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What Happens Before? A Field Experiment Exploring How Pay and Representation Differentially Shape Bias on the Pathway Into Organizations

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Little is known about how discrimination manifests before individuals formally apply to organizations or how it varies within and between organizations. We address this knowledge gap through an audit study in academia of over 6,500 professors at top U.S. universities drawn from 89 disciplines and 259 institutions. In our experiment, professors were contacted by fictional prospective students seeking to discuss research opportunities prior to applying to a doctoral program. Names of students were randomly assigned to signal gender and race (White, Black, Hispanic, Indian, Chinese), but messages were otherwise identical. We hypothesized that discrimination would appear at the informal "pathway" preceding entry to academia and would vary by discipline and university as a function of faculty representation and pay. We found that when considering requests from prospective students seeking mentoring in the future, faculty were significantly more responsive to White males than to all other categories of students, collectively, particularly in higher-paying disciplines and private institutions. Counterintuitively, the representation of women and minorities and discrimination were uncorrelated, a finding that suggests greater representation cannot be assumed to reduce discrimination. This research highlights the importance of studying decisions made before formal entry points into organizations and reveals that discrimination is not evenly distributed within and between organizations.

Keywords: discrimination, pathways, race, gender, audit study

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Substantial evidence suggests that discrimination persists in today's labor market, affecting hiring, pay, promotion, and other rewards (e.g., see Altonji & Blank, 1999; Bertrand & Mullainathan, 2004; Cole, 1979; Long, & Fox, 1995; Pager & Quillian, 2005; Pager, Western, & Bonikowski, 2009; Stauffer & Buckley, 2005; Valian, 1999). Many have argued that discrimination contributes to the underrepresentation of women and minorities, particularly at the highest echelons of organizations (Bertrand, Goldin, & Katz, 2010; Smith, 2002), despite widespread efforts to promote diversity (Dobbin, Kim, & Kalev, 2011; Kalev, Dobbin, & Kelly, 2006).

Three important gaps limit our ability to understand and address labor market discrimination. First, our existing knowledge is primarily based on extensive documentation of how women and minorities are differentially treated relative to White males *attempting to enter* organizations at "gateways" (Chugh & Brief, 2008), but we know little about discrimination that may occur along "pathways" in the informal processes *leading up to the attempt to enter* (Chugh & Brief, 2008). Second, while most metrics studied show differences in treatment by gender and race, few studies allow for causal inference, and to our knowledge, none have been broad enough to explore the magnitude and extent of discrimination across different types of organizations. As a result, greater knowledge of *where* (meaning, in which types of organizations) and *when* (under what conditions) discrimination may play a *causal* role in explaining observed racial and gender differences is needed. Finally, studies of discrimination in which individuals realize they are being observed (e.g., qualitative and laboratory studies) may suffer from social desirability bias and thus

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fail to measure implicit, unconscious, or unintentional bias, which many have argued could be a more pernicious problem than explicit, conscious, or unintentional bias in the modern era (e.g., Bertrand, Chugh, & Mullainathan, 2005; Dovidio & Gaertner, 1998; Greenwald & Banaji, 1995; Newman & Krzystofiak, 1979; Quillian, 2006; Sue, 2010; Valian, 1999). To the extent that unconscious bias may be contributing to discrimination, unobtrusive methods for studying discrimination are critical. In this article, we address each of these gaps in order to deepen our understanding of discrimination.

Our article focuses on what happens *before* someone chooses to apply to an organization, using a methodology allowing for causal inference and measurement of both conscious and unconscious bias, within and across different types of organizations. Specifically, we employ an audit experiment methodology. This methodology relies on pairs of matched testers who differ only on race, gender, or some other dimension of interest, and who attempt to obtain a desired outcome using identical techniques while treatment differences are measured (Pager, 2007; Quillian, 2006). Recent audit studies across a wide range of contexts offer causal evidence with high external validity that discrimination continues to disadvantage minorities and women relative to White males with the same credentials. This research has shown that White job candidates receive a 50% higher callback rate for interviews than identical Black job candidates (Bertrand & Mullainathan, 2004), Black and Latino job applicants with clean records are treated like Whites just released from prison (Pager, Western & Bonikowski, 2009), Blacks and Hispanics receive fewer opportunities to rent and purchase homes than Whites (Turner et al., 2002; Turner & Ross, 2003), and women receive fewer interviews and offers than men for jobs in high-priced restaurants (Neumark, Bank, & Van Nort, 1996). Further, pregnant women receive more hostile treatment than nonpregnant women when applying for jobs (Morgan et al., 2013), obese job applicants receive fewer job interviews than nonobese applicants based on hiring managers' implicit biases (Agerström & Rooth, 2011), and women and minority prospective PhDs, collectively, receive less support than White males from prospective academic advisors when seeking meetings for a week in the future (Milkman, Akinola, & Chugh, 2012). These past audit studies examining discrimination have primarily focused on documenting the existence of discrimination and measuring its magnitude but have left unaddressed the critically important question of how levels of discrimination may vary across organizational environments. In this article, we examine how characteristics of the organizational environment, such as its representation of women and minorities, its constituents' areas of expertise, and its average pay levels relate to discrimination.

The Setting: Academia

We conduct our audit study with professors in U.S. universities. Academia is an ideal setting for an experiment examining discrimination in organizations for several reasons. First, academia serves as an entry point for nearly all professions, and increasing female and minority representation among faculty in academia (which first requires increasing representation among those receiving doctorates) is associated with higher educational attainment for female and minority students, respectively (Sonnert, Fox, & Adkins, 2007; Trower & Chait, 2002). Second, academia is, pragmatically, an ideal context for a field experiment due to the ease of building a database describing its workforce, as information about virtually all U.S. faculty members is easily retrievable online (e.g., race, gender, disciplinary affiliation, institutional affiliation, and status), as is reliable archival data describing characteristics of its workforce by discipline and institution type (U.S. Department of Education, National Center for Educational Statistics, 2004; U.S. News & World Report, 2010). Finally, the heterogeneity of academics along a number of interesting and observable dimensions (e.g., area of study) makes academia an ideal setting for exploring the characteristics of an organization (e.g., student body demographics, faculty demographics, and average salary) that may exacerbate (or reduce) bias. At the same time, all tenure-track academics receive the same basic training (a doctoral degree) and conduct the same basic job functions (teaching students and conducting research). Thus, while holding education and job function constant, we are able to explore how organizational characteristics of theoretical interest relate to levels of discrimination.

In academia, the majority (60%) of full professors at U.S. postsecondary institutions are White males, and 28% are female, 7% are Asian, 3% are Black, and 3% are Hispanic (U.S. Department of Education, 2010). For many groups, underrepresentation begins as early as the doctoral stage (U.S. Department of Education, 2012). Further, within academia, women and minorities consistently fare worse than White males in terms of pay (Ginther, 2006; Ransom & Megdal, 1993; Toutkoushian, 1998), promotions (Cole, 1979; Ginther, 2006; Long, Allison, & McGinnis, 1993; Perna, 2001), job prospects (Kolpin & Singell, 1996; Moss-Racusin et al., 2012; Nakhaie, 2007; Sonnert, 1990; Steinpreis, Anders, & Ritzke, 1999), funding opportunities (Ginther et al., 2011), and overall treatment (Clark & Corcoran, 1986; Gersick, Dutton, & Bartunek, 2000; Johnsrud & Sadao, 1998; Turner, Myers, & Creswell, 1999). Our focus on bias in education also extends to research on conscious and unconscious race and gender bias by teachers in the K–12 educational context (e.g., Harber et al., 2012; Tobin & Gallagher, 1987). Under circumstances where bias would be expected to arise (i.e., when students request future support from a prospective mentor), we investigate whether and where women and minorities[1] considering graduate school may experience disproportionately less support in the early, informal processes leading up to the decision to apply. We propose that differential treatment at this pathway stage is a possible factor in the underrepresentation of women and minorities in the ranks of both doctoral students and professors.

Specifically, we present new analyses of a field experiment in which 6,548 tenure-track professors at 259 top U.S. universities in 109 different PhD-granting disciplines were contacted by fictional

[1] Note that throughout this article, we will use the term "women and minorities" to refer to all students in our study besides White males. Past research suggests that, relative to White males, the other student groups included in our study (White females, Black males and females, Hispanic males and females, Indian males and females, and Chinese males and females) may be disadvantaged by negative stereotypes (Bartlett & Fischer, 2011; Cuddy, Fiske, & Glick, 2007; Steele & Aronson, 1995; Weyant, 2005; Heilman, 2001; Katz & Braly, 1933; Kim & Yeh, 2002; Lee & Fiske, 2006; Lin et al., 2005; Nosek et al., 2007; Rudman & Glick, 2001; Steele, 1997). When we make statements about "women and minorities, collectively" we are collectively referring to the treatment of White females grouped with all racial minorities studied (be they male or female).

prospective doctoral students seeking a meeting to discuss research opportunities along the pathway to graduate school. The names of the "students" were randomly assigned to signal gender and race (White, Black, Hispanic, Indian, Chinese), but their messages were otherwise identical. Our outcome of interest is whether faculty responded to these inquiries; in particular, we zoom in on inquiries sent about future (rather than same-day) interactions, which have been shown to give rise to bias (Milkman, Akinola & Chugh, 2012). By exposing faculty in various disciplines to students who differ only in race and gender, we can examine the extent to which race and gender consciously or unconsciously influence decision making. We provide direct, quantitative evidence of whether, where, and when members of the Academy fail to offer women and minorities, collectively, the same encouragement, guidance, and research opportunities offered to White men prior to formally applying to a doctoral program.

Discrimination at Gateways Versus Pathways

Gateways are the entry points into valued organizations, communities, or institutions, whereas *pathways* describe the more fluid processes that influence one's ability to access an entry point and succeed after entry (Chugh & Brief, 2008). Positive outcomes along pathways and at gateways can determine success in organizations. Past research examining race and gender discrimination in organizations and in the Academy has focused largely on the obstacles that women and minorities face at formal gateways to those institutions (e.g., in admissions decisions and hiring decisions; see Attiyeh & Attiyeh, 1997; Bertrand & Mullainathan, 2004; Kolpin & Singell, 1996; Moss-Racusin et al., 2012; Pager, Western, & Bonikowski, 2009; Steinpreis, Anders, & Ritzke, 1999) and on the formal evaluation of performance of these groups once they have entered (e.g., grades, promotions, pay, job satisfaction, turnover; see Castilla & Benard, 2010; McGinn & Milkman, 2013; Sonnert & Fox, 2012; Tolbert, Simons, Andrews, & Rhee, 1995; Toutkoushian, 1998).

However, before an individual can be granted or denied admission to an organization or begin to compete for accolades, she must decide whether or not to apply to an organization. Self-assessments shaped by others' treatment of her can influence such decisions (Correll, 2001; Correll, 2004; Hoxby & Avery, 2012). It is therefore critical to examine race and gender discrimination that may occur along pathways leading to gateways, which influence whether an individual elects to apply to an institution (Fernandez & Sosa, 2005).

For example, along the pathway to higher education, students must perceive opportunities, receive encouragement and mentorship from teachers, friends, and parents, and complete the necessary prerequisites, such as standardized testing (Correll, 2001; Correll, 2004; Hoxby & Avery, 2012). Notably, the decision about whether to pursue a doctorate occurs at a critical career stage when many potential academics leave the pipeline (Seymour & Hewitt, 1997; U.S. Department of Education, 2009). If women and minorities are ignored at a higher rate than White males by prospective mentors when considering doctoral study, they may be more likely to be (a) discouraged from applying for a doctorate; (b) disadvantaged in navigating the admissions process, having received less guidance than White males on components of their application, (c) disqualified from serious consideration due to a lack of the very research experience they attempted to acquire, and (d) disconnected from the informal networks that undergird pathway processes both inside and outside academia.

Informal mentorship received along pathways in organizations can confer significant benefits (Eby et al., 2008; Ragins & Cotton, 1999; Underhill, 2006). For instance, student-faculty mentoring is considered essential for learning beyond the classroom (Jacobi, 1991; Pascarella, 1980) and is especially critical for graduate education (Clark, Harden, & Johnson, 2000). Faculty mentors can play multiple roles, such as shaping a student's professional identity and his or her understanding of potential career paths (Austin, 2002). Women and minorities in particular benefit from constructive mentoring relationships (Thomas & Higgins, 1996), especially when the mentor and mentee have an effective strategy for dealing with cross-race differences (Thomas, 1993).

Unlike gateways, which are typically characterized by discrete timeframes and structured entrance processes, pathways are more informal and tacit, creating an environment where unconscious and subtle manifestations of bias may be particularly likely to arise. Bias may emerge from the activation and application of stereotypes (Gilbert & Hixon, 1991), which can harm how women and minorities are perceived. We propose that in the context of academia, negative stereotypes may affect the degree to which women and minorities receive mentorship along pathways to academia. Commonly, Black students are stereotyped as not intelligent and/or not hardworking (Cuddy, Fiske, & Glick, 2007; Steele & Aronson, 1995); Hispanic students are stereotyped as not educated and not fluent in English (Weyant, 2005; Lee & Fiske, 2006); Chinese students are stereotyped as un-American, not fluent in English, and/or possessing fraudulent credentials (Bartlett & Fischer, 2011; Katz & Braly, 1933; Kim & Yeh, 2002); and Indian students are stereotyped as foreign and difficult to understand (Lee & Fiske, 2006; HBS Working Knowledge, 2005; UsingEnglish.com, 2007). Chinese and Indian students also evoke positive academic "model minority" stereotypes (Lin et al., 2005). Females are associated with their own set of negative stereotypes, such as a lack of competence, poor math skills, and/or a lack of professional ambition (Nosek et al., 2007; Heilman, 2001; Rudman & Glick, 2001; Steele, 1997).

A growing body of research has demonstrated that these "implicit biases," or prejudices, exist outside of conscious awareness, persist even as our explicit attitudes evolve (Greenwald & Banaji, 1995) and predict behaviors such as negative interracial contact (McConnell & Leibold, 2001), biases in medical decision-making (Green et al., 2007), and hiring discrimination (Rooth, 2010). Further, researchers have argued that despite laws prohibiting overtly racist behaviors in the workplace, subtle manifestations of racism persist, including inequitable treatment, neglect, ostracism, and other forms of "microaggression" (Sue, 2010) and "microinequities" (Fox & Stallworth, 2005; Pierce, 1970; Rowe, 1990). Moreover, though relatively harmless in isolation, these microaggressions accumulate and when "delivered incessantly . . . the cumulative effect to the victim and to the victimizer is of an unimaginable magnitude" (Pierce, 1970).

We propose that an understudied force that may contribute to the underrepresentation of women and minorities in doctoral programs is discrimination they experience as they initiate contact with potential mentors along pathways to the Academy. This discrimination may deter them—even passively and perhaps unintentionally—from entering the pool of applicants for doctoral programs. Specifically, we focus on whether faculty respond to inquiries from prospective doctoral students seeking mentorship in the form of encouragement, guidance, and research opportunities. Replying (vs. not replying) to an e-mail from a student seeking research experience and considering a doctorate, the outcome variable of interest in our study, is the most visible signal that a faculty member has not entirely dismissed or overlooked the prospective student's interest.

Our focus on pathways, particularly those preceding gateways, aligns well with the theory of cumulative disadvantage (Clark & Corcoran, 1986; DiPrete & Eirich, 2006; Merton, 1968), which presumes underrepresentation to be the result of many small differences in how members of minority groups are treated early in their careers, or a function of one small difference at an early stage that "accumulate[d] to [create] large between-groups differences" (Ginther et al., 2011). Such mechanisms of cumulative (dis)advantage are frequently invoked as explanations for inequality (Clark & Corcoran, 1986; DiPrete & Eirich, 2006; Merton, 1968); yet, to our knowledge, previous empirical research has not examined the possibility that even passive discouragement as individuals consider whether to apply for opportunities may contribute to underrepresentation. For this reason, we examine the treatment of women and minorities at the point when prospective students contemplate applying to graduate school and seek guidance and encouragement from potential doctoral mentors.

The breadth of our field experiment gives us the ability to address the critical question of whether any discrimination that arises when students seek future interactions with faculty is evenly distributed or instead more pronounced under certain conditions. Specifically, we hypothesize that a given group's representation in an organization relates to the degree of discrimination that group experiences when requesting future opportunities due to the influence of "homophily," or the tendency to prefer associating with those similar to us (e.g., see McPherson, Smith-Lovin, & Cook, 2001). Additionally, linking research on systems and processes that perpetuate social inequality (Blau & Kahn, 1999), pollution theories of discrimination (Goldin, 2013), and recent studies on the influence of money on ethicality and generosity (Piff et al., 2010; Caruso, Vohs, Baxter, & Waytz, 2013; Piff et al., 2012) to the important issue of discrimination, we hypothesize that discrimination varies by discipline and by average faculty pay in the discipline. We provide our theoretical basis for these hypotheses next.

Theoretical Basis for Hypothesis Linking Discrimination and Representation

We propose that discrimination in academia and beyond will be moderated by the characteristics of the context in which an interaction occurs. Extensive prior social psychology research suggests that discrimination will vary as a function of the organizational context in which actors are embedded (for a review, see Yzerbyt & Demoulin, 2010). For instance, people's values, which vary across organizational contexts, have been shown to relate to stereotype activation (Moskowitz et al., 1999; Towles-Schwen & Fazio, 2003) and thus would be expected to influence the degree to which discrimination manifests itself across environments.

In the academic context, a critical social and structural division associated with professional values is one's academic discipline. Disciplines vary along multiple dimensions (see Becher, 1994), including, for example, subject matter, style of intellectual inquiry, the nature of the knowledge pursued (e.g., cumulative, reiterative, pragmatic, functional, utilitarian), demographic composition, and culture (e.g., competitive, individualistic, entrepreneurial). Academic disciplines are thus likely to vary in their levels of receptivity to women and minorities, and past studies have shown that this variability may be driven by the role that employer and constituency preferences play in influencing diversity. For instance, Tolbert and Oberfield (1991) theorize that heterogeneity in the gender composition of a university may result from multiple dynamics, including employer, constituency, and employee preferences, and they find empirical support for the role played by employer and constituency preferences in shaping heterogeneity in a university's gender composition. Given that we are studying discrimination in academia, where there is substantial variability in the constituencies and cultures of academic disciplines, we would expect to see considerably more heterogeneity in levels of discrimination across different academic disciplines than would be expected by chance. If such variability indeed exists, a question of considerable theoretical interest then becomes what characteristics of a discipline we would expect to exacerbate discrimination.

Theories of group attachment suggest that individuals are motivated to select categorization processes that privilege certain groups over others. Specifically, social identity theory and accompanying research have demonstrated that people tend to categorize themselves as similar or different from others based on shared identity-relevant traits (Tajfel & Turner, 1986), such as race and gender (Cota & Dion, 1986; Frable, 1997; Porter & Washington, 1993). These shared identities draw individuals together, creating a perception of similarity, which leads to attraction (Byrne, 1971; Lincoln & Miller, 1979; Hogg & Terry, 2000), strong social ties (Ibarra, 1992), and better treatment of demographic in-group than out-group members. This tendency toward "homophily," or showing greater affinity toward members of one's own demographic group relative to others (e.g., see McPherson, Smith-Lovin, & Cook, 2001), can result in organizational members providing preferential treatment to those who share their demographics when promoting, hiring, judging, and mentoring others (Kanter, 1977; Price & Wolfers, 2010; Ragins & McFarlin, 1990). This research, if applied to the context of academia—a context comprised predominantly of White males—suggests that minorities and women may experience discrimination from majority group members who do not share their race or gender. Further, this discrimination may be more pronounced in parts of the Academy that are more predominantly composed of White males.

By the same token, the tendency toward homophily suggests that minorities and women may exhibit less discriminatory behavior than White males toward those who share their race or gender, such that greater representation of women and minorities in an organization might decrease discrimination. Moreover, greater representation of minorities and women can produce other benefits for these groups, including higher work satisfaction, commitment, and reduced turnover (Williams & O'Reilly, 1998; Zatzick, Elvira & Cohen, 2003), likely due to the combined benefits of homophily and the redefined social constructions of identity that can emerge in contexts where a given group is well-represented (Ely, 1995).

The "lack-of-fit" theory (Heilman, 1983, 1995, 2001) also suggests that greater representation of a given minority group might decrease discrimination. According to this theory, a lack of congruence between attributes stereotypically ascribed to a poorly represented group and those stereotypically ascribed to a better represented group contributes to a belief that underrepresented group members are not a good "fit" for particular jobs. Any negative expectations ensuing from perceptions of lack of fit can adversely affect how decision makers view and treat less-represented group members, thus perpetuating the lower representation. Greater representation of a minority group in a given organization, however, should increase the perceived fit between those exhibiting stereotypical traits of that minority group and the organization in question, thus improving treatment of those in the minority and reducing bias.

While a small number of studies have hinted that increases in representation under certain conditions carry risks for women and minorities (e.g., McGinn & Milkman, 2013; Tolbert et al., 1995), most findings suggest that bias against women and minorities is likely to decline in settings where they are better represented. Taken together, theories on group attachment, social identity, implicit bias, homophily, and lack of fit suggest that women and minorities will experience biased treatment relative to White males based on the degree to which these groups are already represented in the organization. Thus, we hypothesize the following:

> *Hypothesis 1:* As the representation of women and minorities in disciplines and universities increases, discrimination against those groups decreases.

Theoretical Basis for Hypothesis Linking Discrimination and Income

It has been well established that White males are overrepresented relative to other groups in the highest paying jobs (Bertrand & Hallock, 2000; Braddock & McPartland, 1987; Morrison & von Glinow, 1990; Oakley, 2000). This gap has been attributed to numerous factors, including differences in qualifications, wage structure, the rewards for skills and employment in particular sectors, and discrimination against women and minorities in these settings (Blau & Khan, 1999; Braddock & McPartland, 1987). Is it also possible that discrimination is greater in higher-paying jobs than lower-paying jobs?

The pollution theory of discrimination (Goldin, 2013) suggests that this may be true. According to this theory, members of an occupation may perceive its prestige to be threatened, or "polluted," by the entry of an underrepresented group member. Individuals from underrepresented groups are often judged by group stereotypes, rather than by their own individual qualities. If the underrepresented group's stereotypical qualities are perceived to be inferior to those of the dominant group, and if the underrepresented group member is brought into the occupation, then members may make a pollution attribution—that the group has lowered its standards and thus polluted the quality of its membership—rather than simply assuming that the individual met the standards of the group. Theoretically, such perceptions can lead to discrimination that keeps underrepresented group members out of the occupation. Given that the prestige of an occupation may increase with pay (e.g., Duncan, 1961), well-represented groups in highly paid occupations may be more sensitive to the potential for women and minorities to "pollute" their occupations' prestige, fueling discriminatory behavior against women and minorities.

Recent psychological research has demonstrated that income strongly affects ethicality and generosity (Piff et al., 2010; Piff et al., 2012). Specifically, wealthier individuals make less ethical and less generous decisions in correlational studies than poorer individuals (Piff et al., 2010; Piff et al., 2012). In addition, priming money experimentally also reduces ethicality and generosity (Gino & Pierce, 2009; Vohs, Mead & Goode, 2006). Across a series of experiments, participants primed with money (relative to a neutral prime) volunteered significantly less time to help others and donated significantly less money to a charitable fund for students in need (Vohs, Mead, & Goode, 2006). In correlational studies, wealthier individuals were found to make more unethical driving decisions, violating traffic laws more frequently and placing pedestrians at greater risk, and wealthier individuals were more likely to lie, cheat, take valued goods from others, and endorse unethical behavior at work (Piff et al., 2012). In other words, across research using multiple methods (both studies that treat wealth as a trait and those that explore the effects of priming money), the same negative association between money and generosity as well as ethicality arises.

A key question is why both wealthier individuals and those primed to focus on wealth or abundance tend to be both less ethical and less generous than others. The dominant theory, summarized by Kraus et al. (2012), is that these individuals exhibit a reduced sense of empathy and connectedness with others. For instance, wealthier individuals demonstrate less empathetic accuracy than members of lower socioeconomic groups, and those induced to feel that they are higher in socioeconomic status (SES) than others are worse than others at identifying emotions on pictures of faces (Kraus, Côté, & Keltner, 2010). In addition, in interactions with strangers, less wealthy individuals engage more fully (e.g., through greater eye contact) than wealthier individuals (Kraus & Keltner, 2009).

Prior research has also linked income to an endorsement of systems that perpetuate social inequality (Jost & Banaji, 1994). Specifically, participants primed to think about money (vs. those exposed to a neutral prime) were shown to (a) perceive the prevailing U.S. social system to be significantly more fair and legitimate, (b) be significantly more willing to rationalize social injustice, and (c) express a greater preference for group-based discrimination (Caruso et al., 2013). This research suggests a causal link between income and race and gender discrimination. If higher incomes reduce egalitarianism, generosity, and racial tolerance, and increase support for systems that perpetuate social inequality, they may also produce discrimination. Given that there is variance in salary across academic disciplines, reflecting heterogeneity in income/wealth among professors, we hypothesize the following:

> *Hypothesis 2:* Discrimination against women and minorities will be more severe in disciplines and at universities in which professors are better paid.

Research Design and Method

We test our hypotheses through an audit experiment. Audit experiments are designed to measure discrimination by evaluating whether otherwise identical applicants for a valued outcome receive different treatment when race and/or gender-signaling information (such as the name atop a résumé or the appearance of someone acting out a script) is randomly varied (see Pager, 2007 for a discussion of this methodology; see also Bertrand & Mullainathan, 2004; Pager et al., 2009; Rubineau & Kang, 2012). We present new analyses of data from an audit experiment previously described by Milkman, Akinola, and Chugh (2012).

Study Participants

The primary criterion for selecting faculty participants for inclusion in our study was their affiliation with a doctoral program at one of the 259 universities on the U.S. mainland ranked in *U.S. News and World Report*'s 2010 "Best Colleges" issue. From these universities, we identified 6,300 doctoral programs and approximately 200,000 faculty affiliated with those programs. We then randomly selected one faculty member from each doctoral program, yielding 6,548 faculty subjects.[2] From university Web sites, we collected each professor's e-mail address, rank (full, associate, assistant, or n/a), as well as university and department affiliations. Research assistants determined the gender of faculty participants by studying the faculty names, visiting their Web sites, examining photos, and reading research summaries containing gendered statements (e.g., "she studies"). An automated technique was initially used for racially classifying faculty 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 & Perkins, 1996), and (b) 1,200 Chinese and 2,690 Indian surnames (Lauderdale & Kestenbaum, 2000). These lists were compared with 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 Web sites. Further, research assistants generated racial classifications for faculty who were White, Black, or another race besides Hispanic, Indian, or Chinese. This process involved visiting faculty Web sites, examining faculty curriculum vitae, 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.

The faculty sample was selected in two different ways to facilitate a statistical examination of the impact of shared race between the student and professor. First, we identified an entirely random (and thus representative) sample of 4,375 professors (87% White, 2% Hispanic, 1% Black, 3% Indian, 4% Chinese, 3% Other; 69% Male). Second, we oversampled faculty who were not White, offering us the necessary statistical power to test whether minorities are less (or more) biased toward students sharing their race. Thus, 2,173 additional minority faculty were picked for inclusion in the study (29% Hispanic, 21% Black, 21% Indian, 29% Chinese, 68% Male),[3] ensuring a sufficiently large sample for an analysis of same-race faculty-student pairs.

In all of our graphs and summary statistics, with the exception of the table of unadjusted means and correlations (see Table 2), 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 overrepresented in our random assignment algorithm, details in the section entitled Experimental Stimuli and Procedures).[4] Thus, all graphs and summary statistics can be interpreted as reporting results from a representative faculty sample (Cochran, 1963). Notably, however, all results and figures remain meaningfully unchanged if sample weights are removed.

Experimental Stimuli and Procedures

All e-mails from prospective students sent to faculty were identical except for two components. First, the race (White, Black, Hispanic, Indian, Chinese) and gender signaled by the name of the sender was randomly assigned. We relied on previous research to help generate names signaling both the gender and race (White, Black, Hispanic, Indian, Chinese) of fictional students in our study (Bertrand & Mullainathan, 2004; Lauderdale & Kestenbaum, 2000). We also looked to U.S. Census data documenting the frequency with which common surnames belong to White, Black, and Hispanic individuals and examined websites recommending baby names targeted at different racial groups. These sources provided a guide for generating a list of 90 names for potential use

[2] The study was executed in two segments. In March, 2010, a small pilot study was carried out, and in April 2010, the primary study was conducted. The pilot study conducted in March of 2010 included 248 faculty—one randomly selected tenure-track faculty member from 248 of the set of 259 universities (the 11 universities omitted from our pilot were omitted due to data collection errors). It also included just two fictional prospective doctoral students—Lamar Washington and Brad Anderson. The primary study conducted in April of 2010 included a single tenure-track faculty member from each of the 6,300 doctoral programs at the U.S. universities, meaning we included an average of 24 faculty members per university. One affiliated, tenure-track faculty member was randomly selected from each doctoral program to participate, and each of the 20 prospective student names listed in Table 1 was included in the April 2010 study. The data from the pilot study did not differ meaningfully from those in the primary study thus we combined these data, and therefore, a small number of departments have two faculty members represented in our sample. Our results are all robust to including an indicator variable for pilot data, which is never significant.

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

[4] 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., because professors in PhD granting departments in Engineering and Computer Science are 77.8% White and the study included 1,125 Engineering and Computer Science faculty, the expected number of White Engineering and Computer Science faculty is $1{,}125^{*}0.778 = 875$). 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 e-mails from students of a given race, *s*, is calculated assuming balanced randomization. This is simply $e_{r,d}/5$ because there are five student races represented in our study (e.g., the expected number of White faculty in computer science and engineering departments receiving e-mails from White 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 e-mails from students of a given race, *s* (e.g., 151 White faculty in engineering and computer science departments actually received e-mails from White 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 White faculty of engineering and computer science is $175/151 = 1.1592$.

Table 1
Race and Gender Recognition Survey Results for Selected Names

Race	Gender	Name	Rate of race recognition	Rate of gender recognition
White	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%*

Note. We conducted a survey to test how effectively a set of 90 names signaled different races and genders. Thirty-eight participants who had signed up to complete online paid polls through Qualtrics and who had received a Master's degree (87.5%) or PhD (12.5%) were recruited to participate in a survey online. Their task was to predict the race or gender associated with a given name for a set of 90 names. We selected the two names of each race and gender from these surveys with the highest net recognition rates on race (avg. = 97%) and gender (avg. = 98%) to use in our study. For additional discussion of this selection procedure see Appendix. 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). A version of this table also appears as Supporting Table S1 in Milkman, Akinola, and Chugh (2012).
*** $p < .001$.

in our study, nine of each race and gender of interest. A survey pretest described in the note accompanying Table 1 was used to select a subset of 20 of these names for use in our study, which are listed in Table 1 along with their correct race and gender recognition rates in this survey pretest.

Second, half of the e-mails indicated that the student would be on campus that very day, while the other half indicated that the student would be on campus 1 week in the future (next Monday).[5] The precise wording of e-mails received by faculty was as follows:

> Subject Line: 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]

E-mails were queued in random order and designated to be sent at 8 a.m. in the time zone corresponding to the relevant faculty member's university. To minimize the time faculty spent on our study, we prepared (and promptly sent) a series of scripted replies cancelling any commitments from faculty that had been elicited and curtailing future communications. See the Appendix for details regarding the human subjects protections in this study.

Assignment of faculty to experimental conditions was stratified by their gender, race, rank, and time zone (EST, CST, MST, and PST) to ensure balance on these dimensions across conditions. In addition, as described above, we ensured that same-race faculty-student pairings were overrepresented to allow for a statistically powered examination of the effects of matched race. First, two thirds of the White faculty from the representative sample of 4,375

[5] Previous analyses of this audit experiment demonstrated that discrimination arises when choices are made for the future but not for today (Milkman, Akinola, & Chugh, 2012). The design of the study described in this article measures discrimination at both time points but zooms in on observed bias in choices made for the future by carefully controlling for the timing of decisions (and for the lack of bias in choices made for today) in all presented regression analyses.

Table 2
Table of Correlations and Unweighted Descriptive Statistics for Variables Included in Regression Analyses

			Level 2: Academic discipline characteristics									
(Part 1)	Mean	Std. dev.	Faculty % Black	Faculty % Hispanic	Faculty % Asian	Faculty % minority	Faculty % female	PhDs % Black	PhDs % Hispanic	PhDs % Asian	PhDs % minority	Avg. faculty salary
Level 2: Academic discipline characteristics												
Faculty % Black	5.637	3.959	—									
Faculty % Hispanic	3.395	2.855	.19	—								
Faculty % Asian	11.503	8.112	−.18	−.01	—							
Faculty % minority	16.831	8.388	.34	.11	.85	—						
Faculty % female	32.718	19.233	.35	.31	−.55	−.33	—					
PhD students % Black	9.499	2.177	.53	−.19	−.08	.16	.16	—				
PhD students % Hispanic	6.576	1.248	.33	.07	−.25	−.06	.29	.50	—			
PhD students % Asian	7.381	1.871	−.12	.05	.61	.54	−.30	−.32	−.26	—		
PhD students % minority	24.143	2.940	.46	−.10	.22	.43	.05	.75	.63	.28	—	
Avg. Faculty Salary	$59,372	$13,265	−.36	−.22	.72	.49	−.58	−.19	−.42	.65	.09	—
Level 2: University characteristics												
Undergraduates % Black	8.845	11.497	.05	−.01	−.04	−.02	.05	.07	.02	−.06	.02	−.03
Undergraduates % Hispanic	7.922	7.760	.02	.01	−.00	.01	.01	.02	.02	−.01	.02	−.02
Undergraduates % Asian	10.804	9.855	.01	.10	.07	.07	−.04	−.04	.01	.08	.02	.02
Undergraduates % minority	32.628	16.948	.05	.06	.02	.04	.01	.03	.03	.01	.04	−.01
Undergraduates % female	50.916	7.270	.08	.06	−.19	−.13	.22	.05	.09	−.08	.02	−.14
University faculty % minority	18.806	8.433	.05	.03	−.01	.02	.02	.04	.00	−.00	.03	.00
University faculty % female	36.228	6.905	.06	.01	−.14	−.10	.18	.07	.07	−.06	.04	−.10
Public school	0.680	0.467	−.02	−.04	.02	.01	−.03	.01	−.04	−.01	−.01	.02
School rank (*U.S. News*)	95.682	68.723	.02	−.11	−.05	−.04	.04	.11	.03	−.10	.03	−.02
Northeast	0.245	0.430	.01	.02	.03	.03	−.02	−.01	.01	.04	.02	.02
South	0.344	0.475	−.01	−.05	−.02	−.02	.01	.02	−.00	−.07	−.02	−.00
Midwest	0.236	0.425	−.00	.02	−.02	−.02	.03	−.01	−.01	.01	−.01	−.02
West	0.175	0.380	−.00	.02	.02	.02	−.02	−.01	.00	.03	.01	.01
Level 1 variables												
Professor Hispanic	0.106	0.308	.02	.09	−.03	−.02	.05	−.00	.01	−.01	−.01	−.04
Professor Black	0.079	0.270	.14	−.00	−.10	−.03	.12	.09	.06	−.08	.04	−.09
Professor Chinese	0.124	0.329	−.06	−.05	.16	.12	−.14	.01	−.05	.09	.04	.12
Professor Indian	0.089	0.284	−.06	−.06	.19	.15	−.17	−.02	−.06	.09	.02	.16
Professor other race	0.017	0.131	.04	.02	−.00	.02	.01	.01	−.01	−.01	−.00	−.01
Professor male	0.685	0.465	−.11	−.09	.22	.15	−.31	−.06	−.09	.12	−.01	.21
Professor assistant	0.254	0.435	.01	−.00	−.02	−.02	.04	.01	.00	−.03	−.01	−.02
Professor associate	0.265	0.441	.01	.02	−.03	−.02	.06	.01	−.01	−.04	−.02	−.05
Professor other/unknown rank	0.049	0.216	−.00	−.02	−.03	−.03	.02	−.02	−.02	−.01	−.02	−.01
Request for today	0.495	0.500	−.02	.00	.02	.01	.00	−.01	−.01	.01	−.01	−.00
Student female	0.483	0.500	−.01	.01	.01	.00	−.00	−.02	.00	.01	−.01	.01
Student Black	0.195	0.396	.06	−.02	−.08	−.05	.07	.05	.05	−.07	.01	−.08
Student Hispanic	0.204	0.403	.01	.06	−.03	−.02	.04	.00	.01	−.00	.00	−.03
Student Asian	0.378	0.485	−.07	−.05	.13	.09	−.13	−.03	−.06	.07	.00	.13
Student minority	0.777	0.416	−.00	−.01	.05	.05	−.04	.02	−.02	.01	.02	.05
Student Chinese	0.202	0.402	−.04	−.01	.08	.05	−.08	−.02	−.04	.04	−.00	.07
Student Indian	0.176	0.381	−.05	−.05	.09	.06	−.08	−.02	−.03	.05	.01	.10
Student and professor both Black	0.071	0.257	.12	−.00	−.10	−.03	.10	.09	.05	−.08	.04	−.08

(*table continues*)

Table 2 (*continued*)

			Level 2: Academic discipline characteristics									
(Part 1)	Mean	Std. dev.	Faculty % Black	Faculty % Hispanic	Faculty % Asian	Faculty % minority	Faculty % female	PhDs % Black	PhDs % Hispanic	PhDs % Asian	PhDs % minority	Avg. faculty salary
Student and professor both Hispanic	0.096	0.295	.02	.08	−.02	−.01	.04	.00	.00	−.01	−.00	−.04
Student and professor both Indian	0.069	0.253	−.05	−.05	.18	.14	−.14	−.02	−.06	.09	.02	.14
Student and professor both Chinese	0.096	0.295	−.06	−.04	.15	.11	−.12	.01	−.04	.08	.04	.11
Student and professor both female	0.150	0.357	.07	.07	−.13	−.08	.20	.03	.06	−.06	.01	−.12

	Level 2: University characteristics												
	Undergrads % Black	Undergrads % Hispanic	Undergrads % Asian	Undergrads % minority	Undergrads % female	Faculty % minority	Faculty % female	Public school	Rank (*U.S. News*)	Northeast	South	Midwest	West
Level 2: University characteristics													
Undergraduates % Black	—												
Undergraduates % Hispanic	−.09	—											
Undergraduates % Asian	−.18	.29	—										
Undergraduates % minority	.44	.57	.66	—									
Undergraduates % female	.29	.15	−.08	.16	—								
University faculty % minority	.67	.17	.11	.58	.15	—							
University faculty % female	.26	.01	−.31	−.08	.65	.14	—						
Public school	.09	.00	−.20	−.16	−.02	.09	.17	—					
School rank (*U.S. News*)	.37	.08	−.46	−.06	.23	.11	.46	.43	—				
Northeast	−.11	−.06	.14	.05	−.19	−.09	−.15	−.39	−.22	—			
South	.30	.05	−.25	.03	.22	.12	.12	.15	.21	−.41	—		
Midwest	−.07	−.26	−.21	−.28	−.10	−.00	.09	.12	.01	−.32	−.40	—	
West	−.17	.30	.38	.22	.04	−.05	−.08	.12	−.02	−.26	−.33	−.26	—
Level 1 variables													
Professor Hispanic	−.04	.15	.03	.06	.02	.04	.01	.03	−.01	−.02	−.03	.00	.05
Professor Black	.16	−.05	−.04	.05	.05	.12	.03	−.02	.02	−.01	.06	.01	−.07
Professor Chinese	−.01	−.02	.00	−.01	−.05	−.00	−.02	.03	.00	−.01	.01	.02	−.02
Professor Indian	.03	.01	−.00	.02	−.03	.04	−.00	.03	.03	−.01	.02	.02	−.03
Professor other race	.00	.06	.05	.06	.00	.01	−.00	−.02	.02	.04	−.01	−.02	−.01
Professor male	−.02	−.02	.00	−.01	−.07	−.02	−.08	.02	−.01	−.01	−.01	.00	.01
Professor assistant	.01	−.01	−.07	−.04	−.00	−.00	.02	.02	.04	−.03	.05	.02	−.04
Professor associate	.04	−.01	−.06	−.02	.02	.02	.04	.01	.06	−.00	.03	−.00	−.03
Professor other/ unknown rank	.02	−.00	−.05	−.03	.02	−.01	.04	.03	.04	−.04	.04	−.00	−.01
Request for today	−.02	.00	.00	−.01	.00	−.00	.02	.01	−.02	−.01	.00	.01	−.01
Student female	−.02	−.03	−.00	−.02	−.03	−.01	−.02	.00	−.03	.02	−.02	.02	−.01

(*table continues*)

Table 2 (*continued*)

	Level 2: University characteristics												
	Undergrads % Black	Undergrads % Hispanic	Undergrads % Asian	Undergrads % minority	Undergrads % female	Faculty % minority	Faculty % female	Public school	Rank (*U.S. News*)	Northeast	South	Midwest	West
Student Black	.10	−.05	−.05	.01	.05	.06	.04	−.01	.02	−.00	.04	−.00	−.05
Student Hispanic	−.03	.09	.02	.04	.01	.02	−.00	.03	−.00	−.02	−.02	.01	.04
Student Asian	−.03	−.01	.02	−.01	−.05	−.03	−.04	.02	−.01	.01	−.00	−.00	−.00
Student minority	.04	.02	−.01	.03	−.00	.05	−.01	.04	.01	−.02	.02	.00	−.01
Student Chinese	−.02	−.01	.01	−.01	−.04	−.01	−.03	.02	−.01	−.00	.01	−.00	−.01
Student Indian	−.02	−.01	.02	−.01	−.03	−.02	−.02	.01	−.00	.01	−.01	−.01	.01
Student and professor both Black	.16	−.06	−.05	.05	.05	.12	.03	−.01	.02	−.00	.06	.01	−.08
Student and professor both Hispanic	−.03	.14	.02	.06	.02	.05	.01	.03	−.01	−.02	−.02	.01	.04
Student and professor both Indian	.02	.01	−.00	.02	−.03	.02	−.00	.02	.03	−.01	.02	.02	−.04
Student and professor both Chinese	−.01	−.01	.00	−.01	−.03	−.00	−.01	.02	−.01	−.02	.02	.02	−.02
Student and professor both female	.00	.01	.01	.02	.04	−.00	.04	−.02	.01	.02	−.02	.00	−.00

	Level 1 variables																				
	Professor										Student										
	Hispanic	Black	Chinese	Indian	Other race	Male	Asst.	Assoc.	Other rank	Request for today	Female	Black	Hispanic	Asian	Minority	Chinese	Indian	Student, prof. both Black	Student, prof. both Hispanic	Student, prof. both Indian	Student, prof. both Chinese
Level 1 variables																					
Professor Hispanic	—																				
Professor Black	−.10	—																			
Professor Chinese	−.13	−.11	—																		
Professor Indian	−.11	−.09	−.12	—																	
Professor other race	−.05	−.04	−.05	−.04	—																
Professor male	−.04	−.09	.04	.08	−.02	—															
Professor assistant	.04	.06	.13	.01	.03	−.14	—														
Professor associate	.06	.02	−.01	−.03	.01	−.06	−.35	—													
Professor other/unknown rank	.02	.00	−.04	−.00	.00	−.04	−.13	−.14	—												

(*table continues*)

Table 2 (*continued*)

	Level 1 variables																				
	Professor										Student										
	Hispanic	Black	Chinese	Indian	Other race	Male	Asst.	Assoc.	Other rank	Request for today	Female	Black	Hispanic	Asian	Minority	Chinese	Indian	Student, prof. both Black	Student, prof. both Hispanic	Student, prof. both Indian	Student, prof. both Chinese
Request for today	.00	.00	−.01	.00	.01	−.01	.00	−.00	−.01	—											
Student female	.00	−.00	−.01	−.01	−.01	.01	−.00	.01	.01	.01	—										
Student Black	−.15	.52	−.12	−.10	.00	−.05	.01	−.01	.01	−.02	−.03	—									
Student Hispanic	.60	−.14	−.15	−.13	−.01	−.02	−.01	.06	.02	.01	.02	−.25	—								
Student Asian	−.25	−.20	.34	.28	.01	.07	.04	−.03	−.02	.01	.03	−.38	−.40	—							
Student minority	.15	.13	.14	.12	.00	.01	.05	.01	.00	−.01	.03	.26	.27	.42	—						
Student Chinese	−.16	−.13	.54	−.12	−.00	.03	.06	−.01	−.03	.00	.02	−.25	−.26	.65	.27	—					
Student Indian	−.15	−.12	−.13	.49	.01	.05	−.02	−.03	.01	.01	.02	−.23	−.23	.59	.25	−.23	—				
Student and professor both Black	−.10	.94	−.10	−.09	−.04	−.08	.05	.01	.01	−.00	.00	.56	−.14	−.22	.15	−.14	−.13	—			
Student and professor both Hispanic	.95	−.10	−.12	−.10	−.04	−.03	.03	.07	.02	.00	.01	−.16	.64	−.25	.18	−.16	−.15	−.09	—		
Student and professor both Indian	−.09	−.08	−.10	.87	−.04	.07	.01	−.03	.01	.01	.01	−.13	−.14	.35	.15	−.14	.59	−.08	−.09	—	
Student and professor both Chinese	−.11	−.10	.87	−.10	−.04	.03	.13	−.01	−.03	.01	.01	−.16	−.17	.42	.18	.65	−.15	−.09	−.11	−.09	—
Student and professor both female	.03	.06	−.02	−.06	.01	−.62	.09	.05	.02	.01	.44	.02	.03	−.03	.01	−.01	−.02	.05	.03	−.04	−.01

Note. Avg. = average; Prof. = professor; Assoc. = associate; Asst. = assistant. All correlations of greater than |.03| are significant at $p < .05$.

professors, and all non-White faculty from this representative sample, were randomly assigned to one of the experimental conditions in our study with equal probability, except that no professors in this group were assigned to receive an e-mail from a student who shared his or her race. Then, all oversampled non-White faculty ($N = 2{,}173$) as well as the final third of White faculty ($N = 1{,}294$) were assigned to receive e-mails from students of their race (e.g., oversampled Hispanic faculty received e-mails from Hispanic students). For these participants, only the gender of the prospective student and the timing of the student's request (today vs. next week) were randomized.

In total, 6,548 e-mails were sent from fictional prospective doctoral students to the same number of faculty. Experimental cell sizes varied somewhat (depending on our rate of identification of minority faculty who were oversampled to allow for statistically meaningful rates of matched-race faculty-student pairs, and as a result of our pilot study, which only included White male and Black male students); cell size by prospective student race and gender were as follows: White male ($N = 791$), White female ($N = 669$), Black male ($N = 696$), Black female ($N = 579$), Hispanic male ($N = 668$), Hispanic female ($N = 671$), Indian male ($N = 572$), Indian female ($N = 578$), Chinese male ($N = 661$), and Chinese female ($N = 663$).

Archival Data

To categorize the academic disciplines of faculty in our study, we relied on archival data and 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, 6 years prior to our study) and classifies faculty into one of 11 broad and 133 narrow academic disciplines (see: http://nces.ed.gov/surveys/nsopf/). The NSOPF survey results are available as summary statistics describing various characteristics of survey respondents both by broad and narrow academic discipline (U.S. Department of Education, 2004).

A research assistant examined each faculty member'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 could not be identified and 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 109 of the NSOPF's 133 narrow disciplinary categories (see Appendix Table A2 for a list of categories). NSOPF survey data about each broad and narrow discipline was merged with our experimental data.

Research assistants also classified the U.S. Census Region where each university was located (West, Midwest, Northeast, or South).[6] Further, for each of the national U.S. universities ranked in *U.S. News and World Report's* "Best Colleges" issue, *U.S. News* reports numerous facts describing the university during the 2009–2010 academic school year that were also merged with our experimental data.

We examine how several variables quantifying the representation of women and minorities relate to the treatment of women and minorities in our study. Specifically, using NSOPF data, we examine the percentage of faculty in a discipline who are women and members of different racial groups (White, Black, Hispanic, and Asian), as well as the percentage of doctoral-level students in a discipline who are members of different racial groups (White, Black, Hispanic, and Asian).[7] At the university level, *U.S. News* reports on the demographic breakdown of the undergraduate student body (female, White, Black, Hispanic, and Asian) as well as the percentages of a university's faculty who are female and minorities.

We also examine how the average 9-month faculty salary in a discipline according to the 2004 NSOPF survey relates to the treatment of women and minorities in our study. Although distinct from pay, *U.S. News* also reports on whether each school is a private or public institution (37% of those in our sample are private; 63% are public). Notably, private schools pay $34,687 higher yearly salaries than public schools, on average (Byrne, 2008).

Finally, each school's *U.S. News* ranking (1–260) is also included in our analyses.

Statistical Analyses

To study the effects of representation and pay on faculty members' level of responsiveness to e-mails from women and minorities relative to White males, we rely on a hierarchical linear modeling (HLM) strategy.[8] This strategy allows us to account for the fact that we observe a cross-classification of faculty by two higher-level factors: disciplines and universities.[9] To handle this data structure while modeling the influences of discipline and university characteristics requires the use of cross-classified random effects models. Specifically, we thus rely on the following cross-nested two-level Bernoulli binary response HLM model specification throughout our primary analyses:

Level 1 Model:

$$\text{prob}(\mathit{response\_received}_{ijk} = 1 \mid \pi_{jk}) = \phi_{ijk}$$
$$\log[\phi_{ijk}/(1 - \phi_{ijk})] = \pi_{0jk} + \pi_{1jk} * (\mathit{min\text{-}fem}_{ijk}) + \Pi_{jk} * \theta$$

Level 2 Model:

$$\begin{aligned}\pi_{0jk} &= \theta_0 + b_{00j} + c_{00k} + (\gamma_{01}) * \mathit{university\_moderator}_j + \\ &\quad (\beta_{01}) * \mathit{discipline\_moderator}_k + \Gamma_j * \varphi \\ \pi_{1jk} &= \theta_{10} + (\gamma_{101}) * \mathit{university\_moderator}_j \\ &\quad + (\beta_{101}) * \mathit{discipline\_moderator}_k\end{aligned}$$

where $\mathit{response\_received}_{ijk}$ is an indicator variable that takes on a value of one when faculty member i in discipline j at university k

[6] This map was used for classification: https://www.census.gov/geo/maps-data/maps/pdfs/reference/us_regdiv.pdf

[7] Note that the NSOPF does not include statistics about the percentage of students who are female nor does the NSOPF provide statistics on Chinese and Indian faculty (or students) separately—they report on a single "Asian" category.

[8] Note that when summarizing the treatment of students across the 10 broad disciplinary categories designated by the NSOPF, we rely on OLS and logistical regression analyses.

[9] Note that in our data, disciplines and universities are cross-classified—neither is nested within the other (e.g., faculty at multiple universities work in the same discipline, and faculty in many disciplines work at the same university).

responded to the e-mail requesting a meeting and zero otherwise,[10] *min-fem*$_{ijk}$ 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, *discipline_moderator*$_k$ is a variable (grand mean centered, if continuous) that corresponds to a given moderator of interest at the level of a faculty member's narrow discipline (e.g., pay in a given narrow discipline), *university_moderator*$_k$ is a variable (grand mean centered, if continuous) that corresponds to a given moderator of interest at the level of a faculty member's university, Π_{jk} is a vector of other individual-level control variables, θ is a vector of regression coefficients, Γ_j is a vector of university-level control variables, and φ is a vector of regression coefficients. Π_{jk} includes indicators for whether the professor contacted: was Black, Hispanic, Indian, or Chinese; was a member of another minority group besides those listed previously; was male; was an assistant, associate, or full professor or a professor of unknown rank;[11] was the same race as the student e-mailing and Black; was the same race as the student e-mailing and Hispanic; was the same race as the student e-mailing and Indian; was the same race as the student e-mailing and Chinese; was the same gender as the student e-mailing and female; and asked to meet with the student today (as opposed to next week). In previous analyses of data from this audit experiment, we found that discrimination primarily arises in decisions made for the future (Milkman, Akinola, & Chugh, 2012). Thus, we also control for the interaction between an indicator for a student being on campus today and indicators for the student's race and gender, allowing us to zoom in on examining differences in the treatment of White males versus other students that arise at a delay. Γ_j includes indicators for whether the contacted professor's university is located in the Northeast, South, or Midwest U.S. Census region.

To separately examine the treatment of each minority group studied, we rely on the HLM analysis strategy described above but replace the predictor variable *min-fem*$_{ijk}$ with nine indicators for the nine race and gender groups studied besides White males (e.g., a dummy variable for White female students, for Black male students, etc.; White males are the omitted category). In some analyses we have information about the representation of females, Blacks, Hispanics, and Asians in a given university or discipline. In those analyses, we rely on the HLM analysis strategy described above but replace the predictor variable *min-fem*$_{ijk}$ with four indicators for whether the student is female, Black, Hispanic, or Asian as well as an interaction between the female indicator and each race indicator. In these cases where *min-fem*$_{ijk}$ is replaced, our Level 2 model includes additional equations (like the equation predicting π_{1jk}) predicting coefficients on each new indicator of interest from the level one model. For instance, if our Level 1 model becomes $\log[\phi_{ijk}/(1 - \phi_{ijk})] = \pi_{0jk} + \pi_{1jk}{}^{*}female_{ijk} + \pi_{2jk}{}^{*}black_{ijk} + \pi_{3jk}{}^{*}hispanic_{ijk} + \pi_{4jk}{}^{*}asian_{ijk} + \Pi_{jk}{}^{*}\theta$, then our level two model estimates separate equations to predict π_{1jk}, π_{2jk}, π_{3jk}, and π_{4jk}, each taking the form: $\pi_{ijk} = \theta_{i0} + (\gamma_{i01})^{*}university\_moderator_j + (\beta_{i01})^{*}discipline\_moderator_k$.

Our regression results include controls for each of the various variables used to select our sample and allocate assignment to conditions (see Experimental Stimuli and Procedures section above). Including these controls in regressions allows us to draw inferences about our data after accounting for our experiment's purposefully unbalanced random assignment, making it possible to interpret regression results as if the population studied were a representative sample of faculty (Winship & Radbill, 1994).

Our reported HLM results are robust to relying on alternative analytical strategies. Specifically, we derive the same basic results with the same dependent variables and predictors, regardless of whether we use a cross-nested HLM approach or an OLS or logistic regression approach that clusters standard errors by both a faculty member's academic discipline and university affiliation. While all three analytical methods are reasonable, we believe the HLM approach is ideal due to the cross-nested nature of our data.

Results

Descriptive Statistics

Summary statistics. We examine whether a given e-mail generates a reply from a given professor in our experiment within 1 week, by which point responses had essentially asymptoted to zero (with 95% of responses received within 48 hr and just 0.4% arriving on the seventh and final day of our study). Table 2 shows unadjusted descriptive statistics and correlations for all variables included in our study. Sixty-seven percent of the e-mails sent to faculty from prospective doctoral students elicited a response. Further, White women as well as members of each minority group studied experienced directionally lower response rates than White males.

Summarizing discrimination as a function of broad academic discipline. Table 3 and Figures 1a and 1b provide summary statistics describing the characteristics and behavior of faculty in the 10 different broad academic disciplines in our sample. Notably, as Figure 1a shows, the raw average response rate to White males is directionally higher than the raw average response rate to minorities and females, collectively (referred to hereafter as the "discriminatory gap"), in all but one broad discipline (fine arts). Further, the gaps depicted here vary considerably in magnitude, suggesting that bias may not be evenly distributed across disciplines. Figure 1b plots the discriminatory gap in every discipline based on average response rates to minorities and females, but breaks out the race/gender of the student to show the treatment of each group studied. Figure 1b demonstrates that the summary

[10] Nearly all faculty responses to students in our study conveyed a willingness to offer assistance or guidance, but due to scheduling constraints, many encouraging faculty responses did not include an immediate offer to meet with the student on the requested date. We find that all bias against women and minorities in this experiment occurs at the e-mail response stage. Specifically, faculty respond to (and therefore also agree to meet with) women and minorities, collectively, at a significantly lower rate than White males. However, once a faculty member responds to a student, no additional discrimination is observed on the decision of whether to respond affirmatively or negatively. In other words, all discrimination observed on the decision of whether to meet with a student results from e-mail nonresponses, which is thus the outcome variable on which we focus our attention. Additional variables collected include the speed of that response and whether the faculty member agreed to meet with the student.

[11] We have repeated our primary analyses dropping faculty of unknown rank and our results are robust to this exclusion. Note that faculty of unknown rank are simply tenure-track faculty who our undergraduate research assistants were unable to classify as assistant versus associate versus full professors based on readily available information on their faculty Web sites.

Table 3
Descriptive Statistics for Faculty Included in Study by Broad Discipline and University Type (Public vs. Private)

	N	# of Narrow subdisciplines*	Avg. base (9-month) salary	Sample-weighted representation						
				Female	White	Black	Hispanic	Chinese	Indian	Other race
Broad discipline										
Business	265	7	$63,651	26%	85%	2%	1%	4%	5%	4%
Education	441	16	$45,897	55%	91%	2%	2%	2%	1%	3%
Engineering & computer science	1,125	14	$71,107	15%	78%	1%	1%	8%	8%	4%
Fine arts	209	8	$38,023	38%	92%	1%	1%	4%	1%	2%
Health sciences	343	12	$69,222	46%	91%	2%	0%	3%	1%	2%
Human services	188	10	$49,257	43%	87%	4%	2%	1%	1%	5%
Humanities	668	5	$46,375	38%	90%	2%	2%	2%	2%	2%
Life sciences	1,051	9	$70,123	24%	90%	0%	1%	4%	3%	2%
Natural, physical sciences & math	850	9	$60,245	18%	85%	1%	1%	7%	4%	3%
Social sciences	1,379	19	$52,889	38%	90%	2%	2%	2%	2%	3%
University type										
Public	4,450	105	$X	30%	87%	1%	2%	5%	4%	2%
Private	2,098	100	$X+$34,687	32%	88%	1%	1%	4%	2%	3%

Note. The 9-month salaries reported here are lower than those paid at many top institutions but reflect the average salaries across disciplines sampled by the NSOPF, which "includes a nationally representative sample of . . . faculty . . . at public and private not-for-profit 2- and 4-year institutions in the United States" (http://www.icpsr.umich.edu/icpsrweb/ICPSR/series/194).

statistics describing the discriminatory gap by discipline presented in Figure 1a are not driven by the treatment of a particular race or gender of student, although, notably, Indian and Chinese students experience particularly pronounced discrimination, inconsistent with stereotypes of Asians as "model minorities" (Teranishi, 2010).

Notably, the levels of bias faced across both disciplines and the nine female and minority groups studied are highly correlated. Where bias against one specific minority group (e.g., Chinese women) is larger, in general, so too is bias against the other minority groups studied (e.g., Black men, White women, etc.). Specifically, of the 36 paired correlation coefficients produced by comparing columns from Figure 1b, 94% (or all but two) are positive, and the average correlation is 0.49 (median correlation = 0.54).[12] In other words, we see empirical support for our theoretically justified a priori design decision to create a single category encompassing women and minorities, collectively, in our study of bias. While we also present results broken down group by group, our hypothesis tests and analyses more broadly center on examining the treatment of women and minorities, collectively (i.e., individuals who are not White males).

We next conduct statistical tests to evaluate whether or not the summary statistics presented thus far represent significant bias and significant variability in bias across broad disciplines. In exploring these summary statistics, we rely on both logistic and OLS regression models to test for the significance of the effects depicted in Figures 1a and 1b. Table 4, Model 1 presents coefficient estimates and their associated standard errors from a logistic regression predicting the magnitude and significance of the discrimination against women and minorities, collectively, in each broad academic discipline. Table 4, Model 2 presents coefficient estimates and standard errors from the same analysis repeated using an OLS regression model. Models 1 and 2 present statistical estimates (from regression equations) of the same discriminatory gaps depicted in Figures 1a and 1b through summary statistics. Specifically, Table 4 presents the coefficient estimates from regressions in which an e-mail response is predicted by interactions between (a) an indicator for whether a student is a minority or female and (b) indicators for each broad academic discipline studied (e.g., business, fine arts, etc.). The regression coefficients on these interaction terms capture the magnitude of the predicted discriminatory gap for each discipline. These regressions include indicators for a professor's discipline and standard control variables (for faculty race, rank, student-faculty demographic match, census region, request for today, and the interaction between request for today and an indicator for whether a student is a minority or female). In Table 4, seven of the 10 discipline-by-discipline estimates of the "discriminatory gap" when students make requests of faculty for the future—a measure of the bias against women and minorities, collectively, relative to White males—are statistically significant in both regression Models 1 and 2 (*p*s < 0.05), and two more are at least marginally significant in both models (humanities and fine arts; $p < .10$). These results indicate that in all broad disciplines except health sciences, when making requests of faculty for the future, women and minorities, collectively, are ignored at rates that differ from White male students. Interestingly, in the fine arts, the discriminatory gap detected favors women and minorities, collectively, while in all other disciplines White males are at a relative advantage.

[12] Another way of capturing the correlation in bias faced by the nine different groups studied is to look at the Cronbach's alpha assessing the "scale reliability" of the discrimination detected against these different groups across disciplines. When we calculate this Cronbach's alpha with data points corresponding to discrimination levels in each of the 10 disciplines studied from Figure 1b, we find that it is 0.88, confirming that indeed, collapsing the bias detected across these nine different groups into a single measure of overall bias against all students besides White males is a reasonable empirical approach.

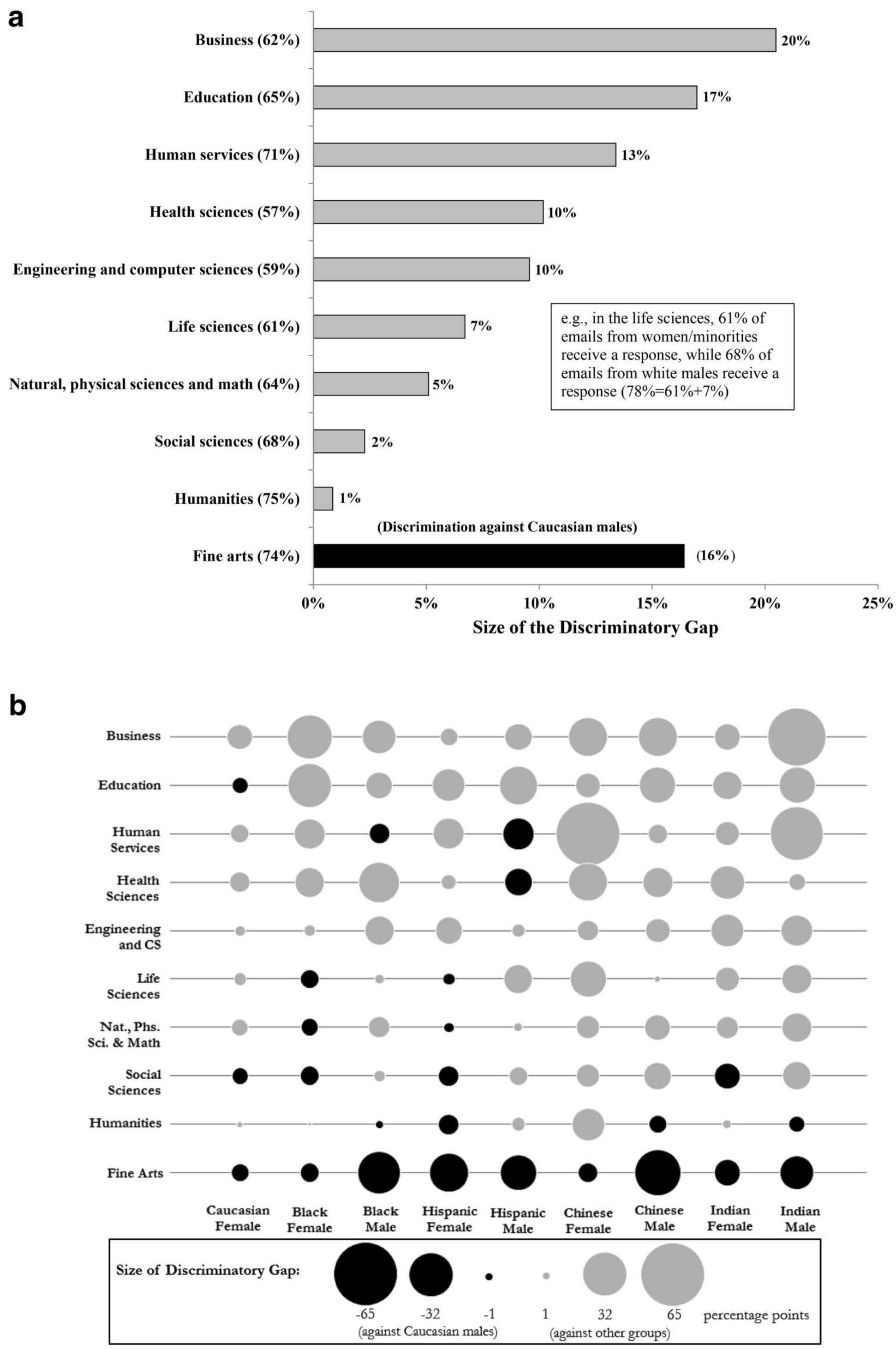

Figure 1. Figures a and b show the raw, sample-weighted size of the discriminatory gap faced by women and minorities by broad discipline. Narrower disciplinary categories are also analyzed later in our article. **a. Discriminatory Gap: White Males versus Other Students**. (Note: Response rate to minorities and females, collectively, appears in parentheses after a discipline's name. Discrimination against White males in black. Discrimination against women and minorities collectively, in gray.) **b. Discriminatory Gap: White Males versus Students of Each Race/Gender Combination**. (Note: Discrimination against White males in black. Discrimination against women and minorities in gray. Disciplines are sorted by the size of the discriminatory gap.)

Table 4
Logistic Regression (Model 1) and Ordinary Least Squares Regression (Model 2) to Predict Response Rates to White Males Versus Women and Minorities, Collectively, as a Function of Broad Academic Discipline

	Model 1		Model 2	
	Logistic regression		OLS regression	
Predictor	*B*	*SE*	*B*	*SE*
Bias by academic discipline				
(Student Minority or Female) × (Business)	−1.324**	(0.459)	−0.253**	(0.073)
(Student Minority or Female) × (Education)	−1.028***	(0.131)	−0.192***	(0.028)
(Student Minority or Female) × (Human Services)	−0.963***	(0.284)	−0.173**	(0.053)
(Student Minority or Female) × (Health Sciences)	−0.491	(0.891)	−0.106	(0.194)
(Student Minority or Female) × (Engineering and Computer Science)	−0.513**	(0.173)	−0.112**	(0.039)
(Student Minority or Female) × (Life Sciences)	−0.490*	(0.196)	−0.105*	(0.041)
(Student Minority or Female) × (Natural, Physical Sciences and Math)	−0.374***	(0.098)	−0.079***	(0.021)
(Student Minority or Female) × (Social Sciences)	−0.374*	(0.166)	−0.079*	(0.034)
(Student Minority or Female) × (Humanities)	−0.385^	(0.222)	−0.079^	(0.042)
(Student Minority or Female) × (Fine Arts)	0.271^	(0.144)	0.066*	(0.029)
Academic discipline				
Business	1.665***	(0.428)	0.841***	(0.064)
Education	1.606***	(0.111)	0.833***	(0.023)
Human services	1.679***	(0.227)	0.843***	(0.041)
Health sciences	0.771	(0.879)	0.680**	(0.191)
Engineering and computer science	0.770***	(0.193)	0.681***	(0.043)
Life sciences	0.800***	(0.187)	0.687***	(0.039)
Natural, physical sciences and math	0.883***	(0.090)	0.705***	(0.019)
Social sciences	0.930***	(0.161)	0.715***	(0.033)
Humanities	1.226***	(0.208)	0.773***	(0.040)
Fine arts	0.406***	(0.104)	0.596***	(0.023)
Control variables				
Professor Hispanic	−0.128	(0.295)	−0.028	(0.065)
Professor Black	−0.383	(0.240)	−0.085	(0.057)
Professor Chinese	−0.086	(0.142)	−0.020	(0.032)
Professor Indian	0.009	(0.206)	0.002	(0.046)
Professor other race	−0.139	(0.197)	−0.031	(0.045)
Professor male	0.073	(0.077)	0.016	(0.017)
Professor assistant	0.168***	(0.052)	0.035**	(0.011)
Professor associate	−0.056	(0.072)	−0.012	(0.016)
Professor other/unknown rank	−0.564***	(0.144)	−0.132***	(0.035)
Request for today	−0.273*	(0.119)	−0.055*	(0.023)
(Student Minority or Female) × (Request for Today)	0.378**	(0.130)	0.078**	(0.026)
Student and professor both Black	0.237	(0.272)	0.053	(0.064)
Student and professor both Hispanic	0.304	(0.309)	0.066	(0.068)
Student and professor both Indian	−0.005	(0.201)	−0.001	(0.045)
Student and professor both Chinese	0.424**	(0.160)	0.091*	(0.036)
Student and professor both female	0.108	(0.096)	0.023	(0.021)
Northeast	0.031	(0.101)	0.007	(0.022)
South	0.115	(0.089)	0.025	(0.019)
Midwest	0.082	(0.106)	0.018	(0.023)
Observations	6,519[a]		6,519[a]	

Note. OLS = ordinary least squares. Standard errors clustered by student name, constant suppressed.
[a] We exclude data points for the 29 professors working in departments that could not be classified.
^ Significant at the 10% level. * Significant at 5% level. ** Significant at 1% level. *** Significant at the 0.1% level.

Notably, the regression analyses presented in Table 4 and the summary statistics presented in Table 2 suggest that discrimination may play a greater role in impeding the careers of those who are not White males in certain disciplines than in others. Specifically, a Wald Test of the hypothesis that the discriminatory gaps estimated across disciplines are jointly equal to one another indicates that our coefficient estimates of the size of the discriminatory gap by discipline differ significantly more from one another than would be expected by chance in both Model 1 and Model 2 (Model 1: $\chi^2 = 106.69$; $p < .001$; Model 2: $F = 9.26$, $p < .001$). For example, discrimination against women and minorities, collectively, making requests of faculty for the future is greater in disciplines such as business and education than in the social sciences and natural sciences (for all four paired comparisons in both Models 1 and 2, *p*s < 0.05).

Table 5 presents coefficient estimates from logit and OLS regressions using the same specification as Table 4, but breaking out the race/gender of the student to show levels of discrimination against each group studied (e.g., White females, Black males, etc.). Like Figure 1b, this table shows that the patterns of bias against each individual group studied follow the same general trends observed when grouping women and minorities together.

Table 5

Logistic Regression (Model 3) and Ordinary Least Squares Regression (Model 4) to Predict Response Rates to White Males Versus Women and Minorities Broken Down by Group, as a Function of by Broad Academic Discipline

	Model 3		Model 4	
	Logistic regression		OLS regression	
Predictor	*B*	*SE*	*B*	*SE*
Bias by academic discipline				
(Student White Female) × (Business)	−0.825^	(0.500)	−0.145^	(0.081)
(Student White Female) × (Education)	0.168	(0.510)	0.009	(0.060)
(Student White Female) × (Human Services)	−0.449	(0.462)	−0.073	(0.078)
(Student White Female) × (Health Sciences)	−0.525	(0.900)	−0.116	(0.197)
(Student White Female) × (Engineering and Computer Science)	−0.224	(0.161)	−0.046	(0.037)
(Student White Female) × (Life Sciences)	−0.312	(0.288)	−0.065	(0.062)
(Student White Female) × (Natural, Physical Sciences and Math)	−0.405***	(0.100)	−0.085***	(0.021)
(Student White Female) × (Social Sciences)	0.071	(0.219)	0.013	(0.043)
(Student White Female) × (Humanities)	−0.237	(0.197)	−0.047	(0.037)
(Student White Female) × (Fine Arts)	−0.119^	(0.065)	−0.019	(0.015)
(Student Black Male) × (Business)	−1.024*	(0.456)	−0.185*	(0.072)
(Student Black Male) × (Education)	−1.124***	(0.187)	−0.214***	(0.043)
(Student Black Male) × (Human Services)	−0.653**	(0.240)	−0.108*	(0.043)
(Student Black Male) × (Health Sciences)	−0.355	(0.964)	−0.077	(0.214)
(Student Black Male) × (Engineering and Computer Science)	−0.448*	(0.216)	−0.099^	(0.051)
(Student Black Male) × (Life Sciences)	−0.252	(0.295)	−0.052	(0.065)
(Student Black Male) × (Natural, Physical Sciences and Math)	−0.466	(0.410)	−0.100	(0.095)
(Student Black Male) × (Social Sciences)	−0.235	(0.161)	−0.048	(0.033)
(Student Black Male) × (Humanities)	−0.326	(0.400)	−0.063	(0.080)
(Student Black Male) × (Fine Arts)	0.694**	(0.267)	0.154**	(0.053)
(Student Black Female) × (Business)	−1.918***	(0.503)	−0.397***	(0.090)
(Student Black Female) × (Education)	−1.199***	(0.133)	−0.231***	(0.030)
(Student Black Female) × (Human Services)	−1.203**	(0.440)	−0.226*	(0.096)
(Student Black Female) × (Health Sciences)	−0.283	(0.900)	−0.060	(0.197)
(Student Black Female) × (Engineering and Computer Science)	−0.605***	(0.161)	−0.135***	(0.036)
(Student Black Female) × (Life Sciences)	0.170	(0.305)	0.034	(0.057)
(Student Black Female) × (Natural, Physical Sciences and Math)	−0.207*	(0.105)	−0.043^	(0.021)
(Student Black Female) × (Social Sciences)	−0.270^	(0.153)	−0.056^	(0.031)
(Student Black Female) × (Humanities)	−0.291	(0.245)	−0.058	(0.046)
(Student Black Female) × (Fine Arts)	0.182	(0.360)	0.048	(0.081)
(Student Hispanic Male) × (Business)	−1.074	(0.972)	−0.198	(0.196)
(Student Hispanic Male) × (Education)	−1.141***	(0.083)	−0.217***	(0.017)
(Student Hispanic Male) × (Human Services)	(omitted)[a]		0.089*	(0.040)
(Student Hispanic Male) × (Health Sciences)	0.075	(0.966)	0.015	(0.208)
(Student Hispanic Male) × (Engineering and Computer Science)	−0.483*	(0.194)	−0.104*	(0.044)
(Student Hispanic Male) × (Life Sciences)	−0.686***	(0.175)	−0.151***	(0.036)
(Student Hispanic Male) × (Natural, Physical Sciences and Math)	−0.242	(0.235)	−0.050	(0.048)
(Student Hispanic Male) × (Social Sciences)	−0.511**	(0.192)	−0.108*	(0.041)
(Student Hispanic Male) × (Humanities)	−0.365^	(0.212)	−0.075^	(0.039)
(Student Hispanic Male) × (Fine Arts)	0.681***	(0.075)	0.139***	(0.011)
(Student Hispanic Female) × (Business)	−0.727	(0.461)	−0.124^	(0.072)
(Student Hispanic Female) × (Education)	−0.719	(0.562)	−0.126	(0.114)
(Student Hispanic Female) × (Human Services)	−0.454*	(0.226)	−0.078^	(0.041)
(Student Hispanic Female) × (Health Sciences)	−0.346	(0.930)	−0.075	(0.203)
(Student Hispanic Female) × (Engineering and Computer Science)	−0.165	(0.213)	−0.034	(0.046)
(Student Hispanic Female) × (Life Sciences)	−0.287	(0.273)	−0.060	(0.056)
(Student Hispanic Female) × (Natural, Physical Sciences and Math)	0.262***	(0.061)	0.050**	(0.014)
(Student Hispanic Female) × (Social Sciences)	−0.132	(0.175)	−0.027	(0.035)
(Student Hispanic Female) × (Humanities)	0.087	(0.560)	0.011	(0.100)
(Student Hispanic Female) × (Fine Arts)	0.055	(0.385)	0.019	(0.082)
(Student Chinese Male) × (Business)	−1.968***	(0.446)	−0.400***	(0.068)
(Student Chinese Male) × (Education)	−1.139***	(0.247)	−0.219***	(0.050)
(Student Chinese Male) × (Human Services)	−1.067***	(0.251)	−0.201***	(0.044)
(Student Chinese Male) × (Health Sciences)	−0.840	(1.013)	−0.186	(0.226)
(Student Chinese Male) × (Engineering and Computer Science)	−0.781***	(0.230)	−0.170**	(0.053)
(Student Chinese Male) × (Life Sciences)	−0.225	(0.191)	−0.056	(0.040)
(Student Chinese Male) × (Natural, Physical Sciences and Math)	−0.795***	(0.194)	−0.173***	(0.043)

(*table continues*)

Table 5 (*continued*)

Predictor	Model 3 Logistic regression B	Model 3 Logistic regression SE	Model 4 OLS regression B	Model 4 OLS regression SE
(Student Chinese Male) × (Social Sciences)	−0.783***	(0.151)	−0.172***	(0.031)
(Student Chinese Male) × (Humanities)	−0.440	(0.641)	−0.097	(0.118)
(Student Chinese Male) × (Fine Arts)	0.588	(0.450)	0.117	(0.072)
(Student Chinese Female) × (Business)	−1.390**	(0.440)	−0.270***	(0.067)
(Student Chinese Female) × (Education)	−0.969***	(0.270)	−0.188**	(0.055)
(Student Chinese Female) × (Human Services)	−2.887***	(0.415)	−0.617***	(0.086)
(Student Chinese Female) × (Health Sciences)	−0.750	(0.894)	−0.165	(0.196)
(Student Chinese Female) × (Engineering and Computer Science)	−0.644***	(0.170)	−0.141**	(0.038)
(Student Chinese Female) × (Life Sciences)	−0.806**	(0.277)	−0.177**	(0.062)
(Student Chinese Female) × (Natural, Physical Sciences and Math)	−0.362	(0.262)	−0.083	(0.051)
(Student Chinese Female) × (Social Sciences)	−0.706***	(0.151)	−0.154***	(0.031)
(Student Chinese Female) × (Humanities)	−1.099***	(0.232)	−0.235***	(0.047)
(Student Chinese Female) × (Fine Arts)	0.158	(0.561)	0.041	(0.119)
(Student Indian Male) × (Business)	−2.220***	(0.462)	−0.471***	(0.076)
(Student Indian Male) × (Education)	−1.011***	(0.198)	−0.188***	(0.043)
(Student Indian Male) × (Human Services)	−2.188***	(0.215)	−0.463***	(0.038)
(Student Indian Male) × (Health Sciences)	−0.544	(0.897)	−0.120	(0.197)
(Student Indian Male) × (Engineering and Computer Science)	−0.788***	(0.184)	−0.178***	(0.043)
(Student Indian Male) × (Life Sciences)	−0.836***	(0.263)	−0.190**	(0.061)
(Student Indian Male) × (Natural, Physical Sciences and Math)	−0.580***	(0.061)	−0.126***	(0.014)
(Student Indian Male) × (Social Sciences)	−0.679***	(0.154)	−0.149***	(0.032)
(Student Indian Male) × (Humanities)	0.201	(0.565)	0.025	(0.086)
(Student Indian Male) × (Fine Arts)	0.801	(0.870)	0.168	(0.150)
(Student Indian Female) × (Business)	−0.715	(0.445)	−0.132^	(0.067)
(Student Indian Female) × (Education)	−1.277***	(0.255)	−0.248***	(0.059)
(Student Indian Female) × (Human Services)	−0.495^	(0.261)	−0.090^	(0.044)
(Student Indian Female) × (Health Sciences)	−0.778	(0.905)	−0.177	(0.199)
(Student Indian Female) × (Engineering and Computer Science)	−0.625^	(0.376)	−0.138	(0.089)
(Student Indian Female) × (Life Sciences)	−0.885***	(0.181)	−0.201***	(0.038)
(Student Indian Female) × (Natural, Physical Sciences and Math)	−0.513***	(0.084)	−0.111***	(0.018)
(Student Indian Female) × (Social Sciences)	0.269	(0.193)	0.039	(0.035)
(Student Indian Female) × (Humanities)	−0.515*	(0.226)	−0.104*	(0.044)
(Student Indian Female) × (Fine Arts)	0.126	(0.298)	0.035	(0.065)
Academic discipline				
Business	1.715***	(0.438)	0.852***	(0.067)
Education	1.638***	(0.124)	0.840***	(0.025)
Human services	1.723***	(0.235)	0.854***	(0.044)
Health sciences	0.811	(0.889)	0.689***	(0.195)
Engineering and computer science	0.823***	(0.203)	0.693***	(0.045)
Life sciences	0.849***	(0.195)	0.698***	(0.041)
Natural, physical sciences and math	0.932***	(0.107)	0.716***	(0.023)
Social sciences	0.967***	(0.171)	0.723***	(0.035)
Humanities	1.259***	(0.220)	0.780***	(0.043)
Fine arts	0.444***	(0.118)	0.604***	(0.025)
Control variables				
Professor Hispanic	−0.107	(0.290)	−0.024	(0.063)
Professor Black	−0.324	(0.243)	−0.070	(0.055)
Professor Chinese	−0.089	(0.148)	−0.020	(0.033)
Professor Indian	0.011	(0.205)	0.002	(0.046)
Professor other race	−0.105	(0.213)	−0.023	(0.048)
Professor male	0.013	(0.087)	0.003	(0.019)
Professor assistant	0.173***	(0.052)	0.036**	(0.011)
Professor associate	−0.051	(0.076)	−0.011	(0.017)
Professor other/unknown rank	−0.578***	(0.143)	−0.133***	(0.034)
Request for today	−0.275*	(0.121)	−0.056*	(0.024)
(Student White Female) × (Request for Today)	0.335*	(0.157)	0.067*	(0.031)
(Student Black Female) × (Request for Today)	0.485**	(0.179)	0.101*	(0.037)
(Student Black Male) × (Request for Today)	0.321*	(0.155)	0.066^	(0.033)
(Student Hispanic Female) × (Request for Today)	0.216	(0.377)	0.044	(0.077)
(Student Hispanic Male) × (Request for Today)	0.501***	(0.153)	0.104**	(0.031)
(Student Chinese Female) × (Request for Today)	0.449**	(0.150)	0.094**	(0.031)

(*table continues*)

Table 5 (*continued*)

Predictor	Model 3		Model 4	
	Logistic regression		OLS regression	
	B	*SE*	*B*	*SE*
(Student Chinese Male) × (Request for Today)	0.482***	(0.140)	0.100**	(0.029)
(Student Indian Female) × (Request for Today)	0.402***	(0.124)	0.083**	(0.025)
(Student Indian Male) × (Request for Today)	0.243*	(0.124)	0.048^	(0.025)
Student and Professor both Black	0.104	(0.248)	0.022	(0.056)
Student and Professor both Hispanic	0.162	(0.305)	0.035	(0.066)
Student and Professor both Indian	0.211	(0.223)	0.048	(0.050)
Student and Professor both Chinese	0.620**	(0.203)	0.135**	(0.045)
Student and Professor both female	−0.014	(0.126)	−0.003	(0.027)
Northeast	0.032	(0.109)	0.007	(0.024)
South	0.102	(0.091)	0.022	(0.020)
Midwest	0.071	(0.108)	0.015	(0.024)
Observations	6,509[a,b]		6,519[b]	

Note. OLS = ordinary least squares. Standard errors clustered by student name, constant suppressed.
[a] 10 data points dropped because variable perfectly predicts outcome. [b] We exclude data points for the 29 professors working in departments that could not be classified.
^ Significant at the 10% level. * Significant at 5% level. ** Significant at 1% level. *** Significant at the 0.1% level.

Our remaining analyses of discrimination across disciplines examine discrimination at the level of a professor's *narrow* academic discipline (e.g., accounting, chemistry, music; see NSOPF, 2004 and Appendix Table A2 for discipline classifications), where we have 89 disciplines to examine rather than 10.[13] Looking at levels of discrimination across these 89 more narrow disciplinary categories, offers a sufficiently large sample of disciplines to investigate our hypotheses regarding the factors that moderate the size of the discriminatory gap (H1 and H2).

Hypothesis Testing With Hierarchical Linear Models

Representation of females and minorities as a moderator of discrimination (Hypothesis 1). We next estimate a series of hierarchical linear models to explore whether differences in discrimination across narrow disciplines or universities are correlated with variance in the representation of women and minorities. Said simply, we test whether disciplines or universities with more minorities (in aggregate, or from specific groups) and women are less likely to show bias against these groups when they make requests of faculty for the future (H1).

In Table 6, Model 5, to determine whether differences in discrimination across narrow disciplines are correlated with variance in the representation of minorities or females in those disciplines, we rely on the regression specification described in the section entitled Statistical Analyses, including moderator variables that capture the percentage of female, Black, Hispanic, and Asian faculty and Black, Hispanic, and Asian graduate students in each professor's narrow discipline according to the 2004 NSOPF survey. As the section entitled Statistical Analyses details, in analyses that disaggregate women and minorities, we both include these moderators as main effects and also interact them with an indicator for a prospective student in the relevant demographic group (female, Black, Hispanic, or Asian). Appendix Table A1 describes each of the primary predictor variables included in Table 6 (and in Tables 7–9).[14] Model 5 shows that none of these interaction terms significantly predicts faculty responsiveness to prospective graduate students. Model 6 shows that aggregating minority groups together by combining Black, Hispanic, and Asian faculty into a single "minority faculty" group and similarly combining minority doctoral-level students produces the same null results. Together, these results suggest that representation (as captured by our demographic composition variables) is not predictive of bias.

Although this finding may seem surprising, our modeling strategy already accounts for any direct benefits of a female or minority student contacting a faculty member sharing his or her race or gender by including indicator variables accounting for matched race and gender. Thus, the only remaining path through which representation could impact response rates is by affecting the behavior of faculty who do not share a student's race or gender. However, across all models in Table 6, we also observe almost no benefits to women or minority students contacting faculty who share their demographics, consistent with recent work by Moss-Racusin et al. (2012) and consistent with Greenberg and Mollick (2014): only Chinese students experience significant benefits from contacting same-race faculty. Thus, we find essentially no evidence that the treatment of women and minorities is better in disciplines with higher female and minority representation.

Before turning away from the possibility that faculty in areas with greater representation of women and minorities are less biased against women and minorities, we look at additional measures capturing the representation of women and minorities across the different universities in our sample using available data on

[13] Faculty in our sample represented 109 of the 133 narrow NSOPF disciplines. Twenty of the 109 narrow disciplinary categories in which faculty in our study were classified were disciplines for which the 2004 NSOPF survey reported no data, leaving us with 89 analyzable narrow disciplines.

[14] For example, in Model 6, the first predictor listed is the variable "*Faculty % Black,*" and the coefficient estimate on this predictor captures the main effect of a 1-point increase in the percentage of Black faculty at a university on the likelihood of receiving a response. The second predictor listed is the interaction term "(*Fac%Black*) x (*Black Student*)," which represents the effect of a 1-point increase from the grand mean in the percentage of Black faculty at a university on a Black student's likelihood of receiving a response.

Table 6
HLM Estimated Effects of Students' Race and Gender, the (Mean Centered) Demographic Composition of a Professor's University and Academic Discipline, and the Interaction Between Minority Student Status and These Discipline and University Demographics on Whether Professors Respond to E-Mails

Predictor	Model 5		Model 6		Model 7		Model 8	
	B	*SE*	*B*	*SE*	*B*	*SE*	*B*	*SE*
Academic discipline characteristics								
Faculty % Black	0.007	(0.012)			0.010	(0.012)		
(Fac % Black) × (Black Student)	−0.002	(0.020)			−0.004	(0.021)		
Faculty % Hispanic	0.014	(0.015)			0.015	(0.015)		
(Fac % Hispanic) × (Hispanic Student)	−0.001	(0.023)			−0.004	(0.024)		
Faculty % Asian	−0.006	(0.007)			−0.008	(0.007)		
(Fac%Asian) × (Asian Student)	0.000	(0.009)			0.003	(0.009)		
Faculty % Minority			−0.002	(0.009)			−0.003	(0.009)
(Fac % Minority) × (Minority Student)			−0.005	(0.009)			−0.004	(0.009)
Faculty % Female	0.004	(0.003)	0.007**	(0.002)	0.005^	(0.003)	0.007**	(0.003)
(Fac % Female) × (Female Student)			−0.001	(0.003)	−0.002	(0.003)	−0.002	(0.003)
PhD Students % Black	−0.004	(0.023)			−0.013	(0.023)		
(PhD%Black) × (Black Student)	−0.036	(0.038)			−0.027	(0.039)		
PhD Students % Hispanic	0.027	(0.032)			0.038	(0.033)		
(PhD % Hispanic) × (Hispanic Student)	0.040	(0.058)			0.013	(0.060)		
PhD Students % Asian	−0.005	(0.027)			−0.005	(0.028)		
(PhD % Asian) × (Asian Student)	−0.052	(0.038)			−0.062	(0.040)		
PhD Students % Minority			0.007	(0.024)			−0.001	(0.025)
(PhD % Minority) × (Minority Student)			−0.003	(0.026)			0.005	(0.027)
University characteristics								
Undergraduates % Black					−0.009**	(0.003)		
(Und % Black) × (Black Student)					0.002	(0.005)		
Undergraduates % Hispanic					0.004	(0.005)		
(Und % Hispanic) × (Hispanic Student)					−0.017*	(0.008)		
Undergraduates % Asian					−0.007^	(0.004)		
(Und % Asian) × (Asian Student)					0.009	(0.006)		
Undergraduate % Minority							−0.004	(0.005)
(Und % Minority) × (Minority Student)							0.001	(0.005)
Undergraduates % Female					−0.003	(0.008)	−0.002	(0.008)
(Und % Female) × (Female Student)					−0.004	(0.010)	−0.005	(0.010)
Univ Faculty % Minority							−0.009	(0.010)
(UFac % Minority) × (Minority Student)							0.003	(0.011)
Univ Faculty % Female					−0.009	(0.008)	−0.011	(0.008)
(UFac % Female) × (Female Student)					0.013	(0.011)	0.013	(0.011)
Control variables								
Professor Hispanic	−0.050	(0.270)	−0.054	(0.269)	−0.051	(0.283)	−0.027	(0.282)
Professor Black	−0.216	(0.302)	−0.224	(0.300)	−0.187	(0.312)	−0.199	(0.310)
Professor Chinese	−0.118	(0.169)	−0.096	(0.169)	−0.109	(0.176)	−0.111	(0.175)
Professor Indian	−0.035	(0.192)	0.002	(0.192)	−0.095	(0.199)	−0.037	(0.199)
Professor other race	−0.152	(0.209)	−0.141	(0.208)	−0.173	(0.212)	−0.145	(0.211)
Professor male	0.044	(0.087)	0.044	(0.087)	0.075	(0.091)	0.070	(0.090)
Professor assistant	−0.057	(0.068)	−0.061	(0.068)	−0.051	(0.071)	−0.064	(0.071)
Professor associate	0.189**	(0.073)	0.183*	(0.073)	0.210**	(0.077)	0.198**	(0.076)
Professor other/unknown rank	−0.608***	(0.125)	−0.611***	(0.125)	−0.516***	(0.131)	−0.532***	(0.130)
Request for today	−0.269^	(0.163)	−0.268^	(0.163)	−0.274	(0.169)	−0.272	(0.169)
Student female	−0.190	(0.178)	−0.186	(0.179)	−0.147	(0.186)	−0.141	(0.186)
Student Black	−0.400*	(0.169)			−0.373*	(0.174)		
Student Hispanic	−0.409*	(0.177)			−0.332^	(0.184)		
Student Asian	−0.662***	(0.152)			−0.630***	(0.159)		
Student minority			−0.530***	(0.135)			−0.477***	(0.140)
(Student Black) × (Student Female)	0.185	(0.242)			0.210	(0.251)		
(Student Hispanic) × (Student Female)	0.486*	(0.243)			0.430^	(0.252)		
(Student Asian) × (Student Female)	0.253	(0.212)			0.179	(0.220)		
(Student Minority) × (Student Female)			0.278	(0.192)			0.233	(0.199)
(Student White Female) × (Request for Today)	0.358	(0.241)	0.349	(0.241)	0.385	(0.250)	0.366	(0.250)
(Student Black Female) × (Request for Today)	0.517*	(0.245)	0.541*	(0.222)	0.449^	(0.256)	0.502*	(0.231)
(Student Black Male) × (Request for Today)	0.333	(0.233)	0.446*	(0.216)	0.369	(0.241)	0.446*	(0.224)
(Student Hispanic Female) × (Request for Today)	0.215	(0.239)	0.465*	(0.217)	0.255	(0.248)	0.517*	(0.225)
(Student Hispanic Male) × (Request for Today)	0.452^	(0.236)	0.496*	(0.216)	0.442^	(0.244)	0.502*	(0.223)

(*table continues*)

Table 6 (*continued*)

Predictor	Model 5 *B*	Model 5 *SE*	Model 6 *B*	Model 6 *SE*	Model 7 *B*	Model 7 *SE*	Model 8 *B*	Model 8 *SE*
(Student Chinese Female) × (Request for Today)	0.330	(0.224)	0.210	(0.217)	0.334	(0.231)	0.178	(0.224)
(Student Chinese Male) × (Request for Today)	0.582**	(0.227)	0.485*	(0.219)	0.673**	(0.237)	0.577*	(0.229)
(Student Indian Female) × (Request for Today)	0.471*	(0.227)	0.323	(0.220)	0.479*	(0.235)	0.304	(0.227)
(Student Indian Male) × (Request for Today)	0.193	(0.227)	0.078	(0.219)	0.208	(0.237)	0.099	(0.228)
Student and professor both Black	−0.001	(0.328)	0.056	(0.319)	0.043	(0.341)	0.108	(0.330)
Student and professor both Hispanic	0.090	(0.297)	0.246	(0.286)	0.094	(0.312)	0.206	(0.300)
Student and professor both Indian	0.295	(0.227)	0.137	(0.220)	0.413^	(0.236)	0.222	(0.228)
Student and professor both Chinese	0.659***	(0.202)	0.503*	(0.196)	0.658**	(0.211)	0.518*	(0.205)
Student and professor both female	−0.030	(0.125)	−0.027	(0.124)	−0.003	(0.130)	−0.003	(0.129)
Northeast	−0.008	(0.086)	−0.006	(0.086)	−0.045	(0.094)	−0.056	(0.091)
South	0.097	(0.082)	0.104	(0.082)	0.158	(0.093)	0.135	(0.086)
Midwest	0.057	(0.088)	0.063	(0.087)	0.001	(0.100)	0.002	(0.097)
Observations	6,206[a]		6,206[a]		5,766[a,b]		5,766[a,b]	

Note. HLM = hierarchical linear modeling; Fac = faculty. Faculty are cross-classified by university (258, Level 2) and academic discipline (89, Level 2). Table A1 in the appendix defines primary predictor variables in this table.
[a] For 20 of the 109 narrow disciplinary categories into which faculty were classified, the 2004 NSOPF survey reported no data. These observations corresponded to 313 data points from our study, which we excluded from our analyses. We also exclude data points for the 29 professors working in departments that could not be classified. [b] For 15 of the universities studied, information is missing about the student or faculty composition. This missing data leads us to drop 440 data points in Models 6 and 7.
^ Significant at the 10% level. * Significant at 5% level. ** Significant at 1% level. *** Significant at the 0.1% level.

minority and female representation at these institutions. In Table 6, Model 7 we add moderator variables to our model for the proportion of Blacks, Hispanics, Asians,[15] and females in a university's undergraduate population and for the proportion of faculty at a university who are female, as reported by *U.S. News and World Report* (U.S. News & World Report, 2010). Again, we find no relationship between representation and bias. In fact, the only significant relationship we detect is a reduction in the response rate to Hispanic students at universities with higher Hispanic representation—a result that goes in the opposite of the direction one would expect if greater representation were associated with reduced discrimination. Model 8 shows that aggregating minority groups by combining Black, Hispanic, and Asian undergraduates into a single "minority undergraduate" group produces the same null results. These analyses thus provide further evidence that faculty discrimination is unaltered by the proportion of women and minorities in a professor's work environment.

Pay as a moderator of discrimination (Hypothesis 2). In examining summary statistics from our data, we observe an impressive correlation (with insufficient sample size to reach statistical significance, $N = 10$) between average faculty salary and the size of the discriminatory gap by *broad* discipline ($r_{\text{OLS-regression-estimated-discriminatory-gap,pay}} = 0.4$), consistent with our second hypothesis. Average 9-month salaries reported in the 2004 NSOPF survey by *narrow* discipline in our sample varied from $30,211 (dance) to $118,786 (medicine) with a standard deviation of $13,265, and Figure 2 reveals a strong correlation between average salary by narrow discipline and the size of the discriminatory gap in our raw data as well, supporting Hypothesis 2.

In an HLM analysis exploring the relationship between the average salary in a discipline and discrimination shown in Table 7, Model 12, we find a strong, significant relationship between the average salary in a faculty member's discipline and the size of the discriminatory gap. On average, the fitted odds that a student who is not a White male will receive a response from a given faculty member when making a request for the future are 0.84 times what they would be if that same student contacted a faculty member in a discipline with a $10,000 lower 9-month average salary ($p = .012$), but there is no predicted change in the response rate to White males associated with a change in salary ($p = .761$). Notably, as shown in Table 8, Model 13, if we disaggregate the nine separate female and minority groups studied, greater bias is observed when students contact faculty with a request for the future in higher-paid disciplines for every single student demographic group, and these effects are not only directional but also at least marginally significant for Black females, Hispanic females, Chinese females, Chinese males, Indian females, and Indian males.

In addition to espousing different values than their public counterparts, private institutions also pay higher salaries ($34,687 higher on average; Byrne, 2008); therefore, we investigate whether levels of discrimination differ between public ($N_{\text{public}} = 163$) and private universities ($N_{\text{private}} = 96$). The raw, average size of the sample-weighted discriminatory gap experienced by minorities and females, collectively, is 11.0 percentage points at private schools and 3.6 percentage points at public schools. In HLM analyses, we find a meaningful difference in discrimination by institution type, even controlling for a university's prestige with its *U.S. News* ranking (2010). Table 7, Model 12 presents the results of HLM analyses testing the difference in the size of the discriminatory gap when prospective students make future requests of faculty by university type. On average in the population, when a faculty member works at a public school, the fitted odds that he will respond to a student who is not a White male making a request of him for the future are 1.19 times what they would be if he worked at a private school ($p < .001$), whereas the fitted odds of a professor responding to a White male are actually lower at a private school than a public school. In other words, the discrimi-

[15] *U.S. News* provides statistics about a single category of "Asian" students and provides no statistics on the ethnic breakdown of university faculty.

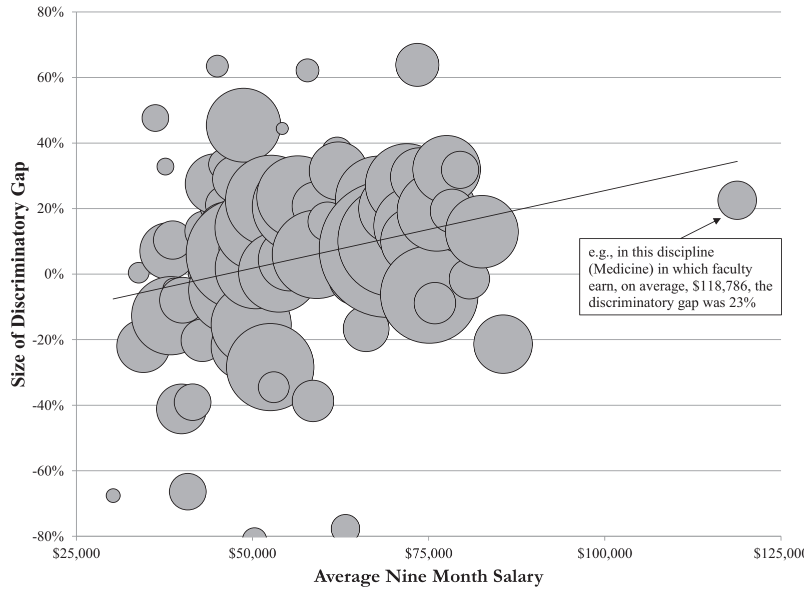

Figure 2. Raw, sample-weighted discriminatory gap experienced by minority and female students, collectively, relative to White males as a function of the average 9-month salary in a faculty member's narrow NSOPF discipline. Note: Each bubble represents one discipline and bubble sizes are proportional to the study's sample size in a given discipline. Negative numbers indicate discrimination against White males, positive numbers indicate discrimination against women and minorities, collectively.

natory gap is dramatically larger at private schools than at public schools.

Figure 3 plots summary statistics illustrating the raw magnitude of the discriminatory gap for each race/gender group studied at public versus private schools, highlighting that the public-private gap is persistent across all groups included in our research. As shown in Table 9, Model 14, if we disaggregate the nine separate female and minority groups studied, every single group studied faces significant bias when making requests of faculty for the future at private schools with the exception of Hispanic females who only face marginally significant bias at private schools. Further, every single group studied faces significantly *less* bias at public schools than private schools with the exception of Hispanic males who only face marginally significantly reduced bias at public schools.

Interestingly, Models 11 and 12 in Table 7 highlight two measures of status that are unrelated to discrimination in our sample. Model 11 reveals that a school's *U.S. News* ranking is not significantly correlated with the school's level of discrimination (p = .98). Model 12 shows that a faculty member's academic rank (assistant, associate, or full professor) is also a nonsignificant predictor of discrimination (p = .94).

Discussion

Through a field experiment set in academia, we show that when making decisions about the future, faculty in almost every academic discipline exhibit bias favoring White males at a key pathway to the Academy. We also demonstrate that this discrimination varies more than would be expected by chance across different broad academic disciplines. Additionally we explore characteristics shared by the disciplines most biased in favor of White males, offering insights into factors that may contribute to the widespread underrepresentation of women and many minority groups. In exploring the causes of this variation, we find no relationship between representation in a discipline (or university) and levels of discrimination, contradicting our first hypothesis. However, we do find a strong, robust relationship between pay and discrimination, whereby faculty in higher-paid disciplines are more responsive to White males than to other students, supporting our second hypothesis. We also find at least marginally significantly greater discrimination against every female and minority student group requesting help for the future from faculty at private universities (which pay higher salaries) than at public universities.

Our study is the first to experimentally explore discrimination not only at an early career, pathway stage but also (a) with a representative faculty sample and (b) with a subject pool unbiased by the prospect of being observed by researchers. Our findings offer evidence that discrimination affects prospective academics seeking mentoring at a critical early career juncture in the fields of business, education, human services, engineering and computer science, life sciences, natural/physical sciences and math, social sciences, and marginally in the humanities. In addition, we find that White males face discrimination in the fine arts. Notably, the magnitude of the discrimination we find is quite large. In business, the most discriminatory discipline we observe in our study, women and minorities seeking guidance are collectively ignored at 2.2 times the rate of White males, and even in the least discriminatory academic discipline—the humanities (where discrimination does not reach statistical significance)—women and minorities are still collectively ignored at 1.4 times the rate of White males when seeking guidance in the future. Such differences in treatment could have meaningful career consequences for individuals and for society.

Table 7
HLM Estimated Effects of Students' Race and Gender, Characteristics of Faculty's University and Academic Discipline, and the Interaction Between Female or Minority Student Status, Collectively, and These Discipline and University Characteristics on Whether Faculty Respond to E-mails

	Model 9		Model 10		Model 11		Model 12	
Predictor	*B*	*SE*	*B*	*SE*	*B*	*SE*	*B*	*SE*
Academic discipline characteristics								
Avg. Faculty Salary × 10^3	0.000	(0.006)	0.000	(0.000)	0.001	(0.006)	0.002	(0.006)
(Salary) × (Minority or Female Student)	−0.015*	(0.007)	−0.016*	(0.007)	−0.016*	(0.007)	−0.017*	(0.007)
University characteristics								
Public school			−0.577***	(0.179)	−0.526**	(0.199)	−0.553**	(0.198)
(Public) × (Minority or Female Student)			0.706***	(0.188)	0.701***	(0.209)	0.727***	(0.209)
School rank (*U.S. News*) × 10^3					−0.815	(1.331)	−0.688	(1.332)
(School Rank) × (Minority or Female Student)					0.390	(1.409)	−0.120	(1.410)
Faculty status								
Professorial rank							0.029	(0.084)
(Prof Rank) × (Minority or Female Student)							−0.007	(0.089)
Control variables								
Professor Hispanic	−0.043	(0.269)	−0.020	(0.269)	−0.017	(0.269)	0.034	(0.267)
Professor Black	−0.221	(0.299)	−0.223	(0.300)	−0.214	(0.300)	−0.168	(0.299)
Professor Chinese	−0.114	(0.168)	−0.117	(0.168)	−0.110	(0.168)	−0.059	(0.168)
Professor Indian	−0.042	(0.191)	−0.039	(0.191)	−0.035	(0.191)	−0.006	(0.191)
Professor other race	−0.168	(0.208)	−0.173	(0.208)	−0.160	(0.208)	−0.128	(0.208)
Professor male	0.056	(0.081)	0.057	(0.081)	0.059	(0.081)	0.040	(0.081)
Professor assistant	−0.062	(0.068)	−0.061	(0.068)	−0.051	(0.069)		
Professor associate	0.183*	(0.073)	0.179*	(0.073)	0.186*	(0.073)		
Professor other/unknown rank	−0.602***	(0.124)	−0.603***	(0.125)	−0.594***	(0.125)		
Request for today	−0.241	(0.163)	−0.239	(0.164)	−0.240	(0.164)	−0.227	(0.164)
Student minority or female	−0.410***	(0.129)	−0.429***	(0.130)	−0.431***	(0.136)	−0.429**	(0.135)
(Student White Female) × (Request for Today)	0.577**	(0.212)	0.576**	(0.213)	0.571**	(0.213)	0.562**	(0.213)
(Student Black Female) × (Request for Today)	0.503*	(0.217)	0.495*	(0.218)	0.491*	(0.218)	0.479*	(0.218)
(Student Black Male) × (Request for Today)	0.351^	(0.212)	0.348	(0.213)	0.348	(0.213)	0.336	(0.212)
(Student Hispanic Female) × (Request for Today)	0.451*	(0.212)	0.451*	(0.213)	0.450*	(0.213)	0.441*	(0.213)
(Student Hispanic Male) × (Request for Today)	0.404^	(0.212)	0.399^	(0.213)	0.396^	(0.213)	0.384^	(0.213)
(Student Chinese Female) × (Request for Today)	0.188	(0.212)	0.184	(0.213)	0.186	(0.213)	0.171	(0.212)
(Student Chinese Male) × (Request for Today)	0.388^	(0.215)	0.388^	(0.216)	0.388^	(0.216)	0.385^	(0.215)
(Student Indian Female) × (Request for Today)	0.314	(0.215)	0.308	(0.216)	0.302	(0.216)	0.288	(0.215)
(Student Indian Male) × (Request for Today)	−0.014	(0.214)	−0.009	(0.215)	−0.016	(0.215)	−0.036	(0.215)
Student and professor both Black	0.017	(0.318)	0.025	(0.318)	0.017	(0.318)	0.000	(0.318)
Student and professor both Hispanic	0.199	(0.286)	0.171	(0.286)	0.166	(0.286)	0.127	(0.285)
Student and professor both Indian	0.155	(0.220)	0.151	(0.220)	0.153	(0.220)	0.147	(0.219)
Student and professor both Chinese	0.492*	(0.196)	0.493*	(0.196)	0.483*	(0.196)	0.494*	(0.196)
Student and professor both Female	0.038	(0.108)	0.042	(0.108)	0.045	(0.108)	0.043	(0.108)
Northeast	0.002	(0.086)	0.021	(0.090)	0.022	(0.090)	0.026	(0.090)
South	0.113	(0.081)	0.110	(0.081)	0.127	(0.082)	0.129	(0.082)
Midwest	0.075	(0.087)	0.073	(0.087)	0.076	(0.087)	0.084	(0.086)
Observations	6,206[a]		6,206[a]		6,206[a]		6,206[a]	

Note. HLM = hierarchical linear modeling; Avg. = average. Faculty are cross-classified by university (258, Level 2) and academic discipline (89, Level 2). Table A1 Appendix defines primary predictor variables in this table.
[a] For 20 of the 109 narrow disciplinary categories into which faculty were classified, the 2004 NSOPF survey reported no data. These observations corresponded to 313 data points from our study, which we excluded from our analyses. We also exclude data points for the 29 professors working in departments that could not be classified.
^ Significant at the 10% level. * Significant at 5% level. ** Significant at 1% level. *** Significant at the 0.1% level.

Further, our findings reveal how seemingly small, daily decisions made by faculty about guidance and mentoring can generate discrimination that disadvantages women and minorities. These microinequities (Rowe, 1981, 2008) and microaggressions (Sue, 2010) may often arise on the pathways that lead to (or emerge after) gateways. Our work raises the question of how discrimination, even if unintended, in the way faculty make informal, ostensibly small choices might have negative repercussions (Petersen, Saporta, & Seidel, 2000), especially as seemingly small differences in treatment can accumulate (DiPrete & Eirich, 2006; Valian, 1999).

Broadly, our research contributes to the literature on discrimination in organizations broadly and in academia specifically in multiple important ways. We answer the question of *where* in academia discrimination is most severe, revealing that the fields of business and education exhibit the greatest bias and that the humanities and social sciences exhibit the least. More relevant to organizational scholars, we explore characteristics shared by disciplines

Table 8
HLM Estimated Discrimination Against Women and Minorities Broken Down by Group as a Function of Average Faculty Salary by Discipline

Predictor	Model 13 *B*	Model 13 *SE*
University characteristics		
Public school	0.095	(0.070)
School rank (*U.S. News*) × 10^3	−0.816^	(0.455)
Academic discipline characteristics		
Avg. Faculty Salary × 10^3	0.000	(0.006)
Bias by salary		
(Student White Female) × (Avg. Faculty Salary × 10^3)	−0.010	(0.009)
(Student Black Female) × (Avg. Faculty Salary × 10^3)	−0.016^	(0.009)
(Student Black Male) × (Avg. Faculty Salary × 10^3)	−0.012	(0.009)
(Student Hispanic Female) × (Avg. Faculty Salary × 10^3)	−0.017^	(0.009)
(Student Hispanic Male) × (Avg. Faculty Salary × 10^3)	−0.007	(0.009)
(Student Chinese Female) × (Avg. Faculty Salary × 10^3)	−0.015^	(0.009)
(Student Chinese Male) × (Avg. Faculty Salary × 10^3)	−0.017^	(0.009)
(Student Indian Female) × (Avg. Faculty Salary × 10^3)	−0.018^	(0.009)
(Student Indian Male) × (Avg. Faculty Salary × 10^3)	−0.021*	(0.009)
Student White female	−0.143	(0.178)
Student Black female	−0.346^	(0.186)
Student Black male	−0.362*	(0.169)
Student Hispanic female	−0.065	(0.187)
Student Hispanic male	−0.397*	(0.178)
Student Chinese female	−0.653***	(0.183)
Student Chinese male	−0.601***	(0.181)
Student Indian female	−0.470*	(0.187)
Student Indian male	−0.665***	(0.183)
Control variables		
Professor Hispanic	−0.020	(0.270)
Professor Black	−0.182	(0.300)
Professor Chinese	−0.133	(0.170)
Professor Indian	−0.061	(0.192)
Professor other race	−0.132	(0.209)
Professor male	0.013	(0.085)
Professor assistant	−0.056	(0.069)
Professor associate	0.195**	(0.073)
Professor other/unknown rank	−0.606***	(0.125)
Request for today	−0.244	(0.163)
(Student White Female) × (Request for Today)	0.317	(0.241)
(Student Black Female) × (Request for Today)	0.477^	(0.245)
(Student Black Male) × (Request for Today)	0.303	(0.233)
(Student Hispanic Female) × (Request for Today)	0.190	(0.239)
(Student Hispanic Male) × (Request for Today)	0.411^	(0.235)
(Student Chinese Female) × (Request for Today)	0.390^	(0.236)
(Student Chinese Male) × (Request for Today)	0.517*	(0.240)
(Student Indian Female) × (Request for Today)	0.353	(0.243)
(Student Indian Male) × (Request for Today)	0.216	(0.241)
Student and professor both Black	−0.047	(0.326)
Student and professor both Hispanic	0.062	(0.296)
Student and professor both Indian	0.333	(0.234)
Student and professor both Chinese	0.663**	(0.211)
Student and professor both Female	−0.055	(0.121)
Northeast	0.025	(0.090)
South	0.130	(0.082)
Midwest	0.068	(0.087)
Observations	6,206[a]	

Note. HLM = hierarchical linear modeling; Avg. = average. Faculty are cross-classified by university (258, Level 2) and academic discipline (89, Level 2).
[a] For 20 of the 109 narrow disciplinary categories into which faculty were classified, the 2004 NSOPF survey reported no data. These observations corresponded to 313 data points from our study, which we excluded from our analyses. We also exclude data points for the 29 professors working in departments that could not be classified.
^ Significant at the 10% level. * Significant at 5% level. ** Significant at 1% level. *** Significant at the 0.1% level.

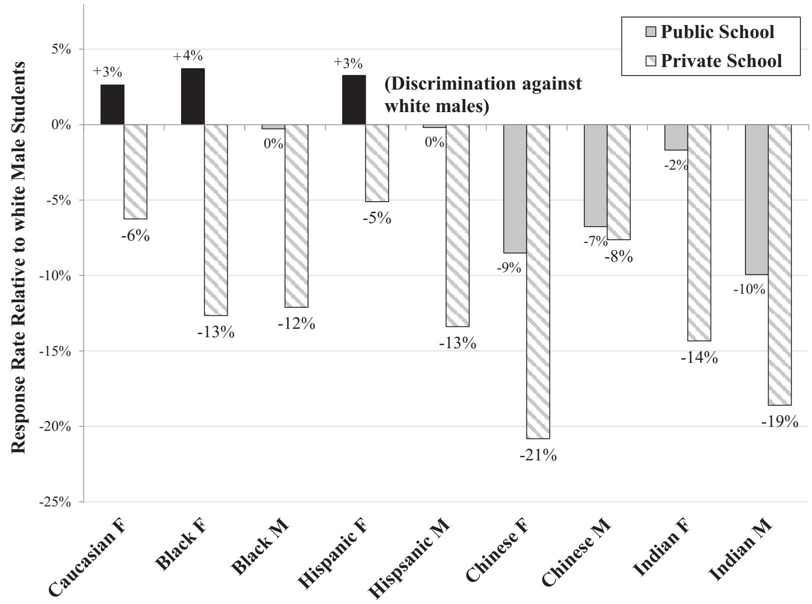

Figure 3. Raw, sample-weighted average size of the discriminatory gap faced by female and minority students at public versus private universities. Note: Discrimination against White males in black. Discrimination against women and minorities in gray.

that are most biased against women and minorities, collectively. We find that higher pay is correlated with greater discrimination (both within disciplines and across lower- vs. higher-paying [public vs. private] institutions) and that, somewhat surprisingly, higher representation of women and minorities in a discipline or university does not protect against discrimination. We discuss possible explanations for these findings next.

Pay and Discrimination

We have found evidence supporting our hypothesis that discrimination is greater in higher-paid professional environments. We based this prediction on past research showing that underrepresentation of women and minorities is more extreme in the highest-paying jobs (Braddock & McPartland, 1987. Morrison & von Glinow, 1990; Oakley, 2000), that those who are well-represented in an occupation may be more sensitive to the entry of others due to concerns about prestige pollution (Goldin, 2013), and that high incomes reduce egalitarianism and generosity (Caruso et al., 2013; Piff et al., 2010; Piff et al., 2012). Convergent findings can increase our confidence that this finding is robust; indeed, we find a strong correlation between bias (measured with survey questions) and self-reported pay in a nonacademic population as well.[16] Our results provide support for the possibility that those with higher incomes are more biased than those with lower incomes against women and minorities.

Importantly, however, there are alternative explanations for the finding that higher-paid faculty and faculty at private schools are more biased. One possibility is that the populations of faculty who *choose* (or are selected) to work in higher-paid fields and at private (vs. public) institutions have different values and priorities than other faculty. The very fact that levels of underrepresentation vary across disciplines highlights that different types of people fill the faculty ranks in different areas of the Academy. For instance, women pursue careers in math and science at markedly lower rates than men (Handelsman et al., 2005). Further, individuals select unevenly into disciplines on many dimensions other than race and gender (e.g., mathematical ability, vocabulary, social skills); therefore, it may be that more discriminatory individuals prefer to work in higher-paid fields and at private institutions. While we cannot rule out faculty selection as an explanation for any of our findings, it is not at all clear *why* higher-paid disciplines would attract less egalitarian and more discriminatory faculty, and future research exploring this question is needed.

Another possibility is that the *treatment* of faculty differs across institutions and schools. For instance, differing university policies between private and public institutions might be responsible for the differences detected in discrimination across these two types of schools. Similarly, disciplines with higher pay might tend to instill different values in their faculty, provide them with different training and socialization environments, or institute different policies than those with lower pay, altering observed levels of discrimination. While we cannot rule out the possibility that selection effects, policies, or values drive differential discrimination as a function of faculty pay, it is not clear *why* such a link would exist.

[16] In a survey conducted with 128 MTurk workers (49% male, $M_{age} = 33.2$, 72% White), we find that higher income participants exhibit significantly more bias against women and minorities (measured by combining 17 items from Brigham's, 1993 *Attitudes Toward Blacks Scale* and Pratto, Sidanius, Stallworth, & Malle's, 1994 scale for assessing attitudes about women's rights and racial policy, $\alpha = .89$; $\text{correlation}_{\text{bias,income}} = 0.22$; $p = .012$). We also find that higher social class (measured following Kraus and Keltner (2009)) is strongly correlated with greater race and gender bias ($\text{correlation}_{\text{social\_class,income}} = 0.24$; $p = .007$). See Supplemental materials: MTurk Survey Procedures for full study materials.

Table 9

HLM Estimated Effects of Discrimination Against Women and Minorities Broken Down by Group at Public Versus Private Universities

Predictor	Model 14 *B*	Model 14 *SE*
University characteristics		
Public school	−0.492**	(0.181)
School rank (*U.S. News*) × 10^3	−0.828^	(0.456)
Bias by university type		
Student White female	−0.500*	(0.250)
Student Black female	−0.960***	(0.248)
Student Black male	−0.708**	(0.241)
Student Hispanic female	−0.480^	(0.261)
Student Hispanic male	−0.681**	(0.252)
Student Chinese female	−1.280***	(0.249)
Student Chinese male	−1.006***	(0.255)
Student Indian female	−1.028***	(0.256)
Student Indian male	−1.296***	(0.253)
(Student White Female) × (Public School)	0.511*	(0.259)
(Student Black Female) × (Public School)	0.919***	(0.260)
(Student Black Male) × (Public School)	0.496*	(0.251)
(Student Hispanic Female) × (Public School)	0.572*	(0.260)
(Student Hispanic Male) × (Public School)	0.446^	(0.260)
(Student Chinese Female) × (Public School)	0.899***	(0.254)
(Student Chinese Male) × (Public School)	0.572*	(0.260)
(Student Indian Female) × (Public School)	0.788**	(0.262)
(Student Indian Male) × (Public School)	0.864***	(0.258)
Academic discipline characteristics		
Avg. Faculty Salary × 10^3	−0.013***	(0.002)
Control variables		
Professor Hispanic	−0.002	(0.271)
Professor Black	−0.209	(0.302)
Professor Chinese	−0.127	(0.170)
Professor Indian	−0.019	(0.193)
Professor other race	−0.136	(0.209)
Professor male	0.030	(0.084)
Professor assistant	−0.050	(0.069)
Professor associate	0.189**	(0.073)
Professor other/unknown rank	−0.620***	(0.125)
Request for today	−0.251	(0.164)
(Student White Female) × (Request for Today)	0.324	(0.242)
(Student Black Female) × (Request for Today)	0.442^	(0.247)
(Student Black Male) × (Request for Today)	0.312	(0.234)
(Student Hispanic Female) × (Request for Today)	0.196	(0.240)
(Student Hispanic Male) × (Request for Today)	0.420^	(0.237)
(Student Chinese Female) × (Request for Today)	0.393^	(0.237)
(Student Chinese Male) × (Request for Today)	0.524*	(0.240)
(Student Indian Female) × (Request for Today)	0.350	(0.243)
(Student Indian Male) × (Request for Today)	0.241	(0.242)
Student and professor both Black	−0.010	(0.327)
Student and professor both Hispanic	0.040	(0.297)
Student and professor both Indian	0.241	(0.231)
Student and professor both Chinese	0.639**	(0.209)
Student and professor both Female	−0.020	(0.119)
Northeast	0.022	(0.090)
South	0.121	(0.082)
Midwest	0.061	(0.087)
Observations	6,206[a]	

Note. HLM = hierarchical linear modeling; Avg. = average. Faculty are cross-classified by university (258, Level 2) and academic discipline (89, Level 2).

[a] For 20 of the 109 narrow disciplinary categories into which faculty were classified, the 2004 NSOPF survey reported no data. These observations corresponded to 313 data points from our study, which we excluded from our analyses. We also exclude data points for the 29 professors working in departments that could not be classified.

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

It is likely that multiple processes may have worked in concert to produce the discrimination we detect, or discrimination may be driven by another variable correlated with pay (e.g., status, elitism, etc.). Nonetheless, our findings contribute to a growing body of theory and research linking money and egalitarianism and importantly point toward income as a previously unexplored moderator of race and gender discrimination.

Representation, Shared Characteristics, and Discrimination

We have reported two counterintuitive findings: (a) representation does not reduce bias and (b) there are no benefits to women of contacting female faculty nor to Black or Hispanic students of contacting same-race faculty. These results are consistent with past research showing that, counter to perceptions (Avery, McKay, & Wilson, 2008), stereotypes are potentially held even by members of the groups to which the stereotypes apply (Nosek, Banaji, & Greenwald, 2002) and that female scientists are just as biased against female job applicants as male scientists (Moss-Racusin et al., 2012). Importantly, our findings suggest that although past work has shown benefits accruing to females and minorities from increases in female and minority representation in a given organization, these benefits may be the result of mechanisms other than reduced discrimination, such as the availability of role models or changes in culture associated with increasing demographic diversity. Our work reveals that when a field boasts impressive representation of minorities and women within its ranks, this cannot be assumed to eliminate or even necessarily reduce discrimination. More specifically, no discipline, university, or institution in general should assume that its demographic composition will immunize it against the risk of exhibiting discrimination.

Our work suggests that the role of increased representation in determining levels of discrimination is a complex one. For example, cross-race dyadic interactions have been shown to be less comfortable than same-race interactions; such experiences could lead to a heightened aversion to further such interactions (Avery et al., 2009). The relationship of representation to discrimination may be moderated by important variables, such as racial climate (Ziegert & Hanges, 2005) and community relations (Brief et al., 2005). It is also possible that discrimination occurs for different reasons at different levels of representation. For instance, we find that in universities where there was a greater representation of Hispanic students, there was a significant increase in discrimination against Hispanics. This finding could be driven by the desire to have a more diverse student make-up in settings where certain groups are well-represented. However, discrimination where minorities are underrepresented may be due to bias and other forces hindering the progression of non-White males.

As extensive past research has highlighted, the underrepresentation of women and minorities in nearly every academic discipline may be attributed to bias and other forces, including isolation, availability of mentors, preferences, lifestyle choices, occupational stress, devaluation of research conducted primarily by women and minorities, and token-hire misconceptions (Ceci et al., 2011; Correll, 2001; Croson & Gneezy, 2009; Menges & Exum, 1983; Turner, Myers, & Creswell, 1999). Because bias is merely one of many forces that presumably accumulate to produce underrepresentation, the inability of the discrimination we measured to solely explain representation gaps should not come as a surprise. Ultimately, our results document that discrimination remains a problem in academia and highlight where this particular presumed contributor to underrepresentation most needs attention.

Implications and Recommendations for Organizations and Individuals

It has been suggested that changing the attitudes of minorities and women toward challenging career paths and making the work environment more accommodating of varied cultures and lifestyles will increase diversity (e.g., Rosser & Lane, 2002), yet our findings highlight that these efforts will likely be insufficient to entirely close the representation gap. In addition to taking critically important steps to increase diversity on the "supply side," our research suggests that achieving parity will also require tackling bias on the "demand side."

Natural approaches to combating discrimination in organizations focus on altering procedures at formal gateway decision points. Our findings underscore the need for attention to the possibility of discrimination at *every* stage when members of organizations make decisions about how to treat aspiring colleagues, including informal interactions that organizations are unlikely to monitor but may be able to influence (Rowe, 1981, 2008). Thus, our findings suggest that systems to prevent discrimination in *formal processes* (such as hiring and admission in academia) should be partnered with systems to nudge decision-makers away from the unintended biases that affect their *informal decisions*.

Informal decisions are also particularly likely to be characterized by contexts with incomplete, ambiguous, or unverified information. It is in these contexts that bias is more likely to occur as exemplified by studies in which Black job candidates and college applicants experience more bias when their qualifications are ambiguous, rather than clearly strong or clearly weak (Dovidio & Gaertner, 2000; Hodson, Dovidio, & Gaertner, 2002). In our experiment, we used an unfamiliar domain name in the prospective student's e-mail address, offered no background information about the individual, and a faculty member who tried to Google the prospective student's e-mail address or name would not find more information about the individual. One can speculate from our data that faculty may have been more likely to view this as a "red flag" when interacting with prospective students from certain groups. Individuals from groups that are more likely to face bias may benefit from providing more detail when introducing themselves and intentionally reducing any sources of ambiguity about their legitimacy and credentials.

Additionally, while our study contributes to our understanding of discrimination in organizations broadly, policymakers and university leaders should be aware of the particular need for academic programs designed to combat discrimination, particularly in high-paying disciplines and at private universities. Increasing female and minority representation among university faculty and graduate students is associated with higher educational attainment and engagement for female and minority students, respectively, sending an important signal to students about who can climb to the highest levels of the academic ladder (Bettinger & Long, 2005; Griffith, 2010; Rask & Bailey, 2002; Sonnert, Fox, & Adkins, 2007; Trower & Chait, 2002).

The Treatment of Specific Student Groups

It is worth noting that throughout our study, when we describe bias against "women and minorities, collectively," we mean that White women as well as students who are Black, Hispanic, Indian and Chinese, collectively, face bias (see Footnote 1). While biased treatment of these groups, collectively, relative to White males is the focus of our primary analyses, for the reader interested in a specific group, we do break out each of our findings for every subgroup included in our study (e.g., White females, Black males, Chinese females, etc.). It is worth emphasizing that although the treatment of White women (relative to White men) follows the same general patterns as the treatment of racial minorities, White women face less bias when making requests of faculty for the future than many other groups studied (particularly Chinese and Indian students). In fact, they only face significant bias when making requests for the future of faculty (a) at private schools or (b) if we zoom in on the natural, physical sciences and math or (marginally) business. Further, on average, minority females face directionally less bias than minority males, as our figures illustrate.

Limitations

Our article has a number of limitations. First, we examine just one type of organization where bias may hinder career progress. Second, we focus narrowly on a specific pathway to the Academy that is just one moment in the lengthy process in which prospective academics engage. Third, there are important limitations associated with using names to signal race. For instance, many foreign nationals use anglicized names, yet in our study we intentionally selected nonanglicized names to reduce racial ambiguity. Further, it is important to note that names may signal numerous identity characteristics other than race (e.g., class, birthplace, linguistic proficiency), making it difficult to single out race as the sole source of the discriminatory behavior we observed in our study.

Finally, prevailing theories regarding the causes of discrimination distinguish between taste-based discrimination, which refers to race or gender animus as a motivation for discrimination (see Becker, 1971), and statistical discrimination, which assumes that a cost-benefit calculus devoid of animus underlies observed discrimination (Fernandez & Greenberg, 2013; Phelps, 1972). Both theories of discrimination assume that individuals *consciously* discriminate (Bertrand, Chugh, & Mullainathan, 2005), yet our research design was intended to capture both conscious and unconscious discrimination. Unfortunately, our experimental design prevents us from disentangling whether statistical, taste-based, implicit, or explicit discrimination underlies the bias we detect.

Conclusion

Ultimately, the goal of this research is to advance our understanding of the barriers before entry that thwart greater representation of women and minorities in organizations where they are currently underrepresented. The continued underrepresentation of women and minorities means that many of the most talented individuals, who have the potential to make significant contributions to organizations and inspire the next generation of employees and students, may not be progressing on the pathway to achieve their potential. By addressing what happens before prospective doctoral students enter academia, we hope to also shape what happens after.

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(*Appendix follows*)

Appendix

Background on Data Collection and Analysis

Human Subjects Protections

The two lead authors of this article 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)). Both IRB's concluded that 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 toward those most willing to talk with students. Two weeks after the study's launch, each study participant received an e-mail debriefing him/her on the research purpose of the message he or she had recently received from a prospective doctoral student. Every piece of information that could have been used to identify the participants in our study was deleted from all study databases within 2 weeks of the study's conclusion.

Table A1
Description of Primary Predictor Variables Included in Regression Analyses (see Tables 4–9)

Name	Description
Student [Category]	Indicator variable that takes on a value of one when the prospective PhD student who sent a meeting request is a member of [Category]. For example, *Student Hispanic* takes on a value of one when the student is Hispanic and zero otherwise.
Academic discipline characteristics	
Faculty % [Category] (also Fac%[Category])	The percentage of faculty in the contacted professor's academic discipline who are members of [Category]. For example, Faculty % Black would be the percentage of faculty in the contacted professor's discipline who are Black.
PhD Students % [Category] (also PhD%[Category])	The percentage of PhD students in the contacted professor's academic discipline who are members of [Category]. For example, PhD Students % Minority would be the percentage of PhD students in the contacted professor's discipline who are members of the minority groups we study here (Black, Hispanic, or Asian).
Avg. Faculty Salary (also Salary)	The average 9-month salary in the contacted professor's academic discipline according to the 2004 NSOPF.
University characteristics	
Undergraduates % [Category] (also Und%[Category])	The percentage of undergraduates at the contacted professor's university who are members of [Category]. For example, Undergraduates % Asian would be the percentage of undergraduates at the contacted professor's university who are Asian.
Univ Faculty % [Category] (also UFac%[Category])	The percentage of faculty at the contacted professor's university who are members of [Category]. For example, Univ Faculty % Female would be the percentage of faculty at the contacted professor's university who are Female.
Public School (also Public)	Indicator variable that takes on a value of one when the contacted professor works for a public university and zero otherwise.
School Rank (*U.S. News*)	The *U.S.* News and World Report 2010 ranking (1–260) of the contacted professor's university.
Faculty–student demographic match	
Professor and Student Both [Category]	Indicator variable that takes on a value of one when the contacted professor and the prospective PhD student who sent the meeting request are both members of the same [Category]. For example, Professor and Student Both Hispanic takes on a value of one when both the professor and student are Hispanic and zero otherwise.
Faculty status	
Professorial Rank (also Prof Rank)	Variable capturing the contacted professor's level of academic rank, which takes on a value of 1 for assistant professors, 2 for associate professors, and 3 for full professors.

(*Appendix continues*)

Table A2
NSOPF Narrow Disciplinary Categories

Narrow subdisciplines within each broad discipline studied									
Business	Education	Engineering and computer science	Fine arts	Health sciences	Human services	Humanities	Life sciences	Natural, physical sciences and math	Social sciences
(1) Accounting and related services	(1) Curriculum and instruction	(1) Architecture and related services	(1) Art history, criticism & conservation	(1) Clinical/ medical lab science/ allied	(1) Legal professions and studies, other	(1) English language and literature/ letters	(1) Agriculture and related sciences	(1) Mathematics	(1) Area/ethnic/ cultural/ gender studies
(2) Business admin/ management/ operations	(2) Educational administration/ supervision	(2) Computer science	(2) Design & applied arts	(2) Dentistry	(2) Family/ consumer sciences, human sciences	(2) Foreign languages/ literature/ linguistics	(2) Natural resources and conservation	(2) Statistics	(2) Communication/ journalism/ related programs
(3) Finance/ financial management services	(3) Educational/ instructional media design	(3) Computer software and media applications	(3) Drama/ theatre arts and stagecraft	(3) Health & medical administrative services	(3) Parks, recreation and leisure studies	(3) Philosophy	(3) Biochemistry/ biophysics/ molecular biology	(3) Astronomy & astrophysics	(3) Communication technologies
(4) Human resources management and services	(4) Elementary education and teaching	(4) Information science/ studies	(4) Fine and studio art	(4) Allied health and medical assisting service	(4) Health and physical education/ fitness	(4) Religion/ religious studies	(4) Botany/ plant biology	(4) Atmospheric sciences and meteorology	(4) Law
(5) Marketing	(5) Student counseling/ personnel services	(5) Computer/ info science/ support services, other	(5) Music, general	(5) Allied health diagnostic/ intervention/ treatment	(5) Theology and religious vocations	(5) History	(5) Microbiological sciences & immunology	(5) Chemistry	(5) Multi/ interdisciplinary studies
(6) Business/ management/ marketing/ related, other	(6) Education, other	(6) Biomedical/ medical engineering	(6) Music history, literature, and theory	(6) Medicine, including psychiatry	(6) Public administration		(6) Genetics	(6) Geological & earth sciences/ geosciences	(6) Behavioral psychology
(7) Management information systems/ services	(7) Early childhood education and teaching	(7) Chemical engineering	(7) Visual and performing arts, other	(7) Mental/ social health services and allied	(7) Social work		(7) Physiology, pathology & related sciences	(7) Physics	(7) Clinical psychology
	(8) Special education and teaching	(8) Civil engineering	(8) Dance	(8) Nursing	(8) Public administration & social services other		(8) Zoology/ animal biology	(8) Physical sciences, other	(8) Education/ school psychology
	(9) Secondary education and teaching	(9) Computer engineering		(9) Pharmacy/ pharmaceutical sciences/ admin	(9) Criminal justice		(9) Biological & biomedical sciences, other	(9) Science technologies/ technicians	(9) Psychology, other
	(10) Adult and continuing education/ teaching	(10) Electrical & communications engineering		(10) Public health	(10) Fire protection				(10) Anthropology (except psychology)

(*Appendix continues*)

Table A2 (*continued*)

Narrow subdisciplines within each broad discipline studied									
Business	Education	Engineering and computer science	Fine arts	Health sciences	Human services	Humanities	Life sciences	Natural, physical sciences and math	Social sciences
	(11) Teacher education specific levels, other	(11) Engineering technologies/ technicians		(11) Rehabilitation & therapeutic professions					(11) Archeology
	(12) Teacher education specific subject areas	(12) Environmental/ environmental health engineering		(12) Veterinary medicine					(12) International relations & affairs
	(13) Bilingual & multicultural education	(13) Mechanical engineering							(13) Political science and government
	(14) Ed assessment	(14) Engineering, other							(14) Geography & cartography
	(15) Higher education								(15) Criminology
	(16) Library science								(16) Economics
									(17) Sociology
									(18) Urban studies/ affairs
									(19) Social sciences, other

Note. NSOPF = National Study of Postsecondary Faculty. Our detailed analyses of discrimination across disciplines (presented in Tables 6–8) examine discrimination at the level of a professor's narrow academic discipline as defined by the NSOPF (2004). The mapping of the 89 narrow NSOPF disciplines into the 10 broad NSOPF disciplines summarized in Figure 1 and Table 3 is shown here.

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