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AFFIRMATIVE ACTION BANS AND BLACK ADMISSION OUTCOMES: SELECTION-CORRECTED ESTIMATES FROM UC LAW SCHOOLS

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ABSTRACT

The consequences of banning affirmative action depend on schools' ability and willingness to avoid it. This paper uses rich application-level data to estimate the effect of the 1996 University of California affirmative action ban---the first and largest ban---on black admission advantages at UC law schools. Controlling for selective attrition from applicant pools, I find that the ban reduced the black admission rate from 61% to 31%. This implies that affirmative action ban avoidance is far from complete and suggests that affirmative action at law schools passes the constitutional test of not being easily replaced by non-racial alternatives. I further find that the affirmative action ban far from eliminated cross-sectional black admission advantages, which remained as high as 63 percentage points for applicants at the margin of being accepted or rejected. This suggests that UC schools were technologically able to sustain substantially higher black admission rates after the ban but were either unwilling or legally unable to do so.

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I Introduction

Black students in the United States would be dramatically underrepresented at top universities if admission decisions were made purely on the basis of academic credentials and without regard to race (Kane 1998; Bowen and Bok 2000; Espenshade, Chung, and Walling 2004; Rothstein and Yoon 2008). Universities that value diversity therefore practice affirmative action: awarding admission advantages to black applicants on the basis of race. However, affirmative action is in legal jeopardy: seven states have banned the practice at their public universities, and the U.S. Supreme Court has indicated that it expects to extend these bans nationwide by 2030.[1]

The consequences of a broader ban hinge on the extent to which universities are able and willing to sustain black admission advantages (Chan and Eyster 2003; Arcidiacono 2005; Card and Krueger 2005; Fryer, Loury, and Yuret 2007; Epple, Romano, and Sieg 2008; Hinrichs 2012). This cannot be estimated using aggregate data from existing state-level bans because bans change the composition of applicant pools. This paper uses application-level data to estimate the effect of the 1996 University of California (UC) affirmative action ban—the first and largest state-level ban—on black admission advantages at the UC's flagship law schools holding the applicant pool constant.

Figure 2 conveys the empirical challenge for the case of UC Berkeley's law school. The ban had no lasting effect on the black-white admission rate difference. However, the ban permanently reduced black enrollment by half, arithmetically because the black share of the applicant pool permanently declined by half.[2] Two distinct mechanisms can explain this pattern of effects, with opposite implications for the effects of a nationwide ban.

First, Berkeley may have used black-correlates like low family income to sustain most of its pre-ban black admission advantages, but large numbers of black applicants of all credential levels may have nevertheless declined to apply to a "black unfriendly" school with lower black enrollment (Long 2004; Card and Krueger 2005; Dickson 2006; Fryer, Loury, Yuret 2007). A nationwide ban may therefore have little lasting effect on black enrollments, since future black lawyers would have few or no alternative schools to apply to (Arcidiacono 2005; Epple, Romano, and Sieg 2008). On the other hand, the UC ban may have dramatically and permanently reduced black admission advantages, inducing low-credentialed black students who could no longer gain admission to stop applying (Chan and Eyster 2003; Card and Krueger; Hinrichs 2012). In this case Berkeley would have suffered a large

[1] The most recent Supreme Court decision on affirmative action (*Grutter v. Bollinger* 2003) concluded with the widely quoted warning "We expect that 25 years from now [in 2028], the use of racial preferences will no longer be necessary to further the interest approved today" because "race-conscious admissions policies must be limited in time." The Court avoided new pronouncements in *Fisher v. University of Texas at Austin* (2013).

[2] UC Los Angeles's law school admissions exhibited a similar pattern. Yield rates remained largely unchanged.

permanent reduction in black enrollment even without applicant pool attrition, and a nationwide ban could be expected to have large negative effects as well.

Thus a key empirical question is: did the UC affirmative action ban dramatically reduce black admission rates, holding the applicant pool constant? I answer this question in administrative application-level data on all 25,499 applications submitted to law schools nationwide between 1990 and 2006 by 5,353 undergraduates from an elite college. I focus on law school admissions at UC Berkeley and UC Los Angeles, respectively ranked sixth and fifteenth nationwide by *U.S. News and World Report* and very disproportionately attended by elite college graduates. In this paper "Berkeley", "UCLA", and "UC schools" always refer to these two law schools. Cross-sectional admission differences by race in these data are similar to those documented in undergraduate admissions, and law school admissions hold center stage in affirmative action debates within economics (Sander 2004; Rothstein and Yoon 2008) and before the Supreme Court (*Grutter v. Bollinger* 2003).

Correcting for selective attrition from applicant pools is possible in this context because law school admissions are unusually formulaic. In basic specifications, I hold the applicant pool constant at pre-ban levels along three directly observed characteristics—test score, undergraduate grade point average, and race—that together correctly predict over 89% of admission decisions. In preferred specifications and along the lines of Dale and Krueger (2002), I further hold constant a powerful summary measure of not-directly-observed applicant strength, inferred from admission decisions at non-UC schools. This inferred strength measure is based on the intuition that if an applicant was consistently admitted at non-UC schools in spite of weak observed credentials, the applicant was likely strong on commonly valued unobserved credentials like recommendation letters. The presence of thousands of independent screens at non-UC schools is a major advantage of these data.

The basic finding of the paper is that when holding applicant characteristics constant at pre-ban levels, the UC affirmative action ban reduced black admission rates by half—from 61% to 31%. These results are robust to the choice of controls (academic credentials, inferred strength, and California residency), specification (semi-parametric reweighting and nonlinear regressions), and counterfactual (allowing for pre-period trends and nationwide trends). Hence, the ban dramatically reduced black admission advantages in this sample, suggesting that the aggregate patterns of Figure 1 can be explained by large selective attrition from the applicant pool.

UC schools nevertheless sustained large cross-sectional black admission advantages under the ban: I estimate that black admission rates would have fallen to 8% (not just 31%) had all races been subjected to observed pre-ban white admission standards based on LSAT, GPA, and inferred strength.[3] Why

[3]Since I condition on inferred strength, this means that post-ban black admission advantages were not simply due

then did UC schools not sustain even larger black advantages? I use the pattern of black admission advantages to distinguish between two broad possibilities: UC schools were technologically unable to sustain substantially larger advantages because they had access only to weak usable black-correlates like low family income, or they were in fact technologically able to sustain larger advantages but were either unwilling or legally unable to do so.

I find that UC schools were likely technologically able to sustain substantially larger black admission advantages, possibly even restoring pre-ban black admission rates. Though post-ban black admission advantages averaged 23 percentage points, I estimate that the advantage was 63 percentage points at the intermediate credential levels where applicants were on the margin of being accepted or rejected. Hence, post-ban UC schools used unobserved black-correlates (e.g. low family income and newly solicited diversity essays) to admit blacks at a 63 percentage point higher rate than observably similar whites. If post-ban schools had placed arbitrarily high weight on those black-correlates, they obviously would have admitted black applicants at higher rates, possibly even restoring pre-ban rates.[4] UC schools chose not to—a rational decision if they sufficiently valued the academic strength of admitted cohorts relative to racial diversity (Chan and Eyster 2003; Fryer, Loury, and Yuret 2007; Epple, Romano, and Sieg 2008), or if higher black admission rates would have triggered litigation for noncompliance (as in Coate and Loury 1993).

This paper helps to anchor a large quantitative literature on the effects of affirmative action bans. Prominent papers simulate nationwide bans assuming that bans *eliminate* cross-sectional black admission advantages (Arcidiacono 2005; Krueger, Rothstein, and Turner 2006; Rothstein and Yoon 2008), or alternatively that they have no effect on black advantages due to university avoidance (Fryer, Loury, and Yuret 2007). By controlling for selective attrition, I find that in the case of UC law schools the truth lay approximately in the middle: the ban reduced cross-sectional black admission advantages by just over half. Hence, evaluations of broader affirmative action bans in similar contexts should assume large reductions in cross-sectional black advantages while also allowing for quantitatively large advantages to remain, consistent with theoretical avoidance predictions being quantitatively important in practice (Chan and Eyster 2003; Fryer, Loury, and Yuret; Epple, Romano, and Sieg 2008).

The results extend existing empirical work on affirmative action bans. The large decline in black admission advantages in spite of the black-white admission rate parity shown in Figure 1 suggests that applicant responses to affirmative action bans (Long 2004; Card and Krueger 2005; Dickson 2006) can

to black applicants being stronger on characteristics like recommendation letters that are commonly valued across law schools. Results are similar when omitting inferred strength.

[4] Post-ban UC schools could obviously have generated a 63 percentage point black-white admission rate difference if the black-correlate information was equally powerful at all (not just intermediate) credential levels.

be quantitatively important for understanding net effects on admission outcomes. The finding further suggests that the large negative effects on black enrollment at elite schools of affirmative action bans estimated in Arcidiacono, Aucejo, Coate, and Hotz (2011) and Hinrichs (2012) were not merely driven by black students choosing to apply to more "black-friendly" schools. Antonovics and Backes (2014) report in parallel work that the UC affirmative action ban reduced observed black admission advantages in UC undergraduate admissions, though their data do not allow them to account for selection into applicant pools on unobserved credentials, to evaluate pre-ban and nationwide trends, or to quantify the potential for larger post-ban black advantages. This paper is also the first application-level analysis of the effects of an affirmative action ban on professional school admissions.

The results suggest two implications for policy. Legally, the constitutionality of affirmative action requires that there be no "workable race-neutral alternatives to achieve the diversity the university seeks" (*Grutter v. Bollinger* 2003). If one defines "workable" as "feasible and worth the opportunity cost", then the finding that UC schools fell far short in sustaining black admission advantages is revealed-preference evidence that race-neutral alternatives (e.g. low family income and diversity essays) were in fact far from workable from the UC's perspective.[5] Positively, achieving substantially larger black advantages under a ban is likely feasible but may require policies that mandate higher admissions weight on black-correlates (e.g. low family income and diversity essays) than schools would choose on their own. For example, the State of Texas followed its court-ordered affirmative action ban by requiring each University of Texas campus to admit the majority of their undergraduates based on a single criterion (high school class rank) that very disproportionately benefited minority applicants at the expense of schools' preferred measures of applicant strength (Long and Tienda 2008).

The remainder of the paper is organized as follows. Section II describes the UC affirmative action ban. Section III introduces the data. Section IV presents the results. Section V concludes.

II Legal and Institutional Environment

II.A Legal Environment

On November 5, 1996, California became the first state to ban affirmative action—awarding admission preference to underrepresented minorities on the basis of race—when voters approved Proposition 209 to amend the state constitution to read: "The state shall not discriminate against, or grant preferential treatment to, any individual or group on the basis of race, sex, color, ethnicity, or national origin in the operation of public employment, public education, or public contracting." In particular, no University

[5] The Supreme Court emphasized opportunity costs: workability "does not require exhaustian of every conceivable race-neutral alternative" or forcing "a university to choose between maintaining a reputation for excellence or fulfilling a commitment to provide educational opportunities to members of all racial groups" (*Grutter v. Bollinger*).

of California applicant is to be preferred to another on the basis of race. The ban went into effect immediately at UC law schools.[6] Six other states have since passed similar bans.[7]

Legally, the UC affirmative action ban prohibits the use of race in choosing among applicants but permits the use of applicant characteristics that correlate with race as long as those characteristics have defensible non-racial justification if challenged in court. For example, UC schools are free to use of low family income (which correlates with black status) because broadening socioeconomic access is considered to be independently valuable to universities, but the use of participation in a black-focused extracurricular group would almost certainly be considered illegal. Law school admission decisions are made by a small group of selectors applying subjective criteria with little transparency, so the actual information used is unknown. UC schools (which refer throughout this paper to Berkeley and UCLA law schools) were not bound by any other new laws.[8]

Nationally, the U.S. Supreme Court in 5-4 rulings in both 1978 (*Regents of the University of California v. Bakke*) and 2003 (*Grutter v. Bollinger*) upheld the federal constitutionality of affirmative action, keeping the practice legal at all public universities not subject to a statewide ban. The Court's rationale is that although the U.S. Constitution guarantees equal protection to all races under the law, "the educational benefits that flow from a diverse student body" are a "compelling governmental interest" that justifies the use of race when there are no "workable race-neutral alternatives that will achieve the diversity the university seeks" (*Grutter v. Bollinger*). However, the Court concluded *Grutter v. Bollinger* with the widely quoted warning "We expect that 25 years from now [in 2028], the use of racial preferences will no longer be necessary to further the interest approved today" because "race-conscious admissions policies must be limited in time." Affirmative action is currently legal at all private universities but affirmative action may in principle be banned there too; perhaps as a result, most of the nation's top private universities petitioned the Court in 2003 in detailed amicus briefs to keep it legal at public universities.[9]

[6] The ban went into effect one year later at UC undergraduate campuses. The state constitutional amendment superceded the 1995 UC Board of Regents SP-1 resolution, which would have ended affirmative action beginning in 1997 and was later repealed to no legal effect.

[7] The six other states currently under affirmative action bans are Arizona, Florida, Michigan, Nebraska, New Hampshire, and Washington. Georgia and Texas had temporary bans.

[8] Soon after the ban, the State of California guaranteed that high school seniors graduating in the top 4% of their high schools would gain admission to at least one UC campus but not necessarily the one of their choice. With eight UC campuses, this had little binding effect on undergraduate admissions at the elite campuses of Berkeley and UCLA. No such guarantee applied to law school admissions.

[9] States can ban affirmative action at their private universities, and the U.S. Supreme Court could possibly extend a ban to private universities that accept federal funds (almost all of them). The U.S. Congress could pass legislation under its interstate commerce authority to ban the use of race at private universities that accept out-of-state applicants (as it did at businesses with out-of-state customers) though such a policy has not been actively debated.

II.B Institutional Responses

UC application forms changed immediately after the ban. Since 1996, application forms have stated that race is not a criterion for admission, and the page requesting applicant race has been diverted to a UC statistical department and not reported to admission offices. Application forms instead solicited new information that correlates with race (law school applicants are rarely interviewed). For example before the ban, Berkeley gave applicants ten short unconnected prompt options for the personal statement, eight of which did not refer to diversity or disadvantages. Immediately after the ban and ever since, all ten were replaced by a single lengthy one that invited applicants to discuss their contributions to "the diversity of the entering class" and their backgrounds including "a personal or family history of cultural, educational, or socioeconomic disadvantage." In 1998, Berkeley added a full-page socioeconomic questionnaire to its application form requesting information such as college attendance rates of high-school friends and whether the applicant was raised by a single parent. Beginning in 2001, UCLA solicited declarations of interest in a Critical Race Studies program and instituted admission preference for interested applicants.

UC administrators strongly opposed the ban before it passed and were not systematically replaced after it passed. As the California political climate turned against affirmative action in 1995, the UC president, UC vice-presidents, and the chancellor of each UC campus united to "unanimously urge, in the strongest possible terms," the continuation of affirmative action.[10] Berkeley's dean added "The need to diversify the legal profession is not a vague liberal ideal: it is an essential component to the administration of justice."[11] The day after voters approved the ban, the UC president announced that the question facing the university was "How do we establish new paths to diversity consistent with the law?"[12] One year after the ban, Berkeley's dean launched an audit of policies and procedures "to see whether we can achieve greater diversity" after "dire" admission results.[13] Berkeley's dean and the UC president continued in their posts through 2000 and 2003, respectively. Christopher Edley, a vocal proponent of affirmative action and adviser to President Bill Clinton on the topic, served as Berkeley's dean from 2004 to 2013. Other institutional features like the number of first-year enrollees remained nearly unchanged.

[10] 1995 "Statement Supporting Affirmative Action by UC President, Chancellors, and Vice Presidents", http://www.development.umd.edu/Diversity/Response/Action/policy.

[11] 1995 press release, http://www.berkeley.edu/news/berkeleyan/1995/0524/regents.html.

[12] 1996 "Letter from President Richard C. Atkinson to the University Community Re: Passage of Proposition 209", http://www.universityofcalifornia.edu/news/
article/20607.

[13] 1997 Berkeley press release, http://berkeley.edu/news/berkeleyan/1997/0820/kay.html.

III Data

III.A Source, Variables, and Sample Restrictions

This paper's primary dataset—which I call the Elite Applications to Law School (EALS)—comprises administrative application-level data on 67% of an elite college's seniors and graduates who applied to law schools nationwide between the fall of 1990 and the fall of 2006. Applications to every U.S. law school are submitted through the Law School Admissions Council, which records application information and admission decision for every application filed.[14] Two-thirds of applicants choose to release their data to their colleges' administrators, and I obtained and digitized seventeen years of a single college's data. The college is elite, is not on the west coast, and has never been subject to an affirmative action ban. Subsection B investigates possible selection over time into the EALS, and Section IV accounts for selection over time into the Berkeley and UCLA applicant pools.

The EALS contains six variables for each application: applicant race, LSAT test score (integers between 120 and 180), undergraduate grade point average (GPA) to two decimal places on a 4.00 scale, application year, law school submitted to, and admission decision. I standardize LSAT and GPA to each have mean zero and standard deviation one across applicants. Motivated semi-parametrically in Subsection D and used in figures, I summarize applicants' LSAT and GPA scores with a scalar measure I call "academic strength" equal to the standardized sum of standardized LSAT and standardized GPA, similar to the rescaling that Kling, Liebman, and Katz (2007) employ in a different context. Application years 1990-1991 through 2001-2002 as well as 2005-2006 also contain applicant state of permanent residence; for these years, I digitized a California resident indicator for Berkeley and UCLA applications only.

The raw data contain 38,200 applications of 6,072 applicants to 187 law schools. I restrict the analysis sample to the 94.3% of applicants listed as white, Asian, black, or Hispanic and the 78.9% of applications submitted to UC Berkeley, UCLA, or one of the fifteen most-applied-to schools that were never subject to an affirmative action ban. These fifteen schools correspond closely to the top-ranked law schools according to *U.S. News and World Report*, so I refer to them only somewhat imprecisely as the "top fifteen non-UC law schools."[15] The 170 other schools received relatively few applications in the EALS and are poor control schools for Berkeley and UCLA because these 170 other schools are less selective. The final seventeen-school EALS sample comprises 25,499 applications submitted by

[14] Academic credentials are verified through third-party reports, and race is reported by applicants where dishonest answers are grounds for revocation of an admission offer, expulsion from law school, or disbarment. To the extent that any applicants misreported their race, the EALS race variable nevertheless represents the race that was reported to schools on application forms.

[15] Deviations from *U.S. News* rankings are usually explained by a lower-ranked school being located in a large city.

5,353 applicants. Results reported in the main text restrict to the 17,814 applications from only the 3,774 black or white applicants; the appendix reports results using all races. See Online Appendix A for additional data-coding details.

III.B Summary Statistics

Table 1 lists summary statistics. The EALS sample is 61% white, 10% black, 19% Asian, and 10% Hispanic. Black applicants on average possess LSAT scores and GPA's 1.1 and 1.0 standard deviations lower, respectively, than white applicants. Online Appendix Figures 1a-c use non-parametric densities of these academic characteristics to illustrate the first order stochastic dominance of the black and Hispanic distributions by the white and Asian distributions. This stochastic dominance motivates universities' use of affirmative action in order to achieve racially diverse cohorts. Online Appendix Figure 1d plots means of academic strength over time by race among EALS applicants; post-ban and pre-ban means are very similar within races, suggesting little differential selection over time into the EALS. Section IV accounts for differential selection over time into the Berkeley and UCLA applicant pools.

Berkeley received applications from 28% of all applicants (1,594, making it the seventh-most-applied-to school in this sample) and UCLA received applications from 14% of all applicants (777, the thirteenth most in this sample); see Online Appendix Table 1 for additional comparisons. These schools received relatively few applications from black students—60 before the ban and 67 after the ban at Berkeley, and 31 before the ban and 27 after the ban at UCLA—which is unsurprising given the relatively small size of elite professional school cohorts. The EALS nevertheless provides sufficient statistical power because within-race admission decisions are largely determined by academic credentials.

III.C Race and Admission in the Pre-Ban Cross Section

Figure 2a displays the semi-parametric relationship between LSAT, GPA, and admission within race-school-years in the EALS, using a 5% random sample of all 23,128 applications submitted to non-UC schools (Online Appendix Figure 2 displays the 100% sample, intelligible only in color). Each application's admission decision is plotted in (LSAT, GPA) space, where each application's LSAT score has been re-centered by the estimated race-school-year fixed effect in order to account for selectivity differences across races, schools, and years. Specifically I fit a probit regression of admission on standardized LSAT (mean zero and standard deviation one), standardized GPA, and school-year-race fixed effects; add each application's estimated school-year-race effect to its LSAT value; and plot individual application decisions in GPA vs. adjusted LSAT space. Applications above and to the right of the best-fit admission threshold line have high enough LSAT and GPA scores to have a predicted admission probability of more than 50%, while those below and to the left do not.[16]

The best-fit line correctly predicts 89.1% of all admission decisions, and incorrect predictions are concentrated near the line. The ratio of the coefficients on LSAT and GPA in the underlying probit is 0.95, indicating that a one standard deviation higher LSAT is about as valuable in the admissions cross section as a one standard deviation higher GPA. When useful for subsequent illustrations, I therefore summarize an applicant's academic strength as the standardized (mean zero, standard deviation one) unweighted sum of standardized LSAT and standardized GPA. Figure 2b confirms that the semi-parametric relationship between academic strength and admission within race-school-years is well-approximated by a univariate probit regression of admission on academic strength alone. I refer to such a curve relating admission to academic strength as an admission rule in academic strength.

Figure 2c plots fitted admission rules for blacks and whites in pre-ban Berkeley and UCLA admissions.[17] For ease of comparison, each school's fitted rules have been shifted horizontally by an additive constant so that the admission probability for whites equals 0.5 at academic strength 0. The graph shows that there are levels of academic strength at each school where blacks were nearly assured admission and whites were nearly assured rejection. Berkeley's black and white admission rules are separated by 1.90 standard deviations of academic strength, implying black status is observed to be worth more than the difference between an A- GPA and a B- GPA for a given LSAT in the pre-ban cross section.[18] At UCLA, the difference is 1.39 standard deviations. Had pre-ban black applicants to each school been subjected to the observed pre-ban white admission standards, Berkeley's black admission rate is predicted to have been 6% rather than the actual 57%, and UCLA's to have been 10% rather than 65%. I formally document these differences in Section IV.D. These black-white differences in the EALS are similar in magnitude to those found in the universe of law school applicants to elite schools like Berkeley and UCLA (Rothstein and Yoon 2008) and in undergraduate admissions (Kane 1998; Bowen and Bok 2000; Espenshade, Chung, and Walling 2004).[19]

Online Appendix Figure 3 plots admission rules by race and shows that admission responds sim-

[16] The probit model is $\Pr(ADMITTED_{istr}) = \Phi(\beta_1 LSAT_i + \beta_2 GPA_i + \gamma_{str})$ where i denotes an applicant and γ_{str} denotes the school-year-race fixed effects. Adjusted LSAT equals $LSAT_i + \hat{\gamma}_{str}/\hat{\beta}_1$. The slope of the best-fit admission threshold line in Figure 2a is 0.95, equal to $-\hat{\beta}_1/\hat{\beta}_2$.

[17] For each school I estimate the probit model $\Pr(ADMITTED_{it}) = \Phi(\beta_1 ACADEMICSTRENGTH_i + \beta_2 BLACK_i + \gamma_t)$ using pre-ban black and white applications, where $BLACK_i$ is a black indicator and γ_t denotes year fixed effects.

[18] That is, $\hat{\beta}_2/\hat{\beta}_1 = 1.90$ in the underlying Berkeley regression.

[19] Using individual-level data on matriculants but not applications, Rothstein and Yoon estimate that black enrollment at elite law schools would have been 90% lower under white admission standards.

ilarly strongly to academic strength for blacks and for whites. This appendix figure also illustrates pre-ban admission rules for Hispanics and Asians, as well as non-parametric densities of applicant academic strength by race at Berkeley, UCLA, and the average non-UC school. Roughly speaking, Hispanic applicants enjoyed smaller cross-sectional admission advantages than blacks. For simplicity and statistical power, this paper focuses on black admission outcomes. In unreported results, the effects of the ban on Hispanic admission decisions are similar to those reported for blacks in Section IV.B (they are large and statistically significant), while the analysis of cross-sectional admission advantages conducted in Section IV.E produces relatively uninformative confidence intervals when done for Hispanics.

IV Results

In this section, I use the EALS to estimate the effect of the UC affirmative action ban on black admission rates at Berkeley and UCLA, holding applicant characteristics constant. Such selection correction is empirically important in the EALS: in unreported results, less-academically-credentialed black applicants were substantially less likely to apply after the ban.[20] I first display the time series of selection-corrected admission rates for black and white applicants at UC and non-UC schools using semi-parametric reweighting on academic strength. Visually apparent parallel pre-ban trends in black and white admission rates at UC and non-UC schools motivate difference-in-differences (DD) and triple-difference (DDD) estimates of the ban on black admission rates at UC schools. I then report parametric DD and DDD estimates that account for the fact that a lower black admission rate frees up slots for applicants of all races. I then evaluate robustness by holding constant a proxy for unobserved strength and California residency. Finally, I quantify post-ban black admission advantages and discuss economic mechanisms. All estimates are local to the EALS; elite law schools like Berkeley and UCLA are very disproportionately attended by graduates of elite colleges like the ones in the EALS.

IV.A Visual Evidence

Figure 3 displays the time series of black and white admission rates at Berkeley, UCLA, and non-UC schools, where applicant characteristics have been held constant at pre-ban levels using simple semi-parametric reweighting as in DiNardo, Fortin, and Lemieux (1996). To construct the time series

[20] The effect is economically substantial but marginally statistically significant. I focus on admission decisions rather than application decisions in part because EALS variables explain admission decisions very well but not application decisions, apparently because applicants choose among similarly-ranked schools based on geographical preferences and other factors omitted from the EALS.

of black admission rates at Berkeley, I first compute terciles of academic strength among only pre-ban black applications to Berkeley. Then for each time period shown in the figure, I weight black applications to Berkeley so that each pre-ban-defined tercile receives equal weight when computing the displayed admission rate.[21] I repeat this process for whites at Berkeley and for whites and blacks separately at UCLA and at each non-UC school, averaging resulting admission rates across non-UC schools to construct the plotted non-UC series. This semi-parametric reweighting on academic strength is data-demanding, so I group the data into two pre-ban time periods (1990-1992 and 1993-1995) and two post-ban time periods (1996-2000 and 2001-2006).

The figure shows that at non-UC schools, there was little change over time in the difference between black and white admission rates. At Berkeley the black admission rate rose between 1990-1992 and 1993-1995 about as much as the white admission rate did, thus exhibiting parallel pre-ban trends. Between 1993-1995 and 1996-2000, the black admission rate fell from 64.4% to 33.3% and did not subsequently recover relative to the white admission rate. Figure 3b shows a similar decline at UCLA.

One can use these reweighted admission rates to compute a DDD estimate of the effect of the ban on the black admission rate at each UC school that controls for changes in academic strength—equal to the change in black admission rates at the UC school, minus the change in white admission rates at the UC school and the change in the black-white admission rate difference at non-UC schools. Pooling pre-ban years and post-ban years, the DDD estimate of the effect of the affirmative action ban on Berkeley's black admission rate is -29.9 percentage points, relative to the actual pre-ban black admission rate of 56.7%. For UCLA, the estimate is -40.7 percentage points, relative to the actual pre-ban black admission rate of 64.5%. See Online Appendix Table 2 for the arithmetic. These declines were much larger than those observed at any non-UC school, so the empirical p value on each of these declines relative to the distribution of changes at non-UC schools is 0.

IV.B Regression Estimates

Table 2 reports regression estimates of the effect of the ban on black admission outcomes at each UC school, computed by fitting probit and OLS models based on the following DD specification:

$$\text{(1)} \qquad \Pr\left(ADMITTED_{it}\right) = \Phi(\mathbf{X}_i\boldsymbol{\alpha} + \beta_1 BLACK_i + \beta_2 BLACK_i \times POST_t + \gamma_t)$$

using black and white applications to either UC school, where $ADMITTED_{it}$ is an indicator for whether applicant i's application in year t earned an admission offer; $BLACK_i$ is an indicator of black

[21] That is, each application in time period T with academic strength lying in tercile G receives weight $1/N_{TG}$, where N_{TG} is the number of applications in the sample submitted to Berkeley in time period T with academic strength in tercile G. Quartiles yield similar results; I use terciles because some bin counts are small.

racial status; $POST_t$ is an indicator for the application being submitted after the ban; $\mathbf{X}_i$ is a vector containing LSAT score, GPA, and other covariates depending on the specification; γ_t is a vector of year fixed effects; and $\Phi(\cdot)$ denotes the Normal cumulative distribution function (for probit estimation only). When producing DDD estimates that account for national trends, I include all black and white applications to the top-fifteen non-UC schools and interact the second and third terms with an indicator for the application being submitted to a non-UC school.[22] Standard errors are clustered at the applicant level. Online Appendix Tables 3 and 4 replicate Table 2 using alternative specifications that include all races and control for more interactions.

Columns 3-4 display the basic probit results. Column 3 of panel A shows that when confining attention to applications to Berkeley, I estimate that the ban caused a 40.5 percentage point reduction in the probability of admission, averaged over the characteristics of pre-ban black applicants and relative to the actual pre-ban black admission rate of 56.7%. Controlling for trends at non-UC schools, Column 4 displays a DDD estimate of -35.5 percentage points. Column 4 of panel B reports a DDD estimate for UCLA of -32.8 percentage points, relative to the actual pre-ban black admission rate of 64.5%. These estimates have t statistics between 3 and 7.

A decline in black admission rates relative to whites opens up space in the admitted cohort for both black and white applicants, suggesting that these estimates may somewhat overstate the effect of the ban on black admission rates. I therefore compute an adjusted estimate of the effect of the ban on the black admission rate at each UC school by using the UC-specific coefficients of each regression to compute a probit latent variable value for each black and white pre-ban application according to post-ban criteria and then add a constant to every application's value until the mean predicted admission probability across applications equals the actual admission rate observed among these applications.[23] The resulting estimates are reported in the bottom row of each panel of Table 2; they are only 3-5 percentage points smaller in magnitude than the basic DDD estimates reported above.

IV.C Preferred Estimates and Robustness

The identifying assumption of the DDD estimates in column 4 is that any post-minus-pre changes in the unobserved strength of black applicants relative to white applicants was not local to applicants

[22] The DDD specification is $\Pr(ADMITTED_{ist}) = \Phi(\mathbf{X}_i\boldsymbol{\alpha} + \beta_1 BLACK_i + \beta_2 BLACK_i \times POST_t + \beta_3 BLACK_i \times UC_s + \beta_4 BLACK_i \times POST_t \times UC_s + \gamma_{st})$, where UC_s is an indicator for whether the application was submitted to the UC school being analyzed and γ_{st} is a vector of school-year fixed effects. I weight applications so that each school carries equal weight in each time period (pre-ban and post-ban).

[23] Adding a constant varies selectivity uniformly across applications. I obtain similar results under the alternative method of using the UC-specific coefficients to rank pre-ban applications and then admitting the N highest-ranked applications, where N equals the total number of black and white pre-ban EALS applicants that the UC school admitted.

to UC schools. This paper is motivated by potential selective attrition from applicant pools, so a potential concern is that the ban induced differential selective attrition on unobserved strength, such that post-ban blacks were relatively much weaker on unobserved admission determinants like recommendation letters. I address this first by augmenting equation (1) with an additional inferred strength control, which is based on independent admission decisions akin to Dale and Krueger (2002).

Admission selection criteria are highly correlated across law schools; Figure 2a showed this to be the case for directly observed applicant characteristics (LSAT, GPA, and race).[24] All top law schools solicit and are believed to value additional applicant characteristics like recommendation letters, leadership experience, and a background of no criminal behavior or academic dishonesty. I proxy for such commonly-valued unobserved admission determinants using the intuition that if an applicant predicted to be rejected based on LSAT, GPA, and race is in fact consistently admitted across schools in the EALS, this applicant is likely strong on unobserved characteristics like recommendation letters.

Specifically, I construct an inferred strength variable for each application, equal to the mean admission success that a given applicant experienced in her other applications that is not explained by observed characteristics. For each school s in either the pre-ban (1990-1995) or post-ban (1996-2006) era, I fit:

$$\Pr\left(ADMITTED_{ist}\right) = \Phi(\beta_1 LSAT_i + \beta_2 GPA_i + \beta_3 BLACK_i + \beta_4 HISPANIC_i + \beta_5 ASIAN_i + \gamma_t)$$

using only the applications submitted to school s in the given era. I use the resulting coefficients to compute a predicted admission probability $\Pr\left(ADMITTED_{ist}\right)$ for each application and compute admission residuals $\varepsilon_{ist} = ADMITTED_{ist} - \Pr\left(ADMITTED_{ist}\right)$ for each application. Then for each application ist, I compute inferred strength equal to the leave-out mean of applicant i's admission residuals *from her applications to schools other than* s:[25]

$$INFERREDSTRENGTH_{ist} = \overline{\varepsilon_{is't}}\ ,\ s' \neq s\ .$$

Note that this leave-out-mean formula uses information only from independent screens (admission decisions at schools other than s) to assign the inferred strength value for the applicant's application to school s.

For example, consider an applicant who applied to Berkeley, Harvard, and Northwestern; who had

[24] Characteristics that are valued inconsistently across admissions offices include the applicant's geographic preference and intended legal specialty.

[25] That is, $INFERREDSTRENGTH_{ist} = \frac{1}{S_i - 1}\sum_{s'=1, s' \neq s}^{S_{it}} \varepsilon_{is't}$, where S_{it} equals the total number of schools applied to by applicant i in year t and where the schools applied to by applicant i in year t are indexed 1 to S_{it}. To flexibly handle the small share of applicants who applied to only one school, I assign their applications inferred strength equal to zero and include an indicator for these applicants in all regressions where inferred strength is used.

an admission probability of 0.25 at Harvard and 0.75 at Northwestern based on her LSAT, GPA, race, application year, and the selectivity at Harvard and Northwestern; and who was admitted at both Harvard and Northwestern. This applicant's application to Berkeley would be assigned an inferred strength value of 0.5 ($= [(1 - .25) + (1 - .75)]/2$). More generally, inferred strength ranges from -1 to 1 and is positive for applications submitted by applicants with relatively weak direct observables who were nevertheless accepted at other schools. Likewise, inferred strength is negative for applications submitted by applicants with relatively strong direct observables who were nevertheless rejected at other schools.

Figure 4 demonstrates the predictive power of the inferred strength variable using the full sample of applications. It plots the non-parametric relationship between admission and inferred strength, conditional on the observed credentials used in equation (1). Specifically to construct the graph, I compute inferred strength residuals from an OLS regression of inferred strength on LSAT, GPA, race, and school-year fixed effects and separately compute admission residuals from a probit regression of admission on the same regressors. I then group applications into twenty equal-sized (five-percentile-point) bins based on the inferred strength residuals and plot mean admission residuals within each bin. The strongly upward-sloping relationship shows that inferred strength strongly predicts admission decisions—over and above the predictive power of LSAT, GPA, race, and school-year fixed effects.

Column 6 of Table 2 reports the results of repeating the DDD specification of column 4 with the additional linear control of inferred strength. Both the Berkeley and UCLA results are nearly unchanged: respective DDD effects of -33.9 and -33.5 percentage points, implying black admission rate declines of 30.0 and 30.2 percentage points after accounting for space-opening effects. These are my preferred estimates because this specification uses all of the controls that are available for the full sample. The stability of the results implies little selection on inferred strength, conditional on observed academic credentials. These declines were much larger than those estimated in the EALS at any non-UC school, so the empirical p value of each of these declines across non-UC schools is 0. Averaging these DDD estimates across Berkeley and UCLA, I conclude that the ban reduced the black admission rate from 60.6% to 30.5% in this sample when controlling for selective attrition.

Finally, one may yet be concerned about differential selection on admission determinants that are specific to UC schools. A leading candidate for such a determinant is California residency, which positively predicts admission to UC schools in the EALS. Column 7 reports DD results including the California residency indicator as an additional control, using all applications for which the variable is available (see Section III.A). The estimates are similar to those of column 5 which uses the same specification but excludes California residency, again suggesting no quantitatively important omitted variables bias.

Online Appendix Table 3 replicates Table 2 using applications from all races (white, black, Hispanic, and Asian); the results are very similar to those in Table 2. Online Appendix Table 4 replicates Online Appendix Table 3 while also fully interacting covariates $\mathbf{X}_i$ with race indicators, the post-ban indicator, and the non-UC indicator; the DD results are somewhat larger in magnitude (more negative) than those in Table 2. Finally and for general reference, Online Appendix Table 5 displays OLS estimates of admission regressed on LSAT, GPA, race indicators, and school-year fixed effects for each school type and time period.

IV.D Average Post-Ban Black Admission Advantages

The previous subsection reported the primary selection-corrected estimate of the effect of the ban on black admission rates: a reduction from 60.6% to 30.5% when holding the applicant pool constant at pre-ban levels. This subsection asks whether the ban eliminated cross-sectional black admission advantages. I do so by estimating whether the pre-ban black admission rate would have been substantially lower than 30.5% had both black and white applicants been subjected to the same observed pre-ban white admission standards.

Specifically, I estimate the cross-sectional analogue to equation (1) for each UC school among pre-ban black and white applications:

$$\Pr\left(ADMITTED_{it}\right) = \Phi(\mathbf{X}_i\boldsymbol{\alpha} + \beta_1 BLACK_i + \gamma_t) \tag{2}$$

where $\mathbf{X}_i$ is a vector of LSAT, GPA, and inferred strength and γ_t are year fixed effects.[26] I then use only the estimated coefficient vector $\hat{\boldsymbol{\alpha}}$ and the year fixed effects to compute a probit latent variable value for each application. Finally to account for the fact that a decline in the black admission rate opens up space in the admitted cohort, I add a constant to every application's value until the mean predicted admission probability across applications equals the actual admission rate among these applications.

Columns 1-2 of Table 3a report the results. Whereas Berkeley actually admitted 56.7% of pre-ban black applicants, I estimate that it would have admitted only 5.6% under observed white admission standards. For UCLA, the statistics are 64.5% and 10.4%. Thus averaging across Berkeley and UCLA, I estimate that the black admission rate would have fallen to 8.0% had both black and white applicants been subjected to the same observed pre-ban white admission standards. Thus the ban far from eliminated cross-sectional black admission advantages: holding the applicant pool constant

[26] Results are similar when omitting inferred strength or including Hispanics and Asians in the regression along with Hispanic and Asian indicators.

at pre-ban levels, post-ban UC schools sustained average black admission advantages over observably similar whites equal to 22.5 percentage points (= 30.5% – 8.0%).

IV.E Maximum Post-Ban Black Admission Advantages

The previous subsection estimated that post-ban UC schools sustained average black admission advantages equal to 22.5 percentage points over whites with similar LSAT scores, GPAs, and inferred strength. Since UC schools were able to sustain substantial black advantages, why did they not sustain even larger black advantages? I now use the pattern of black admission advantages to distinguish between two broad possibilities: UC schools were technologically unable to sustain substantially larger black advantages because they had access only to weak usable black-correlates like low family income and diversity essays, or they were technologically able to sustain substantially larger advantages but were either unwilling or legally unable to do so.

To explain, note that if UC schools achieved 22.5 percentage point black admission advantages by valuing both academic credentials and strong black-correlates (e.g. low family income and diversity essays), then black admission advantages in percentage-point terms must have been large at intermediate academic credential levels where applicants were near the margin of acceptance or rejection, and must have been small at low levels where all applicants were rejected and at high levels where all applicants were accepted. This pattern of admission outcomes would suggest that post-ban UC schools were technologically able to achieve much higher black admission advantages under the ban, by up-weighting black-correlates and down-weighting academic credentials. If on the other hand UC schools have already largely abandoned weight on academic credentials in favor of black-correlates, then black admission advantages would equal approximately 22.5 percentage points at all credential levels and UC schools may have already exhausted their technological capabilities to admit black applicants. Thus the key empirical statistic is the maximum black-white admission rate difference observed in post-ban admissions, conditional on observed credentials.

Table 3 column 4 uses the coefficients from equation (2) to estimate the maximum black-white admission rate difference in pre-ban (panel A) and post-ban (panel B) admissions.[27] To demonstrate the information content of the maximum black-white admission rate difference, panel A reports that the maximum black-white admission rate difference estimated in pre-ban admissions was 99 percentage points at both Berkeley and UCLA. This demonstrates that pre-ban UC schools used an extremely strong black-correlate (a pure or nearly pure black indicator) in admissions and suggests that they

[27] The maximum black-white admission rate difference is the maximum probit marginal effect on the black indicator and equals $2 * \Phi(\beta_1/2)$, where $\Phi(\cdot)$ denotes the Normal cumulative distribution function. Results are similar when omitting inferred strength from equation (2).

could have achieved a higher black admission rate by up-weighting this black-correlate relative to observed credentials like LSAT and GPA that correlate negatively with black status. Note that the decisiveness of race can rarely be observed in cross sectional data; it can be observed here because average pre-ban black advantages were so large and because EALS credentials are such powerful predictors of within-race admission decisions.[28]

Panel B reports that in post-ban admissions, the estimated maximum black-white admission rate difference was 57 percentage points at Berkeley and 69 percentage points at UCLA.[29] Bootstrapped confidence intervals are relatively diffuse, but even the lower bounds of 37 and 33 percentage points indicate substantial heterogeneity in post-ban black admission advantages relative to the mean of 22.5 percentage points. Averaging the two point estimates, post-ban UC schools used information (e.g. low family income and diversity essays) that allowed them to generate a 63 percentage point black-white admission rate difference. Had they placed arbitrarily high admission weight on those black-correlates relative to observed credentials like LSAT and GPA, UC schools could likely have admitted black applicants at substantially higher rates. Indeed if black-correlates were equally powerful at all credential levels, then UC schools could obviously have generated a 63 percentage point black-white admission rate difference—more than restoring the 53 percentage point pre-ban difference and thus pre-ban black admission rates. Hence, post-ban UC schools were likely technologically able to sustain substantially higher black admission advantages.

IV.F Enforcement Regime Discussion

In this final subsection, I briefly consider the implications of the results for the university objective function and the economic mechanisms of affirmative action bans. Specifically, I discuss two possible enforcement regimes consistent with the evidence, under the assumption that universities have stable concave preferences over the racial diversity and aggregate non-racial strength of admitted cohorts. See Appendix B for a formal treatment and Section II.B for motivation of the stable preferences assumption.[30]

First and most naturally, the ban may have been implemented as legislated, with UC schools being constrained only in the technology that can be used in admissions: prevented from using pure racial information and allowed at most to use legal black-correlates like low family income and diversity

[28] This can be seen visually in Figure 2c: if observed credentials were weak predictors of within-race admissions decisions, the fitted admission rules would be relatively flat and the maximum black-white admission rate difference (equal to the maximum vertical distance between the black and white admission rules) observed in the data would never approach one even if universities used a pure black indicator.

[29] See Appendix Figure 4 for a visualization.

[30] In particular, I do not discuss the possibility that UC schools abandoned preferences for racial diversity.

essays (Chan and Eyster 2003; Fryer, Loury, and Yuret 2007; Epple, Romano, and Sieg 2008).[31] The dilution of the racial information available for use in admissions increases the opportunity cost of achieving a racially diverse admitted cohort, inducing the university to re-optimize.[32] The finding that UC schools could likely have sustained substantially higher black advantages but chose not to is thus interpreted as reflecting UC schools' relatively strong preferences for maintaining academic and other non-racial excellence. Under this enforcement regime, post-ban admissions would involve avoidance and would be inefficient from the university's perspective in the sense that the post-ban bundle lies inside the pre-ban possibilities frontier (Fryer, Loury, and Yuret 2007).

However, the evidence is consistent with at least one other enforcement regime, modeled by Coate and Loury (1993) in the case of employment discrimination: universities being unconstrained in their admissions technology but constrained to generate relatively small black-white differences in admission rates for applicants with similar observable credentials. The rationale is that courts may find it difficult to observe the information used in admissions and thus may instead infer noncompliance from the extremeness of outcomes, as they do in employment discrimination litigation.[33] Technologically, names (Fryer and Levitt 2004) and other application information likely enabled post-ban universities to infer race quite well; for example, I find that in the yearbooks of the elite college that EALS students attended, 84% of black students list participation in a black-focused extracurricular group (typically listed on law school application résumés), compared to 0% of white students.[34] If universities are indeed constrained only in the magnitude of measurable black-white admission advantages, optimal university behavior is to reduce such advantages down to the maximum level that does not trigger litigation, and to use race to achieve that level. Under this enforcement regime, post-ban admissions would involve evasion and would be efficient from the university's perspective in the sense that the post-ban bundle lies on the pre-ban possibilities frontier, holding the applicant pool constant. These two enforcement regimes differ in their predictions for aggregate non-racial strength but cannot be tested here because non-racial strength is imperfectly measured.

[31] Note that low family income alone was likely insufficient to generate a 63 percentage point advantage. In the Law School Admissions Council Bar Passage Study dataset of matriculants to top law schools in 1991, the maximum black-white stochastic dominance that can be generated conditional on academic credentials is 37 percentage points. Details on this calculation are available upon request.

[32] That is, the university must forego more non-racial strength in order to admit each additional black student, because by weighting an imperfect black correlates, the university will sometimes admit weak white applicants or reject strong black applicants.

[33] The evidentiary standard of proof in such civil cases is merely probable guilt ("preponderance of the evidence").

[34] Without being informed of the purpose, a research assistant used only pictures and names to subjectively identify as many black students as possible (193 in total) in the 1998 and 2004 yearbooks of the elite college, as well as an equal number of non-Hispanic white students in random intervals of printed pictures. The statistics reported in the text refer to the 60% of students who reported a GPA-based honor and thus would likely be competitive at top law schools; the unconditional statistics are 72% and 0%, respectively. The data are available from the author.

V Conclusion

Debates over affirmative action hinge in part on schools' ability and willingness to sustain black admission advantages under an affirmative action ban. This paper used application-level data on a large sample of graduates from an elite college to estimate the effect of the UC affirmative action ban on black admission outcomes at UC Berkeley and UCLA law schools. The novelty of the analysis derived from having data on applications from before and after the ban and with rich enough covariates and independent screens (decisions at non-UC schools) to control for selective attrition on non-racial applicant strength. I found that the affirmative action ban reduced the black admission rate from 61% to 31% when holding the applicant pool constant at pre-ban levels. Cross-sectional post-ban black admission advantages averaged 23 percentage points and were as large as 63 percentage points at intermediate credential levels.

The results have three implications for affirmative action bans in the context of law school admissions. First, affirmative action ban avoidance is far from complete, and evaluations of a nationwide affirmative action ban should assume a large reduction in black admission advantages, while also allowing for large advantages to remain. Second and by revealed preference, UC schools did not consider race-neutral alternatives to affirmative action to be "workable" enough to sustain pre-ban black admission advantages, potentially satisfying an important federal constitutionality requirement for affirmative action. Third, achieving substantially larger black advantages under the ban is likely feasible but may require policies that mandate higher admissions weight on black-correlates (e.g. low family income and diversity essays) than schools would choose on their own, as the State of Texas did under its ban.

The paper motivates at least two areas for future work. First, the effect of a nationwide ban on lower-ranked schools depends not only on the effect of a ban on black admission advantages (identified here) but also on the application behavior of newly rejected black applicants down the hierarchy of schools (Arcidiacono 2005; Epple, Romano, and Sieg 2008). If black students who can no longer gain admission at very top law schools abandon law school altogether, then a nationwide ban can reduce black enrollment everywhere. But if these black students are instead willing to trade down to lower-ranked schools where they can gain admission without affirmative action, then a nationwide ban may reduce black enrollment only at top schools. Credible estimates of the cascading behavior of black applicants would therefore be valuable.

Second and more abstractly, an important question at the intersection of public and labor economics is to what extent do nondiscrimination mandates narrow racial and gender disparities in employment outcomes, and specifically whether they eliminate the use of race and gender in hiring (Freeman 1973; Heckman and Payner 1989; Goldin and Rouse 2000; Oyer and Schaefer 2002; Bertrand and Mullainathan 2004; List 2004). This paper shows that the UC affirmative action ban substantially narrowed racial disparities in admission outcomes but, as discussed in Section IV.F, does not indicate whether it eliminated the use of race altogether. Understanding the admissions technology that yielded substantial cross-sectional black admission advantages may inform our broader understanding of when and why nondiscrimination mandates constrain private decisions.

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Online Appendix A: Details of EALS Data Coding

The first application year's LSAT scores are in a more compact scale than all other years', and I convert them to the modern scale using percentile rank. I de-mean GPA by year to account for modest grade inflation over time. I code "Chicano/Mexican-American", "Hispanic", and "Puerto Rican" as Hispanic. Undergraduate major is available in some years' raw data; it has low statistical power in subsamples and its use would limit the years available for analysis so I omit it. The admission decision for a small percentage of accepted students is classified as rejected when the applicant in fact accepted and deferred an admission offer. The relatively minor importance of this measurement error is suggested visually in Figure 2b, where actual admission rates are close to 100% at high levels of academic strength, rather than plateauing at a smaller number. Year of college graduation is available in all years; I omit it for simplicity but every qualitative result holds when also controlling for a quartic in graduation year. The only other information in the raw data are indicators for whether the applicant took the LSAT more than once, whether the applicant withdrew an application before an admission decision was made, and whether the applicant accepted an admission offer. I exclude withdrawn applications from the analysis, and I do not have sufficient power to analyze matriculation decisions.

The raw data do not contain applicant identifiers, so for each year I create applicant identifiers by treating as coming from the same applicant those applications that match on all of the application-invariant variables; this is a powerful method in large part because GPA is coded to two decimal places. I exclude the fewer than one percent of observations for which this implies that a single applicant submitted multiple applications to the same school.

I do not include the University of Michigan in the group of fifteen most-applied-to schools because it was subject to an affirmative action ban during the sample. I do not analyze Michigan as a treatment school because its bans were effective during the sample only in 2001 and 2006 and I do not have sufficient power to conduct year-by-year difference-in-differences. UC law schools at Davis and Hastings as well as public Texas law schools received few applications in the EALS and similarly do not permit robust inference.

Online Appendix B: Optimal Responses to an Affirmative Action Ban

I use a simple version of recent avoidance models (Chan and Eyster 2003; Fryer, Loury, and Yuret 2007; Epple, Romano, and Sieg 2008) to characterize optimal university admission choices under an affirmative action ban, depending on the enforcement regime. The analysis uses terminology specific to admission decisions under an affirmative action ban but applies generally to acceptance decisions under nondiscrimination laws.

(i) The University's Maximization Problem. The simplest way to model the university's maximization problem is to cast it as a simple two-good consumption problem: the university has concave preferences over the number of black applicants admitted $\bar{r}$ and the aggregate non-racial strength of the admitted cohort. Each applicant is either black or white, the applicant pool is the same pre-ban and post-ban (approximating this paper's selection correction exercise), and all admitted students matriculate. The university faces a binding capacity constraint: it can admit no more than a fixed number $\bar{N}$ of applicants and must reject some applicants.

The university's general maximization problem is:

$$\max_{\bar{r},\bar{s}} u\left(\bar{r},\bar{s}\right) \quad \text{s.t.} \quad N\left(\bar{r},\bar{s}\right) \leq \bar{N}$$

where $N\left(\bar{r},\bar{s}\right)$ is the minimum number of applicants that must be admitted in order to deliver $\bar{r}$ black admits and $\bar{s}$ aggregate non-racial strength. $N\left(\bar{r},\bar{s}\right)$ is an implicit function of the joint distribution of race and non-racial strength in the applicant pool. The university faces a tradeoff in that the admission rule that maximizes the number of black admits is not the one that maximizes aggregate non-racial strength.

The university can admit applicants on the basis of two pieces of information: non-racial strength s_i and a binary signal $BLACKSIGNAL_i \in \{0, 1\}$ of black status. The black signal may be imperfect in that it may not equal one if and only if the applicant is in fact black, but in such cases I will assume that errors are orthogonal to non-racial strength s_i. The optimal admission rule can always be characterized as a "rank-and-yank" rule that admits the $\bar{N}$ applicants that have highest rank according to:

$$rank_i = s_i + \lambda BLACKSIGNAL_i$$

where λ is chosen to maximize university utility. This is true because for any number of admitted black-signaled applicants, the university maximizes aggregate non-racial strength by adopting a threshold rule within each black signal whereby the only admitted applicants are black-signalled applicants with non-racial strength above some $s^*_{BLACKSIGNAL=1}$ and white-signalled applicants with non-racial strength above some $s^*_{BLACKSIGNAL=0}$. Rank-and-yank implements any such pair of threshold rules by setting weight λ equal to $s^*_{BLACKSIGNAL=0} - s^*_{BLACKSIGNAL=1}$.

(ii) Affirmative Action. When affirmative action is not banned, the university is permitted arbitrary use of a pure signal of race in admission decisions. The black signal is pure in that $BLACKSIGNAL_i = 1$ if and only if applicant i is black. Online Appendix Figure 5a illustrates a feasible pair of optimal admission thresholds and illustrates its consequences for black and white applicants. To define the no-affirmative-action benchmark, let s^* be the level of non-racial strength above which there are exactly $\bar{N}$ applicants. This is the race-neutral threshold that would maximize aggregate non-racial strength and corresponds to a rank-and-yank admission rule with $\lambda = 0$. A university practicing affirmative action chooses $\lambda > 0$ and thus adopts a threshold admission rule for blacks at $s^*_{BLACKSIGNAL=1}$ and a separate threshold for whites at $s^*_{BLACKSIGNAL=0} > s^*_{BLACKSIGNAL=1}$. Relative to the no-affirmative-action benchmark, the university practicing affirmative action admits extra blacks (the grid fill pattern) and rejects extra whites (the solid fill pattern).

Online Appendix Figure 5c illustrates the affirmative action budget set in $(\overline{r}, \overline{s})$ space for the simple case of uniform distributions of non-racial strength within each race. The range of weights $\lambda \in [0, \infty)$ traces out the budget constraint (the solid curve). Point A is a potentially optimal bundle under affirmative action. The budget constraint is strictly convex because the first black applicant admitted through affirmative action is almost as strong as the white applicant that must be rejected in order to make room. After that, stronger and stronger white applicants must be rejected to make room for weaker and weaker black applicants.

(iii) Constrained Technology. As written, an affirmative action ban prohibits the university from using a pure signal of race in admission decisions but allows it to use factors like low family income that correlate imperfectly with race and that have plausible non-racial justification. This dilutes the usable racial information available to the university. I model this dilution as fraction p_{black} of black applicants and fraction p_{white} of white applicants possessing the binary signal $BLACKSIGNAL_i$, with $p_{black} - p_{white} < 1$ and for simplicity $p_{black}, p_{white} \perp s_i$. A university placing weight on an impure black signal makes "mistakes" in the sense that the university rejects some applicants that have higher non-racial strength than accepted applicants of the same race, as illustrated in Online Appendix Figure 5. In this way, an affirmative action ban raises the opportunity cost of admitting black applicants.

It can be easily shown that, in the analytically tractable case of uniform distributions of non-racial strength within race,[35] the dilution of black signal purity raises the marginal rate of transformation of admitted blacks for non-racial strength by a factor that is decreasing in the purity of the signal

[35] Without this or a similar assumption, the budget set can be non-convex over some intervals.

$BLACKSIGNAL_i$:

$$\frac{MRT^{CT}_{\bar{r},\bar{s}}}{MRT^{AA}_{\bar{r},\bar{s}}} = \frac{1}{(p_{black} - p_{white})^2} > 1$$

The higher opportunity cost puts the constrained-technology ("CT") budget set in the interior of the affirmative action ("AA") budget set, as illustrated in Online Appendix Figure 5c. As in any two-good consumption problem when the price of one good rises, changes in the consumption bundle hinge on income and substitution effects and are indeterminate when utility is unspecified. If preferences are not Giffen, the optimal post-ban bundle under constrained technology involves fewer admitted black applicants. Bundle B is one such possible bundle.[36]

(iv) Constrained Measurable Disparities. Online Appendix Figure 5c also depicts an alternative enforcement regime: unable to enforce the letter of the law because the information used in admissions may be unobservable, courts may instead impose a *de facto* limit on the black-white admission rate difference among observably similar applicants as can be measured by courts (e.g. conditional on LSAT, GPA, and inferred strength) or, equivalently here, the total number of admitted blacks. This constraint creates a kink in the university's budget constraint, and the optimal response of a post-ban university with a pure signal of race is to continue using race, only more modestly than before the ban. This lands the university at a bundle like C where aggregate non-racial strength rises and the number of admitted blacks falls.

[36] Earlier avoidance models put structure on the university's preferences in order to deliver more specific predictions. In Chan and Eyster (2003), $\bar{r}$ and $\bar{s}$ enter separably and linearly. Under this and technology restrictions, the admissions office may respond to a ban by deliberately introducing idiosyncratic noise—an imperfect racial proxy when blacks are concentrated at lower levels of the non-racial strength distribution—into admission decisions and generate non-Giffen outcomes. Fryer, Loury, and Yuret (2007) assume that the post-ban university uses imperfect racial proxies to admit the same number of black applicants as it did pre-ban.

TABLE 1
Applicant Characteristics by Race

	Share of applicants	LSAT score (sd 6.7)	Undergraduate GPA (sd 0.33)	Academic strength (mean 0, sd 1)	Admission rate
A. All Applicants (N = 5,353, collectively submitting 25,499 applications to top-17 schools)					
White	60.8%	167.3	3.47	0.24	41%
Black	9.7%	159.9	3.15	-0.98	56%
Asian	19.4%	167.6	3.52	0.33	41%
Hispanic	10.1%	162.8	3.31	-0.48	39%
B. Applicants to Berkeley (N = 1,594)					
White	56.6%	167.5	3.47	0.23	31%
Black	8.0%	160.8	3.13	-0.92	43%
Asian	24.2%	167.0	3.49	0.21	36%
Hispanic	11.3%	162.3	3.31	-0.53	34%
C. Applicants to UCLA (N = 777)					
White	55.0%	165.4	3.38	-0.09	54%
Black	7.5%	159.6	3.03	-1.17	53%
Asian	24.5%	165.2	3.43	-0.06	60%
Hispanic	13.1%	159.8	3.23	-0.89	35%

Notes - Panel A lists mean applicant characteristics for the Elite Applications to Law School sample used in the paper. The sample comprises the 5,353 applicants who together submitted 25,499 applications over seventeen years to Berkeley, UCLA, and the top-fifteen law schools that were never subject to an affirmative action ban. LSAT is the standardized test score used in law school admissions and ranges from 120 to 180. Undergraduate grade point average is the cumulative undergraduate GPA on a 4.00 scale. Academic strength is a scalar index of the strength of an applicant's academic credentials, equal to the standardized (mean zero and standard deviation one) sum of standardized LSAT and standardized GPA (see Figure 2 for the semi-parametric motivation). Panels B and C list the same statistics for applicants to Berkeley and UCLA, respectively. Online Appendix Table 1 lists summary statistics on application behavior and comparisons to the nationwide population of law school applicants.

TABLE 2
Selection-Corrected Effect of the Ban on Black Admission Rates

Dependent Variable:	Admission						
	OLS		Probit (average marginal effect)				
	(pp)	(pp)	(pp)	(pp)	(pp)	(pp)	(pp)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Berkeley							
Black × Post-ban	-39.7	-31.8	-40.5	-35.5	-40.0	-33.9	-43.6
	(6.8)	(7.3)	(5.4)	(6.3)	(5.3)	(6.5)	(5.5)
National trend controls		x		x		x	
Inferred strength control					x	x	x
CA residency control							x
N (applications)	1,029	17,329	1,029	17,329	1,029	17,329	779
Clusters (applicants)	1,029	3,754	1,029	3,754	1,029	3,754	779
Actual pre-ban black admission rate	56.7	56.7	56.7	56.7	56.7	56.7	56.7
Δ implied by Black × Post-ban effect	-34.2	-27.4	-35.7	-31.1	-35.6	-30.0	-39.7
B. UCLA							
Black × Post-ban	-48.1	-41.6	-35.3	-32.8	-35.0	-33.5	-31.1
	(10.5)	(10.4)	(11.1)	(11.0)	(11.2)	(11.1)	(10.5)
National trend controls		x		x		x	
Inferred strength control					x	x	x
CA residency control							x
N (applications)	485	16,785	485	16,785	485	16,785	371
Clusters (applicants)	485	3,736	485	3,736	485	3,736	371
Actual pre-ban black admission rate	64.5	64.5	64.5	64.5	64.5	64.5	64.5
Δ implied by Black × Post-ban effect	-41.6	-35.9	-32.1	-29.2	-32.0	-30.2	-29.2

Notes - Each column reports a coefficient from a difference-in-differences (DD) regression using black and white applications in the Elite Applications to Law School dataset at Berkeley (panel A) or UCLA (panel B). Standard errors clustered by applicant are in parentheses. Columns 1-2 use OLS regressions while the remaining columns use probit regressions and report marginal effects averaged over the UC school's pre-ban black applicants. The odd-numbered columns use the DD specification of equation (1): admission regressed on a black indicator, a black indicator interacted with a post-ban indicator, year fixed effects, LSAT, and GPA; column 5 additionally controls for inferred strength, and column 7 additionally controls for a California residency indicator that is available only for applications to UC schools and in certain years. The inferred strength variable uses independent admission decisions to proxy for unobserved admission determinants like recommendation letters that are omitted from the EALS, similar to Dale and Krueger (2002); see Section IV.C or Figure 4 for details. The even-numbered columns use a triple-difference version of equation (1) that controls for national trends by including in the regression all applications to the top-fifteen non-UC schools and by interacting the black indicator and the black-times-post-ban interaction with a UC school indicator; the coefficient on this latter interaction is reported. These regressions include school-year fixed effects and are weighted so that each school receives equal weight in each time period (pre-ban and post-ban). The final row in each panel reports estimates of the change in the admission rate that pre-ban black applicants are predicted to have experienced had the ban been in effect, accounting for the minor space-opening effect of a decline in black admission rates. Each estimate in these rows is computed by using the UC-specific coefficients of each regression to compute a probit latent variable value for each black and white pre-ban application according to post-ban criteria, then adding a constant to every application's value until the mean predicted admission probability across applications equals the actual admission rate observed among these applications. Online Appendix Tables 3 and 4 replicate this table using alternative specifications.

TABLE 3
Black-White Admission Rate Differences in Pre-ban and Post-ban Admissions

	Actual black admission rate	Hypothetical black admission rate under white coefficients	Average conditional black-white admission rate difference (col. 1 minus col. 2)	Maximum conditional black-white admission rate difference across covariate values
	(%)	(%)	(pp)	(pp)
	(1)	(2)	(3)	(4)
A. Pre-ban				
Berkeley	56.7	5.6	51.1	99.1
	[43.6, 69.5]	[1.2, 11.4]	[38.7, 62.5]	[97.1, 100.0]
UCLA	64.5	10.4	54.1	98.8
	[46.7, 80.6]	[2.2, 21.0]	[37.0, 70.5]	[92.5, 100.0]
B. Post-ban				
Berkeley	31.3	13.5	17.8	56.8
	[20.4, 43.4]	[7.1, 20.6]	[9.3, 27.0]	[36.8, 75.6]
UCLA	40.7	21.1	19.6	68.7
	[23.1, 60.0]	[7.9, 37.6]	[6.2, 34.1]	[33.6, 98.9]

Notes - Each cell reports an estimate of either a black admission rate or a black-white admission rate difference using the Elite Applications to Law School dataset. Ninety-five percent confidence intervals are computed using one thousand bootstrapped samples of each school-time period and are listed in brackets. Only black and white applications are used. Column 1 lists the actual black admission rate in the specified school-time period. Column 2 reports the black admission rate that is predicted to have prevailed if black applicants had been subjected to observed white admission standards, calculated by estimating equation (2) which is a probit regression of admission on LSAT, GPA, inferred strength, a black indicator, and year fixed effects and then using the coefficients other than on the black indicator to predict admission probabilities for each applicant and accounting for the minor space-opening effect of a decline in black admission rates as described in Section IV.D (results are similar without the space-opening correction). Reported estimates are means of these predict admission probabilities. See Section IV.C or Figure 4 for the definition of inferred strength; results are similar when omitting it. Column 3 equals the difference between columns 2 and 1 and is an estimate of the average black-white admission rate difference for this school-time period's black applicants, conditional on observed covariates. Empirically, applications with high levels of LSAT, GPA, and inferred strength are accepted at high rates regardless of race, and applications with low levels are accepted at low rates regardless of race. But at intermediate covariate levels, the black-white admission rate difference is large. Column 4 reports an estimate of the maximum black-white admission rate difference conditional on covariates, equal to largest probit marginal effect on the black indicator across covariate levels. See Figure 2b for an illustration of the reasonableness of the probit functional form in EALS decisions.

ONLINE APPENDIX TABLE 1
Application Behavior and Comparison of Applicant Characteristics

A. Application Behavior in the Full EALS Dataset, 1990-2006

Applications per applicant	5.7
Applications per applicant who applied to Berkeley or UCLA	7.8
Percent of applications sent to schools ranked 1-10	59%
Percent of applications sent to schools ranked 11-20	20%
Percent of applicants who applied to Berkeley	28%
Percent of applicants who applied to UCLA	14%

B. Applications and Applicants in the 17-School EALS Sample Used in the Paper

Applications	25,499
Applicants	5,353
Applications and applicants to Berkeley (7th-most in the 17-school sample)	1,594
Applications and applicants to UCLA (13th-most in the 17-school sample)	777

C. Mean Applicant Characteristics in the 17-School EALS Sample Used in the Paper and Nationwide

	EALS (sd)	Nationwide
LSAT	166.2 (6.7)	151.5
GPA	3.43 (0.33)	3.16
White	60.8%	70.9%
Asian	19.4%	7.7%
Black	9.7%	12.4%
Hispanic	10.1%	9.1%
Post-ban	54.8%	

Notes - Panel A lists statistics on the application behavior of Elite Application to Law School applicants, using all complete observations (32,627 applications from 5,692 applicants). The rankings refer to the rankings from the 1998 issue of *U.S. News and World Report*'s "America's Best Graduate Schools". Panel B lists statistics on applications submitted to the seventeen law schools used in the paper; see the notes to Table 1 for details. Panel C lists mean applicant characteristics. The Nationwide column lists statistics for all U.S. law school applicants in application year 2000-2001, the closest available year to the midpoint of the EALS sample. LSAT is the standardized test score used in law school admissions and ranges from 120 to 180. Undergraduate grade point average is the cumulative undergraduate GPA on a 4.00 scale. The Hispanic category includes applicants classified as Chicano/Mexican-American, Hispanic, and Puerto Rican. Post-ban is an indicator for the applicant applying to law school in application year 1996-1997 or later. The 5.4% of EALS applicants who do not report race or list their race as American Indian/Alaskan Native, Canadian Aboriginal, or Other are omitted from EALS statistics in this table and all analyses; the corresponding 7.9% of U.S. applicants are omitted from the U.S. applicant race percentages as well. The nationwide data were collected from various tables at http://www.lsac.org/LSACResources/default.asp.

ONLINE APPENDIX TABLE 2
Selection-Corrected Effect of the Ban on Black Admission Rates
Semi-Parametric Estimates

Admission Rates at Non-UC Schools

	Pre-ban	Post-ban	Difference (pp)
White	40.6%	46.1%	5.5
Black	61.2%	63.0%	1.9
Difference (pp)	20.6	16.9	-3.6

Admission Rates at Berkeley

	Pre-ban	Post-ban	Difference (pp)
White	31.0%	33.9%	2.9
Black	56.7%	26.0%	-30.6
Difference (pp)	25.7	-7.9	-33.6

DDD estimate (percentage points): -29.9
DDD estimate, as % of pre-ban black admission rate: -52.8%

Admission Rates at UCLA

	Pre-ban	Post-ban	Difference (pp)
White	48.0%	60.1%	12.2
Black	64.5%	32.4%	-32.1
Difference (pp)	16.6	-27.7	-44.3

DDD estimate (percentage points): -40.7
DDD estimate, as % of pre-ban black admission rate: -63.0%

Notes - This table constructs the semi-parametric triple-difference estimates of the change in black admission rates at Berkeley and UCLA reported in Section IV.A and Figure 3. Each pre-ban admission rate is an actual admission rate. Each post-ban admission rate is a reweighted estimate of the admission rate that pre-ban applicants of each race and school are predicted to have experienced after the ban; see Section IV.A for the reweighting procedure. The differences computed in the DDD are between pre-ban and post-ban periods, UC and non-UC schools, and black and white races. The non-UC schools are the top-fifteen schools in the EALS that were never subject to an affirmative action ban. See Table 2 for analogous parametric DDD estimates that account for the fact that a decline in black admission rates opens up space in the admitted cohort for members of both races.

ONLINE APPENDIX TABLE 3
Selection-Corrected Effect of the Ban on Black Admission Rates
Using Applications from All Races

Dependent Variable:	Admission						
	OLS		Probit (average marginal effect)				
	(pp)	(pp)	(pp)	(pp)	(pp)	(pp)	(pp)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Berkeley							
Black × Post-ban	-38.1	-30.8	-39.8	-34.8	-38.6	-32.7	-42.5
	(6.9)	(7.3)	(5.6)	(6.4)	(5.5)	(6.7)	(5.8)
National trend controls		x		x		x	
Inferred strength control					x	x	x
CA residency control							x
N (applications)	1,594	24,722	1,594	24,722	1,594	24,722	1,197
Clusters (applicants)	1,594	5,324	1,594	5,324	1,594	5,324	1,197
Actual pre-ban black admission rate	56.7	56.7	56.7	56.7	56.7	56.7	56.7
Δ implied by Black × Post-ban effect	-34.6	-28.0	-36.5	-31.7	-36.0	-30.3	-40.1
B. UCLA							
Black × Post-ban	-45.4	-39.0	-35.9	-32.1	-35.1	-32.0	-33.2
	(10.4)	(10.5)	(10.3)	(10.8)	(10.3)	(10.8)	(10.2)
National trend controls		x		x		x	
Inferred strength control					x	x	x
CA residency control							x
N (applications)	777	23,905	777	23,905	777	23,905	586
Clusters (applicants)	777	5,300	777	5,300	777	5,300	586
Actual pre-ban black admission rate	64.5	64.5	64.5	64.5	64.5	64.5	64.5
Δ implied by Black × Post-ban effect	-41.4	-35.5	-34.6	-30.4	-34.6	-30.9	-33.0

Notes - This table replicates Table 2 using applications from all races (black, white, Asian, and Hispanic). The regressions underlying this table are the same as those underlying Table 2 except that the black indicator is replaced by a vector of black, Asian, and Hispanic indicators.

ONLINE APPENDIX TABLE 4
Selection-Corrected Effect of the Ban on Black Admission Rates
Using Applications from All Races and Controlling for Full Interactions

Dependent Variable:	Admission						
	OLS		Probit (average marginal effect)				
	(pp)	(pp)	(pp)	(pp)	(pp)	(pp)	(pp)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Berkeley							
Black × Post-ban	-47.3	-40.6	-47.2	-46.0	-49.1	-47.7	-50.3
	(7.1)	(7.4)	(4.8)	(5.3)	(4.6)	(5.1)	(4.7)
National trend controls		x		x		x	
Inferred strength control					x	x	x
CA residency control							x
N (applications)	1,594	24,722	1,594	24,722	1,588	24,716	1,192
Clusters (applicants)	1,594	5,324	1,594	5,324	1,588	5,318	1,192
Actual pre-ban black admission rate	56.7	56.7	56.7	56.7	56.7	56.7	56.7
Δ implied by Black × Post-ban effect	-42.9	-36.9	-44.2	-42.9	-44.5	-43.0	-45.6
B. UCLA							
Black × Post-ban	-46.0	-38.0	-44.9	-41.8	-44.7	-41.3	-46.4
	(10.8)	(10.8)	(8.9)	(9.7)	(8.7)	(9.8)	(7.7)
National trend controls		x		x		x	
Inferred strength control					x	x	x
CA residency control							x
N (applications)	777	23,905	777	23,905	777	23,905	586
Clusters (applicants)	777	5,300	777	5,300	777	5,300	586
Actual pre-ban black admission rate	64.5	64.5	64.5	64.5	64.5	64.5	64.5
Δ implied by Black × Post-ban effect	-41.9	-34.6	-42.1	-38.9	-42.4	-38.8	-45.1

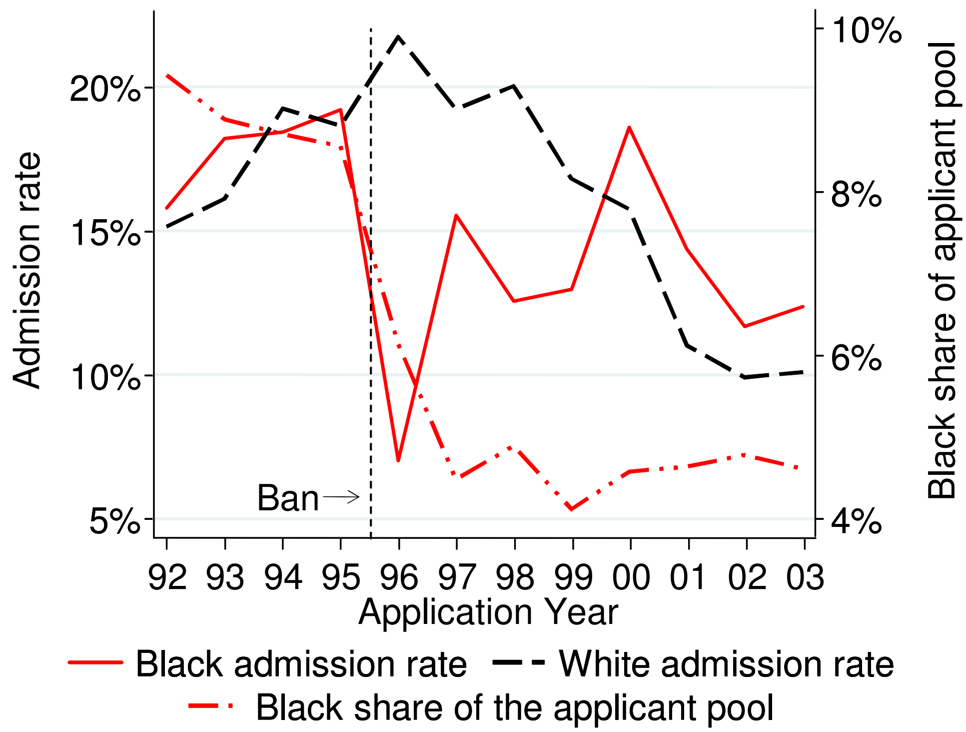
Notes - This table replicates Table 2 using applications from all races (black, white, Asian, and Hispanic) and more interactions. The regressions underlying this table are the same as those underlying Table 2 except for two changes. First, the black indicator is replaced by a vector of black, Asian, and Hispanic indicators. Second, each non-racial covariate (LSAT, GPA, inferred strength, and California residency, depending on the specification) is interacted with each of the DD or DDD variables (the vector of race indicators, the post-ban indicator, the UC-school indicator, and any interactions of these variables). For example, column 1 regresses admission on LSAT, GPA, race indicators, year fixed effects, the race indicators interacted with the post-ban indicator, LSAT interacted with the post-ban indicator, GPA interacted with the post-ban indicator, LSAT interacted with the race indicators, and GPA interacted with the race indicators.

ONLINE APPENDIX TABLE 5
Relationship between Admission and Race by School and Time Period

Dependent Variable:	Admission					
	Non-UC		UC Berkeley		UCLA	
	Pre-ban (pp)	Post-ban (pp)	Pre-ban (pp)	Post-ban (pp)	Pre-ban (pp)	Post-ban (pp)
	(1)	(2)	(3)	(4)	(5)	(6)
Black	64.2	56.4	77.4	31.9	64.7	19.0
	(2.0)	(2.0)	(5.5)	(4.8)	(7.6)	(7.9)
Hispanic	27.0	24.8	48.0	21.1	30.2	3.1
	(2.5)	(1.8)	(6.0)	(3.9)	(8.4)	(5.4)
Asian	4.1	-0.1	8.2	2.6	8.1	3.3
	(1.4)	(1.4)	(3.4)	(3.1)	(4.5)	(4.2)
LSAT (mean=0, sd=1)	22.8	25.2	24.2	17.5	28.1	28.9
	(0.7)	(0.6)	(1.7)	(1.4)	(2.2)	(2.0)
GPA (mean=0, sd=1)	23.4	19.9	22.3	21.6	20.2	19.3
	(0.8)	(0.9)	(1.9)	(1.6)	(2.4)	(2.1)
N (applications)	9,922	13,206	651	943	347	430
Clusters (applicants)	2,374	2,880	651	943	347	430
R-squared	0.444	0.450	0.441	0.363	0.497	0.525

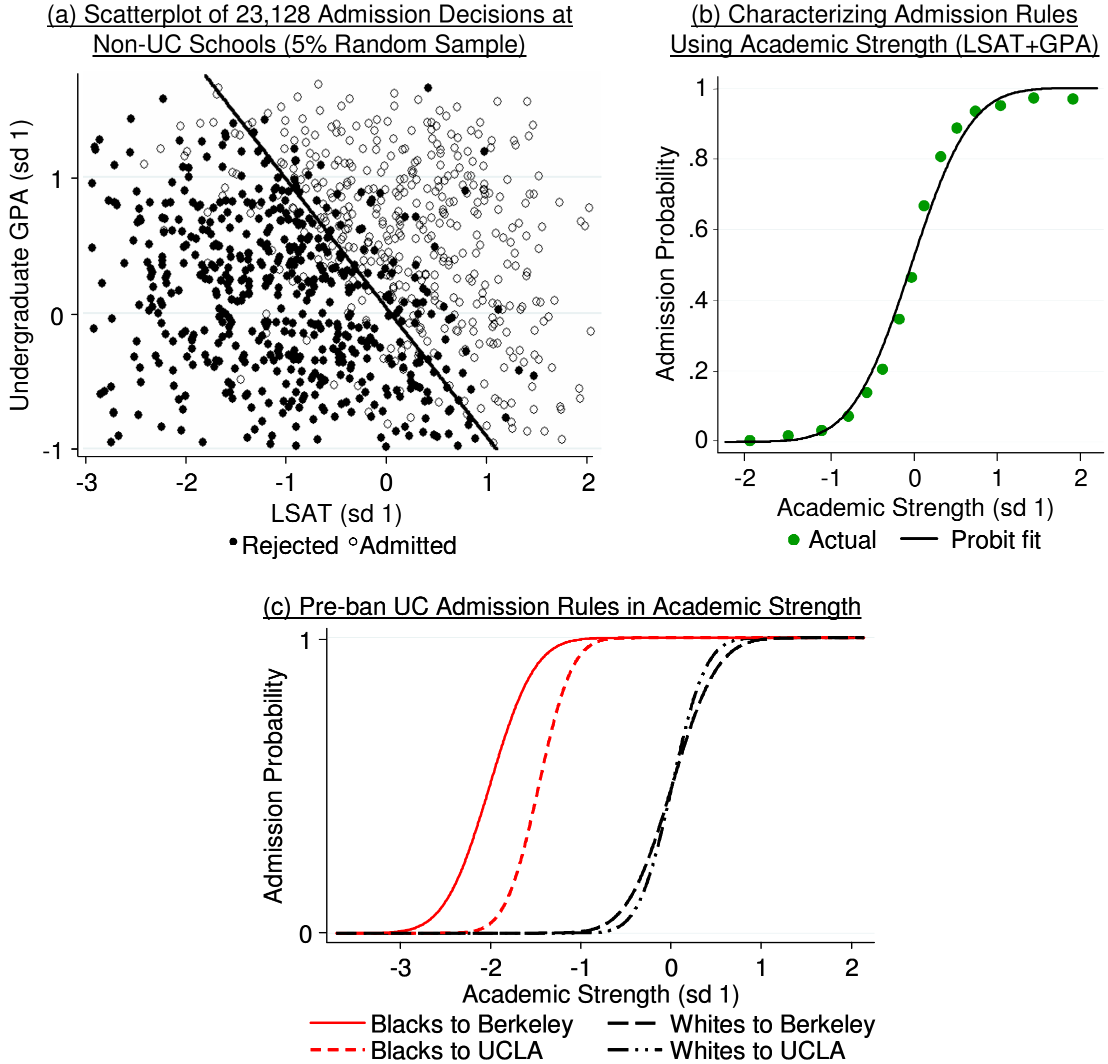
Notes - This table reports coefficient estimates in percentage point units from descriptive OLS regressions of admission on race indicators, LSAT score, undergraduate GPA, and school-year fixed effects. The non-UC schools are the top-fifteen schools in the EALS that were never subject to an affirmative action ban. LSAT and GPA are each standardized across all EALS applicants to have mean zero and standard deviation one. In columns 1-2, I weight applications so that each school carries equal weight. Standard errors are clustered at the applicant level.

FIGURE 1
Berkeley Admission Rates and Racial Mix of Applicants



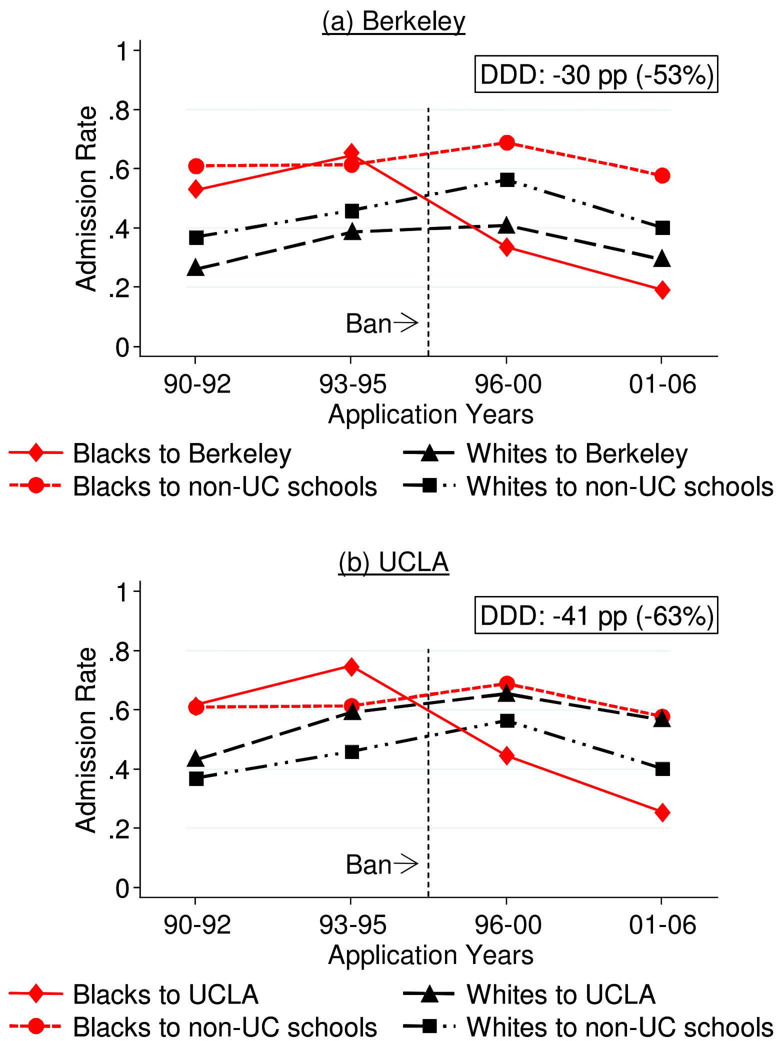
Notes – This graph uses public aggregates reported by the University of California on the universe of applicants to Berkeley to plot the time series of overall admission rates by race and the black share of the applicant pool at Berkeley. Application year refers to the autumn of the application year. These unconditional aggregates contain no information on applicant credentials by race. The post-ban recovery in black admission rates relative to white admission rates is consistent with Berkeley learning to sustain most of its pre-ban black admission advantages and black students of all credential levels declining to apply to a "black unfriendly" school—or alternatively with the ban permanently reducing black admission advantages and low-credential black students learning that applying was futile and declining to apply. The data were available from the author.

FIGURE 2
Race, Academic Credentials, and Admission under Affirmative Action



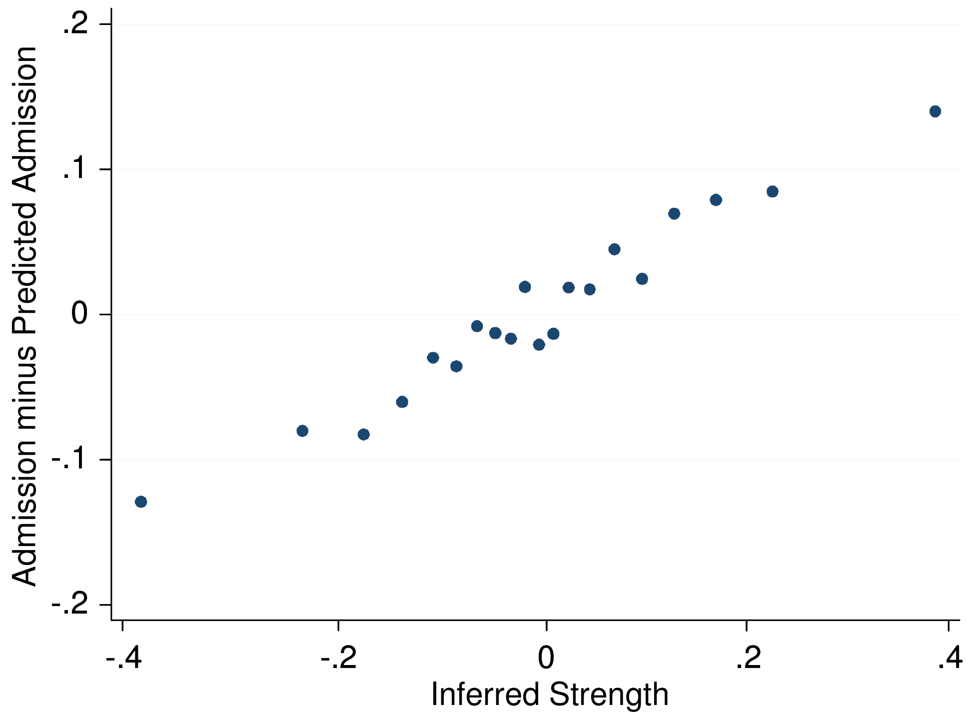
Notes – Figure 2a plots standardized LSAT score (mean zero and standard deviation one), standardized undergraduate GPA, and the actual admission decision for a 5% random sample of the 23,128 Elite Applications to Law School (EALS) applications submitted to the top-fifteen non-UC schools that were never subject to an affirmative action ban. Online Appendix Figure 2 displays the full sample in color. To account for cross-school selectivity differences, each application's LSAT has been additively shifted by its school-year-race fixed effect from a probit regression of admission on LSAT, GPA, and these fixed effects (see Section III.C); the overlaid best-fit admission threshold line correctly predicts 89.1% of admissions decisions. The regression indicates that a one standard deviation higher LSAT is about as valuable in the admissions cross section as a one standard deviation higher GPA. Thus when useful, I summarize an application's LSAT and GPA with the scalar index academic strength, equal to the standardized sum of standardized LSAT and standardized GPA. Figure 2b plots admission rates within fifteen academic strength bins using all 23,128 non-UC applications and overlays the univariate probit fit, where each application's academic strength has been additively shifted by its school-year-race fixed effect from a probit regression of admission on academic strength and these fixed effects. Figure 2c plots probit-fitted "admission rules" by race at UC schools before the 1996 affirmative action ban, derived from a regression of admission on academic strength, a black indicator, and year fixed effects using pre-ban black and white applications to Berkeley, and separately for UCLA. For ease of comparison, each school's pair of admission rules has been horizontally shifted by an additive constant so that the predicted admission probability for whites equals 0.5 at academic strength 0.

FIGURE 3
Selection-Corrected Admission Rates by Race



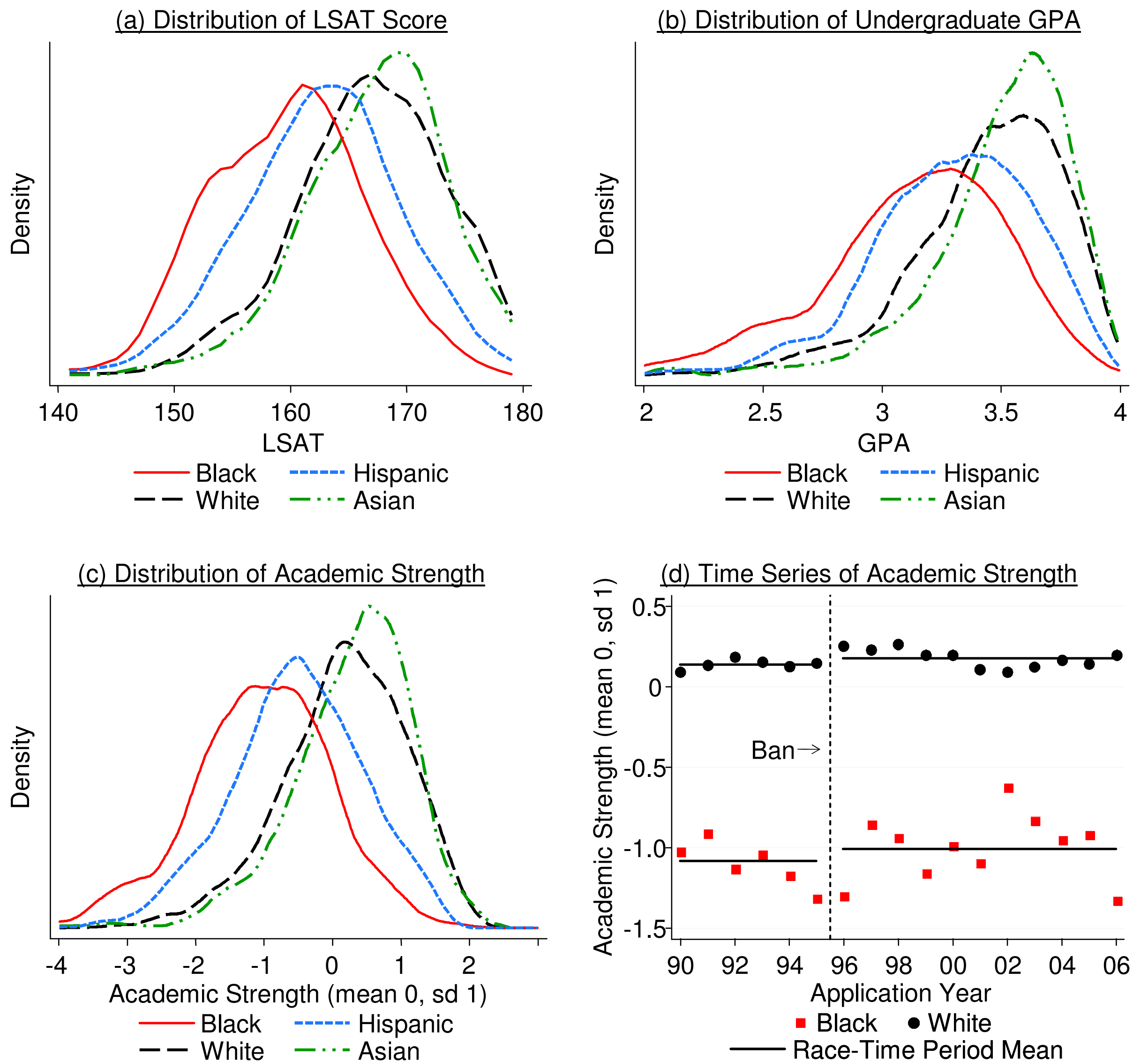
Notes – This figure displays the time series of black and white admission rates at Berkeley, UCLA, and non-UC schools, where applicant characteristics have been held constant at pre-ban levels using semi-parametric reweighting as in DiNardo, Fortin, and Lemieux (1996). To construct the time series of black admission rates at Berkeley, I first compute terciles of academic strength among pre-ban black applications to Berkeley. Then for each time period shown in the figure, I weight black applications to Berkeley so that each pre-ban-defined tercile receives equal weight when computing the displayed admission rate. I repeat this process for whites at Berkeley and for whites and blacks separately at UCLA and at each non-UC school, averaging across non-UC schools to construct the non-UC series. This semi-parametric reweighting on academic strength is data-demanding, so I group the data into two pre-ban time periods (1990-1992 and 1993-1995) and two post-ban time periods (1996-2000 and 2001-2006). Pooling all pre-ban years and all post-ban years, the triple-difference (DDD) estimate of the effect of the ban on the black admission rate at each UC school is overlaid, with the DDD estimate as a fraction of the pre-ban admission rate in parentheses. Online Appendix Table 2 lists the numbers underlying these DDD estimates. Table 2 reports parametric DDD estimates that account for the minor space-opening effect of a decline in black admission rates.

FIGURE 4
Inferred Strength and Admission Rates



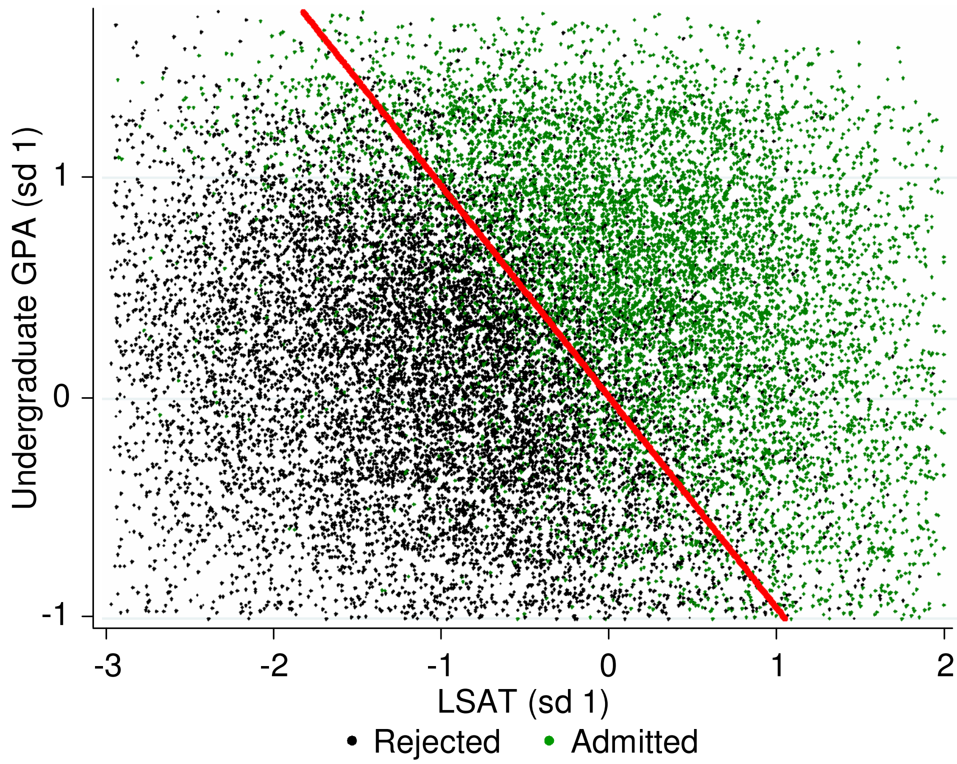
Notes – This graph displays the power of the inferred strength variable (motivated by Dale and Krueger 2002) to predict admission, conditional on other covariates. The triple-difference regressions underlying Table 2 column 4 do not control for admission factors that are omitted from the EALS such as recommendation letter strength. I proxy for such unobserved admission determinants using the intuition that if an applicant predicted to be rejected based on LSAT, GPA, and race is in fact consistently admitted across schools in the EALS, this applicant is likely strong on commonly-valued unobserved characteristics like recommendation letters. Specifically I construct the inferred strength variable for an application submitted by applicant *i* to school *s* equal to the mean across all applications submitted by applicant *í* to schools other than *s* of residuals from within-school regressions of admission on LSAT, GPA, race indicators, and time-period fixed effects. Then to construct the graph, I compute inferred strength residuals from an OLS regression of inferred strength on LSAT, GPA, race, and school-year fixed effects, and I compute admission residuals from a probit regression of admission on the same covariates. I then group applications into twenty equal-sized (five-percentile-point) bins based on the inferred strength residuals and plot mean admission residuals within each bin.

ONLINE APPENDIX FIGURE 1
Distribution of Academic Characteristics By Race



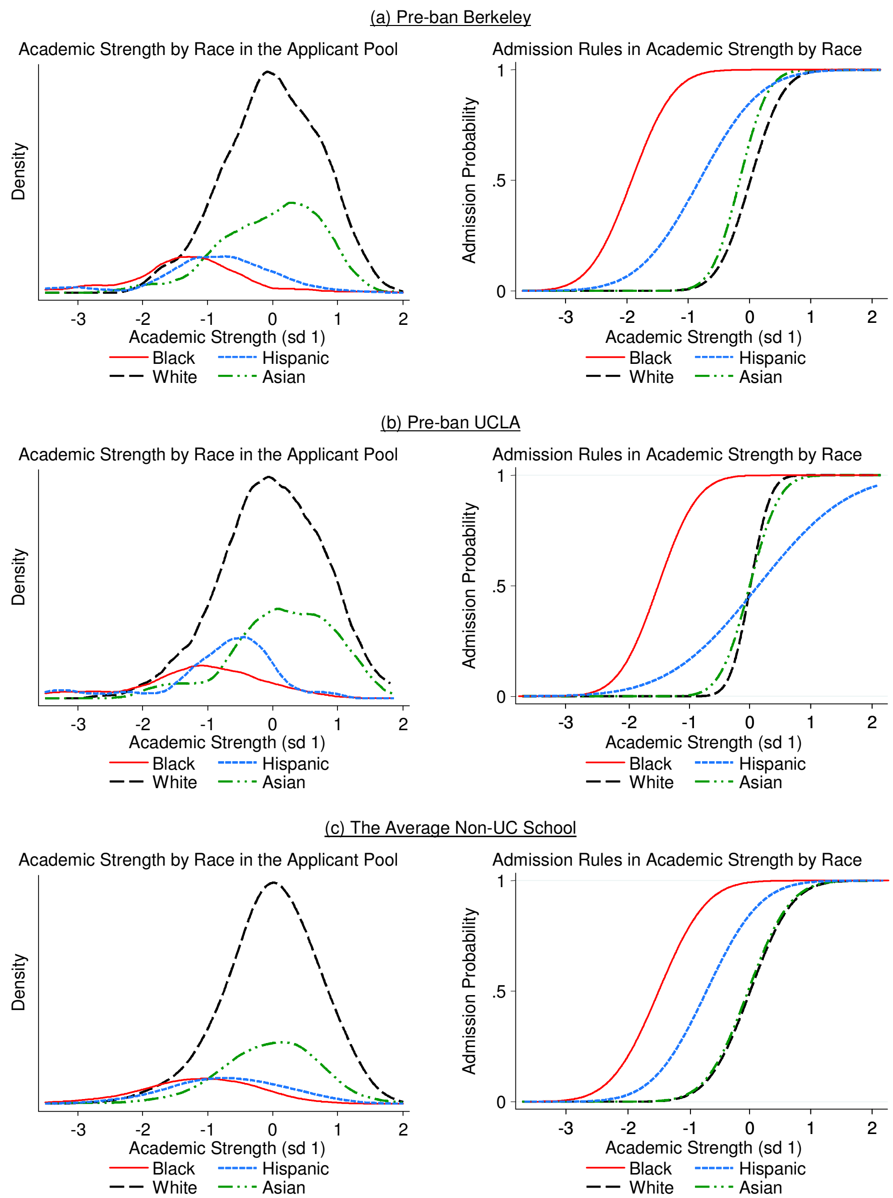
Notes – This figure displays the distribution of academic characteristics by race among Elite Application to Law School (EALS) applicants in the paper's main sample: the 94% of EALS applicants who applied to Berkeley, UCLA, and/or one of the top-fifteen non-UC schools that were never subject to an affirmative action ban. LSAT is the standardized test score used in law school admissions and ranges from 120 to 180. Undergraduate grade point average is the cumulative undergraduate GPA on a 4.00 scale. Academic strength is a scalar index of the strength of an applicant's academic credentials, equal to the standardized (mean zero and standard deviation one) sum of standardized LSAT and standardized GPA (see Figure 2 for the semi-parametric motivation). Each displayed density is estimated non-parametrically using an Epanechnikov kernel with Silverman bandwidth. Application year refers to the autumn of the application year.

ONLINE APPENDIX FIGURE 2
Scatterplot of 23,128 Admission Decisions at Non-UC Schools



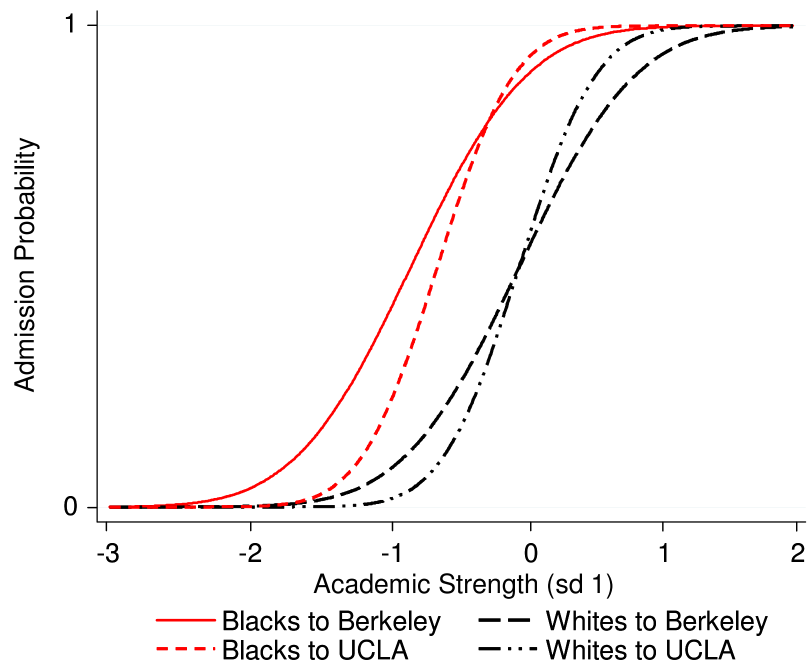
Notes – This figure is intelligible only in color. It replicates Figure 2a except that it plots all 23,128 applications to non-UC schools, rather than just a 5% random sample. See the notes to that figure for details.

ONLINE APPENDIX FIGURE 3
Academic Strength and Admission Rules under Affirmative Action



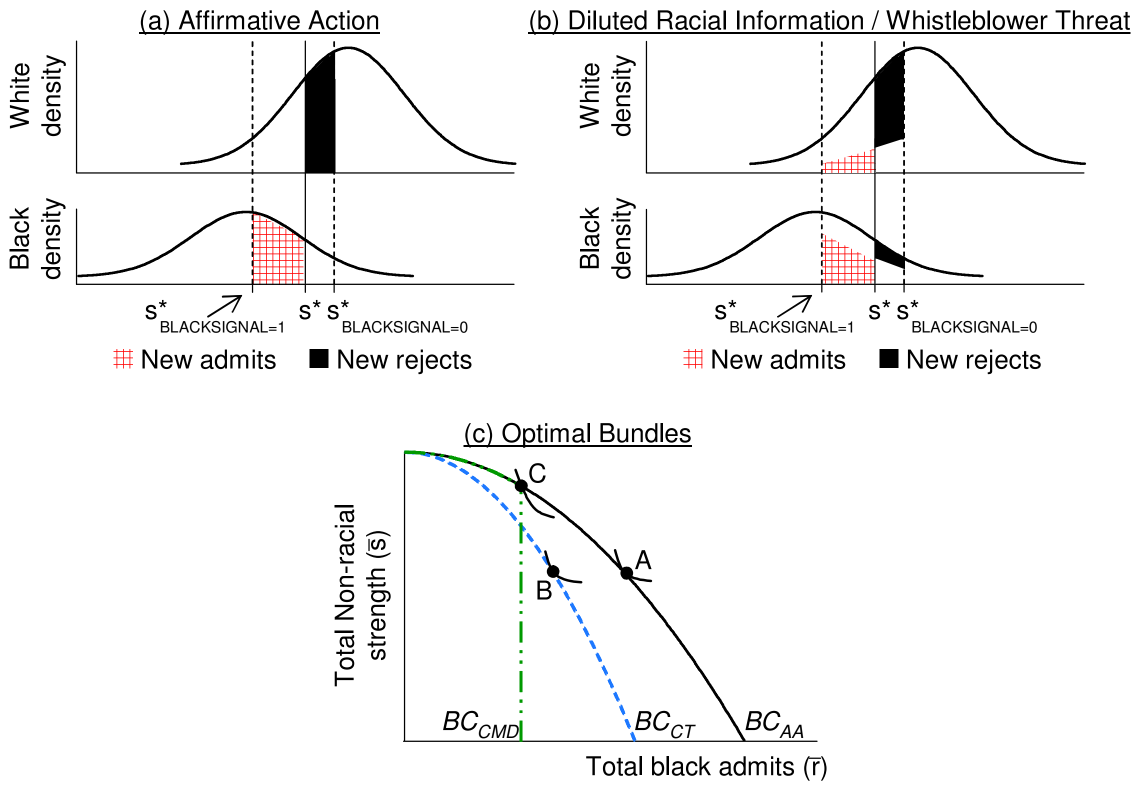
Notes – This figure plots academic strength by race in the applicant pool and the admission rules in academic strength (defined and motivated in Figure 2) by race in the EALS at pre-ban Berkeley, pre-ban UCLA, and the average non-UC school in the average year. The left-hand-side panels display the density of applicants by academic strength and race. To construct these, I pool all years within each school-race, estimate each school-race's density non-parametrically using an Epanechnikov kernel with Silverman bandwidth, shift each school's distributions horizontally by an additive constant so that the white mode lies at academic strength 0, and then (for the set of non-UC schools only) average densities across schools. The right-hand-side panels display fitted admission rules by race constructed similarly to Figure 2c except that admission is allowed to respond to academic strength differently for each race. For each school type, the fits derive from a probit regression of admission on academic strength, race indicators, interactions among the race indicators and academic strength, and school-year fixed effects. The non-UC regression is weighted so that each school carries equal weight in each time period (pre-ban and post-ban), consistent with regressions elsewhere in the paper.

ONLINE APPENDIX FIGURE 4
Black-White Differences in Post-ban Admissions



Notes – This figure replicates Figure 2c for post-ban applicants. It plots fitted admission rules by race at UC schools after the affirmative action ban, derived from a probit regression of admission on academic strength, a black indicator, and year fixed effects using black and white post-ban applicants to Berkeley, and separately for UCLA. See the notes to Figure 2c for the definition of academic strength. For ease of comparison, each school's pair of admission rules has been shifted horizontally by an additive constant so that the predicted admission probability for whites equals 0.5 at academic strength 0. The maximum vertical distance between the Berkeley curves is 56 percentage points and between the UCLA curves is 63 percentage points, slightly smaller than the estimates reported in Table 3 column 4 that condition more flexibly on covariates. The horizontal distance between the Berkeley curves indicates that black status is observed to have been worth 0.86 standard deviations of academic strength in the post-ban cross section; for UCLA, the figure is 0.66 standard deviations.

ONLINE APPENDIX FIGURE 5
Admissions under an Affirmative Action Ban



Notes – This figure illustrates the simple model detailed in Online Appendix B in which the applicant pool is held fixed and the university has concave preferences over the number of black applicants admitted and the aggregate non-racial strength of the admitted cohort. The university can admit applicants on two pieces of applicant information: non-racial strength and a signal of black status. Panels (a) and (b) depict applicant densities in non-racial strength; "new" refers to the effects of placing positive weight on the black signal. Panel (c) plots budget sets under the simplification of uniform distributions of non-racial strength; the graph omits feasible but always-dominated bundles by defining the x-intercept as the number of black applicants admitted if the university were to maximize only non-racial strength and the y-intercept as the aggregate non-racial strength achieved if the university were to maximize only the number of admitted blacks. Under affirmative action ("AA"), the black signal is pure. If a ban constrains the racial information available to the university ("constrained technology", or "CT"), the university can use only an imperfect signal of black status. This increases the non-racial strength the university must forego to admit each additional black applicant and pushes the CT budget side inside the AA budget set. If instead a ban constrains the black-white admission rate difference among observably similar applicants ("CMD") without constraining their technology, the post-ban university can use its pure black signal to achieve any bundle in its AA budget set, so long as the number of admitted blacks does not exceed a *de facto* limit.