What the Students for Fair Admissions Cases Reveal About Racial Preferences*

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Abstract

Using detailed admissions data made public in the *SFFA v. Harvard* and *SFFA v. UNC* cases, we examine how racial preferences for under-represented minorities (URMs) affect their admissions to Harvard and UNC-Chapel Hill. At Harvard, the admit rates for typical African American applicants are on average over four times larger than if they had been treated as white. For typical Hispanic applicants the increase is 2.4 times. At UNC, preferences vary substantially by whether the applicant is in-state or out-of-state. For in-state applicants, racial preferences result in an over 70% increase in the African American admit rate. For out-of-state applicants, the increase is more than tenfold. Both universities provide larger racial preferences to URMs from higher socioeconomic backgrounds.

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1 Introduction

The debate over affirmative action in the United States has been going on for decades, in part because it is difficult to evaluate the impact of a policy when its features and implementation are opaque. Data on admissions—particularly at elite universities—is tightly guarded, making it challenging to identify both the students who benefit from racial preferences and the importance of race in admissions decisions. Existing empirical studies of the impact of racial preferences on minority admissions in the U.S. provide an incomplete picture as the models cannot account for key components of the students' applications.[1]

In this paper, we use data and analyses made public in the *SFFA v. Harvard* and *SFFA v. UNC* lawsuits to measure how racial preferences impact admissions, where racial preferences operate in the admissions process, and the heterogeneity in how they operate. We contribute to the literature in multiple ways. First, we use exceptionally detailed applicant-level data, allowing us to more accurately estimate the role of race in admissions decisions. Second, we bring together information on Harvard and UNC to show how affirmative action is practiced in different contexts and to provide deeper insight into the admissions strategies uncovered in the publicly available documents.[2] Finally, we estimate the impact of affirmative action in a more recent period that is characterized by increasingly competitive admissions at elite colleges and universities (Smith, 2018).

Our analysis is based on administrative data on domestic applicants to Harvard's Classes of 2014–2019 and to UNC's Classes of 2016–2021. The data span three levels of selectivity due to the way that out-of-state applicants are treated at UNC. Out-of-state admissions are much more competitive than in-state as UNC faces penalties if more than 18% of its enrollees are out-of-state. Including all domestic applicants, the admit rate is 51.9% for UNC in-state, 16.6% for UNC out-of-state, and 6.7% for Harvard. Both sets of data track

[1] See Bowen and Bok (2000); Espenshade, Chung, and Walling (2004); Long (2004); Arcidiacono (2005); Espenshade and Chung (2005) and Antonovics and Backes (2014).

[2] While our models of Harvard admissions appear elsewhere in the academic literature, those studies did not focus on URM admissions advantages, nor did they use any data from UNC. Our prior academic work has studied the preferences given to legacies and athletes at Harvard (Arcidiacono, Kinsler, and Ransom, 2022c) and how these preferences have changed over time (Arcidiacono, Kinsler, and Ransom, 2022b), as well as whether Harvard discriminates against Asian Americans compared to whites (Arcidiacono, Kinsler, and Ransom, 2022a) and how it recruits applicants differentially based on race (Arcidiacono, Kinsler, and Ransom, 2022d).

measures of socioeconomic background, test scores and grades, as well as each university's internal ratings of the applicants.

The richness of the applicant data enables us to create highly accurate admissions models at both schools. Our models of Harvard admissions follow the ones used in Arcidiacono, Kinsler, and Ransom (2022a,c), but we now focus on the implications for URMs. For Harvard, we primarily focus on models that remove applicants who are athletes, legacies, connections of donors, and children of faculty and staff (ALDC) as including these applicants distorts the importance of factors such as academics for non-ALDC applicants.[3] The models of UNC admissions decisions take a similar approach, but distinguish between in-state and out-of-state applicants.[4]

We rely on a selection-on-observables approach to identify the role race plays in the admissions processes at each of the schools. The key assumption is that, after accounting for an extensive set of applicant observables, the remaining unobservables affecting admissions are orthogonal to race. To the extent that this assumption is violated, we are likely underestimating the impact of racial preferences. African American and Hispanic applicants to Harvard and UNC have observables that are associated with substantially lower admissions rates than their non-URM counterparts. A standard assumption in the economics literature (Altonji, Elder, and Taber, 2005; Oster, 2019) is that selection on the observables goes in the same direction as selection on the unobservables. This assumption is reasonable in our context since schools typically recruit African Americans and Hispanics more aggressively than whites and Asian Americans (Arcidiacono, Kinsler, and Ransom, 2022d). Aggressive recruiting would imply that not only are the observables of URM applicants weaker on average, but that, conditional on observed attributes, the unobserved attributes of African Americans and Hispanics will also tend to be worse.

Estimates of the admissions models show similar qualitative patterns in how racial preferences operate for UNC in-state, UNC out-of-state, and Harvard. In all three cases, large admissions advantages exist for Hispanics, with even stronger preferences for African Amer-

[3]See Arcidiacono, Kinsler, and Ransom (2022a, pp. 152–153) for a detailed discussion of how the inclusion of ALDC applicants affects the model estimates.

[4]Like in the Harvard models, a subset of applicants are removed for whom the admissions process appears to be different. These applicants are virtually guaranteed admission and include groups like recruited athletes. See Document 160-1 Section 2.2.1.

icans. But while the broad patterns are similar, the impact of racial preferences is substantially different across the three pools. Consider first Harvard and UNC in-state admissions for African Americans. The average marginal effect of race for African Americans (relative to white applicants) is lower at Harvard than for UNC in-state: 7.29 versus 12.7 percentage points. While these findings seem to suggest that racial preferences are more impactful for in-state UNC admissions, this is misleading since the overall admit rate is so much lower at Harvard. In the absence of racial preferences, African American applicants to Harvard and UNC in-state would be admitted at rates of 2.25% and 17.8%, respectively. Thus, the 7.29 percentage-point marginal effect at Harvard results in a quadrupling of the African American admit rate, while the 12.7 percentage point increase at UNC in-state increases the African American admit rate by a factor of 1.7.

UNC uses much larger racial preferences in its out-of-state admissions process, regardless of whether we examine average marginal effects or the implied percent changes in admit rates. The average marginal effect of race for out-of-state African Americans is 15.6 percentage points which corresponds to an admit rate without racial preferences of 1.5%. Hence, racial preferences in UNC out-of-state admissions increase the African American admit rate more than tenfold.[5]

The average marginal effects of race measure how the removal of racial preferences affects individual applicants assuming the standards Harvard and UNC use for admission remain unchanged for remaining applicants. However, these effects will overstate the changes in racial composition if Harvard and UNC did not consider race since, if no other adjustment is made, too few applicants would be admitted. Thus, we also consider how racial preferences affect the racial distribution of admits holding fixed the total number of admits in each pool. Treating all applicants as white (thereby removing racial preferences) and solving for the new distribution of admits results in substantial changes in the racial composition of admits. Our estimates imply that removing racial preferences—while holding fixed all other preferences, the applicant pool, and the total number of admits—would lower the share of admits who were African Americans to less than 5% at Harvard, less than 2% at out-of-state

[5]The same patterns hold for Hispanics across the three pools, though the preferences are smaller. Namely, the average marginal effect of race for Hispanic out-of-state UNC applicants (relative to white out-of-state applicants) is 14.2 percentage points which corresponds to an admit rate without racial preferences of 6.0%.

UNC, and 5.6% at in-state UNC. The observed admit shares in each of these pools are 15.5%, 11.2%, and 8.7%, respectively. This alternative method of measuring the impact of race also indicates that preferences are largest in the out-of-state admissions process at UNC.

There are at least two reasons why racial preferences are particularly large for out-of-state African American applicants to UNC. First is a cascading effect. Because racial preferences are so strong at the top schools, out-of-state African American students who otherwise would have applied to UNC do not do so because they have better options.[6] Second, despite larger out-of-state preferences, admitted out-of-state African Americans and Hispanics still have stronger credentials than in-state applicants because admission is much more competitive out-of-state. As a result, out-of-state African Americans will be better situated to handle UNC coursework than their in-state counterparts. Thus, if UNC values both racial diversity and academic fit it is natural to provide stronger preferences for out-of-state applicants.

We also document that both institutions give smaller racial preferences to URM applicants from disadvantaged socioeconomic backgrounds.[7] The ability to compete in the classroom and ultimately graduate may partly explain this behavior. In all three pools, the estimated gap in admissions probabilities between advantaged white and advantaged African American (Hispanic) applicants is significantly larger than the gap in admissions probabilities between disadvantaged white and disadvantaged African American (Hispanic) applicants, all else equal. The differences in the racial gaps across socioeconomic status indicate that disadvantaged URM applicants benefit from affirmative action, but do not receive any additional admissions premium associated with being disadvantaged.[8] As the preferences for URM applicants are very large, giving additional preferences based on disadvantaged status may

[6] Among the three pools, the share of applicants who are African American is smallest for the UNC out-of-state pool. This cascading effect results in a U-shaped relationship between college quality and African American representation (Figure 1 in Arcidiacono, Khan, and Vigdor, 2011).

[7] At Harvard, admissions officers mark whether they believe the applicant comes from a modest family background, creating a disadvantaged flag in the data. At UNC, we use whether the applicant was first-generation college as our measure of disadvantage.

[8] At Harvard, this monolithic treatment of URM applicants extends beyond typical applicants. URM legacies get a legacy bump that is substantially smaller than the bump white legacies get. Similar bump reductions are seen for minorities with donor connections. See Table 3 of Arcidiacono, Kinsler, and Ransom (2022c). These patterns are also consistent with universities trying to satisfy diversity constraints on the basis of racial classifications alone. Both Harvard and UNC count students as “Black” if they are mixed-race, and Massey et al. (2007) has shown that Black immigrants or the children of Black immigrants make up as much as 40% of total Black enrollment at Ivy league schools.

result in low-income URM students being too far behind in the classroom and possibly not graduating. Additionally, advantaged URM students may be better prepared for the social environment at an elite university or can describe their racial experiences in a way that resonates better with admissions officers.

Our primary findings indicate that URM representation at Harvard and UNC would decline significantly if racial preferences were eliminated, everything else constant. We also show that if admissions had been based on test scores and grades alone, the reduction in URM representation would be even more dramatic.[9] The very low representation of URMs when admissions is based on academics alone illustrates the substantial racial disparities in educational experiences prior to college. Selective colleges seeking to have a student body that reflects the racial diversity of its applicant pool must necessarily factor race heavily into admissions decisions. But the result of these large racial preferences is that URMs typically arrive at college with significantly less academic preparation than their white and Asian American counterparts. This preparation gap in turn affects within-school sorting into majors (Arcidiacono, Aucejo, and Spenner, 2012; Bleemer and Mehta, 2021) and cross-racial friendships (Arcidiacono, Khan, and Vigdor, 2011; Arcidiacono et al., 2013). Affirmative action in college admissions remains controversial, but directly confronting the sizable preparation gaps across races would maintain racial diversity without relying on large racial preferences.[10]

2 Data and Admissions Processes

2.1 Data

Our analysis of Harvard and UNC admissions is based on anonymized applicant-level data provided by each of the defendants as part of the *SFFA v. Harvard* and *SFFA v. UNC*

[9] Many countries use test scores, sometimes coupled with grades, as their sole criteria for admission. Sometimes countries also give additional points based on geography, ethnicity, or socioeconomic status. These admissions formulas have been used in economic research by Ding and Lehrer (2007) in China, Hastings, Neilson, and Zimmerman (2014) in Chile, Riehl (2022) in Colombia, Kirkeboen, Leuven, and Mogstad (2016) in Norway, and Krishna, Lychagin, and Frisancho (2018) in Turkey.

[10] For example, work on No-Excuses charter schools has shown them to be effective in closing racial achievement gaps (Angrist, Pathak, and Walters, 2013; Dobbie and Fryer, 2013; Curto and Fryer, 2014; Fryer, 2014; Angrist et al., 2016).

lawsuits. For Harvard, we focus on data from 142,728 domestic, non-transfer applicants to the Classes of 2014–2019 who are not ALDC. For UNC, our data covers 57,225 in-state applicants and 105,632 domestic out-of-state applicants to the Classes of 2016–2021.[11]

The primary applicant-level data from each institution is exceptionally rich. Both datasets contain information on a variety of demographic and socioeconomic characteristics of the applicant, including the individual's self-reported race or ethnicity.[12] In addition to conventional data on high school grades and standardized test scores, each dataset contains extensive information on other applicant characteristics, as well as admissions officers' ratings of the applicant on academic and non-academic dimensions. Being able to observe these ratings is what separates the quality of our data from what has been used in existing work on this topic (Espenshade, Chung, and Walling, 2004; Antonovics and Backes, 2014; Arcidiacono, Aucejo, and Hotz, 2016; Hinrichs, 2020).[13]

It is important to note that we no longer have direct access to either of these datasets. Rather, we utilize various publicly available documents from the lawsuits—most notably the plaintiff's expert witness reports (Document 415-8 and Document 415-9 for Harvard, and Document 160-1; Document 160-2 and Document 160-3 for UNC)—but also other litigation documents such as depositions, trial transcripts and internal documents. These publicly available documents contain all the statistics and regression coefficients shown in the current paper. However, we present results as if they are original to ease the exposition.[14]

[11]We remove applicants from special recruiting categories—recruited athletes, recipients of prestigious scholarships, musicians, etc.—as well as those that were eventually withdrawn or had other coding errors. This amounts to about nine percent of all domestic applicants. See Appendix Table A1 for complete details.

[12]Due to self reporting, a small fraction of applicants (≈7% at Harvard and ≈5% at UNC) do not report a race or ethnicity. Throughout our analysis we treat these applicants as a separate racial group. Those who report multiple races or ethnicities are classified in the following order: African American if one of their responses is African American; Hispanic if one of their responses is Hispanic but none are African American; Asian American if one response is Asian American but no other response is African American or Hispanic; and white otherwise. In the Harvard analysis, we group together Hispanics with Native Americans and Hawaiian/Pacific Islanders.

[13]Harvard collects more detailed socioeconomic data and its officers rate applicants on a larger number of dimensions, so the Harvard data is generally richer than the UNC data.

[14]It should also be noted that the publicly available documents are not written for an academic audience nor have they been peer-reviewed outside of the other expert witnesses.

2.2 Admissions Processes

Both institutions employ a "holistic" admissions process that considers a wide array of applicant attributes and reviews each applicant on an individual basis in a supposedly non-formulaic way. Harvard and UNC acknowledge that race is one of the factors they consider.[15] Indeed, employing race holistically is a necessary condition for using race at all given the 2003 Supreme Court rulings in *Gratz v. Bollinger* and *Grutter v. Bollinger*. The takeaway from these rulings was that affirmative action is legal because of the educational benefits of diversity; however, it cannot be applied in a formulaic manner through quotas or points-based systems and its use must be "narrowly tailored" to the institution's goal of having a diverse student body.[16]

Although both institutions follow broadly similar "holistic" admissions strategies, their actual implementation differs in substantial ways.[17] The primary difference between the two institutions is the degree of scrutiny applied to each application. While each institution considers a wide variety of factors in its admissions process—including academics, extracurricular activities, and personal qualities—Harvard requires much more effort from both its applicants and admissions officers. In addition to high school grades and standardized test scores, both institutions rely on admissions officers to rate applicants in a number of dimensions. At UNC, applicants are rated in five different categories, while at Harvard there are nine ratings given by officers.

Table 1 provides an overview of how applications are scored at each institution. The table focuses on the subjective ratings assigned by admissions officers.[18] At UNC, the subjective ratings are meant to capture applicants' achievement in academics, extracurriculars and personal qualities. At Harvard, applicants are rated on these three dimensions in addition to athletics, high school teacher/counselor support, and performance on an interview with

[15] For Harvard see https://www.harvard.edu/admissionscase/admissions-process/. For UNC see https://admissionslawsuit.unc.edu.

[16] An open question is whether the current implementation of affirmative action is consistent with these rulings, with the Supreme Court expected to rule in the *SFFA v. Harvard* and *SFFA v. UNC* lawsuits sometime in 2023.

[17] See Document 415-8 and Document 160-1 for more detailed descriptions of the admissions processes at Harvard and UNC.

[18] Admissions decisions are also based on applicant demographics, high school grades and standardized test scores. During the time period of our data, both institutions required applicants to take either the SAT or ACT.

an alum. Harvard's high school support ratings are based on two separate letters from high school teachers and a letter from a guidance counselor. Harvard also gives an overall rating that shows how competitive the applicant is based on their characteristics as well as the preferences (e.g. racial, legacy, etc.) Harvard offers in the admissions process. Both Harvard and UNC have components of their application that are not directly scored but may affect the other ratings. At Harvard this includes application essays; at UNC this includes the one required letter of recommendation.

Table 1 shows that "holistic" admissions are defined differently across universities in part based on the resources available to review applications. The Harvard applicant data is richer than UNC's both in terms of the ratings in Table 1 but also on other measures of the applicant's background. As a result, our models of Harvard admissions include many more controls than our models of UNC admissions.

3 Descriptive Analysis

This section illuminates descriptive patterns relating race, socioeconomic status, academic and non-academic preparation, and admissions. These descriptive patterns motivate our modeling choices in Section 4. We consider three separate domestic applicant pools throughout the paper: typical (non-ALDC) applicants to Harvard, out-of-state applicants to UNC, and in-state applicants to UNC. Throughout the paper, we present results across pools in decreasing order of selectivity.

3.1 Racial Composition and Aggregate Admit Rates by Applicant Pool

Table 2 shows the racial representation among applicants and admits of each pool, as well as aggregate admit rates by race and pool.[19] Harvard's applicant pool, which draws significantly from all regions of the United States, has larger shares of Asian American and Hispanic applicants than the two UNC pools.

[19]The numbers for whites and Asian Americans at Harvard were previously reported in Arcidiacono, Kinsler, and Ransom (2022a).

The third column for each school in Table 2 shows admit rates, both overall and by race. The overall admit rate at Harvard (5.45%) is less than half that of out-of-state UNC (13.52%) which is in turn less than one-third that of in-state UNC (47.92%).[20] Within the pools, some striking patterns emerge. For in-state UNC applicants, Asian Americans have the highest admit rates, followed by whites, Hispanics and African Americans. For out-of-state UNC and Harvard applicants, whites have the lowest admit rates, followed by Asian Americans. African Americans at Harvard have the highest overall admit rate (7.58%, 55% higher than whites) while out-of-state Hispanics at UNC have the highest (20.18%, 85% higher than whites). These descriptive trends point to substantial heterogeneity in terms of how a university's selectivity and racial preferences might interact.

3.2 Race and Socioeconomic Status (SES)

We now document how gender and socioeconomic characteristics interact with race and admission. Table 3 presents demographic characteristics of each applicant pool by race, conditional on the admission outcome. We measure socioeconomic status in three ways: (*i*) an economically disadvantaged flag assigned by Harvard officers;[21] (*ii*) whether the applicant is in the first generation of their family to attend college; and (*iii*) whether the applicant applied for an application fee waiver.

Looking first at the applicant columns, African Americans are most likely to be labeled disadvantaged followed by Hispanics, Asian Americans, and whites. The same ordering holds across all pools in the rates of applying for a fee waiver and first generation college status, though in the latter case Hispanics sometimes have higher rates than African Americans. Note that the selectivity of a pool changes in tandem with its socioeconomic status; for example, 13.9% of African American applicants to Harvard are first-generation compared to

[20]These numbers are lower than what was reported in the Introduction because of the removal of ALDC applicants (Harvard) and those from recruiting categories that were essentially automatically admitted (UNC). See Appendix Table A1 for complete details.

[21]The disadvantaged indicator refers to the officer's opinion as to whether the applicant comes from "a very modest economic background" (Trial Exhibit P001). There is no specific family income threshold listed. The same document notes that "In the past, admitted students who had been staff identified as 'Disadvantaged=Y' were found to be economically needy 78% of the time."

The Harvard data also includes information on parental education but we omit it because information that is consistent across years for this variable is not available in the UNC data.

over 39% of in-state UNC applicants.[22]

A comparison across applicant and admit columns shows that overall admit rates by race mask substantial heterogeneity at the intersection of race, class, and selectivity of the pool. At Harvard, the disadvantaged share of white and Asian American admits is over twice as high as the disadvantaged share of white and Asian American applicants. But for African Americans, the share of admits who are disadvantaged is *lower* than the corresponding share of applicants. In both UNC pools, there is less representation of low-SES students in the admitted pool than in the applicant pool for every race, and this is especially true for African Americans. These patterns provide suggestive evidence that racial preferences may be more heavily targeted to African Americans who are not low-SES.

3.3 Race and Academic Background

The average admit rates by race mask differences in academic background across races as well as how academic background is related to admissions. We now use Tables 3 and 4 to describe how race and academic background relate to admission.

3.3.1 Average differences

The last three rows of each panel of Table 3 show average SAT math and verbal z-scores and high school GPA conditional on race, admission, and applicant pool. The SAT scores are standardized within a university, so each Harvard racial group is standardized to all Harvard applicants, and UNC in-state and out-of-state groups are standardized to one common pool. For UNC, we show the high school class percentile (0–100 scale) due to inconsistencies in the grading scales for high school GPA.

Table 3 shows large racial differences in SAT scores and GPA. African American applicants have SAT math and verbal scores that are roughly one standard deviation lower than white applicants in each of the three pools. On nearly all academic metrics, Asian Americans have the highest scores, followed by whites, Hispanics, and African Americans.[23]

[22]Fee waiver is an exception as rates can be higher at Harvard. Examination of the admissions web sites of both schools suggests the process is less onerous to get a fee waiver at Harvard.

[23]For UNC in-state, there are two exceptions with whites having higher verbal scores and class ranks than Asian Americans.

These patterns are striking given that URMs have the highest unconditional admit rates in the Harvard and out-of-state UNC applicant pools.[24] Within UNC and conditional on race, the out-of-state pool is stronger than the in-state state pool on each academic meaure.

3.3.2 Differences in admit rates and racial composition across academic index deciles

We next explore the distribution of academic preparation by race and applicant pool. For Harvard, we use the college's academic index, which is created by Harvard's admissions office and is a weighted average of the applicant's SAT score, high school GPA, and SAT II subject test scores.[25] UNC does not use an academic index for its applicants. In order to use both the information in SAT scores and in high school grades in one measure, we create an academic index by summing the z-scores of the applicant's composite SAT score and the applicant's high school GPA, where the z-scores are computed within applicant pools.[26]

Table 4 shows deciles of the academic index by race and applicant pool.[27] Given Harvard's and out-of-state UNC's low admit rates, the racial distribution of those with the strongest academic backgrounds is more informative regarding the impact of racial preferences in admissions than are the average differences in academic preparation across races discussed in Table 3. It is helpful to keep in mind that, if the sole criterion for admission in each of these pools was the academic index, then only applicants in the highest deciles would be admitted. For Harvard, this would be only the top decile—since Harvard's admit rate for typical applicants is well below 10%. For out-of-state UNC, it would be the top two deciles, and for in-state UNC it would be the top five deciles.

Table 4 shows, by race and applicant pool, the share of applicants in each academic

[24]These patterns extend to other academic measures such as SAT II subject tests and Advanced Placement (AP) tests at Harvard. However, these additional measures are not available in the UNC database.

[25]Prior to 2020, the University of California system also used an academic index composed of standardized test scores and high school GPA (Arcidiacono, Aucejo, and Hotz, 2016; Bleemer, 2022).

[26]Note that this in contrast to the z-scores reported in Table 3 which were done at the university level. We standardize within applicant pool because in Section 4 we estimate separate admissions models for each applicant pool. UNC's state-mandated cap on out-of-state enrollment ensures that admissions are much more competitive out-of-state. Note also that we restrict high school GPAs to those on a 4-point scale, resulting in smaller sample sizes especially for out-of-state.

[27]Note that the decile information for Harvard in Panel A of Table 4 is also presented in Arcidiacono, Kinsler, and Ransom (2022d).

index decile as well as the average admit rate for those in that decile. Those with the lowest academic indices are in the first decile; those with the highest are in the tenth decile. Table 4 shows that the academic index is strongly correlated with admission: admit rates are monotonically increasing in the index in each pool for nearly all deciles and races.[28] Those in the first decile have virtually no chance of admission in any of the pools regardless of race.

Given the strong relationship between academics and admissions, it is important to understand how different racial groups are distributed across the academic deciles in each applicant pool. Table 4 shows that, in each pool, the modal Asian American is found in the top decile, while the modal African American and Hispanic is in the bottom two deciles. In each pool, over 32% of African Americans fall in the first decile and over 52% fall in the first two deciles.[29] These patterns are not unique to Harvard and UNC. Arcidiacono, Aucejo, and Hotz (2016) and Bleemer (2022) document large racial gaps in academic preparation at University of California institutions, while the Department of Justice's investigation of Yale (Document 1) shows that the racial distribution across the academic index deciles at Yale is very similar to that of Harvard. These patterns reflect substantial differences in pre-college preparation across races coupled with universities recruiting African American and Hispanic students with weaker test scores in an effort to get more minority representation. Data from the College Board in 2019 for high school graduates shows that 25% of Asian Americans scored above a 1400 compared to 8% of whites, 2% of Hispanics, and 1% of African Americans (College Board, 2019, p. 5).

Given (*i*) higher admit rates for African Americans and Hispanics than Asian Americans and whites at Harvard and for out-of-state UNC, (*ii*) African Americans and Hispanics having substantially lower academic indices, and (*iii*) the strong correlation between the academic index and admissions probabilities, it must be the case that admit rates within a decile differ substantially across races. This is exactly what we see. In nearly every admissions decile of each applicant pool, African Americans are admitted at the highest

[28] There are only two exceptions: (*i*) in-state UNC African Americans, who have a slightly lower admit rate in the 10th decile than in the 9th decile; and (*ii*) out-of-state UNC Asian Americans, who have a slightly lower admit rate in the 3rd decile than in the 2nd decile. Each case falls in a relatively thin part of the distribution that is susceptible to greater variance due to small sample sizes.

[29] These numbers are largest for the Harvard pool, in part driven by Harvard's recruiting practices (Arcidiacono, Kinsler, and Ransom, 2022d).

rate, followed by Hispanics, then whites, then Asian Americans.[30]

In some cases, the racial differences in admit rates are extremely large: in the fifth decile, African Americans at Harvard are admitted at a rate that is 12 times higher than Asian Americans, almost nine times higher than whites, and more than double that of Hispanics. For this same decile among out-of-state UNC applicants, African Americans' admit rate is nearly 33 times higher than Asian Americans', over 14 times higher than whites', and over 2.5 times higher than Hispanics. These same admit rate ratios are much smaller for in-state UNC applicants, but still quite sizable. In the fifth decile, African Americans are admitted at a rate that is 2.55 times higher than Asian Americans, 2.45 times higher than whites, and 35% higher than Hispanics. African Americans in the fourth decile (the 30th to 40th percentile of applicants) have admit rates higher than Asian Americans in the top decile at Harvard and higher than the ninth decile for out-of-state UNC.

In keeping with these universities' holistic admissions processes, admission is also clearly a function of more than just academics as admission rates for all races are positive in the lower deciles and, with the exception of UNC in-state, far from 100% even in the highest decile. Table 4 implies that, had admissions been based solely on the academic index, African Americans would make up less than 1% of Harvard admits, less than 2% of out-of-state UNC admits, and 4.3% of in-state UNC admits.[31] The similar numbers for Asian Americans are 51.7%, 26.7%, and 14.0%.

3.4 Race and Subjective Application Ratings

The results of the preceding subsections suggest the possibility of large racial preferences, especially for Harvard and UNC out-of-state. But it is also possible that African American and Hispanic applicants are stronger on the criteria outside of standardized test scores and

[30] There are only a few exceptions to this statement, but in each case the trend is only minimally violated. In the top decile for in-state UNC, African Americans have the lowest admit rate. In the bottom decile for in-state UNC, Hispanics have a higher admit rate than African Americans. Whites have a higher admit rate than Hispanics in the second decile of Harvard, the first decile of out-of-state UNC, and the top decile of in-state UNC. Asian Americans have higher admit rates than whites in the third decile of Harvard and the top two deciles of out-of-state UNC.

[31] Calculations at Harvard entail randomly sampling from the 10th decile; for UNC out-of-state taking everyone in the 10th decile and randomly sampling from the 9th decile; and for UNC in-state taking everyone in the top five deciles and randomly sampling from the sixth decile to fill the class.

high school grades that Harvard and UNC use in admissions. Here we examine the racial composition of scoring well on Harvard's and UNC's subjective ratings.

Table 5 shows measures of strength by race in each rating and across application pools. At Harvard, we show results for the four profile ratings (academic, extracurricular, athletic, and personal), the school support ratings (teacher 1, teacher 2 and counselor) and the alumni interviewer ratings (alumni personal and alumni overall).[32] UNC employs a more limited set of admissions criteria and only uses five ratings: the program and performance ratings (which together measure academic preparation), the extracurricular rating, the essay rating and the personal quality rating. For Harvard, we show the likelihood of each group receiving a score of 2 or better on a 5-point scale (where lower numbers are better). For UNC, we show average rating scores on a 10-point scale (where higher numbers are better) for the program, performance and extracurricular ratings, as well as the likelihood of earning an above-median score on the essay and personal quality ratings.[33]

We first discuss the academic ratings in Table 5. For Harvard, Asian Americans record high academic ratings at a 60% rate, compared to 45% for whites, 16% for Hispanics and 9% for African Americans. For UNC, Asian Americans score the highest on the program rating (essentially, the number of AP or college-level courses taken), but whites score the highest on the performance rating (a function of grades). Out-of-state Hispanics actually score higher on average than out-of-state whites on the program rating, but African Americans score the lowest on both ratings in both UNC pools.

Turning to the non-academic ratings, Table 5 shows that the extracurricular rating exhibits similar racial patterns to academics, though muted. At Harvard and in both UNC pools, African Americans have the lowest extracurricular ratings followed by Hispanics. Asian Americans have the highest extracurricular ratings at Harvard and UNC out-of-state, with whites having the highest for UNC in-state. Patterns for the Harvard school support and alumni interviewer ratings are the same as for academics and extracurriculars. And the same patterns hold for UNC's essay rating in both pools, though UNC out-of-state Hispanics

[32]A subset of these numbers have been previously reported in Arcidiacono, Kinsler, and Ransom (2022a) and Arcidiacono, Kinsler, and Ransom (2022c).

[33]We would have preferred to harmonize the scales on these ratings, but that is infeasible since we no longer have access to the individual-level data.

have similar essay ratings to whites.

The patterns on non-academic subjective ratings discussed so far mimic those of the academic index and the academic subjective ratings. The personal rating exhibits inconsistent racial patterns between the two universities. At Harvard, Asian Americans are least likely to earn a high score on the personal rating, with whites scoring the highest, followed by African Americans and Hispanics. On the other hand, in both UNC pools, whites are least likely to score above the median on the personal quality rating with Hispanics scoring the highest. African Americans and Asian Americans have similar personal ratings in both pools, ahead of whites and behind Hispanics. The other anomalous rating is Harvard's athletic rating, where whites score the highest, followed by Hispanics, African Americans and Asian Americans.[34]

In summary, the results of this section show that, across all applicant pools, URM applicants tend to be worse on both the academic and non-academic criteria used in admissions. Combined with the fact that overall admissions rates often exhibit large differences across races, this suggests that impact of racial preferences may be quite large in magnitude. We analyze this formally in the next section.

4 Modeling University Admissions

Estimating the impact of racial preferences in admissions is challenging from a number of perspectives. As discussed in the previous section, applicants from distinct racial groups can have significantly different non-race characteristics relevant for admissions. In addition, admissions decisions are just one part of a process that also includes application and matriculation choices of students. In this section we first develop a theoretical model of admissions that shows how university preferences over quality and demographics of its enrollees map into enrollment decisions. Using the theoretical model as a guide, we then present and estimate an empirical framework that is consistent with the theoretical model.

[34] As we show in Arcidiacono, Kinsler, and Ransom (2022c), LDCs (legacies, connections of donors, and children of faculty staff) of all races score higher on this rating than typical applicants, with white LDCs scoring especially high.

4.1 Theoretical Model

We model the university as valuing two aspects of its enrolled student body: student quality, $x \in \Re^+$, and the number of matriculants from different demographic groups.[35] Students belong to one of G mutually exclusive groups. For example, one group could be socioeconomically disadvantaged African Americans. Student quality refers to all attributes which the university values (both observed and unobserved to the researcher) other than group identity. In the population of applicants from group $g \in \{1, \ldots, G\}$, x is distributed according to a cumulative distribution function $\Phi_g(x)$ with a corresponding probability density function $\phi_g(x)$.[36] The university receives N_g applications from group g. Admitted students of group g with quality x matriculate at a rate $f_g(x)$. The university can enroll at most $\overline{N}$ students.

We assume that the university has convex preferences over overall student quality and total enrollees of each group. Given this preference structure, the solution to the university's maximization problem can be characterized by a series of cutoff qualities for each group with everyone at or above the cutoff c_g for group g admitted and all others rejected. Without loss of generality, we normalize the benefits the university receives from enrolling members of group 1 to depend solely on the quality of the enrollees from group 1. The university then solves the following constrained optimization problem:

$$\max_{c_1,\ldots,c_G} U\left(a, b_2, \ldots, b_G\right) \text{ s.t. } \sum_{g=1}^{G} N_g \int_{c_g}^{\infty} \phi_g(x) f_g(x) dx = \overline{N} \tag{1}$$

$$a := \sum_{g=1}^{G} N_g \int_{c_g}^{\infty} x \phi_g(x) f_g(x) dx \qquad \text{(quality of enrollees)}$$

$$b_g := N_g \int_{c_g}^{\infty} \phi_g(x) f_g(x) dx, \; g = 2, \ldots, G \quad \text{(total enrollees of group } g\text{)}$$

where $U(a, b_2, \ldots, b_G) : \Re^G \to \Re$ is continuous with $U_a'(\cdot) > 0$, $U_a''(\cdot) \leq 0$, and for $z \in \{b_2, \ldots, b_G\}$ $U_z'(\cdot) \neq 0$, with $U_z''(\cdot) \geq 0$ if $U_z'(\cdot) < 0$ and $U_z''(\cdot) \leq 0$ if $U_z'(\cdot) > 0$. The conditions on the derivatives with respect to b_g permit the normalized group (b_1) to be

[35] This model is an extended version of the model in Arcidiacono, Kinsler, and Ransom (2022b).

[36] The quality of applicants from each group can be affected by affirmative action and direct recruiting practices. In practice, this will likely mean that the quality distribution of URM applicants or disadvantaged applicants is shifted left relative to other groups.

relatively preferred ($U'_z(\cdot) > 0$) or not preferred ($U'_z(\cdot) < 0$) to each of the other groups.

The first order conditions of the Lagrangian with respect to c_1 and c_g ($g > 1$) yield:

$$0 = -\frac{\partial U}{\partial a} N_1 c_1 \phi_1(c_1) f_1(c_1) + \lambda N_1 \phi_1(c_1) f_1(c_1) \quad (2)$$
$$0 = -\frac{\partial U}{\partial a} N_g c_g \phi_g(c_g) f_g(c_g) - \frac{\partial U}{\partial b_g} N_g \phi_g(c_g) f_g(c_g) + \lambda N_g \phi_g(c_g) f_g(c_g) \quad (3)$$

Combining these two first order conditions gives the differences in admissions cutoffs between group 1 and group $g > 1$:

$$c_1 - c_g = \frac{\partial U}{\partial b_g} \left(\frac{\partial U}{\partial a} \right)^{-1} \quad (4)$$

This expression is intuitive: the more value the university places on enrolling members of group g relative to group 1, the larger the gap in the two cutoffs; the more value the university places on student quality, the smaller the gap in the two cutoffs.

For the purposes of estimating the impact of racial preferences on admissions decisions, the magnitude of the gap in the two cutoffs is the parameter of interest since this is what determines how many applicants of each group are ultimately admitted. However, the gaps in admission cutoffs only map directly to the structural preference parameters $\frac{\partial U}{\partial b_g}$ and $\frac{\partial U}{\partial a}$ in certain cases. If $U(a, b)$ can be expressed as $U\left(a + \sum_{g=2}^{G} \varphi_g b_g\right)$ with $\varphi_g > 0$, i.e. quality and the number of enrollees of different demographic groups are perfect substitutes, then $c_1 - c_g$ will be exactly equal to φ_g.[37] The cutoffs for each group then map one-to-one with the structural preference parameters driving admissions decisions. Absent linearity, the gap in the cutoffs is a reduced form parameter that captures a mix of preference parameters and other model features related to group size, quality, and matriculation tendencies.[38] While the structural preference parameters could be useful for understanding university behavior under some counterfactual policies,[39] the differences in cutoffs ultimately determine admissions and

[37] To set the scale of utility we normalize the coefficient on quality to one.

[38] Rather than allow the university to have utility over the number of matriculants, we could allow the university to care about the number of graduates from each group. This would require introducing a graduation probability $q_g(x)$ in the equations for b_g, where b_g would now reflect the expected number of graduates from each group. As a result, the right hand side of Equation 4 would now be scaled by $q_g(c_g)$, meaning that the difference in cutoffs would also depend on graduation probabilities.

[39] Because the model does not endogenize application or matriculation, it cannot be used in isolation to

it is not important for our study whether these gaps are driven by preferences for a particular group, group differences in academic or non-academic preparation, scarcity of applicants from a group, or low yield of a group.

4.2 Empirical Model

The theoretical model translates directly into the empirical models we estimate. Namely, denote the quality of the applicant i, x_i, as depending on observable characteristics z_i and unobservable (to the researcher but not the university) characteristics ϵ_i as follows:

$$x_i = z_i\beta + \epsilon_i \tag{5}$$

The β parameters then give the weights for the different characteristics in the quality index. An applicant from group g is admitted if:

$$z_i\beta + \epsilon_i > c_g \tag{6}$$

When ϵ_i follows a logistic distribution, this translates directly into a logit model of admissions. The difference between c_g and c_1 is captured by including indicator terms for each $g > 1$. As shown in the previous subsection, when group enrollees and applicant quality are perfect substitutes, the coefficients on these interaction terms directly give the university's preference for the different groups relative to the normalized group.[40]

We implement our theoretical framework by estimating separate logit models of admission for Harvard applicants, UNC out-of-state applicants, and UNC in-state applicants. These models include race indicators, sometimes interacted with gender and disadvantaged status, to capture the preferences admissions officers give to these groups relative to white students. Our models account for applicant quality using the incredibly detailed applicant-level data available for each sample, including academics, demographics, and admissions staff ratings.[41]

study policies that drastically impact these margins.

[40]As is standard in discrete choice models, these parameters are identified up to the logit variance scale parameter.

[41]Consistent with our theoretical model, we assume that applicant quality is defined irrespective of race. We provide auxiliary evidence that this is the case in Appendix B.

The data made available from both lawsuits are extremely rich, especially for Harvard. In the paragraphs that follow, we briefly discuss some of the key modeling choices that allow us to flexibly capture applicant quality and the role of race. Our broad approach is similar across our modeling of admissions at Harvard and UNC and we include many of the same types of variables to capture applicant quality. All of our admissions models include indicators for admissions cycle, ensuring that each year, the average predicted probability of admission matches that of the data. Our preferred models at both institutions include a detailed list of demographic and academic variables, such as first-generation status, SAT scores, and high school GPA.[42] Additionally, admissions staff at Harvard and UNC rate applicants according to their academic performance and extracurricular activities.[43] For each rating, we include separate indicator variables for the various rating levels. Finally, our preferred models at both institutions allow for heterogeneity in the impact of race according to gender and either disadvantaged status (Harvard) or first-generation college (UNC).

Although the admissions models across Harvard and UNC capture many of the same applicant features, there are some differences. First, the Harvard admissions office measures and generates a larger number of applicant attributes relative to UNC (see Table 1). For example, Harvard admissions staff create a 'disadvantaged' indicator using information about parental occupation and education level. In addition, Harvard generates applicant ratings based on teacher and guidance counselor recommendations, and incorporates alumni ratings based on in-person interviews.[44] The Harvard data set also includes information on applicants' high school and neighborhood from the College Board and US Census Bureau, respectively. The inclusion of these and other variables in our preferred admissions model for Harvard implies a larger number of controls as compared with UNC.[45]

[42]For the UNC sample, we impute SAT scores for applicants who only report ACT scores. To do this, we regress SAT math and verbal scores on ACT component scores for applicants who report both standardized test measures as well as a set of demographic characteristics. For applicants missing both SAT and ACT scores, we include a missing indicator interacted with race. We take a similar approach for applicants who are missing high school GPA or high school rank. For additional details see Section 3.4.3 of Document 160-2 and Sections 2.3.3–2.3.5 of Document 160-3.

[43]While Harvard creates a personal rating for each applicant, our preferred model excludes this rating since there is ample evidence that it incorporates racial preferences. However, the inclusion of this rating has little impact on the estimated racial preferences for URM applicants. We also do not use Harvard's overall rating as it was acknowledged that Harvard uses race in that rating. See Document 415-9.

[44]On the other hand, UNC admissions staff generate an essay rating, which Harvard does not utilize.

[45]One variable included in the UNC models that is excluded from Harvard is legacy status. Legacy status

A second difference in the preferred models for Harvard and UNC is the inclusion of interactions between demographics and the admission cycle at Harvard. During the applicant review process, Harvard closely tracks the makeup of the admitted class and how it compares with admitted classes in previous years.[46] By interacting admission cycle with applicant attributes, we allow for the possibility that Harvard balances race, gender, disadvantaged status, and intended major within each admitted class. Excluding these interactions in the UNC admissions models means that the estimates reflect the average weight UNC gives these attributes across admissions cycles.

Table 6 gives an overview of the included variables across the different applicant pools for three types of model specifications: sparse, academics, and preferred. The sparse models include basic demographics, while the academic models add test scores, high school grades, and other measures of academic performance. Finally, our preferred models add institutional ratings and interactions. We present the three types of admissions models to illustrate how estimates of racial preferences change as controls are added, and also to highlight differences in the predictive power of various controls across samples. Our preferred Harvard model contains approximately 320 covariates, while our preferred UNC models each contain approximately 115 covariates.[47]

While our preferred admissions models contain an abundance of key applicant covariates, there remain features observed by the admissions office that are not directly included. For example, we do not incorporate information related to research experience, academic or non-academic awards, advanced placement scores, or misconduct. These student attributes may be captured in the academic, extracurricular, and personal ratings assigned by the admissions office, but not perfectly so. To identify racial preferences in admissions, we rely on the assumption that any remaining unobservables are orthogonal to race. Violations of

plays a minor role in UNC in-state admissions. Out-of-state legacy applicants receive a preference, but they are a relatively small share of the applicant pool. In contrast to Harvard, there is no evidence in the record that the inclusion of legacy applicants alters the relative weights of other applicant attributes in either of the UNC admissions models.

[46] They do so through 'one-pagers'. See Trial Exhibit P164 for an example.

[47] The controls used for modeling out-of-state and in-state admissions to UNC are identical. The difference in the number of covariates between Harvard and UNC is even starker when considering that some of the covariates in UNC are interactions between missing values and characteristics such as race; missing data is much less of an issue for Harvard.

this assumption are likely to lead us to understate the magnitude of racial preferences since, as Section 3 demonstrates, URM applicants have characteristics that are associated with substantially lower admissions rates than their non-URM counterparts. It is typical in the economics literature to assume that selection on the observables goes in the same direction as selection on the unobservables (Altonji, Elder, and Taber, 2005; Oster, 2019). This is also a reasonable assumption in our context since schools typically recruit African Americans and Hispanics more aggressively than whites and Asian Americans (Arcidiacono, Kinsler, and Ransom, 2022d).

4.3 Model Fit and Estimates

Table 7 displays selected coefficient estimates for various model specifications. The first three columns list coefficients for applicants to Harvard, the middle three columns are estimates for UNC out-of-state applicants, and the final three columns reflect estimates for UNC in-state applicants.[48] The bottom of the table indicates which controls are included, the total number of controls, sample size, and model fit as measured by the Pseudo R^2.

Prior to discussing individual parameter estimates, we first comment on the ability of our models to fit the data. Logit models with Pseudo R^2 values between 0.2 and 0.4 are considered to have achieved an excellent fit (McFadden, 1979). While none of our sparse models achieve this threshold, all of our admissions models that include academic characteristics yield Pseudo R^2 values above 0.2. Interestingly, adding academics increases model fit by substantially more in the UNC samples. This could reflect a greater reliance on objective measures at UNC due to the high administrative costs of implementing holistic admissions.[49] Our preferred admissions models for Harvard and both UNC samples have extremely high Pseudo R^2 values, well above 0.5.

To put these values in perspective, we also calculate the predictive accuracy of our models. The following process is completed separately for each applicant pool using the preferred

[48]The model coefficients for Harvard are also presented in Arcidiacono, Kinsler, and Ransom (2022a).

[49]In addition to UNC putting more weight on academics in admissions choices relative to Harvard (as demonstrated in Table 4), another contributing factor to the high Pseudo R^2 values could be greater variation in academic preparation among UNC applicants. Data limitations preclude us from directly comparing the variance of academic credentials across samples.

specification. For each applicant, we first construct an admission index based on their observed characteristics and the estimated coefficients. We then sort applicants within each admissions cycle according to these indices and fill admission slots starting with applicants with the highest index, admitting applicants until the total number matches what is seen in the data. We then compare how our predicted admitted classes match the actual admitted classes. Overall accuracy is then defined as the share of predicted admit/reject decisions that match the observed outcomes. We also calculate accuracy separately for admits and rejects.

Table 8 indicates that our preferred admissions models are highly accurate for all three admissions systems.[50] Overall accuracy is above 92% for each model, which given the high rejection rates may not be surprising. Yet, the models predict admits extremely well despite the low probabilities of admission. As the admit rates are higher for in-state UNC, the fit for admits is especially good. Figure 1 further illustrates this point, plotting the density of model-predicted admissions probabilities for in-state UNC applicants. The predictions are bimodal, placing substantial mass close to zero and close to one. Figure 2(a) breaks out the predicted probabilities separately for those are actually admitted and rejected. Predicted probabilities for admits (rejects) are almost always very close to one (zero), corresponding to the second (first) mode in Figure 1.[51]

Our initial focus on model fit is driven by two ideas. First, to the extent that our models fit the data well, it suggests that the scope for omitted variable bias is reduced since we have incorporated most of the key applicant characteristics affecting admissions decisions. For example, if we could perfectly predict admissions decisions, bias in the race coefficients would have to be driven by an unobservable that is perfectly correlated with the component

[50] The accuracy estimates for UNC are exact. For Harvard, exact accuracy numbers are not available in the public record. However, we can simulate accuracy estimates using Pseudo R^2 values and the baseline admit probabilities. Additional details on this procedure are provided in Arcidiacono, Kinsler, and Ransom (2022a). We check the validity of this approach by simulating accuracy numbers for the in-state and out-of-state UNC models and find that our simulated values are within one percentage point of the true accuracy rates.

[51] Given the excellent fit, one may be concerned that our models are overfit. Given the data in the public record, we cannot evaluate this claim for Harvard. However, for UNC we used k-fold cross validation to asses out-of-sample model fit. Doing so produces overall out-of-sample accuracy rates of 91.9% for UNC in-state and 93.2% for UNC out-of-state which are striking close to the corresponding numbers in Table 8 of 92.1% and 93.3%.

of race that is orthogonal to all the other covariates in the model. Such a situation would be very unlikely. Second, when the variance of the unobserved components of admissions is small, the magnitude of the parameter estimates will tend to be large. Estimated coefficients in a logit model measure the impact of the observed variable scaled by the variance of the unobservables. It is important to keep this in mind when comparing model coefficients across specifications for a given applicant pool or across applicant pools.

Turning back to the coefficient estimates in Table 7, there are a number of similar patterns across the three admissions systems. First, as controls are added, the coefficients for African American and Hispanic tend to increase.[52] The increasing magnitude of the African American and Hispanic coefficients as controls are added is in part the result of the shrinking role of unobserved factors. However, it is also the case that African American and Hispanic applicants are weaker on the observed characteristics that positively affect admissions (as discussed in the previous section), forcing the estimated race coefficients to compensate when controls are included. In our preferred specifications, the African American and Hispanic coefficients are large, positive, and statistically significant, consistent with Harvard and UNC practicing affirmative action.[53]

Another feature common across applicant pools is the way race interacts with disadvantaged status. In our preferred models, disadvantaged white applicants receive a bonus relative to their more advantaged white peers. This can be seen in the positive coefficients on the disadvantaged indicator in the Harvard sample and the first-generation college indicator in the UNC samples. However, disadvantaged African American applicants do not receive the same admissions preference relative to their more advantaged African American peers. In all three samples, the coefficient on the interaction between African American and disadvantaged is negative and similar in magnitude to the baseline disadvantaged coef-

[52] Note that for the in-state UNC sample, the coefficients for African American and Hispanic start out negative, reflecting their lower unconditional admit rates as seen in Table 2. However, once academics are included, these coefficients become large and positive, similar to the Harvard and UNC out-of-state samples.

[53] These findings are highly robust to changes in both the estimation sample and controls. Column (6) of Table A2 shows that the African American and Hispanic coefficients increase slightly (as does model fit) if we control for the personal rating in our model of Harvard admissions. Table A3 further shows that the inclusion of legacy applicants, donor-connected applicants, or applicants whose parents work at Harvard does not change the basic magnitude of either the race coefficients or the Pseudo-R^2 values. Finally, the race coefficients for in-state applicants to UNC are robust to the inclusion of high school fixed effects, as seen in Table A5.

ficient. A similar pattern emerges for Hispanic applicants in all three samples, though not as extreme. These patterns indicate that the primary beneficiaries of racial preferences are higher-socioeconomic-status African American and Hispanic applicants. Their admissions boost relative to advantaged white applicants is larger than the admissions boost disadvantaged African American and Hispanic applicants experience relative to disadvantaged white applicants. For UNC in-state and Harvard, the lack of a disadvantaged bonus for minority applicants may reflect issues related to making sure admits are academically competitive. The fact that it also occurs for UNC out-of-state—where these minority admits are more academically prepared than their in-state counterparts—points to a different phenomenon. One possibility is that higher-socioeconomic-status minorities transition more smoothly to the social environment at an elite university, and are thus more likely to persist, leading admissions officers to prefer these applicants. Another possibility is that advantaged minority applicants explain more effectively their experiences as minorities in a way that resonates with admissions officers.

One key difference across samples is how Asian Americans are treated. In our preferred model for Harvard admissions, the baseline Asian American coefficient is negative and statistically significant. In the UNC out-of-state and in-state samples the baseline Asian American coefficient is positive, but small in magnitude and not significantly different from zero.[54] Consistent with Asian Americans being discriminated against at Harvard, models of the personal rating also show a penalty against Asian Americans at Harvard but no evidence of a penalty in the personal quality rating in either of the UNC pools.[55]

The model coefficients are helpful for understanding whether a given feature is rewarded or penalized in a statistically significant manner by admissions staff at Harvard and UNC. Previous work estimating preferences in college admissions report odds ratios as a way to contextualize the impact of a particular attribute (Espenshade, Chung, and Walling, 2004). However, odds ratios will be sensitive to the fit of the model because estimated coefficients measure the impact of the observed variable scaled by the variance of the unobservables.

[54] For female Asian American applicants, the admissions penalty at Harvard remains negative and significant, but is smaller than for males. At UNC, female Asian American applicants do not experience a statistically significant penalty or preference.

[55] See Arcidiacono, Kinsler, and Ransom (2022a) for a more comprehensive treatment of Asian American discrimination at Harvard.

Since our models fit the admissions data extremely well, our odds ratios will be massive and not particularly informative. For example, the odds of being admitted to Harvard for African American applicants is approximately 43 times that of white students. A similar calculation for UNC out-of-state applicants indicates an odds ratio of approximately 474. In the next section, we use our model estimates to measure the impact of racial preferences in a more informative manner.

5 Measuring the Impact of Racial Preferences

We now use our estimates to quantify racial preferences using a variety of methods. First, we examine average marginal effects. This approach shows what would happen to minority applicant chances of admissions had they instead marked their race as white, holding fixed their other characteristics. Second, we quantify the effects of racial preferences for minority admits. That is, we quantify how many of these admits would have been rejected absent racial preferences, explicitly taking into account that, since they were admitted, this group is positively selected based on their unobservables.

When racial preferences are removed for all applicants, additional spots in the class are freed up. Our third method examines the effects of removing racial preferences holding the application decisions of applicants fixed as well as fixing how universities rank students according to non-race based attributes, but ensuring that the number of admitted students remains the same both with and without racial preferences. It is likely the case that both students and universities would respond to a ban on racial preferences and in the last subsection we speculate on what these responses may look like.

5.1 Average Marginal Effects

To better characterize the importance of racial preferences in admissions, we first calculate the average marginal effect of being an African American or Hispanic applicant using our preferred admissions models. The first two columns of Table 9 present the average admit rate for African American and Hispanic applicants with affirmative action (status quo) and when racial preferences are eliminated (setting all race-related coefficients to zero). The third column is the average marginal effect, or the difference between the first two columns. The final column calculates the percent change in average admissions probability when racial preferences are eliminated.

The first panel of the table shows that the average marginal effect is 7.29 percentage points for African Americans applicants to Harvard. This is off a baseline average admit rate of 2.25%, suggesting that racial preferences quadruple the African American admit rate.[56] Similar calculations indicate that racial preferences increase the Hispanic admit rate by almost two and a half times. The results indicate that affirmative action leads African American and Hispanic applicants to be significantly more likely to be admitted relative to their observationally equivalent white and Asian American peers.

In Panels B and C of Table 9 we report similar statistics for UNC out-of-state and in-state applicants. For African American out-of-state applicants, the average admission probability with racial preferences in place is 17.1%. In the absence of racial preferences, we estimate that African American applicants would be admitted at a rate of 1.5%. Thus, racial preferences boost the likelihood of admission for out-of-state African American applicants by a factor of more than eleven. Out-of-state Hispanic applicants are admitted at a rate of 20.3% on average with racial preferences, but only at a rate of 6.0% when racial preferences are eliminated. While the difference for Hispanic applicants is not quite as large as it is for African American applicants, racial preferences still boosts the average admission rate by more than triple.

For in-state UNC applicants, racial preferences significantly impact admissions probabilities, though the effects are smaller than for UNC out-of-state and Harvard admissions. The average admissions probability for African Americans with racial preferences in place is 30.5%. We estimate that without racial preferences, this average would drop to 17.8%, nearly cutting the admit rate in half. The drop in the Hispanic admit rate is not as severe, falling from 41.0% to 31.2% when racial preferences are eliminated.

The marginal effects presented in Table 9 reflect the average changes in admissions prob-

[56] The quadrupling calculation comes from adding the baseline admit rate to the average marginal effect and then dividing by the baseline admit rate; i.e. $(2.25 + 7.29)/2.25 = 4.24$. Note that the sum of the average marginal effect and the baseline (9.54%) is higher than the overall admit rate reported in Table 2. This is partly due to the handling of perfect predictions: some applicants have characteristics that guarantee rejection regardless of their race.

abilities for African American and Hispanic applicants. However, as discussed in the previous section, the impact of racial preferences appears to be quite different according to socioeconomic status. We examine this heterogeneity by calculating average marginal effects separately by socioeconomic status for out-of-state and in-state UNC applicants. Consistent with the underlying model estimates, out-of-state African American and Hispanic applicants whose parents attended college have average marginal effects of race 67% and 94% higher than their first-generation same-race peers. The corresponding numbers for in-state applicants are 60% and 33%, respectively.[57] The smaller marginal effects of race for first generation college students primarily reflects the difference in admit rates when racial preferences are present. When racial preferences are eliminated, the within-race gaps in admissions probabilities by socioeconomic status shrink considerably.

Similar patterns are bound to hold for Harvard, but there is no direct evidence in the public record on differences in marginal effects by disadvantaged status. However, we can use the model coefficients to determine how the probability of admission would change for a disadvantaged (non-disadvantaged), male, white applicant if he had been treated as a disadvantaged (non-disadvantaged), male, African American applicant. Assume that the white applicant of each type has a 5% probability of being admitted. This implies a particular value for the admissions index, or observed applicant strength. Using this as a base, we can add the race-related coefficients to determine the admissions probability when race is altered.[58] If a white, male, not disadvantaged applicant with a 5% chance of admission were instead an African American applicant, all else equal, his admission probability would rise to 69.6%. However, a white, male, disadvantaged applicant with a 5% chance of admission

[57] See Table 3.4 of Document 160-2 for additional details.

[58] Consider, for example, a male, non-disadvantaged white applicant with a baseline probability of admission of p. The index of observables, Z, for this applicant according to the log odds formula is given by

$$Z = \ln\left(\frac{p}{1-p}\right)$$

which is the inverse of the standard logit formula. If this applicant were instead African American, we would simply add the African American coefficient β_B to the index so that the new admissions index would be $Z + \hat{\beta}_B$. The new admissions probability would then be given by $\frac{\exp(Z+\hat{\beta}_B)}{1+\exp(Z+\hat{\beta}_B)}$. A similar calculation can be made for various combinations of gender and disadvantaged status. The additional complication is that coefficients related to the interactions between African American and gender and African American and disadvantaged also need to be differenced out when applicable.

would only see his admission probability rise to 32.1% if he were instead treated as an African American applicant. The precise magnitude of these changes will depend on the initial probability of admission, but the differential racial effects of disadvantaged status will remain.

5.2 Admit Rates for Previous Admits

Another way of showing the impact of racial preferences is to consider how many African American and Hispanic admits are admitted primarily because of racial preferences. Because Harvard and UNC admissions staff utilize information that we do not directly observe in the data, we cannot perfectly predict which individuals would or would not be admitted if racial preferences were removed. That said, our models fit the data remarkably well, as shown in Table 8.

Even though our models do not predict admissions outcomes perfectly, we do know the range of unobserved factors an applicant must have had in order to be admitted when racial preferences were in place. With this information and the estimates of the model, it is possible to calculate the probability that a given applicant would have been admitted absent racial preferences. The strength of this approach is that, since it only focuses on admitted students, it takes into account that the applicant's unobserved characteristics are strong enough to gain them admission when racial preferences are present.[59]

The formula for these admission probabilities follows directly from Bayes rule. Let $y = 1$ if an African American applicant was admitted in the status quo environment (i.e. the environment with racial preferences). Let $y' = 1$ if the applicant would have been admitted without racial preferences. Let X denote the observed characteristics of the applicant. Since we do not see the applicant's unobserved characteristics, we can only form a probability that the applicant would be admitted in the absence of racial preferences. Let the conditional probability that the applicant would be admitted absent racial preferences given that the applicant was admitted in the status quo environment be given by $P(y' = 1|y = 1, X)$.

[59]This is the same approach used in Arcidiacono, Kinsler, and Ransom (2022c) where there it was used to calculate the admissions advantages given to ALDC applicants.

Then, using Bayes rule, we can express this as:

$$
\begin{aligned}
P(y' = 1|y = 1, X) &= \frac{P(y = 1|y' = 1, X)P(y' = 1|X)}{P(y = 1|X)} \\
&= \frac{P(y' = 1|X)}{P(y = 1|X)}
\end{aligned} \tag{7}
$$

where the second line follows from the fact that, if the applicant would have been admitted without racial preferences, then the probability of being admitted with racial preferences is one. The reason it is one is because turning off racial preferences means it is more difficult for African American applicants to be admitted. Hence, if the applicant would have been admitted without racial preferences, then the applicant would certainly have been admitted in an environment with racial preferences.

Both of the terms on the right hand side are known since we can calculate them using the logit formula. The term in the denominator effectively adjusts for the fact that the applicant had unobservables that were good enough to lead to admission in the status quo case. This term is the predicted probability of admission taken directly from the model estimates. The term in the numerator is the same predicted probability but calculated as though the applicant were white.

The results of this exercise are displayed in Table 10. For Harvard, the public record only has information for these calculations that include ALDC applicants, so the sample is slightly different.[60] Panel A shows that, among African American admits to Harvard, only 30% would continue to be admitted in the absence of racial preferences. For Hispanic admits, the corresponding share is 46%.[61] The results for out-of-state UNC admits are listed in Panel B and are even more striking. If out-of-state African American admits to UNC were treated as white, their average probability of admission would be 8.7%, a 91.3 percentage point decrease given that they were admitted when racial preferences were in place. For out-of-state Hispanic admits, removing racial preferences would result in an

[60] The model with ALDC applicants includes controls for recruited athlete, legacy, double legacy, dean's interest list, and faculty/staff child.

[61] Both of these numbers are inflated because of the ALDC applicants. Like what is seen for disadvantaged applicants, ALDC African American and Hispanic applicants do not get the full bump for their ALDC status. But when racial preferences are turned off, they do get the full ALDC bump, partially mitigating the admissions losses.

average probability of admission of 29.2%, a 70.8 percentage point decrease. Panel C shows that if racial preferences were eliminated at UNC, in-state African American and Hispanic admits would see their likelihood of admission fall, but by significantly less than for out-state UNC or Harvard admits.

The estimated racial preferences are quite large, and especially so for UNC out-of-state, yet we suspect that we are understating the true extent of affirmative action. A standard assumption in the economics literature is that unobserved attributes move in the same direction as observed attributes (Altonji, Elder, and Taber, 2005). This assumption is reasonable in our context since we know Harvard recruits African Americans and Hispanics more aggressively than whites and Asian Americans (Arcidiacono, Kinsler, and Ransom, 2022d) and suspect that UNC does as well. As a result, we would expect that African American and Hispanic applicants are weaker on the observed attributes that predict admissions, and that, conditional on observables, they are also weaker on the unobserved attributes that predict admissions.

For both Harvard and UNC, we find that African American and Hispanic applicants are significantly weaker on the observed attributes that predict admission. For each Harvard applicant, we calculate their observed admission index, or the sum of the applicant attributes weighted by the model coefficients. Appendix Table A6 illustrates that African American and Hispanic applicants are highly concentrated at the bottom of the admissions index distribution, regardless of whether we use all applicant attributes, non-academic attributes, or non-academic ratings to construct the admissions index. Appendix Table A7 shows the results of a similar exercise for out-of-state and in-state UNC admits. We first construct admissions indices for all out-of-state and in-state applicants. Using these indices, we find that the median African American (Hispanic) *admit* is always below the 20th (40th) percentile of the corresponding admissions index for white or Asian American *applicants*. This results in distributions of admissions indices for admits that have little overlap: half of African American out-of-state (in-state) admits come into UNC at the 2nd (10th) percentile of the white distribution or below.

5.3 Capacity Constraints

The analysis of the previous two sections focuses on measuring how the removal of racial preferences affects individual applicants, assuming the standards Harvard and UNC use for admission remain unchanged for the remaining applicants. However, if these schools removed racial preferences for all applicants simultaneously, the average marginal effect would overstate the policy's impact since, if no other adjustment is made, too few applicants would be admitted. In this section, we investigate the racial distribution of the admitted classes to Harvard and UNC in the absence of racial preferences, holding fixed the applicant pool, preferences for all other attributes, *and* the total number of admits. This is equivalent to the theoretical model of Section 4.1 where (i) the differences in the non-race based cutoffs (i.e. for disadvantaged status and female) were held fixed and (ii) the cutoff for the normalized group (c_1) was adjusted such that the number of admits is held constant (so assuming away differences in matriculation rates).

This exercise is an alternative approach to measuring the impact of racial preferences and is not meant to estimate the impact of an affirmative action ban. In particular, when we remove racial preferences we do not allow schools to adjust their preferences for all other applicant attributes. Prior research has shown that when schools are forced to eliminate direct racial preferences, the weights given to other applicant attributes adjust to blunt the impact of such a policy (Chan and Eyster, 2003; Epple, Romano, and Sieg, 2008; Antonovics and Backes, 2014). Moreover, we assume that the applicant pool is unchanged. If affirmative action was eliminated, a greater number of highly qualified URM applicants would be likely to apply to schools like UNC as their chances of being admitted at more selective universities would decline.[62] We return to these general equilibrium concepts in the next subsection.

Using our preferred models, we calculate an admissions index for each applicant absent racial preferences. We construct the index by setting the race coefficients to zero, but keeping all other coefficients the same.[63] To fill the class in each admissions cycle, we then adjust the

[62] Bleemer (2022) illustrates this phenomenon in the context of California's affirmative action ban.

[63] In order for the preferred model to match the racial distribution of the admitted class in every admission cycle, we add race-by-year interactions to our preferred model for Harvard. Coefficient estimates are provided in Table B.8.1R of Document 415-9. The race-by-year coefficients ensure that the estimated model perfectly matches the actual number of admits in each racial group in every year. For UNC, we simply estimate our preferred admissions models separately by year. See Tables A.4.5.R and A.4.6.R of Document 160-2 for

admissions index of all applicants by a constant such that the average admission probability without racial preferences matches the average admission probability with racial preferences. Numerically, we solve for an index adjustment ϕ_t^* in each admissions group g (Harvard, UNC out-of-state, UNC in-state) and cycle t, such that

$$\overline{p}_{gt} = \frac{1}{N_{gt}} \sum_{i=1}^{N_{gt}} \frac{\exp(X_{igt}\hat{\beta}_{g,NR} + \phi_{gt}^*)}{1 + \exp(X_{igt}\hat{\beta}_{g,NR} + \phi_{gt}^*)} \tag{8}$$

where $\overline{p}_{gt}$ is the actual average probability of admission, N_{gt} is the size of the relevant applicant pool, X_{igt} are the observed characteristics, and $\hat{\beta}_{g,NR}$ are the estimated coefficients on these characteristics with the coefficients on race and all race interactions set to zero.[64] Finding the ϕ_{gt}^* that solves this equation guarantees that when we aggregate the individual admission probabilities under the assumption of no racial preferences, we maintain the exact number of admits each year.[65]

The results of this exercise are displayed in Table 11. The first panel shows the total number of admits and the share of admits by race with racial preferences—essentially the status quo. The bottom panel shows the same statistics in the absence of racial preferences, in addition to the percentage change from the status quo.

The first column of Table 11 shows that the number of African American admits to Harvard for the classes of 2014–2019 would have declined from 1,163 to 324 in the absence of racial preferences. Column 2 shows that the African American share of the admitted classes would drop from 15.5% to 4.3%, a 72% drop (column 3). Hispanic representation at Harvard would also have declined significantly, with the Hispanic share of admits dropping from 15.8% to 7.8%. Both white and Asian American representation increase, though the increase is significantly larger for Asian Americans. The number of Asian Americans admitted would increase from 2,013 to 2,812, an increase of over 37%.

In the absence of racial preferences, UNC would experience similar changes to the racial composition of admits for the classes of 2016–2021. In the out-of-state applicant pool,

details.

[64] In all samples, we maintain the race interactions with missing scores since these are meant to capture racial differences in mean scores for those whose scores are unobserved.

[65] We do not model the equilibrium impact on the application margin since our data only includes applicants.

the numbers of African American and Hispanic admits would plummet, falling by 1,397 and 1,083—drops of 88% and 59%, respectively. The model predicts that 544 more Asian Americans would be admitted, a 20% increase. The percentage increase would be even higher for whites at 28%, resulting in 1,938 more admits.

Consistent with the previous section, removing racial preferences would have smaller effects for UNC in-state applicants. Here African American and Hispanic admits would fall by 864 and 273, respectively (in terms of percentages, by 36% and 19%). The number of white admits would increase by 5.8%, or an additional 1,109 admits. The number of Asian Americans admitted in-state would rise by 110, or a 3.3% increase.

5.4 Responses to Affirmative Action Bans

The analysis of the prior subsection holds fixed applications to the two schools as well as their non-race rankings of the applicants. Should affirmative action be banned, we may expect reactions along multiple margins. At the application margin, both students and universities would change their behavior by either changing their application portfolios (students) or their recruiting strategies (universities). In the model of Section 4.1, this would be reflected by changes to N_g, the number of applicants from each group, as well as $\phi_g(x)$, the distribution of student quality for group g. Higher-ranked universities that currently employ racial preferences would likely see more applications from newly competitive white and Asian American applicants. While there would seem to be little room to increase URM applications at the most elite institutions given current recruiting practices (Arcidiacono, Kinsler, and Ransom, 2022d), there is one avenue by which URM applications may increase. Namely, many elite schools restrict where applicants can apply early. To the extent that, for example, URMs previously admitted to Stanford are now rejected, some of these applicants may then apply to Harvard regular action. Outside of the most elite institutions, we may expect to see rises in applications from URMs who would have been previously been admitted to places like Harvard.

Universities may also respond to affirmative action bans by changing their admissions criteria. Antonovics and Backes (2014) show that an affirmative action ban led selective public universities in California to lower their emphasis on academics and give more weight to being from less affluent backgrounds in making their admissions decisions. This partially undoes the ban's effect on the racial composition of the class by placing more weight on characteristics that are positively correlated with URM status. Our analysis shows that—absent any equilibrium response—those who benefit most from racial preferences are URMs from more advantaged backgrounds. Indeed, breaking out the capacity constraint analysis in Section 5.3 for Harvard show that the number of advantaged African American admits would drop by 80%, while the number of disadvantaged African American admits would drop by 52%.[66] While universities then have an incentive to shift upward the weight they place on characteristics that correlate with both being African American and from an advantaged background, finding such characteristics may prove difficult. If universities follow what is seen in Antonovics and Backes (2014), we would expect to see the number of advantaged African American admits fall even further as universities place more weight on disadvantaged status, but the losses for disadvantaged African Americans would be partially undone.

The removal of affirmative action at the most selective schools would also work to undo the consequences of an affirmative ban at the next tier of schools. With the removal of affirmative action, the drop in URM admits at top schools would increase the supply of URMs for schools in the next tier down. Hence we would expect the consequences of a ban on racial preferences at UNC on URM enrollment to be much more drastic when done in isolation. But if the schools above UNC can no longer consider race, schools like UNC would expect to see a significant improvement in the quality of their applicant pool, with these new applicants mitigating the losses from UNC no longer being able to directly consider race.

6 Conclusion

Using detailed admissions data and analyses made public in the *SFFA v. Harvard* and *SFFA v. UNC* cases, we examine how race influences the admissions process at Harvard and UNC-Chapel Hill. Racial preferences exhibit the same qualitative patterns in each of the three pools we consider. Each pool shows large racial preferences for Hispanic applicants with even larger preferences for African American applicants relative to white applicants. Moreover, in

[66] See Table 8.3R of Document 415-9 for details.

each pool, socioeconomically advantaged African American and Hispanic applicants receive larger bumps (relative to advantaged whites) than disadvantaged African American and Hispanics (relative to disadvantaged whites).

But the degree to which these racial preferences affect admissions decisions for underrepresented minorities differs substantially across the three pools. For Harvard and UNC out-of-state, both of which have very competitive admissions, racial preferences result in a respective quadrupling and tenfold increase in the admit rate of African Americans. For UNC in-state, where the baseline admit rate is much higher, racial preferences increase the African American admit rate by around 70%.

One of the primary reasons racial preferences are so large stems from the substantial racial disparities in college preparation. Had admissions been based on academics alone, African Americans and Hispanics would respectively make up less than 1% and 3% of admits at Harvard, less than 2% and 9% of out-of-state admits at UNC, and less than 5% of in-state UNC admits for both groups. As illustrated in Arcidiacono, Kinsler, and Ransom (2022b), admission to elite institutions is becoming more competitive, leading colleges to increasingly draw from the right tail of the academic preparation distribution. Without any meaningful narrowing of racial gaps in college preparation, racial preferences could well increase over time in order to keep URM representation at its current levels—further exacerbating within-college racial differences in academic preparation.

Perhaps in recognition of these preparation gaps, many colleges are moving away from using standardized test scores altogether. But this will likely further target racial preferences towards socioeconomically advantaged African American and Hispanic applicants. This is because higher socioeconomic backgrounds appear to be more strongly correlated with nonacademic factors used in admissions processes than with academic factors.[67] Yet, the targeting of racial preferences to socioeconomically advantaged URM applicants seems inconsistent with the primary aims of affirmative action, which are to improve the learning experience by having a diverse student body and to compensate for historical wrongs

[67] Arcidiacono, Kinsler, and Ransom (2022c) show that it is on Harvard's nonacademic ratings that legacies, connections of donors, and children of faculty do especially well. Alvero et al. (2021) show that parental income has a stronger correlation with the content and style of student admission essays than it does with the SAT.

in the US context—though only the former has been found to be constitutional. Socioeconomically advantaged African American and Hispanic applicants bring diversity along one dimension, but may be more similar to their advantaged white peers than their disadvantaged counterparts along other dimensions. Given the substantial government subsidies that universities receive, the unveiling of how racial preferences affect admissions—as well as the extent of preferences for legacies and athletes—may lead to more accountability in the way that admissions processes operate.

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Figures and Tables

Table 1: Ratings Used in Application Scoring at Harvard and UNC

Criterion	Harvard rating	UNC rating
Academics	Academic	Program, Performance
Extracurriculars	Extracurricular	Extracurricular
Personal Qualities	Personal	Personal Quality, Essay
Athletics	Athletic	
High School Support	Counselor letter, Two teacher letters	
Alumni Interview	Alumni overall, Alumni personal	
Other	Overall	

Sources: Discussion in Document 415-9 (Harvard) and Document 160-1 (UNC).

Note: UNC requires one letter of recommendation and Harvard requires essays, but these are not directly scored. Rather, they may be used as inputs into the scoring of other ratings.

Table 2: Applicant Shares, Admit Shares, and Admit Rates (%) by Race and Applicant Pool

	Harvard			UNC Out-of-State			UNC In-State		
	Applicant Share	Admit Share	Admit Rate	Applicant Share	Admit Share	Admit Rate	Applicant Share	Admit Share	Admit Rate
White	40.34	36.15	4.89	60.35	48.69	10.91	64.82	68.80	50.86
African American	10.97	15.25	7.58	9.07	11.24	16.74	13.59	8.66	30.53
Hispanic	12.59	14.22	6.16	8.54	12.75	20.18	6.27	5.36	40.96
Asian American	28.32	26.62	5.13	15.39	18.89	16.60	10.51	11.75	53.56
Total	142,728	7,784	5.45	105,632	14,281	13.52	57,225	27,422	47.92

Sources: Table B.3.1R of Document 415-9 (Harvard), Table 2.1 of Document 160-1 (UNC), and author calculations.

Notes: The Harvard sample includes typical (non-ALDC) applicants for the Classes of 2014–2019. The UNC samples include non-special applicants for the Classes of 2016–2021. See text for further description of the relevant samples.

Race/ethnicity is defined similarly across the Harvard and UNC datasets, with the exception that Hispanics at Harvard are grouped with Native Americans and Hawaiian/Pacific Islanders. Domestic, non-special applicants outside of the four major race/ethnicity categories are included in the total row.

Table 3: Admit and Applicant Characteristics by Race and Applicant Pool

	White		African American		Hispanic		Asian American	
	Applicant	Admit	Applicant	Admit	Applicant	Admit	Applicant	Admit
Panel A: Harvard								
Admitted	4.89	100.00	7.58	100.00	6.16	100.00	5.13	100.00
Female	45.62	43.14	59.61	55.01	50.41	45.98	49.30	52.65
Disadvantaged	6.36	14.61	29.21	28.48	24.33	37.40	10.85	21.86
1st-gen college	4.28	4.05	13.90	7.67	21.90	19.96	8.07	9.65
Applied for fee waiver	8.20	12.15	42.63	28.14	35.58	35.59	13.16	18.39
SAT math (z-score)	0.15	0.56	-1.07	0.14	-0.63	0.28	0.43	0.77
	(0.81)	(0.50)	(1.10)	(0.67)	(1.05)	(0.64)	(0.72)	(0.37)
SAT verbal (z-score)	0.33	0.72	-0.68	0.41	-0.39	0.44	0.33	0.74
	(0.75)	(0.43)	(1.08)	(0.56)	(1.05)	(0.59)	(0.79)	(0.41)
HS GPA (z-score)	0.18	0.50	-0.45	0.31	-0.04	0.45	0.22	0.52
	(0.85)	(0.52)	(1.17)	(0.76)	(0.97)	(0.62)	(0.81)	(0.47)
N	57,582	2,814	15,664	1,187	17,970	1,107	40,415	2,072
Panel B: UNC Out-of-State								
Admitted	10.91	100.00	16.74	100.00	20.18	100.00	16.60	100.00
Female	60.53	55.26	66.13	66.79	59.48	60.35	55.56	54.74
1st-gen college	8.78	7.22	27.95	19.00	22.14	14.94	12.63	8.90
Applied for fee waiver	3.58	2.63	34.60	25.67	17.35	12.63	9.37	6.63
SAT math (z-score)	0.08	0.80	-0.98	-0.08	-0.27	0.40	0.60	1.20
	(0.78)	(0.54)	(0.99)	(0.70)	(0.88)	(0.61)	(0.77)	(0.41)
SAT verbal (z-score)	0.24	1.02	-0.72	0.24	-0.07	0.64	0.38	1.17
	(0.81)	(0.57)	(1.04)	(0.71)	(0.91)	(0.64)	(0.88)	(0.57)
HS class percentile (0–100)	88.44	96.75	79.88	94.01	85.57	95.34	88.53	97.14
	(12.47)	(4.60)	(18.01)	(6.36)	(14.92)	(5.64)	(13.00)	(3.92)
N	63,744	6,954	9,585	1,605	9,023	1,821	16,252	2,698
Panel C: UNC In-State								
Admitted	50.86	100.00	30.53	100.00	40.96	100.00	53.56	100.00
Female	58.83	60.67	67.19	70.09	61.83	61.22	56.44	56.97
1st-gen college	15.69	13.21	39.20	33.57	46.73	40.48	24.68	20.04
Applied for fee waiver	5.97	5.06	43.46	37.99	33.10	28.91	14.08	12.19
SAT math (z-score)	-0.31	0.06	-1.31	-0.73	-0.84	-0.37	0.04	0.47
	(0.80)	(0.66)	(0.87)	(0.69)	(0.88)	(0.73)	(0.95)	(0.73)
SAT verbal (z-score)	-0.14	0.25	-1.14	-0.51	-0.68	-0.16	-0.20	0.27
	(0.88)	(0.73)	(0.96)	(0.81)	(0.99)	(0.83)	(1.03)	(0.84)
HS class percentile (0–100)	86.34	93.58	79.26	91.56	81.57	91.81	83.94	92.78
	(13.13)	(6.17)	(17.24)	(7.80)	(16.00)	(7.46)	(15.33)	(6.96)
N	37,094	18,865	7,775	2,374	3,589	1,470	6,017	3,223

Sources: Table B.3.1R of Document 415-9 (Harvard) and Tables 2.3.R–2.4.R of Document 160-2 (UNC).

Notes: Standard deviations are reported in parentheses below continuous variables. The Harvard sample includes typical (non-ALDC) applicants for the Classes of 2014–2019. The UNC samples include non-special applicants for the Classes of 2016–2021. See text for further description of the relevant samples.

Table 4: Applicant Shares and Admit Rates (%) by AI Decile, Race, and Applicant Pool

	White		African American		Hispanic		Asian American	
Decile	Applicant Share	Admit Rate	Applicant Share	Admit Rate	Applicant Share	Admit Rate	Applicant Share	Admit Rate
Panel A: Harvard								
1	4.91	0.00	37.95	0.03	19.98	0.00	3.75	0.00
2	7.67	0.39	23.08	1.03	20.94	0.32	5.07	0.20
3	10.57	0.56	14.68	5.19	16.32	1.95	6.56	0.64
4	11.07	1.82	8.24	12.76	12.17	5.50	7.49	0.86
5	13.33	2.57	5.75	22.41	9.59	9.13	9.61	1.86
6	10.31	4.20	3.26	29.72	6.01	13.65	8.97	2.49
7	12.28	4.79	2.85	41.12	5.29	17.28	11.23	3.98
8	11.28	7.53	2.09	44.48	4.57	22.93	13.19	5.12
9	9.95	10.77	1.26	54.59	3.01	26.16	16.21	7.55
10	8.64	15.27	0.85	56.06	2.12	31.32	17.92	12.69
Panel B: UNC Out-of-State								
1	6.77	0.49	39.21	0.45	13.10	0.12	4.41	0.00
2	9.36	0.52	19.01	5.71	12.28	1.27	6.45	0.28
3	10.31	0.89	11.85	14.36	10.81	3.61	7.30	0.25
4	10.57	1.52	8.84	29.85	10.25	9.28	8.62	1.04
5	10.85	2.90	6.00	39.61	10.06	15.97	9.05	1.38
6	10.99	5.34	4.52	46.10	9.06	22.20	10.19	4.56
7	10.90	9.24	3.89	57.74	8.38	30.35	10.72	6.51
8	10.55	15.87	2.89	57.87	8.77	33.63	12.39	15.51
9	10.29	26.51	1.99	69.12	8.42	42.41	13.87	27.66
10	9.41	41.58	1.80	73.17	8.86	61.44	16.99	52.89
Panel C: UNC In-State								
1	5.18	0.70	32.74	1.02	16.85	1.37	6.54	0.27
2	7.74	3.08	20.65	10.69	14.99	5.21	7.31	1.90
3	9.27	7.76	14.00	28.77	13.78	22.48	7.53	6.24
4	10.26	17.83	9.61	49.24	11.75	38.42	8.23	16.91
5	10.87	29.56	7.49	71.23	10.51	53.72	7.95	28.67
6	11.13	47.31	6.01	80.09	9.41	67.69	8.66	44.38
7	11.49	69.40	4.04	88.49	6.89	81.09	10.23	56.97
8	11.64	84.08	2.73	94.63	7.18	87.50	10.87	74.40
9	11.71	94.07	1.84	97.10	4.95	96.49	12.86	88.36
10	10.70	98.85	0.89	97.01	3.70	98.44	19.82	98.16

Sources: Tables 5.1R and 5.2R of Document 415-9 (Harvard) and Tables 3.1–3.4 of Document 160-1 (UNC).

Notes: The Harvard sample includes typical (non-ALDC) applicants for the Classes of 2014–2019. The UNC samples include non-special applicants for the Classes of 2016–2021. At Harvard, the Academic Index is computed by the admissions office as a weighted average of overall SAT score, high school GPA, and average SAT II scores. It ranges from 60–240. At UNC, the admissions office does not compute an academic index, so we define the academic index as the sum of two z-scores: one for the applicant's overall SAT score (math and verbal) and one for high school GPA. Any applicant with an invalid or missing high school GPA is excluded. The deciles do not necessarily overlap across pools: All deciles are computed specific to the given pool.

Table 5: Internal Applicant Ratings by Race and Applicant Pool

	White	African American	Hispanic	Asian American
Panel A: Harvard—Share (%) Receiving a 2 or Better (1-5 Scale)				
Academic	45.29	9.19	16.74	60.21
Extracurricular	24.35	15.54	16.83	28.23
Athletic	12.79	6.82	7.51	4.81
Personal	21.27	19.01	18.68	17.64
Teacher 1	30.42	17.12	21.59	30.79
Teacher 2	27.13	14.80	18.84	27.41
Counselor	25.28	13.86	16.47	25.12
Alumni Personal	49.92	42.98	41.39	50.33
Alumni Overall	36.49	20.84	23.61	40.89
Panel B: UNC Out-of-State—Average or Share (%) Receiving a 5 or Better (1-10 Scale)				
Average and Std. Dev.				
Program	6.40	5.51	6.70	7.57
	(2.60)	(2.78)	(2.79)	(2.47)
Performance	7.51	5.75	6.80	7.22
	(2.02)	(2.24)	(2.14)	(2.10)
Extracurricular	5.98	5.41	5.76	6.01
	(1.13)	(1.36)	(1.23)	(1.24)
Share (%)				
Essay > 5	15	12	15	20
Personal Quality > 5	20	24	27	24
Panel C: UNC In-State—Average or Share (%) Receiving a 5 or Better (1-10 Scale)				
Average and Std. Dev.				
Program	6.45	5.66	6.19	7.53
	(2.42)	(2.75)	(2.62)	(2.44)
Performance	7.02	5.42	6.09	6.60
	(2.16)	(2.19)	(2.22)	(2.29)
Extracurricular	5.75	5.15	5.29	5.59
	(1.16)	(1.36)	(1.34)	(1.33)
Share (%)				
Essay > 5	10	6	8	13
Personal Quality > 5	18	20	23	20

Sources: Calculations are based on data presented in Trial Exhibit P621 (Harvard) and Tables 2.3.R–2.4.R of Document 160-2 (UNC).

Notes: Standard deviations in parentheses. The Harvard sample includes typical (non-ALDC) applicants for the Classes of 2014–2019. The UNC samples include non-special applicants for the Classes of 2016–2021.

At Harvard, lower rating scores indicate stronger applicants. At UNC, higher rating scores indicate strength. Those with missing ratings at Harvard are coded as not having received a 2 or better. There are very few observations with missing ratings at UNC and these observations are dropped from the analysis.

The shares in Panels B and C are rounded to the nearest whole number due to how these quantities were originally reported in Document 160-2.

Table 6: Overview of Controls Used in Admissions Models

	Harvard			UNC		
Covariate	Sparse	+Academics	Preferred	Sparse	+Academics	Preferred
Demographics						
Race/ethnicity	✓	✓	✓	✓	✓	✓
Female	✓	✓	✓	✓	✓	✓
Disadvantaged	✓	✓	✓			
1^{st}-gen college	✓	✓	✓	✓	✓	✓
Early Action/Decision	✓	✓	✓	✓	✓	✓
Fee waiver	✓	✓	✓	✓	✓	✓
Financial aid	✓	✓	✓			
Mother's Education	✓	✓	✓			
Father's Education	✓	✓	✓			
Year	✓	✓	✓	✓	✓	✓
Docket × Year	✓	✓	✓			
Intended Major	✓	✓	✓			✓
Legacy				✓	✓	✓
Child of Faculty				✓	✓	✓
Academics						
SAT math		✓	✓		✓	✓
SAT verbal		✓	✓		✓	✓
SAT II		✓	✓			
GPA		✓	✓		✓	✓
HS class percentile					✓	✓
Harvard Academic Index		✓	✓			
Rank among UNC applicants from HS					✓	✓
Does not meet min. admission requirements					✓	✓
Ratings						
Academic rating			✓			
Extracurricular rating			✓			
Athletic rating			✓			
Teacher 1 rating			✓			
Teacher 2 rating			✓			
Counselor rating			✓			
Alumni personal rating			✓			
Alumni overall rating			✓			
Academic 2+ × Extracurricular 2+			✓			
Academic 2+ × Athletic 2+			✓			
Extracurricular 2+ × Athletic 2+			✓			
Program rating						✓
Performance rating						✓
Activity rating						✓
Essay rating						✓
Personal Quality rating						✓
Interactions						
Female × Major			✓			
Female × Race			✓			✓
Disadvantaged × Race			✓			
1^{st}-gen × Race						✓
Early Action × Race			✓			
Demographics × Year			✓			
Local characteristics						
College Board HS characteristics			✓			
Census Bureau neighborhood characteristics			✓			
Total No. of Controls	120	132	319	19	62	115

Sources: Figure 7.1 of Document 415-8, Appendix E of Document 419-141, Trial Exhibit P164 (Harvard); Figure 4.1 and Appendix A.3 of Document 160-1 and p. 21 of Document 160-2 (UNC); and author calculations.

Notes: The out-of-state and in-state models at UNC are identically specified. See source documents for further details.

Table 7: Selected Coefficients from Admissions Logits

	Harvard Typical			UNC Out-of-state			UNC In-state		
	Demographics	+Academics	Preferred	Demographics	+Academics	Preferred	Demographics	+Academics	Preferred
African American	0.531	2.417	3.772	0.866	4.766	6.162	-0.589	1.851	3.542
	(0.040)	(0.050)	(0.105)	(0.033)	(0.077)	(0.125)	(0.029)	(0.057)	(0.119)
Hispanic	0.425	1.273	1.959	0.980	2.484	3.000	-0.131	1.24	1.993
	(0.039)	(0.044)	(0.085)	(0.031)	(0.071)	(0.104)	(0.038)	(0.070)	(0.148)
Asian American	0.057	-0.434	-0.466	0.781	0.196	0.077	0.235	-0.133	0.148
	(0.032)	(0.035)	(0.070)	(0.026)	(0.055)	(0.079)	(0.029)	(0.057)	(0.104)
Female	-0.044	0.254	0.163	-0.157	0.333	-0.075	0.104	0.198	0.112
	(0.025)	(0.027)	(0.110)	(0.019)	(0.025)	(0.040)	(0.018)	(0.031)	(0.046)
Disadvantaged	1.183	1.257	1.660						
	(0.042)	(0.048)	(0.138)						
1^{st}-gen college	-0.004	0.174	-0.014	-0.172	0.912	1.889	-0.304	0.647	1.168
	(0.052)	(0.059)	(0.167)	(0.033)	(0.044)	(0.075)	(0.024)	(0.040)	(0.063)
Early Action/Decision	1.616	1.456	1.410	0.846	0.727	0.828	0.981	0.571	0.512
	(0.032)	(0.035)	(0.104)	(0.020)	(0.025)	(0.030)	(0.020)	(0.034)	(0.042)
Application Fee Waived	-0.153	0.484	0.697	-0.135	0.360	0.349	-0.083	0.359	0.349
	(0.041)	(0.047)	(0.063)	(0.039)	(0.051)	(0.061)	(0.030)	(0.050)	(0.063)
Female × African American			-0.099			0.081			-0.469
			(0.114)			(0.107)			(0.121)
Female × Hispanic			0.117			0.357			-0.166
			(0.104)			(0.094)			(0.152)
Female × Asian American			0.229			0.107			-0.247
			(0.082)			(0.075)			(0.121)
Disadvantaged × African American			-1.577						
			(0.143)						
Disadvantaged × Hispanic			-0.582						
			(0.133)						
Disadvantaged × Asian American			0.144						
			(0.119)						
1^{st}-gen × African American						-1.343			-1.027
						(0.136)			(0.124)
1^{st}-gen × Hispanic						-0.986			-0.392
						(0.136)			(0.159)
1^{st}-gen × Asian American						-0.554			-0.148
						(0.130)			(0.143)
Observations	142,728	142,700	128,422	105,623	105,623	105,116	57,225	57,225	57,225
No. of controls	120	132	319	17	58	111	17	58	111
Pseudo R^2	0.078	0.260	0.556	0.073	0.420	0.588	0.056	0.588	0.727
Demographic Variables	✓	✓	✓	✓	✓	✓	✓	✓	✓
Academic Variables		✓	✓		✓	✓		✓	✓
Ratings Variables			✓			✓			✓
Demographic Interactions			✓			✓			✓
HS and Neighborhood Variables			✓						

Sources: Table B.7.1R of Document 415-9 (Harvard) and Tables A.4.1.R and A.4.2.R of Document 160-2 (UNC).

Notes: Each column represents a separate logit model. Harvard results are pooled across the Classes of 2014–2019. UNC results are pooled across the Classes of 2016–2021 admissions cycles. "Disadvantaged" refers to socioeconomic disadvantage as classified by Harvard staff, "1^{st}-gen college" indicates first-generation college student status, and "Early Action/Decision" indicates that the application was considered under early decision (UNC) or early action (Harvard). See Table 6 for details on other controls included in each model. Additional models and coefficients are presented in Appendix Tables A2–A3 (Harvard) and A4–A5 (UNC). Hispanics are pooled with Native Americans and Hawaiian/Pacific Islanders in the Harvard models, but are separate from those groups in the UNC models.

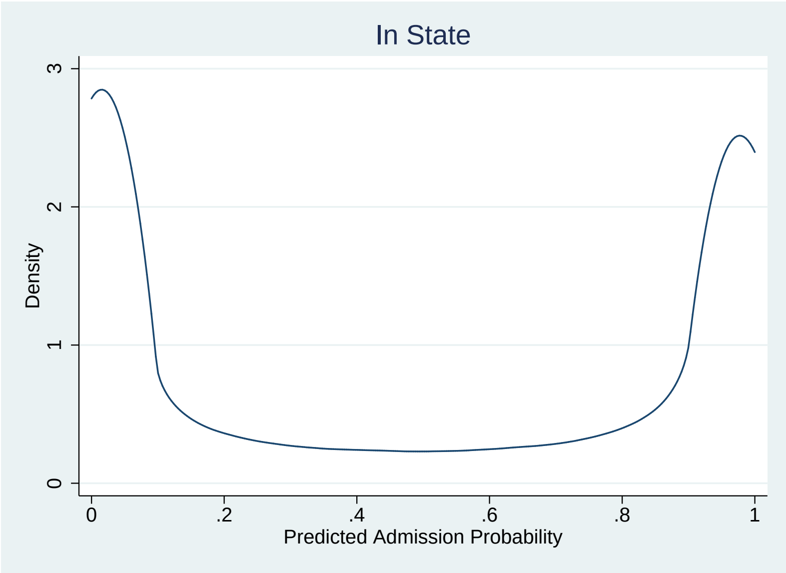
Table 8: Accuracy (%) of Preferred Admissions Models

Model	Accuracy for Admits	Accuracy for Rejects	Overall Accuracy
Panel A: Model Performance			
Harvard	64.1	99.1	96.1
UNC Out-of-State	75.4	96.1	93.3
UNC In-State	91.8	92.5	92.1
Panel B: Random Assignment			
Harvard	5.45	94.55	90.05
UNC Out-of-State	13.9	86.5	76.7
UNC In-State	48.1	52.2	50.2

Sources: Appendix D of Arcidiacono, Kinsler, and Ransom (2022a) (Harvard) and Tables 3.1–3.2 of Document 160-2 (UNC).

Note: Results from preferred admissions models in Table 7. Accuracy is defined as the percentage of total observations that are correctly predicted to be admitted or rejected. Harvard accuracy numbers calculated from simulations of data in the public record.

Figure 1: Unconditional Distribution of UNC In-State Predicted Admit Probabilities

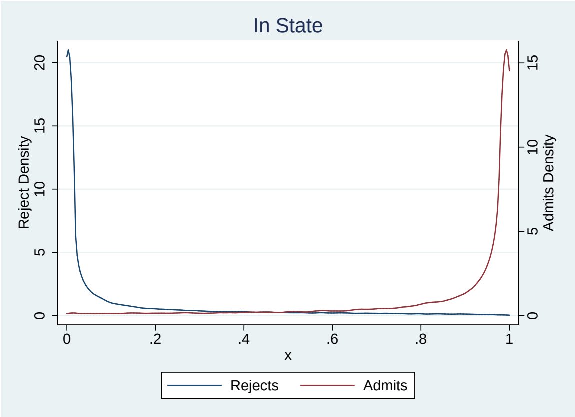


Source: Figure 1 of Document 160-2.

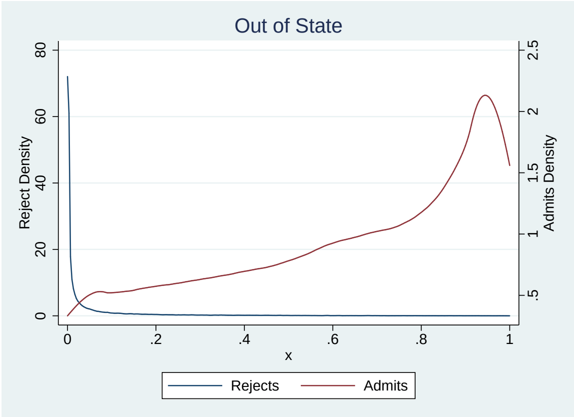
Notes: Results pooled across the Classes of 2016–2021 admissions cycles. Predicted probabilities are taken from the preferred models in Table 7.

Figure 2: Conditional Distribution of Predicted Admit Probabilities by UNC Applicant Pool

(a) Conditional density, In-state



(b) Conditional density, Out-of-state



Source: Figures 2–3 of Document 160-2.

Notes: Results pooled across the Classes of 2016–2021 admissions cycles. Predicted probabilities are taken from the preferred models in Table 7.

Table 9: Average Marginal Effects of Racial Preferences

	Average Admit Rate (%) with Racial Preferences	Average Admit Rate (%) without Racial Preferences	Average Marginal Effect (pp) of Race	Percentage Increase due to Racial Preferences
Panel A: Harvard Typical				
African American	9.54	2.25	7.29	324
Hispanic or Other	7.16	2.97	4.19	141
Panel B: UNC Out-of-State				
African American	17.1	1.5	15.6	1,040
Hispanic	20.3	6.0	14.2	237
Panel C: UNC In-State				
African American	30.5	17.8	12.7	71
Hispanic	41.0	31.2	9.7	31

Sources: Table 8.2N of Document 415-9 and surrounding text (Harvard), and Tables 3.3–3.4 of Document 160-2 (UNC).

Notes: Harvard results are pooled across typical applicants to the Classes of 2014–2019. UNC results are pooled across the Classes of 2016–2021. Average marginal effects are expressed in percentage points and are based on the preferred models reported in Table 7.

Table 10: Admit Rates (%) of Previously Admitted Applicants Absent Racial Preferences

	African American	Hispanic
Panel A: Harvard including ALDC		
Status quo	100.0	100.0
No racial preferences	30.0	46.1
Panel B: UNC Out-of-State		
Status quo	100.0	100.0
No racial preferences	8.7	29.2
Panel C: UNC In-State		
Status quo	100.0	100.0
No racial preferences	57.8	75.8

Source: Table 3 of Exhibit 287 (Harvard) and Table 3.1 of Document 160-3 (UNC).

Note: No-racial-preferences admit rates are calculated using the preferred models reported in Table 7.

Table 11: Effects of Removing Racial Preferences in the Presence of Capacity Constraints

	Harvard Typical			UNC Out-of-State			UNC In–State		
	Number of Admits	Share of Admits	Percentage Change	Number of Admits	Share of Admits	Percentage Change	Number of Admits	Share of Admits	Percentage Change
Panel A: Data									
White	2,704	36.1		6,954	48.7		18,865	68.8	
African American	1,163	15.5		1,605	11.2		2,374	8.7	
Hispanic	1,188	15.8		1,821	12.8		1,470	5.4	
Asian American	2,013	26.9		2,698	18.9		3,223	11.8	
Panel B: No racial preferences									
White	3,195	42.6	18.2%	8,878	62.2	27.7%	19,889	72.5	5.4%
African American	324	4.3	-72.1%	208	1.5	-87.7%	1,532	5.6	-35.5%
Hispanic	581	7.8	-51.1%	738	5.2	-59.5%	1,212	4.4	-17.6%
Asian American	2,812	37.5	39.7%	3,260	22.8	20.8%	3,370	12.3	4.6%

Sources: Table 8.1R of Document 415-9 (Harvard) and Tables 4.4.R–4.5.R of Document 160-2.

Notes: Results pool across admissions cycles and correspond to the preferred models reported in Table 7. Admissions probabilities are computed holding fixed the size of the admitted class. Shares do not sum to 100 within column and panel because smaller groups (e.g. Native American, Hawaiian, Missing) are omitted.

The percentage changes reported in Panel B come from subtracting the number of admits in Panel B from the number of admits in Panel A and dividing by the number of admits in Panel A.

A Supporting Figures and Tables

Table A1: UNC Sample Selection

	Out-of-State			In-State		
	Admits	Applicants	Remaining observations	Admits	Applicants	Remaining observations
Initial sample	21,165	135,289	135,289	32,315	65,123	65,123
Withdrawal, incomplete	0	7,772	127,517	0	2,840	62,283
	0.0%	5.7%		0.0%	4.4%	
Any rating zero	70	382	127,135	234	315	61,968
	0.3%	0.3%		0.7%	0.5%	
Any special	4,249	4,273	122,862	4,577	4,590	57,378
	20.1%	3.2%		14.2%	7.0%	
Foreign	2,565	17,230	105,632	82	153	57,225
	12.1%	12.7%		0.3%	0.2%	
Previous admit	0	0	105,632	0	0	57,225
	0.0%	0.0%		0.0%	0.0%	
Total removed	6,884	29,657	–	4,893	7,898	–
Total remaining	14,281	105,632	105,632	27,422	57,225	57,225

Source: Tables A.2.1 and A.2.2 of Document 160-1.

Notes: Results pooled across the Classes of 2016–2021 admissions cycles. Percentages denote the number of observations removed as a percentage of the initial number of observations.

"Any rating zero" refers to if any of the five application ratings were assigned a score of 0, which is outside the range of possible values (1–10).

"Any special" refers to recruited athletes or members of the more than 30 other special recruiting categories. These applicants all had admit rates exceeding 97%. Non-athletic special categories include elite scholarships such as the Morehead-Cain, Pogue or Robertson, or excellence in music or drama.

Table A2: Selected Coefficients, Admissions Models of Typical Harvard Applicants

	(1)	(2)	(3)	(4)	(5)	(6)
African American	0.531	2.417	2.671	2.851	3.772	3.876
	(0.040)	(0.050)	(0.074)	(0.078)	(0.105)	(0.112)
Hispanic	0.425	1.273	1.286	1.339	1.959	2.027
	(0.039)	(0.044)	(0.063)	(0.067)	(0.085)	(0.091)
Asian American	0.057	-0.434	-0.565	-0.378	-0.466	-0.330
	(0.032)	(0.035)	(0.052)	(0.055)	(0.070)	(0.074)
Female	-0.044	0.254	0.228	0.271	0.163	0.141
	(0.025)	(0.027)	(0.064)	(0.088)	(0.110)	(0.116)
Disadvantaged	1.183	1.257	1.497	1.606	1.660	1.535
	(0.042)	(0.048)	(0.071)	(0.108)	(0.138)	(0.147)
1st-gen college	-0.004	0.174	0.161	-0.018	-0.014	0.058
	(0.052)	(0.059)	(0.059)	(0.127)	(0.167)	(0.178)
Early Action	1.616	1.456	1.371	1.348	1.410	1.440
	(0.032)	(0.035)	(0.055)	(0.084)	(0.104)	(0.110)
Female × African American			-0.035	-0.067	-0.099	-0.088
			(0.086)	(0.089)	(0.114)	(0.121)
Female × Hispanic			0.063	0.068	0.117	0.098
			(0.079)	(0.082)	(0.104)	(0.110)
Female × Asian American			0.107	0.095	0.229	0.200
			(0.065)	(0.067)	(0.082)	(0.087)
Disadv × African American			-0.984	-1.094	-1.577	-1.540
			(0.107)	(0.111)	(0.143)	(0.151)
Disadv × Hispanic			-0.270	-0.350	-0.582	-0.583
			(0.098)	(0.104)	(0.133)	(0.140)
Disadv × Asian American			0.015	0.006	0.144	0.147
			(0.092)	(0.095)	(0.119)	(0.126)
Academic Rating=4					-3.990	-3.915
					(0.626)	(0.633)
Academic Rating=2					1.425	1.941
					(0.090)	(0.128)
Academic Rating=1					4.094	5.122
					(0.156)	(0.185)
Extracurricular Rating=4					-1.301	-1.122
					(0.393)	(0.408)
Extracurricular Rating=2					1.990	1.810
					(0.082)	(0.108)
Extracurricular Rating=1					4.232	4.215
					(0.169)	(0.187)
N	142,728	142,700	142,700	136,061	128,422	128,082
Pseudo R Sq.	0.078	0.260	0.262	0.283	0.556	0.604
Demographics	✓	✓	✓	✓	✓	✓
Academics		✓	✓	✓	✓	✓
Race and Gender Interactions			✓	✓	✓	✓
HS and NBHD Variables				✓	✓	✓
Ratings (excluding Personal)					✓	✓
Personal Rating						✓

Source: Data presented in Table B.7.1R of Document 415-9.

Notes: All models include year indicators and year interactions. Standard errors reported below each coefficient in parentheses. In models (3)-(6), the race coefficients reflect preferences for male, non-disadvantaged students. The excluded ratings categories are a 3. See Table 6 in the text for details on other controls included in each model.

Table A3: Selected Coefficients, Admissions Models of All Harvard Applicants

	(1)	(2)	(3)	(4)	(5)	(6)
African American	0.486	2.290	2.604	2.815	3.596	3.674
	(0.038)	(0.047)	(0.071)	(0.075)	(0.097)	(0.103)
Hispanic	0.393	1.190	1.271	1.338	1.908	1.959
	(0.037)	(0.042)	(0.061)	(0.064)	(0.081)	(0.086)
Asian American	0.047	-0.400	-0.529	-0.321	-0.389	-0.257
	(0.030)	(0.032)	(0.050)	(0.053)	(0.066)	(0.070)
Female	-0.025	0.245	0.247	0.258	0.177	0.155
	(0.023)	(0.025)	(0.058)	(0.081)	(0.099)	(0.105)
Disadvantaged	1.172	1.243	1.494	1.616	1.640	1.527
	(0.041)	(0.047)	(0.070)	(0.106)	(0.132)	(0.139)
1^{st}-gen college	0.012	0.180	0.165	-0.033	-0.066	-0.001
	(0.051)	(0.057)	(0.058)	(0.124)	(0.159)	(0.168)
Early Decision	1.632	1.448	1.394	1.426	1.480	1.531
	(0.029)	(0.032)	(0.047)	(0.075)	(0.092)	(0.096)
Legacy	1.238	1.650	1.697	1.720	2.141	2.329
	(0.046)	(0.051)	(0.059)	(0.123)	(0.155)	(0.164)
Faculty or Staff Child	1.260	1.410	1.692	1.875	2.472	2.630
	(0.139)	(0.159)	(0.310)	(0.319)	(0.359)	(0.353)
Dean's/Director's List	1.495	1.931	2.379	2.449	3.301	3.246
	(0.053)	(0.059)	(0.356)	(0.366)	(0.417)	(0.417)
Disadv × African American			-1.023	-1.121	-1.582	-1.565
			(0.104)	(0.108)	(0.135)	(0.142)
Disadv × Hispanic			-0.278	-0.356	-0.618	-0.616
			(0.096)	(0.102)	(0.127)	(0.133)
Disadv × Asian American			0.020	0.023	0.159	0.162
			(0.090)	(0.093)	(0.115)	(0.121)
Legacy × African American			-0.725	-0.716	-0.792	-0.872
			(0.214)	(0.223)	(0.281)	(0.297)
Legacy × Hispanic			-0.536	-0.672	-0.779	-0.736
			(0.183)	(0.192)	(0.235)	(0.240)
Legacy × Asian American			0.398	0.331	0.626	0.612
			(0.142)	(0.150)	(0.187)	(0.195)
Other Special × African American			-0.882	-0.788	-1.261	-1.267
			(0.349)	(0.364)	(0.485)	(0.529)
Other Special × Hispanic			-0.729	-0.692	-1.343	-1.328
			(0.230)	(0.243)	(0.287)	(0.295)
Other Special × Asian American			0.377	0.491	0.515	0.471
			(0.160)	(0.175)	(0.208)	(0.219)
N	148,769	148,741	148,741	141,701	134,365	134,349
Pseudo R Sq.	0.136	0.294	0.297	0.318	0.555	0.599
Demographics	✓	✓	✓	✓	✓	✓
Academics		✓	✓	✓	✓	✓
Race and Gender Interactions			✓	✓	✓	✓
HS and NBHD Variables				✓	✓	✓
Ratings (excluding Personal)					✓	✓
Personal Rating						✓

Source: Data presented in Table B.7.2R of Document 415-9.

Notes: All models include year indicators and year interactions. Standard errors reported below each coefficient in parentheses. In models (3)-(6), the race coefficients reflect preferences for male, non-disadvantaged, non-LDC students. The excluded ratings categories are a 3. See Table 6 in the text for details on other controls included in each model.

Table A4: Selected Coefficients, UNC Out-of-State Admissions Logits

	(1)	(2)	(3)	(4)
African American	0.866	4.766	5.934	6.162
	(0.033)	(0.077)	(0.095)	(0.125)
Hispanic	0.980	2.484	3.054	3.000
	(0.031)	(0.071)	(0.083)	(0.104)
Asian American	0.781	0.196	0.09	0.077
	(0.026)	(0.055)	(0.065)	(0.079)
Female	-0.157	0.333	0.032	-0.075
	(0.019)	(0.025)	(0.030)	(0.040)
1st-gen college	-0.172	0.912	1.367	1.889
	(0.033)	(0.044)	(0.052)	(0.075)
Regular Admissions	-0.846	-0.727	-0.809	-0.828
	(0.020)	(0.025)	(0.030)	(0.030)
Legacy	1.866	3.412	4.741	4.769
	(0.037)	(0.055)	(0.071)	(0.072)
Waiver	-0.135	0.360	0.259	0.349
	(0.039)	(0.051)	(0.060)	(0.061)
Female × African American				0.081
				(0.107)
Female × Hispanic				0.357
				(0.094)
Female × Asian American				0.107
				(0.075)
1st-gen × African American				-1.343
				(0.136)
1st-gen × Hispanic				-0.986
				(0.136)
1st-gen × Asian American				-0.554
				(0.130)
Academic Variables		✓	✓	✓
Ratings Variables			✓	✓
Heterogeneity Variables				✓
Observations	105,623	105,623	105,137	105,116
Pseudo R^2	0.073	0.420	0.586	0.588

Source: Table A.4.2.R of Document 160-2.

Notes: Results pooled across the Classes of 2016–2021 admissions cycles. "1st-gen college" refers to First Generation College student, "regular admissions" indicates that the application was not considered under early action, "legacy" indicates that the applicant has a parent who graduated from UNC, and "waiver" refers to having the application fee waived. See Table 6 in the text for details on other controls included in each model.

Table A5: Selected Coefficients, UNC In-State Admissions Logits

	(1)	(2)	(3)	(4)	(5)	(6)
African American	-0.589	1.851	2.863	3.542	3.599	3.986
	(0.029)	(0.057)	(0.073)	(0.119)	(0.123)	(0.138)
Hispanic	-0.131	1.24	1.771	1.993	1.997	2.313
	(0.038)	(0.070)	(0.086)	(0.148)	(0.152)	(0.164)
Asian American	0.235	-0.133	-0.011	0.148	0.167	0.167
	(0.029)	(0.057)	(0.069)	(0.104)	(0.106)	(0.115)
Female	0.104	0.198	0.035	0.112	0.124	0.177
	(0.018)	(0.031)	(0.039)	(0.046)	(0.047)	(0.052)
1^{st}-gen college	-0.304	0.647	0.926	1.168	1.174	1.142
	(0.024)	(0.040)	(0.050)	(0.063)	(0.065)	(0.072)
Regular Admissions	-0.981	-0.571	-0.503	-0.512	-0.499	-0.604
	(0.020)	(0.034)	(0.042)	(0.042)	(0.044)	(0.048)
Legacy	0.193	0.38	0.447	0.467	0.48	0.351
	(0.025)	(0.040)	(0.050)	(0.051)	(0.052)	(0.057)
Waiver	-0.083	0.359	0.277	0.349	0.355	0.165
	(0.030)	(0.050)	(0.062)	(0.063)	(0.065)	(0.074)
Faculty Child	0.195	0.502	0.76	0.762	0.754	0.333
	(0.069)	(0.119)	(0.147)	(0.148)	(0.151)	(0.170)
Female × African American				-0.469	-0.516	-0.628
				(0.121)	(0.126)	(0.138)
Female × Hispanic				-0.166	-0.109	-0.156
				(0.152)	(0.158)	(0.170)
Female × Asian American				-0.247	-0.274	-0.357
				(0.121)	(0.124)	(0.133)
1^{st}-gen × African American				-1.027	-0.985	-1.088
				(0.124)	(0.129)	(0.143)
1^{st}-gen × Hispanic				-0.392	-0.343	-0.437
				(0.159)	(0.165)	(0.179)
1^{st}-gen × Asian American				-0.148	-0.148	-0.001
				(0.143)	(0.147)	(0.161)
Academic Variables		✓	✓	✓	✓	✓
Ratings Variables			✓	✓	✓	✓
Heterogeneity Variables				✓	✓	✓
HS Fixed Effects Sample					✓	✓
HS Fixed Effects model						✓
Observations	57,225	57,225	57,225	57,225	53,504	53,504
Pseudo R^2	0.056	0.588	0.725	0.727	0.724	0.754

Source: Table A.4.1.R of Document 160-2.

Notes: Results pooled across the Classes of 2016–2021 admissions cycles. "1^{st}-gen college" refers to First Generation College student, "regular admissions" indicates that the application was not considered under early action, "legacy" indicates that the applicant has a parent who graduated from UNC, and "waiver" refers to having the application fee waived. See Table 6 in the text for details on other controls included in each model.

Table A6: Racial Distribution of Harvard Typical Applicants (%) by Strength on Observed Factors Affecting Admission

Index Decile	White	African American	Hispanic	Asian American
Panel A: Admissions index				
5 or lower	45.8	78.6	69.5	38.1
6	11.1	5.1	6.9	11.3
7	11.2	4.2	6.0	12.0
8	10.7	3.9	5.9	12.8
9	10.7	4.1	5.9	12.8
10	10.5	4.1	5.7	13.1
Panel B: Non-academic admissions index				
5 or lower	48.0	59.9	56.9	46.6
6	10.6	8.0	8.8	10.4
7	10.4	8.2	8.5	10.7
8	10.4	8.0	8.1	10.9
9	10.3	7.5	8.4	11.0
10	10.3	8.4	9.4	10.4
Panel C: Non-academic ratings admissions index				
5 or lower	45.7	68.4	64.2	43.9
6	10.5	7.2	7.4	11.3
7	10.9	7.3	8.0	10.6
8	10.8	6.5	7.3	11.1
9	10.8	5.7	6.8	11.7
10	11.3	5.0	6.3	11.3

Source: Tables 7.3R, 7.4R, and 7.5R of Document 415-9. Results for preferred model displayed.

Notes: Numbers indicate the percentage of applicants within each cell. Each column sums to 100.

Decile refers to the ranking of typical applicants on the given dimension of their estimated admissions index. The admissions index includes all covariates in the admissions model except race and the admissions cycle. The non-academic admissions index excludes test scores, grades and academic ratings from the admissions index. The non-academic ratings admissions index excludes all admissions model covariates except the following Harvard ratings: extracurricular, athletic, school support, and alumni ratings.

Table A7: Where UNC African American and Hispanic Admits Fall on the Asian American and White UNC Admissions Index Distribution

	Median African American		Median Hispanic		
	Percentile of Applicant Dist.	Percentile of Admit Dist.	Percentile of Applicant Dist.	Percentile of Admit Dist	*N*
Out-of-State Asian American	8	1	29	7	16,202
In-State Asian American	18	8	30	20	6,017
Out-of-State White	12	2	36	10	63,550
In-State White	16	10	30	24	37,094

Source: Table 5.1.R of Document 160-2.

Note: Results come from the preferred model in Table 7.

B Academic Quality and Race

Our theoretical model of Section 4.1 assumes that applicant quality is defined similarly for those of different races. A coarse check on this assumption is to use the aggregate data from Table 4 and regress the log-odds of admission—by academic index decile and race—on decile, race indicators, and their interaction for each of our three applicant pools. We find that for (non-ALDC) Harvard and UNC in-state applicants, the link between academic index decile and the log-odds of admissions are not statistically different across racial groups. For UNC out-of-state applicants, the slope relating the decile to the log-odds of admission is smaller for African American applicants (about 70% of the white slope) and steeper for Asian American applicants. These last results are consistent with selection operating differently for the UNC out-of-state pool. Namely, African Americans with exceptionally strong academics are substantially more likely to be admitted to universities ranked above UNC than their Asian American counterparts. This will result in negative (positive) selection at the top of the academic distribution for African Americans (Asian Americans), selection that will be handled in the admissions model through the extensive controls available. Overall, the results suggest that schools value academics similarly within-race.

In the Harvard case we can provide more auxiliary evidence of applicant quality being defined similarly across race. Table 4.1N of Document 160-2 shows different robustness checks with regard to whether there is a penalty against Asian Americans relative to white applicants. In one of those robustness checks, the model is estimated on only white and Asian American applicants. This model produces virtually identical results for the average marginal effect of being Asian American (relative to white) as one where all races are included and race is interacted with disadvantaged status.[A1] Had including African American and Hispanic applicants affected, for example, the coefficients on the academic variables, the average marginal effect for Asian Americans would have been affected as well due to Asian Americans being so much stronger on academics than their white counterparts. These results stand in contrast to the case where ALDC applicants are included. Including these applicants reduces the importance of both academics and extracurriculars in admissions. See Table 6

[A1] The coefficients for these models are not in the public record.

of Arcidiacono, Kinsler, and Ransom (2022c).