The Academic Consequences of Affirmative Action Bans Combined with Diversity Targets[1]

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December 2024

This paper examines the problem of a college affected by both a legal ban on affirmative action in admissions and pressure to raise enrollment of underrepresented minorities (URMs), as exemplified by UCLA, which adopted a holistic admissions process in 2006 in response to protests over low URM enrollment. The new process increased the URM share of admitted students by about 3 percentage points, but the primary effects of the changes were on admissions decisions *within* racial/ethnic groups. Within all groups, admission rates for applicants with high SAT scores and low income and parental education declined. Measured relative to UCLA's pre-2006 revealed preferences, achieving the increase in URM admissions via holistic admissions was roughly 4-5 times as costly as doing so via a simple reallocation of slots between groups. Had UCLA complied with a stricter interpretation of the affirmative action ban, it would have been significantly more costly.

[1] The author would like to thank [list to come] for helpful comments and Tim Groseclose and Rick Sander for helpful discussions about the data used in this paper. The viewpoint expressed in the paper is that of the author and not of any organization with which he is affiliated. This paper received no research support, apart from indirectly via the author's employment at Dartmouth, and the author has no financial conflicts of interest to disclose.

The Regulation of College Admissions and Its Unintended Consequences

In *Students for Fair Admissions (SFFA) v. Harvard* and *SFFA v. University of North Carolina* (2023), the U.S. Supreme Court banned affirmative action in college admissions decisions. Colleges are nevertheless likely to face internal and external pressure to enroll higher shares of Underrepresented Minority (URM) students than they would without affirmative action. Colleges will therefore be forced to satisfy two, somewhat incompatible, constraints.

This paper examines the problem they face. It does so first theoretically, and then by empirically examining the experience of UCLA, which also faced these twin constraints in 2006. California voters banned affirmative action in 1996, leading to a decline in the enrollment share of URM students, and especially Black students, at its state universities (Figure 1). Protests about the issue in 2006 led UCLA to redesign its admissions process to attempt to both follow the law and respond to the protests.

As predicted by the model, the primary effects of UCLA's policy changes were *within* racial groups. The Black share of admitted students rose from 2.3 to 3.7 percent, and the share of Hispanic/Native American students from 13.5 to 15.1 percent.[2] I estimate that the changes in the admissions process that produced these relatively modest shifts in racial composition affected the admissions probabilities within racial groups in a way that altered the admissions decisions of 12 percent of admitted students, or about 4 times as many students as represented by the increased URM enrollment shares.

Again as predicted by the model, admission probabilities rose for students whose characteristics were more similar to the average URM applicant, and particularly to the average Black applicant. This manifested in shifts in apparent emphasis on specific academic and socioeconomic metrics. Within academic metrics, admissions decisions began to reward grades more than SAT scores, especially SAT I Math scores. Within socioeconomic metrics, decisions shifted towards rewarding attending low-test-score high schools (relatively more associated with Black applicants), as opposed to low family income or

[2] The data I use in this paper aggregate Hispanic and Native American applicants for privacy reasons, and so I will do so throughout the paper. I will also follow the convention of referring to Black and Hispanic/Native American applicants collectively as Underrepresented Minorities (URMs).

parental educational attainment (more associated with Hispanic/Native American applicants). At the same time, the overall advantage given to applicants from poorer backgrounds declined, plausibly because the new emphasis on URM shares came at the expense of an earlier emphasis on socioeconomic status.

Were it not for the California anti-affirmative action law, as well as already extant U.S. Supreme Court decisions, UCLA could have increased URM enrollment by simply implementing a quota, and then making undistorted decisions within each racial group. If one views the pre-2006 admissions decisions as informative about UCLA's preferences, then its post-2006 admissions achieved increases in Black and non-Black URM admission shares at a utility cost that was about 4-5 times as high as could have been achieved under quotas.

The UCLA episode is interesting in that it allows us to examine real-world admission decisions under an affirmative action ban and how they respond to a tightening of the activism constraint. Past work that has compared the cost of achieving a given racial/ethnic mix under affirmative action and color-blind admissions has done so using simulated admissions decisions (e.g., Fryer, Loury, and Yoret, 2008; Long, 2014). Real-world admissions decisions might respond to a tightening of constraints less "efficiently", in the sense of minimizing changes to within-group decisions, to the extent they are constrained by a need to motivate admissions process changes on non-racial grounds. Some of the apparent inefficiencies in UCLA's changes could be rationalized by this additional constraint. That said, whether UCLA actually complied with the anti-affirmative action law is in dispute, especially after its 2006 changes. Given this, it is perhaps especially surprising that was not able to achieve increased URM shares at lower cost.

It is worth acknowledging that "costly" is in terms of UCLA's utility as inferred from its pre-2006 admissions decisions. It reflects social welfare only to the extent that UCLA's decisions did. Prior to 2006, UCLA gave roughly equal weight to test scores and grades in its admissions decisions, which is consistent with the roughly equal predictive power they have in predicting college grades.[3] In addition, UCLA gave

[3] The literature on the predictive power of standardized tests and high school grades in predicting performance in college is extensive. University of California (2020) covers the UC system in 2005 and 2007 and concludes that test

an admissions preference to students with lower socioeconomic backgrounds, as proxied by family income, parental education, and high school test scores. While these preferences may strike many as reasonable, if pre-2006 decisions reflected outdated thinking combined with inertia, then the 2006 changes may not have been distortionary at all. Indeed it may be legally necessary for UCLA to argue that this is so, if the alternative is to attribute the admissions process changes to a racial motivation. In any setting in which we are attempting to draw conclusions about welfare, we must do so relative to a set of preferences, whether assumed or inferred from decisions. But in this setting, conclusions may be complicated by the fact that the twin constraint problem might itself be an impetus for a college to rethink its preferences.

The constraints faced by UCLA in 2006 have arguably now been imposed nation-wide. *SFFA v. Harvard* (2023) was filed in 2013, and the potential for the case to culminate in a Supreme Court decision restricting affirmative action was anticipated from its filing. Colleges have been revising their admissions processes over the last decade in ways anticipated by UCLA's changes, in some cases going well beyond by making standardized testing optional, or even refusing to consider it. The consequences of the twin constraint problem are potentially larger when they are imposed at the national level – for both colleges and applicants. If every college shifts toward seeking applicants with particular characteristics, they will be harder to find than if one college does so in isolation, creating larger tradeoffs. If every college shifts away from valuing other characteristics, it can lead to materially worse outcomes for applicants with those characteristics. Moreover, anticipation of these shifts can alter investments that high school students make.

The data used in this paper were first used in Sander (2012) and Groseclose (2014), who focus on whether UCLA complied with anti-affirmative action law. Mare (2014) uses non-public administrative data from an overlapping time period to study the same question. All three papers find non-zero

scores and high school grades are roughly equally predictive of both first-year and longer-run college outcomes. Conclusions from other contexts may vary: Friedman, Sacerdote, and Tine (2024) find test scores are much more predictive of college performance than grades for Ivy-Plus college students, and Chetty, Deming, and Friedman (2023) find test scores are more predictive of earnings and prestigious graduate school and employment outcomes at Ivy-Plus schools.

regression coefficients on racial/ethnic group indicator variables, but they differ as to their interpretation. I will have nothing new to say about UCLA's legal compliance with then-extant law, but will instead focus on the impact of the 2006 changes within racial groups, which I find to have been consequential for more individuals.

Other papers have studied related University of California admissions policies. Antonovics and Backes (2014) examine how University of California admissions changed after the passage of Proposition 209, finding a large reduction in the apparent admissions preference for URMs, a decline in the association between admissions and SAT scores, a small increase in the association with grades, and an increase in the apparent admissions preference for lower socioeconomic backgrounds (their Figure 1). This is consistent with theory predicting that colleges seeking to maintain diversity under an affirmative action ban will admit students who are with more URM-like characteristics. My results suggest that the switch to holistic admissions reversed some of these changes (in the preferences for URMs versus low socioeconomic status) and reinforced others (the shift from test scores to grades).[4]

Bleemer (2023) examines University of California admissions from 1994-2021, including the passage of Proposition 209, the change to holistic admissions at each UC campus, and the implementation of policies favoring students with grades in the top percent of their high school. His focus is on the effect of holistic admissions and top-percent policies on URM admission and enrollment, not on their effects on admission decisions within racial groups. UCLA introduced a top-percent policy in 2001 and a modified policy in 2012. Bleemer (2023) concludes that the 2001-11 version of the top-percent policy, which was in force during the entire sample period of this paper, had limited impact on URM admissions at Berkeley and UCLA (p. 7).

This paper is also related to papers that simulate attempts to achieve racial diversity using color-blind admissions. Fryer, Loury, and Yuret (2008) simulate color-blind admissions using data from the *College and Beyond* dataset for the high school class of 1989 (originally used by Bowen and Bok, 1998),

[4] Long and Tienda (2008) examine admissions changes at UT-Austin, Texas A&M, and Texas Tech after a 1996 state-level ban on affirmative action. Their findings are largely consistent with Antonovics and Bakces (2014): preferences for URM applicants decreased sharply and the association of admissions with SAT scores fell.

finding color-blind admissions to be about 3 times as costly as traditional affirmative action.[5] Long (2014) compares the cost of traditional and "proxy-based" affirmative action that would have achieved the same URM shares at the University of Texas, also finding the latter to be about 3 times as costly.[6] Ellison and Pathak (2021) compare a neighborhood-based affirmative action admissions scheme for selective Chicago public high schools with color-sighted affirmative action, finding it to be 4 times as costly.[7]

These ratios are not directly comparable to what I observe in the UCLA example, for two reasons that at least partially offset. The college admissions papers consider fully color-blind admissions: admissions decisions that would achieve a zero coefficient on racial/ethnic indicator variables in regressions predicting admissions decisions. As mentioned above, UCLA did not achieve zero racial regression coefficients, especially after 2006; this should have reduced its cost of achieving diversity. On the other hand, the color-blind approaches of Fryer, Loury, and Yuret (2008) and Long (2014) use the racial composition of an applicant's zip code or school as a "race-neutral" proxy for socioeconomic disadvantage. This allows colleges to favor applicants from heavily-URM zip codes or schools over those with otherwise similar socioeconomic backgrounds. It is unclear whether a court enforcing an anti-affirmative law would allow this. Absent this, color-blind admissions would become significantly more costly, as I discuss in more detail below.

The remainder of the paper is organized as follows. Section II presents a model of college admissions under the twin constraints. Section III provides background on the UCLA admissions changes in 2006, and then analyzes the changes empirically. Section IV considers how stricter legal constraints

[5] I calculate this using the predicted college GPA ranking of students admitted under simulations of no affirmative action, traditional affirmative action, and admissions that achieve approximately the same racial/ethnic mix using "color-blind" admissions. With no affirmative action indexed to 100, traditional affirmative action achieves student performance of 98.54, while color-blind admissions achieves 95.79 (based on an equal-weighted average of the seven colleges in the sample, Table 6).

[6] I calculate this using the predicted college GPAs of students admitted under simulations of no affirmative action, traditional affirmative action, and "proxy-based" affirmative action of 2.951, 2.944, and 2.929, respectively (Table 4).

[7] Ellison and Pathak (2021) report this ratio in their abstract. It comes from a comparison of purely test-score-based admissions, admissions with explicit racial and socioeconomic preferences, and admissions with neighborhood-based preferences. Mean test scores are 99.05, 98.75, and 97.85 under the three systems (Figure 4).

would have affected UCLA. Section V discusses the implications of UCLA's experience for today.

II. A theoretical analysis of regulatory constraints

College admissions can be thought of as a constrained optimization problem. An unconstrained college would admit a class of students expected to maximize its objectives. These objectives are likely multi-dimensional and we would expect the college to take into account interactions between the students. We can think of the college as observing a vector of characteristics for each applicant $\vec{x}_i$ and selecting the N students that maximize its utility $U(\vec{x}_1, \dots, \vec{x}_N)$.

The simplest approach is to assume that a college admits students knowing who will attend. In practice, they can often at least approximate this, by first admitting one or more rounds of students who they would want to enroll regardless of which other students accept, learning those admits' enrollment decisions, and then admitting additional students from a waitlist. In this way, it can defer final decisions about marginal applicants until they know the composition of the rest of the class.

Many constraints colleges face in making admissions decisions constrain the class of students who ultimately enroll. Publicly reported statistics about racial group membership or socioeconomic status are for enrolled students. Constraints arising from the need to staff sports teams or orchestras also constrain students who enroll. For these constraints, we can add a term to the optimization problem of the form $\lambda \cdot F(\vec{x}_1, \dots, \vec{x}_N)$., where $F(\vec{x}_1, \dots, \vec{x}_N)$ is a the regulatory constraint (i.e., function of student characteristics that must be kept zero or positive) and λ is the Lagrange multiplier on the constraint.

For example, suppose a college faces pressure to meet benchmarks on two characteristics: URMs and low-income Pell Grant recipients. Their optimization problem will be to maximize

$$U(x_1, \dots, x_N) + \lambda_u(\sum u_i - \underline{u}) + \lambda_p(\sum p_i - \underline{p})$$

where u_i and p_i indicate whether student i is a URM or received a Pell Grant, and $\underline{u}$ and $\underline{p}$ are the benchmarks (expressed as a number of students). If the constraints bind, colleges will give applicants

bonuses for membership in the two categories, where the bonuses are proportional to the Lagrange multipliers on the two constraints.

Now suppose that $\underline{u}$ increases, while $\underline{p}$ remains the same. At the new constrained optimum, λ_u is likely to be higher, increasing the bonus received by URM applicants. At the same time, if URM status and Pell Grant recipiency are positively correlated, λ_p should be lower in the new constrained optimum, reducing the admissions preference received by non-URM Pell Grant recipients. Moreover, so long as both constraints continue to bind and so long as the incremental URM enrollments include a higher proportion of Pell Grant recipients than the non-URM enrollees they replace, increases in URM enrollments will come at least partly at the expense of non-URM Pell Grant recipients.

The regulation of affirmative action typically involves analysis of admissions decisions rather than the characteristics of students who ultimately enroll, however, and so imposes constraints on who gets admitted.[8] In this case, thinking separately about admission and enrollment decisions may be important. The constraint would then take the form $\lambda \cdot G(\vec{x}_1, \ldots, \vec{x}_N; \vec{x}_1, \ldots, \vec{x}_M)$., where $\vec{x}_1, \ldots, \vec{x}_M$ are the characteristics of the applicants who are admitted but do not enroll.

I will begin though with the simpler case, where every admitted applicant enrolls, and then subsequently consider the impact of non-enrollment on the problem. I assume a college must satisfy courts, who will assess whether it is compliant with anti-affirmative action law using regression analysis. I will further assume for simplicity that the law requires a zero coefficient in a regression of admissions outcomes y_i on a URM indicator variable u_i, controlling for applicants' observable characteristics. The coefficient on u_i will be zero if:

$$\sum [y_i - E(y_i|x'_i)](u_i - \bar{u}) = 0$$

where $E(y_i|x'_i)$ is the expected admission probability for applicant i, conditional on x'_i, a subset of x_i that excludes race. This subset x'_i would also exclude soft information that an admissions office would observe but that would not be included in a regression, such as disclosures of race made in application

[8] Examples of such analysis include Groseclose (2014), Mare (2012), and Sander (2012) for UCLA or the expert reports Arcidiacono (2018) and Card (2017) for *SFFA v. Harvard*.

essays. It would also exclude any control variables that a court found to be inappropriate proxies for race, such as, conceivably, the racial composition of applicants' zip codes or schools.

Errors in well-formed expectations are independent of the conditioning variables, or any function of those variables. As a result, the above condition can be rewritten as:

$$\sum y_i[u_i - E(u_i|x'_i)] = 0$$

In words, the requirement that URMs not be admitted at higher rates than one would expect conditional on their observable characteristics also implies that admitted applicants cannot be more likely to be URMs than one would expect given their other observable characteristics.

Suppose a college faces a combination of pressure to admit a certain number of URMs, combined with a legal ban on affirmative action, enforced using regression coefficients as described above. The optimization problem becomes to maximize

$$U(x_1, \ldots, x_N) + \lambda_u \left(\sum y_i u_i - \underline{u}\right) + \lambda_a \left(\sum y_i [E(u_i|x'_i) - u_i]\right)$$

The combination of the two constraints forces the college to admit students whose expected probabilities of being a URM sum to $\underline{u}$.

Fryer, Loury, and Yuret (2008) obtain a similar result, but through a different set of assumptions.[9] They model colorblind admissions, in which a college does not observe race, and achieves its target for $\underline{u}$ by conditioning its admissions decisions on its expectation of race based on other observable characteristics. In my model, colleges observe race, but are forced to admit students as if they did not due to the need to obtain a zero regression coefficient. The variables included in x'_i may differ under these approaches. Under unregulated colorblind admissions, x'_i could include anything observed by the admissions officers, including soft information such as the content of essays. Under regression-governed admissions, x'_i would only include variables that courts allow to be included as control variables in a regression. Courts might be reluctant to include subjective scores that summarize soft information, as

[9] Earlier theoretical work by Chan and Eyster (2003) also finds that an affirmative action ban leads colleges to alter their within-group selection of applicants.

exemplified by the debate over personality scores in *SFFA v. Harvard*, and they might also prohibit socioeconomic variables that proxy for race too closely, like the racial composition of zip codes or schools.

When $\underline{u}$ increases for a college under a no-affirmative-action constraint, as it did for UCLA in 2006, it is forced to alter the mix of students it admits so that their predicted URM membership matches the new, higher $\underline{u}$. So long as the college complies with the no-affirmative-action constraint, whether the increased pressure benefits a particular applicant depends entirely on their characteristics, not their race. Increased pressure is good for non-URM applicants with characteristics similar to URM applicants.

Perhaps less obviously, increased pressure is bad for URM applicants with characteristics similar to non-URM students. Consider a Black math Olympiad winner. Admitting such a student would help the college get to $\underline{u}$. But it would also signal to a future court econometrician that the college valued math Olympiads, likely obligating them to admit other Olympiad winners, the vast majority of whom are white or Asian. When both constraints bind, an increase in $\underline{u}$ will help applicants with higher values of $E(u_i|x'_i)$, regardless of their race.

That an increase in pressure to increase URM enrollment would harm the admissions chances of the highest-achieving URM applicants strikes me as unintended by either advocates for or opponents of affirmative action. Presumably those on both sides of the debate, and most in the middle, would prefer that the college admit the most qualified students within each racial group, and perhaps especially the most qualified URMs.

It also follows that requiring compliance with a no-affirmative-action rule makes the achievement of any URM representation threshold more costly in terms of the tradeoff of academic qualifications. This can be illustrated by Table 1, which reports the share of applicants in the UCLA sample falling into different ranges on variables capturing academic qualifications. The table focuses on the SAT Math score and the weighted high school GPA (i.e., GPA with a bonus point for designated honors courses), the two academic metrics that exhibit the strongest and weakest correlations with race

in the UCLA data (the others considered were SAT Reading, SAT Writing, the SAT Subject test average, and Unweighted GPA).

Suppose UCLA wants 3.7 and 15.1 percent of its admitted students to be Black and Hispanic/Native American, respectively, the shares it achieved in 2007-9. But it also needs to achieve these percentages while still complying with the no-affirmative action constraint. Suppose further, for simplicity, that it expects the court econometrician to use SAT Math or GPA bin indicator variables as the control variables in its regression. This implies that UCLA must admit its students from SAT Math and GPA bins that collectively match the desired racial composition.

Given the approximate linearity of the relationship between achievement levels and demographic percentages, doing so would yield average SAT Math scores and weighted GPAs of roughly 605 and 3.9, respectively, well below the actual 2007-9 means of 678 and 4.18.[10] The large tradeoff in qualifications needed to achieve relatively modest shifts in demographic percentages, at least while complying with the no-affirmative-action constraint, is a result of the modest slope of the relationship between qualifications and mean demographic characteristics, as well as the large difference between the demographics of the highest-achieving students and the applicant pool.

What if colleges care about the URM share of enrolling students, but the law is concerned with admissions decisions, and enrollment probabilities are not 100%? In this case, the optimization problem becomes maximizing:

$$U(x_1, \dots, x_N) + \lambda_u \left(\sum y_i e_i u_i - \underline{u} \right) + \lambda_a \left(\sum y_i [E(u_i | x'_i) - u_i] \right)$$

where e_i is an indicator for whether an admitted applicant enrolls. In words, the non-enrolling admitted students enter the no-affirmative-action constraint but not the URM-enrollment constraint. Admitting a URM student who does not enroll becomes unambiguously costly for the college, since it makes satisfying no-affirmative-action regulation harder without increasing minority enrollment. Admitting a non-URM student who does not enroll has the reverse effect. So in addition to the other incentives

[10] In 2008, UCLA was ranked 66th based on the mean of its SAT Math interquartile range, in IPEDS data. Had its SAT Math score been 70 points lower, it would have been ranked around 238th.

discussed above, colleges would have a stronger reason to admit URM students that are likely to enroll, and to attract the URM students they do admit. The reverse would be true for non-URM applicants. They would also have an incentive to favor applicants whose observable characteristics predicted a positive gap in URM and non-URM enrollment rates.

UCLA in 2006 faced an environment where many other colleges were likely to continue to practice affirmative action. There was therefore a range of qualifications where a candidate was likely to have better options than UCLA if they were URM but not if they were non-URM. Given the lower net prices offered by Ivy League colleges to lower-income applicants, this might be particularly true in lower income ranges. UCLA would have had an additional incentive to avoid admitting these candidates, since they would increase the URM share of admits, tightening the no-affirmative-action constraint, without yielding additional URM enrollments. UCLA would have an incentive to avoid applicants on the borderline of enrollment, since the URM-non-URM enrollment rate gap would be highest there, and instead admit less-qualified, higher-income applicants who were safer bets. Again, this strikes me as an unintended consequence that would be viewed as undesirable by many.

Figure 2 plots the share of admitted students who enroll by race and combined SAT score. The enrollment rate is clearly lower for students with higher scores, especially for URM students with higher scores. Strikingly, none of the 66 Black students admitted with a 2190 combined SAT score or better over the 6-year sample enrolled in UCLA. This makes the dilemma depicted in Table 1 even more fraught, since the demographics of high-performing students are even less diverse when one adjusts for the fact that URM students with top scores and grades are especially unlikely to enroll.

Arguably, this analysis is a bit too stark. Tests for compliance with anti-affirmative action law are unlikely to be univariate as in Table 1. Moreover, there is substantial controversy about whether bans on affirmative action require zero coefficients on race. Race can be correlated with characteristics that are observed by the college but not the regulator, and therefore a regulator might observe a non-zero coefficient arising from an unbiased admissions process. The parties in *SFFA v. Harvard* differ sharply on whether the non-zero regression coefficients reported in Arcidiacono (2018, Table B.7.1) are indicative of illegal discrimination. In discussing the UCLA case, Mare (2012, pp 3-4) concludes that, once he controls

for the characteristics of applicants, he finds "disparities in outcomes that favor some groups [White, African Americans, and Latinos] and disfavor others [Asian Americans]," but also notes that "the holistic ranking process for Freshman admissions at UCLA appears to work much as intended" and "whether these discrepancies are considered small or large is a normative, policy issue – not a scientific one."

Even if colleges affected by affirmative action bans are permitted non-zero coefficients, so long as the size of these coefficients is constrained, they will still face incentives to alter their admissions decisions as described above. Moreover, it is worth contemplating what the impact of a zero-regression-coefficient constraint would be, given that it is at least possible that the courts will someday impose one.

III. Admissions at UCLA from 2004-9

This section analyzes undergraduate admissions at UCLA from 2004-9. As described in Groseclose (2014), in May 2006, UCLA experienced protests critical of the decline in the Black enrollment share following the passage of Proposition 209. UCLA altered its admissions process in response, switching from a system in which academic ability, personal qualities, and life challenges were assessed separately to one where candidates were assessed "holistically" at each step of the process.[11] The sample period includes 3 years before and after this change.

The data used in this paper were obtained by Tim Groseclose and Richard Sander through a Public Records Act request.[12] When the data were released by UCLA, it made several alterations to

[11] Groseclose (2014, Chapter 1) quotes UCLA Chancellor Norm Abrams asking the Committee on Undergraduate Admissions and Relations with Schools, on which Groseclose was serving, to adopt a holistic admissions process and explicitly citing low numbers of Black and URM students as the rationale for the change: "First, I want to say how much I favor and respect faculty governance. I don't want to pressure you. But at the same time, we worry about many of the same things. I want to report to you what we are hearing from the outside world. Several constituencies are distressed and upset about the very low number of African American freshmen. The political angst and concern is enormous. … The numbers of underrepresented minorities on campus are too small. … I ask that you make the whole admissions process holistic. Not only that, I have a further request: This is that you do it quickly and adopt the exact same process that Berkeley currently uses."

[12] Groseclose (2014, Chapter 6) describes the negotiations with UCLA over the release of the data. I obtained the data from Richard Sander's website (https://web.archive.org/web/20200919020555/http://seaphe.org/?page_id=678), which is no longer available, but the data are also available at https://timgroseclose.com/uclaadmissions.

prevent the identification of individuals. Sex and gender were not disclosed. Standardized test scores and grade point averages were disclosed in bins. Geographic information was almost entirely omitted; the dataset does include a variable for whether a student is a California resident, but it is only disclosed for white and Asian students. It is however also possible to identify students who attended a public high school in California from the fact that the schools' Academic Performance Index (API) decile is included in the data, since APIs are only calculated for California public high schools. The specific admission year is also not disclosed; the data only indicate whether the application was before or after the change in the admissions process.

While the UCLA dataset is less rich than the confidential administrative datasets used by other papers, it does distinguish between Black and non-Black URMs, which is helpful given that the 2006 policy changes appear to have been particularly motivated by increasing Black enrollment.[13] Perhaps more importantly, it is publicly available. Moreover, it spans a period of policy change, allowing a pre/post analysis of the effects of the policy.[14]

For simplicity, the analysis will focus on applications to the College of Letters and Science, which accounts for 79 percent of applications. The analysis will exclude applications that were cancelled or withdrawn before receiving an admissions decision, as well as applications with missing GPA or test score data. It also excludes about 1.3 percent of applications with only ACT scores rather than SAT scores. Unfortunately UCLA used relatively wide bins for ACT scores (6 bins total, compared with 14 for each SAT exam) and only the ACT composite score is available, making the available test score information much less informative for these applications. The remaining sample includes 211,564 applications from the six

[13] Of the papers with admissions microdata that I have cited above, Antonovics and Backes (2014) and Long (2014 and 2015) have data that aggregates Black and non-Black URMs, while Chetty, Deming, and Friedman (2023), Fryer, Loury, and Yuret (2008), and Long and Tienda (2008) can distinguish between them. Bleemer (2023, p. 5) reports having "15-catgeory ethnicity" but his analysis aggregates URMs.

[14] The other publicly available dataset I am aware of is a collection of admissions data from 42 state universities available at affirmativeactiondebate.org. These data were obtained by public record requests by Richard Sander and mostly from the years 2005-7. These data omit California, but the UC admissions data used in Antonovics and Backes (2014) [and originally used in Antonovics and Sander (2013)] may also be available upon request from Richard Sander (need to confirm).

years.[15]

III.A. Summary Statistics

Table 2 reports summary statistics for all applicants, admitted applicants, and enrolling students from the pre-holistic and holistic samples. UCLA received slightly more applications in the later period, but admitted and enrolled roughly the same number of applicants. Test score and grade point averages are higher for admitted students than for applicants, but lower for those admitted students who enroll, as is typical.

Whereas the test score and grade averages, socioeconomic characteristics, and racial/ethnic composition of the applicant pool appear similar in the pre-holistic and holistic samples, changes in the averages for admitted and enrolling students suggest that admissions process changes had an impact. The share of admitted and enrolling students who are Black is much higher in the later sample, and the share who are Hispanic or Native American also increased (these groups were aggregated by UCLA for privacy reasons). UCLA breaks out Asian Americans from Southeast Asian backgrounds, and this category was roughly flat.[16] The increase in Black, Hispanic, and Native American share was balanced by a decline in the shares of other Asian Americans and well the Other/Unknown category.

The combined SAT scores of admitted and enrolling students are 20 and 32 points lower, respectively, but weighted and unweighted GPAs rose by around 0.03-0.04 for admitted students and 0.04-0.06 for enrolling students. The admitted and enrolling students have higher average family incomes and parental education after the change to holistic admissions.[17] The share of students coming from out of state or from private high schools in California increased, as evidenced by missing API data.

[15] Table A1 summarizes the number of applications excluded from the sample, by reason.
[16] This category is called "Vietnamese/Filipino" in the data, but includes other Southeast Asian backgrounds according to Groseclose (2014).
[17] Family income is adjusted for neither inflation nor the downturn in the California economy in 2008-9 and is missing or top coded for over half of observations. The differences in average parental education between the pre-holistic and holistic samples are therefore more readably interpretable than differences in income.

Table 3 reports summary statistics by racial/ethnic groups, with the test score, grade, and socioeconomic variables standardized. Black and Hispanic/Native American applicants have below-average test scores and grades, with larger differences for SAT scores than grades. Both groups of URM applicants are also below average on the socioeconomic variables, especially Hispanic/Native American applicants. Black applicants are most similar to Hispanic/Native American applicants in attending low-performing California public high schools, as measured by Academic Performance Index (API) decile, and most different in parental education. Black applicants are more likely to have a parent with some college education, but not a Bachelors' degree, than any other group, whereas Hispanic/Native American applicants are the most likely to have parents with a high school education or less.

The changes in the summary statistics for admitted students under holistic admissions in Table 2 are only partly consistent with what one would expect from Table 3. For admitted students, the combined share of Black and Hispanic/Native American students rose from 15.8% to 18.8%; for Other Asian and Other/Unknown students it fell from 41.9% to 38.8%. A shift of 3% of admissions from groups that are 0.2-0.3 standard deviations above the mean to groups that are -0.6 to -0.8 below the mean should lower the average by about 0.03 standard deviations, or about 3 points on each SAT test. The drop of 20 points combined across the 3 SAT tests is therefore about twice what one would have expected. Moreover, one would have expected GPAs and socioeconomic variable averages to decline, but instead they rose.

This suggests that the transition to holistic admissions influenced outcomes in ways that went beyond a reallocation of slots between racial/ethnic groups. Before turning to more formal analysis, Table 4 examines how admission rates change by race and socioeconomic variables under holistic admissions. Overall admission rates rise for Black applicants, and they fall for the other categories (the table excludes the Other/Unknown and International categories for brevity, but admission rates decline for these groups too). Admissions rates rise for Blacks in all socioeconomic categories, more or less equally, but for the other groups, they decline sharply for applicants with the lowest levels of income or parental education. Consistent with the predictions of the competing-pressures model in Section II, the shift to holistic admissions appears to have made it more difficult for low-income, non-Black applicants

to be admitted to UCLA.

III.B. Predictors of admissions under pre-holistic and holistic admissions

Table 5 presents a single logit regression predicting admissions decisions using observable applicant characteristics.[18] Each variable is interacted with a binary variable indicating applications in the holistic sample. Continuous variables are standardized as in Table 3. Standard errors allow for two-dimensional clustering on the identity of the first two admissions readers.[19]

The association between admissions decisions and SAT scores declined in the holistic period, except for the subject exams. In contrast, the association with grades became stronger. Applicants from low socioeconomic backgrounds (low-income and low-parental-education families and low-performing schools) were more likely to be admitted in the pre-holistic period. Under holistic admissions, this became less true with respect to family income and education but a bit more true with respect to school API. Applicants from private California schools and out-of-state schools became more likely to be admitted. Controlling for all of the above, Black applicants became more likely to be admitted under holistic admissions and international applicants much less likely.

It is helpful to put the coefficients on Black and Hispanic/Native American by comparing them with prior work. Antonovics and Backes (2014, Figure 1) found a marginal effect of being URM on admissions probability at UCLA of 0.34 in 1995-97 (prior to Proposition 209) and 0.05 in 2004-6. My

[18] I find the logit specification yields better calibrated predicted admission probabilities for applicants with low predicted probabilities; probit tends to underestimate such admission probabilities. This is likely due to the higher-kurtosis type-one extreme value distribution better approximating the distribution of the error term than the normal distribution.

[19] I use the Stata command *clus_nway* of Kleinbaum, Stuart, and Tushman (2013) which implements the procedure of Cameron, Gelbach, and Miller (2011). There is probably more correlation in the residual component of admissions decisions than is allowed for in this clustering scheme. Unfortunately, the suppression of information in order to keep individuals from being identifiable eliminates variables around which clustering might have occurred, such as state and high school. I did experiment with adding either API decile (11 possible values, including missing) or API decile interacted with an indicator for the holistic sample (22 values). API decile should nest high schools, except in cases where they change deciles during the sample period, although the number of cluster groups is unfortunately too few for clustering to be asymptotically valid (e.g., Angrist and Pischke, 2008, Section 8.3.2). Table A2 compares standard errors as presented in Table 5 with standard errors that allow for an additional dimension of clustering on either API decile, API decile interacted as described, as well as no clustering at all. For the most part, statistical inference about the signs of coefficients is unaffected.

results, which have a richer set of academic and socioeconomic controls, imply an average marginal effect being URM of 0.08 in 2004-6 and 0.12 in 2007-9, if I weight Black and non-Black URMs by their shares of the applicant pool. Taking these results together suggests that admissions at UCLA was still meaningfully constrained by Proposition 209 after 2006.

The racial preferences implied by the coefficients in Table 5 are also smaller than those estimated in studies of selective private college admissions. Espenshade, Chung, and Walling (2004) report that the ratio of logit regression coefficients for racial/ethnic indicator variables and SAT scores imply that Black and Hispanic students have the same admission odds as white students with SAT scores that are 230 and 185 points higher (out of 1600), respectively (p. 1431). If I estimate a version of Table 5 that also includes only the sum of the SAT Math and Reading scores and racial/ethnic indicators, the coefficients for UCLA imply 57 and 130 point advantages for Black and Hispanic/Native American applicants in the pre-holistic period and 120 and 116 in the holistic period, respectively.[20]

The regression in Table 5 imposes a linear relationship between the continuous variables and the log odds ratio of admission. Table A3 estimates a version of Table 5 that replaces each continuous variable with indicator variables for each of its possible values.[21] This increases the number of independent variables from 45 to 199, but increases the pseudo r-squared only from 0.444 to 0.475. While this is sufficient to reject the hypothesis that the relationships are all linear with a p-value less than 0.0001, it is arguably a modest gain in explanatory power. This is consistent with the fact that relationships appear to be roughly linear in the tables. The main exception to this statement is that there appears to be a relatively flat region in the relationship between SAT scores and admission between roughly 500 and 650. Nevertheless, the non-linear specification provides better out-of-sample prediction of admissions decisions, and therefore I will use it in what follows.

For subsequent analysis, it will be helpful to create a more parsimonious set of variables that captures these findings. I create indexes of test scores, grades, and socioeconomic status that aggregate

[20] The apparent advantage given Hispanic/Native American applicants is larger in these regressions than in Table 5 since, for comparability with Espenshade, Chung, and Walling (2004), I do not control for socioeconomic variables.
[21] To avoid conflating the number of subject exams taken with the average score, the subject exam average is calculated based on the bin midpoints and then rebinned into the original 14 30-point-wide bins.

the variables according to how they were related to admissions in the pre-holistic period by estimating the flexible regression in Table 5 (i.e., Table A3) on the pre-holistic sample and then calculating the components of the predicted log-odds ratio associated with test scores, grades, and socioeconomic variables. In order to avoid issues associated with overfit, I split the pre-holistic sample in half (even and odd observations, as ordered in the publicly available data) and use coefficients estimated on one sample to construct predicted value components for the other. For consistency, I take the split-sample approach when constructing predicted logs odd ratio components for the holistic sample based on pre-holistic relationships (i.e. using coefficients from odd-numbered observations to calculate predicted values for even-numbered observations, and vice versa).

Table 6 presents a version of the flexible version of Table 5 (i.e., Table A3) that substitutes these predicted values for the full set of test score, grade, and socioeconomic variables. The coefficients on these variables for the pre-holistic sample are close to one as one would expect. That they are slightly less than one is likely due to overfit, but the fact that they are so close to one suggests that these issues are mild, even when allowing for non-linearity as described above. The regressions also include the API decile variables separately, to allow for changes in the relationship between admissions, school performance, and individual-level socioeconomic variables. They also include indicators for racial/ethnic groups and interactions of every variable with a holistic-sample indicator.

The coefficients on the interaction terms summarize the results in Table 5 above. Test scores lost about 43 percent of their association with admission while grades' association increased by 28 percent. Low socioeconomic status lost about 64 percent of its association, but this was offset by an increase in the association with low school API. The standard deviation of three predicted log odds ratio variables are 1.94, 1.62, and 1.27, respectively, and are essentially identical in the two samples. Taken together, this suggests that in the pre-holistic sample, test scores were a bit more important than grades in explaining admissions, while in the holistic sample, grades became much more important.[22] Versions of

[22] Specifically, in the pre-holistic sample, test scores alone (econometrically) explained 1.43 = (1.94/1.62)^2 as much variance in outcomes as grades alone, with the remainder accounted for by the other factors and the joint effect of grades and test scores. In the holistic sample, test scores alone explained only 0.28 = ((0.57*1.94)/(1.281*1.62))^2 as much as grades alone.

Tables 5 and 6 that disaggregate the sample by racial/ethnic group find that these changes occurred to roughly similar extent in each group (Tables A4-A6).

Another way of summarizing the changes under holistic admissions is to conduct a direct test of the prediction of Section II that colleges that seek to increase URM admissions under a no-affirmative-action constraint will shift their choice of students within racial groups towards those with observable characteristics that are more similar to URM students. I first predict the race/ethnicity of each applicant using a non-linear multiominal logit model with the same academic and socioeconomic bin indicator variables as in Table A3.[23] I then include the predicted log odds ratio of being Black, Hispanic, and SE Asian in a model predicting admissions that also controls for applicants academic and socioeconomic qualifications.

Table 7 presents the results of these tests. I modify the specification in Table 6 by constraining the coefficients on the test score and grade log odds ratio components to be identical and I omit the API variables. This causes any shifting of weights within academic or socioeconomic variables to be interpreted as a towards applicants that are predicted to be URM. The results suggest that in the holistic period, admissions decisions within racial/ethnic groups shifted towards applicants that were more similar on observables to Black applicants, but not more similar to Hispanic/Native American applicants. This would be consistent with the fact that the Black coefficient in a regression predicting admissions in the holistic period (e.g., the sum of the main effect and interaction in Tables 5 or 6) is much larger than the Hispanic/Native American coefficient, and therefore the coefficient that is more likely to be constrained by in the manner contemplated in Section II. The shift towards admitting candidates with

[23] A linear version of the multinomial logit model is presented in Table A7; Table A8 reports the coefficients for membership in Black and Hispanic groups from the non-linear version. The variables most associated with being URM in a multivariate context are a low SAT Math score, low unweighted GPA, low income, and low school API. Low parental education is more associated with being Hispanic/Native American than being Black, and a high average SAT subject score is positively associated with being Hispanic but negatively associated with being Black. This last result may be related to the fact that 57 percent of Hispanic/Native American applicants take one or both Spanish SAT Subject tests, compared with 9.5 percent for other groups. Hispanic/Native American applicants who take a Spanish subject exam score on average about 180 points higher on that exam than on the average of the SAT Reading and Writing exams. Presumably for at least some of these applicants, Spanish is spoken at home. The same is true of the Chinese, Korean, and Japanese subject tests and other Asian applicants, except that the prevalence of taking one of the three subject tests is lower among these applicants (26 percent) and the score differences are smaller (about 160, 140, and 110 points, respectively).

characteristics similar to Black applicants appears to have occurred to roughly equal extents within each racial/ethnic group.

III.C. Decomposing the changes under holistic admissions

One can think of three things as having changed between the pre-holistic and holistic samples. First, the number of applications rose by 16 percent, while UCLA admitted roughly the same number of students. Second, UCLA altered the racial/ethnic mix of their admitted students. Third, it altered how it made admissions decisions within groups. This section decomposes the changes in the characteristics of admitted students as reported in Table 2 into these three components.

Table 8 begins by comparing the average characteristics of the students actually admitted during the pre-holistic period with the characteristics of all applicants, weighted by their predicted probability of admission as estimated using the within-ethnic-group version of the regressions in Table 6 (Table A6). Unsurprisingly, these characteristics are essentially identical.[24] It next uses these regressions to predict the probability that each holistic-period applicant would be admitted, assuming that UCLA had continued to use pre-holistic weights on each characteristic but had raised the threshold for admission to yield the same lower overall admission rate as in the holistic period (column B). The test scores and grades are slightly higher in this column, reflecting the fact that UCLA can be a little more selective given the larger applicant pool (with roughly the same overall test score and grade averages, as shown in Table 2).

In the next step, we assume that UCLA kept the same within-group regression weights on characteristics, but raised or lowered the threshold for each group as needed to achieve the racial/ethnic mix it actually achieved in the holistic period (column C). This can be interpreted as UCLA taking a "traditional affirmative action" approach to increasing diversity. Relative to column B, the test score

[24] They would be exactly identical if admission probabilities were estimated using a linear probability model.

averages drop, e.g. by total of 6 points across the SAT Math, Reading, and Writing. This is roughly consistent with the back-of-the-envelope calculation in the discussion of Table 3 above.

The final step is to allow the regression weights to change as they did under holistic admissions. Column D weights applicants by their predicted admission probabilities as estimated in the holistic sample, which line up well with the actual characteristics of the students admitted. Consistent with the results above, the shift from pre-holistic to holistic weights (while holding racial/ethnic mix constant) implies much lower SAT scores (a total of 22 points across the SAT Math, Reading, and Writing), higher grades, higher income and parental education, but lower school API. Considering only SAT scores, the shift to holistic admissions was about 4.7 times as costly as the shift in racial/ethnic mix alone (22+6 divided by 6).

This results can be summarized by examining how the mean predicted log odds ratio components change in each step. These variables capture different aspects of applicants' admissibility, as reflected in pre-holistic admissions decisions. Switching from actual to predicted pre-holistic admits has no effect, as one would expect. The larger pool allows UCLA to select applicants that it prefers on both the test score and grade dimensions. This is partly offset by the higher share of applicants coming from higher-API schools and either private schools or outside California during the holistic period, which reduces the low socioeconomic status (SES) component of the score. Changing the racial/ethnic mix to the higher URM shares of the holistic period reduces the two academic components, but increases the low-SES components; the net effect is -0.044. Switching to holistic weights sharply reduces the test score component, but this is offset by an increase in the grades component. The low SES component also declines slightly, leaving a net effect of -0.163. In other words, relative to UCLA's pre-2006 preferences, the total cost of the shift to holistic admissions was also about 4.7 times as high as the cost of the shift in the racial/ethnic mix alone (i.e., 0.163+0.044 divided by 0.044).

Taken together, this suggests that the shift to the holistic-era racial/ethnic mix could have been accomplished in a way that was about 20 percent as costly, at least as measured relative to how UCLA assessed candidates prior to the change.

III.D. Winners and losers

The admission probabilities estimated in columns B and D of Table 8 sum to 27,898, the number of students admitted in the holistic sample. The difference in the probability in column D and B provides an estimate of the impact of the change to holistic admissions, including the effects on racial/ethnic mix, on a particular candidate. These changes in probabilities can be aggregated by types of applicant to provide a sense of how holistic admissions reallocated slots.

Table 9 summarizes the impact on each racial/ethnic group. For each group, the table reports the share holistic-period applicants for whom the estimated impact of holistic admissions is positive, as well as the average magnitude of the increases and decreases. These can then be aggregated to provide an estimated of the number of students who were admitted under holistic admissions who would not have been under the pre-holistic system, as well as those who were not admitted but would have been. By construction, these two must be equal.

Unsurprisingly, the vast majority of Black applicants benefit from the new admissions process. A plurality of Hispanic/Native American applicants also benefit. Perhaps more surprisingly, white applicants are the group with the largest net benefit, at least in terms of total estimated slots gained. There are also large numbers of Hispanic/Native American and SE Asian applicants who are harmed by the new system, and even a few Black applicants.

Table 9 also suggests that the number of individual applicants affected by the change to holistic admissions was larger relative to the number of slots reallocated between racial/ethnic groups. The absolute differences in predicted admissions probabilities imply that 3,736 applicants had their admissions decision altered, or 13.4 percent of admitted students. The probabilities imply an increase in URM admissions of 722. This implies that about 5 admissions decisions were affected for every additional URM admitted.[25]

[25] The estimate that 3,736 applicants had their admissions decision altered by the shift to holistic admissions is likely overstated, since some variation in regression coefficients from the 2004-6 to the 2007-9 sample would have

The analysis above suggests that positive weight given to high SAT scores and low socioeconomic status by the pre-holistic system declined in holistic period. So we might expect the beneficiaries of the new system to be low-SAT, high-SES, and those harmed to be the reverse. Table 10 disaggregates the sample by racial/ethnic group, SAT scores, and parental education (with some categories aggregated for readability). Within each racial/ethnic group, predicted admission probabilities increased for low-SAT, high-SES applicants and decreased for high-SAT, low-SES applicants. The border between positive and negative changes is different for the different groups, but the Black applicants with the highest SAT scores are estimated to be harmed by the new system, especially those with low parental education.

One might worry that this result is an artifact of the approach used to estimate admission probabilities. Table 11 reports the actual admission rates for subsets of applicants with either high SATs and low SES or the reverse. Actual admission rates for the former group declined by 10 percentage points, while they increased by just under a percentage point for the latter group (in the context of an overall admission rate that declined by 3 percentage points).

For high-SAT, low-SES, Black applicants, the admission rate fell by 20 percentage points. It should be noted though that given that there were only 77 such applicants in the 3-year holistic sample, only roughly 15 students were affected, or about 5 per year. Moreover, the enrollment rate for admitted high-SAT, low-SES Black students is extremely low (2.6 percent), suggesting that almost all had options they preferred to UCLA.

Nevertheless, this result suggests that the speculation in Section II that the twin constraints imposed by affirmative action bans and diversity targets could produce perverse outcomes for very highly qualified and deserving Black applicants was not idle. Of greater numerical consequence though is the fact that Table 11 suggests that roughly 1000 high-SAT, low-SES, non-Black applicants would have

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been expected even in the absence of admissions process changes. To understand the extent to which estimated admissions probabilities will vary even if the underlying process is unchanged, I split the 2007-9 sample in thirds, and estimate two out-of-sample admissions probabilities for each third, one from each of the other thirds. When I compare these admissions probabilities, the changes imply that about 615 admissions decisions would have been altered. If I were comparing estimates from two full three-year samples with each other, rather than from thirds of a three-year sample, coefficients would likely vary less between subsamples. Thus the estimate of 3,736 in Table 9 is much larger than what one would expect in the absence of admissions process changes.

been admitted under pre-holistic admissions but were not under holistic admissions. The yield rate for admitted students in this group is 12.5 percent, so UCLA was likely the best option for a significant number of the 1000 who were not admitted.

III.E. Mechanisms

The UCLA dataset also includes some information from intermediate steps in the admissions process, such as scores given to applicants by individual readers. This information was of interest to past analysts (Sander, 2012; Mare, 2012; Groseclose, 2014) who were primarily interested in whether certain racial/ethnic groups were admitted at higher rates, controlling for observable characteristics, since it would potentially point to where in the process the difference in outcomes emerged. For this analysis, we can likewise use the information to understand why the holistic-period admissions decisions weighed characteristics differently *within* racial/ethnic groups.

The first step in the admissions process that we observe is participation outreach programs, which target students with certain backgrounds or academic interests.[26] The specific program participated in is suppressed in the public data, so I treat them collectively. Both before and after the switch to holistic admissions, participation in these programs was more related to a low SES and/or URM racial background than to academic characteristics, suggesting that the programs targeted to these groups of applicants were larger. Both before and after the switch to holistic admissions, roughly one-third of California public school applicants and one-quarter of other applicants participated in these programs.

[26] Groseclose (2014) provides a list furnished to him by UCLA: ATDP (Academic Talent Development Program), Cal-SOAP, CAMP (California Alliance for Minority Participation in Science), CBOP (Career Based Outreach Program), COSMOS, Early Academic Outreach Program (EAOP), Educational Guidance Center (EGC), Educational Talent Search, UCSF Internships, GEAR UP, MESA (Mathematics, Engineering, Science Achievement) including MESA Schools Programs, SUCCESS through Collaboration and California Community College Program, PDP (Professional Development Program), Puente Program, UC College Prep Initiative (UCCP), UCSC SAGE (Students Acquiring "A-G" Expectations), Upward Bound, Young Entrepreneurs at Haas (available at https://timgroseclose.com/uclaadmissions).

The subsequent admissions process differed under pre-holistic and holistic admissions. Under pre-holistic admissions, most applications were read by three readers. Two readers (called reader A and reader B in the data) assessed the applicant academically and assigned one of six possible scores.[27] About 4.5 percent of applications were referred to an additional reader, typically when the first two differed. These scores are then aggregated into an academic rank. A final reader assigned scores capturing applicants' "personal achievement" (e.g., extracurriculars) and "life challenges" (e.g., low school API; single-parent household). The academic rank and personal and life challenge scores were then used to make the admissions decision.

Table 12 presents logit (for binary outcomes) and ordered logit (for score variables) predicting the outcome of the various stages of the admissions process. The individual academic reader scores are primarily explained by test scores and grades. Controlling for these variables, applicants of higher SES and from higher-API schools received higher scores, while Black applicants received lower scores. This might reflect other aspects of the file that the academic readers were reacting to that were correlated with these variables, or it might reflect a bias in the process. When the individual reader scores were aggregated into the academic rank, all of the results were reinforced a bit. In other words, controlling for the two reader scores, the final academic rank score was higher for applicants with better test scores, higher graders, from higher-SES backgrounds and better scores, and who were not Black.

The determinants of the life challenges score are very different. It is explained primarily by low SES, with Black, Hispanic/Native American, and international applicants receiving higher scores conditional on SES. Personal scores are not well predicted by the available variables (pseudo $R^2 < 0.06$), which is unsurprising. Strong personal scores are weakly correlated with good test scores and grades and higher SES backgrounds.

The penultimate column in Table 12 predicts admissions decisions with fixed effects for the possible values of academic, life challenge, and personal scores. It therefore tests what may influence

[27] The six scores ranged from 1 (good) to 6 (poor) and were each assigned to roughly one-sixth of the applicants. For clarity, in what follows I reverse the ordering so that high numbers are always better. A small number of applications are scored 0 or 8; these indicate either a missing score or missing information. Applicants receiving either score from readers A or B are excluded from Table 12.

final decisions, conditional on these scores. It appears that applicants from California public high schools and those with higher test scores are more likely to be admitted, controlling for reader scores. The final column displays the relationship between the explanatory variables and the final outcome, and is essentially the same regression as in Table 5, albeit for the subset of the pre-holistic sample with reader scores.

For each significant coefficient in the final column, one can see where in the process it comes from. The strong relationship between admissions and test scores and grades comes via the academic reader scores, with some reinforcement from the correlation with personal scores and, for test scores, the final decision making. The positive coefficient on Black and Hispanic/Native American appears to arise from the life challenge score, as well as partly from higher life challenge and personal scores being given to outreach program participants.

Finally, it is worth noting that it is arguably misleading to call this process "pre-holistic." The process considered the whole applicant, albeit with different readers focusing on different aspects of the case.

Under the holistic process, applicants were assigned to two readers, who evaluated the candidate holistically. About 7.3 percent of applications received a supplemental review, but this was less related to disagreement among the first two readers that under the pre-holistic process, as 7.1 percent of applications with identical scores from the first two readers also received supplemental review. The results of these reviews were combined into a holistic score, which influenced admissions decisions.

Table 13 presents regressions predicting the determinants of each stage of the holistic process. The determinants of outreach participation are similar to the pre-holistic period, but the relationship between participation and both holistic scores and admissions decisions appears much stronger. Both reader scores, holistic scores, and final admissions decisions display similar patterns with respect to their determinants. The regression predicting holistic scores controlling for reader scores suggest these patterns get reinforced at that stage. Supplemental review is positively correlated with admission conditional on other observables, and receiving it appears related to being low SES, Black or

Hispanic/Native American, and to not being an international applicant. The regressions predicting admission conditional on reader scores, holistic score, supplemental review, and outreach participation suggest that the above-mentioned patterns get further reinforced at that stage.

The results in Section III.A suggested that holistic admissions differed from pre-holistic admissions in 6 broad ways: 1) it placed lower weight on test scores, 2) it placed higher weight on grades, 3) it placed lower weight on low personal socioeconomic status, 4) it placed higher weight on low school API, 5) controlling for all of the above, there was a larger partial correlation between admissions and being Black or Hispanic/Native American, and 6) the reverse was true for International applicants.

Comparing Tables 12 and 13 suggests that the source of the shift in emphasis from test scores to grades occurred in the reader scores. A plausible explanation would be if readers were instructed to place more emphasis on grades and less on test scores. The decline in preference for low SES may be related to the fact that there is no longer a score in the admissions process focused on life challenges. Readers and the admissions officers who aggregate scores into admissions decisions take low SES into account, but to a lesser extent than previously. The increased preference for applicants from low-API schools also seems to enter via both the reader scores and their aggregation into admissions decisions.

Finally, consistent with what has been observed by Sander (2012), Mare (2012), and Groseclose (2014), the partial correlation between admissions decisions and racial/ethnic group membership arises largely via the increased weight given outreach program participation, the aggregation of reader scores into a holistic score, the selection of applicants for supplemental review, and the translation of the holistic score into admissions decisions. Very little appears in the initial holistic reader scores themselves.

IV. UCLA Admissions Under Alternative Enforcement Regimes

The results presented above collectively suggest that UCLA was caught between two pressures in 2006: increased activist pressure to increase Black and other URM enrollments, and state law banning affirmative action (Proposition 209). They responded as predicted by the analysis in Section II, they

altered how they made decisions within racial/ethnic groups in ways that favored applicants with observable characteristics more similar to Black applicants. Responding in this way altered many more admissions decisions than would have been affected by a reallocation of slots across groups, and at least as measured relative to its apparent pre-2006 preferences, was about 4-5 times as costly. The changes in admissions favored students that had low SAT scores and, perhaps more surprisingly, high SES.

That increasing the URM share of admitted students by about 3 percentage points proved so costly is perhaps surprising given that UCLA partially achieved the increase by allowing its Black regression coefficient to increase. What if it had instead been forced to keep its racial coefficients the same as in pre-holistic period? Or alternatively, what if it had been forced to practice "color-blind" admissions and achieve racial regression coefficients of zero?

To speak to these questions, I conduct simulations of admissions decisions in the holistic period under alternative assumptions about the allowable size of coefficients on racial/ethnic indicator variables and the amount of additional "color-blind" affirmative action. I begin by simulating admissions probabilities assuming UCLA's preferences over academic and social economic variables were reflected by its pre-holistic period admissions decisions. Specifically, I run a logit regression that is very similar to Table 6, but with no API variables and the coefficients on test scores and grades constrained to be equal. In other words, I predict admission decisions using the sum of the test-score and grade log odds ratio components, the low-SES log odds ratio component, and the racial/ethnic indicator variables. Coefficients on the first two variables are about 0.99 and the racial/ethnic coefficients are very close to those in the left column of Table 6.

To simulate admissions decisions with pre-holistic preferences over academic and socioeconomic variables and no traditional or color-blind affirmative action, I set each applicant's admissions log odds ratio equal to:

$$\ln\left(\frac{p_i}{1-p_i}\right) = \beta_{academic} \cdot \left(x^i_{scores} + x^i_{grades}\right) + \beta_{low_ses} \cdot x^i_{low_ses} + c$$

where the x variables are the log odds ratio components measured above, the betas are the near-one regression coefficients mentioned above, and the constant c is set so that the probabilities sum to 27,898 and therefore yield the correct expected number of admitted students.

The results of this simulation are reported in the upper left cell of Table 14. Zero affirmative action would have yielded admitted students that were 1.8% Black and 13.4% Hispanic/Native American. The table also reports the average combined SAT score and the test-score, grades, and low-SES log odds ratio components, which provide an indication of how attractive a pre-holistic UCLA would have found its admitted students on those dimensions.

In the middle-left and lower-left cells, I add the appropriate pre-holistic and post-holistic racial/ethnic coefficients to each applicants' log odds ratio, in each case adjusting the constant to achieve the correct expected number of admitted students. Each step adds about 0.7% and 1.0% to the Black and Hispanic/Native American share of admitted students and lowers the average combined SAT score by 4 points. This is roughly what one would expect given the differences in SAT scores between groups.[28] This reflects the efficiency of increasing diversity through traditional affirmative action.

The center and right columns in Table 14 assume that UCLA adds additional diversity to its admitted students by preferencing students who would be predicted to be Black using non-racial characteristics. Specifically, I add to each applicant's admission log odds ratio the predicted log odds ratio for being Black from Table 9, multiplied by a coefficient. I set this coefficient and the constant c to yield 27,898 admitted students and the same 3.71% Black share of admitted students we observe in the holistic sample. In words, I assume UCLA does as much traditional affirmative action as is permitted (either zero, its pre-holistic or its holistic-period amount) and then as much additional color-blind affirmative action as is needed to get to a 3.7% Black share.

[28] Admitted Black, Hispanic/Native American, and non-URM students in the holistic sample have average combined SAT scores of 1722, 1762, and 1983, respectively. A transfer of 0.7% and 1.0% of admissions from non-URM to Black and Hispanic/Native American applicants would therefore be affected to lower average combined SAT scores by (1983-1722)*.007+(1983-1762)*.01 = 4 points.

If we compare the differences between the left and right columns of Table 14 for different variables, we can estimate the tradeoffs involved in increasing diversity through color-blind affirmative action. An increase of 1% in the Black share of admitted students is accompanied by an increase of about 6% in the Hispanic/Native American share and a decline in average combined SAT scores of about 70 points. This is about 4 times as large as the decline one would have expected from the reallocation of slots between groups.[29] It follows that approximately 75 percent of the decline is arising from within-group changes in admissions decisions.

The discussion in Groseclose (2014) suggests that UCLA was under particular pressure to increase the Black share of admitted students. The much larger increase in the Black regression coefficient under holistic admissions (Table 5) and larger Black regression coefficients in the supplemental review and final decision stages of the holistic process (Table 13) suggests that increasing the Black share of admitted students was a priority for admissions. The simulations in Table 14 point to an additional inefficiency in color-blind admissions, at least if the goal is increasing Black admissions specifically. It is difficult to target Black applicants through color-blind methods without also admitting a lot of additional Hispanics/Native Americans. While the cost of increasing the URM share of admitted students may be about 4 times as high through color-blind methods as through traditional affirmative action, the cost of increasing Black student enrollment is about 13 times as high.[30,31]

[29] A transfer of 1% and 6% of admissions from non-URM to Black and Hispanic/Native American applicants would be affected to lower average combined SAT scores by (1983-1722)*.01+(1983-1762)*.06 = 16 points.

[30] Comparing the top left and bottom left cells in Table 14 implies that an increase of 1.36% in the Black admitted student share through a change from zero to post-holistic racial/ethnic coefficients would have lowered SAT scores by 8 points. Comparing the top left and top right cells implies that an increase of 1.87% in the Black enrollment share would have lowered average combined SAT scores by 144 points. The ratio of these ratios is (144/1.87%)/(8/1.36%) = 13.1.

[31] The calculations in the two prior paragraphs express the cost of achieving increases in diversity in SAT scores, but conclusions are very similar if we compare test-score or total log odds ratios. The ratio of 13.1 in the above footnote is (1.066/1.87%)/(0.064/1.36%) = 12.1 measured using test-score log odds ratios and (0.776/1.87%)/(0.034/1.36%) = 16.6 using total log odds ratios. If we use changes in URM shares rather than Black shares in the denominators, the three ratios are (144/14.00%)/(8/3.46%) = 4.45, (1.066/14.00%)/(0.064/3.46%) = 4.12, and (0.776/14.00%)/(0.034/3.46%) = 5.64 for SAT scores, test scores, and total log odds ratio, respectively. The conclusion that color-blind affirmative action is about 4 times as costly as a means of increasing URM shares but 13 times as costly as a means of increasing Black shares is therefore relatively robust to measuring cost more broadly.

One can also express the cost of color-blind and color-sighted approaches to increasing diversity in terms of the number of admissions decisions altered. Color-sighted affirmative action by definition does not alter the ranking of applicants within each racial group, and so only transfers slots from one group to another. If I compare the admissions probabilities in the upper left corner of Table 14 with those for the fully color-sighted admissions at the lower right corner, they imply a transfer of approximately 1502 slots from other Asian (1256 slots) and international (246 slots) applicants to Black (521 slots), Hispanic/Native American (477 slots), White (435 slots), SE Asian (61 slots), and Other (8 slots). The color-blind affirmative action in the upper right corner of Table 14 achieves the same increase in Black admits of 521, but alters 8,014 admissions decisions in the process, or 28.7 percent of the total.

This issue with the inability of color-blind affirmative action to target Blacks specifically does not emerge in Fryer, Loury, and Yuret (2008, Table 6).[32] While this could be related to the lower share of Hispanic applicants in their sample, it is likely largely due to their use of the Black zip code share, which is by far the strongest predictor of race (their Table 4). Their method is essentially assuming that color-blind affirmative action could give large preferences to applicants from Black neighborhoods over applicants from Hispanic neighborhoods with similar socioeconomic characteristics. It remains to be seen whether courts would consider this to be permissible.[33] While the goal of Fryer, Loury, and Yuret (2008) may have been to provide a best-case scenario for color-blind admissions, the legally permissible reality may be much worse than emerges in their analysis.

When focusing on the ratios of the costs of different methods, it is possible to lose track of how costly the combination of requirements for zero regression coefficients and even modest amounts of diversity can be. Table 1 provides an intuitive sense of why this is so. If UCLA was required to achieve zero racial coefficients in a regression that controlled only for SAT Math score bins, and it sought a 3.7% Black share of admitted students, it would need to admit students with roughly a 605 average Math SAT

[32] Long (2014) analyzes URMs as a group and does not distinguish between Blacks and non-Black URMs.
[33] Long (2015) discusses variables that correlate with URM status and which might be legally permissible to include in college admissions decisions. He is skeptical that the most correlated variables he examines (speaking Spanish at home and the race of one's best friend) would be acceptable, even in the pre-*SFFA v. Harvard* legal environment (p. 15).

score. If I repeat this exercise for the post-holistic sample and the other exams, I get 617, 602, and 612 for the SAT Math, Reading, and Writing exams, yielded an average combined score of 1831.

The simulation in the upper right corner of Table 14 reflects a similar exercise, albeit one where we assume the econometrician also controls for SAT subject tests, grades and socioeconomic variables. These extra control variables help, but perhaps less than one might have expected. The average combined SAT score of 1867 is well below the 1983 UCLA actually achieved, as well as the 2003 and 2011 simulated under color-sighted and no affirmative action, respectively. Had UCLA attempted to combine the small increases in diversity it achieved with zero racial regression coefficients, it would have turned the largest undergraduate program at southern California's flagship public university into something far more mainstream.

V. Implications for today

Why should we be interested in undergraduate admissions at one university, 15-20 years in the past? Arguably, it is because all U.S. selective colleges are now caught between the same two pressures. Pressure to meet threshold levels of URM enrollment is essentially universal at selective colleges. And it is widely anticipated that stricter anti-affirmative-action rules may result from the Supreme Court's decision in *SFFA v. Harvard*. In particular, it is conceivable that the Court may impose a zero-regression-coefficient constraint as in Section II.

A zero-regression-coefficient constraint, combined with pressure to maintain current levels of URM enrollment, would make it difficult for colleges to admit high-achieving students of any race. Blacks and Hispanics remain underrepresented among the highest-achieving students. Table 15 reports racial/ethnic group shares for students entering college in 2019 and for students attaining high scores on SAT and AP tests.[34]

[34] 2019 is chosen since it was the last year unaffected by the COVID pandemic and associated test-optional policies.

Suppose a college wishes to admit a class that is 7% Black and 13% Hispanic/Native American, as the Ivy League collectively did in 2019. Suppose it also needs to obtain a zero coefficient on race in a regression predicting admissions decisions and therefore needs make admission decisions that are uncorrelated with race, once qualifications are controlled for. It can therefore only admit students whose qualifications are similar to those of a population that is 7% Black and 13% Hispanic/Native American. The data in Table 15 suggest that this would severely limit the number of students a college could admit who score better than 1200 on the SAT, or 4s or 5s on AP exams. If essentially every college faces the same constraint, there will likely not be enough room for highly qualified applicants at selective colleges. Many highly qualified applicants will likely become available to the most attractive colleges that are not constrained by a combination of an affirmative action ban and diversity targets. The excess supply of qualified candidates may however be ultimately mitigated by the incentive effects of the changes in admissions, if potentially highly qualified candidates choose to focus on other things in high school.

Prior work has pointed out that achieving racial diversity with color-blind admissions will require larger tradeoffs of academic qualifications than color-sighted admissions. UCLA's experience suggests that these tradeoffs might be even larger in practice than in simulations. That UCLA's admission process changes were so costly is perhaps surprising given the modest increases in URM enrollment shares it achieved and the rather large racial regression coefficients it allowed itself. Should colleges in 2024 attempt to maintain their current URM enrollments while obtaining zero racial regressions coefficients, as the courts may require, they will essentially be forced to abandon selective admissions. This strikes me as likely to be viewed as undesirable by all sides of the affirmative action debate.

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Appendix

Admissions Simulations under Alternative Assumptions

In this Appendix, I present three additional versions of the simulations of color-blind and color-sighted affirmative action in Table 14, under alternative assumptions.

Test-Blind Admissions

Since the time of the sample period, the information available to admissions officers from standardized tests has been steadily reduced. The SAT merged its Reading and Writing exams into a single test in March 2016 and eliminated its Subject exams in 2021. The COVID pandemic disrupted test administration, contributing to a 31 percent reduction in the number of high school seniors who took the SAT between the classes of 2020 and 2021.[35] The entire University of California system announced a test-blind policy beginning with the class entering in 2022, in which neither SAT nor ACT scores would be considered.

Accordingly, the reader might be interested in how test-blind admissions would have worked in the UCLA sample in this paper. To assess this, I conduct the same exercise as in Table 14, except that I use test-blind versions of both UCLA's pre-holistic preferences and the multinomial logit that predicts applicants' race/ethnicity. Specifically, I rerun the regression predicting pre-holistic admission decisions on the non-test-score variables included in Table A3 (the flexible version of Table 5). The pseudo R^2 falls from 0.484 to 0.333 when test score variables are excluded, indicating the role that test scores played in admissions decisions. I do the same for the multinomial logit predicting applicants' race/ethnicity in the holistic sample (Table A8); here the pseudo R^2 falls from 0.213 to 0.135, likewise reflecting the partial correlation between race/ethnicity and standardized test scores.

[35] College Board, *SAT Suite of Assessments Annual Report*, 2020 and 2021.

The upper left corner of Table A9 reports results for the no affirmative action scenario in which UCLA admits students in the post-holistic sample based on its pre-holistic preferences over grades and socioeconomic variables, as estimated in a regression without test scores. With no affirmative action, test-blind admissions yields higher Black and Hispanic/Native American shares of admitted students than test-aware admissions (2.6% vs. 1.8% and 15.7% vs. 13.4%, respectively), consistent with how test-optional or test-blind admissions are often considered to be a substitute method for achieving diversity (e.g., Garg, Li, and Monachou, 2021; Dessein, Frankel, and Karik; 2024).

Unsurprisingly, test-blind admissions yields much lower average SAT scores.[36] In Table 14, color-blind affirmative action yielded average total SAT scores that were 144 points lower compared with no affirmative action, but yielded a URM share of admitted students that was 14.00 percent points higher (1.87% for Blacks and 12.13% for Hispanic/Native Americans). Test-blind admissions yields SAT scores that are 92 points lower than under test-aware admissions without affirmative action and increases URM shares only by 2.97 percentage points (0.74% for Blacks and 2.23% for Hispanics/Native Americans).[37] As a means of increasing URM admitted shares, test blind admissions is about 3 times as costly as color-blind admissions, which as discussed above is much more costly than traditional affirmative action.

Perhaps more surprisingly, test-blind admissions does not yield students with significantly higher grades or markedly different socioeconomic status. Table A9 also reports the average predicted log ratio components of admitted students on the test score, grades, and low socioeconomic status dimensions. These are based on preferences inferred from UCLA's pre-holistic admissions decisions using the model in Table A3, including the test score variables; they are therefore the same variable reported in Table 14, and thus can be compared across the two tables. If we compare the upper-right corners of Tables 14 and A8, and thus sets of admitted students that are comparably racially diverse, the log odds ratio components for test scores, grades, and low SES are -0.647, 0.052, and -0.103 higher under test-blind admissions, respectively. When admissions are test-blind, admissions officers use grades and high

[36] This is in contrast to the results of studies of test-optional policies from both before (e.g., Saboe and Terrizzi, 2019) and after (Cascio, Sacerdote, Staiger, and Tine, 2024) the pandemic, which conclude they have small effects, since most students with high scores choose to disclose.
[37] This statement is based on a comparison of the upper left corners of Tables A8 and 14.

socioeconomic status as proxies, but they are weak enough proxies that the differences are small. The most important feature of test-blind admissions is that it admits students with lower test scores.

Test-blind admissions might be expected to especially negatively affect low-SES students who score high. The simulation suggests that the high-SAT, low-SES students that were estimated to be harmed by holistic admissions in Table 10 would be further harmed by test-blind admissions. The actual admission rates for these students was 76% under pre-holistic admissions and 67% under holistic admissions; under simulated test blind admissions, the admission rate is 44%. For Black students in this category, the pre-holistic actual, holistic actual, and test-blind admission rates are 74%, 53%, and 37%, respectively.

Assuming no pre-holistic preference for low-SES applicants

The simulations in Table 14 inferred UCLA's preferences for high test scores, high grades, and lower socioeconomic status from its pre-holistic admissions decisions. This section presents a version of the simulations that omit the apparent preference for low-SES applicants. One rationale for doing so is that the low-SES preference might have been a form of color-blind affirmative action would be rendered superfluous once the color-blind or sighted affirmative action contemplated by the simulations is introduced. Alternatively, the low-SES preference might have arisen from a need to hit a certain threshold, as in the competing pressures model in Section II. If the policies contemplated in the simulations also reach the threshold for low-SES admitted students, then the need for an additional preference would be eliminated.

Table A9 reports versions of the simulations in Table 14 that omit the pre-holistic preference for low-SES applicants. In each scenario, admitted students are more academically accomplished but higher SES than in Table 14. Conclusions about the relative costs of color-sighted and color-blind affirmative action are not much altered. Comparing the top-right and top-left corners of Table A10, we conclude that color-blind affirmative action reduces SAT scores by 144 points and increases the Black and Hispanic/Native American share of admitted students by 2.18% and 12.1%, respectively. Color-sighted

affirmative action reduces SAT scores by 20 points, and increases the shares by 2.18% and 7.32%. Color-blind affirmative action costs 7.2 times as many SAT points per increase in Black admitted student share, or 4.8 times as many SAT points per increase in the URM share. The ratios are 8.7 and 5.8 per increase in Black and URM admitted student shares if we use the sum of the two academic log odds ratio components.

It should be noted that with no low-SES preference or color-blind affirmative action, the simulated admitted classes become much higher-SES than either the actual pre-holistic or holistic classes (Table 6). The version with the low-SES preference is arguably more realistic, given that it is more consistent with the actual admissions decisions.

Incorporating enrollment decisions

As discussed in Section II, colleges typically care about the characteristics of the classes that actually attend, rather than those they admit. Enrolling a racially diverse class through color-blind admission methods is complicated by the fact that URM applicants enroll at lower rates than equally qualified non-URM applicants (Figure 2). URM applicants may have better outside options, to the extent affirmative action is being practiced at other colleges.

Estimating enrollment probabilities is complicated by the fact that we only observe enrollment decisions for students who were actually admitted. Plausible selection stories can be told in both directions. UCLA might be more likely admit students who were more qualified in ways observable to admissions, but not the econometrician. These students might be less likely to enroll if they are also more attractive to colleges they prefer to UCLA. On the other hand, UCLA might be more likely to admit students who geographically closer or are otherwise a better fit; these students might be more likely to enroll than otherwise identical non-admitted students.

To incorporate enrollment decisions into the simulations as well as possible, I estimate enrollment probabilities using a Heckman model, which corrects for sample selection on observable

characteristics.[38] I then repeat the simulations in Table 14, but report statistics for expected enrolling students rather than admitted students (i.e., I weight applicants by the product of the admission and enrollment probabilities, rather than by the admission probability). For simulations of color-sighted and color-blind affirmative action, I assume UCLA targets the racial/ethnic mix of its enrolling students, rather than its admitted students (Table A12).

Conclusions about the relative cost of color-blind affirmative action are more pessimistic than those in Table 14, consistent with the discussion of the issue in Section II. Color-sighted affirmative action increased the Black and Hispanic/Native American shares of enrolled students by 3.01% and 2.50%, respectively, at a cost of 13 SAT points and 0.07 in the sum of log odds ratio components. Color-blind affirmative action achieves similar increases in URM shares, at a cost of 78 SAT points and 0.634 in the sum of the log odds ratio components. It is therefore 6 or 9 times as costly, depending on the metric used.

[38] Predicted enrollment probabilities are virtually identical if I instead simply estimate enrollment probabilities on the sample of admitted students with no sample selection correction (Table A11).

Figure 1. Black and URM shares of newly enrolled full-time undergraduate students at UCLA (IPEDS data)

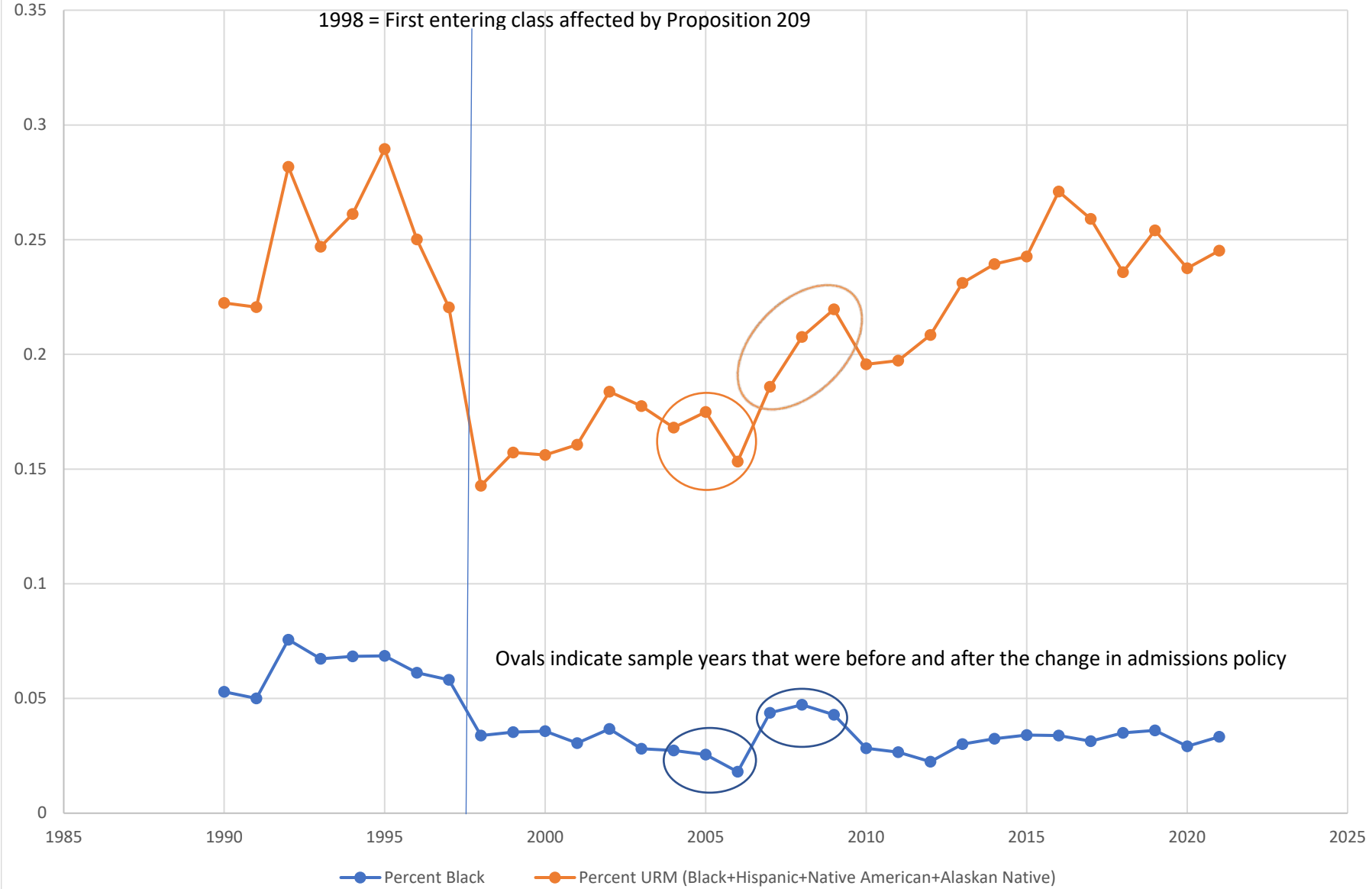


Figure 2. Enrollment rates (conditional on admission) by SAT combined score and race

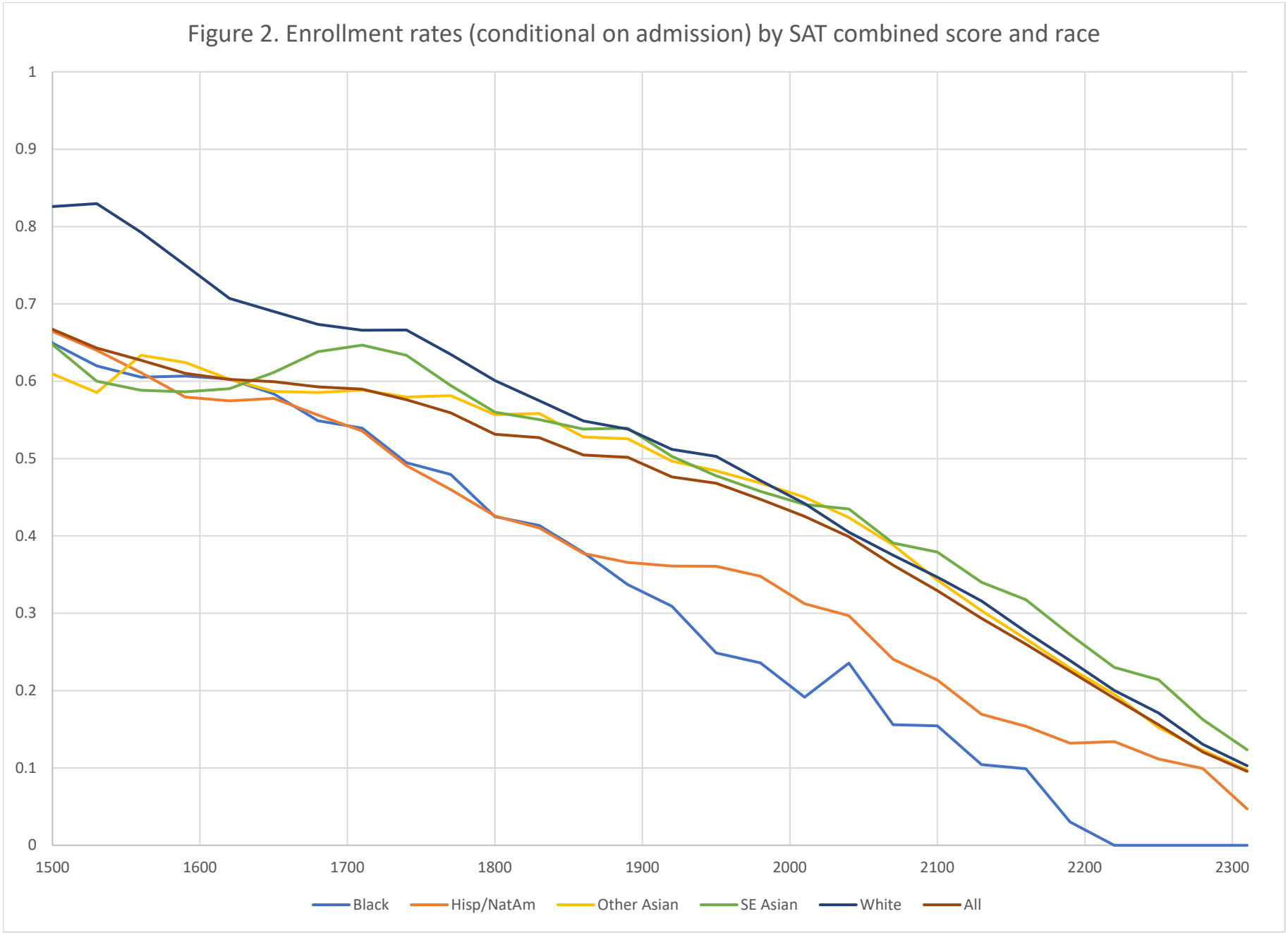


Table 1. Black and Hispanic/Native American share of UCLA applicant pool, by SAT Math score and weighted GPA, pre-holistic sample

Panel A. SAT Math Score

			Share of applicants in range who are	
Score range	Applicants	Admitted	Black	Hispanic/Native Am.
390 or less	1,589	11	18.0%	54.8%
400 - 420	1,497	31	14.5%	50.9%
430 - 450	2,331	104	11.5%	48.3%
460 - 480	3,617	339	11.5%	42.0%
490 - 510	4,837	604	9.1%	35.2%
520 - 540	6,473	950	7.5%	28.6%
550 - 570	7,811	1126	5.9%	21.9%
580 - 600	9,409	1584	4.3%	17.3%
610 - 630	10,810	2001	3.1%	13.1%
640 - 660	13,193	3211	2.3%	9.5%
670 - 690	11,079	3806	1.5%	6.7%
700 - 720	11,376	5018	1.0%	4.8%
730 - 750	5,283	2866	0.8%	3.5%
760 or more	8,522	5387	0.4%	2.3%
Total	97,827	27,038	4.0%	15.8%

Panel B. Weighted GPA

			Share of applicants in range who are	
	Applicants	Admitted	Black	Hispanic/Native Am.
3.5 or less	22,058	386	7.9%	21.8%
3.6	5,568	313	5.1%	19.1%
3.7	6,563	491	4.4%	18.3%
3.8	7,843	772	3.6%	16.3%
3.9	7,669	1064	3.4%	15.8%
4	10,578	2423	3.1%	14.7%
4.1	7,982	2671	2.6%	14.2%
4.2	7,722	3598	2.4%	12.5%
4.3 or more	21,844	15320	1.7%	10.4%
Total	97,827	27,038	4.0%	15.8%

This table reports the number of applicants, the number admitted, and the share of applicants who are Black and Hispanic/Native American by the applicant's math SAT score and Weighted GPA (i.e., GPA with bonus points for advanced courses).

Table 2. Summary statistics

	Applied		Admitted		Enrolled	
	2004-6	2007-9	2004-6	2007-9	2004-6	2007-9
Observations	97,827	113,737	27,038	27,898	10,630	10,655
Test scores and grades						
SAT Math	624	622	678	673	654	643
SAT Reading	593	591	656	650	625	615
SAT Writing	602	602	669	660	640	629
SAT Subject Average	618	619	678	675	652	644
GPA (Unweighted)	3.55	3.56	3.78	3.81	3.72	3.76
GPA (Weighted)	3.91	3.93	4.18	4.22	4.11	4.17
Socioeconomic characteristics						
Family income	76,582	77,838	76,742	80,373	70,748	75,943
Income missing	25.0%	24.2%	27.5%	28.4%	21.4%	22.6%
High School API decile	7.93	8.07	7.89	7.93	7.47	7.42
API missing (not CA Public HS)	25.8%	28.3%	24.4%	29.0%	17.5%	22.2%
Parental education	5.55	5.50	5.58	5.70	5.24	5.41
Parental education missing	5.5%	6.3%	5.6%	6.9%	4.9%	6.1%
Racial/ethnic background						
Black	4.0%	4.4%	2.3%	3.7%	2.3%	4.8%
Hispanic/Native American	15.8%	18.2%	13.5%	15.1%	15.7%	18.1%
SE Asian	9.0%	8.7%	7.9%	7.8%	9.7%	10.0%
Other Asian	29.7%	28.8%	33.7%	31.7%	31.5%	27.5%
Other	7.3%	6.0%	8.2%	7.1%	7.3%	5.9%
International	2.9%	4.1%	2.9%	3.2%	2.8%	1.8%
White	31.2%	29.9%	31.6%	31.3%	30.7%	31.8%
Additional detail on SAT subjects						
3 or more subject exams	47.4%	63.3%	62.3%	78.7%	57.8%	73.3%
4 or more subject exams	15.2%	18.8%	25.0%	30.4%	21.4%	25.4%
Took Math 1	53.6%	8.8%	43.7%	7.2%	48.8%	7.1%
Took Math 2	52.8%	73.9%	69.7%	83.3%	62.9%	80.8%
Took US History	45.4%	54.2%	51.3%	59.9%	51.3%	60.5%
Took World History	3.7%	6.1%	4.8%	8.4%	4.1%	7.4%
Took Literature	33.6%	50.4%	29.2%	46.0%	32.0%	49.8%
Took Biology (Molecular or Ecology)	23.3%	30.0%	31.3%	38.0%	27.4%	34.9%
Took Physics or Chemistry	21.7%	27.1%	31.0%	38.0%	24.6%	30.3%
Took Spanish	16.5%	18.7%	16.4%	19.2%	17.8%	21.1%
Took Asian language (Chinese, Japanese, Korean)	9.3%	9.7%	9.0%	9.1%	9.3%	7.2%
Tool other European language (French, German, Italian)	3.6%	4.0%	4.1%	4.3%	3.3%	2.9%
Took Hebrew	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%
Took Latin	0.4%	0.5%	0.8%	0.7%	0.4%	0.4%

Test scores, GPAs, and family income are reported in bins. Bins are 30 points wide for SAT scores, 0.1 wide for weighted GPA, 0.25 wide for unweighted GPA, and $10,000 wide for income. The averages reported above are of bin midpoints, with the exception of SAT scores of 760 and above or 390 and below (reported as 770 and 380, respectively), weighted GPAs of 4.25 and above or 3.55 and below (reported as 4.3 and 3.5, respectively), unweighted GPA of 3.0 or below (reported as 2.875), and income of $100,000 or more (reported as $105,000).

Parental education is reported for the more educated parent and is scaled as follows: 1 = no high school, 2 = some high school, 3 = high school graduate, 4 = some college, 5 = two-year college graduate, 6 = bachelor's degree, 7 = graduate degree.

High school Academic Performance Index (API) decile is available only for California public high schools. It ranges from 1 (low) to 10 (high).

For observations with missing income, parental education, or high school API, maximum values are included in the averages above and used in regressions. For all three variables, test scores and grades are similar for observations with maximal and missing values.

Table 3. Standardized summary statistics by racial/ethnic group, combined sample of applicants

	Black	Hispanic/Nat.Am.	SE Asian	Other Asian	Other	International	White
Observations	8,974	36,176	18,690	61,736	13,982	7,457	64,549
Test scores and grades							
SAT Math	-0.89	-0.83	-0.22	0.41	0.16	0.73	0.14
SAT Reading	-0.54	-0.57	-0.29	0.11	0.29	-0.18	0.33
SAT Writing	-0.60	-0.62	-0.33	0.15	0.29	-0.04	0.32
SAT Subject Average	-0.99	-0.38	-0.42	0.34	0.11	0.81	0.03
GPA (Unweighted)	-0.54	-0.28	0.00	0.01	0.11	0.13	0.18
GPA (Weighted)	-0.52	-0.28	0.00	0.06	0.13	-0.11	0.15
Socioeconomic characteristics							
Family income	-0.34	-0.56	-0.29	-0.08	0.26	0.19	0.44
High School API decile	-0.44	-0.76	-0.26	0.19	0.21	0.51	0.28
Parental education	-0.10	-0.86	-0.24	0.04	0.32	0.32	0.42
Income missing	16.6%	11.9%	13.0%	20.6%	45.8%	25.5%	35.1%
API missing (not CA Public HS)	27.6%	19.7%	20.1%	19.7%	33.8%	70.5%	34.0%
Parental education missing	4.5%	2.9%	4.7%	5.8%	16.5%	7.6%	5.8%
Education of more educated parent							
No high school (1)	0.9%	18.9%	5.7%	4.1%	1.7%	0.8%	0.1%
Some high school (2)	2.5%	10.3%	5.0%	3.3%	1.6%	1.2%	0.3%
High school graduate (3)	13.1%	17.9%	10.6%	10.2%	6.0%	5.8%	3.9%
Some college (4)	19.1%	14.4%	13.3%	7.8%	6.6%	4.4%	6.8%
Two-year degree (5)	8.2%	5.6%	7.3%	4.4%	3.5%	2.5%	3.8%
Bachelor's degree (6)	23.1%	14.1%	35.8%	26.0%	21.6%	37.1%	26.0%
Graduate degree (7)	33.2%	18.8%	22.2%	44.3%	59.0%	48.3%	59.1%

Continuous variables (test scores, GPAs, income, API decile, and parental education) are standardized. Parental education is scaled 1-7 as indicated in the table. The table includes the combined pre-holistic and holistic samples.

Table 4. Admission rates in the preholisic and holistic samples, by socioeconomic variables and racial/ethnic group

		Black		Hisp/NatAm/SE Asian		Other Asian/White	
	Total applications	Pre	Holistic	Pre	Holistic	Pre	Holistic
Family income							
$40,000 or less	48,001	17.4%	21.2%	28.3%	22.1%	31.6%	23.0%
$40-100,000	51,676	14.9%	20.5%	21.7%	20.4%	26.7%	24.1%
$100,000 or more	59,967	13.9%	19.6%	19.0%	19.2%	28.7%	26.2%
Missing	51,920	13.9%	20.8%	21.2%	21.5%	31.9%	30.2%
Education of more educated parent							
High school or less (1-3)	37,996	18.4%	25.3%	29.2%	21.7%	33.7%	21.2%
Some college or Associate's (4-5)	29,819	16.1%	19.6%	23.0%	18.8%	23.2%	19.6%
Bachelor's (6)	52,453	12.9%	19.6%	17.6%	20.1%	24.0%	23.2%
Graduate (7)	78,789	15.0%	19.8%	22.8%	23.3%	33.4%	30.8%
Missing	12,507	16.0%	18.8%	16.4%	18.4%	29.5%	28.2%
High School Academic Performance Index (API) decile							
Bottom 3 deciles	23,552	19.2%	27.1%	30.1%	26.7%	36.0%	34.3%
Decile 4-6	27,554	15.5%	21.9%	24.2%	21.6%	29.8%	28.8%
Decile 7-8	30,278	13.6%	18.0%	19.9%	19.0%	28.5%	26.1%
Decile 9	24,813	13.9%	15.1%	21.2%	18.0%	28.2%	23.9%
Decile 10	47,921	17.1%	17.0%	23.7%	17.4%	30.6%	23.9%
API missing (not CA Public HS)	57,446	12.5%	18.9%	18.4%	17.6%	28.4%	28.3%
Total	211,564	15.4%	20.6%	23.8%	20.9%	29.6%	26.4%

Note: International and other racial/ethnic group applicants are included in total applicants.

Table 5. Logit regression predicting admission

	Main effects	Interactions
Test scores and grades		
SAT Math	0.427***	-0.248***
	(0.0253)	(0.0292)
SAT Reading	0.568***	-0.217***
	(0.0283)	(0.0365)
SAT Writing	0.689***	-0.303***
	(0.0181)	(0.0224)
SAT Subject Average	0.456***	-0.0332
	(0.0491)	(0.0465)
3 or more subject exams	0.457***	-0.0126
	(0.0392)	(0.0448)
GPA (Unweighted)	0.496***	0.229***
	(0.0444)	(0.0665)
GPA (Weighted)	1.187***	0.370***
	(0.0475)	(0.0924)
Socioeconomic characteristics		
Family income	-0.373***	0.209***
	(0.0351)	(0.0293)
Income missing	0.156***	-0.0501
	(0.0305)	(0.0373)
High School API decile	-0.586***	-0.162***
	(0.0295)	(0.0279)
API missing (not CA Public HS)	0.0544	0.321***
	(0.0747)	(0.0788)
Parental education	-0.623***	0.456***
	(0.0296)	(0.0305)
Parental education missing	0.0194	0.0421
	(0.0303)	(0.0471)
Racial/ethnic background (white omitted)		
Black	0.861***	0.676***
	(0.106)	(0.109)
Hispanic/Native American	0.324***	0.0750
	(0.0549)	(0.0754)
SE Asian	0.0946*	-0.0403
	(0.0485)	(0.0586)
Other Asian	-0.0222	-0.0202
	(0.0383)	(0.0444)
Other	0.122***	-0.0735
	(0.0386)	(0.0598)
International	0.563***	-0.957***
	(0.0483)	(0.206)
Constant	-2.479***	-0.640***
	(0.0516)	(0.129)
Observations	211,564	
Pseudo R^2	0.444	

This table reports the results of a single regression predicting admissions, including the indicated variables and their interactions with a binary variable indicating applications in the holistic admissions sample. All continuous variables are standardized while binary variables are unaltered. At the mean admission rate of approximately 0.25, the slope of the logistic function is about 0.2, so marginal effects of variables on admission probabilities can be obtained by multiplying coefficients by that number. Standard errors allow for two-dimensional clustering based on the identity of the first and second application reader.

Table 6. Logit regressions predicting admission -- combined sample

	Admission	
	Main effects	Interactions
Components of predicted log odds ratio		
Test scores	0.990***	-0.430***
	(0.0251)	(0.0226)
Grades	0.996***	0.281***
	(0.0295)	(0.0561)
Low socioeconomic status (SES)	0.984***	-0.637***
	(0.0456)	(0.0344)
Academic Performance Index		
High School API decile	-0.00600	-0.508***
	(0.0247)	(0.0314)
API missing (not CA Public HS)	0.00140	0.329***
	(0.0847)	(0.0877)
Racial/ethnic background (white omitted)		
Black	0.700***	0.689***
	(0.105)	(0.107)
Hispanic/Native American	0.224***	0.184**
	(0.0524)	(0.0752)
SE Asian	0.0955**	-0.0968*
	(0.0378)	(0.0512)
Other Asian	-0.105***	0.0517
	(0.0314)	(0.0416)
Other	0.0930**	-0.0147
	(0.0364)	(0.0593)
International	0.517***	-0.836***
	(0.0577)	(0.212)
Constant	2.648***	-0.877***
	(0.0906)	(0.0813)
Observations	211,564	
Pseudo R^2	0.461	

This table reports the results of a single regression predicting admission using the indicated variables and their interactions with an binary variable indicating applications in the holistic sample. The first three independent variables are components of the predicted log odds ratio of admission, estimated using the pre-holisitic sample. For each group of variables -- test score (SAT, Subject test average, indicator for taking 3 or more subject tests), grade (weighted and unweighed GPA), and SES (Income, high school API, and parental education variables, plus indicators for missing values) -- the values for each observation are mulitplied by coefficients from the pre-holistic regression and added. Standard errors allow for two-dimensional clustering based on the identity of the first and second application reader.

Table 7. Logit regressions predicting admission -- holistic sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Racial/ethnic group	All	All	All	All	All	Black	Hisp/NA	SE Asian	Other Asian	White
Components of predicted log odds ratio (from non-linear version of Table 5, estimated on pre-holistic sample)										
Test scores + grades	0.797***	0.920***	0.918***	0.918***	0.937***	0.540***	0.782***	1.067***	1.087***	0.965***
	(0.0280)	(0.0300)	(0.0308)	(0.0311)	(0.0323)	(0.0758)	(0.0201)	(0.0259)	(0.0186)	(0.0409)
Low SES	0.715***	0.404***	0.434***	0.435***	0.424***	0.254***	0.470***	0.315***	0.538***	0.318***
	(0.0327)	(0.0340)	(0.0278)	(0.0254)	(0.0235)	(0.0738)	(0.0402)	(0.0530)	(0.0336)	(0.0427)
Predicted log odds ratio of membership in racial/ethnic group (from non-linear multinominal logit model)										
Black		0.476***	0.491***	0.491***	0.398***	0.299***	0.265***	0.546***	0.483***	0.402***
		(0.0191)	(0.0189)	(0.0189)	(0.0197)	(0.0578)	(0.0336)	(0.0429)	(0.0363)	(0.0381)
Hispanic/Native American			-0.0332*	-0.0309**	-0.0405***	0.0671	0.0342	-0.108**	-0.199***	-0.151***
			(0.0185)	(0.0144)	(0.0127)	(0.0603)	(0.0238)	(0.0505)	(0.0303)	(0.0315)
SE Asian				-0.00468	0.0550**	0.0476	-0.0195	0.0796*	0.150***	0.180***
				(0.0212)	(0.0227)	(0.0529)	(0.0323)	(0.0416)	(0.0262)	(0.0237)
Racial/ethnic background (white omitted)										
Black					1.156***					
					(0.0768)					
Other racial/ethnic group FEs					X					
Observations	113,737	113,737	113,737	113,737	113,737	5,023	20,674	9,894	32,701	34,016
Pseudo R^2	0.390	0.399	0.399	0.399	0.408	0.225	0.372	0.439	0.483	0.390

This table contains logit regressions predicting admission. The academic and social economic status log odds ratio variables are the same as in Table 6. The race/ethnic group predicted log odds ratio variables are from a non-linear version of the multinominal logit regression in Table A7 (estimated with bin indicators as in Table A3). Standard errors allow for two-dimensional clustering based on the identity of the first and second application reader.

Table 8. Decomposition of changes in admited student summary statistics

	Pre-holisitic			Holisitic			Impact ratio
	Actual	A	B	C	D	Actual	(D - B)/(C - B)
Applications	97,827			113,737			
Admits	27,038			27,898			
Test scores and grades							
SAT Math	678	678	683	679	673	673	2.3
SAT Reading	656	655	658	657	649	650	9.0
SAT Writing	669	668	668	667	659	660	5.6
SAT Subject Average	678	677	684	680	673	675	2.6
3 or more subject exams	62.3%	62.2%	80.2%	79.7%	77.7%	78.7%	
GPA (Unweighted)	3.78	3.78	3.79	3.79	3.81	3.81	
GPA (Weighted)	4.18	4.18	4.20	4.20	4.22	4.22	
Socioeconomic characteristics							
Family income	76,742	76,833	78,203	78,003	80,622	80,373	
Income missing	27.5%	27.5%	27.6%	27.6%	28.1%	28.4%	
High School API decile	7.89	7.89	8.10	8.01	7.93	7.93	
API missing (not CA Public HS)	24.4%	24.4%	28.2%	27.2%	29.0%	29.0%	
Parental education	5.58	5.58	5.56	5.53	5.69	5.70	
Parental education missing	5.6%	5.6%	6.4%	6.2%	6.7%	6.9%	
Racial/ethnic background							
Black	2.3%	2.3%	2.2%	3.7%	3.7%	3.7%	1.0
Hispanic/Native American	13.5%	13.5%	14.0%	15.1%	15.1%	15.1%	1.0
SE Asian	7.9%	7.9%	7.5%	7.8%	7.8%	7.8%	1.0
Other Asian	33.7%	33.7%	34.8%	31.7%	31.7%	31.7%	1.0
Other	8.2%	8.2%	7.2%	7.1%	7.1%	7.1%	1.0
International	2.9%	2.9%	5.4%	3.2%	3.2%	3.2%	1.0
White	31.6%	31.6%	28.8%	31.3%	31.3%	31.3%	1.0
Predicted log odds ratio components							
Total	3.088	3.088	3.324	3.280	3.117	3.117	4.7
Test scores	1.603	1.603	1.766	1.704	1.492	1.492	4.4
Grades	1.423	1.423	1.538	1.527	1.674	1.674	
Low SES	0.062	0.062	0.019	0.048	-0.049	-0.049	

Columns A, B, C, and D average for applicants weighted by admission probabilities estimated in different ways:

A Pre-holisitic regression

B Pre-holistic weights on characteristics, adjusted to yield holisitic-sample overall admission rate

C Pre-holisticweights, adjusted to yield holisitic-sample admission rate for each racial/ethnic group

D Post-holistic regression

A -> B captures impact of larger holisitic-period applicant pool

B -> C captures impact of increase in diversity

C -> D captures impact of changes in weights on characteristics within racial/ethnic groups

The ratio (D - B)/(C - B) captures the relative costs of achieving the same shift in racial/ethnic mix through holistic admissions compared with a reallocation of slots between groups. It is negative for grade and most socioeconomic variables, since holistic admissions increases average GPA and socioeconomic status, and thus has the opposite effect of a reallocation of slots. I therefore report it only for test score variables and the overall log odds ratio, which captures overall candidate quality as inferred from UCLA's pre-2006 preferences.

Table 9. Estimated impact of change to holisitic admissions on individual applicant's admission probabilities

	Black	Hisp/NatAm	SE Asian	Other Asian	Other	Intl	White	Total
Number of applicants (in holisitic sample)	5,023	20,674	9,894	32,701	6,806	4,623	34,016	113,737
Share with increased probability (Table 8 Col D > Col B)	93.4%	61.2%	39.8%	28.9%	42.0%	33.5%	58.5%	48.4%
Change in probability, conditional on increasing	9.1%	6.5%	11.0%	6.3%	5.8%	0.9%	6.4%	6.8%
Change in probability, conditional on decreasing	-4.8%	-6.4%	-6.1%	-6.2%	-4.8%	-20.7%	-4.1%	-6.4%
Average absolute change	8.9%	6.5%	8.0%	6.2%	5.2%	14.0%	5.4%	6.6%
Expected number changed from decline to admit	429	826	434	594	165	13	1,275	3,736
Expected number changed from admit to decline	16	517	360	1,441	189	635	576	3,736

This table compares the predicted probabilities from Columns B and D in Table 8 to identify winners and losers from holisitic admissions.

Table 10. Estimated impact of change to holisitic admissions on predicted admission probability (Table 8, Col D vs. B)

Panel A. Black applicants

	Parental education (more educated parent)			
Sum of SAT scores	High school or less	Some college/Associates	Bachelor's	Graduate
2200 or more			-3.0%	-9.0%
2100-2190	-14.0%	-8.1%	-2.5%	-1.1%
2000-2090	-7.2%	0.2%	8.6%	6.2%
1900-1990	-1.0%	5.0%	9.8%	8.8%
1800-1890	5.6%	9.7%	11.3%	10.6%
1700-1790	3.3%	10.4%	10.0%	9.7%
1600-1690	4.8%	8.8%	10.2%	8.8%
1500-1590	5.1%	9.8%	8.5%	7.9%
1400-1490	9.1%	10.6%	7.4%	7.6%
Less than 1400	11.2%	8.0%	6.9%	5.7%

Panel B. Hispanic, Native America, or SE Asian applicants

	Parental education (more educated parent)			
Sum of SAT scores	High school or less	Some college/Associates	Bachelor's	Graduate
2200 or more	-11.7%	-9.6%	-9.7%	-12.2%
2100-2190	-18.2%	-15.1%	-4.6%	-7.6%
2000-2090	-16.0%	-8.2%	2.0%	-0.4%
1900-1990	-14.4%	-1.8%	6.4%	4.7%
1800-1890	-9.3%	3.2%	8.8%	6.5%
1700-1790	-6.7%	4.3%	7.5%	5.9%
1600-1690	-6.2%	3.8%	5.2%	4.9%
1500-1590	-2.7%	4.0%	5.1%	4.1%
1400-1490	2.8%	4.3%	3.9%	3.0%
Less than 1400	4.1%	2.3%	1.7%	1.8%

Panel C. White or Other Asian applicants

	Parental education (more educated parent)			
Sum of SAT scores	High school or less	Some college/Associates	Bachelor's	Graduate
2200 or more	-16.9%	-14.9%	-7.3%	-7.0%
2100-2190	-20.2%	-12.0%	-4.1%	-4.9%
2000-2090	-20.5%	-7.8%	1.1%	0.7%
1900-1990	-15.6%	-2.4%	4.7%	4.4%
1800-1890	-11.3%	0.8%	5.1%	4.9%
1700-1790	-9.2%	1.8%	4.0%	4.0%
1600-1690	-7.9%	1.8%	2.9%	2.8%
1500-1590	-5.1%	1.1%	1.9%	2.2%
1400-1490	-1.8%	0.9%	1.0%	1.2%
Less than 1400	0.1%	0.4%	0.2%	0.4%

This table compares the predicted admission probabilities from Columns B and D of Table 8 for applicants by their combined SAT score, parental education, and race. The red, shaded cells are the high-SAT low-SES appicants for whom admission probabilities declined under holistic admissions.

Table 11. Change in actual admission probabilities for high SAT/low SES and low SAT/high SES applicants

	High SAT, low SES		Low SAT, High SES	
	Preholistic	Holistic	Preholistic	Holistic
Black	73.8%	53.2%	11.7%	17.4%
	65	77	2,092	2,691
Hispanic / Native American	71.3%	66.3%	13.8%	16.6%
	474	505	4,601	6,088
SE Asian	81.1%	69.6%	14.1%	17.3%
	444	546	4,666	5,195
Other Asian	76.3%	67.4%	15.6%	15.9%
	4,462	4,871	14,406	16,103
Other	77.7%	68.6%	17.4%	17.9%
	871	901	4,162	3,921
International	79.9%	57.1%	20.4%	9.8%
	259	609	1,980	3,097
White	74.7%	67.5%	16.8%	18.2%
	3,144	2,976	19,962	23,353
Total	76.0%	66.9%	16.0%	16.8%
	9,719	10,485	51,869	60,448

The table reports admission probabilities and number of applicants by racial/ethnic group in the preholisitic and holisitic samples for two categories of applicants. The High SAT/Low SES are those in cells on Table 10 for which holisitic admissions is estimated to have reduced admission probabilities for Black applicants by more than 2 percentage points. The Low SAT/High SES are those with SAT scores below 2000 and at least one parent with a Bachelor's degree or higher.

Table 12. Regressions predicting components of pre-holisitic admissions process

Specification	Logit	Ordered logit					Logit	
Dependent variable	Outreach	Reader A	Reader B	Academic	Life Challenges	Personal	Admitted	Admitted
Components of predicted log odds ratio								
Test scores	-0.00705	1.145***	1.027***	0.210***	-0.139***	0.182***	0.204***	1.018***
	(0.00638)	(0.0220)	(0.0429)	(0.0145)	(0.0110)	(0.00515)	(0.0208)	(0.0135)
Grades	0.0853***	1.754***	1.870***	0.185***	-0.00830	0.190***	0.0506	1.026***
	(0.00642)	(0.0515)	(0.0368)	(0.0182)	(0.00884)	(0.00372)	(0.0308)	(0.0212)
Low SES	0.223***	-0.0685***	-0.0491***	-0.0736***	2.238***	-0.104***	0.0127	1.032***
	(0.0157)	(0.0126)	(0.0123)	(0.0104)	(0.0706)	(0.00882)	(0.0362)	(0.0279)
Academic Performance Index								
High School API decile	-0.103***	0.0322***	0.0248**	0.00718*	0.0571***	-0.0186***	0.00254	-0.00279
	(0.00975)	(0.00957)	(0.0106)	(0.00429)	(0.0189)	(0.00539)	(0.00949)	(0.00944)
API missing (not CA Public HS)	0.124***	-0.216***	-0.100	-0.0887***	0.225*	0.163**	-0.747***	-0.0271
	(0.0316)	(0.0485)	(0.176)	(0.0283)	(0.130)	(0.0670)	(0.166)	(0.0862)
Racial/ethnic background (white omitted)								
Black	0.872***	-0.341***	-0.400***	-0.167***	0.730***	-0.0502	0.0577	0.641***
	(0.0581)	(0.0608)	(0.0631)	(0.0372)	(0.0539)	(0.0428)	(0.115)	(0.0820)
Hispanic/Native American	0.419***	-0.0326	-0.0206	-0.0148	0.423***	-0.166***	-0.0403	0.228***
	(0.0397)	(0.0356)	(0.0406)	(0.0270)	(0.0280)	(0.0297)	(0.0656)	(0.0458)
SE Asian	0.206***	0.0469	0.000972	-0.0366***	-0.0516	-0.111***	-0.335***	-0.110***
	(0.0259)	(0.0352)	(0.0415)	(0.0132)	(0.0343)	(0.0304)	(0.0485)	(0.0326)
Other Asian	0.232***	0.0216	-0.0212	-0.0268	-0.0345	0.0187	-0.0136	0.107***
	(0.0405)	(0.0314)	(0.0311)	(0.0173)	(0.0312)	(0.0338)	(0.0481)	(0.0381)
Other	0.191***	-0.0102	-0.0613	0.0309*	0.202***	-0.247***	-0.0699	0.0884**
	(0.0423)	(0.0435)	(0.0377)	(0.0169)	(0.0364)	(0.0201)	(0.0521)	(0.0371)
International	-0.240	-0.559	-0.365	-0.654	1.121***	1.014*	1.938	2.341
	(0.642)	(0.618)	(0.533)	(0.634)	(0.378)	(0.557)	(12.57)	(2.018)
Outreach participation		0.0286**	0.0165	-0.0162	0.535***	0.719***	-0.114***	
		(0.0132)	(0.0179)	(0.0128)	(0.0624)	(0.0184)	(0.0377)	
Fixed effects for Reader A and B score				X				
Fixed effects for Academic, Life Challenge, and Personal scores values							X	
Observations	92,711	92,711	92,711	92,711	92,711	92,711	92,711	92,711
Pseudo R^2	0.0686	0.482	0.483	0.810	0.396	0.0569	0.819	0.493

This table presents logit regressions for binary outcomes (outreach participation and admission) and ordered logit regressions for admission reader scores. The scores take on one of 6 values and are reordered so high is good. Standard errors allow for two-dimensional clustering based on the identity of the first and second application reader.

Table 13. Regressions predicting components of holisitic admissions process

Specification	Logit	Ordered Logit		Logit	Ordered Logit		Logit	
Dependent variable	Outreach	Reader A	Reader B	Supp review	Holistic score		Admitted	
Components of predicted log odds ratio								
Test scores	0.0294***	0.517***	0.578***	-0.0742***	0.183***	0.626***	0.0953***	0.663***
	(0.00512)	(0.0176)	(0.0210)	(0.00986)	(0.0101)	(0.0160)	(0.0141)	(0.0162)
Grades	0.0846***	1.470***	1.379***	-0.0303**	0.314***	1.564***	0.204***	1.455***
	(0.00440)	(0.0442)	(0.0472)	(0.0119)	(0.0159)	(0.0350)	(0.0209)	(0.0342)
Socioeconomic variables	0.145***	0.139***	0.140***	0.661***	0.0382***	0.171***	0.146***	0.366***
	(0.00911)	(0.0104)	(0.0118)	(0.0209)	(0.0131)	(0.00971)	(0.0235)	(0.0138)
Academic Performance Index								
High School API decile	-0.113***	-0.118***	-0.126***	0.0253***	-0.0484***	-0.154***	-0.110***	-0.210***
	(0.00413)	(0.00591)	(0.00523)	(0.00757)	(0.00512)	(0.00477)	(0.0114)	(0.00679)
API missing (not CA Public HS)	0.169***	0.300***	0.344***	0.180***	0.0413*	0.379***	-0.409***	0.316***
	(0.0161)	(0.0229)	(0.0206)	(0.0394)	(0.0240)	(0.0187)	(0.0681)	(0.0288)
Racial/ethnic background (white omitted)								
Black	0.738***	0.315***	0.300***	0.841***	0.386***	0.469***	1.014***	1.509***
	(0.0339)	(0.0404)	(0.0386)	(0.0567)	(0.0473)	(0.0371)	(0.0859)	(0.0753)
Hispanic/Native American	0.321***	0.182***	0.215***	0.265***	0.169***	0.269***	0.187***	0.491***
	(0.0200)	(0.0227)	(0.0224)	(0.0481)	(0.0257)	(0.0207)	(0.0589)	(0.0343)
SE Asian	0.263***	0.0674***	0.105***	-0.239***	0.0330*	0.116***	-0.337***	-0.00806
	(0.0201)	(0.0224)	(0.0178)	(0.0480)	(0.0181)	(0.0200)	(0.0540)	(0.0262)
Other Asian	0.222***	0.179***	0.163***	-0.0544	-0.000167	0.200***	-0.0947	0.0906**
	(0.0284)	(0.0272)	(0.0221)	(0.0699)	(0.0322)	(0.0228)	(0.0915)	(0.0453)
Other	0.103***	0.126***	0.154***	-0.146***	0.0820***	0.170***	-0.0230	0.0611*
	(0.0238)	(0.0257)	(0.0225)	(0.0526)	(0.0271)	(0.0216)	(0.0664)	(0.0343)
International	-0.104***	-0.283	0.0271	-1.218***	0.351**	-0.122	-6.226***	-0.826***
	(0.0338)	(0.217)	(0.140)	(0.209)	(0.174)	(0.175)	(0.508)	(0.282)
Outreach		0.441***	0.417***	0.483***	0.138***		0.219***	
		(0.0209)	(0.0188)	(0.0343)	(0.0189)		(0.0341)	
Supplemental review					0.187***		2.518***	
					(0.0417)		(0.0541)	
Fixed effects for Reader A and B score values					X		X	
Fixed effects for Holistic score values							X	
Observations	109,726	109,726	109,726	109,726	109,726	109,726	104,528	109,726
Pseudo R^2	0.0424	0.321	0.316	0.173	0.835	0.287	0.744	0.451

This table presents logit regressions for binary outcomes (outreach participation, supplemental review, and admission) and ordered logit regressions for admission reader and holistic scores. The reader and holistic scores take on one of 6 values and are reordered so high is good. Standard errors allow for two-dimensional clustering based on the identity of the first and second application reader.

Table 14. Simulated admissions decisions for the post-holistic sample

Racial/ethnic coefficients		Additional "color-blind" preference for applicants predicted to be Black: None	Additional "color-blind" preference for applicants predicted to be Black: 3.71% share target
Zero	Percent Black	1.84%	3.71%
	Percent Hispanic/Native American	13.43%	25.56%
	SAT combined	2011	1867
	Predicted log odds ratios	3.336	2.560
	Test score	1.778	0.712
	Grades	1.547	1.011
	Low SES	0.011	0.837
Pre-holistic	Percent Black	2.50%	3.71%
	Percent Hispanic/Native American	14.36%	21.69%
	SAT combined	2008	1925
	Predicted log odds ratios	3.321	2.955
	Test score	1.756	1.168
	Grades	1.537	1.257
	Low SES	0.028	0.531
Post-holistic	Percent Black	3.20%	3.71%
	Percent Hispanic/Native American	15.53%	18.34%
	SAT combined	2003	1973
	Predicted log odds ratios	3.302	3.196
	Test score	1.714	1.506
	Grades	1.534	1.443
	Low SES	0.054	0.247

Additional points of comparison		Color sighted admissions	Actual admits
	Percent Black	3.71%	3.71%
	Percent Hispanic/Native American	15.13%	15.13%
	SAT combined	2003	1983
	Predicted log odds ratios	3.288	3.117
	Test score	1.710	1.492
	Grades	1.533	1.674
	Low SES	0.045	-0.049

This table reports the characteristics of simulated classes of admitted students from the post-holistic period. In the upper left cell, students are admitted according to their predicted log odds ratio of admission from a regression on the pre-holistic sample, with all racial/ethnic group coefficients set to zero and the constant adjusted to achieve the correct number of expected admissions (27,898). This regression uses the specification in Table A3 (the flexible version of Table 5). In the middle left and lower left cells, the exercise is repeated, but the racial/ethnic coefficients are set to match the pre-holistic and post-holistic regressions, respectively. On the right side, the predicted log odds ratio of being Black from Table 8 is added to the predicted log odds ratio of admission, multiplied by a coefficient that is adjusted to yield the actual share of Black admitted students (3.71%). The constant is also adjusted to continue to yield the correct expected number of admissions. The "color-sighted admissions" cell uses the predicted log odds ratios from the upper-left cell and applies the racial coefficients necessary to achieve the racial/ethnic mix of the actual holistic admitted applicangts, and the "actual admits" cell reports the characteristics of those applicants.

Table 15. Racial/ethnic group shares in 2019

	Black	Hisp/NatAm	Asian	White	Other
Share of US SAT takers	12.2%	25.8%	10.3%	42.7%	9.0%
Share of students scoring 1400+ on SAT	1.7%	7.3%	36.8%	48.8%	5.4%
Share of students scoring 1200-1390 on SAT	4.5%	14.8%	17.3%	58.4%	5.0%
Share of students scoring 1000-1190 on SAT	9.3%	24.1%	8.4%	50.5%	7.8%
Share of AP exams taken	6.3%	23.0%	15.6%	48.9%	6.3%
Share of scores of 5 on AP exams	1.8%	13.8%	26.7%	50.9%	2.3%
Share of scores of 4 on AP exams	3.0%	16.8%	18.9%	54.9%	7.5%
Share of STEM AP exams taken	5.8%	17.0%	20.8%	50.5%	5.9%
Share of scores of 5 on STEM AP exams	1.2%	7.1%	34.6%	49.9%	7.2%
Share of scores of 4 on STEM AP exams	2.3%	10.2%	24.5%	56.3%	6.7%
Share of high-level STEM AP exams taken	5.1%	16.5%	21.5%	50.5%	6.4%
Share of scores of 5 on high-level STEM AP exams	1.1%	4.5%	25.4%	33.8%	35.2%
Share of scores of 4 on high-level STEM AP exams	2.3%	9.8%	25.0%	56.2%	6.7%
Entering students					
All colleges	12.0%	21.4%	6.9%	48.9%	10.8%
Ivy league colleges	7.4%	12.8%	20.9%	36.8%	22.1%

Source: SAT Suite Annual Report 2019; AP National Summary 2019; IPEDS

Note: Racial/ethnic group shares of students scoring in different SAT ranges are approximate, due to rounding in the underlying reports. STEM AP exams include math, science, and computer science. High-level STEM exams exclude Calculus AB, Computer Science Principles, and Physics 1 and 2 (which are algebra-based).

Table A1. Applications excluded from sample

	Total	Preholistic	Holistic
All applications to College of Letters and Science	232,985	106,447	126,538
Cancelled or Withdrawn	2,812	1,318	1,494
No GPA information[1,2]	1,457	269	1,188
Missing SAT and ACT[2]	7,846	3,869	3,977
No SAT Subject tests[2]	5,558	1,745	3,813
Only one SAT Subject test[2]	569	290	279
Complete test score information, but no SAT (i.e. ACT + SAT Subjects only)	3,179	1,129	2,050
Sample with a decision, complete test and grade information, and SAT scores	211,564	97,827	113,737

1. 82% of applications excluded for missing GPAs are international applications
2. Only 7% of applications with missing test score or GPAs are admitted, compared with 26% with complete test and grade information

Table A2. Logit regression predicting admission -- robustness of standard errors to clustering

	Coeff	Standard errors			
Main effects		Robust	Table 5	T5+API	T5+API*Post
Test scores and grades					
SAT Math	0.427***	(0.0192)	(0.0253)	(0.0439)	(0.0438)
SAT Reading	0.568***	(0.0182)	(0.0283)	(0.0458)	(0.0481)
SAT Writing	0.689***	(0.0187)	(0.0181)	(0.0265)	(0.0255)
SAT Subject Average	0.456***	(0.0196)	(0.0491)	(0.0913)	(0.0949)
3 or more subject exams	0.457***	(0.0200)	(0.0392)	(0.0548)	(0.0594)
GPA (Unweighted)	0.496***	(0.0225)	(0.0444)	(0.0779)	(0.0792)
GPA (Weighted)	1.187***	(0.0208)	(0.0475)	(0.130)	(0.127)
Socioeconomic characteristics					
Family income	-0.373***	(0.0146)	(0.0351)	(0.0489)	(0.0497)
Income missing	0.156***	(0.0255)	(0.0305)	(0.0349)	(0.0346)
High School API decile	-0.586***	(0.0157)	(0.0295)	(0.0968)	(0.0951)
API missing (not CA Public HS)	0.0544**	(0.0245)	(0.0747)	(0.116)	(0.114)
Parental education	-0.623***	(0.0158)	(0.0296)	(0.0452)	(0.0446)
Parental education missing	0.0194	(0.0439)	(0.0303)	(0.0241)	(0.0235)
Racial/ethnic background (white omitted)					
Black	0.861***	(0.0735)	(0.106)	(0.129)	(0.134)
Hispanic/Native American	0.324***	(0.0377)	(0.0549)	(0.0797)	(0.0787)
SE Asian	0.0946**	(0.0407)	(0.0485)	(0.0959)	(0.0942)
Other Asian	-0.0222	(0.0254)	(0.0383)	(0.0549)	(0.0569)
Other	0.122***	(0.0381)	(0.0386)	(0.0374)	(0.0378)
International	0.563***	(0.0616)	(0.0483)	(0.127)	(0.0977)
Constant	-2.479***	(0.0291)	(0.0516)	(0.0693)	(0.0723)
Interactions with holistic					
Test scores and grades					
SAT Math	-0.248***	(0.0257)	(0.0292)	(0.0517)	(0.0502)
SAT Reading	-0.217***	(0.0246)	(0.0365)	(0.0590)	(0.0569)
SAT Writing	-0.303***	(0.0254)	(0.0224)	(0.0292)	(0.0264)
SAT Subject Average	-0.0332	(0.0267)	(0.0465)	(0.0868)	(0.0928)
3 or more subject exams	-0.0126	(0.0289)	(0.0448)	(0.0627)	(0.0595)
GPA (Unweighted)	0.229***	(0.0331)	(0.0665)	(0.0839)	(0.150)
GPA (Weighted)	0.370***	(0.0308)	(0.0924)	(0.144)	(0.229)
Socioeconomic characteristics					
Family income	0.209***	(0.0197)	(0.0293)	(0.0380)	(0.0457)
Income missing	-0.0501	(0.0350)	(0.0373)	(0.0411)	(0.0546)
High School API decile	-0.162***	(0.0217)	(0.0279)	(0.0575)	(0.105)
API missing (not CA Public HS)	0.321***	(0.0335)	(0.0788)	(0.0600)	(0.132)
Parental education	0.456***	(0.0207)	(0.0305)	(0.0495)	(0.0455)
Parental education missing	0.0421	(0.0586)	(0.0471)	(0.0363)	(0.0374)
Racial/ethnic background (white omitted)					
Black	0.676***	(0.101)	(0.109)	(0.102)	(0.178)
Hispanic/Native American	0.0750	(0.0502)	(0.0754)	(0.0920)	(0.0974)
SE Asian	-0.0403	(0.0540)	(0.0586)	(0.102)	(0.104)
Other Asian	-0.0202	(0.0346)	(0.0444)	(0.0426)	(0.0741)
Other	-0.0735	(0.0534)	(0.0598)	(0.0546)	(0.0613)
International	-0.957***	(0.0827)	(0.206)	(0.203)	(0.148)
Holistic sample indicator	-0.640***	(0.0450)	(0.129)	(0.167)	(0.155)
Observations			211,564		
Pseudo R^2			0.444		

This table examines the robustness of the standard errors reported in Table 5 to different procedures for adjusting for correlations within the error term

Robust = Heteroskedasticity robust, but no adjustment for clustering

Table 5 = Adjusts for two-dimensional clustering within applications read by the same first two readers

Table 5 + API = Adjusts for an additional dimension of clustering with API deciles

Table 5 + API*Post = Adjusts for an additional dimension of clustering with API deciles interacted with a holistic sample indicator

Table A3. Regressions predicting admissions with flexible functional forms for test scores, grades, and socioeconomic variables

	SAT Math		SAT Reading		SAT Writing		Subject Test Average	
	Main effect	Interaction	Main effect	Interaction	Main effect	Interaction	Main effect	Interaction
Test score range (760+ omitted)								
390 or less	-3.423***	2.046***	-4.674***	2.131***	-3.382***	1.137***	1.025***	-0.698*
	(0.345)	(0.371)	(0.289)	(0.326)	(0.258)	(0.303)	(0.338)	(0.407)
400-420	-2.633***	1.770***	-4.143***	2.817***	-3.684***	2.047***	-0.765***	0.333
	(0.218)	(0.248)	(0.211)	(0.238)	(0.207)	(0.242)	(0.236)	(0.280)
430-450	-2.128***	1.417***	-2.587***	1.346***	-3.470***	1.962***	-1.074***	0.229
	(0.137)	(0.168)	(0.113)	(0.146)	(0.134)	(0.166)	(0.147)	(0.186)
460 - 480	-1.211***	0.710***	-1.402***	0.251**	-1.932***	0.766***	-0.972***	-0.156
	(0.0957)	(0.127)	(0.0853)	(0.118)	(0.0885)	(0.120)	(0.107)	(0.143)
490 - 510	-0.861***	0.386***	-1.109***	0.129	-1.529***	0.308***	-1.090***	-0.187
	(0.0793)	(0.107)	(0.0761)	(0.104)	(0.0740)	(0.104)	(0.0895)	(0.122)
520 - 540	-0.694***	0.282***	-1.077***	0.113	-1.449***	0.371***	-1.116***	-0.131
	(0.0684)	(0.0941)	(0.0686)	(0.0948)	(0.0659)	(0.0926)	(0.0805)	(0.109)
550 - 570	-0.832***	0.189**	-1.001***	0.0860	-1.500***	0.476***	-1.263***	-0.0324
	(0.0626)	(0.0861)	(0.0638)	(0.0878)	(0.0619)	(0.0858)	(0.0743)	(0.0997)
580 - 600	-0.834***	0.206***	-0.929***	0.0893	-1.354***	0.456***	-1.413***	0.274***
	(0.0563)	(0.0773)	(0.0595)	(0.0817)	(0.0561)	(0.0779)	(0.0695)	(0.0929)
610 - 630	-0.872***	0.276***	-0.709***	-0.0274	-1.199***	0.422***	-1.207***	0.0902
	(0.0516)	(0.0716)	(0.0564)	(0.0780)	(0.0525)	(0.0732)	(0.0653)	(0.0877)
640 - 660	-0.719***	0.207***	-0.473***	-0.227***	-0.982***	0.276***	-0.976***	0.0224
	(0.0465)	(0.0645)	(0.0548)	(0.0756)	(0.0504)	(0.0702)	(0.0624)	(0.0835)
670 - 690	-0.431***	-0.0418	-0.277***	-0.193***	-0.647***	0.0741	-0.677***	-0.149*
	(0.0449)	(0.0618)	(0.0539)	(0.0748)	(0.0486)	(0.0677)	(0.0600)	(0.0801)
700 - 720	-0.223***	-0.142**	-0.0815	-0.210***	-0.420***	0.0429	-0.413***	-0.207***
	(0.0424)	(0.0597)	(0.0561)	(0.0781)	(0.0485)	(0.0683)	(0.0588)	(0.0776)
730 - 750	-0.108**	-0.118*	-0.0298	-0.233***	-0.278***	0.0196	-0.184***	-0.193**
	(0.0495)	(0.0662)	(0.0593)	(0.0815)	(0.0522)	(0.0743)	(0.0596)	(0.0774)
Took 3 or more subject tests	0.442***	-0.0534*						
	(0.0213)	(0.0307)						
Unweighted GPA (3.75 to 4.0 omitted)								
Less than 3.00	-1.834***	-0.212						
	(0.130)	(0.175)						
3.0 to 3.25	-1.464***	-0.165						
	(0.0795)	(0.115)						
3.25 to 3.5	-0.924***	-0.499***						
	(0.0444)	(0.0657)						
3.5 to 3.75	-0.405***	-0.582***						
	(0.0272)	(0.0372)						
Weighted GPA (4.3 or more omitted)								
3.5 or less	-3.104***	0.270**						
	(0.0857)	(0.120)						
3.6	-2.375***	-0.535***						
	(0.0766)	(0.119)						
3.7	-2.250***	-0.510***						
	(0.0642)	(0.100)						
3.8	-2.182***	-0.624***						
	(0.0529)	(0.0810)						
3.9	-1.987***	-0.487***						
	(0.0469)	(0.0679)						
4.0	-1.526***	-0.639***						
	(0.0358)	(0.0505)						
4.1	-1.097***	-0.629***						
	(0.0349)	(0.0476)						
4.2	-0.649***	-0.586***						
	(0.0331)	(0.0438)						
Socioeconomic variables (top value omitted)	Income catgeory		API decile		Parental education			
Bottom	1.100***	-0.638***	1.926***	0.562***	2.233***	-1.585***		
	(0.0776)	(0.109)	(0.0751)	(0.101)	(0.0633)	(0.0854)		
2nd	1.104***	-0.613***	2.180***	0.0566	1.826***	-1.330***		
	(0.0520)	(0.0719)	(0.0666)	(0.0900)	(0.0700)	(0.0936)		
3rd	0.966***	-0.590***	1.521***	0.125	1.359***	-1.008***		
	(0.0484)	(0.0667)	(0.0580)	(0.0821)	(0.0444)	(0.0609)		
4th	0.668***	-0.399***	0.908***	0.471***	0.581***	-0.410***		
	(0.0487)	(0.0672)	(0.0564)	(0.0808)	(0.0421)	(0.0592)		
5th	0.214***	-0.0704	0.437***	0.657***	0.466***	-0.366***		
	(0.0534)	(0.0731)	(0.0612)	(0.0817)	(0.0529)	(0.0748)		
6th	0.116**	0.0110	0.554***	0.240***	-0.107***	0.125***		
	(0.0552)	(0.0764)	(0.0518)	(0.0741)	(0.0281)	(0.0385)		
7th	0.104*	-0.0332	0.268***	0.308***				
	(0.0557)	(0.0779)	(0.0464)	(0.0652)				
8th	0.0117	0.123	0.144***	0.313***				
	(0.0570)	(0.0791)	(0.0447)	(0.0624)				
9th	-0.0400	0.160**	0.186***	0.0849				
	(0.0570)	(0.0803)	(0.0386)	(0.0536)				
10th	0.0315	-0.0283						
	(0.0608)	(0.0844)						
Socioeconomic variable missing	0.0121	0.0455	-0.0956***	0.355***	-0.122**	0.144**		
	(0.0301)	(0.0413)	(0.0306)	(0.0426)	(0.0501)	(0.0674)		
Racial/ethnic group (white omitted)								
Black	0.707***	0.534***						
	(0.0660)	(0.0859)						
Hispanic/Native American	0.217***	0.166***						
	(0.0387)	(0.0526)						
SE Asian	0.0948**	-0.0305						
	(0.0419)	(0.0580)						
Other Asian	-0.112***	-0.0134						
	(0.0284)	(0.0396)						
Other	0.0901**	-0.0739						
	(0.0418)	(0.0600)						
International	0.515***	-1.105***						
	(0.0662)	(0.0880)						
Constant	2.666***	-0.163						
	(0.0748)	(0.103)						
Observations	211,564							
Pseudo R^2	0.475							

This table presents a version of the regression in Table 5 that substitutes indicators for all possible values of the test score, GPA, and socioeconomic variables. Standard errors allow for two-dimensional clustering based on the identity of the first and second application reader.

Table A4. Logit regressions predicting admission for broad racial/ethnic groups

	Other asian		White		Black/Hispanic/SE Asian	
Test scores and grades	Main	Interaction	Main	Interaction	Main	Interaction
SAT Math	0.398***	-0.0428	0.472***	-0.243***	0.472***	-0.322***
	(0.0485)	(0.0612)	(0.0492)	(0.0548)	(0.0430)	(0.0533)
SAT Reading	0.692***	-0.204***	0.368***	-0.108**	0.580***	-0.391***
	(0.0269)	(0.0419)	(0.0418)	(0.0504)	(0.0511)	(0.0583)
SAT Writing	0.867***	-0.377***	0.615***	-0.309***	0.613***	-0.219***
	(0.0450)	(0.0591)	(0.0355)	(0.0418)	(0.0389)	(0.0454)
SAT Subject Average	0.402***	-0.0765	0.654***	-0.170***	0.297***	0.0167
	(0.0520)	(0.0673)	(0.0580)	(0.0642)	(0.0420)	(0.0513)
3 or more subject exams	0.429***	0.00177	0.507***	-0.131**	0.392***	0.0482
	(0.0444)	(0.0636)	(0.0499)	(0.0579)	(0.0384)	(0.0576)
GPA (Unweighted)	0.779***	0.316***	0.427***	0.204**	0.322***	0.170***
	(0.0684)	(0.0960)	(0.0978)	(0.101)	(0.0470)	(0.0651)
GPA (Weighted)	1.373***	0.758***	1.219***	0.444***	1.002***	0.432***
	(0.0618)	(0.0965)	(0.0564)	(0.111)	(0.0399)	(0.0563)
Socioeconomic characteristics						
Family income	-0.362***	0.205***	-0.372***	0.204***	-0.443***	0.253***
	(0.0362)	(0.0436)	(0.0464)	(0.0510)	(0.0274)	(0.0372)
Income missing	0.157***	-0.0625	0.159***	-0.0937	0.0642	0.0921
	(0.0421)	(0.0629)	(0.0480)	(0.0621)	(0.0719)	(0.0909)
High School API decile	-0.627***	-0.270***	-0.456***	-0.0711	-0.627***	-0.116**
	(0.0411)	(0.0552)	(0.0505)	(0.0551)	(0.0469)	(0.0473)
API missing (not CA Public HS)	-0.133	0.289***	3.82e-05	0.279***	0.171*	0.371***
	(0.0938)	(0.112)	(0.0756)	(0.0840)	(0.0919)	(0.103)
Parental education	-0.789***	0.613***	-0.422***	0.391***	-0.569***	0.406***
	(0.0393)	(0.0458)	(0.0448)	(0.0519)	(0.0334)	(0.0389)
Parental education missing	0.166*	-0.0699	-0.0896	0.135	0.0186	-0.0986
	(0.0859)	(0.117)	(0.0722)	(0.0941)	(0.131)	(0.159)
Racial/ethnic background (SE Asian omitted)						
Black					0.574***	0.621***
					(0.0783)	(0.0869)
Hispanic/Native American					0.143***	0.0477
					(0.0442)	(0.0607)
Constant	-2.761***	-1.253***	-2.504***	-0.606***	-2.196***	-0.628***
	(0.0776)	(0.127)	(0.0431)	(0.168)	(0.0645)	(0.0916)
Observations	61,736		64,549		63,840	
Pseudo R^2	0.531		0.408		0.410	

The regression in Table 5 is repeated for specific racial/ethnic groups. Standard errors allow for two-dimensional clustering based on the identity of the first and second application reader.

Table A5. Logistic regressions predicting admission by racial/ethnic group, underrepresented groups

	Black		Hisp/NatAm		SE Asian	
Test scores and grades	Main effects	Interactions	Main effects	Interactions	Main effects	Interactions
SAT Math	0.383***	-0.304***	0.533***	-0.324***	0.356***	-0.171
	(0.0822)	(0.108)	(0.0480)	(0.0641)	(0.0808)	(0.109)
SAT Reading	0.347***	-0.367***	0.587***	-0.377***	0.621***	-0.333***
	(0.0970)	(0.124)	(0.0724)	(0.0803)	(0.0528)	(0.0854)
SAT Writing	0.371***	-0.199	0.653***	-0.243***	0.647***	-0.139*
	(0.142)	(0.132)	(0.0540)	(0.0722)	(0.0535)	(0.0782)
SAT Subject Average	0.205*	-0.0402	0.342***	-0.0180	0.430***	-0.0361
	(0.106)	(0.121)	(0.0476)	(0.0632)	(0.0817)	(0.105)
3 or more subject exams	0.292**	0.112	0.379***	0.0705	0.486***	-0.00240
	(0.126)	(0.137)	(0.0607)	(0.0837)	(0.0738)	(0.0989)
GPA (Unweighted)	0.170	0.0167	0.418***	0.191***	0.225***	0.545***
	(0.155)	(0.118)	(0.0404)	(0.0575)	(0.0642)	(0.111)
GPA (Weighted)	0.964***	0.152	0.941***	0.449***	1.131***	0.988***
	(0.104)	(0.127)	(0.0451)	(0.0660)	(0.0846)	(0.143)
Socioeconomic characteristics						
Family income	-0.418***	0.381***	-0.462***	0.197***	-0.422***	0.271***
	(0.0863)	(0.0783)	(0.0317)	(0.0480)	(0.0565)	(0.0701)
Income missing	0.0353	0.164	0.0537	0.0821	0.0745	0.0371
	(0.191)	(0.233)	(0.0899)	(0.123)	(0.0810)	(0.130)
High School API decile	-0.457***	-0.0911	-0.627***	-0.124**	-0.736***	-0.145*
	(0.102)	(0.0910)	(0.0527)	(0.0622)	(0.0612)	(0.0784)
API missing (not CA Public HS)	-0.0712	0.590***	0.270***	0.337***	0.143	0.329**
	(0.197)	(0.219)	(0.0874)	(0.119)	(0.129)	(0.164)
Parental education	-0.370***	0.114	-0.604***	0.418***	-0.634***	0.529***
	(0.0909)	(0.102)	(0.0414)	(0.0482)	(0.0379)	(0.0554)
Parental education missing	0.546*	-0.640*	-0.114	0.129	-0.0725	-0.0903
	(0.304)	(0.386)	(0.173)	(0.215)	(0.185)	(0.262)
Constant	-1.513***	-0.0894	-2.068***	-0.637***	-2.310***	-1.334***
	(0.172)	(0.149)	(0.0734)	(0.0933)	(0.0795)	(0.145)
Observations	8,974		36,176		18,690	
Pseudo R^2	0.297		0.424		0.463	

The regression in Table 5 is repeated for specific racial/ethnic groups. Standard errors allow for two-dimensional clustering based on the identity of the first and second application reader.

Table A6. Logit regressions predicting admission for specified racial/ethnic groups

	Black	Hisp/NatAm	SE Asian	Other Asian	White
Components of predicted log odds ratio					
Test scores	0.593***	0.942***	1.015***	1.052***	1.003***
	(0.129)	(0.0351)	(0.0352)	(0.0236)	(0.0367)
Grades	0.700***	0.833***	0.838***	1.213***	0.970***
	(0.0737)	(0.0234)	(0.0356)	(0.0223)	(0.0456)
Low SES	0.657***	0.876***	0.964***	1.134***	0.991***
	(0.119)	(0.0416)	(0.0564)	(0.0421)	(0.0646)
Academic Performance Index					
High School API decile	-0.00974	-0.0433	-0.114**	-0.0341	0.0611
	(0.0701)	(0.0569)	(0.0531)	(0.0448)	(0.0491)
API missing (not CA Public HS)	-0.243	0.117	0.00948	-0.108	-0.0649
	(0.180)	(0.0932)	(0.139)	(0.0982)	(0.0831)
Interactions with holistic sample indicator variable					
Post*Test scores	-0.423***	-0.557***	-0.424***	-0.374***	-0.398***
	(0.0821)	(0.0373)	(0.0489)	(0.0292)	(0.0324)
Post*Grades	0.0975*	0.356***	0.706***	0.422***	0.300***
	(0.0506)	(0.0333)	(0.0655)	(0.0468)	(0.0630)
Post*SES	-0.409***	-0.499***	-0.731***	-0.819***	-0.749***
	(0.0948)	(0.0467)	(0.0655)	(0.0496)	(0.0671)
Post*API	-0.386***	-0.430***	-0.552***	-0.654***	-0.451***
	(0.0936)	(0.0695)	(0.0699)	(0.0594)	(0.0610)
Post*API missing	0.714***	0.392***	0.368**	0.230**	0.297***
	(0.205)	(0.126)	(0.171)	(0.115)	(0.0923)
Constant	-0.995***	-1.294***	-0.453***	-0.536***	-0.752***
	(0.275)	(0.144)	(0.173)	(0.0977)	(0.117)
Post	1.766***	2.588***	2.616***	2.878***	2.656***
	(0.449)	(0.130)	(0.126)	(0.0812)	(0.122)
Observations	8,974	36,176	18,690	61,736	64,549
Pseudo R^2	0.298	0.443	0.477	0.545	0.425

The regression in Table 6 is repeated for specific racial/ethnic groups. Standard errors allow for two-dimensional clustering based on the identity of the first and second application reader.

Table A7. Multinominal logit regressions predicting race/ethnicity -- holistic sample

	(1) Black	(2) Hisp/NatAm	(3) SE Asian	(4) Other Asian	(5) Other	(6) Intl
Test scores and grades						
SAT Math	-0.542***	-0.794***	0.316***	0.572***	0.000680	0.801***
	(0.0244)	(0.0144)	(0.0232)	(0.0187)	(0.0254)	(0.0637)
SAT Reading	0.0769**	-0.384***	-0.296***	-0.628***	-0.201***	-1.291***
	(0.0316)	(0.0216)	(0.0224)	(0.0205)	(0.0259)	(0.0546)
SAT Writing	-0.143***	-0.344***	-0.409***	-0.287***	-0.000379	-0.599***
	(0.0288)	(0.0211)	(0.0232)	(0.0198)	(0.0249)	(0.0985)
SAT Subject Average	-0.325***	1.089***	0.0236	0.879***	0.373***	2.011***
	(0.0270)	(0.0212)	(0.0187)	(0.0203)	(0.0306)	(0.0587)
3 or more subject exams	0.0986***	0.463***	0.251***	0.492***	0.267***	0.558***
	(0.0309)	(0.0237)	(0.0249)	(0.0226)	(0.0278)	(0.0751)
GPA (Unweighted)	-0.423***	-0.283***	-0.194***	-0.290***	-0.176***	0.245***
	(0.0273)	(0.0177)	(0.0232)	(0.0168)	(0.0269)	(0.0580)
GPA (Weighted)	0.0841**	0.00769	0.204***	-0.0485***	0.0367	-0.771***
	(0.0354)	(0.0201)	(0.0241)	(0.0163)	(0.0263)	(0.103)
Socioeconomic characteristics						
Family income	-0.514***	-0.184***	-0.363***	-0.457***	-0.413***	-0.321***
	(0.0241)	(0.0156)	(0.0177)	(0.0144)	(0.0237)	(0.0307)
Income missing	-0.134***	-0.523***	-0.806***	-0.447***	0.497***	-0.592***
	(0.0441)	(0.0301)	(0.0399)	(0.0236)	(0.0388)	(0.0271)
High School API decile	-0.422***	-0.468***	-0.139***	0.105***	-0.0582**	-0.273***
	(0.0211)	(0.0141)	(0.0171)	(0.0146)	(0.0227)	(0.0397)
API missing (not CA Public HS)	0.648***	0.598***	-0.109***	-0.375***	0.181***	2.317***
	(0.0415)	(0.0276)	(0.0303)	(0.0338)	(0.0345)	(0.251)
Parental education	-0.0909***	-0.890***	-0.516***	-0.448***	-0.236***	-0.211***
	(0.0214)	(0.0145)	(0.0170)	(0.0148)	(0.0230)	(0.0346)
Parental education missing	0.0400	0.750***	0.849***	0.679***	1.092***	0.784***
	(0.0786)	(0.0524)	(0.0546)	(0.0335)	(0.0382)	(0.0580)
Constant	-2.456***	-1.049***	-1.038***	-0.0231	-1.849***	-3.964***
	(0.0347)	(0.0217)	(0.0237)	(0.0242)	(0.0273)	(0.764)
Observations	113,737					
Pseudo R^2	0.197					

This table contains a single multinomial logit model predicting racial/ethnic group membership in the holistic sample. White is the omitted group. Standard errors allow for two-dimensional clustering based on the identity of the first and second application reader.

Table A8. Multinomial logit regressions predicting racial/ethnic group membership with flexible functional forms for test scores, grades, and socioeconomic variables

	SAT Math		SAT Reading		SAT Writing		Subject Test Average	
	Black	Hispanic/NA	Black	Hispanic/NA	Black	Hispanic/NA	Black	Hispanic/NA
Test score range (760+ omitted)								
390 or less	2.452***	3.073***	-0.0280	1.151***	0.926***	1.694***	0.725***	-4.169***
	(0.236)	(0.130)	(0.201)	(0.142)	(0.200)	(0.152)	(0.272)	(0.227)
400-420	1.993***	2.481***	-0.0270	1.129***	0.597***	1.293***	0.891***	-3.734***
	(0.232)	(0.124)	(0.215)	(0.130)	(0.196)	(0.156)	(0.230)	(0.169)
430-450	1.910***	2.400***	0.0188	1.056***	0.622***	1.278***	0.650***	-3.335***
	(0.210)	(0.112)	(0.188)	(0.125)	(0.167)	(0.113)	(0.243)	(0.154)
460 - 480	1.729***	2.252***	0.0822	1.029***	0.545***	1.094***	0.437*	-2.972***
	(0.207)	(0.0960)	(0.186)	(0.115)	(0.166)	(0.114)	(0.232)	(0.135)
490 - 510	1.640***	1.960***	0.210	0.915***	0.471***	0.951***	0.296	-2.522***
	(0.198)	(0.0986)	(0.170)	(0.113)	(0.155)	(0.101)	(0.222)	(0.130)
520 - 540	1.407***	1.764***	0.110	0.773***	0.334**	0.787***	0.243	-2.040***
	(0.201)	(0.0972)	(0.168)	(0.0966)	(0.146)	(0.0975)	(0.221)	(0.126)
550 - 570	1.172***	1.429***	0.225	0.602***	0.279*	0.631***	0.142	-1.600***
	(0.206)	(0.0957)	(0.180)	(0.106)	(0.148)	(0.0900)	(0.213)	(0.128)
580 - 600	1.105***	1.212***	0.206	0.446***	0.205	0.539***	0.00547	-1.198***
	(0.214)	(0.0943)	(0.164)	(0.0956)	(0.144)	(0.0900)	(0.219)	(0.120)
610 - 630	0.947***	0.946***	0.210	0.304***	0.183	0.340***	-0.0496	-0.879***
	(0.203)	(0.0968)	(0.175)	(0.0876)	(0.143)	(0.0952)	(0.218)	(0.122)
640 - 660	0.764***	0.681***	0.251	0.208**	-0.0343	0.320***	-0.216	-0.644***
	(0.202)	(0.0883)	(0.167)	(0.0896)	(0.151)	(0.0870)	(0.223)	(0.115)
670 - 690	0.616***	0.421***	0.206	0.107	0.0345	0.233**	-0.204	-0.428***
	(0.208)	(0.0912)	(0.176)	(0.0894)	(0.158)	(0.0914)	(0.232)	(0.117)
700 - 720	0.283	0.309***	0.156	0.0110	0.121	0.179*	-0.193	-0.345***
	(0.234)	(0.101)	(0.171)	(0.104)	(0.174)	(0.0949)	(0.225)	(0.115)
730 - 750	0.419*	0.112	0.188	-0.136	0.168	0.0930	-0.410*	-0.121
	(0.228)	(0.105)	(0.193)	(0.103)	(0.164)	(0.113)	(0.243)	(0.126)
Took 3 or more subject tests	0.123***	0.348***						
	(0.0420)	(0.0329)						
Unweighted GPA (3.75 to 4.0 omitted)								
Less than 3.00	1.220***	0.873***						
	(0.107)	(0.0724)						
3.0 to 3.25	0.943***	0.758***						
	(0.0922)	(0.0577)						
3.25 to 3.5	0.698***	0.546***						
	(0.0893)	(0.0508)						
3.5 to 3.75	0.412***	0.355***						
	(0.0717)	(0.0417)						
Weighted GPA (4.3 or more omitted)								
3.5 or less	-0.286**	-0.100						
	(0.112)	(0.0640)						
3.6	-0.302***	-0.168**						
	(0.114)	(0.0731)						
3.7	-0.382***	-0.123*						
	(0.121)	(0.0717)						
3.8	-0.271***	-0.0173						
	(0.104)	(0.0670)						
3.9	-0.337***	-0.0533						
	(0.101)	(0.0662)						
4.0	-0.345***	-0.0889*						
	(0.0913)	(0.0530)						
4.1	-0.328***	-0.0132						
	(0.101)	(0.0567)						
4.2	-0.200**	-0.0261						
	(0.0975)	(0.0515)						
Socioeconomic variables (top value omitted)	Income catgeory		API decile		Parental education			
Bottom	1.309***	0.0732	1.874***	1.949***	0.469*	4.323***		
	(0.131)	(0.103)	(0.126)	(0.104)	(0.253)	(0.197)		
2nd	1.123***	0.207***	1.097***	1.567***	0.819***	3.162***		
	(0.0926)	(0.0684)	(0.118)	(0.0919)	(0.136)	(0.118)		
3rd	1.056***	0.440***	0.907***	1.191***	0.283***	1.609***		
	(0.0895)	(0.0572)	(0.0934)	(0.0772)	(0.0727)	(0.0482)		
4th	1.218***	0.785***	0.628***	0.969***	0.307***	1.074***		
	(0.0888)	(0.0602)	(0.0949)	(0.0668)	(0.0623)	(0.0432)		
5th	0.879***	0.580***	0.510***	0.704***	0.267***	0.880***		
	(0.0858)	(0.0639)	(0.0936)	(0.0721)	(0.0864)	(0.0597)		
6th	0.792***	0.501***	0.458***	0.459***	-0.0478	0.245***		
	(0.102)	(0.0649)	(0.0945)	(0.0634)	(0.0522)	(0.0387)		
7th	0.846***	0.463***	0.253***	0.361***				
	(0.0898)	(0.0649)	(0.0769)	(0.0603)				
8th	0.571***	0.378***	-0.000816	0.210***				
	(0.108)	(0.0668)	(0.0879)	(0.0656)				
9th	0.478***	0.249***	-0.196**	0.127**				
	(0.0944)	(0.0668)	(0.0790)	(0.0567)				
10th	0.425***	0.386***						
	(0.110)	(0.0678)						
Socioeconomic variable missing	-0.110*	-0.429***	0.483***	0.554***	0.0740	0.625***		
	(0.0609)	(0.0417)	(0.0625)	(0.0441)	(0.0928)	(0.0650)		
Observations	113737							
Pseudo R^2	0.213							

This table presents a version of the regression in Table A7 that substitutes indicators for all possible values of the test score, GPA, and socioeconomic variables. For space reasons, only the coefficients predicting membership in the Black and Hispanic/Native American groups are reported (White is again the omitted group), but the regression predicts membership in all groups as in Table A7. Standard errors allow for two-dimensional clustering based on the identity of the first and second application reader.

Table A9. Simulated admissions decisions for the post-holistic sample (assuming test-blind admissions)

Racial/ethnic coefficients		Additional "color-blind" preference for applicants predicted to be Black: None	3.71% share target
Zero	Percent Black	2.58%	3.71%
	Percent Hispanic/Native American	15.66%	25.17%
	SAT combined	1919	1818
	Predicted log odds ratios	2.490	1.862
	Test score	0.925	0.065
	Grades	1.524	1.063
	Low SES	0.042	0.734
Pre-holistic	Percent Black	2.55%	3.71%
	Percent Hispanic/Native American	14.72%	24.18%
	SAT combined	1924	1822
	Predicted log odds ratios	2.509	1.881
	Test score	0.962	0.098
	Grades	1.524	1.063
	Low SES	0.023	0.721
Post-holistic	Percent Black	3.98%	3.71%
	Percent Hispanic/Native American	16.64%	14.91%
	SAT combined	1915	1933
	Predicted log odds ratios	2.459	2.527
	Test score	0.886	1.033
	Grades	1.507	1.564
	Low SES	0.066	-0.069

Additional points of comparison		Color-sighted admissions	Actual admits
	Percent Black	3.71%	3.71%
	Percent Hispanic/Native American	15.13%	15.13%
	SAT combined	1919	1983
	Predicted log odds ratios	2.478	3.117
	Test score	0.922	1.492
	Grades	1.520	1.674
	Low SES	0.036	-0.049

This table presents a version of the simulations in Table 14 that omits test scores from admission decisions. A "test-blind" version of UCLA's pre-2006 preferences is inferred from predicting admissions decisions using the non-test score variables in Table 5. The pre-holistic and holistic racial/ethnic coefficients added in the middle and lower left cells are likewise from regressions that omit test scores. The predicted log odds ratio of being Black used in the right column is likewise from a multinomial logit regression that omits test scores.

Table A10. Simulated admissions decisions for the post-holistic sample (assuming no pre-holistic SES preference)

		Additional "color-blind" preference for applicants predicted to be Black	
Racial/ethnic coefficients		None	3.71% share target
Zero	Percent Black	1.53%	3.71%
	Percent Hispanic/Native American	7.81%	19.91%
	SAT combined	2056	1912
	Predicted log odds ratios	3.145	2.598
	Test score	2.067	1.077
	Grades	1.591	1.198
	Low SES	-0.513	0.323
Pre-holistic	Percent Black	2.10%	3.71%
	Percent Hispanic/Native American	8.52%	15.92%
	SAT combined	2054	1970
	Predicted log odds ratios	3.136	2.916
	Test score	2.055	1.490
	Grades	1.588	1.421
	Low SES	-0.506	0.005
Post-holistic	Percent Black	2.74%	3.71%
	Percent Hispanic/Native American	9.43%	13.17%
	SAT combined	2051	2011
	Predicted log odds ratios	3.128	3.060
	Test score	2.025	1.757
	Grades	1.595	1.543
	Low SES	-0.492	-0.239
Additional points of comparison		Color-sighted admissions	Actual admits
	Percent Black	3.71%	3.71%
	Percent Hispanic/Native American	15.13%	15.13%
	SAT combined	2036	1983
	Predicted log odds ratios	3.093	3.117
	Test score	1.925	1.492
	Grades	1.573	1.674
	Low SES	-0.405	-0.049

This table presents a version of the simulations in Table 14 that omits UCLA's apparent pre-2006 preference for low socialeconomic status from each of the models used to simulate admission probabilities.

Table A11. Heckman probit and uncorrected probit regressions predicting enrollment conditional on admission -- holistic sample

	Heckman probit model		Uncorrected probit
	Enrollment	Admission	Enroll if admitted
Test scores and grades			
SAT Math	-0.144***	0.0966***	-0.132***
	(0.0156)	(0.00955)	(0.0157)
SAT Reading	-0.268***	0.197***	-0.240***
	(0.0166)	(0.00953)	(0.0153)
SAT Writing	-0.130***	0.204***	-0.0953***
	(0.0184)	(0.00985)	(0.0158)
SAT Subject Average	-0.230***	0.201***	-0.197***
	(0.0185)	(0.00992)	(0.0168)
3 or more subject exams	-0.177***	0.225***	-0.138***
	(0.0225)	(0.0117)	(0.0200)
GPA (Unweighted)	-0.377***	0.289***	-0.325***
	(0.0273)	(0.0116)	(0.0249)
GPA (Weighted)	-0.323***	0.805***	-0.152***
	(0.0568)	(0.0112)	(0.0238)
Socioeconomic characteristics			
Family income	0.0748***	-0.0838***	0.0608***
	(0.0121)	(0.00743)	(0.0117)
Income missing	-0.160***	0.0675***	-0.152***
	(0.0218)	(0.0143)	(0.0222)
High School API decile	0.191***	-0.385***	0.125***
	(0.0228)	(0.00769)	(0.0114)
API missing (not CA Public HS)	-0.383***	0.201***	-0.357***
	(0.0217)	(0.0134)	(0.0216)
Parental education	0.0560***	-0.0864***	0.0409***
	(0.0125)	(0.00757)	(0.0119)
Parental education missing	0.0935***	0.0366	0.103***
	(0.0351)	(0.0233)	(0.0356)
Racial/ethnic background (white omitted)			
Black	-0.733***	0.868***	-0.594***
	(0.0617)	(0.0287)	(0.0485)
Hispanic/Native American	-0.314***	0.199***	-0.286***
	(0.0301)	(0.0187)	(0.0300)
SE Asian	0.0456	-0.00455	0.0461
	(0.0320)	(0.0213)	(0.0327)
Other Asian	-0.0728***	-0.0405***	-0.0819***
	(0.0216)	(0.0143)	(0.0218)
Other	-0.114***	0.0144	-0.114***
	(0.0337)	(0.0227)	(0.0344)
International	-0.221***	-0.209***	-0.268***
	(0.0564)	(0.0296)	(0.0548)
Rho	-0.305***		
	(0.094)		
Constant	1.371***	-1.551***	0.820***
	(0.165)	(0.0146)	(0.0297)
Observations	113,737		27,898
Pseudo R^2	NA		0.125

This table reports the results of a Heckman probit model and an uncorrected probit model that predicts enrollment conditional on admission to UCLA. Standard errors allow for clustering based on the identity of the first application reader.

Table A12. Simulated admissions decisions for the post-holistic sample (taking account of enrollment probabilities)

		Additional "color-blind" preference for applicants predicted to be Black	
Racial/ethnic coefficients		None	4.77% enrollment share target
Zero	Percent Black	1.76%	4.77%
	Percent Hispanic/Native American	15.63%	18.29%
	SAT combined	1935	1857
	Predicted log odds ratios	2.699	2.065
	Test score	1.178	0.653
	Grades	1.253	0.919
	Low SES	0.268	0.494
Pre-holistic	Percent Black	2.55%	4.77%
	Percent Hispanic/Native American	16.99%	18.76%
	SAT combined	1930	1882
	Predicted log odds ratios	2.693	2.331
	Test score	1.151	0.839
	Grades	1.245	1.048
	Low SES	0.297	0.444
Post-holistic	Percent Black	3.43%	4.77%
	Percent Hispanic/Native American	18.49%	19.49%
	SAT combined	1924	1900
	Predicted log odds ratios	2.663	2.497
	Test score	1.104	0.952
	Grades	1.232	1.139
	Low SES	0.327	0.406

Additional points of comparison	Color-sighted admissions	Actual enrollees
Percent Black	4.77%	4.77%
Percent Hispanic/Native American	18.13%	18.13%
SAT combined	1922	1887
Predicted log odds ratios	2.629	2.290
Test score	1.085	0.714
Grades	1.226	1.392
Low SES	0.318	0.184

This table presents a version of the simulations in Table 14 that adjusts for differences in the predicted enrollment probabilities of admitted students (estimated using a version of the Heckman model in Table A11 that allows for non-linearity as in Tables A3 and A8). The left column is identical to Table 14, except that in the reported statistics applicants are weighted by the product of their admission and conditional enrollment probabilities instead of by their admission probability. In the right column, the additional preference for applicants predicted to be Black is set to yield a predicted enrolling class that matches the actual 4.77% Black share in the holistic sample. In the color-sighted admissions cell, the racial/ethnic coefficients are likewise set to yield the racial/ethnic mix of the holistic period enrolling students.

Table A12 (alt). Simulated admissions decisions for the post-holistic sample (taking account of enrollment probabilities -- estimated with no correction for sample selection)

		Additional "color-blind" preference for applicants predicted to be Black	
Racial/ethnic coefficients		None	4.77% enrollment share target
Zero	Percent Black	1.76%	4.77%
	Percent Hispanic/Native American	15.63%	18.29%
	SAT combined	1935	1857
	Predicted log odds ratios	2.699	2.065
	Test score	1.177	0.653
	Grades	1.253	0.919
	Low SES	0.268	0.494
Pre-holistic	Percent Black	2.55%	4.77%
	Percent Hispanic/Native American	16.99%	18.76%
	SAT combined	1930	1882
	Predicted log odds ratios	2.683	2.330
	Test score	1.147	0.839
	Grades	1.241	1.048
	Low SES	0.296	0.444
Post-holistic	Percent Black	3.43%	4.77%
	Percent Hispanic/Native American	18.49%	19.49%
	SAT combined	1924	1900
	Predicted log odds ratios	2.663	2.497
	Test score	1.103	0.951
	Grades	1.232	1.139
	Low SES	0.327	0.406
Additional points of comparison		Color-sighted admissions	Actual admits
	Percent Black	4.77%	4.77%
	Percent Hispanic/Native American	18.13%	18.13%
	SAT combined	1922	1887
	Predicted log odds ratios	2.629	2.290
	Test score	1.085	0.714
	Grades	1.225	1.392
	Low SES	0.318	0.184

This table is identical to Table A12, except that the conditional enrollment probabilities are estimated with no Heckman correction (i.e., they are estimated using a probit model on the sample of admitted students).