141) that were listed as graduate students in the chemistry departments of these universities, either on graduate student directory websites or on individual laboratory websites. We then sent them email invititations to complete a survey using the Qualtrics online survey platform.[5]

We received a total of 1,330 responses corresponding to a response rate of 15 percent.[6] The baseline survey included a set of basic demographic questions, as well as questions on undergraduate education, year of enrollment in the PhD program, progress in the PhD program, and field of specialization. We asked about career preferences using both standard Likert-scale measures and counterfactual choice questions. Regarding beliefs, we asked respondents to rate their chances of publishing in *Nature*, *Science*, or *Cell*—the most prestigious science journals—to rate their chances of becoming a tenure-track faculty in a research-intensive university, and the share of students in their program they believe eventually become tenure-track faculty in a research-intensive university (see Appendix D for the exact survey questions). Finally, we asked respondents whether they would agree to be contacted in a follow up survey and if so to provide us with a permanent email address that we could use for future contact. Table A.1 in Appendix A shows means and standard deviations for several key variables from the baseline survey.

We combined the baseline survey with an information provision experiment. After completing the baseline survey, respondents were randomly selected into the treatment group or

[5] To increase the response rate, we sent two reminder emails and offered a lottery with possibility of winning one of 10 Amazon gift certificates worth $100 each. The choice of using this type of lottery was informed by Sauermann and Rauch (2013).

[6] One issue we encountered was that some of the individuals we contacted reported having already graduated, presumably reflecting the fact that some online directories and websites were not entirely up to date. We excluded such responses from our analysis sample. Adjusted for the presence of students who already graduated among the people we contacted, our response rate was around 18 percent.

one control group. The treatment groups received one of the two versions of a thank-you message via email with information related to the labor market, while the control group received no message at all. The randomization procedure was block randomization, where we stratified respondents' institutions based on a department's Shanghai Ranking. Note that for a subset of universities, we further did an individual-level randomization in a subset of universities as a pilot for another study on role models (see Figure 1).

To carry out the randomization, we created triads of departments of similar ranks, and within each triad assigned one department to the information treatment, one to the control, and one to individual randomization. Thus, one university of three in the block was randomly chosen as the historical information treatment group, so that all respondents to the baseline survey at this university received the first message with historical placement rate information. For the second university, respondents were in the control group. In the final university, survey respondents were individually randomized into one of the three groups (historical information, role model, or control). An advantage of this design is that for the historical information treatment, we have both individuals whose peers were also treated, and individuals whose peers were not treated. This randomization design was intended to enable us to measure potential spillovers from the treatment, if the treated individuals share information with their peers. However, sample size limitations prevent us from fully leveraging this aspect of the randomization.

Thus, survey respondents were assigned to one of the following three groups:

1) Historical information treatment group: Students received the email linking to the historical information on graduates' placement, along with all other survey respondents from the same university receiving the same link.

2) Control group: Students did not receive any email along with other survey respondents from the same university not receiving any email.

3) Individual randomization group (pilot): Within this group, some students randomly received the received the email linking to the historical information on graduates' placement, some students received the email linking to the ACS profiles website, and some students did not receive any email.

We use only the first and the second group only in this analysis. The second group—those who did not receive any email in the block-randomized university—as the control group and the omitted category in all specifications.[7] Our variables of interest are indicator variables for the historical information treatment group, and we present specifications both with and without controls.

The group receiving the historical information treatment message linked to a custom-built website providing information on historical actual academic placement rates by graduate institution in a tabular format.[8] These placement rates were well below 10 percent for all institutions so the information communicated was mainly an update on the difficulty of becoming a tenure-track faculty in a research department.[9]

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[7] We also estimate the treatment effects of the historical placement information when pooling the block-randomized and individually randomized groups. See Table A.5.

[8] The historical placement records were based on previously collected data from Proquest Dissertations and Abstracts and the ACS directory of graduate research (Gaulé and Piacentini 2018). Specifically, we collected data on students graduating from U.S. chemistry graduate programs between 2008 and 2010 and matched their names to a 2015 list of chemistry faculty in research-intensive universities. We then computed the share of graduating students who had become faculty by 2015, by graduating department. For more details, see Appendix E. We published this data, together with a detailed explanation how the data was constructed on the custom-built website https://chemistryplacementdata.com/. The website was not advertised in any way. Web analytics confirm that the overwhelming majority of visits to the website originated from the survey emails.

[9] The second message linked to information about nonacademic careers (role model treatment), in the form of a real webpage from the ACS called "Chemists in the Real World." This was a pilot for another study.

Not all respondents clicked on the link embedded in the message. Note that we expected that some respondents may not want to acquire the information, and thus wanted to give them a choice about whether they viewed the information. While we did not track individual clicks, we estimated that a lower bound of 35 percent of survey respondents in the historical information treatment group who received the link visited the custom-built website, versus around 1 percent of respondents in the control group (see Appendix G for details about measurement of visits to the historical placement information website). While only a subset of treated individuals acquired the information, we nonetheless find that the treatment (being offered the link) changed subsequent beliefs.

In order to measure the impact of the intervention on respondents' beliefs and plans, we contacted our respondents again roughly one year after the baseline survey and asked them to complete a follow-up survey.[10] In the follow-up survey we repeated several questions from the baseline survey. We again incentivized responses by sending two reminder emails and offering a lottery to win a $100 Amazon gift certificate upon completing the survey. We obtained 500 complete responses from the entire sample of the baseline survey, roughly 38 percent of the initial survey respondents. In this analysis of the block-randomized historical information treatment group vs. block-randomized control group only, we will analyze 347 responses. In our analysis of the baseline beliefs, we will show results for both the full 1,330 respondents to the baseline survey and show the beliefs for the 347 who were in the block-randomized treatment and control group who responded to both surveys in the Appendix.

Table A.2 in Appendix A reports means and standard deviations for several variables from the follow-up survey. We complemented the follow-up survey with hand-collected information on

[10] We excluded those who indicated in the first survey not to be contacted again.

the current position of baseline survey respondents who were expected to graduate, such as whether they were doing a postdoc or working in industry for descriptive statistics, see Table A.3 in Appendix A). This information was collected in the summer of 2019 and 2021, roughly two to four years after the baseline survey. We collected this information irrespective of whether individuals answered the second survey but only for students who were expecting to graduate in 2017-2020 at the time when they were filling in the baseline survey.

Table A.4 shows differences in the characteristics of respondents to our follow-up survey to those who completed the baseline survey only. We see some differences in observable characteristics, as students from higher-ranked programs, foreign students, and students further along in the program were less likely to respond to the follow-up compared to those earlier in the program. We estimate all regressions including these controls. Importantly, we do not see differential attrition in the treatment group receiving the historical placement information treatment and for the actual outcomes collected, we have information for all baseline survey respondents, and therefore attrition is not a concern for those outcomes.

RESULTS

Prevalence of Biased Beliefs

Do graduate students know how difficult it is to publish in the most prestigious scientific journals, and to become a tenure-track faculty member in a research-intensive university? Are individuals overconfident about their own ability; in particular, do they overestimate their position in the ability distribution?

One way we measure biased beliefs is by eliciting respondents' beliefs about their chances of publishing as a first author in *Nature*, *Science*, or *Cell* before the end of their PhDs. When testing the survey, we had been warned that this is a very rare event. Indeed, only 1 in 200 chemistry PhD students reaches this milestone.[11] A group of 1,301 students would thus be expected to collectively generate six or seven first-authored *Nature*, *Science*, or *Cell* publications. Yet, by aggregating the beliefs of the respondents, we find that they expect to collectively produce 310 first-authored *Nature*, *Science*, or *Cell* publications. Figure 2 plots the distribution of the respondents' beliefs about their chances of publishing in *Nature*, *Science*, or *Cell* by the end of their PhD studies.

(Insert Figure 2 about here)

We also asked respondents to rate their own chances of becoming a tenure-track faculty member in a research-intensive U.S. university. The distribution of those beliefs is displayed in Figure 3.[12] In recent years, the share of chemistry PhD students becoming tenure-track faculty members in a research-intensive university was around 5 percent. For instance, in 2016, a listing of chemistry faculty openings listed 152 tenure-track positions in research-intensive U.S. universities while 2,700 students graduated in this same year.[13] Our own calculations, which are based on matching names from comprehensive lists of PhD graduates and faculty members in chemistry departments, suggest a similar rate. Again, the respondents collectively display optimistic beliefs although to a lesser degree than for *Nature/Science/Cell* publications. Specifically, if all the beliefs of the respondents were correct, 320 students in our sample would

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[11] Authors' calculations based on chemistry PhD graduates listed in Proquest and *Nature/Science/Cell* bibliometric data.

[12] This is for the full sample of baseline survey respondents but those who were in the block randomized historical information treatment and block-randomized control group had similar baseline beliefs, as shown in Appendix Figure A1.

[13] Note that the graduating PhD students would hardly ever place straight into tenure-track faculty in a research-intensive university and that the faculty openings would typically be filled with individuals having graduated 2-4 years previously. By research-intensive universities, we mean universities classified either as R1 or R2 in the Carnegie classification, which also closely match the set of universities with a doctoral program in chemistry. There are more than 200 research-intensivesuch universities in the United States. Besides being relatively easy to measure, placements in research-intensive universities are precisely those that junior scholars aspiring to an academic career with a focus on research would target. The figure of 152 openings is based on the results of a community effort to help applicants by identifying all relevant positions (see http://chemjobber.blogspot.com/).

become tenure-track faculty members in a research-intensive university, while only 66 of them would actually become faculty in Chemistry departments based on historical averages.

We also asked respondents about their *peer* beliefs—their beliefs on what share of PhD students in their programs eventually become tenure-track faculty members in a research-intensive university. By asking about others in their program, we focus on information regarding the state of market. By contrast, the beliefs about the own chance to become faculty also incorporates beliefs about one's own ability as well as preferences for the academic career.

(Insert Figures 3 and 4 about here)

The distribution of beliefs about the share of peers becoming faculty in research-intensive universities is displayed in Figure 4. Interestingly, the mean beliefs about the share of students becoming faculty (24.5 percent) are actually slightly higher than the mean beliefs about the own chance to become faculty (24 percent).[14] So, what looked like an above-average effect might be incorrect beliefs about the market as a whole. While there was some variation across programs, no program had a share higher than 10 percent in the historic placement data. Slightly less than 30 percent of the respondents answered between 0 and 10 percent, and thus essentially had correct beliefs about the state of the market. A further 25 percent of respondents were mildly optimistic, answering that between 11 percent and 20 percent of peers will become faculty. The remainder—45 percent of respondents—were wildly optimistic with answers far above the observed average.

In summary, these descriptive statistics suggest that overoptimistic beliefs about publishing and placement are widespread among graduate students. However, we also observe heterogeneity in beliefs, with some individuals having correct beliefs, and others being biased to various extents.

[14] As discussed earlier, both aggregate evidence and historical placement data suggest that this share is around 5 percent.

Who holds optimistic beliefs?

We now explore descriptively whether the heterogeneity in beliefs can be related to observable characteristics. For this, we regress each of the three types of beliefs on student gender, foreign status, time since enrollment in the program, and a dummy variable for top-10 program (based on the Shanghai Ranking).

(Insert Table 1 about here)

Table 1 displays the results. Foreign students are considerably more optimistic about publishing and placement (Table 1, columns 1 and 2). Foreign students may be higher ability on average due to a tougher selection to get into U.S. PhD programs (Gaulé and Piacentini 2013). However, they also seem to be less informed about the tightness of the U.S. academic market (Table 1, column 3). Perhaps surprisingly, studying at a top-10 school is not associated with more optimistic beliefs.

While the literature has documented gender differences in overconfidence (e.g., Murciano-Goroff 2019; Niederle and Vesterlund 2007), we notably find few gender differences in beliefs in our sample. We find that female and male students are equally likely to hold optimistic beliefs about their chances to publish in *Nature*, *Science*, or *Cell*. Female students are slightly more optimistic about the aggregate state of the academic market, that is, their peers' chances of getting a tenure track job in a research-intensive university (see Figures A.2), but we observe no gender differences in beliefs about one's own chances. However, for the same level of beliefs about their peers, men tend to have higher beliefs about their own changes (see Figure A.3).

Time since enrollment in the PhD program is a strong predictor of holding optimistic beliefs: Students in their first or second year of study are the most optimistic, though there is no statistical difference between students in their third and subsequent years. The results are consistent with Stephan and Ma (2005), Sauermann and Roach (2012, 2016), Sauermann and Roach, and Gibbs, McGready, and Griffin (2015).

(Insert Table 2 about here)

We also investigate whether holding optimistic beliefs about the share of students becoming faculty is associated with preferences for academic careers (see Table 2). We measure these preferences by asking how likely respondents are to do a postdoc or to choose a prestigious postdoc vs. an industry research job or a teaching position in a hypothetical choice question.[15] We find that respondents' beliefs about the share of students becoming faculty is strongly correlated with preferences for continuing an academic path. This holds despite the fact that we are controlling for key observable correlates of holding optimistic beliefs, such as being a foreign student or being in the first or second year of study.

As discussed earlier, in this discipline, moving straight from doctoral studies to tenure-track positions in research intensive universities is virtually impossible. However, by choosing postdoctoral training, a scientist keeps open the possibility of subsequently landing a tenure-track faculty position, a job that she often perceives to be highly desirable. The option to access this career path, while uncertain and risky, is part of the returns to doing a postdoc. Students who underestimate how difficult it is to obtain a tenure-track faculty position in a research-intensive university should thus be expected to find the postdoctoral option more attractive, which is exactly what we find.

However, as in previous studies that have documented overoptimism among scientists (e.g., Sauermann and Roach 2016), these results are descriptive in nature. We cannot rule out that

[15] See Appendix D for wording of question.

students who have optimistic or biased beliefs may also have other characteristics that drive preferences for doing a postdoc. It is thus unclear whether exogenously inducing updates in the beliefs could lead to changes in career preferences. The next section describes the results of the intervention where we provided information to a random sample of the baseline survey respondents, and then followed up with them one year later.

Effects of the Information Treatment

We first consider the effect of the intervention on beliefs using the sample of students who answered both the initial and final survey one year later. As in the descriptive analysis, we observe two types of beliefs: the beliefs about peers (which share of students in their program become faculty) and the self-beliefs (own chance of becoming faculty). Since we asked the exact same questions on beliefs in the initial and final surveys, we can track the evolution of beliefs over time and whether they were impacted by the treatment.

(Insert Table 3 and Table 4 about here)

Figures 5 and 6 and Tables 3a and 3b show the effect of the information treatment on the changes in beliefs between the two surveys (final minus initial beliefs). Note that the mean change in either type of beliefs is negative, suggesting that students become more pessimistic over time. The point estimates for the effect of information on beliefs about the share of peers becoming faculty are small and statistically insignificant (Table 3a). However, the information treatment had a statistically significant effect on the changes in beliefs on own chances of becoming faculty, where receiving the information lowered beliefs about one's own changes of getting a tenure track faculty position by approximately 3.8 percentage points (see Table 3b). The effect is similar in magnitude to the mean of the dependent variable, suggesting that individuals who received the information became less optimistic about their chances to become faculty members at a faster rate than those who did not.

It is puzzling that we find an effect of the information intervention on self-beliefs but not on beliefs about peers. Prior to the intervention, we had expected that the intervention might impact both types of beliefs and that, if anything, the effect might be weaker for the beliefs of one's own chances.

We next examine whether there was differential response to the treatments in who updated their beliefs. Figure 7 shows that those with higher initial self-beliefs (those who are most optimistic regarding their own chances of becoming faculty) were more likely to update their beliefs in response to the historical information treatment. Table 4 shows this in a regression, where we include interactions with the information treatment dummy with dummies for quintiles of the baseline beliefs measures. We find that the greatest declines are among those with the highest quintiles of baseline beliefs for both types of beliefs (self and peer), i.e. those for whom initial beliefs were most biased.

In Table A.5 we estimate heterogeneity in response to the treatment by our main covariates: gender, foreign status, and a dummy variable for a top-10 program. Here we see that there are no significant differences in the interaction terms.

Now that we have established that the information treatment did impact beliefs about one's own chances of becoming faculty, we proceed to investigate whether the information interventions impacted career preferences and actual career choices. For the latter, we can also include baseline survey respondents who did not complete the final survey, as we code career choices using publicly available information. Given that the historical placement information intervention led to a downward adjustment in the beliefs of their own chance of becoming faculty, we would expect postdocs to become less desirable in the treatment group (relative to the controls), and fewer people actually choosing postdocs. However, as Tables 5 shows, we find no effect of the historical placement information intervention on preferences for doing a postdoc or actually taking up a postdoc position after graduation.[16]

(Insert Table 5 and 6)

Finally, we consider the effect of the interventions on additional outcomes: satisfaction with the PhD as a career choice and perceived attractiveness of a faculty position and a government research and development position. Surprisingly, we do not see an effect of the information treatment on satisfaction with pursuing a PhD as a career choice (Table 6a). However, the information treatment did significantly increase the perceived attractiveness of an academic faculty position (Table 7b). To the extent that the historical placement information made respondents realize that becoming a faculty member is more difficult than they expected, this may have counterintuitively reinforced the perceived attractiveness of academic careers.

DISCUSSION

This paper studies the beliefs of science PhD students regarding the academic job market and how these beliefs impact their preferences for different types of careers and their decisions upon graduating using a novel survey of chemistry graduate students combined with arandomized information intervention. While we focus on chemistry, other STEM fields such as biology and physics share many of the same institutional features, including limited faculty opening and a high prevalence of postdocs.

[16] This finding echoes Sauermann and Roach (2016), who find in a descriptive analysis no systematic evidence of a relationship between perceived demand for jobs in academia and the choice of postdoctoral training.

We find considerable evidence that graduate students are excessively optimistic regarding the state of academic job market, their chances to become faculty, and their chances to publish in the very best scientific journals. Students early in the program, as well as foreign students, are more likely to hold excessively optimistic beliefs. Holding such beliefs is in turn associated with intentions to engage in postdoctoral training after the PhD.

Providing information on historical placement rates appears to influence beliefs one year later, with treated individuals adjusting their perceived chances of becoming faculty members. We find that the greatest declines are among those respondents for whom initial beliefs (both for peers and themselves) were most biased. We also find evidence that the historical information treatment led to an increase in the perceived attractiveness of faculty positions. However, we do not observe effects on satisfaction with choosing the PhD as a career choice, nor do we see an effect of the interventions on actual career choices two to four years after the PhD (for a subsample of respondents who had graduated).

Taken together, these results provide further questions about the role of information in postgraduate human capital investments. On the one hand, the beliefs of graduate students are often biased, and providing historically accurate information leads to an adjustment in beliefs, especially among those who initially had higher beliefs. On the other hand, the change in beliefs we induced experimentally lead to limited changes in career preferences and aspirations, and we do not detect impacts on actual career outcomes.

There are several possible reasons for the limited effects on stated career aspirations and actual outcomes. The experience of going through postdoctoral training may be enjoyable in itself or may be desirable for visa or dual-career considerations. Moreover, postdoctoral training is still valued in many industry and government positions. Finally, it could be that other preferences known to drive scientists' behavior (e.g., prestige or the puzzle-solving nature of practicing science) are already quite strong at this point in training, so there was minimal impact of the information on actual career preferences and choices. Moreover, given the sequential nature of educational choices, and that these are individuals who are already far along in their training trajectory, switching costs may be high. It would be interesting for future research to explore how *prospective* graduate students may respond to information about the careers of PhD-holders.

Another reason may be due to the types of information we provided. Perhaps an intervention impacting beliefs more strongly would lead to observable changes in actions. Only 35 percent of individuals who received the link to the historical information treatment actually acquired the information. While this did cause beliefs to change on average, we may have seen larger impacts if more individuals acquired the information. Additionally, our sample size was relatively limited, and having more statistical power would have allowed us to test for further heterogeneity in which types of students responded more or less to the information.

While we cannot differentiate between these explanations in the current study, our findings nonetheless suggest that there is a strong rationale for departments to provide better career information, about both academic and nonacademic careers, to prospective and actual students.

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Tables and Figures

Figure 1. Experimental Design

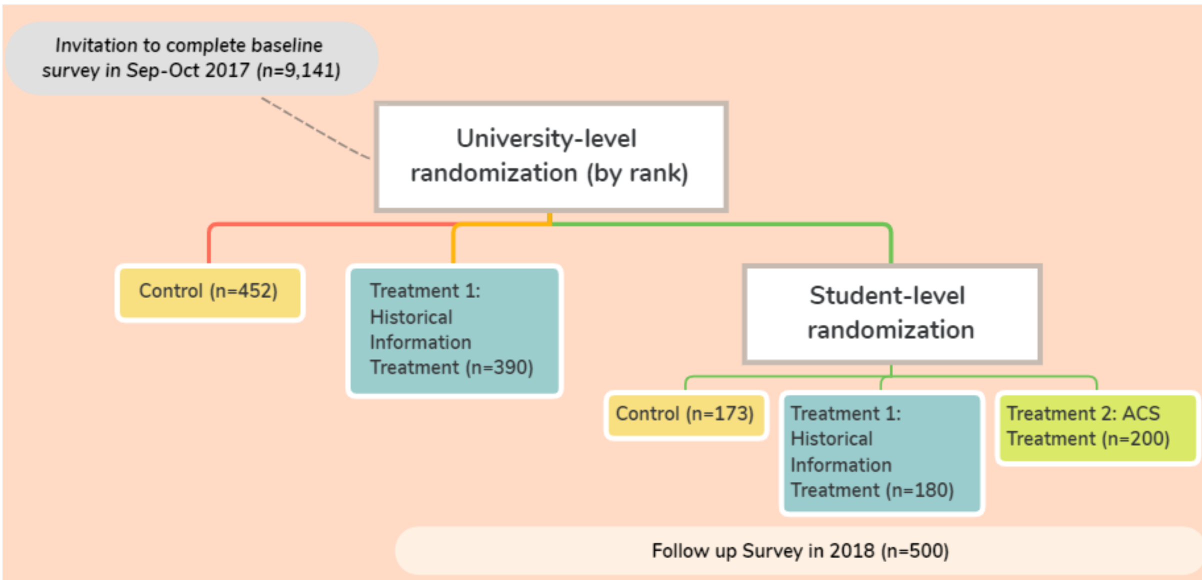


Figure 2. Respondents' Beliefs about Their Own Chance to Publish in *Nature*, *Science*, or *Cell*

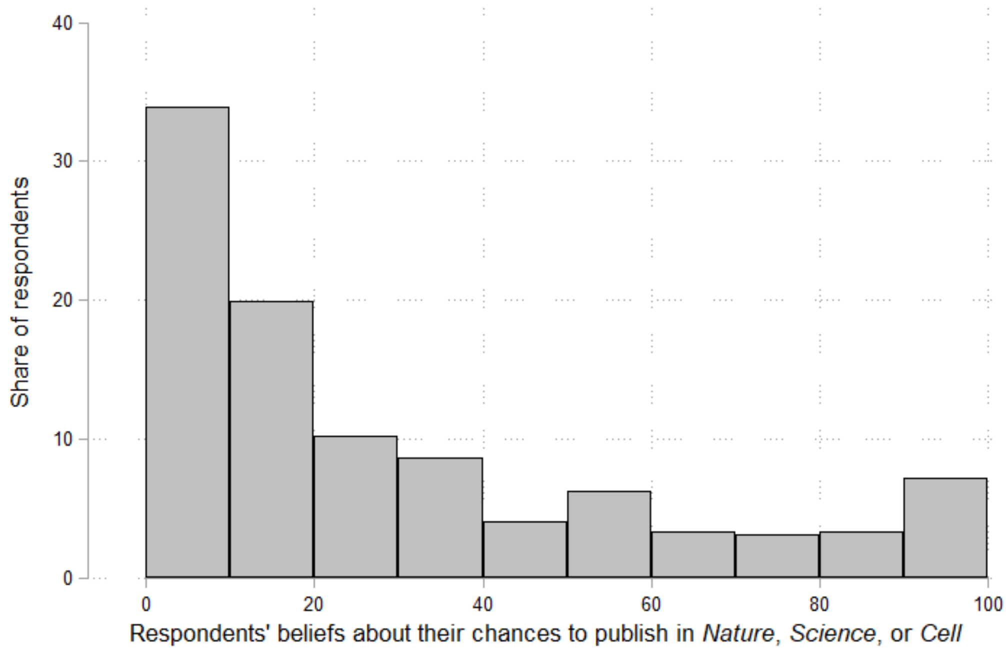
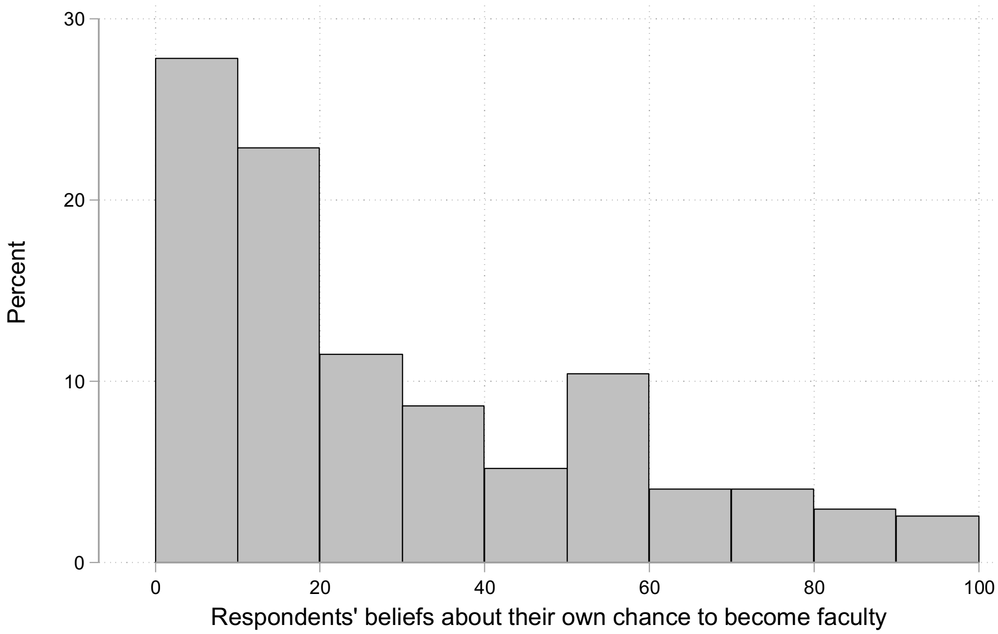
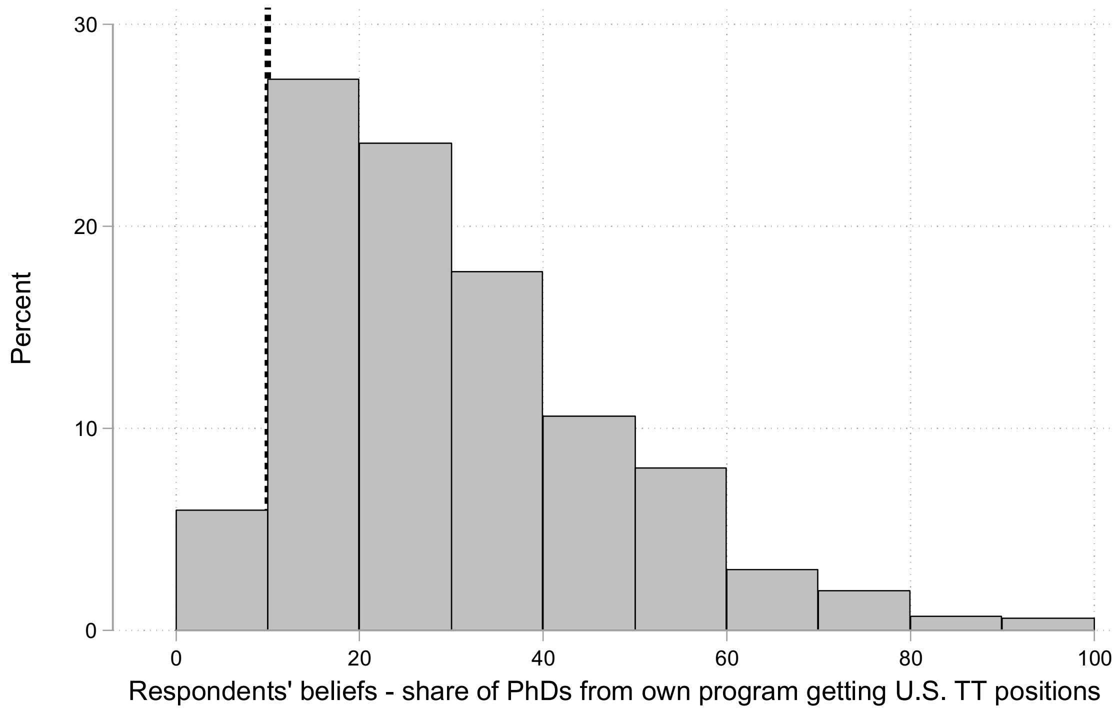


Figure 3. Respondents' Beliefs about Their Own Chance of Becoming Tenure Track Faculty



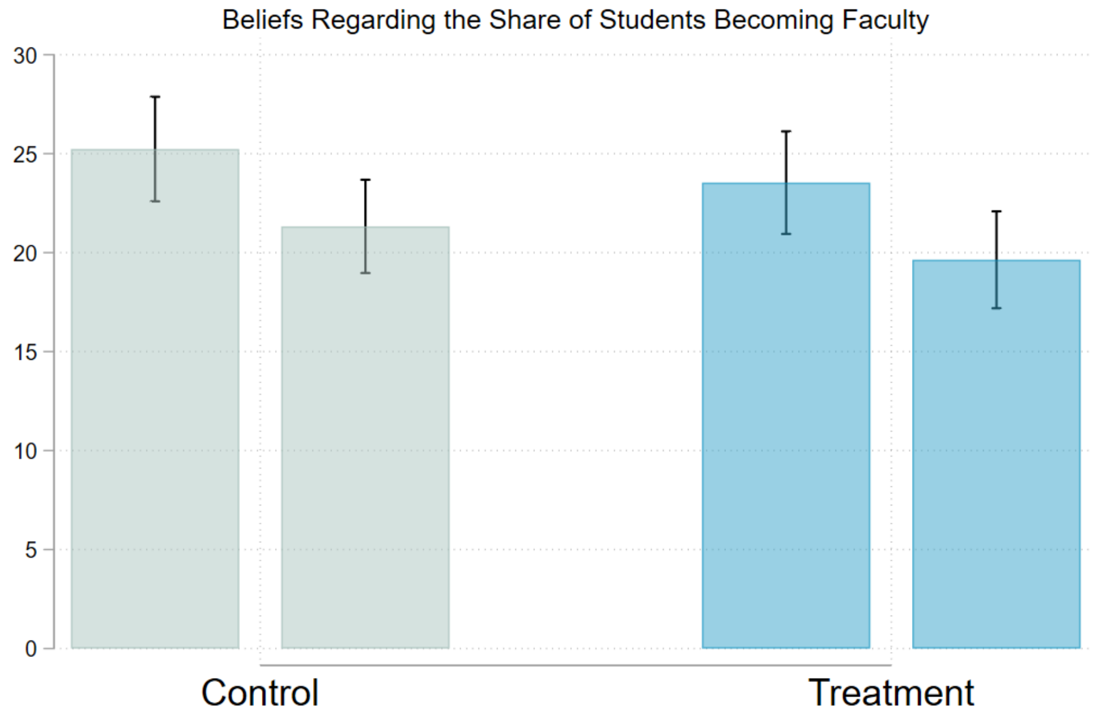
Notes: Beliefs about own chance of becoming tenure track faculty in a research-intensive university.

Figure 4. Respondents' Beliefs about the Share of PhD Graduates from Their Program Becoming Faculty



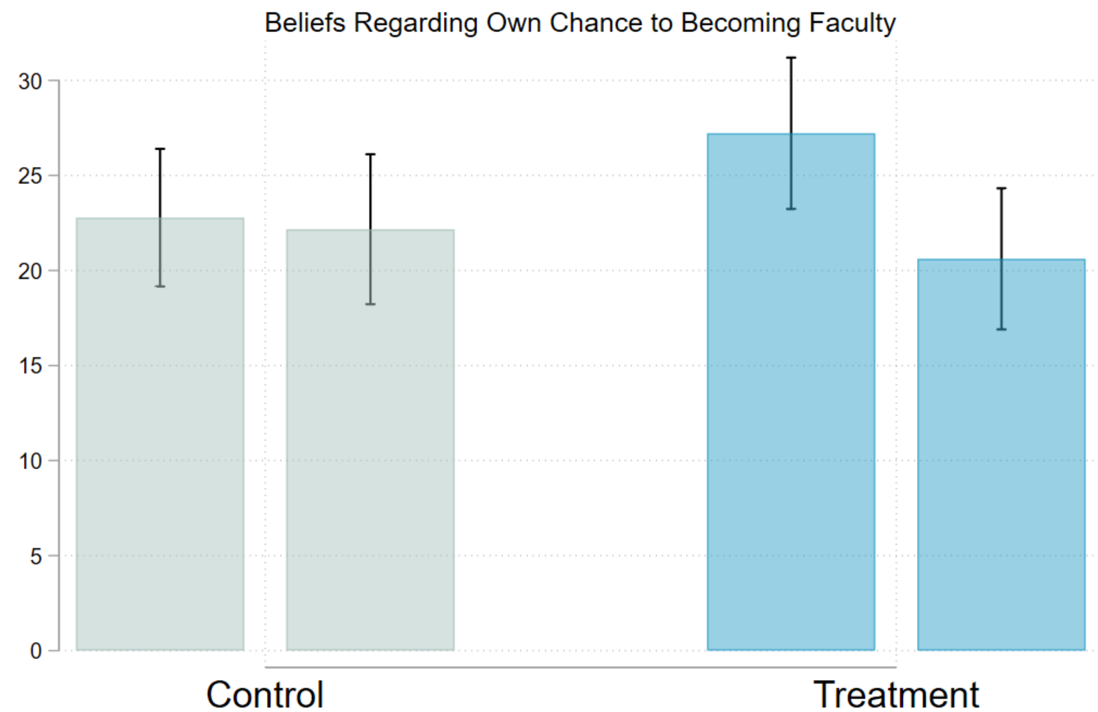
Notes: Beliefs about share of peers becoming tenure track faculty in a research-intensive university.

Figure 5. Beliefs Regarding the Share of Students Becoming Faculty



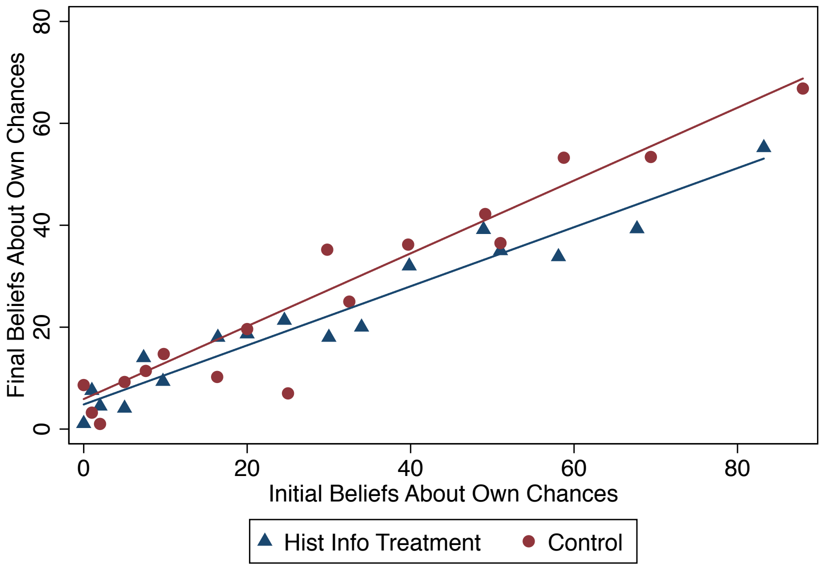
Notes: Within each group, the bar on the left denotes the mean belief before intervention, and the bar on the right the mean belief after intervention.

Figure 6. Beliefs Regarding Own Chance to Become Faculty



Notes: Within each group, the bar on the left denotes the mean belief before intervention, and the bar on the right the mean belief after intervention.

Figure 7. Initial vs. Posttreatment Beliefs



Notes: Beliefs about own chances to become tenure-track faculty in a research-intensive university.

Table 1. Who Holds Overoptimistic Beliefs?

	(1)	(2)	(3)
	D.V.= Respondents' beliefs		
	Own chance to publish in *Nature*/*Science*/*Cell*	Own chance of becoming TT faculty	Percentage of students becoming TT faculty
Female	0.359	−1.155	2.396**
	(1.616)	(1.380)	(0.971)
Foreign student	9.400***	8.343***	3.798***
	(1.914)	(1.587)	(1.120)
Top-10 school	−1.897	−2.625	−1.349
	(1.969)	(1.679)	(1.181)
First-year student	17.753***	9.789***	7.355***
	(2.233)	(1.890)	(1.331)
Second-year student	9.512***	6.713***	4.558***
	(2.152)	(1.829)	(1.287)
Third-year student	0.767	1.522	1.414
	(2.200)	(1.874)	(1.319)
Obs.	1,301	1,333	1,330
Mean of D.V.	24.907	23.953	24.472
R2	0.073	0.048	0.039

NOTE: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.The dependent variables are the respondents' beliefs regarding (1) their chances to publish in *Nature*, *Science*, or *Cell* as a first author by the end of their PhD, (2) their chances to become tenure-track faculty in a research-intensive U.S. university, and (3) the percentage of students becoming become tenure-track faculty in a research-intensive U.S. university. All the beliefs are expressed on a scale from 0 to 100. The omitted category for time in the program is fourth year and above. Robust standard errors in parentheses.

Table 2. Optimistic Beliefs and Preferences for Academia

	(1) D.V.= Likelihood of doing a postdoc	(2) D.V.= Choosing postdoc among three options
Respondents' beliefs—share of students becoming faculty	0.205***	0.086**
	(0.050)	(0.038)
Female	−2.102	−2.559*
	(1.743)	(1.350)
Foreign student	12.085***	10.575***
	(2.012)	(1.586)
Top-10 school	−1.219	1.747
	(2.139)	(1.640)
First-year student	6.000**	5.779***
	(2.401)	(1.878)
Second-year student	3.566	3.599**
	(2.298)	(1.801)
Third-year student	1.897	−1.419
	(2.383)	(1.832)
Obs.	1271	1312
Mean of D.V.	54.155	25.524
R2	0.055	0.056

NOTE: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
The dependent variables are (1) the likelihood of doing a postdoc as reported in the baseline survey (percentage out of one hundred), and (2) the likelihood (out of 100) of choosing the postdoc when offered a counterfactual choice between a postdoc, research position in industry, or a teaching position (see Appendix D). The variable of interest is the respondents' beliefs on the share of students becoming faculty (also out of 100). The omitted category for time in the program is fourth year and above. Robust standard errors in parentheses.

Table 3a. Effect of Information on Beliefs of Share of Students Becoming Faculty

	(1)	(2)	(3)
	D.V.= Change in beliefs of the share of students becoming faculty		
Historical placement info treatment	0.008	0.615	-0.855
	(1.660)	(1.735)	(1.511)
Obs.	316	316	316
Controls	None	Demographics	Demographics + Initial beliefs
Mean of D.V.	−3.902	−3.902	−3.902
R2	0.000	0.026	0.307

Table 3b. Effect of Information on Beliefs of Own Chance of Becoming Faculty

	(1)	(2)	(3)
	D.V.= Changes in beliefs of own chance of becoming faculty		
Historical placement info treatment	-5.995^{***}	-4.977^{**}	-3.755^{**}
	(1.621)	(1.902)	(1.900)
Obs.	316	316	316
Controls	None	Demographics	Demographics + Initial beliefs
Mean of D.V.	−3.589	−3.589	−3.589
R2	0.020	0.091	0.255

NOTE: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. These regressions are run on the sample of survey respondents who answered both the initial and follow-up survey. For a, the dependent variable is the change in beliefs on the share of students becoming faculty (belief in the final survey minus belief in the initial survey). For b, the dependent variable is the change in beliefs on the respondents' own chance to become faculty (belief in the final survey minus belief in the initial survey). Specification (1) does not include any controls. Specification (2) includes controls for gender, foreign status, time in the program and university rank. In specification (3) we additionally control for the initial level of beliefs. Clustered standard errors in parentheses. The cluster is a group of two universities of similar rank which was used to stratify the block randomization.

Table 4. Heterogeneity: Effects of Information on Peer and Own Beliefs by Quintiles of Baseline Beliefs

	(1) Change in beliefs of the share of students becoming faculty	(2) Changes in beliefs of own chance to become faculty
Historical placement info treatment	2.681 (1.663)	-0.294 (3.625)
Historical placement info treatment × Initial beliefs quintile2	1.468 (4.947)	-3.627 (4.670)
Historical placement info treatment × Initial beliefs quintile3	-4.801 (4.058)	4.985 (5.112)
Historical placement info treatment × Initial beliefs quintile4	-3.241 (3.693)	-7.075 (7.396)
Historical placement info treatment × Initial beliefs quintile5	-14.157* (6.920)	-10.948* (5.736)
N	316	316
Controls	Demographics + Initial beliefs	Demographics + Initial beliefs
Mean of D.V.	−3.902	−3.589
R2	0.322	0.262

NOTE: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
These regressions are run on the sample of survey respondents who answered both the initial and follow-up survey. The coefficients are dummies for quintiles of the baseline beliefs interacted with the historical information treatment dummy (quintile 1 is omitted). Controls include gender, foreign status, time in the program and university rank. Clustered standard errors in parentheses. The cluster is a group of two universities of similar rank which was used to stratify the block randomization.

Table 5. Effect of Information on Postdoc Post-PhD

	(1)	(2)	(3)
	D.V.= Started a postdoc after PhD		
Historical placement info treatment	0.036 (0.042)	0.021 (0.048)	0.025 (0.047)
Obs.	455	455	455
Controls	None	Demographics	Demographics + Initial beliefs
Mean of D.V.	0.336	0.336	0.336
R2	0.001	0.019	0.091

NOTE: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. These regressions are run on the sample of survey respondents who as of September 2017 were expecting to graduate in 2017, 2018, 2019 and 2020, irrespective of whether they answered the final survey afterwards. The dependent variable is whether the person actually started a postdoc as determined by manual searches. Specification (1) does not include any controls. Specification (2) includes controls for gender, foreign status, time in the program and university rank. In specification (3) we additionally control for the initial level of beliefs. Clustered standard errors in parentheses. The cluster is a group of two universities of similar rank which was used to stratify the block randomization.

Table 6a. Effect of Information on Satisfaction with the PhD as a Career Choice

	(1)	(2)	(3)
	D.V.= Changes in satisfaction with the PhD as a career choice		
Historical placement info treatment	0.281	0.175	0.098
	(0.310)	(0.339)	(0.325)
N	313	313	313
Controls	None	Demographics	Demographics + Initial beliefs
Mean of D.V.	2.658	2.658	2.658
R2	0.003	0.044	0.087

Table 6b. Effect of Information on Perceived Attractiveness of Faculty Position

	(1)	(2)	(3)
	D.V.= Changes in the attractiveness of TT faculty positions		
Historical placement info treatment	0.237^{***}	0.275^{**}	0.292^{**}
	(0.077)	(0.112)	(0.113)
N	316	316	316
Mean of D.V.	−0.291	−0.291	−0.291
R2	0.012	0.052	0.065

NOTE: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. These regressions are run on the sample of survey respondents who answered both the initial and follow-up survey. For a, the dependent variable is the change in respondents' satisfaction with choosing a PhD as career track. For b, the dependent variable is the change in perceived attractiveness of tenure-track faculty positions in a research-intensive university (reported attractiveness in the final survey minus reported attractiveness in the initial survey). Attractiveness is measured on a 1–5 scale. Specification (1) does not include any controls. Specification (2) includes controls for gender, foreign status, time in the program and university rank. In specification (3) we additionally control for the initial level of beliefs regarding the own chance to become faculty. Clustered standard errors in parentheses. The cluster is a group of two universities of similar rank which was used to stratify the block randomization.

Appendix Tables and Figures

Appendix A: Descriptive Statistics and Covariate Balance

Table A.1. Descriptive Statistics on Baseline Survey Respondents (n=1,330)

	Mean	S.D.
Chances of publishing in *Nature*/*Science*/*Cell*	24.91	29.90
Chance of becoming TT faculty in a U.S. research-intensive university	24.47	17.76
Share of students becoming faculty in U.S. research-intensive university	23.95	25.38
Likelihood of doing a postdoc	54.13	31.32
Likelihood of choosing postdoc among three options	25.52	24.75
Female	0.42	0.49
Foreign	0.28	0.45
Top-10 school	0.20	0.40
Year in doctoral program		
First year	0.19	0.39
Second year	0.21	0.40
Third year	0.19	0.40
Field of study		
Analytical chemistry	0.11	0.32
Biological/biochemistry	0.18	0.38
Inorganic chemistry	0.16	0.37
Medical/clinical/pharmaceutical chemistry	0.01	0.12
Organic chemistry	0.18	0.38
Physical chemistry	0.16	0.36
Polymer chemistry	0.04	0.20
Theoretical/computational chemistry	0.07	0.25
Other	0.09	0.28
Obs.	1,330	

Table A.2. Descriptive Statistics on final survey respondents (n=316)

	Mean	S.D.
Change in beliefs on the share of students becoming faculty	−3.90	15.42
Changes in beliefs on own chance to become faculty	−3.59	21.04
Historical placement info treatment	0.50	0.50
Female	0.47	0.50
Foreign	0.18	0.39
Year in doctoral program		
First year	0.23	0.42
Second year	0.28	0.45
Third year	0.19	0.40
Field of study		
Analytical chemistry	0.12	0.32
Biological/biochemistry	0.18	0.38
Inorganic chemistry	0.16	0.37
Medical/clinical/pharmaceutical chemistry	0.02	0.12
Organic chemistry	0.19	0.38
Physical chemistry	0.17	0.38
Polymer chemistry	0.04	0.20
Theoretical/computational chemistry	0.06	0.24
Other	0.07	0.26
Obs.	316	

Table A.3. Descriptive Statistics on Sample with Actual Placement Data (n=455)

	Mean	S.D.
Started a postdoc	0.34	0.47
Change in beliefs on the share of students becoming faculty	0.29	0.45
Changes in beliefs on own chance to become faculty	0.16	0.36
Historical placement info treatment	0.54	0.50
Female	0.42	0.49
Foreign	0.28	0.45
Top-10 school	0.19	0.39
Year in doctoral program		
First year	0.20	0.40
Second year	0.20	0.40
Third year	0.19	0.39
Field of study		
Analytical chemistry	0.13	0.33
Biological/biochemistry	0.19	0.39
Inorganic chemistry	0.16	0.37
Medical/clinical/pharmaceutical chemistry	0.01	0.10
Organic chemistry	0.17	0.38
Physical chemistry	0.16	0.37
Polymer chemistry	0.04	0.19
Theoretical/computational chemistry	0.06	0.23
Other	0.09	0.28
Obs.	455	

Table A.4. Is There Differential Selection into the Follow-up Survey?

	(1) Responded follow-up survey	
Historical placement info treatment	−0.045	(0.035)
Foreign student	−0.133***	(0.040)
Female	0.038	(0.034)
Top-10 school	0.106**	(0.033)
First-year student	0.163***	(0.045)
Second-year student	0.228***	(0.035)
Third-year student	0.088	(0.060)
Field study		
Analytical chemistry	-0.066	(0.063)
Biological/biochemistry	-0.069	(0.056)
Inorganic chemistry	-0.042	(0.059)
Medical/clinical/pharmaceutical chemistry	0.115	(0.164)
Physical chemistry	-0.026	(0.059)
Polymer chemistry	−0.029	(0.097)
Theoretical/computational chemistry	-0.018	(0.081)
Other	−0.047	(0.052)
Constant	0.359***	(0.052)
Obs.	806	
Mean of D.V.	0.392	

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
The sample is restricted to block randomized recipients only.
Organic chemistry excluded.
Standard errors in parentheses.

Table A.5. Heterogeneity: Effects of the Interventions on Peer and Own Beliefs

	(1)	(2)	(3)	(4)	(5)	(6)
	Change in beliefs of the share of students becoming faculty			Changes in beliefs of own chance to become faculty		
Covariate →	**Female**	**Foreign**	**Top Univ.**	**Female**	**Foreign**	**Top Univ.**
Historical placement info treatment	0.396	-0.600	0.446	-5.622***	-3.779*	-2.029
	(2.063)	(1.464)	(1.269)	(1.803)	(1.827)	(3.211)
Historical placement info treatment × Covariate	-2.652	-1.389	-1.581	3.926	0.135	-2.089
	(3.250)	(4.029)	(2.068)	(3.156)	(6.068)	(2.967)
N	316	316	316	316	316	316
Mean of D.V.	-3.902	-3.902	-3.902	-3.589	-3.589	-3.589
R2	0.309	0.307	0.308	0.258	0.256	0.256

Notes: These regressions are run on the sample of survey respondents who answered both the initial and follow-up survey. The coefficients are dummies for the covariate listed at the top interacted with the historical information treatment dummy. Controls include gender, foreign status, time in the program and university rank. Clustered standard errors in parentheses. The cluster is a group of two universities of similar rank which was used to stratify the block randomization.

Figure A.1. Respondents' Beliefs about the Share of PhD Graduates from Their Program Becoming Faculty – Respondents in Block Information and Control groups only

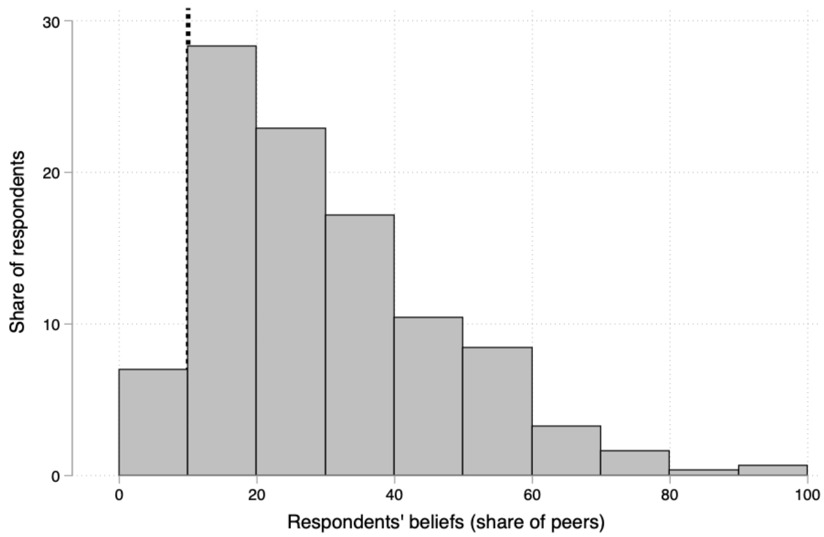


Figure A.2. Gender Differences in Beliefs about the Share of PhD from Their Program Becoming Faculty

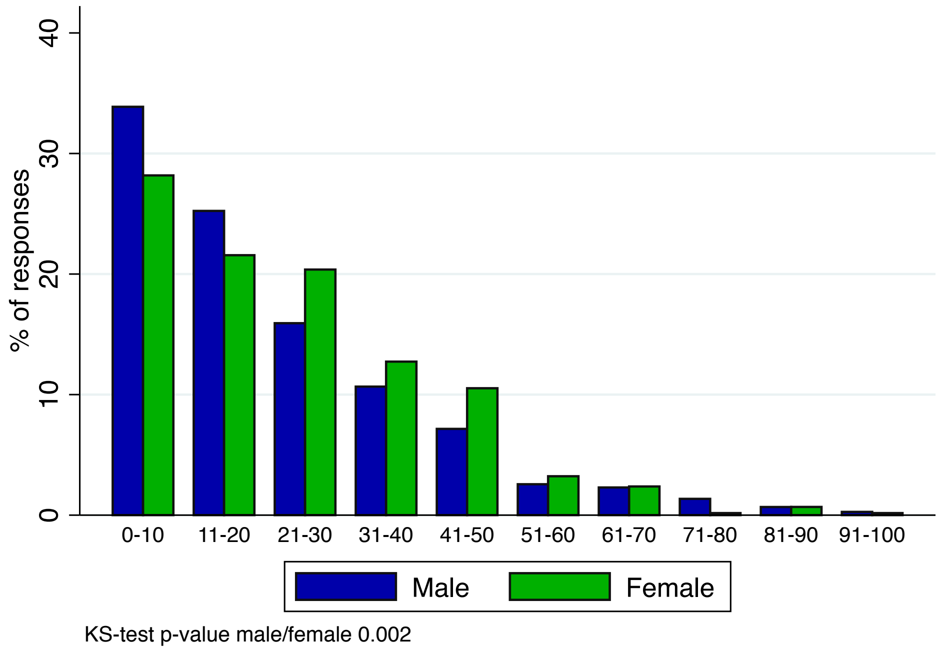
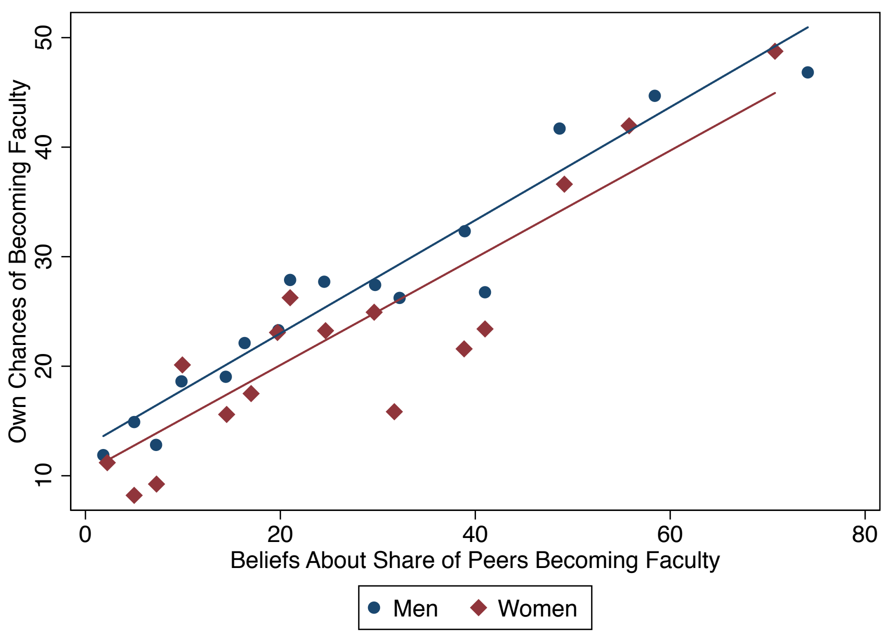


Figure A.3. Beliefs of Own Chances and Peers' Chances, by Gender



Notes: Beliefs about share of peers becoming tenure track faculty in a research-intensive university.

Appendix B: Universities Included in the Sampling Frame

Arizona State University
California Institute of Technology
Carnegie Mellon University
Colorado State University
Columbia University
Cornell University
Duke University
Emory University
Georgia Institute of Technology
Harvard University
Indiana University
Iowa State University
Johns Hopkins University
Massachusetts Institute of Technology
North Carolina State University
Northwestern University
Princeton University
Purdue University
Rice University
Stanford University
State University of New York at Buffalo
Texas A&M University
The Ohio State University
The Pennsylvania State University
The University of Texas at Austin
University of California, Berkeley
University of California, Davis
University of California, Irvine
University of California, Los Angeles
University of California, Riverside
University of California, San Diego
University of California, Santa Barbara
University of Chicago
University of Colorado
University of Delaware
University of Florida
University of Houston
University of Illinois at Urbana-Champaign
University of Maryland, College Park
University of Massachusetts Amherst
University of Michigan
University of Minnesota
University of North Carolina at Chapel Hill
University of Pennsylvania
University of Pittsburgh
University of South Florida
University of Southern California
University of Utah
University of Virginia
University of Washington
University of Wisconsin-Madison
Washington State University
Washington University in St. Louis
Yale University

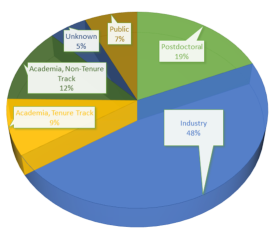
Appendix C: Information on Graduates' Placements from University Webpages

no information — **full information**

Number of universities

70%	**11%**	**12%**	**5%**	**2%**
39 universities provide no information on placements	**6 universities** provide aggregate data on placements	**7 universities** list graduates' hiring institutions	**3 universities** match graduates and hiring institutions (some graduates)	**1 university** matches graduates and hiring institutions (all graduates)

Example



chem.duke.edu/graduate/placements

Example

Placement of Students

One of the joys of academia is seeing bright young people become productive scientists and managers as they advance their careers after their time at Purdue. This is the primary reward of a teaching carrier. Here are some of the institutions our graduates and postdocs have recently joined:

Amgen	Intel
Argonne Nat'l Laboratory	Iowa State University
BASF	Lawrence Livermore
Bayer	Max Planck Institute
Battelle Columbus	Merck & Co.
Beyond Genomics	MDS Sciex
Bioanalytical Systems	Novartis
Dow Chemical	Ohio State Univ.
Gilead Laboratories	Pfizer
Griffin Analytical Technologies	Procter & Gamble
GSK	Roche
Eli Lilly	Sandia Nat'l Laboratory
Endocyte	Schering Plough
Environment Canada	ThermoFinnigan
Exxon	Waters
	Wyeth

www.chem.purdue.edu/Analytical/placement.php

Example

Alexander Matthew David, Ph.D., Chemistry

Job Title and Organization

Sr. Scientist, Celgene Corp.

First Position After Graduate School

Postdoctoral studies at UCSD and then Sr. Scientist at TetraLogic pharmaceuticals

Career Skills Graduate Students Should Develop

Project management and leadership skills with a diverse and multi-disciplinary technical skill set.

Advice for Graduate Students

Do what you love and be prepared to work long and hard at it.

https://secure.rackham.umich.edu/graduate-student-success/alumni-profiles/

PLACEMENT AFTER PRINCETON

Graduates of the Chemistry Program at Princeton University begin their careers at a wide variety of excellent companies and institutions around the world. Listed below are our graduates by name, graduate advisor and employment upon completion of their doctoral degree.

2015 | 2014 | 2013 | 2012 | 2011 | 2010 | 2009
2008 | 2007 | 2006 | 2005 | 2004

Year / Name	Advisor	Destination at conclusion of Ph.D.
2015		
Ali, Mazhar	Cava	Researcher, IBM Almaden Research Center, San Jose, CA
Alleva, Jennifer	MacMillan	Gilead Sciences, Foster City, CA
Baroudi, Kristen	Cava	Scientist, Lumenari, Inc., Lexington, KY
Boaz, Nicholas	Groves	Assistant Professor of Chemistry, North Central College, Naperville, IL
Capacci, Andrew	MacMillan	Scientist I, Biogen, Cambridge, MA

chemistry.princeton.edu/graduate/after-princeton

NOTE: We visited websites of 56 U.S. chemistry research-intensive universities in search for the information they publish on their graduates' placements. We looked through their graduate studies' main pages, graduate student handbooks, career pages, alumni profiles, and news section.

Appendix D: Selected Survey Questions

Measuring beliefs about the academic job market

Q. What do you think is the percent chance (or chances out of 100) that you will eventually have a tenure-track position in a U.S. research-intensive university?

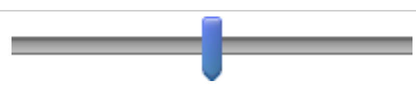
	Not likely	Somewhat likely	Very likely
	0 10 20 30 40	50 60	70 80 90 100
How likely you will have a tenure-track position in the US? ()			

Q. Approximately what share of PhD graduates from your PhD program do you think eventually obtain a tenure-track position in a US research-intensive university? (0 means "None" and 100 means "All").

	0 10 20 30 40 50 60 70 80 90 100
Share of students with a tenure-track position in the US ()	

Measuring beliefs about postdoctoral training

Q. What do you think is the percent chance (or chances out of 100) that you will do a postdoc after your PhD?

	Not likely	Somewhat likely	Very likely
	0 10 20 30 40	50 60	70 80 90 100
How likely are you to do a postdoc? ()			

Measuring career preferences – counterfactual choice question

Q. Now we want to ask you to do some simple evaluations of potential job offers. Imagine that you have just completed your dissertation and are looking for **a full-time position**.
First, suppose you have the following job offers and you need to choose between them. Please rate how likely you are to accept one of them rather than the other. For each job offer, choose the percent chance (out of 100) of choosing each one. **The total chances given to each offer should add up to 100.**

_______ **Job Offer #1:** Research Scientist/Engineer at Private Sector Firm (e.g. DuPont, Novartis) **Annual Salary:** $90,000 (1)

_______ **Job Offer #2:** Postdoctoral Research Fellow at Top U.S. university (e.g. Berkeley, MIT) **Annual Salary:** $50,000 (2)

_______ **Job Offer #3:** Assistant Professor at top liberal arts college (e.g. Swarthmore College) **Annual Salary:** $70,000 (3)

Q. Putting job availability aside, how attractive do you personally find each of the following careers?

	Not at all attractive (1)	Mostly not attractive (2)	Neutral (3)	Mostly attractive (4)	Very attractive (5)
Academic faculty with an emphasis on research (1)	○	○	○	○	○
Academic faculty with an emphasis on teaching (2)	○	○	○	○	○
Government research and development position (3)	○	○	○	○	○
Government (other) (6)	○	○	○	○	○
Industry position with an emphasis on research and development (4)	○	○	○	○	○
Industry (other) (5)	○	○	○	○	○

Appendix E: Measuring Historical Placement Rates

Overview

The objective of this data collection effort was to understand what share of PhD graduates from U.S. chemistry departments become faculty members themselves (in research-intensive universities), and differences across schools. To reach this objective, we collected data on students graduating from U.S. chemistry graduate programs between 2008 and 2010 and matched their names to a 2015 list of chemistry faculty in research-intensive universities. We then computed the share of graduating students who had become faculty by 2015, by graduating department.

Data sources

The database "Proquest Dissertations and Abstracts" was used to obtain the list of chemistry dissertations completed between 2008 and 2010. Proquest Dissertations and Abstracts includes the names of students, the year and university of graduation as well as a subject classification for the thesis, among other information. While the database itself is generally thought to be quite comprehensive, it does not clearly indicate from which department the student graduated. This implies that one must deduce whether it was a chemistry dissertation from the subject classification.

For lists of chemistry faculty, we relied on the ACS Directory of Graduate Research, available online at dgr.rints.com. This resource, meant to help prospective graduate students choose a graduate program, has an extensive listing of faculty members in U.S. PhD-granting chemistry, chemical engineering, and biochemistry programs. The ACS Directory of Graduate Research was used to create a list of faculty members in U.S. research-intensive universities, where research intensive is defined as "R1" or "R2" in the Carnegie classification.

An important limitation is that it does not list faculty members outside the United States as well as in nonchemistry departments, where PhD chemistry graduates may find employment as university faculty with a focus on research.

Matching

The list of graduate students was matched to the list of faculty using last names, initials, first names, year of graduation, and university of graduation. The matching algorithm is robust enough to handle cases of variations in spelling of first names, inconsistent reporting of middle names, or individuals changing last names.

Limitations of the placement data

The placement data presented here have a few important limitations.

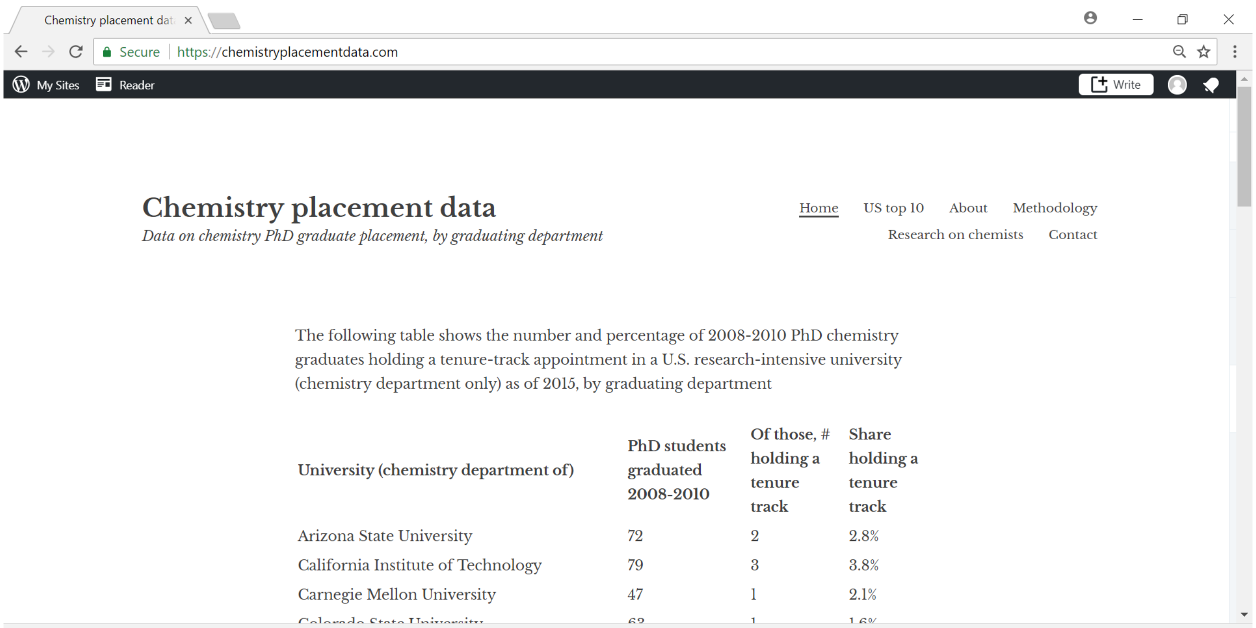
First, some truncation bias arises from the fact that faculty placements are observed as of 2015, while the list of students include students who graduated relatively recently (say, 2010) and may have obtained a faculty position in 2016 or 2017, or may obtain a faculty position in the future.

Second, the placement data fail to capture placement in nonchemistry departments that may employ chemistry PhD students, as well as placements outside the United States.

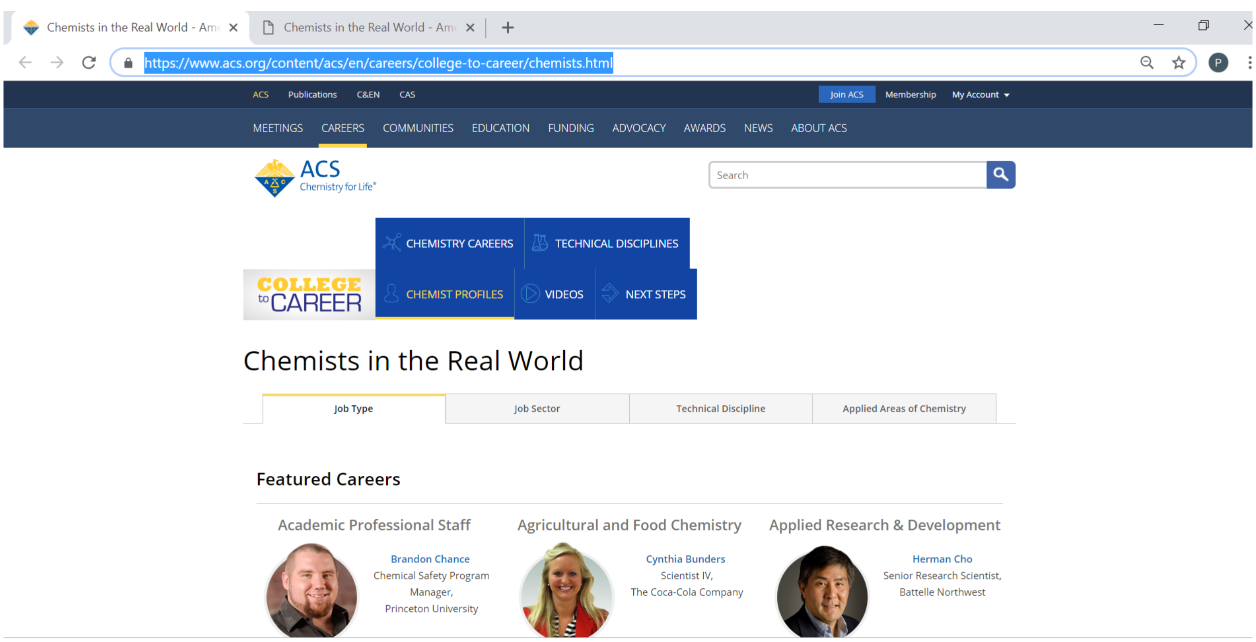
Third, students outside chemistry departments may be mistakenly assigned to the chemistry department if the subject classification of their thesis is close to chemistry, which could impact the placement measures.

Appendix F: Websites Linked in the Thank-You Emails

Custom-built website with historical placement information



American Chemical Society "Chemists in the Real World" website listing profiles of professional scientists in both academic and industry occupations



Appendix G: Web Analytics on Visits to the Website with Historical Placement Information

Figure G1: Share of visitors accessing the website: www.chemistryplacementdata.com by source

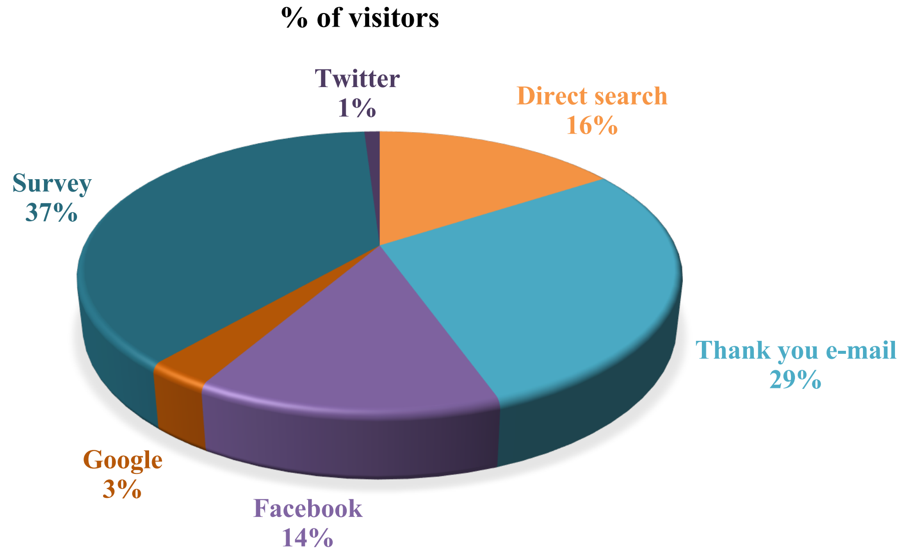


Figure G2: Share of Respondents Who Visited Website According to Treatment Status