HETEROGENEITY IN DISCRIMINATION?: A FIELD EXPERIMENT*

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ABSTRACT: We provide evidence from the field that levels of discrimination are heterogeneous across contexts in which we might expect to observe bias. We explore how discrimination varies in its extent and source through an audit study including over 6,500 professors at top U.S. universities drawn from 89 disciplines and 258 institutions. Faculty in our field experiment received meeting requests from fictional prospective doctoral students who were randomly assigned identity-signaling names (Caucasian, Black, Hispanic, Indian, Chinese; male, female). Faculty response rates indicate that discrimination against women and minorities is both prevalent and unevenly distributed in academia. Discrimination varies meaningfully by discipline and is more extreme in higher paying disciplines and at private institutions. These findings raise important questions for future research about how and why pay and institutional characteristics may relate to the manifestation of bias. They also suggest that past audit studies may have underestimated the prevalence of discrimination in the United States. Finally, our documentation of heterogeneity in discrimination suggests where targeted efforts to reduce discrimination in academia are most needed and highlights that similar research may help identify areas in other industries where efforts to reduce bias should focus.

JEL Codes: D03, J71, I20

*We thank Max Bazerman, Eric Bradlow, Stephan Meier, Ruth Milkman, Michael Norton and Amanda Pallais for their insightful feedback. We also thank seminar participants at Cornell, Harvard, the University of Pennsylvania, UCLA, Columbia, NYU, Rutgers, the 2010 Society for Judgment and Decision Making conference, the 2011 Behavioral Economics Annual Meeting, the 2011 Stanford Institute for Theoretical Economics, the 2011 Subjective Probability, Utility and Decision Making Conference, and the 2011 Academy of Management Conference. We are grateful to Fabiano Prestes, Stan Liu, and many incredible RAs for their research assistance. This research was conducted with support from the Russell Sage Foundation and the Wharton Dean's Research Fund. All data collection and analysis was conducted by the first two authors with IRB approval.

1. Introduction

Discrimination based on race and gender remains an insidious problem, and its presence in the field has been rigorously documented (Ayres and Siegelman, 1995; Altoni and Blank, 1999; Goldin and Rouse, 2000; Bertrand and Mullainathan, 2004; List, 2004; Pager, Western and Bonikowski, 2009; Milkman, Akinola and Chugh, in press). Further, psychology research conducted in the laboratory has demonstrated that the severity of discrimination can differ depending on features of both the evaluator and the evaluation context (e.g. beliefs, values, personality characteristics, gender, ingroup / outgroup membership, relative status) (Fershtman and Gneezy, 2001; Yzerbyt and Demoulin, 2010). In other words, we have evidence from the field that levels of discrimination meaningfully affect outcomes for women and minorities, and we have evidence from the laboratory showing that in a controlled environment, levels of discrimination vary systematically across contexts. Together, these two robust sets of findings suggest that discrimination is unlikely to be evenly distributed across society. However, field research to date has focused almost exclusively on documenting the presence of discrimination, without devoting close attention to measuring whether its severity varies meaningfully as a function of the context examined.

In this paper, we present an analysis of data collected through an audit study set in academia. We show that discrimination is not evenly distributed across academic disciplines and universities, but instead, is more extreme in higher paying academic disciplines and private institutions. The heterogeneity we identify in discrimination advances our understanding of what drives bias against women and minorities, suggests that bias may have been underestimated in some past audit studies, and indicates where anti-discrimination policies are most needed in the academy.

Evidence from recent audit studies indicates that across a wide range of settings, discrimination continues to dramatically disadvantage minorities and women relative to Caucasian males with the same credentials. For example, white job candidates receive a 50% higher callback rate for interviews than identical Black job candidates (Bertrand and Mullainathan, 2004); Black and Latino job applicants with clean records are treated like whites just released from prison (Pager, Western and Bonikowski, 2009); white males receive significantly lower price quotes on new cars than do Blacks or females (Ayres and Siegelman, 1995); and Black, Hispanic, Chinese, Indian and female prospective PhD students receive less attention from faculty than Caucasian males (Milkman, Akinola and Chugh, in press). Further, one important type of heterogeneity in discrimination has been well-documented in the field: minorities generally exhibit less bias against members of their own racial group. Referees in basketball and baseball make less biased calls against players who share their race (Price and Wolfers, 2010; Parsons, Sulaemon, Yates and Hammermesh, 2011), and professors exhibit less discrimination against prospective minority students of their race (Milkman, Akinola and Chugh, in press).

However, beyond the research exploring same-race bias, there are limited results from the field exploring heterogeneity in discrimination. In the context of housing, audit studies have revealed some differences in discrimination across markets, with Hispanic homebuyers experiencing dramatically more discrimination in New York City than Los Angeles, though Black homebuyers face similar levels of bias across metropolitan areas (Fix and Struyk, 1993). In medicine, there is evidence that second year medical students exhibit more discrimination towards Black patients than first year medical students (Rubineau and Kang, in press). Yet, in the context of employment, while audit research in Boston and Chicago showed that Black entry-level job applicants experience discrimination relative to white applicants, there were no detectable differences in levels of bias across occupation, industry or employer size (Bertrand and Mullainathan, 2004).

These limited findings may be largely attributable to the constraints of the data that has been collected in most past research designed to explore discrimination in the field. Many past audit studies have involved relatively small samples, which have prevented researchers from extensively exploring heterogeneity in levels of bias (Ayres and Siegelman, 1995; Pager, Western and Bonikowski, 2009; Altoni and Blank, 1999; Fix and Struyk, 1993). The employment audit study described above relied on a large sample of 1,300 employers, but it included only those employers advertising in the *Boston Globe* or *Chicago Tribune* for positions in sales, administrative support, clerical and customer services, and limited data was collected on employer heterogeneity (Bertrand and Mullainathan, 2004). For instance, important variables such as employer demographics, employer specialty, or who specifically made hiring decisions were not available. Given these data limitations, it may not be surprising that so little heterogeneity in levels of race and gender discrimination has been documented in past field research.

Understanding heterogeneity in race and gender discrimination is important for several reasons. First, furthering our understanding may shed light on the extent to which levels of race and gender bias documented in past audit studies can be assumed to generalize across settings. If variables like salary, for instance, have an important impact on levels of bias, then past audit studies that have focused primarily on low-paying professions may have under- or over-estimated the degree of bias in the population (Bertrand and Mullainathan; Pager, Western and Bonikowski, 2009; Altoni and Blank, 1999). Second, by studying heterogeneity we can identify areas experiencing the most bias where policy makers should focus on deploying anti-discrimination policies. Finally, documenting heterogeneity in discrimination may point to likely moderators of discrimination that are worthy of further study because they may help explain why discrimination persists in society and how it can be reduced.

In this paper, we explore whether U.S. university professors in particular disciplines and institutions are more likely to discriminate against prospective doctoral students. Academia is a promising context for exploring where discrimination is most severe because academics are heterogeneous along a number of interesting and observable dimensions. Professors are heterogeneous in their areas of academic specialization (e.g., economics, chemical engineering, history, nursing), and each specialty differs measurably in its average salary as well as its student and faculty race and gender composition. Furthermore, professors work for institutions that vary in meaningful ways including their perceived quality/rigor, whether they are publicly or privately funded, and the diversity of their student bodies. By exploring where discrimination is most severe in academia, we are able to examine the impact of a wide range of potential moderators of race and gender discrimination with implications for theories about what drives discrimination.

Another benefit of studying academia is that it is an environment where the societal costs of discrimination are meaningful. Increasing female and minority representation among university faculty is associated with higher educational attainment for female and minority students, respectively (Trower and Chait, 2002). Currently, the majority (60%) of full professors at U.S. postsecondary institutions are white males while 28% are female, 7% are Asian, 3% are Black, and 3% are Hispanic (U.S. Department of Education, 2010), which sends an important signal to students about who can climb to the highest levels of the academic ladder. Understanding where discrimination is most severe in academia has the potential to yield direct policy recommendations for addressing the important question of how to increase the diversity of the academy. Specifically, by identifying academic settings where discrimination is most prevalent, we can inform policy makers about where interventions aimed at reducing discrimination in the academy are most needed.

Additionally, academia offers a pragmatically unique context for a field experiment of this nature due to the ease of building a database describing its workforce. Information about virtually all faculty members is easily retrievable via the internet. This made it feasible to build our audit study's participant sample from the full universe of faculty at the U.S. universities of interest and to obtain data on each faculty member's race, gender, disciplinary affiliation, institutional affiliation, and tenure status. Additionally, reliable surveys exist describing the average salary levels and demographic makeup of academics by discipline and type of institution, furthering our ability to conduct interesting analyses with our data. To our knowledge, few (if any) other professions are as richly described as academia by publicly available records.

To evaluate whether discrimination is spread evenly throughout academia, we conducted an audit study. Our audit study included a random sample of 6,548 professors from 6,300 different Ph.D. granting departments at 258 top-ranked U.S. universities. We report on new analyses of the data gathered from this experiment (previously described in Milkman, Akinola and Chugh (in press)). We experimentally examined faculty responsiveness to meeting requests emailed by prospective male and female doctoral students of varying races who expressed an interest in working with the contacted professor. This gateway to the academy, through which prospective students receive informal, but critical encouragement, or discouragement, to formally apply to doctoral programs, has been left unexamined. Instead, past research on gateways to the academy has primarily focused on student performance at universities (Fletcher and Tienda, 2010) and admissions outcomes (Carnevale and Rose, 2004).

Each professor in our study was emailed by a single, (fictional) prospective student interested in doctoral study. Following past research (Bertrand and Mullainathan, 2004), students' names were randomly assigned to signal race (Caucasian, Black, Hispanic, Chinese, or Indian) and gender. The outcome of interest was whether a given email elicited a response within one week of its receipt. We examine whether the difference in professors' response rates to minorities and women relative to Caucasian males (the "discriminatory gap"), varies as a function of a faculty member's academic discipline (classified using the 11 *broad* and 133 *narrow* categories recognized by the National Study of Postsecondary Faculty (NSOPF) (U.S. Department of Education, 2004) and university affiliation. We find that the discriminatory gap is largest at private universities and in the highest-paid academic disciplines, indicating where anti-discrimination programs are most needed and suggesting avenues for future research on where and why bias is most severe.

2. Methods

2.1 Subjects

We began by constructing a faculty subject pool for inclusion in our audit study. The primary criteria for selecting faculty participants was their affiliation with a doctoral program at one of the 260 National U.S. Universities that *U.S. News and World Report* ranked in their 2010 "Best Colleges" issue (Best Colleges 2010: National Universities, 2010). The one exception to this selection criteria was that the two schools ranked by U.S. News that were located outside of the mainland of the United States (the University of Hawaii Manoa and the University of Alaska Fairbanks) were excluded. At the top 258 U.S. universities in our final study sample, we identified 6,300 doctoral programs and approximately 200,000 faculty affiliated with those programs. We then selected one to two faculty from each doctoral program, yielding 6,548 faculty subjects. From university websites, we collected each professor's email address, rank (full, associate, assistant or n/a), gender, race (Caucasian, Black, Hispanic, Chinese, Indian, or Other), as well as university and department affiliations. Table I presents summary statistics describing our study's faculty subject pool.

Research assistants determined the gender of faculty study participants by studying the faculty names, visiting their websites, examining photos, and reading research summaries containing gendered statements (e.g., "she studies"). An automated technique was initially used for racial classification followed by manual validation by research assistants. The automated technique relied on lists of: (a) the 639 highest-frequency Hispanic surnames as of 1996 (Word and Perkins, 1996), and (b) 1,200 Chinese and 2,690 Indian surnames (Lauderdale and Kestenbaum, 2000). These lists were compared to the surnames of each faculty member, and if a surname match was identified, a faculty member was classified as a member of the associated racial group. Next, these automated classifications were validated for Hispanic, Indian and Chinese faculty by research assistants who again visited faculty websites. Further, research assistants generated racial classifications for faculty who were Caucasian, Black or another race besides Hispanic, Indian or Chinese by visiting faculty websites, examining faculty CV's, and relying on Google image searches to find pictures of faculty on the internet. In rare instances when research assistants determined it was not possible to reliably classify a faculty member's race, another professor whose race could be validated was chosen as a replacement representative of the doctoral program in question.

In sample construction, we sought adequate statistical power to investigate how minority faculty respond to students of their own race as well as students in other groups (see analyses in (Milkman, Akinola and Chugh, in press)). 4,375 professors were selected at random (87% Caucasian, 2% Hispanic, 1% Black, 3% Indian, 4% Chinese, 3% Other; 68% Male). We then oversampled non-Caucasians and constructed a second group composed of 2,173 minority professors (29% Hispanic, 21% Black, 21% Indian, 29% Chinese; 68% Male)[1]. The final sample of faculty included in the study was composed of 43% full professors, 27% associate professors, 25% associate professors, and 5% professors who were either of emeritus or unknown rank. Fifty five percent of professors in the final sample were located in the EST time-zone, 28% were located in CST, 5% in MST and 12% in PST.

In all graphs and summary statistics reported here, observations are sample weighted to account for the oversampling of minority faculty members in our study and unbalanced random assignment of faculty to conditions (same-race faculty-student pairs were over-represented in our random assignment algorithm, details in Section 2.2). Thus, all graphs and summary statistics can be interpreted as reporting results from a representative faculty sample (Cochran, 1963).

2.2 Experimental Stimuli

Generating appropriate names for the fictitious students contacting faculty was a critical component of our experimental design. We relied on previous research to help generate names signaling both the gender and race (Caucasian, Black, Hispanic, Indian, Chinese) of these fictional students (Bertrand and Mullainathan, 2004; Lauderdale and Kestenbaum, 2000). We also looked to U.S. Census data documenting the frequency with which common surnames belong to Caucasian, Black and Hispanic citizens and examined websites recommending baby names targeted at different racial groups. These

[1] While an ideal sample would have had the same representation for each minority group, identifying Hispanic and Chinese faculty with automated techniques was easier than identifying Indian and Black faculty, leading to different success rates with our oversampling strategy.

sources provided a guide for generating a list of 90 names for potential use in our study: 9 of each race and gender of interest.

We pre-tested each of these 90 names by surveying 38 people, all of whom had a Masters Degree (87.5%) or a PhD (12.5%) and who had signed up through Qualtrics to complete online polls for pay. We asked 18 of these survey respondents to complete a survey about the gender conveyed by each of the 90 names in our sample, and we asked 20 respondents to complete a survey about the race conveyed by each of the 90 names in our sample. Participants in the gender survey were asked to “Please make your best guess as to the identity of a person with the following name:” and were required to choose between “Male” and “Female” for each name. Participants in the race survey were also asked to “Please make your best guess as to the identity of a person with the following name:” and were required to choose between “Caucasian”, “Black”, “Hispanic”, “Chinese”, “Indian” and “Other” for each name. Both the gender and the race survey were 10 pages long with questions about a randomly ordered set of 9 names presented on each survey page.

The responses generated by the above survey were tabulated, and we selected the two names for use in our study of each race and gender with the highest net race and gender recognition rates. Table II presents a list of the names used in our study along with their correct race and gender recognition rates in the survey pre-test described above. Respondents accurately identified the selected names at an average rate of 97% and 98% for race and gender respectively.

2.3 Experimental Procedures

Emails requesting a meeting with a professor were all sent to faculty subjects in our audit study on a Monday during the academic school year. The emails were identical except for two components. The race (Caucasian, Black, Hispanic, Indian, Chinese) and gender signaled by the name of the sender was randomly assigned. Also, half of the emails requested a meeting for today, while half requested a meeting one week in the future (next Monday). The emails were worded as follows:

> <u>Subject Line</u>: Prospective Doctoral Student (On Campus Today/[Next Monday])
>
> Dear Professor [Surname of Professor Inserted Here],
>
> I am writing you because I am a prospective doctoral student with considerable interest in your research. My plan is to apply to doctoral programs this coming fall, and I am eager to learn as much as I can about research opportunities in the meantime.
>
> I will be on campus today/[next Monday], and although I know it is short notice, I was wondering if you might have 10 minutes when you would be willing to meet with me to briefly talk about your work and any possible opportunities for me to get involved in your research. Any time that would be convenient for you would be fine with me, as meeting with you is my first priority during this campus visit.
>
> Thank you in advance for your consideration.
>
> Sincerely,
[Student’s Full Name Inserted Here]

A single domain name was purchased for use in our study (which we will refer to as "domain.com" to ensure that the revelation of the actual domain could not identify any faculty participants in our study). Emails from prospective doctoral students were sent from email addresses configured to include the first and last name of the student in question separated by a period (firstname.lastname@domain.com), such as latoya.brown@domain.com. Emails were also set up to ensure that the prospective student's name would appear in a faculty member's inbox as the message's sender (e.g., From: "Latoya Brown"). Finally, accounts were configured and tested to verify that spam filters would not capture emails from domain.com.

Two thirds of the Caucasian faculty from the representative sample of 4,375 professors, and all non-Caucasian faculty from this representative sample, were randomly assigned to one of the gender/race/timing conditions in our study with equal probability (e.g., Female/Black/today). No professors in this group were assigned to receive an email from a student who shared their race, however. Assignment of faculty to conditions was stratified by their gender, race, rank and time zone (EST, CST, MST and PST) to ensure balance on these dimensions across conditions.

All oversampled non-Caucasian faculty (N=2,173) as well as the final third of Caucasian faculty (N=1,294) received emails from students of their race (e.g., oversampled Hispanic faculty received emails from Hispanic students). Both the gender of the prospective student and the timing of the student's request (today vs. next week) were randomized. Assignment of faculty to conditions was again stratified by their gender, rank and time zone (EST, CST, MST and PST) to ensure balance across conditions. As mentioned in Section 2.1 and described in detail in Section 2.6.2, in all graphs and summary statistics reported here, observations are sample weighted so they can be interpreted as reporting results from a representative faculty sample with balanced random assignment to experimental conditions (Cochran, 1963).

In total, 6,548 emails were sent from fictional prospective doctoral students requesting a meeting with a faculty member, or one per professor included in this study. All emails were placed in a queue in random order and designated for sending at 8 am in the time zone corresponding to the relevant faculty member's University. These emails were then sent from four servers at a rate of approximately 100 per minute, and the timestamps when each email left our servers were precisely recorded. To addressees in the EST time zone, 3,584 emails were sent out between 8:00 am and 8:33 am (the timestamp on the last email sent in EST). To addressees in the CST time zone, 1,823 emails were sent out between 8:00 am and 8:16 am (the timestamp on the last email sent in CST). To those in the MST time zone, 325 emails were sent, and they all went out between 8:00 am and 8:03 am MST. Finally, 816 emails were sent to faculty in the PST time zone, and the last email sent in this time zone left our server at 8:07 am PST.

To minimize the amount of time faculty spent on our study, we prepared a polite scripted reply cancelling all meeting requests that elicited "acceptances" from faculty members. When such acceptances to meeting requests were received between 8 am and 8 pm on the day of our study's launch, emails cancelling the meeting were sent within 10 minutes. All acceptances to meeting requests received after 8 pm on the day of the study's launch received an identical, polite cancellation within 2 hours of their receipt. Responses from faculty involving proposals to meet at another time, requests for further information from the student, etc. were also responded to in an equally timely manner but with messages designed to politely cut off all future communication.

We examine whether a given email generates a reply from a given professor in our audit study within one week of the meeting request's dispatch. Sending a response is the most basic acknowledgement that a student's interest in a faculty member was not completely dismissed, which is the primary reason we focus attention on this outcome. Although many faculty in our study did not immediately offer to meet with the student contacting them, this was often due to scheduling constraints, and nearly all responses conveyed a willingness to offer some form of assistance or guidance to the student in question or at least to continue communicating. Thus, whether an email elicited a response is both the most sensitive measure available to us of whether a professor was willing to help a given student and also the most objective measure available of whether a faculty member provided encouragement to a student who expressed an interest in doctoral study.

2.4 Human Subjects Protections

The two lead authors of this paper conducted all data collection and data analysis for the project. Before the start of data collection, the project was carefully reviewed and approved by both of their institutional review boards. Each IRB determined that a waiver of informed consent was appropriate based on Federal regulations (45 CFR 46.116(d)), which state the following:

> *"An IRB may approve a consent procedure which does not include, or which alters, some or all of the elements of informed consent set forth in this section, or waive the requirements to obtain informed consent provided the IRB finds and documents that: (1) The research involves no more than minimal risk to the subjects; (2) The waiver or alteration will not adversely affect the rights and welfare of the subjects; (3) The research could not practicably be carried out without the waiver or alteration; and (4) Whenever appropriate, the subjects will be provided with additional pertinent information after participation."*

This project met all of the stated regulatory requirements for a waiver of informed consent. Informed consent would have eliminated the realism of the study and biased the sample of participants towards those most willing to talk with students. Two weeks after the study's launch, each study participant received an email debriefing him/her on the research purpose of the message he/she had recently received from a prospective doctoral student. Every piece of information that could have been used to identify the faculty participants in our study was deleted from all study databases within two weeks of the study's conclusion.

2.5 Supplementary Data

2.5.1 Data about Academic Disciplines

In order to categorize the academic disciplines of the faculty in our study, we relied on categories created by the U.S. National Center for Education Statistics. This center conducts a National Study of Postsecondary Faculty (NSOPF) at regular intervals (most recently in 2004) and classifies faculty into one of 11 broad and 133 narrow academic disciplines (see: http://nces.ed.gov/surveys/nsopf/). The NSOPF survey results were available in the form of summary statistics describing various characteristics of survey respondents both by broad and narrow academic discipline.

In order to merge data from the NSOPF survey with data from our study, a research assistant examined each participant's academic department and classified that faculty member into one of the NSOPF's 11 broad and 133 narrow disciplinary categories. Of the 6,548 faculty in our study, 29 worked in fields that either could not be classified or identified, and these professors were thus dropped from our analyses. The remaining professors were classified into one of 10 of the NSOPF's 11 broad disciplinary categories (the category with no representation was Vocational Education) and into one of 110 of the NSOPF's 133 narrow disciplinary categories. Twenty-one of the 110 narrow disciplinary categories in which faculty included in our study were classified were disciplines for which the 2004 NSOFP survey reported no data. These observations corresponded to 313 data points from our study, which we excluded from our analyses, leaving us with a total of 89 unique narrow disciplines to examine and 6,206 observations including information about characteristics of a faculty member's narrow academic discipline for inclusion in our regression analyses.

We examine how several variables collected by the NSOFP's 2004 survey affect levels of discrimination in our study. The first variable we explore is the average pay in a discipline (mean = \$59,372; std. dev. = \$13,265). Second, we examine the percentage of faculty in the discipline who are female (mean = 38%; std. dev. = 21%), as well as the percentage that are Caucasian (mean = 85%; std. dev. = 8%), Black (mean = 6%; std. dev. = 4%), Hispanic (mean = 3%; std. dev. = 3%), and Asian (mean = 10%; std. dev. = 8%). Finally, we examine the percentage of Ph.D. students in the discipline who are Caucasian (mean = 76%; std. dev. = 4%), Black (mean = 10%; std. dev. = 3%), Hispanic (mean = 7%; std. dev. = 2%), and Asian (mean = 7%; std. dev. = 2%).[2]

[2] Note that the NSOFP does not include statistics about the percentage of students who are female.

2.5.2 Data about Universities

For each of the 260 national U.S. universities ranked by *U.S. News and World Report* in their 2010 "Best Colleges" issue, *U.S. News* collects and reports a number of facts describing the university during the 2009-2010 academic school year that were merged with our experimental data. First, each school's ranking is reported (1-260). Second, *U.S. News* reports on whether each school is a private or public institution (37% of the universities in our sample are private, and 63% are public). Third, *U.S. News* reports on the percentage of the undergraduate student body that is female (mean = 52%; std. dev. = 9%), as well as the percentage that is Caucasian (mean = 68%; std. dev. = 19%), Black (mean = 11%; std. dev. = 16%), Hispanic (mean = 8%; std. dev. = 9%), and Asian (mean = 9%; std. dev. = 9%). We examine the relationship between each of these university characteristics and the degree of faculty discrimination in response to emails from white males versus women and minorities. For 12 of the universities studied, information is missing about the student body's composition. This missing data leads us to drop 354 data points when we include these predictors in our analysis.

2.6 Statistical Analyses

2.6.1 Regression Spefications

To study the effects of various potential moderators (i.e., department and university characteristics) on the level of responsiveness to emails form women and minorities relative to Caucasian males, we use the following ordinary least squares (OLS) regression specification:

$$\begin{aligned} response\_received_j = \; & \alpha + \beta_1 * moderator_i + \beta_2 * min\text{-}fem_i * moderator_i + \beta_3 * black_i + \beta_4 * hispanic_i + \\ & \beta_5 * indian_i + \beta_6 * chinese_i + \beta_7 * female_i + \beta_8 * black_i * female_i + \beta_9 * hispanic_i * female_i \\ & + \beta_{10} * indian * female_i + \beta_{11} * chinese_i * female_i + \theta' * X_j \end{aligned}$$

where $response\_received_i$ is an indicator variable that takes on a value of one when faculty member i responded to the email requesting a meeting and zero otherwise, $min\text{-}fem_i$ is an indicator variable that takes on a value of one when a meeting request is from a racial minority or female student and a value of zero otherwise, $moderator_i$ is a (standardized) variable that corresponds to a given moderator of interest (e.g., the pay received by faculty in a given academic discipline), $black_i$ is an indicator variable taking on a value of one when a meeting request comes from a Black student and zero otherwise, $hispanic_i$ is an indicator variable taking on a value of one when a meeting request comes from a Hispanic student and zero otherwise, and so on for the indicator variables $indian_i$, $chinese_i$, and $female_i$, and X_i is a vector of other control variables. This vector of control variables includes indicators for whether the professor contacted was: Black; Hispanic; Indian; Chinese; a member of another minority group besides those listed previously; male; an assistant professor; an associate professor, another rank besides assistant, associate or full professor; the same race as the student emailing and Black; the same race as the student emailing and Hispanic; the same race as the student emailing and Indian; the same race as the student emailing and

Chinese; and asked to meet with the student today (as opposed to next week)[3]. The additional variables included in this vector of control variables were: the university's *U.S. News and World Report* 2010 ranking (standardized) and an interaction between the "meeting today" indicator and $min\text{-}fem_i$[7].

We estimate the equation described above using an OLS regression and cluster standard errors by a faculty member's academic discipline and university affiliation. We rely on OLS regression models to evaluate this data because our primary focus is on the interpretation of interaction terms, and Ai and Norton (2003) have demonstrated that standard errors on interaction terms in logistic regressions are often biased and therefore unreliable. However, our findings are qualitatively similar if the analyses presented are repeated using logistic regression models.

Our primary regression results (in Table IV) are presented without sample weights but instead including controls for the various variables used to select our sample and allocate assignment to conditions, which controls for our experiment's unbalanced random assignment (Winship and Radbill, 1994). All regression results are robust to the inclusion of sample weights to account for oversampling minority faculty and unbalanced randomization.

2.6.2 Sample Weighting

A sample weight is assigned to each faculty participant to account for the oversampling of minority faculty members in our study and unbalanced random assignment of faculty to conditions (as described in Section 2.3, same-race faculty-student pairs were over-represented in our random assignment algorithm). In robustness checks including sample weights and in all summary statistics reported (which are always sample-weighted), sample weights are determined for a given observation as a function of the race of the faculty member contacted, r, his or her academic discipline, d, and the race of the student who contacted the faculty member, s, as follows. First, the expected representative number of faculty in a given academic discipline, d, of a given race, r, is calculated (e.g., since professors in Ph.D. granting departments in Engineering and Computer Science are 77.8% Caucasian and the study included 1,125 Engineering and Computer Science faculty, the expected number of Caucasian Engineering and Computer Science faculty is 1,125*0.778 = 875).[4] We refer to this quantity as $e_{r,d}$. Next, the expected number of faculty of a given race, r, in a given discipline, d, receiving emails from students of a given race, s, is calculated assuming balanced randomization. This is simply $e_{r,d}/5$ since there are five student races represented in our study (e.g., the expected number of Caucasian faculty in Computer Science and

[3] This predictor is included because (Milkman, Akinola and Chugh, in press) demonstrates that the interaction between this predictor and $min\text{-}fem_i$ is a strong predictor of faculty responsiveness to emails from prospective doctoral students.

[4] Note that the "true" percentage of professors in a given discipline of a given race is estimated by examining the representative sample of faculty selected for study participation.

Engineering departments receiving emails from Caucasian students is 875/5 = 175). We refer to this quantity as $e_{r,s,d}$. Finally, we calculate the actual number of faculty in a given discipline, *d*, of a given race, *r*, receiving emails from students of a given race, *s* (e.g., 151 Caucasian faculty in Engineering and Computer Science departments actually received emails from Caucasian students). We refer to this quantity as $a_{r,s,d}$. Sample weights are then constructed by taking the ratio: $e_{r,s,d}/a_{r,s,d}$. Thus, the sample weight for Caucasian faculty of Engineering and Computer Science is 175/151 = 1.1592.

3. Results

Sixty-seven percent of the emails sent to faculty from (fictional) prospective doctoral students in our study elicited a response within one week across experimental conditions, indicating that the emails sent to faculty were seen as highly compelling. Notably, all underrepresented groups studied experienced lower response rates than Caucasian males, as reported in a previous paper (Milkman, Akinola and Chugh, in press).

3.1 Confirming Similarity between Names of Matched Race and Gender

In order to confirm that no pair of names of the same race and gender in our study (e.g., Brad Anderson and Steven Smith) yielded significantly different response patterns from one another, we conducted a series of statistical tests. First, we ran a logistic regression in which the outcome variable was *response_received* and the predictor variables were 0/1 indicators for each of the twenty names in our study. We then conducted ten Wald tests – one for each pair of same-gender and race names. These tests evaluated the linear hypothesis that the difference between the coefficient estimates on two names of a given race and gender was equal to zero (e.g., $\beta_{brad\_anderson} - \beta_{steven\_smith} = 0$). None of the ten tests conducted revealed a significant difference in the paired names at a p-value of 0.10 or below, and thus, we grouped each pair of same gender/race names into a single treatment condition in our analyses (e.g., Brad Anderson and Steven Smith were collapsed into a single "Caucasian Male" treatment condition).

3.2 Heterogeneity in Discrimination

We find that the severity of bias exhibited by faculty varies considerably across disciplines. Figure IA illustrates large differences in the discriminatory gap by broad academic discipline.[5] Figure IB illustrates these discriminatory gaps by race/gender, demonstrating that the pattern in Figure IA is not driven by outliers. To evaluate the statistical significance of these patterns, we conduct an ordinary least squares regression to predict whether a given faculty member responds to a given student's email as a function of the student's race and gender, the faculty member's broad discipline, and an interaction between discipline and whether the student is a minority or female, controlling for all observable

[5] Of the 6,548 faculty in our study, 28 worked in fields that could not be classified into disciplines, and these professors are thus dropped from our analyses. Faculty in our sample represented 89 of the 133 narrow NSOPF disciplines and 10 of the 11 broad NSOPF disciplines.

characteristics of the email and its recipient (see Table III). Each of the interaction terms in Table III is statistically significant ($p<0.001$), the interaction terms are jointly significant ($p<0.001$), and the coefficients on the interaction terms differ significantly from one another ($p<0.001$), confirming that bias differs significantly across broad disciplines. Specifically, discrimination against women and minorities relative to white males is higher in disciplines such as business, and engineering and computer science, as compared to the social sciences and humanities.

Disciplines differ on multiple dimensions, including faculty salary, and we investigated how these differences might help explain the patterns illustrated in Figure I. We find a strong correlation (r=0.48) between average salary and the discriminatory gap by broad discipline. We conduct regression analyses to predict whether a given email elicits a response as a function of the salary in a narrow discipline (a more sensitive predictor than salary by broad discipline, with 89 categories rather than 10) and the interaction between salary and whether the student requesting a meeting is a minority or female, again controlling for observable characteristics of the email and its recipient (see Table IV, Model 1). Average salaries reported in the 2004 NSOFP survey by narrow discipline in our sample varied from $30,211 (Dance) to $118,786 (Medicine) with a standard deviation of $13,265 (U.S. Department of Education, 2004). We find that a $13,265 salary increase predicts a four percentage point drop in the response rate to minorities and females, but there is no predicted change in the response rate to Caucasian males. In other words, the predicted discriminatory gap widens by four percentage points for every standard deviation increase in a discipline's salary.

To determine whether this difference is driven by a lower representation of minorities or females in disciplines with lower salaries, we add controls for the percentage of women faculty, minority faculty and minority graduate students in each discipline according to the 2004 NSOFP survey (U.S. Department of Education, 2004)[6]; then, we interact these variables with an indicator for an email sent by a female or minority student (Table IV, Model 2). None of these variables predicts faculty responsiveness, and their inclusion in our regression does not change the estimated relationship between salary and discrimination. Ancillary analyses that break out minority representation predictors into narrower groups (Black, Hispanic, and Asian) yield nearly identical results, offering converging evidence that lower representation of minorities and women does not predict faculty responsiveness.

Private institutions both espouse different values and pay higher salaries than their public counterparts ($34,687 higher on average; Byrne, 2008). To explore implications of these differences, we investigate whether discrimination varies between public and private universities (37% of the universities in our sample are private, and 63% are public). We find a meaningful difference in bias by institution

[6] Statistics are not available describing the percentage of female students by discipline.

type. A sample-weighted[7] analysis of the behavior of all participants in our study indicates that faculty from public universities responded at similar rates to Caucasian males (68%) and to students from underrepresented groups (64%) (logit clustering standard errors by university (163), χ^2=2.58, N=4,437, β= 0.160, p=0.108), but faculty from private universities responded at a significantly higher rate to Caucasian males (77%) than to other students (66%) (logit clustering standard errors by university (96), χ^2=10.32, N=2,082, β= 0.544, p=0.001). In regression analyses, the predicted discriminatory gap is 14 percentage points larger at private institutions than public institutions (see Table IV, Model 3). Figure II shows this gap is remarkably persistent across the minority groups studied. Adding controls for the representation of minorities and females in a university's undergraduate population as reported by *U.S. News and World Report* (2010) neither predicts discrimination nor changes these public-private effects (see Table IV, Model 4).[8] Ancillary analyses that break out minority student representation predictors into narrower groups (Black, Hispanic, and Asian) yield nearly identical results. Further, a school's *U.S. News and World* report ranking (one measure of its quality/prestige) exhibits no correlation with a school's level of discrimination (see Table IV, Model 5).

3.3 Robustness of Reported Results

The results presented in Table IV are meaningfully unchanged in terms of magnitude or statistical significance if the analysis is repeated using: (a) an ordinary least squares regression with sample weights and standard errors clustered by university or (b) an ordinary least squares regression with sample weights and standard errors clustered by narrow academic discipline. Further, the results presented in Table IV are qualitatively similar if the analyses are repeated using logistic regression models, though our primary focus is on the interpretation of interaction terms whose standard errors are often biased and therefore unreliable in logistic regression models (Ai and Norton, 2003). Finally, we observe a pattern of qualitatively similar results to those presented here if we turn our attention to alternative outcome variables such as response speed and whether a meeting request generated an acceptance, though the statistical significance of a number of the results presented here is reduced when these alternative, less sensitive outcome variables are instead examined.[9]

3.4 Effects of Representation without Controlling for Faculty Race, Gender and/or Student-Faculty Racial Match

[7] Observations are weighted to adjust for oversampling minority faculty and unbalanced randomization so that summary statistics can be interpreted as representative of the true faculty population (Cochran, 1963).
[8] For 12 of the universities studied, information is missing about the student body's composition. This missing data leads us to drop 354 data points when we include these predictors in our analysis.
[9] It is important to note that although we observe discrimination in both email response and meeting acceptance rates, after controlling for whether a response was received, we see no additional discrimination between students on the basis of race or gender when we examine meeting acceptance rates.

In the primary analyses presented in Table IV, it is important to note that we control for the race and gender of the faculty member contacted as well as whether the student contacting a faculty member in question shares the faculty member's race (e.g., both the faculty member and student are Black). Thus, these analyses control for any increase in faculty responsiveness as a function of minority representation in a discipline that might be due to increased responsiveness of faculty to students in their demographic group. The only path through which the analyses presented in Table IV allows representation to impact student outcomes is one whereby high rates of minority representation in a given discipline lead faculty of other races to exhibit less bias towards minority students. However, past research has shown that minorities are more helpful to other minorities who share their race (Price and Wolfers, 2010; Milkman, Akinola and Chugh, in press). Thus, it is important to test for this possible pathway whereby increasing representation might reduce discrimination in a discipline via increases in same-race or same-gender helping. We re-run our primary analyses without including controls for faculty race, gender or faculty-student racial match, but sample-weighting our results to adjust for oversampling of minority faculty. In these analyses, we still observe a null effect of minority or female representation in a field or at a university on the size of the discriminatory gap. This is likely due to the fact that even an increase from, for example, 0% Black faculty in our Life Sciences sample (the lowest in-sample Black representation observed) to 4% Black faculty in our Human Services sample (the highest in-sample Black representation observed) is not a substantial enough shift to alter patterns of discrimination meaningfully.

Our experiment and analyses cannot account for the possibility that minority faculty are not only more responsive to same-race student requests but might actively recruit same-race students, which is another important way in which increased minority representation in a discipline might alter bias. Thus, it is important to recognize that this experiment in no way rules out the possibility that some forms of discrimination are reduced in disciplines with greater minority or female representation.

4. Discussion

In this paper, we identify meaningful sources of heterogeneity in discrimination. Specifically, we demonstrate that discrimination is not evenly distributed in academia but rather, varies significantly between disciplines and types of institutions. Importantly, our findings offer key insights into the question of where discrimination is most severe. One answer to that question appears to be: the highest-paid disciplines. However, the heightened levels of discrimination observed in higher-paying academic disciplines raise the critical question of whether this relationship is causal or whether some third variable influences both salaries and discrimination. Higher salaries may lead directly to increased discrimination, or, pay may be higher in disciplines with some other characteristic (e.g., more of a practitioner focus, higher status) that itself increases discrimination for reasons independent of pay. Alternatively, individuals who show higher levels of prejudice could simply be attracted to better compensated professions, either because of the pay or some other dimension.

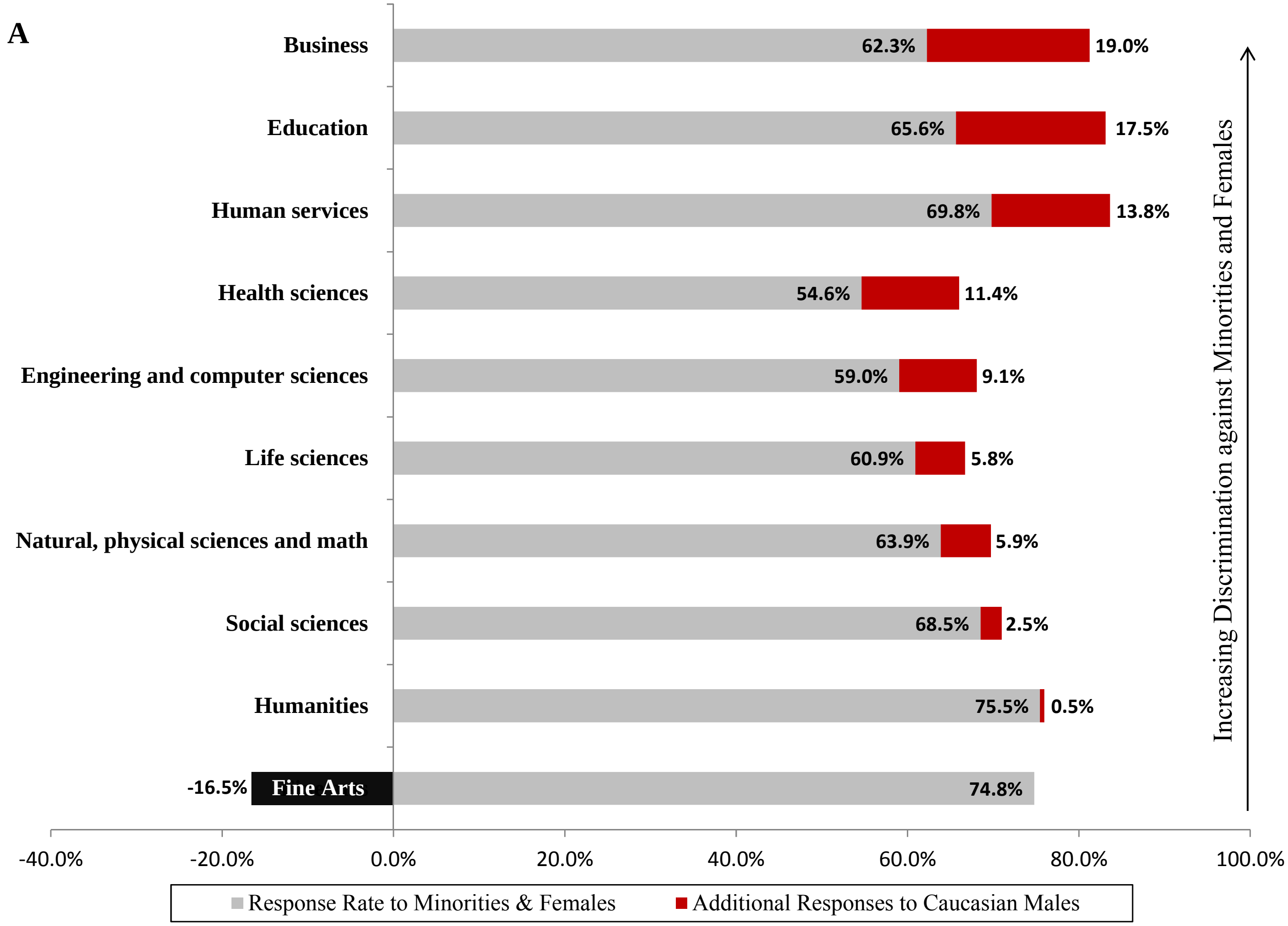
Regardless of the cause, if higher pay is associated with higher levels of bias both inside and outside of the academy, this finding has important implications. First, it calls into question the interpretation of several of the most influential audit studies conducted in recent years measuring levels of employment discrimination, which have explored bias in low-wage environments (Bertrand and Mullainathan, 2004; Pager, Western and Bonikowski, 2009; Altoni and Blank, 1999; Pager and Quillian, 2005). Our findings raise questions about whether levels of bias may have been underestimated in these papers because the employment settings studied were relatively low-income. Second, our findings have implications for the interpretation of persistent male-female and minority-white wage gaps (Altoni and Blank, 1999). If discrimination is greater in higher-paying fields, this may have equilibrium effects, pushing women and minorities into lower-income professions and potentially helping to explain persistent wage gaps. Further, recent data indicates that the male-female wage gap is larger in higher-paid professions (Rampell, 2009), and our findings suggest that this could be due to increased gender discrimination in higher-salary industries.

Our data also offers a second answer to the question of where discrimination is most severe: private institutions. But why do professors at private schools discriminate more against minorities and females than public school professors? One possible explanation is that the populations of faculty who work at public and private institutions have different values and priorities, and thus faculty selection may explain our findings. Another possibility is that pay (which is $34,687 higher on average at private schools; Byrne, 2008) explains both differences in discrimination across disciplines and between public versus private schools. For example, faculty may view pay as a signal of how valuable their time is, which may lead higher paid faculty to be more discriminating about who they assist. A third possibility is that university policies that differ between private and public institutions are responsible for the differences detected. Our data strongly suggests that institutional differences, perhaps related to status, values, or policies, can lead to varying patterns of bias, and the causal explanation should be examined in future research.

For policy makers with an interest in improving the diversity of post-secondary institutions, our findings highlight the fact that efforts to change the skewed demographics of the academy must acknowledge multiple causes of underrepresentation. The best known programs aiming to change the face of the academy do so by focusing on specific disciplines, and they assume the appropriate disciplines to target are those where underrepresentation is most severe (e.g., STEM). Our findings suggest that underrepresentation is just one factor that should inform where efforts to reduce bias are focused and that discrimination is not meaningfully linked to the proportion of minority or female faculty or students in a discipline. Therefore, in addition to focusing resources on disciplines where underrepresentation is most pronounced, programs and policies need to be targeted specifically towards disciplines where bias is the most acute (according to our research: business, education, human services, health sciences and engineering). Further, our findings suggest that eliminating under-representation of women and minorities is not likely to be a panacea for eliminating race and gender discrimination.

Broadly, the findings we present highlight the importance of looking beyond *whether* discrimination exists and gaining deeper insights into *where* discrimination is most prevalent. Such research can help identify where policies designed to combat discrimination are most needed, inform our interpretation of past and future audit research, and advance our understanding of what drives discrimination. We hope this work will inspire future studies designed to disentangle the different possible causal explanations for the heterogeneity in discrimination detected by our audit experiment.

Figure I. Sample-weighted[10] response rates experienced by minority and female students relative to Caucasian males (A) en masse and (B) broken down by race and gender as a function of the faculty member's broad academic discipline. Disciplines are sorted by the size of the average discriminatory gap (with reverse-discrimination shown in black).



[10] Observations are weighted to adjust for design decisions such as oversampling minority faculty and unbalanced randomization so that summary statistics can be interpreted as representative of the U.S. faculty population. See SOM details on the study's sampling methodology.

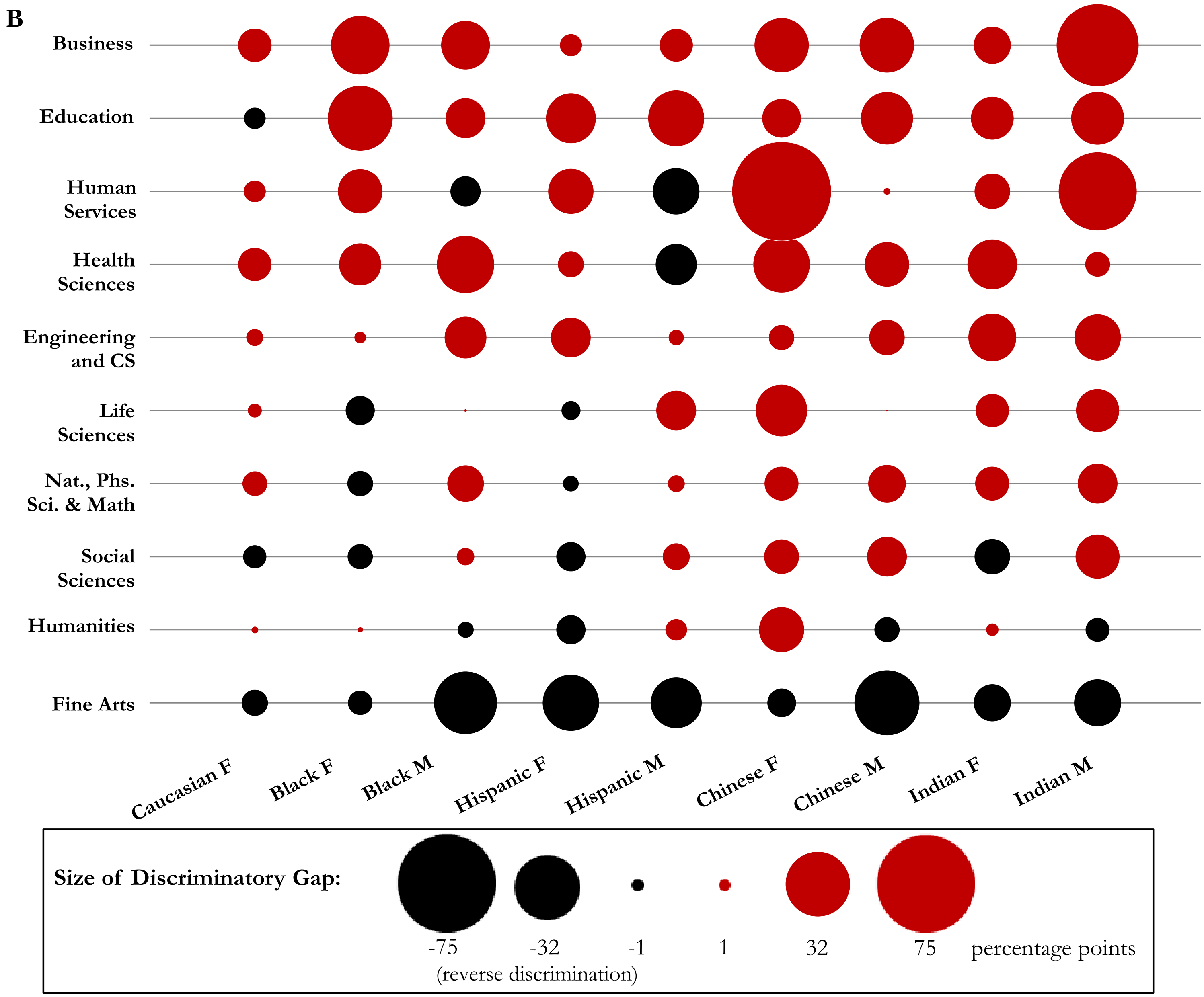

B
Business
Education
Human Services
Health Sciences
Engineering and CS
Life Sciences
Nat., Phs. Sci. & Math
Social Sciences
Humanities
Fine Arts
Caucasian F
Black F
Black M
Hispanic F
Hispanic M
Chinese F
Chinese M
Indian F
Indian M
Size of Discriminatory Gap:
-75
-32
-1
1
32
75
percentage points
(reverse discrimination)

Figure II. Sample-weighted[9] response rates experienced by underrepresented students, relative to Caucasian males, (68% public school; 77% private school) as a function of the faculty member's affiliation with a private or public university.

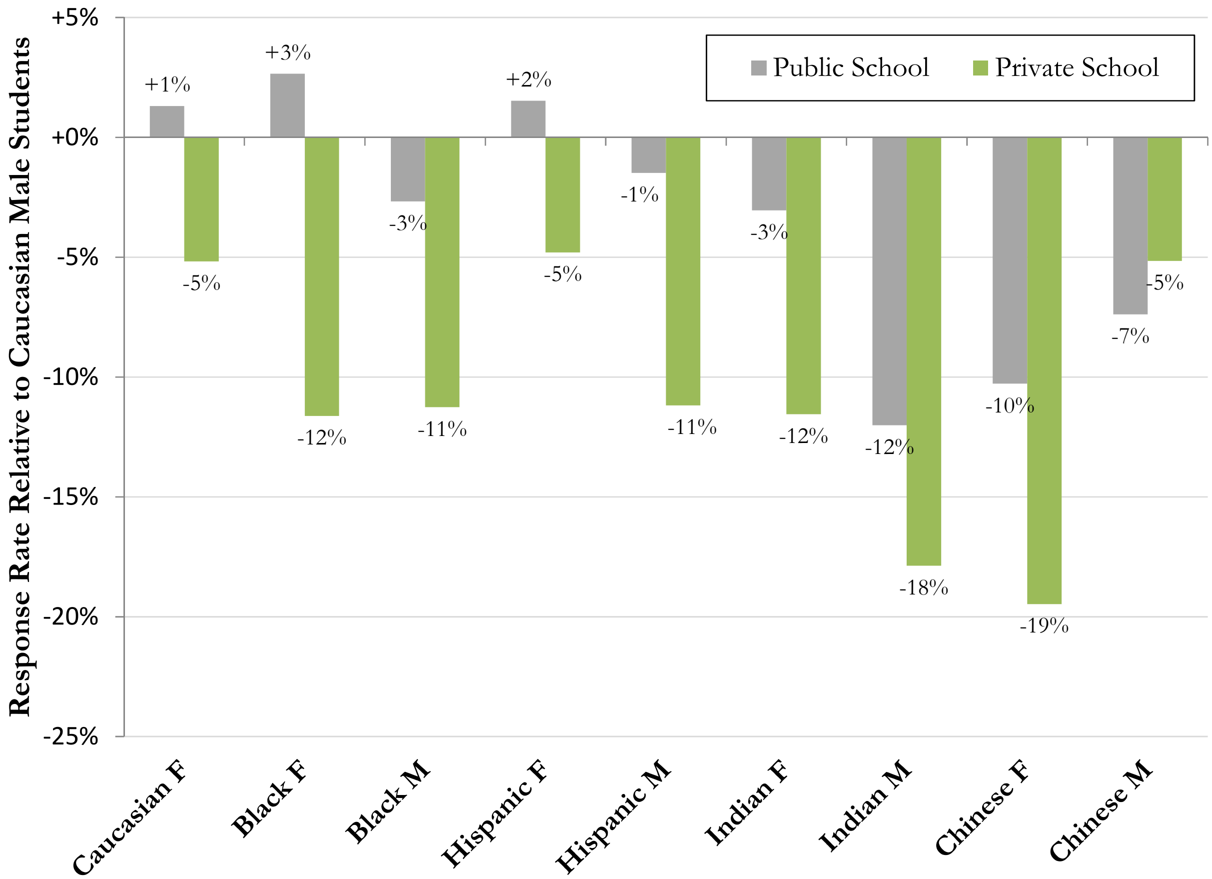


Table I. Summary of Faculty Included in Study by Discipline and University Type

		Sample-Weighted Representation						
Discipline	**N**	**Female**	**Caucasian**	**Black**	**Hispanic**	**Chinese**	**Indian**	**Other Race**
Business	265	26%	85%	2%	1%	4%	5%	4%
Education	441	55%	91%	2%	2%	2%	1%	3%
Engineering and Computer Science	1,125	15%	78%	1%	1%	8%	8%	4%
Fine Arts	209	38%	92%	1%	1%	4%	1%	2%
Health Sciences	343	46%	91%	2%	0%	3%	1%	2%
Human Services	188	43%	87%	4%	2%	1%	1%	5%
Humanities	668	38%	90%	2%	2%	2%	2%	2%
Life Sciences	1,051	24%	90%	0%	1%	4%	3%	2%
Natural, Physical Sciences and Math	850	18%	85%	1%	1%	7%	4%	3%
Social Sciences	1,379	38%	90%	2%	2%	2%	2%	3%
University Type								
Public	4,450	30%	87%	1%	2%	5%	4%	2%
Private	2,098	32%	88%	1%	1%	4%	2%	3%

Table II. Race and Gender Recognition Survey Results for Selected Names[11]

Race	Gender	Name	Rate of Race Recognition	Rate of Gender Recognition
Caucasian	Male	Brad Anderson	100%***	100%***
		Steven Smith	100%***	100%***
	Female	Meredith Roberts	100%***	100%***
		Claire Smith	100%***	100%***
Black	Male	Lamar Washington	100%***	100%***
		Terell Jones	100%***	94%***
	Female	Keisha Thomas	100%***	100%***
		Latoya Brown	100%***	100%***
Hispanic	Male	Carlos Lopez	100%***	100%***
		Juan Gonzalez	100%***	100%***
	Female	Gabriella Rodriguez	100%***	100%***
		Juanita Martinez	100%***	100%***
Indian	Male	Raj Singh	90%*** (10% Other)	100%***
		Deepak Patel	85%*** (15% Other)	100%***
	Female	Sonali Desai	85%*** (15% Other)	100%***
		Indira Shah	85%*** (10% Other; 5% Hispanic)	94%***
Chinese	Male	Chang Huang	100%***	94%***
		Dong Lin	100%***	94%***
	Female	Mei Chen	100%***	94%***
		Ling Wong	100%***	78%*

Reported significance levels indicate the results of a two-tailed, one sample test of proportions to test the null hypothesis that the observed recognition rate is equal to that expected by chance (16.7% for race and 50% for gender). *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

[11] Note that this table also appears in Milkman, Akinola and Chugh (in press).

Table III. Ordinary least squares regression to predict whether faculty respond to emails from prospective doctoral students as a function of broad academic discipline indicators (humanities omitted), interactions between discipline indicators and whether a student is a minority or female, and numerous control variables. Standard errors are clustered by broad academic discipline (N=10) and are shown in parentheses. Observations are sample-weighted.

Business	0.051***
	(0.005)
Business x Minority or Female Student	-0.180***
	(0.005)
Education	0.071***
	(0.006)
Education x Minority or Female Student	-0.158***
	(0.004)
Human Services	0.082***
	(0.005)
Human Services x Minority or Female Student	-0.136***
	(0.008)
Health Sciences	-0.096***
	(0.005)
Health Sciences x Minority or Female Student	-0.105***
	(0.003)
Engineering and Computer Sciences	-0.080***
	(0.004)
Engineering & CS x Minority or Female Student	-0.077***
	(0.003)
Life Sciences	-0.093***
	(0.002)
Life Sciences x Minority or Female Student	-0.045***
	(0.002)
Natural, Physical Sciences & Math	-0.069***
	(0.004)
Natural, Physical Sciences & Math x Minority or Female Student	-0.039***
	(0.003)
Social Sciences	-0.043***
	(0.002)
Social Sciences x Minority or Female Student	-0.021***
	(0.002)
Fine Arts	-0.165***
	(0.004)
Fine Arts x Minority or Female Student	0.155***
	(0.003)
Included Controls: Student: Race, Gender, Race x Gender; Recipient: Race, Gender, Position (Full, Associate, Assistant), School Rank; Request for Now; Request for Now x Minority/Female Student, Faculty-Student Racial Match	
Observations	6,519
R^2	0.03
Wald Test of Hypothesis that Interaction Terms are Jointly Equal to Zero	F(9,9) = 9,2485.75***
Wald Test of Hypothesis that Interaction Terms are Jointly Equal to One Another	F(8,9) = 1296.12***

^Significant at the 10% level. *Significant at 5% level. **Significant at 1% level. ***Significant at the 0.1% level.

Table IV. Ordinary least squares regressions to predict whether faculty respond to emails from prospective doctoral students as a function of students' race, gender, characteristics of faculty's academic discipline and university, and the interaction between minority student status and these faculty characteristics. Standard errors are clustered by university (N=258) and academic discipline (N=89) and are shown in parentheses. All continuous variables were standardized before creating interaction terms.

		(1)	(2)	(3)	(4)	(5)
Academic Discipline Characteristics	**Z-Avg. Faculty Pay**	0.000	0.009	0.014	0.014	0.014
		(0.016)	(0.017)	(0.017)	(0.017)	(0.017)
	Z-Pay x Minority or Female Student	-0.043*	-0.048**	-0.053**	-0.053**	-0.053**
		(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
	Z-Faculty% Minority	-	0.002	0.000	0.000	0.000
		-	(0.010)	(0.010)	(0.010)	(0.010)
	Z-Fac%Minority x Minority Student	-	0.002	0.003	0.005	0.005
		-	(0.012)	(0.012)	(0.013)	(0.013)
	Z-Faculty % Female	-	0.018^	0.018^	0.019^	0.019^
		-	(0.010)	(0.010)	(0.011)	(0.011)
	Z-Fac%Female x Female Student	-	-0.014	-0.014	-0.014	-0.014
		-	(0.013)	(0.013)	(0.014)	(0.014)
	Z-PhD Students % Minority	-	0.002	0.002	-0.004	-0.004
		-	(0.016)	(0.016)	(0.016)	(0.016)
	Z-PhD%Minority x Minority Student	-	-0.004	-0.003	0.001	0.001
		-	(0.018)	(0.018)	(0.018)	(0.018)
University Characteristics	**Public School**	-	-	-0.100***	-0.110***	-0.113***
		-	-	(0.025)	(0.029)	(0.035)
	Public School x Minority or Female Student	-	-	0.140***	0.141***	0.145***
		-	-	(0.029)	(0.034)	(0.039)
	Z-Undergraduate % Minority	-	-	-	-0.024*	-0.024*
		-	-	-	(0.012)	(0.012)
	Z-Und%Minority x Minority Student	-	-	-	0.011	0.011
		-	-	-	(0.013)	(0.013)
	Z-Undergraduate % Female	-	-	-	-0.009	-0.009
		-	-	-	(0.008)	(0.007)
	Z-Und%Female x Female Student	-	-	-	0.005	0.005
		-	-	-	(0.013)	(0.012)
	Z-School Rank (US News)	-0.006	-0.006	-0.010^	-0.006	-0.003
		(0.006)	(0.006)	(0.005)	(0.005)	(0.019)
	Z-School Rank x Minority or Female Student	-	-	-	-	-0.004
		-	-	-	-	(0.021)
Minority Student Characteristics	**Black**	-0.088**	-0.091**	-0.180***	-0.176***	-0.178***
	Hispanic	-0.078*	-0.080*	-0.172***	-0.159***	-0.161***
	Indian	-0.177***	-0.178***	-0.268***	-0.253***	-0.255***
	Chinese	-0.123***	-0.124***	-0.215***	-0.204***	-0.206***
	Female	-0.042	-0.044	-0.134***	-0.128**	-0.130**
	Black x Female	0.059^	0.063*	0.153***	0.146***	0.148***
	Hispanic x Female	0.078*	0.081*	0.172***	0.170***	0.172***
	Indian x Female	0.105*	0.105*	0.194***	0.172***	0.174***
	Chinese x Female	0.015	0.015	0.101*	0.093^	0.095^
Additional Controls: Recipient: Race, Gender, Position (Full, Associate, Assistant); Request for Now; Request for Now x Minority/Female Student, Faculty-Student Racial Match						
Observations		6,206	6,206	6,206	6,206	5,852
R^2		0.02	0.02	0.03	0.03	0.03

^Significant at the 10% level. *Significant at 5% level. **Significant at 1% level. ***Significant at the 0.1% level.

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