# Understanding Discrimination in College Admissions: A Field Experiment[*]

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**Abstract**

We examine the extent and mechanisms by which race affects the college admissions process. We provide evidence from a field experiment where fictitious applicants request application fee waivers from all university admissions counselors in the United States. White applicants are much more likely to receive a waiver, be informed that the application is free, or receive a request for more information than Black or Asian applicants. Our results contrast sharply with previous evidence from acceptance decisions showing bias in favor of Black applicants. We introduce a model of university pricing and use information from counselors' LinkedIn and university profiles, along with university characteristics, to test predictions. We find evidence consistent with agent-taste-based discrimination, where biases stem from counselors' preferences, and profit-maximizing statistical discrimination. Discrimination in university admissions can vary substantially based on the context in which decisions are made.

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# 1 Introduction

The proper role for race to play in college admissions decisions has long been a hotly contested political question, including in repeated cases before the U.S. Supreme Court (Supreme Court of the United States, 1978, 2003a,b, 2013, 2016). In 2023, the debate intensified after the Supreme Court ruled that the use of race in admissions at Harvard University and the University of North Carolina (UNC) violated the Equal Protection Clause of the 14th Amendment (Supreme Court of the United States, 2023). Policy in this domain could be exceptionally important, as the changes in the mechanisms by which race impacts the admissions process affect millions of applicants every year (NCES, 2022) and could substantially influence economic disparities across races (Arcidiacono, 2005; Fryer et al., 2013).

We know little about the impact of race in the many parts of the admissions process across U.S. universities due to three empirical limitations. First, most universities do not publicly release detailed information related to their admissions process. Second, little information is collected on the various interactions admissions counselors have with prospective students. Third, even if admissions data were disclosed, identifying discrimination from observational data is challenging given the presence of potentially confounding factors. The work of Arcidiacono et al. (2023) is a rare exception to these limitations. In a series of papers, they explore detailed admissions data from Harvard and UNC (Arcidiacono et al., 2022a,b,c,d, 2023). They show robust evidence of racial discrimination in acceptance decisions at those universities. However, even these careful analyses can not explore how discrimination differs in other parts of the admissions process or how economic and social factors contribute to heterogeneous discriminatory practices *across* U.S. universities — as they are limited to data from two specific universities.

Rather than a simple binary decision, the college admissions process is arduous and lengthy for both applicants and higher education institutions. Applicants must take exams like the SAT or ACT, research schools, complete the FAFSA, choose where to apply, visit campuses, prepare materials, pay fees, and meet various deadlines. On the other side, colleges handle inquiries, decide on fee waivers, give campus tours, attend college fairs, and go through a multi-step selection process to sort applicants into accepted, waitlisted, or rejected categories. Every stage plays a crucial role in shaping the incoming class.

This paper offers novel experimental evidence of racial discrimination in a key part of the admissions process. We implement a field experiment where fictitious applicants request application fee waivers from admissions counselors in all 4-year universities in the U.S. These fees can be a significant barrier to higher education access for potential applicants, particularly those from minority groups (Hoxby and Turner, 2015; Black et al., 2015). Responses from a survey we conducted with college admissions counselors suggest that requests for application fee waivers are widely prevalent.[1] Moreover, the decision to grant a waiver is often made by individual counselors in a less structured process than acceptance decisions that are typically made by committees or algorithms. Hence, patterns of discrimination may differ between waiver requests and admission decisions.

We find that Black and Asian applicants are about 33 percent and 21 percent more likely to have their requests *de facto* rejected by admissions counselors than White applicants, respectively.[2] In addition, we find that White applicants are nearly 50 percent more likely than Asian applicants to receive a fee waiver and 15 percent more likely than Black applicants to be informed that the fee is temporarily or permanently free.[3] We examine the sentiment of thousands of responses from college counselors and find some evidence that responses to Asian and Black applicants are less polite and enthusiastic than responses to White applicants.

Our results juxtapose starkly with existing evidence of racial discrimination in college admissions, which indicates (at least for Harvard and UNC) substantial discrimination in favor of recruiting and admitting Black applicants, and against Asian applicants, relative to similarly situated

[1]See Appendix A.1 for more details on the survey.

[2]We define a *de facto* rejection as an outcome that gives no path for the applicant to apply for free to the university. If the applicant did not receive a waiver, the counselor did not tell them that the application is free (or free for a given week of the year), and the counselor did not request more information, we code that response as a rejection. This includes, for example, a simple failure to respond at all.

[3]Many universities waive all application fees temporarily (often during a specific week) and others do not charge fees at all.

Whites (Arcidiacono et al., 2022d, 2023). Why might colleges simultaneously discriminate for and against the same racial groups at various stages of the college application and admissions process? And why is that pattern offsetting for Black applicants and amplifying for Asian applicants? We consider a model of an admissions office setting a series of policies and prices to shape the set of students who enroll at their university. Under this model, variation among racial groups in application fees (waivers) must be driven either a) by differences in the demand characteristics of these groups leading to differences in the profit-maximizing policies, a form of *statistical price discrimination*, b) by *principal-taste-based discrimination*, where the admissions policymaker trades off profits against some other welfare-relevant outcome, or c) by *agent-taste-based discrimination*, where a taste for discrimination amongst agents within the office, perhaps amplified with the high cost of monitoring informal interactions, induces a profit-maximizing policymaker to discriminate amongst applicants in the pursuit of profit maximization.

To evaluate these alternative explanations, we manually collect data from counselors' LinkedIn and university profiles and conduct a heterogeneity analysis along university- and counselor-level dimensions. The patterns in university-level heterogeneity are more consistent with statistical price discrimination than taste-based explanations. On the one hand, factors that likely correlate with the demand characteristics of potential applicants, like region, population density, school size, and selectivity, have some statistical relationship with the patterns of discrimination. On the other hand, factors that should affect the importance of revenues, and therefore the costs of expressing principal-taste discrimination (relative to making the net-revenue maximizing choice), like endowments, enrollment changes, or private control, have limited predictive power.

The patterns in counselor-level heterogeneity, however, suggest substantial agent-taste-based discrimination. There are substantial differences in discrimination across counselor gender, race, and experience. Furthermore, higher rates of discrimination amongst less-experienced counselors suggest an important role for agent selection or learning to align their behavior with the preferences of the office. Since acceptance/financial aid decisions are often made by committees while waiver-granting decisions are often made by individual counselors, agent-taste-based discrimination may play a much larger role in waiver-granting decisions (and other decisions made by individuals under little supervision) than acceptance and financial aid decisions.

We contribute to a large literature leveraging field experiments to examine discrimination. Racial/ethnic hiring discrimination continues to be persistent despite the introduction of anti-discrimination laws beginning in the 1960s (Bertrand and Mullainathan, 2004; Carlsson and Rooth, 2007; Pager et al., 2009; Oreopoulos, 2011; Gaddis, 2015; Kline et al., 2022; Jaeger et al., 2023; Kline et al., 2024; Lahey and Beasley, 2024). Additionally, hiring discrimination associated with various other characteristics such as criminal history (Pager, 2003; Baert and Verhofstadt, 2015; Agan and Starr, 2018), gender (Neumark and McLennan, 1995; Azmat and Petrongolo, 2014; Folke and Rickne, 2022), age (Johnson and Neumark, 1996; Neumark et al., 2016, 2019; Carlsson and Eriksson, 2019), university degree type (Deming et al., 2016; Gaddis, 2015), and physical attractiveness (Hamermesh, 2011; Bóo et al., 2013) are substantial and pervasive. Discrimination is also present in the context of local public services (Giulietti et al., 2019; Lahey et al., 2023), in-person and online product markets (List, 2004; Nunley et al., 2011; Zussman, 2013; Ayres et al., 2015), short-term and long-term rental markets (Hanson and Hawley, 2011; Ewens et al., 2014; Hanson and Santas, 2014; Edelman et al., 2017; Gaddis and Ghoshal, 2020; Gaddis and DiRago, 2023), mortgage lending (Hanson et al., 2016), and healthcare (Fumarco et al., 2023), among others. Importantly, despite a large and growing number of correspondence audits examining discrimination across contexts (Gaddis et al., 2021), very few have examined discrimination in the U.S. against Asians in any context (Gaddis et al., 2024b).

Few correspondence audits examine discrimination of any type in the education system. Most research examining racial discrimination in education focuses on the K-12 context (Gaddis et al., 2024a). Three studies have examined the outcomes of racial minority applicants compared to White applicants in college admissions (Hanson, 2017; Druckman and Shafranek, 2020; Brown and Hilbig, 2022). All these studies sent emails requesting basic information about the school — something often attainable without the help of a counselor. Another limitation of these studies is that they focused exclusively on racial discrimination against Black students. The results were mixed. Hanson (2017) found no differential responsiveness to Black applicants, while Druckman and Shafranek (2020) found lower response rates for Black applicants who signalled political valence, only, and Brown and Hilbig (2022) found lower response rates for Black applicants at private schools, only.

## 2 Background

Concerns that some racial groups may suffer discrimination in admissions at elite colleges have led to numerous legal challenges (Supreme Court of the United States, 1978, 2003a,b, 2013, 2016) but the U.S. Supreme Court has historically allowed the use of race in the admissions process. The role of race in college admissions gained notoriety after the *SFFA v. Harvard* case, which — along with a case involving the University of North Carolina (UNC) — raised concerns about race-conscious admissions policies (primarily against Asian Americans). The SFFA claims that Harvard College deliberately discriminated against Asian Americans for their race, violating Title VI of the Civil Rights Act of 1964. This act states "that no person in the United States shall, on the ground of race, color, or national origin, be excluded from participation in, be denied the benefits of, or be subjected to discrimination under any program or activity receiving federal financial assistance." In June 2023, the Supreme Court ruled that Harvard's and UNC's admissions practices violated the Equal Protection Clause of the 14th Amendment, marking a significant shift in the legal stance on affirmative action in college admissions (Supreme Court of the United States, 2023).

Preceding this ruling, using observational data, Arcidiacono et al. (2022a) found robust evidence that the perception of discrimination against Asian Americans in admissions was justified. Leveraging data from the *SFFA v. Harvard* case, the authors uncover a discernible disadvantage for Asian American applicants within the admissions process, persisting even when considering measurable admissions criteria. Still within the context of the *SFFA v. Harvard* case, Arcidiacono et al. (2023) adopt an extensive analytical methodology, incorporating simulations of admissions processes and scrutiny of race's influence on these decisions. Their work quantitatively assesses the extent and impact of the university's racial preferences, concluding these preferences significantly influence admissions results.

In addition, significant disparities in college admissions outcomes between racial groups often persist due to systemic barriers encountered by these groups. One such obstacle is the cost of college application fees, which can deter prospective students from applying to multiple institutions or to more selective universities that might offer greater opportunities. In a survey conducted in 2022, U.S. News and World Report found that among the top 11 universities in the nation, 10 reported charging an average application fee of approximately \$79. This count excludes one university that did not disclose its application fees and includes a three-way tie for the ninth spot. Additionally, of the top 10 ranked liberal arts colleges, the five that imposed application fees charged an average of \$65 (U.S. News & World Report, 2023). These costs may represent substantial barriers for some disadvantaged students, particularly racial minorities, and likely contribute to the racial disparities observed in college enrollment rates. For example, a fee waiver intervention implemented by Hoxby and Turner (2015) led to a substantial increase in low-income students' applications to and enrollment at selective U.S. universities. Hence, by providing these waivers, universities may help ensure that many students, regardless of their financial resources, have the opportunity to apply to a broad range of institutions. This accessibility can significantly influence diversity on college campuses. Odle and Delaney (2023) provide experimental evidence that application fee waivers, when coupled with guarantees of admission and proactive communication (nudges), significantly increase the rate of college applications, particularly among economically disadvantaged groups, racial minority students, and first-generation college applicants.

# 3 Experimental Design

## 3.1 Sample Selection

We conducted a randomized email audit study to investigate the impact of racially-indicative names on the behavior of admissions counselors at U.S. universities related to the granting of application fee waivers. We corresponded with 4,658 unique counselors via email at 1,294 distinct institutions, comprising the full set of counselor e-mail addresses posted on the admissions webpages of the universe of four-year U.S. universities with at least 100 students that are coeducational or male-only.[4] To do so, we compiled a list of institutions from the College Board — which maintains a registry of more than 6,000 schools, colleges, universities, and other educational organizations — using web scraping techniques, followed by filtering out female-only institutions and those with fewer than 100 students. Research assistants then manually collected the email addresses of all counselors from this refined sample of universities. Demographic characteristics such as gender and race (as perceived by research assistants collecting the data) and relevant work experience of counselors in our sample were gathered by manually reviewing their LinkedIn and university website profiles. Finally, we individually contacted each counselor in our sample, posing as a student requesting an application fee waiver. [5] The emails were sent over a five-week period from mid-October to mid-November 2023 during the typical college application season for the fall 2024 admissions.

## 3.2 Randomization of Treatment Conditions

Each sampled email address received a message from a single individual posing as a male college applicant, requesting information and fee waivers due to financial hardship. Each message was randomly assigned a template and an applicant name. There were eight templates, designed to signal two levels of applicant quality (low and high), as indicated by the overall quality of the email

[4] We exclude female-only institutions because all names used in the study are male-indicative.

[5] Some counselors share a common email address, such as "admissions@universityname.edu." We retain these observations even though we do not know the characteristics of the counselor who manages that email.

format and text.[6] The names were selected to indicate membership in one of five racial/ethnic groups (White, Asian[7], Asian/first name White[8], Black, and Hispanic).[9] Each race/ethnicity applicant treatment had eight possible value options signaled through the name and email address. The names assigned to the fictitious applicants are provided in Table 1, and their respective email addresses are listed in Table A.5 found in Appendix A.

Table 1: Names used to convey applicant race/ethnicity

| **White** | **Asian** | **White/Asian** | **Hispanic** | **Black** |
|---|---|---|---|---|
| Thomas Wagner | Mao Zhang | Cody Zhang | Julio Perez | DaQuan Jefferson |
| Richard Hoffman | Jin Chang | Douglas Chang | Javier Martinez | Darnell Banks |
| David Hansen | Peng Chen | Dylan Chen | Alejandro Ramirez | Denzel Booker |
| Zachary Meyer | Wei Li | Jacob Li | Hector Gonzalez | Jamal Singleton |
| Hunter McGrath | Jian Liu | John Liu | Miguel Lopez | Keyshawn Jackson |
| Logan Becker | Lixin Yang | Nicholas Yang | Salvador Ramirez | DeAndre Mack |
| Ryan Andersen | Qian Wang | Scott Wang | Juan Torres | Tyrone Rivers |
| Matthew Larsen | Hong Zhao | Stephen Zhao | Pedro Hernandez | Lamar Washington |

Within each university, we randomize both treatment conditions (name and quality) individually without replacement. We use a within-college but between-subjects design to avoid detection (Lahey and Beasley, 2018; Larsen, 2020; Vuolo et al., 2018). To illustrate an example, consider a university with six counselors. We send each counselor only one email from a fictitious applicant.

[6]Further information can be found in Appendix A.

[7]Although we refer to them as Asian, all names used in the experiment are specifically of Chinese origin. This shorthand from the specific (i.e., Chinese) to the broad panethnic classification (i.e., Asian American) is common in field experiments examining Asian Americans. In fact, a recent meta-analysis finds that among 19 field experiments examining Asian American discrimination, all use Chinese names and and only 8 use other names (e.g., Indian, Korean) alongside Chinese names (Gaddis et al., 2024b). Additionally, other research finds that although respondents view such names as Asian, they are less able to perceive the specific countries of origin for Asian names, lending additional credibility to these names more accurately representing panethnic "Asian Americans" to others (Crabtree et al., 2023).

[8]Some scholars suggest that Asians with anglicized first names might be less likely to experience discrimination (Gaddis et al., 2022). Thus, we test that difference here.

[9]Other scholars note that using names to signal race/ethnicity may also unintentionally signal social class as well (Crabtree et al., 2022, 2023; Gaddis, 2023; Lahey and Barlow, 2018). However, research has not shown whether signals of social class might influence discrimination and whether such social class discrimination might vary across different contexts. Nonetheless, we follow multiple recommendations from the existing literature to maximize the accurate racial/ethnic perception rate and minimize the potential threats to overall treatment validity (Crabtree et al., 2023; Gaddis, 2023).

We randomly select the race/ethnicity of the first applicant from the full set of five applicant group options without replacement until each option is exhausted for the round. For example, if we randomly select a White applicant as the first email option, the second email may only come from the remaining four race/ethnicity applicant groups that are not White. This process continues until we send one email from each racial/ethnic applicant group and then restart the random selection without replacement process with the sixth email. We take this approach to ensure that there is racial/ethnic treatment variation in our requests both within and between universities.

We also randomly assign the email templates signaling applicant quality without replacement. Therefore, if a university has eight or fewer counselors, each counselor receives a unique template. In the rare case that there are nine or more counselors, the templates are repeated, though the applicant's name remains unique.

## 3.3 Signaling Race and Applicant Quality

We signal racial/ethnic identity by selecting names from the empirical distributions of birth record data and lists of validated names to precisely reflect racial and socioeconomic backgrounds, adhering to state-of-the-art practices in the literature (Gaddis, 2017a,b; Crabtree et al., 2023; Gaddis, 2023). We also incorporate independent signals of applicant quality by varying the quality and formality of the content included in the email templates.

We choose names based on empirical evidence of both racial and socioeconomic associations (Gaddis, 2023). In particular, we begin with birth record data from New York State and lists of previously tested names to guide our decisions (Gaddis, 2017a,b; Crabtree et al., 2023). Additionally, we use survey experiment data on racial/ethnic perceptions to narrow our lists to names with $\geq$90 percent congruent racial/ethnic perception for White, Black, and Hispanic signaled names and $\geq$65 percent Asian racial/ethnic perception for Asian names.[10] We select eight male names

[10] Research generally finds that Asian names have lower congruent perception rates than other races/ethnicites. However, rather than be mislabelled as White, Black, or Hispanic, Asian names are more likely to be labelled as "other" or elicit a response as "I don't know." This potentially suggests that racial/ethnic discrimination uncovered against Asians in field experiments using names is a conservative estimate, although our experiment still replicates the real world experience that students who ask for fee waivers would actually face.

per racial/ethnic identity to reduce the potential threat to treatment validity (Gaddis, 2023). Thus, for the White, Asian, Black, and Hispanic identities, our choices represent empirically validated names that are perceived to correspond to the target race/ethnicity at very high rates. With our final racial/ethnic identity — Asian with a White first name — we intend to signal a student whose family is Asian in origin, yet the student has a White first name to signal he was born in the U.S. Recent studies have demonstrated the feasibility of testing this signal across different racial/ethnic groups and immigrant generations (Gaddis et al., 2022). Hence, we test the Asian first and last name signaled identities separately from the White first and Asian last name.

We also create eight distinct email templates of varying quality.[11] While the core message in each email remains consistent — each features a fictitious applicant expressing interest in attending the university, describing his financial difficulties, and requesting an application fee waiver — the quality of the writing varies. Some emails contain grammatically correct, formal language to signal higher-quality applicants, while others deliberately employ grammatical inaccuracies and a casual tone to convey the impression of a lower-quality applicant. These variations help us isolate the impact of perceived applicant quality from racial or ethnic biases, responding to critiques of traditional correspondence studies (Heckman and Siegelman, 1993; Neumark, 2012). Each template is assigned randomly, with applicant identities revealed through various components of the email such as the address, body, signature, and "from" field. These emails originate from several domains, including Gmail, Outlook, Hotmail, and Yahoo. The corresponding email addresses are detailed in Table A.5 located in Appendix A.

## 3.4 Primary Outcomes

We consider four potential outcomes of each request for an application fee waiver. We divide these into (a) one outcome that provides no path toward what the student seeks, (b) one outcome that provides what the student seeks, and (c) two outcomes that are in the middle ground and provide a potential path toward what the student seeks.

[11] Detailed descriptions of the email templates can be found in Appendix A.

First, the waiver can be *de facto* rejected, a term that we define as giving the applicant no path to apply to the university for free. This includes being explicitly denied a waiver, not being informed that the application is free, not being prompted to provide additional information (within a month of the email submission), and simply receiving no response. The overwhelming majority of these rejections are requests that did not receive any response at all.[12] Since some counselors may prefer not to respond rather than issue an explicit denial, we argue that combining non-responses and explicit waiver denials into a single group is a reasonable starting point for detecting discrimination. Second, the counselor may directly grant the waiver, often by sharing a coupon code or web link to apply without paying the fee. Third, the counselor may tell the applicant that applications are temporarily (often in a given week of the year) or permanently free at their university. Finally, the counselor may request more information from the applicant, such as asking them to fill out a form or give more details about their financial situation.[13]

In addition to these four binary dependent variables, we also analyze the tone and sentiments in counselors' email responses to our fictitious applicants. These analyses may reveal racial or ethnic prejudice, impacting students' sense of belonging and motivation to apply, and aiding our understanding of the nature of discrimination in college admissions.

Finally, we administer an optional confidential survey to all admissions counselors in our sample to gain further insights into the college admissions process. In this survey, we explore two key questions: the prevalence of application fee waivers and, most importantly, whether racial factors influence counselors' decisions related to granting application fee waivers.

[12]This outcome is very common in most correspondence audits. See Gaddis (2018).

[13]Table A.4 in the appendix provides additional results based on whether the student received any type of response. We find that Asian and Black students are substantially less likely to receive a response than their White counterparts. Figure A.2 displays the corresponding discrimination ratios, which we describe in Section 4.3.

# 4 Data and Empirical Strategy

## 4.1 Descriptive Statistics

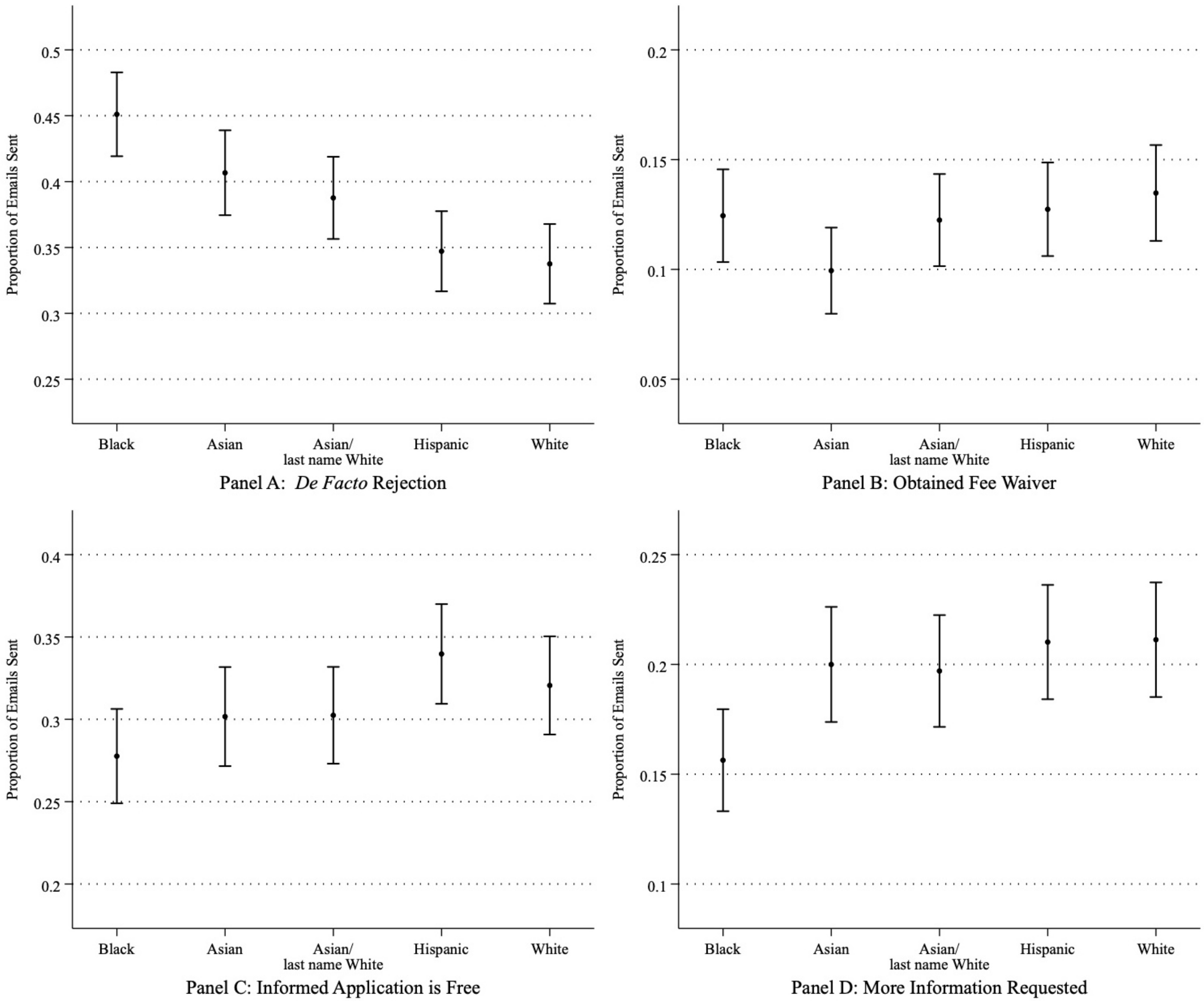
About 64 percent of the emails that were sent received responses. The response rates differed widely across racial/ethnic groups. Emails from White-indicating names received responses at the highest rate of 67 percent, while emails from those with predominantly Black names saw the lowest response rate, 57 percent. Overall, 12 percent of applicants received a fee waiver. Given an overall response rate of 64 percent, this implies that about one-fifth of responses were positive. The probability of waiver approval varied considerably across racial/ethnic groups. White students were the most likely to have their waiver requests granted, with an approval rate of 13 percent, in contrast to Asian students, who had the lowest rate of approval at 10 percent. Figure 1 shows the differences between racial/ethnic groups for each of our four outcomes. We see consistent evidence of differential treatment of Black and Asian applicants compared to White applicants, while differences between Hispanic and White applicants are generally small.[14]

Table 2 displays the proportions of covariates used in our regression models, broken down by the applicant's race/ethnicity. The covariates are divided into two categories: university-level characteristics and email-level characteristics. Each column represents a different racial/ethnic group (Asian, Asian with White first name, Black, Hispanic, and White). This serves as a balancing test, confirming that the randomization protocol was successful. The results indicate that the means (proportions) of covariates are very similar across the five racial/ethnic groups.[15]

[14]Table A.3 in the Appendix presents descriptive statistics for each outcome and racial/ethnic group in tabular form.

[15]The table shows balanced email proportions for Gmail and Outlook across racial/ethnic groups. Some Yahoo emails were lost during the experiment, and Hotmail emails show slight variability. Despite these differences, other covariates are generally balanced.

Figure 1: Means of Main Outcomes, by Racial/Ethnic Group




*Notes:* This figure displays the unadjusted means of each outcome variable categorized by race/ethnicity, with error bars representing 95 percent confidence intervals. Panel A shows whether the student was *de facto* rejected; Panel B shows whether a waiver was granted; Panel C shows whether the student was informed about the application being free; and Panel D shows whether the counselor requested additional information.

Table 2: Balance Table

| | Black | Asian | Asian / first name White | Hispanic | White |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| **University-level covariates** | | | | | |
| *University ownership type* | | | | | |
| Private | 0.598 | 0.601 | 0.611 | 0.605 | 0.615 |
| Public | 0.402 | 0.399 | 0.389 | 0.395 | 0.385 |
| *University size* | | | | | |
| Very large | 0.109 | 0.107 | 0.102 | 0.101 | 0.103 |
| Large | 0.079 | 0.086 | 0.086 | 0.092 | 0.086 |
| Medium | 0.290 | 0.283 | 0.267 | 0.281 | 0.277 |
| Small | 0.522 | 0.524 | 0.544 | 0.525 | 0.534 |
| *University setting* | | | | | |
| Rural | 0.211 | 0.217 | 0.231 | 0.240 | 0.238 |
| Suburban | 0.470 | 0.459 | 0.448 | 0.455 | 0.452 |
| Urban | 0.319 | 0.324 | 0.321 | 0.305 | 0.310 |
| *University selectivity* | | | | | |
| High | 0.055 | 0.049 | 0.063 | 0.063 | 0.066 |
| Medium | 0.415 | 0.403 | 0.395 | 0.407 | 0.397 |
| Low | 0.530 | 0.547 | 0.542 | 0.531 | 0.537 |
| *University geographic region* | | | | | |
| Midwest | 0.294 | 0.287 | 0.278 | 0.269 | 0.290 |
| Northeast | 0.265 | 0.264 | 0.267 | 0.281 | 0.280 |
| South | 0.307 | 0.313 | 0.317 | 0.312 | 0.303 |
| West | 0.134 | 0.136 | 0.137 | 0.138 | 0.127 |
| **Email-level covariates** | | | | | |
| *Message template* | | | | | |
| Message = 1 | 0.124 | 0.124 | 0.125 | 0.122 | 0.124 |
| Message = 2 | 0.124 | 0.126 | 0.124 | 0.126 | 0.125 |
| Message = 3 | 0.126 | 0.125 | 0.126 | 0.126 | 0.126 |
| Message = 4 | 0.124 | 0.124 | 0.124 | 0.126 | 0.122 |
| Message = 5 | 0.126 | 0.126 | 0.125 | 0.125 | 0.126 |
| Message = 6 | 0.126 | 0.124 | 0.127 | 0.124 | 0.126 |
| Message = 7 | 0.124 | 0.125 | 0.127 | 0.123 | 0.125 |
| Message = 8 | 0.126 | 0.125 | 0.125 | 0.126 | 0.124 |
| *Day of the week* | | | | | |
| Sunday | 0.102 | 0.150 | 0.000 | 0.000 | 0.000 |
| Monday | 0.186 | 0.273 | 0.228 | 0.124 | 0.382 |
| Tuesday | 0.077 | 0.017 | 0.241 | 0.126 | 0.158 |
| Wednesday | 0.189 | 0.236 | 0.160 | 0.190 | 0.094 |
| Thursday | 0.118 | 0.068 | 0.122 | 0.280 | 0.165 |
| Friday | 0.301 | 0.168 | 0.178 | 0.279 | 0.155 |
| Saturday | 0.027 | 0.089 | 0.071 | 0.000 | 0.046 |
| *Month of the year* | | | | | |
| October | 0.726 | 0.580 | 0.628 | 0.751 | 0.624 |
| November | 0.274 | 0.420 | 0.372 | 0.249 | 0.376 |
| *Email domain* | | | | | |
| Gmail | 0.374 | 0.339 | 0.378 | 0.376 | 0.375 |
| Hotmail | 0.121 | 0.131 | 0.122 | 0.124 | 0.122 |
| Outlook | 0.504 | 0.398 | 0.499 | 0.500 | 0.378 |
| Yahoo | 0.000 | 0.133 | 0.000 | 0.000 | 0.125 |
| N | 940 | 895 | 939 | 942 | 942 |

*Notes*: Proportions of each independent variable in the regression models, categorized by the student's race/ethnicity.

## 4.2 Empirical Strategy

Our empirical analysis attempts to determine whether admissions counselors behave differently based on an applicant's race/ethnicity. To achieve this, we leverage the exogenous variation in applicant/counselor interactions generated by our experimental design. As discussed in Section 3.4, we focus on dichotomous outcome variables, such as whether or not a fee waiver was granted. We estimate both probit and linear probability models, converting all results to average marginal effects and using White as the base category. For probit models, we estimate equations of the form:

$$P(Y_i = 1|Z_i) = \Phi(\beta_1 Race_i + \sum_{j=1}^{n} \beta_j X_{ij} + \sum_{p=1}^{q} \beta_p U_{ip}), \tag{1}$$

where $Y_i$ is a dichotomous outcome (e.g., whether a fee waiver was granted) for observation $i$ (i.e., a given applicant/counselor interaction); $Race_i$ captures the applicant's race/ethnicity through a set of dummy variables; $X_{ij}$ is a matrix of applicant-level characteristics, including the message template used, the day of the week the email was sent, the month of the year (October or November) the email was sent, and the domain (Gmail, Hotmail, Outlook, or Yahoo!) of the applicant's email address; and $U_{ip}$ is a matrix of university-level characteristics, including private/public ownership, school size (a categorical variable derived from total enrollment)[16], selectivity (a categorical variables based on acceptance rate)[17], Census region[18], and population density (rural, suburban, or urban). Given our randomization protocol, the inclusion of $X$ and $U$ covariates should have little effect on our estimates. Reassuringly, this is indeed the case, as we show in Section 5.

Our linear probability models are similar:

$$P(Y_i = 1|Z_i) = \beta_1 Race_i + \sum_{j=1}^{n} \beta_j X_{ij} + \sum_{p=1}^{q} \beta_p U_{ip} + \varepsilon_i, \tag{2}$$

where $Y_i$, $Race_i$, $X_{ij}$, and $U_{ip}$ are the same as in equation 1. The error term is denoted by $\varepsilon_i$.

[16] We use data from the College Board to classify colleges and universities as small, medium, large, or very large.

[17] We classify universities as highly selective (acceptance rate $\leq$ 30 percent), moderately selective (30 percent $<$ acceptance rate $\leq$ 70 percent), and not selective (acceptance rate $>$ 70 percent).

[18] The Census Bureau divides the U.S. into four principal regions: Northeast, Midwest, South, and West. For more information, visit: https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf.

### 4.3 Calculating Discrimination Ratios

To standardize the comparison of response rates across different racial/ethnic groups for each outcome, we construct discrimination ratios as outlined in Gaddis et al. (2021). Discrimination ratios are appealing in this context because they provide an intuitive, uniform measure that allows for a direct comparison between two racial/ethnic groups. We calculate discrimination ratios by comparing the regression-adjusted response rates for White students (our baseline category) with those of students from other racial/ethnic groups, based on predicted outcomes at the mean values of covariates in our primary linear probability models. By adjusting for covariates, the analysis isolates the effect of race on the likelihood of a given outcome (e.g., fee waiver approval).

The interpretation of discrimination ratios is straightforward: A ratio of 1 indicates equal treatment between groups; ratios below 1 suggest that the given outcome is more common among non-White student groups than among White students; and ratios below 1 denote a higher likelihood of the outcome among non-White student groups than among White students. For the purposes of our analysis, we further transform this measure using natural logarithms. This transformation helps achieve a more normally distributed dependent variable and ensures visual consistency when the ratios are plotted, with values below and above 1 being appropriately distanced from a ratio of 1. Moreover, the natural logarithmic transformation allows for ratios to be interpreted as approximate percentage differences. Figures 2, 3, 4, and 5 depict the discrimination ratios for each of our four outcomes.

# 5 Main Results

## 5.1 *De Facto* Rejections

We begin by considering whether the probability of *de facto* rejection varies according to the applicant's race/ethnicity. Approximately 39 percent of observations fall into this category. Results are depicted in Table 3. We present average marginal effects for each racial/ethnic category derived from probit models (columns 1 and 2) and linear probability models (columns 3 and 4). Our baseline specification (columns 1 and 3) adjusts for factors like email format, timing of the email request (day and month), and applicants' email domain names. In columns 2 and 4, we augment our baseline models with university-specific controls, including characteristics like public/private status, school size, selectivity, and location. The inclusion of these controls is expected to have minimal impact due to the randomization of applicant emails across universities. We note that our coefficients of interest remain nearly identical across all specifications.

All columns in Table 3 show statistically significant differences in the treatment of Asians, Asians with White first names, and Blacks relative to their White counterparts. Each of these groups is substantially more likely than Whites to receive a *de facto* rejection. We detect no difference between Hispanics and Whites. These results not only show that applicants with Asian and Black names are more likely to be rejected, but even applicants with White first names and Asian last names are substantially more likely to be rejected. These differences are large and economically meaningful. Black applicants, for example, are over 30 percent more likely to have their requests *de facto* rejected than White applicants. This level of discrimination is substantially larger than the levels of discrimination previously measured in labor markets (Bertrand and Mullainathan, 2004; Kline et al., 2022).

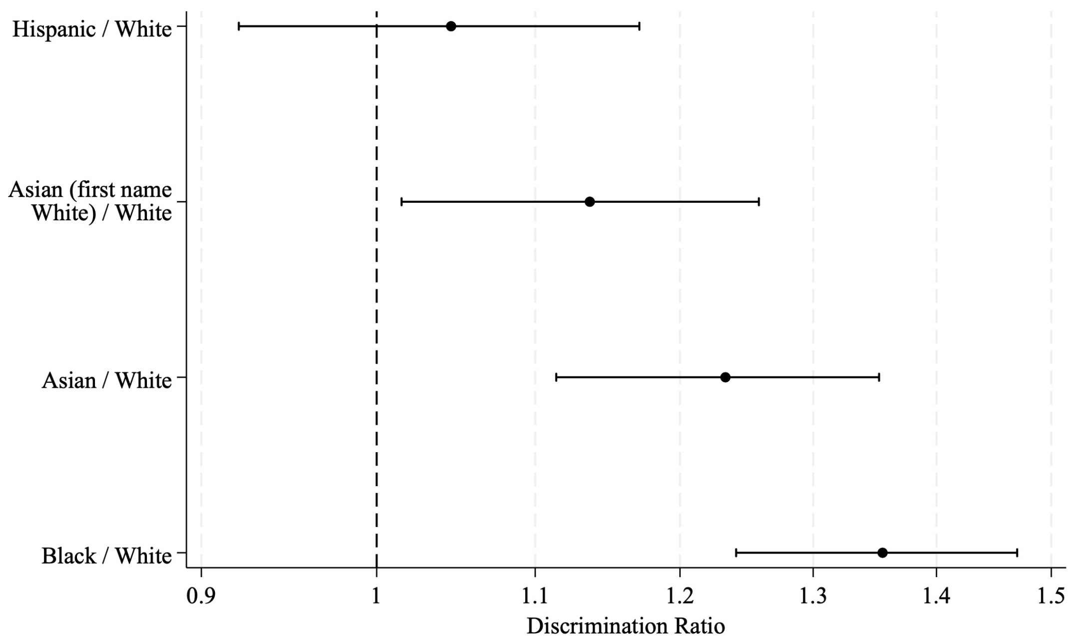
Figure 2 presents discrimination ratios based on predicted outcomes at the mean values of covariates in our principal linear probability models shown in Table 3. White is the base category. All discrimination ratios are above 1, indicating that *de facto* rejection rates are elevated among all non-White student groups relative to White students (although results for Hispanic students do not attain statistical significance).

Table 3: Effects of Race/Ethnicity on *De Facto* Rejections

| | Probit | | OLS | |
|---|---|---|---|---|
| | Baseline | With university controls | Baseline | With university controls |
| | (1) | (2) | (3) | (4) |
| Asian | 0.079*** | 0.080*** | 0.078*** | 0.078*** |
| | (0.023) | (0.023) | (0.023) | (0.023) |
| Asian/first name White | 0.047** | 0.045** | 0.046** | 0.044** |
| | (0.022) | (0.022) | (0.023) | (0.022) |
| Black | 0.119*** | 0.118*** | 0.119*** | 0.118*** |
| | (0.023) | (0.023) | (0.024) | (0.024) |
| Hispanic | 0.016 | 0.014 | 0.015 | 0.013 |
| | (0.023) | (0.023) | (0.023) | (0.023) |
| N | 4,658 | 4,658 | 4,658 | 4,658 |

*Notes*: Coefficients represent average marginal effects. Observations are classified as effective rejections if they were not granted a waiver, informed the application was free, or prompted to provide more information. White is the omitted category. The baseline specification (columns (1) and (3)) controls for the message template used, the day of the week the email was sent, the month of the year (October or November) the email was sent, and the domain (Gmail, Hotmail, Outlook, Yahoo!) of the student's email address. In columns (2) and (4), we augment our baseline model with controls for characteristics of universities (private/public, size, selectivity, Census region, and rural/suburban/urban). Bootstrapped standard errors (10,000 repetitions) are reported in parentheses. $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Figure 2: Discrimination Ratios for *De Facto* Rejections




*Notes:* Discrimination ratios for each non-White student group, using White as the baseline category. Ratios are calculated based on predicted outcomes at the mean values of covariates in our primary linear probability model (column 1 in Table 3). Results shown on a natural log scale. Error bars indicate 95 percent confidence intervals. Results that overlap the dotted line at 1 indicate no statistically significant evidence of discrimination favoring either group. See Section 4.3 for more details. Figure A.3 in the appendix plots the discrimination ratios for each of our four specifications; results are virtually identical.

## 5.2 Waiver Approval Rates

Next, we consider potential differences in the treatment of racial/ethnic groups in the approval of application fee waivers. As in Section 5.1, we estimate probit and linear probability models, including specifications with and without university-specific controls. The results, depicted in Table 4, show differential treatment against Asian applicants compared to their White counterparts, with no notable differences found against other groups. Quantitatively, being Asian is associated with an approximately 4 percentage point decrease in the likelihood of receiving an application fee waiver. Adopting our earlier approach, we convert the coefficients from Table 4 into discrimination ratios as shown in Figure 3. The discrimination ratios for the approval of waiver show unequal treatment with a particular emphasis on Asians having the highest ratios. White applicants are approximately 45 percent more likely to receive a waiver than Asian applicants. White applicants are also about 13 percent more likely to receive waivers than both Black and Asian applicants with a White first name, but these differences are not statistically significant.

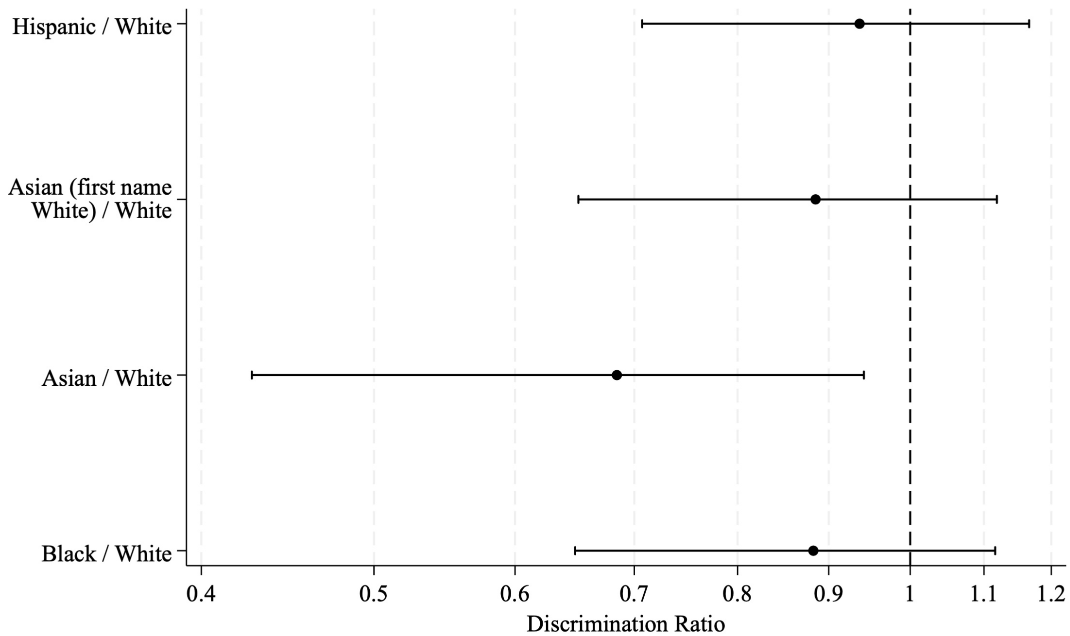
Table 4: Effects of Race/Ethnicity on Waiver Approval

| | Probit | | OLS | |
|---|---|---|---|---|
| | Baseline | With university controls | Baseline | With university controls |
| | (1) | (2) | (3) | (4) |
| Asian | -0.043*** | -0.045*** | -0.044*** | -0.044*** |
| | (0.016) | (0.016) | (0.015) | (0.016) |
| Asian/first name White | -0.017 | -0.019 | -0.016 | -0.016 |
| | (0.016) | (0.016) | (0.016) | (0.016) |
| Black | -0.018 | -0.018 | -0.016 | -0.016 |
| | (0.017) | (0.016) | (0.015) | (0.016) |
| Hispanic | -0.010 | -0.011 | -0.009 | -0.009 |
| | (0.017) | (0.017) | (0.016) | (0.016) |
| N | 4,658 | 4,658 | 4,658 | 4,658 |

*Notes*: Coefficients represent average marginal effects. White is the omitted category. The baseline specification (columns (1) and (3)) controls for the message template used, the day of the week the email was sent, the month of the year (October or November) the email was sent, and the domain (Gmail, Hotmail, Outlook, Yahoo!) of the student's email address. In columns (2) and (4), we augment our baseline model with controls for characteristics of universities (private/public, size, selectivity, Census region, and rural/suburban/urban). Bootstrapped standard errors (10,000 repetitions) are reported in parentheses. $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Figure 3 shows most ratios around or slightly below 1, with a significant exception for the Asians with White first names, where these students receive less favorable treatment in terms of waivers approved.

Figure 3: Discrimination Ratios for Approval of Waiver




*Notes:* Discrimination ratios for non-White student groups, using White as the baseline, are calculated from predicted outcomes at mean covariate values in our primary model (Table 4, column 1). Results shown on a natural log scale. Error bars indicate 95 percent confidence intervals. Results that overlap the dotted line at 1 indicate no statistically significant evidence of discrimination favoring either group. See Section 4.3 for more details. Figure A.3 in the appendix plots the discrimination ratios for each of our four specifications; results are virtually identical.

## 5.3 Free Application Disclosure

Next, we examine whether racial/ethnic differences exist in counselors informing the student that submitting an application costs nothing. In assembling our sample of counselors to include in the experiment, we did not selectively choose universities based on their policy of charging application fees. This led to responses from some counselors stating the irrelevance of a fee waiver, given the absence of a fee. Nevertheless, our randomized experimental design ensures that the distribution of free applications should be approximately uniform across racial/ethnic groups, consistent with the distribution of all university characteristics outlined in Table 2. Despite this, Table 5 shows that counselors are about 4.5 percentage points less likely to inform Black applicants that the application is temporarily or permanently free than White applicants. The discrimination ratios shown in Figure 4 indicate that White applicants are over 15 percent more likely to be informed that an application is free than a Black applicant.

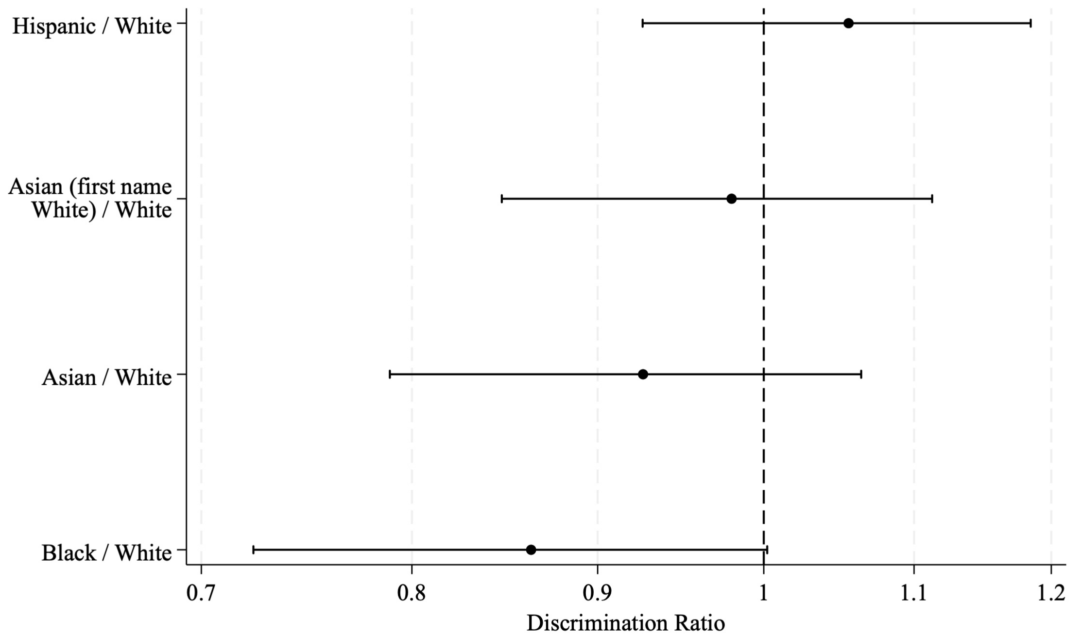
Table 5: Effects of Race/Ethnicity on Being Informed the Application is Free

| | Probit | | OLS | |
|---|---|---|---|---|
| | Baseline | With university controls | Baseline | With university controls |
| | (1) | (2) | (3) | (4) |
| Asian | -0.022 | -0.021 | -0.024 | -0.023 |
| | (0.022) | (0.021) | (0.022) | (0.021) |
| Asian/first name White | -0.006 | -0.007 | -0.006 | -0.008 |
| | (0.022) | (0.021) | (0.022) | (0.021) |
| Black | -0.045** | -0.047** | -0.044** | -0.045** |
| | (0.022) | (0.021) | (0.022) | (0.020) |
| Hispanic | 0.018 | 0.017 | 0.018 | 0.018 |
| | (0.023) | (0.022) | (0.023) | (0.021) |
| N | 4,658 | 4,658 | 4,658 | 4,658 |

*Notes*: Coefficients represent average marginal effects. White is the omitted category. The baseline specification (columns (1) and (3)) controls for the message template used, the day of the week the email was sent, the month of the year (October or November) the email was sent, and the domain (Gmail, Hotmail, Outlook, Yahoo!) of the student's email address. In columns (2) and (4), we augment our baseline model with controls for characteristics of universities (private/public, size, selectivity, Census region, and rural/suburban/urban). Bootstrapped standard errors (10,000 repetitions) are reported in parentheses. $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

In Figure 4, the ratios are close to 1 for most groups, suggesting equal treatment, while the ratio for Black/White is below 1, indicating a bias favoring White students for application-free offers.

Figure 4: Discrimination Ratios for Being Informed the Application is Free




*Notes:* Discrimination ratios for non-White student groups, using White as the baseline, are based on predicted outcomes at mean covariate values in our primary model (Table 5, column 1). Results shown on a natural log scale. Error bars indicate 95 percent confidence intervals. Results that overlap the dotted line at 1 indicate no statistically significant evidence of discrimination favoring either group. See Section 4.3 for details. Figure A.3 in the appendix plots the discrimination ratios for each of our four specifications; results are virtually identical.

## 5.4 Requests for More Information

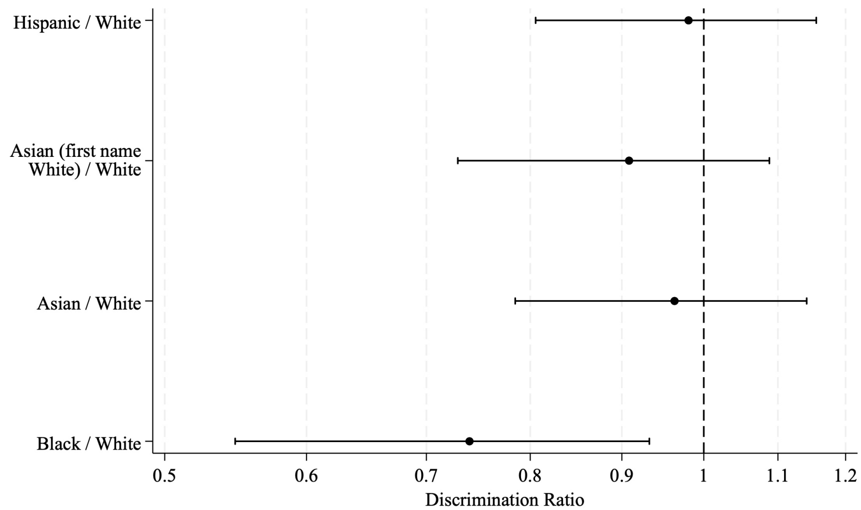
In some cases, counselors responded to our fee waiver requests by soliciting more information about the student's specific circumstances. In many cases, they asked the applicant to fill out a form or to indicate whether they were a resident of the state in which the university was located (among various other questions). Across our full sample, about 19 percent of messages received a response in this category. We find that Black applicants were much less likely to receive this type of response compared to White applicants as showed in Table 6. Figure 5 presents ratios primarily around 1 or slightly below, implying generally equal treatment with minor favorable treatment for White students. The exception is Black students, who receive starkly fewer requests for more information. White applicants are about 35 percent more likely to receive a request for more information than a Black applicant. Although we did not follow up with any of these emails and did not fill out any of the forms that were requested, this outcome is important since it offers a potential path for a fee waiver. The fact that Black applicants are less likely be offered this potential path for a fee waiver is evidence of discrimination against this racial group.

Table 6: Effects of Race/Ethnicity on Counselor Requests for More Information

| | Probit | | OLS | |
|---|---|---|---|---|
| | Baseline | With university controls | Baseline | With university controls |
| | (1) | (2) | (3) | (4) |
| Asian | -0.008 | -0.005 | -0.008 | -0.008 |
| | (0.020) | (0.018) | (0.020) | (0.018) |
| Asian/first name White | -0.019 | -0.014 | -0.019 | -0.016 |
| | (0.019) | (0.017) | (0.019) | (0.017) |
| Black | -0.054*** | -0.048*** | -0.055*** | -0.054*** |
| | (0.019) | (0.017) | (0.019) | (0.017) |
| Hispanic | -0.003 | -0.000 | -0.004 | -0.002 |
| | (0.020) | (0.018) | (0.020) | (0.018) |
| N | 4,658 | 4,658 | 4,658 | 4,658 |

*Notes*: Coefficients represent average marginal effects. White is the omitted category. The baseline specification (columns (1) and (3)) controls for the message template used, the day of the week the email was sent, the month of the year (October or November) the email was sent, and the domain (Gmail, Hotmail, Outlook, Yahoo!) of the student's email address. In columns (2) and (4), we augment our baseline model with controls for characteristics of universities (private/public, size, selectivity, Census region, and rural/suburban/urban). Bootstrapped standard errors (10,000 repetitions) are reported in parentheses. $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Figure 5: Discrimination Ratios for Counselor Requests for More Information




*Notes:* Discrimination ratios for non-White student groups, using White as the baseline, are calculated from predicted outcomes at mean covariate values in our primary model (Table 6, Column 1). Results shown on a natural log scale. Error bars indicate 95 percent confidence intervals. Results that overlap the dotted line at 1 indicate no statistically significant evidence of discrimination favoring either group. See Section 4.3 for more details. Figure A.3 in the appendix plots the discrimination ratios for each of our four specifications; results are virtually identical.

# 6 Sentiment Analysis

We perform a variety of different analyses to examine whether the tone or sentiments in counselors' responses vary based on the student's race/ethnicity.[19] This analysis is helpful for two reasons. First, the tone of counselors' responses might indicate racial or ethnic bias, influencing students' sense of belonging and motivation to continue the application process. Second, it can provide insights into the potentially different sources of discrimination in college admissions.

[19] We were unable to analyze the sentiments of 0.3 percent of counselors' responses because the email accounts were suspended before the text could be recovered.

## 6.1 Sentiment Analysis via Human Evaluators

We start by evaluating the sentiments in counselors' responses using human evaluators. Two research assistants rated each email response. When the two evaluators' judgments differed, a third research assistant reviewed the response and made a final decision. All evaluators were blinded to the race of the student, the characteristics of the counselor, and other relevant information that could introduce bias in their responses.

Evaluators rated each response on two binary measures: 1) whether the tone was generally friendly and polite, and 2) whether the message clearly and explicitly encouraged the student to submit an application. Numerous studies highlight the significance of a college student's sense of belonging for their academic success (Freeman et al., 2007; Strayhorn, 2018; Fan et al., 2021). An unwelcoming or negative tone in communication from an admissions counselor, potentially the first point of contact with the higher education system for some students, could undermine a student's confidence. Moreover, an unwelcoming response could indicate that a counselor might not be as interested in considering an application from a given student.

Table 7 presents the results. Column 1 includes the full sample, in which non-responses are scored as negative responses. This is valuable because antagonism toward a particular racial group may be expressed through non-response rather than an unfriendly or hostile tone. Column 2 narrows the sample to responses only but pools all response types together. Since counselors' sentiments might vary systematically by response type (e.g., a counselor granting a waiver might do so in a different tone than would be employed if asking for more information from the student), Columns 3 through 5 show the results separately for each response type. In the full sample, the responses-only sample, and the sub-sample informing the student that the application is free, we find evidence that Asian applicants are less likely to receive a friendly response than Whites. In the full sample, we also find evidence that Black students are less likely to receive a friendly response, but this appears to be driven by high non-response rates among Black students; in Columns 2-5, we see that Black students are slightly more likely to receive a friendly response than Whites, although the differences are not statistically significant. Finally, in responses where the counselor explains that the application fee for their university is temporarily or permanently free, counselors are more likely to explicitly encourage Black and Hispanic applicants to apply than White applicants.

Table 7: Effects of Race/Ethnicity on Human-Evaluated Sentiments of Responses

| | | | *Sub-Sample* | | |
|---|---|---|---|---|---|
| | Full Sample (1) | Responses Only (2) | Gave waiver (3) | Application is free (4) | Need more info (5) |
| ***Panel A — Counselor Response is Friendly*** | | | | | |
| Asian | -0.073*** | -0.057** | -0.032 | -0.083** | -0.003 |
| | (0.024) | (0.028) | (0.064) | (0.041) | (0.052) |
| Asian/first name White | -0.035 | -0.028 | 0.008 | -0.039 | -0.026 |
| | (0.023) | (0.028) | (0.059) | (0.040) | (0.051) |
| Black | -0.066*** | 0.021 | 0.012 | 0.014 | 0.041 |
| | (0.024) | (0.030) | (0.063) | (0.044) | (0.056) |
| Hispanic | -0.027 | -0.024 | -0.024 | -0.042 | 0.007 |
| | (0.024) | (0.028) | (0.060) | (0.041) | (0.050) |
| ***Panel B — Counselor Response Encourages the Student to Apply*** | | | | | |
| Asian | -0.010 | -0.001 | 0.006 | 0.005 | -0.013 |
| | (0.014) | (0.021) | (0.052) | (0.034) | (0.029) |
| Asian/first name White | 0.007 | 0.019 | 0.012 | 0.036 | -0.020 |
| | (0.013) | (0.020) | (0.050) | (0.033) | (0.026) |
| Black | 0.004 | 0.038 | 0.024 | 0.070* | 0.005 |
| | (0.013) | (0.023) | (0.057) | (0.037) | (0.032) |
| Hispanic | 0.015 | 0.031 | 0.016 | 0.063* | 0.007 |
| | (0.014) | (0.021) | (0.053) | (0.034) | (0.029) |
| N | 4,658 | 2,968 | 567 | 1,431 | 904 |

*Notes*: Coefficients represent average marginal effects from linear probability models. White is the omitted category. We include the same controls as in the baseline specification of our main results: the message template used, the day of the week the email was sent, the month of the year (October or November) the email was sent, and the domain (Gmail, Hotmail, Outlook, Yahoo!) of the student's email address. Bootstrapped standard errors (10,000 repetitions) are reported in parentheses.
$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

## 6.2 Sentiment Analysis via Machine Learning

To supplement the sentiment analysis based on the judgments of human evaluators discussed in Section 6.1, we assess counselors' responses using machine learning sentiment analysis techniques. Following Shapiro et al. (2022), we utilize the Valence Aware Dictionary and Sentiment Reasoner (VADER) algorithm, a lexicon-based textual analysis model that incorporates contextual cues to assign numerical scores to text ranging from mostly negative (1) to mostly positive sentiment (5). Using this approach, we assign a rating from 1 to 5 to each counselor's response.

The vast majority of counselors' responses are courteous and positive, with virtually no counselors being explicitly rude. As a result, approximately 70 percent of the responses in our dataset receive the highest score of 5, leaving little variation to assess heterogeneity by applicant race/ethnicity. To address this issue, we convert the 5-point scale into a binary outcome: a score of 1 represents a sentiment score of 5, and a score of 0 represents any score below 5. The results are depicted in Table 8. Consistent with the findings of Section 6.1 based on human evaluators, we find evidence of lower sentiments toward Asian and Black applicants when non-responses are coded as negative. We also find consistent evidence that Black and Asian students receive more and less positive responses, respectively, compared to Whites when we divide the sample by response type, but these differences are not statistically significant.

Table 8: Effects of Race/Ethnicity on Machine Learning-Evaluated Sentiments of Responses

| | | | *Sub-Sample* | | |
|---|---|---|---|---|---|
| | Full Sample (1) | Responses Only (2) | Gave waiver (3) | Application is free (4) | Need more info (5) |
| Asian | -0.051** | -0.026 | -0.061 | -0.034 | 0.018 |
| | (0.024) | (0.028) | (0.070) | (0.041) | (0.050) |
| Asian/first name White | -0.027 | -0.015 | -0.026 | -0.009 | 0.012 |
| | (0.024) | (0.028) | (0.062) | (0.040) | (0.048) |
| Black | -0.060** | 0.028 | 0.009 | 0.039 | 0.012 |
| | (0.024) | (0.030) | (0.067) | (0.043) | (0.053) |
| Hispanic | -0.013 | -0.005 | 0.018 | 0.005 | -0.016 |
| | (0.024) | (0.028) | (0.065) | (0.040) | (0.050) |
| N | 4,658 | 2,968 | 567 | 1,431 | 904 |

*Notes*: Coefficients represent average marginal effects from linear probability models. White is the omitted category. We include the same controls as in the baseline specification of our main results: the message template used, the day of the week the email was sent, the month of the year (October or November) the email was sent, and the domain (Gmail, Hotmail, Outlook, Yahoo!) of the student's email address. Bootstrapped standard errors (1,000 repetitions) are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

## 6.3 Using Name of Student in Response

While the sentiment analysis approach described by Shapiro et al. (2022) and shown in Table 8 is widely used in the context of news articles, it may overlook many linguistic nuances in the context of emails. For example, saying "Hello" or "Dear John" are both positive, but personalized messages that refer to the applicant by name are likely to be perceived as friendlier. Using the student's name is a sign of respect and may enhance students' feelings of belonging. Thus, we examine whether the race/ethnicity of the student affects the rate at which admissions counselors use the student's name (first or last) in their responses. Relative to Whites, we find that counselors are much less likely to use the names of Asian applicants in their responses. This result may be suggestive of discrimination, but it may also be due to counselors being more concerned about misspelling the names of Asian applicants, among other similar concerns. When we code non-responses as negative for the use of the applicant's name, we also find that Black applicants are much less likely to receive a personalized message than White students.

Table 9: Effects of Race/Ethnicity on Name Appearing in Response

| | | | *Sub-Sample* | | |
|---|---|---|---|---|---|
| | Full Sample (1) | Responses Only (2) | Gave waiver (3) | Application is free (4) | Need more info |
| Asian | -0.013*** | -0.139*** | -0.117* | -0.189*** | -0.114*** |
| | (0.024) | (0.024) | (0.064) | (0.035) | (0.042) |
| Asian/first name White | -0.030 | -0.014 | -0.066 | -0.036 | -0.016 |
| | (0.023) | (0.021) | (0.048) | (0.031) | (0.035) |
| Black | -0.096*** | -0.004 | 0.052 | -0.026 | -0.012 |
| | (0.024) | (0.024) | (0.058) | (0.035) | (0.038) |
| Hispanic | -0.009 | 0.004 | 0.079 | -0.012 | -0.020 |
| | (0.023) | (0.021) | (0.048) | (0.030) | (0.036) |
| N | 4,658 | 2,968 | 567 | 1,431 | 904 |

*Notes*: Coefficients represent average marginal effects from linear probability models. White is the omitted category. We include the same controls as in the baseline specification of our main results: the message template used, the day of the week the email was sent, the month of the year (October or November) the email was sent, and the domain (Gmail, Hotmail, Outlook, Yahoo!) of the student's email address. Bootstrapped standard errors (1,000 repetitions) are reported in parentheses. $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

# 7 Heterogeneity Analysis

To complement our main findings, we perform a heterogeneity analysis to explore whether specific characteristics of admissions counselors or universities influence the impact of race on our primary outcome, *de facto* rejection. This is achieved by stratifying the sample and analyzing subgroups independently. While we acknowledge that the characteristics of admissions counselors and universities cannot be experimentally manipulated, and these results may therefore be subject to confounding, we believe this approach offers valuable suggestive evidence regarding the nature of the discrimination outlined in Section 5.

## 7.1 Admissions Counselor Characteristics

Admissions counselors vary along many dimensions that could be relevant to how they interact with students of different races, including their age, gender, race, personality, professional experience, the extent to which their work activities are monitored, and the expectations set by their universities (including both explicit policy and more subtle pressures). We assess heterogeneity within several of these categories: the counselors' perceived race and gender, whether their email account is personal (e.g., john.smith@university.edu) or collective (e.g., admissions@university.edu), and their years of experience in college admissions.

Counselors of the same race as the student — or of another marginalized race — may feel greater empathy and be more likely than other counselors to grant the student's request. Heterogeneity between male and female counselors could arise due to average differences in personality traits or perceptions of race. Data on counselors' race and gender was gathered manually by research assistants from counselors' LinkedIn profiles. We emphasize that these characteristics are based on subjective assessments based on photographs; hence, hereafter we refer to "perceived race" and "perceived gender." In cases where a counselor did not have a LinkedIn profile or had a profile but lacked a picture, these variables are missing. These variables are also missing in cases where the counselor email address could not be matched to a specific individual (e.g., "admissions@universityname.edu"). Despite these limitations, we successfully collected information on perceived race and perceived gender for 82.5 percent and 88.9 percent of observations, respectively.[20]

[20]The small discrepancy in the proportion of the sample with data on perceived race compared to perceived gender stems from the fact that counselors' race was more often ambiguous (and thus excluded from our analysis) than their gender.

The degree to which counselors' work is accessible to colleagues may influence their behavior. To shed light on these dynamics, we classified each counselor's email account (i.e., the email address used to send the request for the fee waiver) as collective — meaning that multiple employees likely had access to the account — or private. Since a counselor's email responses are presumably more easily monitored when using a collective account, counselors may be more likely to reflect their university's preferences in their interactions with students on a collective account than when using a private account. We define collective accounts as those that contain any of the following words: "admission," "adms," "admin," or "admitme."[21] Nearly 5 percent of our observations fall into this category. By exclusion, the remainder of our sample is defined as private accounts.

Finally, we examine heterogeneity by years of experience in college admissions.[22] We use this measure to proxy for the inculcation of universities' preferences in counselors' behavior. It may take time for counselors to absorb their university's preferences. This information was manually collected from counselors' LinkedIn profiles.[23]

Results are presented in Table 10. The outcome is *de facto* rejection. We estimate stratified samples using ordinary least squares regression and the same set of covariates as in our main specification (column 3 in Table 3). For comparison, results from the full sample are given at the top of Table 10.

Panel A depicts differences by perceived gender. Among male counselors, we find a strong propensity to reject Asian students' requests, while there is no evidence that Asian and White students are treated differently by female counselors. On the other hand, discrimination toward Black students seems concentrated among female counselors; although the point estimate among males is positive and economically meaningful, it falls short of statistical significance. We note

[21]These identifiers were selected from visual inspection of our data.

[22]We include the counselor's tenure at their current institution, as well as any previous experience in college admissions at the same or another institution.

[23]The LinkedIn data was collected in July and August 2024, approximately 10 months after the experiment was conducted. Consequently, counselors with, for example, one year of experience may have only been in the role for a few weeks when they received the fee waiver request.

that although we detect higher rates of rejection among Asians with White first names than White students in the full sample, this effect becomes non-significant in both gender sub-groups; we attribute this to a decrease in power from stratifying the sample.

In Panel B, we stratify the sample by counselors' perceived race. The results for White counselors largely match the full sample, which is not surprising given that White counselors make up nearly three-quarters of our sample. We also detect discrimination against Black students by Black counselors. The coefficients among Asian counselors tend to be very large, indicating severe discrimination, but none attain statistical significance, due perhaps to the small number of observations in this subgroup.

Panel C presents the results by email account type. The results from the private email subgroup closely match the full sample. Although the point estimates for Asians, Asians with White first names, and Black students are large among counselors with collective email accounts, the coefficients are imprecisely estimated; none attain statistical significance. These results should be interpreted cautiously, however, given the small number of observations in the collective email subgroup.

In Panel D, we divide the sample by counselors' experience in college admissions. The results indicate that less experienced counselors engage in more discrimination. Counselors with fewer than two years of experience are more likely to reject requests from Asian and Black students than the average counselor. We also find evidence that counselors with 4-10 years of experience are substantially less likely to reject requests from Hispanic students.

Table 10: Heterogeneous Effects of Race/Ethnicity on *De Facto* Rejection by Counselor Characteristics

| | Asian (1) | Asian/first name White (2) | Black (3) | Hispanic (4) | N |
|---|---|---|---|---|---|
| *Average Effect* | 0.078*** | 0.046** | 0.119*** | 0.015 | 4,658 |
| | (0.023) | (0.023) | (0.024) | (0.023) | |
| ***Panel A — Perceived Gender*** | | | | | |
| Male | 0.107** | 0.031 | 0.061 | -0.003 | 1,478 |
| | (0.043) | (0.040) | (0.043) | (0.042) | |
| Female | 0.029 | 0.045 | 0.135*** | -0.000 | 2,663 |
| | (0.030) | (0.030) | (0.030) | (0.030) | |
| ***Panel B — Perceived Race*** | | | | | |
| Asian | 0.228 | 0.192 | 0.221 | -0.047 | 100 |
| | (0.153) | (0.155) | (0.215) | (0.174) | |
| Black | 0.061 | 0.013 | 0.130* | 0.035 | 563 |
| | (0.073) | (0.073) | (0.070) | (0.035) | |
| Hispanic | 0.041 | -0.126 | -0.017 | -0.002 | 384 |
| | (0.084) | (0.079) | (0.083) | (0.082) | |
| White | 0.067** | 0.068** | 0.115*** | -0.011 | 2,795 |
| | (0.029) | (0.028) | (0.031) | (0.029) | |
| ***Panel C — Email Account Type*** | | | | | |
| Private | 0.073*** | 0.040* | 0.116*** | 0.015 | 4,438 |
| | (0.024) | (0.023) | (0.024) | (0.024) | |
| Collective | 0.165 | 0.154 | 0.188 | 0.010 | 220 |
| | (0.121) | (0.112) | (0.123) | (0.123) | |
| ***Panel D — Experience in College Admissions*** | | | | | |
| $<$ 2 years | 0.124* | 0.043 | 0.147** | 0.079 | 541 |
| | (0.068) | (0.065) | (0.072) | (0.069) | |
| 2-4 years | 0.055 | 0.010 | 0.068 | -0.002 | 1,388 |
| | (0.041) | (0.041) | (0.043) | (0.043) | |
| 4-10 years | -0.015 | 0.014 | 0.073 | -0.093* | 862 |
| | (0.052) | (0.052) | (0.056) | (0.053) | |
| $>$ 10 years | 0.005 | 0.093 | 0.118 | -0.011 | 373 |
| | (0.087) | (0.084) | (0.089) | (0.087) | |

*Notes*: Coefficients represent average marginal effects from linear probability models. White is the omitted category. We include the same controls as in the baseline specification of our main results: the message template used, the day of the week the email was sent, the month of the year (October or November) the email was sent, and the domain (Gmail, Hotmail, Outlook, Yahoo!) of the student's email address. Bootstrapped standard errors (10,000 repetitions) are reported in parentheses. $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

## 7.2 University Characteristics

Next, we investigate potential heterogeneity in treatment effects based on university characteristics. To achieve this, we stratify the sample across several dimensions, including ownership structure, geographic region, population density, institution size, selectivity, endowment per student, and recent enrollment trends. Most of the data for these variables is sourced from the College Board, while information on enrollment trends is obtained from the National Center for Education Statistics (NCES).

Table 11 presents the results of this exercise. As in Section 7.1, we focus on *de facto* rejection as our main outcome of interest. For ease of comparison, the average effect from the full sample is given at the top of the table.

Panel A divides the sample into public and private (i.e., for-profit and not-for-profit) institutions. We find broadly similar results in both sub-groups, with quantitatively similar effects for Asian and Black students. Among private schools, we additionally detect discrimination against Asians with White first names and Hispanic students.

In Panel B, we examine universities in each of the four US regions, as defined by the Census Bureau, separately.[24] Discrimination against Asian and Black students is particularly pronounced in the South and Midwest. We also detect discrimination against Black students in the Northeast. We find no evidence of discrimination at universities in the West, although we note that our sample contains relatively few observations for this subgroup.

Panel C presents results based on the population density of each university's surrounding area. We find that discrimination against Asians, Asians with White first names, and Black students is concentrated in urban universities. Suburban universities also discriminate against Asian and Black students. Among rural universities, we only find evidence of discrimination against Asians with White first names.

In Panel D, we examine heterogeneity by size of the student body. Very large schools exhibit high levels discrimination against Asians, Asians with White first names, and Black students. At the other end of the spectrum, we find that small schools also discriminate against Asians, Asians with White first names, and Black students, but the point estimates are generally smaller than in the full sample. Medium-sized schools discriminate against Black students, and we find no evidence of discrimination among large schools.

[24] The Census regions are defined as follows: Northeast (Connecticut, Maine, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, and Vermont); Midwest (Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin); South (Alabama, Arkansas, Delaware, District of Columbia, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia, and West Virginia); West (Alaska, Arizona, California, Colorado, Hawaii, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington, and Wyoming).

Panel E gives results based on selectivity. We define three tiers of selectivity based on acceptance rates. We consider schools "not selective" if their acceptance rate exceeds 70 percent. "Moderately selective schools accept 30-70 percent of applicants, and "highly selective" schools are those with acceptance rates at or below 30 percent. Due to the small number of extremely selective schools in the US, we do not have sufficient data to attempt a more targeted analysis of elite institutions. We find high levels of discrimination toward Asian and Black students at "not selective" institutions. Moderately selective schools appear to discriminate against Black students but no other racial group. Finally, highly selective schools exhibit high levels of discrimination against Asians with White first names and Hispanic students; the coefficient on Black students among highly selective schools is large but narrowly fails to reach statistical significance at the 10 percent level.

In Panel F, we divide our data into three quantiles based on the size of the school's endowments assets per full-time equivalent undergraduate (FTE) student, which we obtain from the Integrated Postsecondary Education Data System (IPEDS) from NCES.[25] We consider schools below the 33rd percentile to have "small" endowments; schools with endowments between the 33rd and 67th percentiles are considered "moderate," and schools above the 67th percentile are classified as having "large" endowments per student. We generally find little heterogeneity across subgroups. All three categories of institutions discriminate against Asian and Black students to a quantitatively similar extent. Universities with large endowments per student also discriminate against Asians with White first names, an effect absent from the small and moderate subgroups. None of the subgroups exhibit discrimination against Hispanic students.

Finally, we test whether discrimination varies by recent trends in enrollment. One might expect schools with stagnating or declining enrollment to exhibit less discrimination in order to attract as many applicants as possible. We obtain historical data on FTE undergraduate enrollment from the National Center for Education Statistics.[26] We compute the percent change in FTE undergraduate

[25] We use the closest year available, 2022.

[26] Due to a small number of missing values in the National Center for Education Statistics' dataset, 136 observations (2.9 percent of our sample) could not be matched to historical enrollment data and were excluded from this subgroup analysis.

enrollment from the 2016-17 school year to the 2021-22 school year, the most recent year for which data is available. Schools experiencing rising enrollment over this period are classified as "positive," while schools with no change or negative enrollment growth over this period are labeled as "Zero or negative." We find little meaningful difference between subgroups. Both exhibit similar levels of discrimination against Asian and Black students. Additionally, universities with positive enrollment growth discriminate against Asians with White first names. There is no evidence of either group discriminating against Hispanic students.

Table 11: Heterogeneous Effects of Race/Ethnicity on *De Facto* Rejection by University Characteristics

| | Asian (1) | Asian/first name White (2) | Black (3) | Hispanic (4) | N |
|---|---|---|---|---|---|
| *Average Effect* | 0.078*** | 0.046** | 0.119*** | 0.015 | 4,658 |
| | (0.023) | (0.023) | (0.024) | (0.023) | |
| ***Panel A — Ownership Structure*** | | | | | |
| Public | 0.072* | 0.010 | 0.109*** | -0.039 | 1,835 |
| | (0.039) | (0.036) | (0.038) | (0.038) | |
| Private | 0.072** | 0.071** | 0.123*** | 0.052* | 2,823 |
| | (0.029) | (0.029) | (0.031) | (0.030) | |
| ***Panel B — Geographic Region*** | | | | | |
| Northeast | -0.020 | 0.051 | 0.123*** | -0.001 | 1,265 |
| | (0.041) | (0.042) | (0.045) | (0.042) | |
| Midwest | 0.109** | 0.068 | 0.127*** | 0.028 | 1,320 |
| | (0.044) | (0.043) | (0.044) | (0.045) | |
| West | 0.090 | -0.034 | 0.021 | -0.091 | 627 |
| | (0.065) | (0.062) | (0.070) | (0.065) | |
| South | 0.111** | 0.053 | 0.138*** | 0.047 | 1,446 |
| | (0.044) | (0.041) | (0.043) | (0.043) | |
| ***Panel C — Population Density*** | | | | | |
| Rural | 0.060 | 0.085* | -0.012 | -0.030 | 1,059 |
| | (0.051) | (0.048) | (0.050) | (0.049) | |
| Suburban | 0.079** | -0.008 | 0.130*** | 0.030 | 2,129 |
| | (0.034) | (0.033) | (0.035) | (0.035) | |
| Urban | 0.087** | 0.105*** | 0.198*** | 0.023 | 1,470 |
| | (0.040) | (0.039) | (0.042) | (0.041) | |
| ***Panel D — School Size*** | | | | | |
| Small | 0.068** | 0.060* | 0.092*** | 0.026 | 2,469 |
| | (0.032) | (0.031) | (0.033) | (0.032) | |
| Medium | 0.059 | 0.019 | 0.131*** | 0.028 | 1,303 |
| | (0.045) | (0.043) | (0.045) | (0.044) | |
| Large | 0.029 | -0.004 | 0.089 | -0.090 | 400 |
| | (0.080) | (0.078) | (0.081) | (0.076) | |
| Very Large | 0.239*** | 0.140** | 0.289*** | 0.073 | 486 |
| | (0.071) | (0.069) | (0.072) | (0.071) | |
| ***Panel E — Selectivity*** | | | | | |
| Not selective | 0.095*** | 0.045 | 0.128*** | -0.001 | 2,593 |
| | (0.032) | (0.030) | (0.031) | (0.032) | |
| Moderately selective | 0.056 | 0.033 | 0.097** | 0.002 | 1,825 |
| | (0.037) | (0.037) | (0.039) | (0.038) | |
| Highly selective | -0.040 | 0.181** | 0.167 | 0.183** | 240 |
| | (0.096) | (0.089) | (0.103) | (0.093) | |
| ***Panel F — Endowment Per Student*** | | | | | |
| Small | 0.079* | 0.025 | 0.096** | -0.010 | 1,542 |
| | (0.042) | (0.039) | (0.041) | (0.041) | |
| Moderate | 0.068* | 0.028 | 0.109*** | 0.006 | 1,592 |
| | (0.040) | (0.039) | (0.041) | (0.041) | |
| Large | 0.071* | 0.075** | 0.146*** | 0.045 | 1,524 |
| | (0.038) | (0.038) | (0.042) | (0.039) | |
| ***Panel G — Recent Enrollment Change*** | | | | | |
| Positive | 0.072* | 0.073* | 0.127*** | 0.044 | 1,473 |
| | (0.040) | (0.040) | (0.042) | (0.041) | |
| Zero or Negative | 0.082*** | 0.039 | 0.115*** | -0.001 | 3,049 |
| | (0.029) | (0.028) | (0.030) | (0.030) | |

*Notes*: Coefficients represent average marginal effects from linear probability models. White is the omitted category. We include the same controls as in the baseline specification of our main results: the message template used, the day of the week the email was sent, the month of the year (October or November) the email was sent, and the domain (Gmail, Hotmail, Outlook, Yahoo!) of the student's email address. Bootstrapped standard errors (10,000 repetitions) are reported in parentheses. $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

# 8 Discussion and Model

This paper provides new evidence about the presence and mechanisms of racial discrimination in the college admissions process, specifically regarding the approval of application-fee waivers. Our findings indicate that Black and Asian applicants are significantly more likely to face rejection of their fee-waiver requests compared to their White counterparts. This pattern is fairly consistent across college characteristics.

This discrimination seems to span ownership structure, endowment, and enrollment trends, although it is smaller for rural colleges and those in the West. The relationship with selectivity and size is unclear, with the very selective having the highest rates of discrimination against Asian applicants with White first names, as well as Black and Hispanic applicants, but the lowest rates of discrimination against Asian applicants with Asian first names.

Our results juxtapose starkly with existing evidence of racial discrimination in college admissions, which indicates (at least for Harvard and UNC) substantial discrimination in favor of recruiting and admitting Black applicants, and against Asian applicants, relative to similarly situated Whites (Arcidiacono et al., 2022d, 2023). Why might colleges simultaneously discriminate for and against the same racial groups at various stages of the college application and admissions process? And why is that pattern offsetting for Black applicants and amplifying for Asian applicants?

To get at these questions, consider a model of two actors within a university admissions/enrollment-management office setting policies and practices to shape the set of students who enroll at their school. In practice, these decisions consist of many different marketing investments, prices, and admissions criteria, but we will represent them as two policies, one controlled by a manager (denoted $x^p \in \Re$, for principal) and one by an individual admissions counselor (denoted $x^a \in \Re$, for agent). Furthermore, there might be preference misalignment between the management of this office/university and the admissions counselor who enact policy on a daily basis, and this misalignment might make enforcing policy that differs from the agents' preferences costly. The principal can exert costly supervision and monitoring (denoted $s \in \Re^+$) to make it increasingly costly for the agent to choose a policy that deviates from what the principal has chosen.

The principal's payoff is a function of all these choices. Specifically, it is given by

$$V^p(x^a,x^p,s) = v(\pi(x^a,x^p) - \gamma c^p(s) + F) + \alpha^p b^p(x^a,x^p),$$

where $v(\cdot)$ is an increasing and concave function representing the returns to net-revenue (sometimes referred to as "perquisites" in the analysis of non-profit firms (Glaeser and Shleifer, 2001), $\pi(\cdot,\cdot) - F$ is a concave net-revenue function that (without loss of generality) is maximized at profit of $F$ at $(0,0)$, $c^p(\cdot)$ in an increasing and convex cost of supervision, and $b^p(\cdot,\cdot)$ is a concave taste-based bias payoff, that is maximized at $(\beta^p,\beta^p)$. We interpret $\beta^P > 0$ as the principal's taste for discrimination, for reasons over-and-above its impact on net revenues (which appear in $\pi$) and $\alpha^P$ as a parameterization of the strength of that taste.

The agent's payoff is also a function of all these choices. Specifically, it is given by

$$V^a(x^a,x^p,s) = \alpha^a b^a(x^a,x^p) - sc^a(x^a,x^p),$$

where $b^a(\cdot,\cdot)$ is a concave taste-based bias payoff that is maximized at $(\beta^a,\beta^a)$. We interpret $\beta^a$ as the agent's taste for discrimination and $\alpha^a$ as a parameterization of the strength of that taste. Finally, $sc^a(\cdot|\cdot)$ is a convex cost borne by the agent when his action deviates from the principal's action, minimized at $c^a(x|x) = 0$.

Both parties payoffs are common knowledge, and the principal makes his choices first. We abstract away from the informational details of the oversight/supervision game and instead treat it as a two-period dynamic game of complete information. As such, we look for Subgame-Perfect Nash Equilibria (SPNE).

To focus on one driver of discrimination at a time, we consider three special cases.

## 8.1 Pure Statistical Discrimination ($\alpha^a = \alpha^p = 0$)

**Proposition 1.** *If $\alpha^a = \alpha^p = 0$, there is a unique SPNE in the described game. In it, the Agent and Principal choose a policy $x^{p*} = x^{p*} = 0$ for all other parameters.*

If neither the principal nor the agent a taste for discrimination, the equilibrium is for both to make the profit-maximizing choice $(0,0)$. This choice could still include substantial price discrimination. Setting race-specific application and admissions prices can be usefully thought of as a two-part pricing problem. In the purely profit-maximizing setting, Schmalense (1981) shows that it is optimal to set a positive application fee, as long as the cost of reviewing applications is not negative. Moreover, the markup of application fees over the cost of review increases in the elasticity of demand for enrollment, but decreases in the (compensated) elasticity of demand for applications and in the ratio of willingness to pay for enrollment between the average applicant and the marginal applicant. The basic trade-off is that granting admissions waivers leads to more applicants, which is more valuable if the seller has a lot of market power in the enrollment market and if those new applicants improve their power in that market (since the new applicants have less elastic demand).

Under this model, variation among racial groups in application fees (waivers) must be driven either by differences in the demand characteristics of these groups leading to differences in the profit-maximizing policies, a form of *statistical price discrimination*, or by one of two forms of taste-based discrimination, *principal-taste-based discrimination*, where the admissions policymaker trades off profits against some other welfare-relevant outcome, and *agent-taste-based discrimination*, where a taste for discrimination amongst agents within the office, perhaps amplified with the high cost of monitoring informal interactions, **induces** a profit-maximizing policymaker to discriminate amongst applicants (or, better, allow discrimination amongst applicants), in the pursuit of profit maximization.

To the extent that racial differences in fee waivers are driven by statistical price discrimination, we should see more of it where there are bigger differences in relevant demands across applicant racial groups, in the direction predicted by the model. Specifically, we would expect more variation in waivers for colleges with more heterogeneity *across* applicant groups with respect to elasticity of demand for application and with more *within* group heterogeneity in demand for enrollment.

Furthermore, we would expect within those colleges for more waivers to be granted to groups with relatively inelastic demand for enrollment, relatively elastic demand for application, and more heterogeneous willingness to pay for enrollment.

## 8.2 Pure Principal-Taste-Based Discrimination ($\alpha^a = 0$ and $\alpha^p > 0$)

**Proposition 2.** *If $\alpha^a = 0$, while $\alpha^p > 0$, there is a unique SPNE in the described game. In it, the Agent and Principal choose a policy between the profit-maximizing policy and the principal's pure tasted-based policy. The equilibrium policy moves toward the principal's pure taste-based policy as $\alpha^P$ or $F$ increases and is independent of the marginal cost of supervision.*

In a situation where the principal has a taste for discrimination for reasons beyond their impact on profiles, they choose a policy that trades off between two factors. Moving policy toward their discriminatory preference is valuable, but it costs profits/perquisites. With diminishing marginal value of perquisites, the negative revenue consequences are less important as the level of profit increases. This factor suggests more scope for principal-taste-based discrimination when the financial situation of the college is good, such as when schools have plenty of applicants and large endowments. As the agent has no taste for discrimination, their other characteristics (captured in $\beta^a$) and how difficult their tasks are to supervise (captured in $\gamma$) should play no role.

## 8.3 Pure Agent-Taste-Based Discrimination ($\alpha^p = 0$ and $\alpha^a > 0$)

**Proposition 3.** *If $\alpha^p = 0$, while $\alpha^a > 0$, there is a unique SPNE in the described game. In it, the Agent chooses a policy strictly between the profit-maximizing policy and the agent's pure taste-based policy. The principal chooses a policy on the other side of the profit-maximizing policy from the agent's preference. The policies move further from the profit-maximizing choice as the strengths of the agent's tests ($\alpha^a$), the extremeism of the their tastes ($|\beta^a|$), or the cost of supervision ($\gamma$) increases, but the are independent of $F$.*

In the case of pure agent-taste-based discrimination, the principal faces a trade-off. He must weigh the costs of deviating from the profit-maximizing level of discrimination against the costs associated with supervision. The equilibrium deviation from profit-maximizing discrimination actually comes in two forms. First, he allows the agent to hedge toward the agent's preferred policy, since the profit costs of small deviations are second order while the supervisions costs are first order. Second, the principal actually deviates his own policy slightly in the opposite direction from the profit-maximizing one, since that deviation makes supervision more effective.

Unlike the case of discrimination driven by the principal's tastes, we should not expect any change in these choices as the financial circumstance of the college changes. On the other hand, the agent's characteristics, such as the strength and direction of the their tastes will play an important role, as will the difficulty of applying effective supervision.

The heterogeneity results reported in sections 7.2 and 7.1 provide some evidence in favor of statistical price discrimination and agent-taste-based discrimination and against principal-taste-based discrimination as the primary mechanisms driving the patterns of discrimination we observe. The patterns in university-level heterogeneity are more consistent with statistical price discrimination than principal-taste-based discrimination. On the one hand, factors that likely correlate with the demand characteristics of potential applicants, like region, population density, school size, and selectivity, have some statistical relationship with the patterns of discrimination. More selective schools, rural schools, very large schools, and schools in the West and Northeast, seem to discriminate quite differently from their peers. On the other hand, factors that should affect the importance of revenues, and therefore the costs of expressing principal-taste-based discrimination (relative to making the net-revenue maximizing choice), like endowments, enrollment changes, or private control, have limited predictive power.

The patterns in counselor-level heterogeneity, however, suggest substantial agent-taste-based discrimination. The presence of large differences in the rate of discrimination across counselor gender and race suggest that agent-level preferences are playing a substantial role in discrimination.

Moreover, the higher rates of discrimination among less-experienced counselors indicate that agent selection or learning and enculturation may play a crucial role in aligning their behavior with the office's preferences.

# 9 Conclusion

This paper provides new evidence about the presence and mechanisms of racial discrimination in the college admissions process, specifically regarding the approval of application fee waivers. Our findings indicate that Black and Asian applicants are significantly more likely to face rejection of their fee-waiver requests compared to their White counterparts, although the path to that *de facto* rejection differential looks different. For Asian applicants, the difference arises mostly from lower rates of waiver granting. For Black applicants, the difference mostly arises from lower rates of asking for or giving more information about eligibility for fee-waiver programs. The results point out the complexity of achieving equity in college admissions, especially in light of the recent U.S. Supreme Court ruling against race-conscious admissions. Despite the prohibition of using race directly in admissions decisions, our findings demonstrate that race can still influence outcomes through other aspects of the process, such as fee waivers.

The nuances and complexities of discrimination uncovered in this paper reveal that it is not merely the presence of discriminatory practices or preferences but also the context in which they occur that shapes the experiences of minority applicants. For instance, while Black students may be favored in university acceptance decisions (at least at Harvard and UNC, as showed by Arcidiacono et al. (2023)), they are much less likely to receive a response from a counselor with some path for an application fee waiver than White students. This apparently paradoxical finding suggests a layered and multifaceted nature of discrimination. The contrast between our findings and the pattern of pro-Black and anti-Asian discrimination in the more centralized steps in the admissions process outlined by Arcidiacono et al. (2022d, 2023) also suggest a role for organizational design to affect discriminatory practices.

This insight about the complex combination of offsetting and amplifying impacts of discrimination across multiple decisions by multiple actors in complex organizations may apply in contexts beyond higher education. Much work in this literature treats the discriminating organization as a monolith, implicitly assuming some general preferential or statistical driver of its behavior, which the researcher endeavors to estimate. To the extent that different combinations of organizational circumstances and employee/owner preferences can lead to similar patterns of final discrimination, it is important to recognize that heterogeneity, both for forming a more accurate scientific understanding of the phenomena and for designing effective policy interventions to curb discriminatory outcomes.

# References


Agan, A. and Starr, S. (2018). Ban the box, criminal records, and racial discrimination: A field experiment. *The Quarterly Journal of Economics*, 133(1):191–235.

Arcidiacono, P. (2005). Affirmative Action in Higher Education: How do Admission and Financial Aid Rules Affect Future Earnings? *Econometrica*, 73:1477–1524.

Arcidiacono, P., Kinsler, J., and Ransom, T. (2022a). Asian american discrimination in harvard admissions. *European Economic Review*, 144:104079.

Arcidiacono, P., Kinsler, J., and Ransom, T. (2022b). Divergent: The time path of legacy and athlete admissions at harvard. *Journal of Human Resources*.

Arcidiacono, P., Kinsler, J., and Ransom, T. (2022c). Legacy and athlete preferences at harvard. *Journal of Labor Economics*, 40(1):133–156.

Arcidiacono, P., Kinsler, J., and Ransom, T. (2022d). Recruit to reject? harvard and african american applicants. *Economics of Education Review*, 88:102255.

Arcidiacono, P., Kinsler, J., and Ransom, T. (2023). What the students for fair admissions cases reveal about racial preferences. *Journal of Political Economy: Microeconomics*, 1(4):615–668.

Ayres, I., Banaji, M., and Jolls, C. (2015). Race effects on ebay. *The RAND Journal of Economics*, 46(4):891–917.

Azmat, G. and Petrongolo, B. (2014). Gender and the labor market: What have we learned from field and lab experiments? *Labour Economics*, 30:32–40.

Baert, S. and Verhofstadt, E. (2015). Labour market discrimination against former juvenile delinquents: Evidence from a field experiment. *Applied Economics*, 47(11):1061–1072.

Bertrand, M. and Mullainathan, S. (2004). Are Emily and Greg more employable than Lakisha and Jamal? a field experiment on labor market discrimination. *American Economic Review*, 94(4):991–1013.

Black, S. E., Cortes, K. E., and Lincove, J. A. (2015). Academic undermatching of high-achieving minority students: Evidence from race-neutral and holistic admissions policies. *American Economic Review: Papers & Proceedings*, 105(5):604–610.

Bóo, F. L., Rossi, M. A., and Urzúa, S. S. (2013). The labor market return to an attractive face: Evidence from a field experiment. *Economics Letters*, 118(1):170–172.

Brown, J. R. and Hilbig, H. (2022). Locked out of college: When admissions bureaucrats do and do not discriminate. *British Journal of Political Science*, 52(3):1436–1446.

Carlsson, M. and Eriksson, S. (2019). Age discrimination in hiring decisions: Evidence from a field experiment in the labor market. *Labour Economics*, 59:173–183.

Carlsson, M. and Rooth, D.-O. (2007). Evidence of ethnic discrimination in the swedish labor market using experimental data. *Labour Economics*, 14(4):716–729.

Crabtree, C., Gaddis, S. M., Holbein, J. B., and Larsen, E. N. (2022). Racially Distinctive Names Signal Both Race/Ethnicity and Social Class. *Sociological Science*, 9:454–472.

Crabtree, C., Kim, J. Y., Gaddis, S. M., Holbein, J. B., Guage, C., and Marx, W. W. (2023). Validated names for experimental studies on race and ethnicity. *Scientific Data*, 10(1).

Deming, D. J., Yuchtman, N., Abulafi, A., Goldin, C., and Katz, L. F. (2016). The value of postsecondary credentials in the labor market: An experimental study. *American Economic Review*, 106(3):778–806.

Druckman, J. N. and Shafranek, R. M. (2020). The intersection of racial and partisan discrimination: Evidence from a correspondence study of four-year colleges. *The Journal of Politics*, 82(4):1602–1606.

Edelman, B., Luca, M., and Svirsky, D. (2017). Racial discrimination in the sharing economy: Evidence from a field experiment. *American Economic Journal: Applied Economics*, 9(2):1–22.

Ewens, M., Tomlin, B., and Wang, L. C. (2014). Statistical discrimination or prejudice? a large sample field experiment. *The Review of Economics and Statistics*, 96(1):119–134.

Fan, X., Luchok, K., and Dozier, J. (2021). College students' satisfaction and sense of belonging: differences between underrepresented groups and the majority groups. *SN Social Sciences*, 1:1–22.

Folke, O. and Rickne, J. (2022). Sexual harassment and gender inequality in the labor market. *The Quarterly Journal of Economics*, 137(4):2163–2212.

Freeman, T. M., Anderman, L. H., and Jensen, J. M. (2007). Sense of belonging in college freshmen at the classroom and campus levels. *The Journal of Experimental Education*, 75(3):203–220.

Fryer, R. G. J., Pager, D., and Spenkuch, J. L. (2013). Racial disparities in job finding and offered wages. *The Journal of Law and Economics*, 56(3):633–689.

Fumarco, L., Harrell, B., Button, P., Schwegman, D., and Dils, E. (2023). Gender identity, race, and ethnicity-based discrimination in access to mental health care: Evidence from an audit correspondence field experiment. *National Bureau of Economic Research Working Paper*.

Gaddis, S. M. (2015). Discrimination in the credential society: An audit study of race and college selectivity in the labor market. *Social Forces*, 93(4):1451–1479.

Gaddis, S. M. (2017a). How Black Are Lakisha and Jamal? Racial Perceptions from Names Used in Correspondence Audit Studies. *Sociological Science*, 4:469–489.

Gaddis, S. M. (2017b). Racial/Ethnic Perceptions from Hispanic Names: Selecting Names to Test for Discrimination. *Socius*, 3.

Gaddis, S. M. (2018). An introduction to audit studies in the social sciences. In Gaddis, S. M., editor, *Audit Studies: Behind the Scenes with Theory, Method, and Nuance*, pages 1–50. Springer, Cham, Switzerland.

Gaddis, S. M. (2023). Signaling class: An examination of the treatment validity of names used to signal race in bias experiments with methodological recommendations for name selection. *Available at Social Science Research Network*.

Gaddis, S. M., Crabtree, C., Holbein, J. B., and Pfaff, S. (2024a). Racial/ethnic discrimination and heterogeneity across schools in the u.s. public education system: A correspondence audit of principals. *Available at Social Science Research Network*.

Gaddis, S. M., Crabtree, C., and Lee, J. (2024b). Asian american discrimination in north america: A review of research, a meta-analysis, and a call to action. *Available at Social Science Research Network*.

Gaddis, S. M. and DiRago, N. (2023). Audit studies of housing discrimination: Established, emerging, and future research. In McCabe, B. J. and Rosen, E., editors, *The Sociology of Housing: How Homes Shape Our Social Lives*, pages 93–106. The University of Chicago Press, Chicago, IL.

Gaddis, S. M. and Ghoshal, R. (2020). Searching for a roommate: A correspondence audit examining racial/ethnic and immigrant discrimination among millennials. *Socius*, 6:1–16.

Gaddis, S. M., Kreisberg, A. N., and Crabtree, C. (2022). Assessing Immigrant Generation and Citizenship Status from Names. *Available at Social Science Research Network*.

Gaddis, S. M., Larsen, E. N., Crabtree, C., and Holbein, J. B. (2021). Discrimination against black and hispanic americans is highest in hiring and housing contexts: A meta-analysis of correspondence audits. *Available at Social Science Research Network*.

Giulietti, C., Tonin, M., and Vlassopoulos, M. (2019). Racial discrimination in local public services: A field experiment in the united states. *Journal of the European Economic Association*, 17(1):165–204.

Glaeser, E. L. and Shleifer, A. (2001). Not-for-profit entrepreneurs. *Journal of public economics*, 81(1):99–115.

Hamermesh, D. S. (2011). Beauty pays. In *Beauty Pays: Why Attractive People Are More Successful*. Princeton University Press.

Hanson, A. (2017). Do college admissions counselors discriminate? evidence from a correspondence-based field experiment. *Economics of Education Review*, 60:86–96.

Hanson, A. and Hawley, Z. (2011). Do landlords discriminate in the rental housing market? Evidence from an internet field experiment in US cities. *Journal of Urban Economics*, 70(2):99–114.

Hanson, A., Hawley, Z., Martin, H., and Liu, B. (2016). Discrimination in mortgage lending: Evidence from a correspondence experiment. *Journal of Urban Economics*, 92:48–65.

Hanson, A. and Santas, M. (2014). Field Experiment Tests for Discrimination against Hispanics in the U.S. Rental Housing Market. *Southern Economic Journal*, 81(1):135–167. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.4284/0038-4038-2012.231.

Heckman, J. and Siegelman, P. (1993). The urban institute audit studies: Their methods and findings. In Fix, M. and Struyk, R. J., editors, *Clear and Convincing Evidence: Measurement of Discrimination in America*, pages 187–258. The Urban Institute Press, Washington, D.C.

Hoxby, C. M. and Turner, S. (2015). What high-achieving low-income students know about college. *American Economic Review*, 105(5):514–517.

Jaeger, D. A., Nunley, J. M., Seals Jr, R. A., Shandra, C., and Wilbrandt, E. J. (2023). The demand for interns. *Journal of Economic Behavior & Organization*, 209:372–390.

Johnson, R. W. and Neumark, D. (1996). Age discrimination, job separation, and employment status of older workers: Evidence from self-reports.

Kline, P., Rose, E. K., and Walters, C. R. (2022). Systemic discrimination among large us employers. *The Quarterly Journal of Economics*, 137(4):1963–2036.

Kline, P., Rose, E. K., and Walters, C. R. (2024). A discrimination report card. *American Economic Review*, 114(8):2472–2525.

Lahey, J. and Barlow, M. R. (2018). What Race Is Lacey? Intersecting Perceptions of Racial Minority Status and Social Class. *Social Science Quarterly*, 99(5):1680–1698. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/ssqu.12529.

Lahey, J. and Beasley, R. (2018). Technical Aspects of Correspondence Studies. In Gaddis, S. M., editor, *Audit Studies: Behind the Scenes with Theory, Method, and Nuance*, pages 81–101. Springer International Publishing, Cham.

Lahey, J. and Beasley, R. (2024). Correspondence Audit Studies in Public Administration: A systematic review with commentary. *Journal of Behavioral Public Administration*, 7.

Lahey, J. N., Weaver, A. J., and Oxley, D. R. (2023). Do future public servants have more anti-discriminatory behavior? *International Public Management Journal*, 26(1):87–106. Publisher: Routledge _eprint: https://doi.org/10.1080/10967494.2022.2075995.

Larsen, E. N. (2020). Induced competition in matched correspondence tests: Conceptual and methodological considerations. *Research in Social Stratification and Mobility*, 65.

List, J. A. (2004). The nature and extent of discrimination in the marketplace: Evidence from the field. *The Quarterly Journal of Economics*, 119(1):49–89.

NCES (2022). Fall 2022 undergraduate applications. https://nces.ed.gov/ipeds/TrendGenerator/app/answer/10/101. Accessed: March 6, 2023.

Neumark, D. (2012). Detecting discrimination in audit and correspondence studies. *Journal of Human Resources*, 47(4):1128–1157.

Neumark, D., Burn, I., and Button, P. (2016). Experimental age discrimination evidence and the heckman critique. *American Economic Review*, 106(5):303–308.

Neumark, D., Burn, I., and Button, P. (2019). Is it harder for older workers to find jobs? new and improved evidence from a field experiment. *Journal of Political Economy*, 127(2):922–970.

Neumark, D. and McLennan, M. (1995). Sex discrimination and women's labor market outcomes. *Journal of Human Resources*, pages 713–740.

Nunley, J. M., Owens, M. F., and Howard, R. S. (2011). The effects of information and competition on racial discrimination: Evidence from a field experiment. *Journal of Economic Behavior & Organization*, 80(3):670–679.

Odle, T. and Delaney, J. (2023). Experimental evidence on "direct admissions" from four states: Impacts on college application and enrollment. *EdWorkingPaper*, August(23-834). Retrieved from Annenberg Institute at Brown University.

Oreopoulos, P. (2011). Why do skilled immigrants struggle in the labor market? a field experiment with thirteen thousand resumes. *American Economic Journal: Economic Policy*, 3(4):148–171.

Pager, D. (2003). The mark of a criminal record. *American Journal of Sociology*, 108(5):937–975.

Pager, D., Bonikowski, B., and Western, B. (2009). Discrimination in a low-wage labor market: A field experiment. *American Sociological Review*, 74(5):777–799.

Schmalense, R. (1981). Monopolistic two-part pricing arrangements. *The Bell Journal of Economics*, pages 445–466.

Shapiro, A. H., Sudhof, M., and Wilson, D. J. (2022). Measuring news sentiment. *Journal of Econometrics*, 228:221–243. Available online 24 November 2020.

Strayhorn, T. L. (2018). *College students' sense of belonging: A key to educational success for all students*. Routledge.

Supreme Court of the United States (1978). Regents of the university of california v. bakke. Justia US Supreme Court Center. 438 U.S. 265.

Supreme Court of the United States (2003a). Gratz v. bollinger. Justia US Supreme Court Center. 539 U.S. 244.

Supreme Court of the United States (2003b). Grutter v. bollinger. Oyez. Case No. 02-241.

Supreme Court of the United States (2013). Fisher v. university of texas at austin. Oyez. Case No. 11-345.

Supreme Court of the United States (2016). Fisher v. university of texas at austin. Oyez. Case No. 14-981.

Supreme Court of the United States (2023). Students for fair admissions, inc. v. president & fellows of harvard college (harvard corporation). Supreme Court of the United States. No. 20-1199.

U.S. News & World Report (2023). How to apply to college for free. https://www.usnews.com/education/best-colleges/articles/how-to-apply-to-college-for-free#:~:text=an%20application%20fee.-,Get%20a%20Waiver%20From%20a%20High%20School%20Counselor,through%20their%20high%20school%20counselors.

Vuolo, M., Uggen, C., and Lageson, S. (2018). To Match or Not to Match? Statistical and Substantive Considerations in Audit Design and Analysis. In Gaddis, S. M., editor, *Audit Studies: Behind the Scenes with Theory, Method, and Nuance*, pages 119–140. Springer International Publishing.

Zussman, A. (2013). Ethnic discrimination: Lessons from the israeli online market for used cars. *The Economic Journal*, 123(572):F433–F468.

# A Appendix

## A.1 Survey of Admissions Counselors

### A.1.1 Background

To explore the college admissions process further, we disseminated an anonymous survey to all admissions counselors from our email sample.[27] We sought to shed light on two key questions: How prevalent are application fees and application fee waivers? And does race affect counselors' decisions regarding these waivers?

### A.1.2 Results

We received 148 responses. The core results are conveyed in Table A.1. The minority of respondents (41.2 percent) indicated that their institution normally charges an application fee. Nearly all counselors reported receiving a substantial number of waiver requests, suggesting that requests for application fee waivers at universities that have fees are common. Moreover, it is important to note that most of the responses to our survey came from counselors at lower-ranking institutions; the number of requests at high-ranking universities may be much higher than the numbers we found among the respondents to our survey. On average, counselors received about 84 requests for waivers and reported granting about the same number. Note that each university has many counselors, meaning that each university likely receives far more requests for fee waivers than the number indicated by individual counselors.

Table A.1: Summary of Key Survey Response Statistics

| Variable | Obs | Mean | Std. Dev. |
|---|---|---|---|
| Charge Application Fee (Yes) | 148 | 0.412 | 0.494 |
| ***From counselors at application fee-charging schools*** | | | |
| Number of Waiver Requests | 40 | 83.675 | 142.210 |
| Number of Waivers Granted | 29 | 83.448 | 132.719 |
| Waivers Granted/Waivers Requests | 27 | 0.813 | 0.261 |

*Notes:* Summary of responses from counselors at fee-charging schools, excluding two who claimed to grant more waivers than requested. Table A.6 provides summary statistics including these outliers.

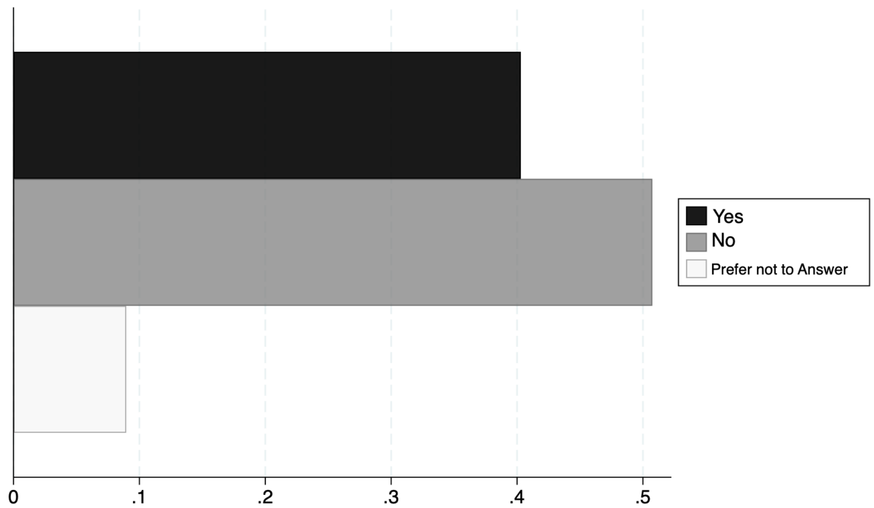
To assess whether students' race affects counselors' waiver-granting decisions, the survey contained the following question: "Does the desire to promote a diverse student body influence your personal decision to grant fee waivers?"[28] The responses, displayed in Figure A.1 and depicted in

[27] As an incentive to participate, we included respondents in a random draw where the winner was selected for a $200 gift card.

[28] Although diversity can be interpreted in many ways, in the context of college admissions the term has historically connoted *racial* diversity.

Table A.2, suggest that applicants' race factors into counselors' discretionary choice to approve or reject application fee waivers. Specifically, approximately 40 percent of admissions counselors reported that they consider diversity factors (and thus likely racial characteristics) when deciding whether to grant application fee waivers.

Figure A.1: Does the Desire to Promote a Diverse Student Body Affect Your Personal Decision to Grant Fee Waivers?




*Notes:* Results show diversity's impact on counselors' waiver decisions, including undisclosed responses ('Prefer not to answer'), but exclude those granting excess waivers.

Table A.2: Does the desire to promote a diverse student body affect your personal decision?

| Diversity | Frequency | Percentage |
|---|---|---|
| Yes | 27 | 40.30% |
| No | 34 | 50.75% |
| Prefer not to answer | 6 | 8.96% |

*Notes*: Percentage of admissions counselors' responses on whether they consider or do not consider diversity when granting application fee waivers.

## A.2 Email Templates

**Email Template - Low Quality Applicant - 1**

[Subject: Waiver Request]

Hello,

I'm emailing you about applying to your university. I will be graduating from High School next spring, and I'm really excited about attending college.

But here's the thing, money is very tight for me and my family right now, and I can't afford the application fee. So, I was wondering if there's any way you could help me out with a fee waiver?

Your university is one of the top places where I wanna be. I am working hard in high school, giving it my all.

Best,

[Full Name]

**Email Template - Low Quality Applicant - 2**

[Subject: Fee Waiver]

Hello,

I'm excited to apply to your university after I graduate next spring. I've been working very hard in high school, and your university is one of my top choices.

But I have a problem – that application fee is a hurdle for me right now. Is there any chance I can get a fee application waiver? Thanks a lot for taking the time to read my email.

Best,

[Full Name]

**Email Template - Low Quality Applicant -3**

[Subject: Application Fee]

Hi,

I hope you're doing well. I'm reaching out to chat about the possibility of getting a fee waiver for my application to your university. I'm excited about the idea of being part of it and pursuing my dreams there.

Unfortunately, money's very limited for me and my family right now. Is there any chance you could help me out with a fee waiver? It'd make a huge difference.

I'm all about the power of education and have put in the effort to keep my grades up and be involved in many important activities outside of class. Thanks for thinking about it. I really appreciate your time, and I'm eagerly waiting to hear from you.

Take care,

[Full Name]

**Email Template - Low Quality Applicant - 4**

[Subject: Financial Need for Waiver]

Hi,

I'm emailing you to talk about getting a waiver on the application fee for your university. I'm super happy about the idea of joining it.

Honestly, I don't have money right now. Things have been very tough financially for my family. Do you think there's any chance you could give me with a fee waiver to apply there? It would mean the world to me.

This means a lot to me, and I can't wait to hear from you.

Sincerely,

[Your Name]

**Email Template - High Quality Applicant- 1**

[Subject: Request for Application Fee Waiver]

Hello,

I hope this email finds you well. I am writing to express my strong interest in applying to your university and to inquire about the possibility of obtaining an application fee waiver. I am thrilled at the prospect of joining the vibrant community there and pursuing my academic aspirations.

However, I wanted to bring to your attention that I am currently facing financial constraints that pose a challenge in covering the application fee. Considering my circumstances, I kindly request your consideration for a fee waiver, which would greatly assist me in navigating the application process.

I firmly believe in the transformative power of education, and I am dedicated to making the most of the opportunity to study there. I have demonstrated a strong commitment to my studies and actively engaged in various extracurricular activities, which have fostered my personal and intellectual growth.

I fully understand the significance of application fees in supporting the university's operations. However, I sincerely hope that you can make an exception in light of my current financial situation. If granted a fee waiver, I assure you that I will approach my studies with utmost dedication and actively contribute to the campus community.

Thank you for considering my request. I genuinely appreciate your attention to this matter.

Best regards,

[Full Name]

**Email Template - High Quality Applicant-2**

[Subject: Help with Application Fee]

Dear [Admissions Counselor's Name or Admissions in general],

I hope this email finds you well. I'm writing to request an application fee waiver for my application to your university. I'm really excited about the prospect of studying at your institution.

Currently, I'm facing financial constraints that make the application fee a challenge. I kindly ask for your consideration in granting a fee waiver to ease this financial burden.

I strongly believe in the power of education and have a track record of maintaining high academics and participating in extracurricular activities. I believe I have much to contribute to your institution If I have the opportunity to apply.

Thank you for your time and attention to my request. I truly appreciate it.

Best regards,

[Full Name]

**Email Template - High Quality Applicant-3**

[Subject: Need for Fee Waiver]

Hello,

I hope you are doing well. I am reaching out to discuss the possibility of securing an application fee waiver for my application to your university. I am genuinely enthusiastic about the prospect of joining your institution.

My family and I are facing some financial challenges at the moment that make managing the application fee very difficult. I am requesting your consideration for a fee waiver to ease this financial strain.

I wholeheartedly believe in the value of education and have consistently maintained strong academic performance and active involvement in extracurricular activities.

I am writing to express my sincere gratitude for your time and attention to my request. I eagerly await your response. Thank you so much.

Best regards,

[Full Name]

**Email Template - High Quality Applicant-4**

[Subject: Need-Base Request for Waiver]

Hello,

I trust this email finds you well. I am contacting you to discuss the possibility of securing an application fee waiver for my application to your university. I am genuinely thrilled about the idea of joining your institution.

But unfortunately, I currently need financial help to cover the application fee. I kindly request your consideration in granting a fee waiver to ease this financial burden my family and I are facing.

I wholeheartedly believe in the transformative power of education and have consistently maintained strong academic performance.

I appreciate your time considering my request and eagerly await for your response.

Best regards,

[Full Name]

## A.3 Tables and Figures

Table A.3: Descriptive Statistics of Main Outcomes

| | Effective Rejection | | Gave Waiver | | Application Free | | Need More Info | | |
|---|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Mean | SD | Mean | SD | *Obs.* |
| Asian | 0.407 | 0.491 | 0.099 | 0.299 | 0.302 | 0.459 | 0.302 | 0.459 | 895 |
| Asian / first name White | 0.388 | 0.487 | 0.122 | 0.328 | 0.302 | 0.460 | 0.302 | 0.460 | 939 |
| Black | 0.451 | 0.498 | 0.124 | 0.330 | 0.278 | 0.448 | 0.278 | 0.448 | 940 |
| Hispanic | 0.347 | 0.476 | 0.127 | 0.334 | 0.340 | 0.474 | 0.340 | 0.474 | 942 |
| White | 0.338 | 0.473 | 0.135 | 0.342 | 0.321 | 0.467 | 0.321 | 0.467 | 942 |

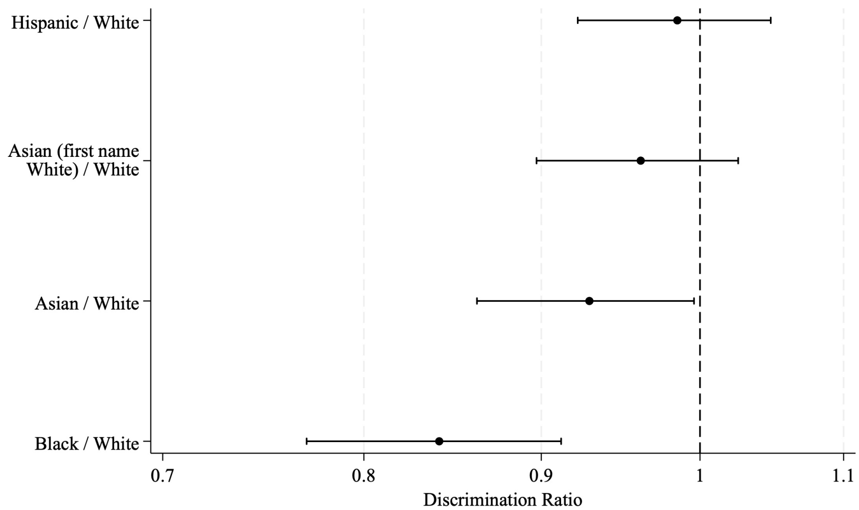
*Notes*: Descriptive statistics, including the mean and standard deviation (SD), for each of our primary outcomes, categorized by the applicant's race/ethnicity.

Table A.4: Effects of Race/Ethnicity on Counselor Response

| | Probit | | OLS | |
|---|---|---|---|---|
| | Baseline | With university controls | Baseline | With university controls |
| | (1) | (2) | (3) | (4) |
| Asian | -0.050** | -0.050** | -0.048** | -0048** |
| | (0.023) | (0.023) | (0.023) | (0.023) |
| Asian/first name White | -0.027 | -0.025 | -0.026 | -0.024 |
| | (0.022) | (0.022) | (0.022) | (0.022) |
| Black | -0.107*** | -0.107*** | -0.108*** | -0.107*** |
| | (0.024) | (0.023) | (0.024) | (0.024) |
| Hispanic | -0.011 | -0.009 | -0.010 | -0.008 |
| | (0.023) | (0.023) | (0.023) | (0.023) |
| N | 4,658 | 4,658 | 4,658 | 4,658 |

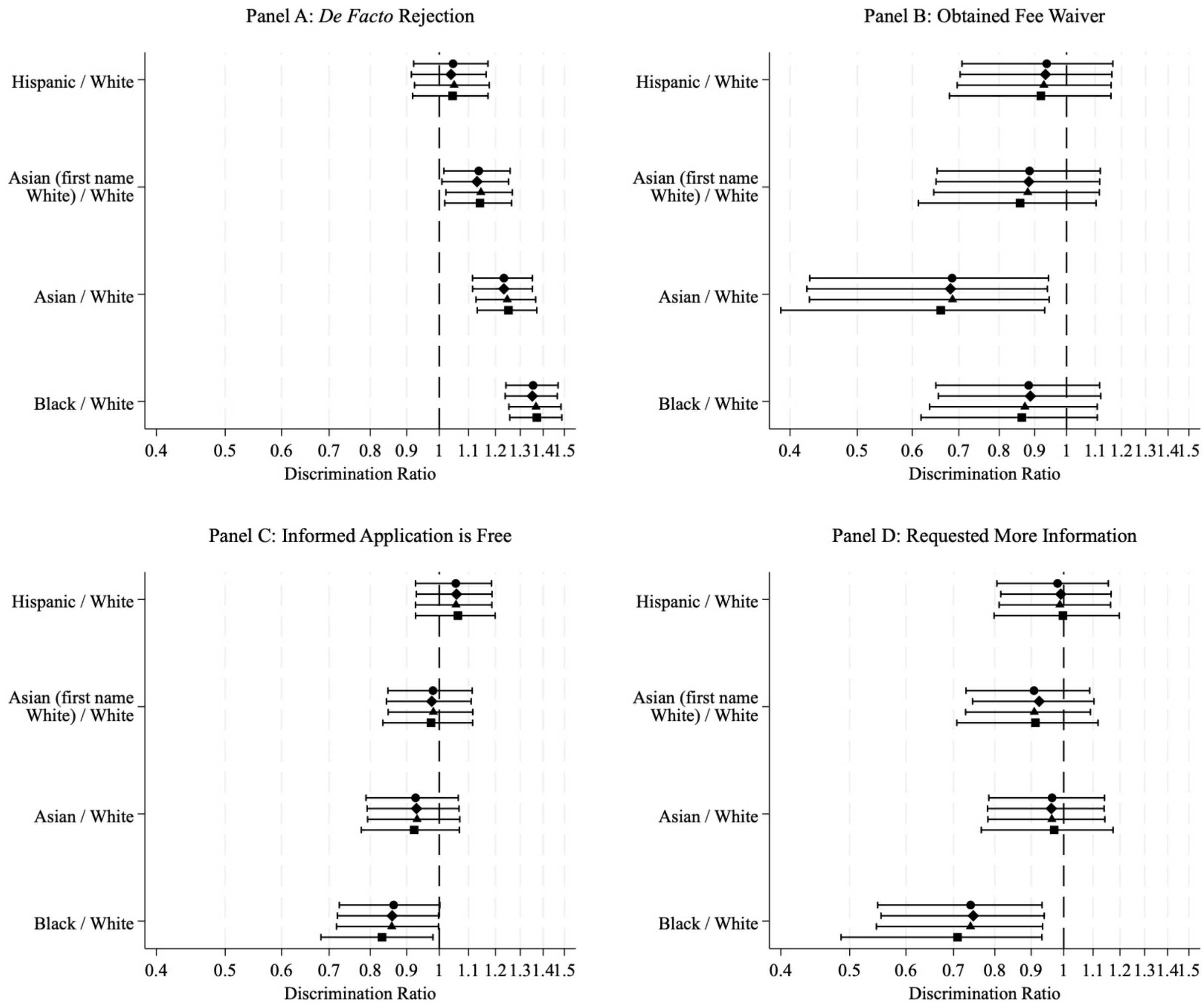
*Notes*: Analysis of admissions counselors' response rates to student emails, showing variations by racial/ethnic background. Specifications used are probit and linear probability models with university-specific controls including institution type, size, selectivity, and location. The specifications also consider baseline factors like email format, dispatch timing, and email domain. The results indicate statistically significant lower response rates for Asian and Black applicants compared to White applicants. Coefficients represent average marginal effects. White is the omitted category. The baseline specification (columns (1) and (3)) controls for the message template used, the day of the week the email was sent, the month of the year (October or November) the email was sent, and the domain (Gmail, Hotmail, Outlook, Yahoo!) of the student's email address. In columns (2) and (4), we augment our baseline model with controls for characteristics of universities (private/public, size, selectivity, Census region, and rural/suburban/urban). Bootstrapped standard errors (10,000 repetitions) are reported in parentheses. $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Figure A.2: Discrimination Ratios for Counselor Response




*Notes:* Figure A.2 displays discrimination ratios derived from principal linear probability models (see Table A.4). Error bars indicate 95 percent confidence intervals. The analysis reveals significant differential treatment against Asian and Black students, with Black students facing the highest levels of discrimination.

Figure A.3: Discrimination Ratios from All Models




*Notes:* The four models for the main outcomes display the discrimination ratios. Error bars indicate 95 percent confidence intervals. Circles represent the baseline OLS specification, diamonds the OLS with university controls, triangles the baseline probit, and squares the probit with university controls. The nearly identical results across all models confirm the success of our randomization protocol.

Table A.5: Email addresses assigned to fictitious applicants

| White | Chinese | White/Asian | Hispanic | Black |
|---|---|---|---|---|
| thomaswagner961@gmail.com | maozhang008@gmail.com | codyzhang30@gmail.com | juliop.fyi2004@gmail.com | daquan.jeff1805@gmail.com |
| richardhoffman1000@outlook.com | jinchengat02@gmail.com | changdouglas04@gmail.com | martinezz0905@gmail.com | banksdarnell0107@gmail.com |
| dhansen_2005@outlook.com | pengchen493@gmail.com | dylanchen48@gmail.com | ale.ramirezjjj@gmail.com | denzelbooker.23@gmail.com |
| zmeyer123@outlook.com | wei_li10@outlook.com | jacobli12@outlook.com | hgonzales47@outlook.com | jamalsingleton1@outlook.com |
| hunter_mcgrath@hotmail.com | jian.liu04@yahoo.com | liujohn17@outlook.com | miguelopez52@outlook.com | keyshawnjackson12@outlook.com |
| loganbecker120@gmail.com | lixinyang10@hotmail.com | nichyang12@outlook.com | salvadoramirez12@hotmail.com | deandremack90@hotmail.com |
| ryanderson079@gmail.com | qwang2003@outlook.com | scottwang12@outlook.com | juan_torres_2006@outlook.com | tironerivers@outlook.com |
| matlarsen1@yahoo.com | hzhao120@outlook.com | stephenzhao123@hotmail.com | pedro_hernandez2006@outlook.com | lamarwashington2@outlook.com |

*Notes*: The division of email addresses by ethnicity corresponds to the order presented in Table 1.

Table A.6: Summary Statistics for Requests and Waivers Including Outliers

| Variable | Observations | Mean | Median | Std. Dev. | Min-Max |
|---|---|---|---|---|---|
| Non-Zero Requests | 42 | 80.7619 | 25 | 139.3241 | 1 - 700 |
| Non-Zero Waivers | 31 | 84.51613 | 25 | 128.2853 | 2 - 500 |
| Ratio Waivers Approved | 29 | 1.06757 | 1 | 0.9924293 | 0.1 - 5 |

*Notes*: Summary of responses from counselors at fee-charging schools, including the two counselors who claimed to grant more waivers than requested

## A.4 Proofs

In the last stage of any SPNE, the agent takes $x^p$ and $s$ as given and chooses $x^{a*}$ to satisfy the FOC

$$\alpha^a b_1^a(x^{a*},x^p) - sc_1^a(x^{a*},x^p) = 0, \tag{3}$$

the solution of which runs continuously from $\beta^a$ (which maximizes the first term) to $x^p$ (which maximizes the second term) as $s$ runs from 0 to $\infty$. The principal, thus, can implement any $x^a$ he desires between these two points by setting

$$s(x_a,x_p) = \frac{\alpha^a b_1^a(x^a,x^p)}{c_1^a(x^a,x^p)}, \tag{4}$$

which increases as from zero to infinity as $x^a$ moves away from $\beta^a$ and towards $x^p$ .

Backing up to the Principal's choice in the first stage, we can substitute for this cost, yielding an objective function

$$v(\pi(x^a,x^p) - \gamma c^p(\frac{\alpha^a b_1^a(x^a,x^p)}{c_1^a(x^a,x^p)}) + F) + \alpha^p b^p(x^a,x^p),$$

where the principal can freely choose any $(x^a,x^p)$ combination where $x^a$ is between $\beta^a$ and $x^p$. Under our assumptions on the functional forms, this objective function in concave with a unique maximum $(x^{a**},x^{p^**})$, and so there is a unique SPNE of the game with the principal's strategy given by $x^{p*} = x^{p**}$, $s^* = s(x^{a**},x^{p**})$, and the agent's strategy in each $(x_p,s)$ sub-game is given by the $x^{a*}(x^p,s)$ satisfying the FOC in equation 3.

It is difficult to characterize these choices in general, but for the three cases presented in the propositions, it is relateively simple.

- $\alpha^P = \alpha^A = 0$: Under these conditions, working through reverse induction, $x^{a*}(x^p,s) = x^p$ for all $(x^p,s)$ with $s > 0$, since that choice minimizes $c_1^a$. For $s = 0$, all $x^a$ deliver the same payoff so all are feasible. Backing up to the principal's choice, the principal's global maximum payoff occurs when $x^a = x^b = 0$ which is feasible for all $s \geq 0$, and dominants any other policy choice for arbitrarily small $s$, so $x^a = \beta$ and $s = 0$ is the unique equilibrium choice.
- $\alpha^a = 0$ and $\alpha^P > 0$: The analysis of the agent's behavior in all the subgames is identical to the case above, and similar to that case the principal can induce the agent to match whatever policy it chooses at $s = 0$. Taking the agent's conformity into account, we can rewrite the principal's FOC as

  $$v'(\pi(x) + F)\pi'(x) + \alpha^p b_1^p(x) = 0, \tag{5}$$

  where $\pi(x) \equiv \pi(x,x)$ and $b^p(x) \equiv b^p(x,x)$. With strictly concave $v(\pi(x) + F)$, maximized at $x = 0$, and strictly concave $\alpha^p \beta^p(x)$, maximized at $\beta^p$, the optimal point must lie in between those two points. As $F$ increases, the $v'(\pi(x) + F)$ decreases, leading to a increase in the optimal $x$. As $\alpha^P$ increases $\alpha^A p'(x)$ increases, leading to an increase in the optimal $x$.
- $\alpha^a > 0$ and $\alpha^P = 0$: In this case, the principal will need to engage in supervision to induce the agent to choose any option other that $\beta^a$. But with $\alpha^p = 0$, the principal's objective function simplifies down to the terms inside the $v(\cdot)$. Specifically, his problem is

$$\max_{x_a,x_p} \pi(x^a,x^p) - \gamma c^p(s^*(x_a,x_p)), \tag{6}$$

which yields a system of FOCs:

$$x_a : \pi_1(x^a,x^p) - \gamma c_1^p(s^*(x_a,x_p))s_1^*(x_a,x_p) = 0 \tag{7}$$

$$x_p : \pi_2(x^a,x^p) - \gamma c_1^p(s^*(x_a,x_p))s_2^*(x_a,x_p) = 0 \tag{8}$$

To illustrate the solution to this problem, consider first the option of setting $x_p \approx x_a \approx 0$. At that point, the first term of the LHS of both conditions is close to zero, since profit is concave and maximized at $(0,0)$. But the supervisory effort required to induce $x_a \approx x_p$ is very large, and so $c_1^p$ is also large. Finally $s_1^*$ and $s_2^*$ have opposite signs, depending on whether $x_a > x_p$ or vice-versa. If $x_p < x_a < \beta^a$ (probably the natural case), then $s_1^* < 0$ since increasing $x_a$ decreases the numerator and increases the denominator in 4. Similarly, $s_2^* > 0$, since increases $x_P$ decreases the denominator in 4. So, this suggests that if $\beta^A > 0$, the optimal choice involves $x_p < 0 < x_a$, while if $\beta^A < 0$ the policy positions are reversed.
To formalize, consider the case where $\beta^A > 0$. We show that the equilibrium must include $x_p < 0 < x_a$. First, the supervisor can only induce an $x_a$ between $x_p$ and $\beta^p$. He would never want to induce $x_a > \beta^a$, because he could always implement $x^p = 0$ and $x^a = \beta^a$ with zero supervision. Similarly, he would never want to choose $x_p < x_a < 0$, because he $x_a = 0$ (a better input for profit) at lower supervision cost. Finally, he would not want to choose $0 < x_p < x_a < \beta^A$, since lowering $x_p$ toward zero would improve profits and decrease supervision costs. Finally, he would never want to choose $0 = x_p < x_a$ (or $x_p < 0 = x_a$), since lowering $x_p$ (raising $x_a$) would save first-order supervision costs but only reduce profits by second-order. Thus, by exclusions, the only possibility is to choose $x_p^* < 0 < x_a^*$. The case for $\beta^a < 0$ is identical.
Finally, consider comparative statics, sticking with the $\beta^a > 0$ case. Obviously, none of these trade-offs are affected by $F$. Increasing $\alpha^A$, $\beta^A$, or $\gamma$ raises the supervision costs, increasing the second term of both FOCs, leading to $x_a$ further above 0 and $x_p$ further below it.