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TOP PERCENT POLICIES AND THE RETURN TO POSTSECONDARY SELECTIVITY

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ABSTRACT
I study the efficacy of test-based meritocracy in college admissions by evaluating the impact of a grade-based "top percent" policy implemented by the University of California. Eligibility in the Local Context (ELC) provided large admission advantages to the top four percent of 2001-2011 graduates from each California high school. I construct a novel longitudinal dataset linking the ELC era's 1.8 million UC applicants to educational and labor market outcomes. I first employ a regression discontinuity design to show that ELC led over 10 percent of barely-eligible applicants from low-opportunity high schools to enroll at selective UC campuses instead of less-selective public colleges and universities. Half of those participants were from underrepresented minority groups, and their average SAT scores were at the 12th percentile of their UC peers. Instrumental variable estimates show that ELC participants' more-selective university enrollment caused increases in five-year degree attainment by 30 percentage points and annual early-career wages by up to $25,000. I then analyze ELC's general equilibrium effects by estimating a structural model of university application, admission, and enrollment with an embedded top percent policy. I find that ELC and counterfactual expansions of ELC substantively increase disadvantaged students' net enrollment at selective public universities. Reduced-form and structural estimates show that ELC participants derived similar or greater value from more-selective university enrollment than their higher-testing peers. These findings suggest that access-oriented admission policies at selective universities can promote economic mobility without efficiency losses.

Keywords: University Admissions, Standardized Tests, Economic Mobility

> "The more capable high school students should have the greater freedom of choice of collegiate institution, and selection procedures should give preference to the more able … [to] predict success in the state colleges."
> —*Technical Committee on Selection and Retention of Students, 1960 California Master Plan for Higher Education*

Since the 1960s, selective public universities in the U.S. have admitted students mostly using test scores and other measures of academic preparation.[1] Many universities provide admissions advantages to certain disadvantaged applicants in order to rectify unequal K-12 learning opportunities and promote socioeconomic mobility, but these "access-oriented" admission policies are controversial on efficiency grounds: students with lower test scores are generally thought to derive smaller (or no) benefits from

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more-elite education when compared to the students admitted by test-based meritocracy (Arcidiacono and Lovenheim, 2016). This study investigates two open questions about the allocation of public higher education in the U.S. First, would lower-testing students benefit from selective university enrollment, and how would their return compare to that received by higher-testing students? Second, can available policies target lower-testing but high-value-add students, and how would implementing those policies shape universities' socioeconomic composition?

I answer these questions by studying an access-oriented admission policy implemented by the University of California (UC) between 2001 and 2011. Eligibility in the Local Context (ELC) was a "top percent" policy that guaranteed selective university admission to applicants whose grades ranked in the top four percent of their high school class.[2] I construct a new UC applicant administrative dataset and use a regression discontinuity design to estimate ELC's effect on barely-eligible applicants' likelihood of admission and enrollment at each UC campus. I then link each applicant to national education records and annual California wages and employ an instrumental variable strategy to estimate the medium-run effects of more-selective university enrollment for ELC participants. Building on these reduced-form findings, I next estimate and validate a structural model of university application, admission, and enrollment with an embedded top percent policy in order to simulate the net effects of top percent policies on universities' enrollment composition. Finally, I extend both the quasi-experimental and structural research designs to investigate the relationship between students' meritocratic standing and their return to enrolling at a more-selective university.

I show that the admissions advantages conferred by ELC eligibility caused over 12 percent of barely-eligible applicants from less-competitive high schools to enroll at four selective UC campuses instead of enrolling at less-selective public colleges. Instrumental variable estimates show that these barely-eligible ELC "participants" became 30 percentage points more likely to earn a college degree within five years — approximately matching the increase in graduation rates of the institutions they attended — and earned higher annual wages by as much as $25,000 between ages 25 and 27. ELC's roughly 600 annual participants came from lower-income and more diverse families than the crowded-out students whom they replaced at UC, and model simulations show that a top percent policy providing equivalent admissions advantages to the top nine percent of each high school's graduates would meaningfully increase those UC campuses' lower-income and underrepresented minority (URM) enrollment (by about five and ten percent, respectively).[3]

Complementing reduced-form and institutional value-added evidence showing that even very low-testing ELC-eligible applicants receive large and above-average wage treatment effects from more-selective enrollment, the paper concludes with evidence that the model-based prediction of each student's meritocratic standing is weakly and *negatively* correlated with their estimated return to university selectivity.

I begin below by providing background on the ten-campus University of California and its 2001 Eligibility in the Local Context policy. I then describe the novel dataset used in this study, which includes far greater detail on 2001-2013 freshman UC applicants' socioeconomic, geographic, and academic characteristics than any previously studied records. Each applicant is linked to the internally-calculated "ELC GPA" used to determine their ELC eligibility as well as National Student Clearinghouse enrollment and degree records and annual California Employment Development Department wage records through 2019.[4]

I next introduce the stacked regression discontinuity research design that I employ to study the reduced-form effects of ELC eligibility on applicant behavior and outcomes. I present evidence to support the design's key identification assumption that applicants' potential outcomes are smooth across their high schools' ELC GPA eligibility thresholds. I then show that ELC eligibility did not substantially affect admissions decisions at UC's most- and least-selective campuses, the former because they did not provide admissions advantages to eligible students and the latter because they were already admitting nearly all high-GPA applicants. However, the UC campuses at San Diego, Davis, Irvine, and Santa Barbara all provided large admissions advantages to ELC-eligible applicants: barely-eligible applicants from the bottom half of California high schools (ranked by SAT scores) became 10 to 35 percentage points more likely to be admitted to each campus as a result of their ELC eligibility. Over 12 percent of those applicants switched into enrolling at one of the four "Absorbing" UC campuses instead of enrolling at a teaching-oriented California State University, a less-selective UC campus, or a local community college.

Because top graduates from more-competitive high schools had little need for ELC eligibility to gain UC admission, almost 90 percent of those barely-eligible ELC participants were from the bottom half of California high schools by SAT. Two-thirds of participants came from families with below-median household incomes and about 45 percent were URM. Barely-eligible participants' average SAT scores were at the 12^{th} percentile of their Absorbing UC peers, altogether suggesting a negatively selected group of students.

Next, I turn to estimation of how ELC eligibility impacted near-threshold ELC participants' educational and labor market outcomes. I show that ELC eligibility caused substantial reduced-form increases in five-year degree attainment, seven-year graduate school enrollment, and early-career annual wages. ELC-eligible applicants became somewhat less likely to earn degrees in STEM fields, but they became more likely to earn any college degree while simultaneously spending fewer years enrolled in college (as a result of reductions in time-to-degree). To identify each of the four Absorbing UC campuses' treatment effects experienced by near-threshold ELC participants, I construct four instrumental variables by interacting the regression discontinuity design with applicants' distance to each campus. I find that enrolling at any of the Absorbing UC campuses increased five-year degree attainment by 30 to 34 percentage points and graduate school enrollment by 22 to 47 percentage points. The estimated effects on wages are noisier: enrolling at UC Davis increased near-threshold participants' annual early-career wages by about $25,000, but the positive wage effects at the other campuses are imprecisely estimated. Near-threshold ELC participants from the bottom quartile of high schools (who would have otherwise enrolled at institutions with 35 percent lower graduation rates on average) received benefits at least as large as those received by participants with better counterfactual enrollments, suggesting large returns to more-selective enrollment even for very disadvantaged applicants.

Having shown that more-selective university enrollment substantially benefits the low-testing students on the margin of ELC eligibility, I next turn to general equilibrium estimation of top percent policies' net effects on universities' student composition and average returns. I embed a top percent policy into a structural model of applicant and university decision-making adapted from Kapor (2020). The model flexibly characterizes students' preferences over universities and models university admissions as maximizing the observed and latent academic caliber of their student bodies. I estimate the model parameters by simulated maximum likelihood, separately identifying admission and enrollment preferences by exploiting the ELC policy, its post-2011 cessation, and distance-to-campus instruments. The resulting parameters align with prior research and successfully replicate the reduced-form effects of ELC eligibility.

I employ the model to conduct a series of counterfactual exercises. I first simulate how ELC shifts Absorbing UC campuses' enrollment composition by switching ELC's admission advantages off (on) in 2010-2011 (2012-2013), allowing each university's regular admissions threshold to adjust in order to maintain its level of enrollment. This allows me to identify the students who are crowded out by ELC, a group otherwise inaccessible in my regression discontinuity analysis. Both strategies provide highly similar results: the 600 annual ELC participants had lower average family incomes by $20,000 and were 15 percentage points more likely to be URM than their crowded-out peers. I also simulate the effect of providing ELC's admissions advantages to the top one, two, and up to the top nine percent of applicants from each California high school. The simulations show that top percent policies are indeed "access-oriented": the nine percent policy increases *net* lower-income and URM enrollment at Absorbing UC campuses each by about 350 students, despite the crowded-out students being negatively-selected relative to the average Absorbing UC student.

Finally, I further exploit the structural model to investigate the broader relationship between students' meritocratic standing and their estimated return to more-selective university enrollment. Abstracting from the ELC policy, I employ a selection-on-unobservables strategy (partially following Dale and Krueger (2002)) to show that the applicants' latent "application merit" — or the preference index used by universities in admissions — is strongly correlated with applicants' future educational and employment success, but not with their estimated return to university selectivity. If anything, the average return to selectivity is *lower* for higher-"merit" applicants. These estimates complement the reduced-form evidence that the return to university selectivity scales similarly for ELC participants with stronger or weaker measured academic preparation. They also complement additional evidence showing that the wage return to near-threshold ELC participants' Absorbing UC campus enrollment equals or exceeds the *average* return to enrolling at those universities, estimating institutions' average "value-added" following Chetty et al. (2020). These findings suggest that the first-order net effect of top percent policies is to reallocate educational resources to high-GPA (and perhaps high non-cognitive skill) disadvantaged applicants without efficiency loss.

This study makes three primary contributions. First, it provides the first estimates of the medium-run impact of selective university admission under an access-oriented admission policy.[5] Expanding prior research that focused on the return to selective enrollment for students on the margin of universities' test-based admissions thresholds (Hoekstra, 2009; Anelli, 2019; Sekhri, 2020), I find that a broad array of students would earn large medium-run returns from selective university access, including many students who currently enroll at states' least-selective postsecondary institutions.[6] This evidence suggests that broadening selective research university access to many high school graduates with low socioeconomic status, as through low-cost access-oriented admission policies, is an impactful and potentially efficient economic mobility lever available to university administrators and state policymakers. While this has been suggested in observational and macroeconomic models (e.g. Chetty et al., 2020; Capelle, 2019) and is assumed by studies focused on encouraging disadvantaged students' more-selective enrollment (e.g. Hoxby and Turner, 2013), it remains contentious in the literature on affirmative action (Arcidiacono, Aucejo, and Hotz, 2016; Bleemer, 2020).

Second, this study provides evidence on the impact of a college admission policy that admits students without regard to their standardized test scores (Black, Cortes, and Lincove, 2016). Since at least 1960, when California enshrined standardized tests in its "Master Plan for Higher Education" to identify "applicants whose educational purposes are properly met by the college and whose abilities and training indicate probable success," public universities have used evidence of tests' "predictive validity" for college grades and retention to justify their rejection of lower-testing applicants (Westrick et al., 2019; Rothstein, 2004). I show that the benefits to more-selective enrollment are at least as large (and likely larger) for high-GPA students whose low SAT scores would typically have disqualified them from selective universities as they are for the higher-SAT students currently admitted to those universities. Indeed, despite being negatively-selected, near-threshold ELC participants' 75 percent average graduation rate was roughly equal to the institutional average (77 percent). As many public universities rethink how their meritocratic admissions policies rank applicants (Saboe and Terrizzi, 2019), these findings show that targeting high-GPA low-SAT applicants could simultaneously broaden university access and increase institutions' economic value-added.

Finally, this study contributes to a nascent structural literature modeling students' school application and enrollment decisions (Arcidiacono, 2005; Epple, Romano, and Sieg, 2006; Howell, 2010; Chade, Lewis, and Smith, 2014; Walters, 2018; Kapor, 2020), providing new detailed information about student and university preferences. The estimated model also provides novel estimates of the relative magnitude and compositional effects of top percent policies with different eligibility thresholds, facilitating straightforward comparison with other access-oriented university admissions policies (Long, 2004).

2 Background and Literature

California has three public higher education systems: the University of California, the teaching-oriented California State University, and the two-year California Community Colleges. The University of California is tasked with educating the top 12.5 percent of California high school graduates at its nine undergraduate campuses: the most-selective Berkeley and Los Angeles (UCLA) campuses, the middle-selective Davis, San Diego, Santa Barbara, and Irvine campuses, and the least-selective Riverside, Santa Cruz, and Merced (founded in 2005) campuses. The system's California-resident freshman enrollment grows in proportion to the state's high school graduates, with about 30,000 such students earning degrees in 2011.

UC employed race-based affirmative action in undergraduate admissions until 1997, after which the practice was banned by ballot proposition. Eligibility in the Local Context was introduced in 2001 to expand access to UC campuses in a race-neutral manner (Atkinson and Pelfrey, 2004). Under ELC, graduates of participating California high schools — which by 2003 included 96 percent of public high schools and 80 percent of private high schools — were guaranteed admission to at least one UC campus if their grades were in the top four percent of their class.[7] Class rank was determined centrally by UC: high schools submitted students' transcripts to the UC Office of the President, which calculated UC-specific "ELC grade point averages (GPAs)" on a four-point scale using certain eligibility-relevant second- and third-year courses.[8] ELC GPAs were weighted — adding one GPA point for each junior-year honors-level course — and rounded to the nearest hundredth. The 96th percentile of ELC GPAs at each high school was selected as the school's "ELC eligibility threshold" in that year, above which students were deemed "ELC-eligible."

ELC-eligible students received a letter in the fall of their senior year informing them of their eligibility, along with the guarantee of admission to at least one UC campus (but no guarantee to any specific campus). Below-threshold students with high GPAs were sent similar letters strongly suggesting that they would be guaranteed admission to at least one UC campus under another UC admissions policy.[9] In order to maintain eligibility, ELC-eligible students had to pass their high school's college-level senior curriculum and take the SAT. Administratively, each UC campus was informed of their applicants' ELC eligibility but retained independence in their admissions decisions.

There was widespread public concern that ELC participants might not be sufficiently prepared for selective university education: "top students in many high-poverty schools are woefully unprepared for college ... many of the new students will simply flunk out and the policy will be discredited" (Orfield, 1998). Nevertheless, though no comprehensive analysis was conducted following an inconclusive short-run program evaluation in 2002 (University of California, 2002), ELC was viewed as having succeeded in fulfilling its aims of increasing admitted students' ethnic and geographic diversity and was expanded in the 2012 admissions year to the top nine percent of each high school class. However, every campus ceased providing substantial admissions advantages to ELC-eligible applicants after this "expansion," forcing the system to coerce UC Merced to admit otherwise-rejected ELC-eligible students and rendering the program practically defunct (see Appendix A). As a result, this study focuses on the pre-2012 ELC policy.[10]

A large literature has examined how access to more-selective universities impacts students' educational and labor market outcomes.[11] Several studies have used quasi-experimental research designs exploiting minimum SAT and GPA admissions thresholds to show that university access increases on-the-margin enrollees' wages at less-selective universities (Zimmerman, 2014; Smith, Goodman, and Hurwitz, 2020), for white men at a more-selective university (Hoekstra, 2009), and for all students at certain selective universities outside the U.S. (Anelli, 2019; Sekhri, 2020), though none of these studies explicitly observe applicants' counterfactual enrollment institutions.[12] Several other studies employ selection-on-observables research designs to control for sample selection bias arising from applicants' varying admission and taste; while Dale and Krueger (2002) find no wage return to university selectivity among a set of highly-selective universities, most studies find that more-selective enrollment conditionally correlates with higher post-graduate wages (Loury and Garman, 1995; Kane, 1998; Brewer, Eide, and Ehrenberg, 1999; Andrews, Li, and Lovenheim, 2016), at least among disadvantaged students (Dale and Krueger, 2014).[13] In the closest context to this study, Cohodes and Goodman (2014) examine a Massachusetts financial aid policy that incentivized students to enroll at less-selective universities, using a regression discontinuity design to find reduced-form declines in institutional graduation rate and students' own four-year degree attainment of 1.5 and 1.9 percentage points, respectively. The present study contributes by employing a rigorous quasi-experimental research design to estimate the medium-run return to more-selective university enrollment for notably disadvantaged applicants, and by explicitly analyzing heterogeneity in the return to more-selective enrollment for students with higher and lower traditional meritocratic rank.

A second literature has studied the effects of race-based affirmative action — another popular access-oriented admission policy — on admission, enrollment, and short-run educational outcomes. Affirmative action causes targeted disadvantaged students to enroll at more-selective institutions in the U.S. (Arcidiacono, 2005; Howell, 2010; Hinrichs, 2012, 2014; Backes, 2012; Antonovics and Backes, 2014; Blume and Long, 2014).[14] However, differences in setting, research design, and data availability have led researchers to conflicting conclusions about affirmative action's impact on degree attainment (Cortes, 2010; Arcidiacono et al., 2014; Bleemer, 2020) and major choice (Rose, 2005; Arcidiacono, Aucejo, and Spenner, 2012; Arcidiacono, Aucejo, and Hotz, 2016; Bleemer, 2020). Closest to the present study, Bleemer (2020) shows that ending race-based affirmative action in California led to decreases in selective university enrollment among targeted applicants, precipitating declines in undergraduate and graduate degree attainment and early-career wages.[15] This study uses a quasi-experimental and transparent identification strategy to clearly delineate the specific and heterogeneous effects of more-selective university enrollment for disadvantaged applicants.

As a result of political and judicial challenges to race-based affirmative action, top percent policies have become increasingly popular among public university systems: 31 percent of Americans live in states that have adopted top percent policies at their public universities. Nevertheless, surprisingly little research has examined their effect on impacted students' outcomes. In California, this likely results from the widespread belief — despite minimal evidence — that Eligibility in the Local Context had a negligible effect on eligible students' enrollment decisions, expressed in academic studies (Rothstein, 2000; Long, 2004, 2007) and policy-oriented briefs and books (UCOP, 2003; Kidder and Gandara, 2015; Zwick, 2017).

A larger literature has studied Texas Top Ten (TTT), a top percent policy that guarantees Texas public university admission to students in the top ten percent of their high school classes by GPA (as determined by the schools). That literature has largely focused on estimating whether TTT's admissions guarantee actually changes high school graduates' university enrollment (Long, Saenz, and Tienda, 2010; Niu and Tienda, 2010; Kapor, 2020); this study contributes by simulating how counterfactual top percent policies with different eligibility thresholds would affect universities' student compositions.[16] Difference-in-difference analysis of TTT's effects on student outcomes are confounded by the state's near-simultaneous cessation of race-based affirmative action, likely explaining Black, Denning, and Rothstein (2020)'s findings that TTT appears to largely increase college-going on the *extensive* margin (switching non-college-goers into selective university enrollment) and that TTT participants do not appear more disadvantaged than the students they replace at selective universities. The present study complements Black, Denning, and Rothstein (2020)'s findings on top percent policies' effects on degree attainment and wages by employing a more textured research design to show that top percent policies generate large returns for relatively disadvantaged participants by increasing the selectivity of their enrollment institutions, and by exploiting those selectivity changes to investigate students' relative returns to more-selective enrollment.[17]

Another literature has studied a wide variety of application-oriented policies like direct information provision (Hoxby and Turner, 2013; Gurantz et al., forthcoming), improved college counselors (Avery, 2013; Castleman and Goodman, 2017), and changes in testing policies (Pallais, 2015; Goodman, 2016) that could increase disadvantaged students' selective university enrollment by increasing disadvantaged students' likelihood of applying to selective universities. I show that low-cost changes in university admission policies provide an alternative policy mechanism that increases disadvantaged student enrollment.

Finally, this study's analysis of heterogeneity in the return to university selectivity contributes to a literature analyzing the role of 'mismatch' in university enrollment, or the theory that "those who attend the most selective colleges and perform less well because of mismatching would have had higher earnings if they had attended the somewhat less selective group of schools" (Loury and Garman, 1993). Recent studies have come to conflicting conclusions about the relative magnitude of "mismatch" effects (Dillon and Smith, 2020; Mountjoy and Hickman, 2020; Bleemer, 2020). The present study provides an unusually transparent research design with which to investigate the relevance of mismatch in the California context of the measurably "mismatched" low-testing (but high-GPA) applicants targeted by top percent policies.

3 Data

I compile three primary data sources to conduct this study. The first, collected contemporaneously for administrative use by the UC Office of the President, covers all 1995-2013 California-resident freshman applicants to any of the nine undergraduate University of California campuses. Each record contains the applicant's home address at the time of application, high school attended, gender, 15-category ethnicity, parental education, SAT or ACT score, and family income, as well as whether they applied to, were admitted to, and/or enrolled at each campus and their intended majors.[18] The UC application data also include ELC eligibility status and ELC GPAs beginning in 2003. After 2011, an additional field denotes students' GPA percentile for each of the top nine percentiles.

I do not directly observe the high-school-specific ELC eligibility thresholds used to determine students' ELC eligibility. I estimate the threshold in each high school year in two ways: as the minimum GPA of an ELC-eligible applicant, or as the threshold that minimizes the number of applicants whose ELC eligibility is misclassified above or below the threshold.[19] In most cases these two are identical, but a small number of noisy ELC eligibility indicators (which could arise from failure to complete the requisite high school courses, faulty data, or other sources) lead to differences at some schools. I use the latter calculation in the main results presented below, yielding minimized Type 1 and 2 errors of 1.3 percent and 2.8 percent respectively, but the presented results are robust to employing the former calculation instead (as shown in appendix tables).

The second dataset, from the National Student Clearinghouse's StudentTracker database, contains UC applicants' enrollment and graduation records across nearly all U.S. two- and four-year colleges and universities.[20] NSC records are censored by a small number of students and institutions, but their near-completeness throughout the study period means that it is highly unlikely that differential NSC reporting could be a substantial factor driving the results presented below.[21] Science, Technology, Engineering, and Mathematics (STEM) majors are categorized by CIP code following the U.S. Department of Homeland Security (2016).[22]

Third, I observe UC applicants' quarterly 2003-2019 wages from the California Employment Development Department, which maintains employment records for unemployment insurance administration.[23] The wage data were linked by reported social security numbers from UC applications and are unavailable for workers outside California, self-employment, and federal employment.[24] Annual wages are measured as the sum of quarterly wages in that year and are CPI-adjusted to 2019 and winsorized at five percent. About 55 percent of applicants in the sample have positive wages in each of seven to nine years after high school graduation.

Each institution in the NSC dataset is geolocated using IPEDS, and distances between applicants and institutions are calculated (as the crow flies) using the geodesic method. California high schools are geolocated using street addresses available from the California Department of Education (with 98 percent success across students) and categorized as rural, urban, or suburban using shapefiles from the National Center for Education Statistics.[25] Additional institutional characteristics are linked from the Integrated Postsecondary Education Data System (IPEDS) and *Opportunity Insights*'s Mobility Report Cards (Chetty et al., 2020).

Table 1 reports summary statistics for 2003-2011 UC applicants.[26] The first column presents demographic characteristics, academic achievement measures, and enrollment decisions for all California-resident freshman applicants to any UC campus between 2003 and 2011, while the second summarizes applicants within 0.3 ELC GPA points of their high schools' ELC eligibility thresholds, the main sample used in the reduced-form analysis below. The latter applicants are academically above average, more likely to be female, and less likely to be Black or Hispanic.[27] The bottom half of the table shows that these applicants are relatively more likely to attend the more-selective "Unimpacted" and "Absorbing" UC campuses — these category names will be discussed below — but less likely to attend the less-selective "Dispersing" UC campuses.

The last four columns of Table 1 show summary statistics by high school quartile, ranking schools by the average SAT scores of near-threshold UC applicants.[28] Because the ELC program admitted four percent of every high school's applicants, there is reason to expect that its impact will be larger at lower-performing high schools where high-GPA students have fewer or lower-quality alternative enrollment options.[29] Indeed, applicants from the bottom quartile of high schools have lower SAT scores by 570 points and are far more likely to attend less-selective state colleges than applicants from the top quartile. Lower-quartile applicants are also much more likely to be Black and Hispanic (URM). Below, I refer to applicants from the bottom half and quartile of California high schools as the "B50" and "B25" samples, respectively.

4 ELC and College Enrollment

4.1 Empirical Methodology

I estimate the reduced-form effect of ELC eligibility on university enrollment using a regression discontinuity design (Hahn, Todd, and van der Klaauw, 2001). Let $Y_i(1)$ and $Y_i(0)$ denote applicant *i*'s potential outcomes if they are ELC-eligible or ineligible, respectively. The effect of ELC eligibility on near-threshold applicants is:

$$LATE_{RD}(Y) = \lim_{GPA \downarrow 0} E[Y_i(1)|GPA] - \lim_{GPA \uparrow 0} E[Y_i(0)|GPA] \tag{1}$$

where *GPA* is the difference between an applicant's ELC GPA and their school's ELC eligibility threshold. I estimate $LATE_{RD}(Y)$ by $\hat{\beta}$ from a linear regression model:

$$Y_{it} = \beta ELC_i + f(GPA_i) + \delta X_i + \alpha_{h_i} + \gamma_t + \epsilon_{it} \tag{2}$$

where ELC_i indicates ELC eligibility, X_i includes gender-ethnicity indicators and a quadratic in SAT scores to absorb spurious variation in Y_{it}, and α_{h_i} and γ_t are high school and application year (t) fixed effects.[30] I estimate Equation 2 stacked across all participating high schools with the error terms ϵ_{it} clustered by $h_i \times t$, the level of treatment assignment.[31]

I estimate Equation 2 using two specifications of f. Because the running variable GPA_i is discrete — ELC GPAs are rounded to the nearest hundredth — my preferred specification is to include third-order polynomials of GPA_i on either side of the eligibility threshold and to estimate the model by OLS. I obtain highly statistically and substantially similar estimates by local linear regression with bias-corrected clustered standard errors following Calonico, Cattaneo, and Titiunik (2014).[32] In both cases, I restrict the sample

Table 1: Descriptive Statistics of 2003-2011 UC Applicants

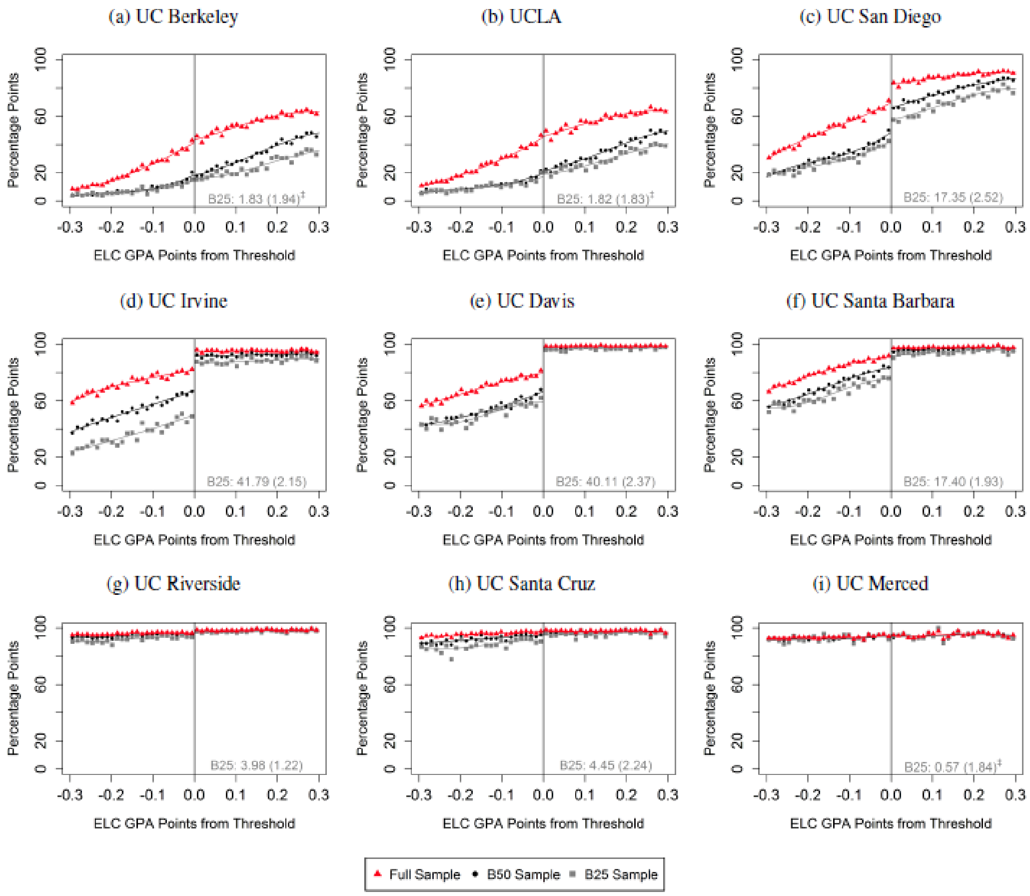
	CA Freshman Applicants	Near ELC Threshold	By SAT Quartile of High School[1]			
			Bottom	Second	Third	Top
% Female	52.5	61.0	64.4	61.8	59.6	58.2
% White	31.9	35.7	13.0	38.1	48.8	43.0
% Asian	31.9	33.0	25.4	34.2	31.7	40.9
% Hispanic	24.2	21.0	50.5	18.2	9.9	5.6
% Black	5.2	3.2	6.9	3.1	1.6	1.0
SAT Score	1706	1843	1533	1787	1941	2104
HS GPA	3.67	4.03	3.81	4.01	4.11	4.19
Parent Income (Median)	60,000	68,700	34,000	70,000	95,000	118,300
% Missing Inc.	11.9	20.9	7.2	16.6	24.2	35.5
Enrollment Rates (%)						
Unimpacted UC	11.2	22.9	12.5	17.2	26.2	35.8
UCLA	5.6	11.0	7.2	8.3	12.8	15.6
Berkeley	5.6	11.9	5.3	8.9	13.4	20.1
Absorbing UC	21.4	29.1	31.7	37.3	30.6	16.8
San Diego	5.0	8.2	6.7	10.3	9.4	6.5
Santa Barbara	5.1	6.6	8.2	7.9	6.9	3.4
Irvine	5.5	6.9	8.2	9.1	7.0	3.1
Davis	5.8	7.4	8.6	10.0	7.2	3.7
Dispersing UC	9.6	5.2	10.9	6.0	3.1	0.8
Santa Cruz	4.0	2.0	2.5	2.7	2.1	0.7
Riverside	4.6	2.6	6.7	2.7	0.8	0.1
Merced	1.0	0.6	1.6	0.6	0.2	0.0
CSU	15.7	11.5	19.7	13.8	9.1	3.2
Community Coll.	7.9	3.9	7.5	5.0	2.5	0.8
CA Private Univ.	7.4	9.7	5.6	8.5	11.4	13.1
Non-CA Univ.	9.7	10.6	3.4	6.7	11.1	21.1
No NSC Enrollment	17.1	7.2	8.6	5.6	6.0	8.5
N	1,751,719	171,441	42,904	42,821	42,900	42,808

Note: Characteristics of 2003-2011 CA-resident freshman UC applicants overall and within 0.3 ELC GPA points of their high schools' ELC eligibility threshold ('Near'). SAT scores out of 2400; converted from ACT or 1600-point SAT if otherwise unavailable. Income is "Missing" when applicant does not report it on their UC application. Enrollment is measured in the fall semester following high school graduation; categories partition all applicants. [1]Applicant-weighted school-year quartiles by the SAT scores of applicants within 0.3 GPA points of their school's ELC eligibility threshold; statistics restricted to near-threshold applicants. Source: UC Corporate Student System and National Student Clearinghouse

to freshman fall California-resident UC applicants within 0.3 GPA points of the eligibility threshold, resulting in the main sample of 171,411 applicants. Because the ELC eligibility threshold is slightly fuzzy, the baseline estimates instrument ELC_i with an indicator for having an above-threshold ELC GPA ($1_{GPA_i \geq 0}$).

The key identifying assumption justifying the regression discontinuity design is that $E[Y_i(1)|GPA]$ and $E[Y_i(0)|GPA]$ are smooth at $GPA = 0$. I discuss and test the potential threats to this smoothness assumption in detail in Appendix B. The primary threat to the smoothness assumption is the possibility of applicants' selection into UC application as a result of being informed of ELC eligibility (which occurred before UC's application deadline). However, as noted above, nearly all students just *below* the eligibility threshold also received letters encouraging UC application, and high-GPA students were very likely to be admitted to many UC campuses even without the ELC policy. Tests of the smoothness assumption fail to reject several of its implications. First, Appendix Table A-1 shows that a detailed set of applicant characteristics — including gender, ethnicity, parental income and education, and SAT score — are smooth across the threshold among all, B50, and B25 UC applicants. Figure A-1 visualizes this smoothness for applicants' predicted five-year degree attainment based on all observed socioeconomic and academic characteristics.[33] Second, there is no evidence of an increase in applicant density above the eligibility threshold that would suggest that above-threshold students bunched into UC application. Third, I successfully replicate the baseline regression discontinuity

Figure 1: Local Effect of ELC Eligibility on Applicants' Likelihood of Admission to each UC Campus



Note: Applicants' likelihood of admission to each UC campus by ELC GPA distance from their high school's ELC eligibility threshold, among all applicants and those from the bottom half (B50) or quartile (B25) of California high schools by SAT. Points are binned averages; lines are cubic fits. Beta estimates are from cubic regression discontinuity models following Equation 2 for the B25 sample, with standard errors in parentheses clustered by high-school-year. Each panel conditions on applying to that UC campus. Applicants from high schools with approximated ELC eligibility thresholds between 3.96 and 4.00 are omitted. ‡ indicates reduced-form estimates with $p > 0.1$ for the null hypothesis ($\hat{\beta} = 0$) when estimated using a local linear model with bias-corrected and cluster-robust confidence intervals following Calonico et al. (2019). Source: UC Corporate Student System.

estimates with a difference-in-difference design comparing above- and below-threshold students before and after 2011, when their admissions advantages ceased.

I also investigate another potential threat to the smoothness assumption: the possible presence of a student "type discontinuity" at ELC eligibility thresholds. If ELC eligibility thresholds tended to occur at exactly 4.0 GPA, then above-threshold students could be positively selected as a result of grades being censored from above. Appendix B provides evidence from Caetano (2015) tests suggesting that this threat is empirically small. I omit all schools with measured thresholds between 3.96 and 4.00 from the main specifications out of an abundance of caution, but the resulting estimates are substantively unchanged.

4.2 Admission and Enrollment

Figure 1 plots the likelihood of admission to each UC campus (conditional on applying to that campus) by the ELC GPA running variable, overall and applicants from the bottom half (B50) or quartile (B25) of high schools by SAT. Admission to UC's most-selective Berkeley and UCLA campuses appears unchanged on either side of the ELC eligibility threshold, implying that those two campuses provided no observable admissions advantage to ELC-eligible applicants. Four other campuses, however — San Diego, Irvine, Davis, and Santa Barbara — provided large admissions advantages to above-threshold students, with larger advantages for students from lower-testing high schools. Near-threshold B25 applicants became an average of 40 percentage points more likely to be admitted to UC Davis and UC Irvine as a result of ELC eligibility. The three least-selective UC campuses, on the other

Table 2: Local Effect of ELC Eligibility on First Enrollment Institution

	University of California Campuses Unimpacted	Absorbing	Dispersing	CSU	Comm. Coll.	CA Priv.	Non-CA	No Coll.
Panel A: Baseline Enrollment Likelihood (%)								
All	26.1	25.8	4.9	11.1	3.4	10.2	11.3	7.2
B50	14.0	32.9	9.0	18.8	6.4	7.1	5.1	6.6
B25	11.5	27.9	12.9	21.7	8.7	5.4	3.2	8.8
Panel B: Local Change in Enrollment Likelihood Caused by ELC Eligibility (p.p.)								
All	0.2	5.9	-1.7	-3.0	-0.8	-0.3	0.4	-0.7
	(0.7)	(0.8)	(0.4)	(0.5)	(0.3)	(0.5)	(0.5)	(0.4)
B50	1.0	12.2	-3.6	-6.0	-1.8	-0.4	-0.2	-1.1
	(0.9)	(1.3)	(0.7)	(1.0)	(0.6)	(0.7)	(0.6)	(0.7)‡
B25	1.2	15.6	-5.1	-7.3	-3.4	0.6	-0.3	-1.3
	(1.2)	(1.8)	(1.2)	(1.6)	(1.0)	(0.9)	(0.7)	(1.1)

Note: Reported coefficients are the estimated baseline (ELC-ineligible) proportion of near-threshold applicants who enroll at each group of institutions in the fall semester following UC application, and the estimated change in enrollment for barely above-threshold ELC-eligible applicants (β). Values in percentages; estimates overall and for students from the bottom half (B50) and quartile (B25) of high schools by SAT. Estimates from cubic regression discontinuity models following Equation 2; standard errors are clustered by school-year and omitted for baseline estimates (which are estimated following Abadie (2002)). ‡ Indicates estimates with $p < 0.1$ for the null hypothesis such that $p \not< 0.05$ (*insignificant* at conventional levels) when estimated using a local linear model with bias-corrected and cluster-robust confidence intervals following Calonico et al. (2019). Source: UC Corporate Student System and National Student Clearinghouse.

hand, were already granting admission to nearly all applicants just below the ELC eligibility threshold; ELC eligibility could hardly impact applicants' likelihood of admission at those schools.[34]

Table 2 presents estimates of ELC's effect on barely-eligible applicants' enrollment at UC and other postsecondary institutions.[35] Panel A shows near-threshold applicants' baseline likelihood of enrollment, while Panel B shows the $\hat{\beta}$ coefficients associated with ELC eligibility. At baseline, about 55 percent of near-threshold B50 students enrolled at a UC campus. Fourteen percent enrolled at Berkeley and UCLA, which are referred to as "Unimpacted" because admissions and net enrollment at those campuses were unchanged at the eligibility threshold. Another 33 percent enrolled at the four UC campuses that provided ELC-eligible applicants with large admissions advantages, termed "Absorbing" because net enrollment increased by 12.2 percentage points (40 percent) at the eligibility threshold. While nine percent of applicants enrolled at the three less-selective "Dispersing" UC campuses at baseline, their enrollment declined by 3.6 percentage points across the threshold as applicants switched into the more-selective Absorbing campuses.[36]

The remaining columns of Table 2 show that barely ELC-eligible B50 applicants' enrollment declined by 6.0 percentage points at the CSU system and by 1.8 percentage points at community colleges. There is no observable change in private or out-of-state university enrollment.[37] These estimates show that near-threshold ELC-eligible applicants became less likely to enroll at less-selective public colleges and universities and more likely to enroll at the Absorbing campuses. This shift in enrollment is larger among B25 applicants, whose Absorbing UC enrollment increased by 16 percentage points, and smaller across all applicants; there is no evidence of net enrollment changes for applicants from the third or fourth high school quartiles.

4.3 Characteristics of Compliers

Who are the near-threshold applicants who enroll at Absorbing UC campuses as a result of their ELC eligibility? Following Abadie (2002), the average fixed characteristic W_i of ELC near-threshold "compliers" can be estimated by $\frac{LATE_{RD}(Absorb_i \times W_i)}{LATE_{RD}(Absorb_i)}$, where $Absorb_i$ indicates enrolling at an Absorbing UC campus, under two technical assumptions:

Table 3: Characteristics of Near-Threshold ELC Compliers

Panel A: Student Characteristics	Female (%)	URM (%)	Rural High School (%)	SAT Score	HS GPA	Family Income[1] ($)	Below-Med. Fam. Inc.[1] (%)
All	68.3	43.9	8.1	1524	3.87	66,900	65.4
	(7.9)	(7.2)	(3.9)	(47.0)	(0.04)	(12,100)	(8.4)
Bottom Quartile	70.7	60.9	3.0	1396	3.76	45,900	78.9
	(7.0)	(7.0)	(3.5)	(31.0)	(0.03)	(5,700)	(6.0)
Second Quartile	59.0	10.3	20.76	1700	3.97	116,000	25.0
	(12.5)	(10.4)	(6.7)	(45.0)	(0.04)	(20,900)	(15.5)
Abs. Mean[2]	56.0	20.1	5.3	1796	3.80	87,300	49.8

Panel B: High School SAT Quartiles	Bottom Quartile	Second Quartile	Third Quartile	Top Quartile
All	57.5	31.0	2.1	9.3
	(7.6)	(7.0)	(7.4)	(5.1)
Abs. Mean[2]	20.0	22.2	24.6	33.2

Note: Reported coefficients are estimated characteristics of near-threshold ELC compliers, or the barely above-threshold students who enroll at Absorbing UC campuses as a result of their ELC eligibility. Estimates for characteristic W_i follow Equation 2, replacing the endogenous variable with an indicator for Absorbing UC enrollment ($Absorb_i$) and defining the outcome as $Absorb_i \times W_i$. Standard errors in parentheses are clustered by school-year. See the text for definition of high school quartiles. ACT scores and 1600-point SAT scores are converted to 2400-point SAT scores using contemporaneous standard formulas. Rural high schools defined following designation from the National Center for Education Statistics. Applicants from high schools with ELC eligibility thresholds between 3.96 and 4.00 are omitted. [1]Family income is missing if not reported on the UC application (12 percent of applicants). Median California household income defined at $76,000 in 2019 dollars; missing-income families are assumed to have above-median income. [2]The true average for freshman CA-resident students who first enrolled at an Absorbing UC campus between 2003 and 2011. Source: UC Corporate Student System and National Center for Education Statistics.

- Random assignment to ELC eligibility. This follows from the regression discontinuity setting.
- Monotonicity: $Absorb_i(1) - Absorb_i(0) \geq 0 \; \forall i \; s.t. \; |GPA_i| < \epsilon$, for some small bandwidth ϵ. This is justified by the admissions patterns shown in Figure 1.

I estimate ELC compliers' characteristics by replacing the endogenous variable in Equation 2 with $Absorb_i$. Table 3 presents $\hat{\beta}$ estimates for a series of characteristics, overall and by school subsample. The last line of each panel shows the mean characteristic of 2003-2011 California-resident freshman enrollees at the four Absorbing UC campuses, allowing comparison between ELC compliers and their eventual peers.

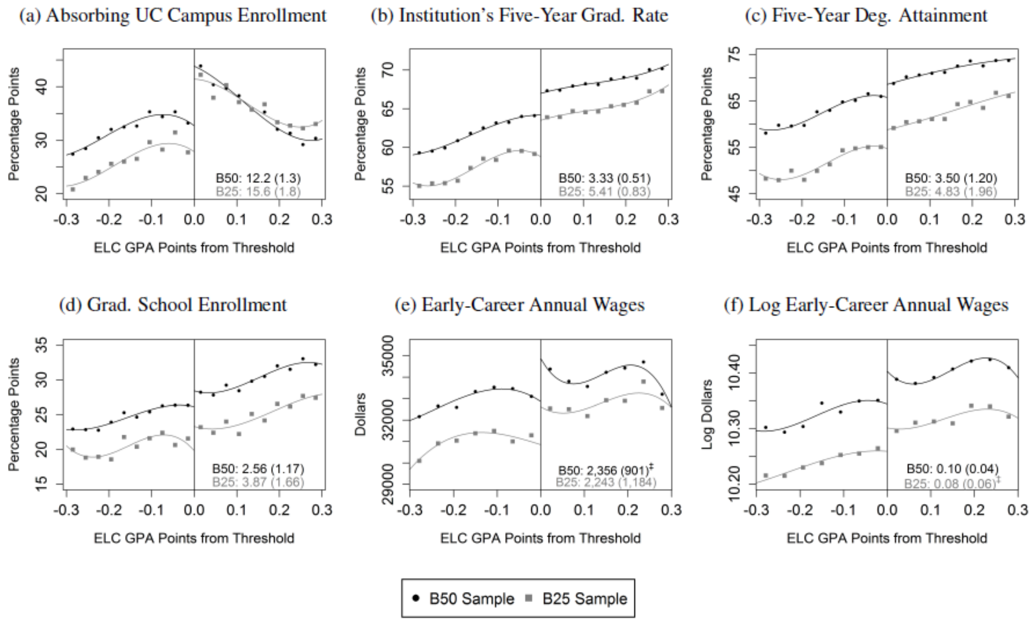
Panel B shows that 58 percent of compliers came from the bottom SAT quartile of high schools and almost 90 percent came from the bottom two SAT quartiles. This sharply contrasts with Absorbing UC campus student bodies, almost 60 percent of whom graduated from schools in the top two quartiles. Because so few near-threshold students from the top half of high schools participated in ELC, the analysis of student outcomes below exclusively focuses on students from the bottom two quartiles.

Panel A presents estimates of compliers' demographic and geographic characteristics. Compliers were more than twice as likely as their future peers to be underrepresented minorities (URM) and were 15 percentage points more likely to come from families with below-median incomes. ELC had less impact on the geographic diversity of UC's student body; about eight percent of compliers were from rural California relative to 5.3 percent of Absorbing campus students. ELC compliers had far lower SAT scores than their eventual peers, by almost 300 SAT points overall and by 400 points among bottom-quartile applicants. Bottom-quartile ELC compliers had average SAT scores at the fifth percentile of Absorbing campus students. However, as a result of the structure of the ELC program, compliers' average high school GPA was comparable to that of their Absorbing campus peers. Near-threshold ELC compliers are thus best understood as relatively disadvantaged students with far lower standardized test scores than their average Absorbing UC peers, though they were top performers at their less-competitive high schools prior to enrollment.

5 Education and Labor Market Outcomes

5.1 Reduced-Form Estimates

Figure 2: Local Effect of ELC Eligibility on UC Applicants' Education and Wage Outcomes



Note: Regression discontinuity plots of applicants' measured outcomes by ELC GPA distance from their high school's ELC eligibility threshold, among applicants from the bottom half (B50) or quartile (B25) of high schools by SAT. Points are binned averages; lines are cubic fits. Beta estimates are from cubic regression discontinuity models following Equation 2, with standard errors in parentheses clustered by high-school-year. Absorbing campus enrollment is measured in the fall semester following UC application. Institutions' graduation rates are defined for institution of first enrollment (within six years after graduating high school); see Appendix D for details. Graduate school enrollment is defined as enrollment at a four-year institution following Bachelor's attainment within seven years of graduating high school. Early-career wages are averaged over California covered wages 7 to 9 years after high school graduation; log wages omit zeroes, and wages are winsorized at 5 percent. Applicants from high schools with approximated ELC eligibility thresholds between 3.96 and 4.00 are omitted. ‡ indicates reduced-form estimates with $p > 0.1$ for the null hypothesis ($\hat{\beta} = 0$) when estimated using a local linear model with bias-corrected and cluster-robust confidence intervals following Calonico et al. (2019). Source: UC Corporate Student System, National Student Clearinghouse, and the California Employment Development Department (Bleemer, 2018).

ELC eligibility caused many barely-eligible UC applicants — from the bottom half (B50) or quartile (B25) of California high schools — to enroll at one of four Absorbing UC campuses instead of enrolling at less-selective public California colleges and universities. Panel (a) of Figure 2 visualizes the sharp increase in Absorbing UC campus enrollment for barely ELC-eligible B50 and B25 applicants.

Panel (b) of Figure 2 shows that above-threshold B50 (B25) students enrolled at institutions with higher graduation rates by 3.3 (5.4) percentage points, indexing institutions' selectivity using a novel five-year graduation rate defined over both two- and four-year institutions.[38] Appendix Table A-4 shows that these institutions are also more measurably selective across a host of alternative selectivity metrics. It also shows that the Absorbing UC campuses have higher sticker prices but similar estimated net prices for students with the family incomes of near-threshold applicants, though Absorbing UC campus enrollment may have increased those students' college costs by decreasing their likelihood of living at home through college.[39]

Panel (c) of Figure 2 shows a sharp increase in B50 and B25 applicants' own likelihood of undergraduate degree attainment within five years of graduating high school. The trends in Panels (b) and (c) appear to mirror each other fairly closely, with a similar flattening of applicants' institutional and own graduation rates just below the eligibility threshold — likely a feature of the college market unrelated to ELC — followed by sharp increases of three to five percentage points at the threshold. Panel (d) shows that applicants' likelihood of graduate school enrollment — defined as post-graduate university enrollment within seven years of high school graduation — also jumps at the eligibility threshold, which likely bodes well for applicants' long-run wages (Altonji and Zhong, 2020). Appendix Figure A-3 and Table A-10 show $\hat{\beta}$ estimates for additional reduced-form educational outcomes across the ELC eligibility threshold, presenting evidence that barely above-threshold students spend fewer years enrolled in undergraduate programs (despite their increased degree attainment) but may be less likely to earn a degree in a STEM field.

Panels (e) and (f) of Figure 2 show the average annual covered California wages and log wages earned by applicants between seven and nine years following high school graduation.[40] The plot shows reduced-form increases in annual wages of about \$2,300 (or 0.10 log points), with some variation in the statistical significance of the various estimates in the polynomial and local linear

Table 4: Instrumental Variable Estimates of the Effect of Absorbing UC Enrollment for ELC Participants

	Absorbing Campus IV	Campus-Specific IVs Davis	UCSD	UCSB	Irvine	F^1
Predicted Grad.[2]		-0.37 (0.52)	-0.38 (0.79)	0.65 (0.91)	-0.46 (0.66)	0.561
Institution's 5-Year Grad. Rate	26.78 (3.83)	24.1 (4.78)	34.3 (7.32)	33.8 (8.76)	24.0 (6.36)	0.235
Grad. Within 5 Years (%)	28.59 (9.92)	32.80 (11.42)	30.47 (17.56)	33.59 (22.19)	30.19 (15.13)	0.987
Earn STEM Degree (%)	-14.28 (8.81)	-7.64 (10.94)	-6.69 (17.27)	-45.63 (20.25)	-20.00 (14.31)	0.060
Enr. At Grad School within 7 Yrs. (%)	20.94 (9.78)	31.08 (11.84)	21.86 (18.11)	46.68 (22.23)	39.42 (15.67)	0.653
Num. Yrs. Pos. CA Wages[3]	0.47 (0.30)	0.33 (0.35)	0.19 (0.48)	-0.14 (1.01)	0.43 (0.45)	0.898
Avg. Early-Career Wages[3]	20,341 (8,199)	24,819 (10,581)	16,095 (13,836)	1,555 (28,973)	7,788 (12,635)	0.049
Avg. Early-Career Log Wages[3]	0.76 (0.33)	0.82 (0.30)	0.20 (0.48)	0.13 (0.64)	0.24 (0.32)	0.011
First Stage F	91.6	106.5	12.8	21.2	62.7	
Conditional F		67.9	53.5	48.2	62.8	

Note: Estimates of the effect of Absorbing UC campus enrollment on educational and labor market outcomes for near-threshold ELC-eligible students, following Equation 2 replacing the instrumented ELC_i variable with an indicator for Absorbing UC campus enrollment in the first column and following Equation 3 for campus-specific effects. Institutions' graduation rates are defined for institution of first enrollment (within six years after graduating high school); see Appendix D. Graduate school enrollment is defined as enrollment at a four-year institution following Bachelor's attainment within seven years of graduating high school. Log distance to Santa Barbara is set to 0 after 2010 to increase instrument strength; see Appendix Table A-6 for unadjusted estimates. Applicants from high schools with ELC eligibility thresholds between 3.96 and 4.00 are omitted. Conditional F statistic estimated following Sanderson and Windmeijer (2016). [1]F-test of the null hypothesis of equality among the four campus enrollment coefficients. [2]The predicted values from an OLS regression (across the full sample of 1995-2013 UC freshman California-resident applicants, excluding the study's primary sample) of five-year NSC graduation on gender by ethnicity indicators, maximum parental education indicators (7 categories), family income, missing income indicator, SAT score, HS GPA, and year indicators. [3]The number of years between 7 and 9 years after high school graduation in which the applicant has positive covered California wages, and the applicants' unconditional average annual wages and conditional average log wages in the period, winsorizing wages at 5 percent. Source: UC Corporate Student System, National Student Clearinghouse, and the California Employment Development Department (Bleemer, 2018).

specifications. Given that ELC only shifts students between California institutions and that there is no measurable change in applicants' number of years of California employment in either sample, it is unlikely that these estimates are explainable by the wage data's restriction to covered California employment.

5.2 Instrumental Variable Estimation

The admission and enrollment patterns discussed above imply that ELC eligibility could cause one of two changes in barely-eligible students' university enrollment: (1) it could lead students to enroll at an Absorbing UC campus instead of a less-selective public institution, or (2) it could lead students to enroll at an Absorbing UC campus instead of *another* Absorbing UC campus. As a result, the most natural instrumental variable strategy for measuring the effect of Absorbing UC campus enrollment — using ELC eligibility as an instrument for Absorbing UC enrollment following Equation 2 — could be biased by changes in student outcomes resulting from between-Absorbing-campus switches, which violate the strategy's monotonicity assumption. While I nevertheless report those estimates in Table 4, I also implement a more robust instrumental variable strategy that separately identifies ELC's treatment effect on the UC applicants who enrolled at each of the four Absorbing UC campuses because of ELC, constructing four instrumental variables by interacting the regression discontinuity design with distance-to-campus measures for each applicant (Card, 1993).[41] In particular, I estimate models of the form:

$$Y_{it} = \sum_{c\in Abs}\left(\beta_c \widehat{ENR}_{ic} + f_c(GPA_i) \times Dist_{ic}\right) + \delta X_i + \gamma_t + \epsilon_{it} \quad (3)$$

where $Dist_{ic}$ is the as-the-crow-flies distance from i's home address to the four UC campuses $c \in Abs$ and the four $\widehat{ENR}_{ic}$ enrollment indicators are instrumented by $\left(1_{GPA_i \geq 0} \times Dist_{ic}\right)$, the interaction between distance-to-campus and having an above-threshold ELC GPA.[42] I omit high school fixed effects because they absorb key geographic variation across applicants, and continue to cluster ε_{it} by school-year.

The second row in Table 4 shows that the ELC participants who enroll at each of the four Absorbing UC campuses experienced similar increases in the five-year graduation rates of their enrollment institution, between 24 and 34 percentage points ($p = 0.24$ from a *F*-test of the coefficients' equality), with an overall average increase of 27 percentage points. Because the four campuses all have highly similar measured graduation rates — ranging from Davis's 74.3 percent to San Diego's 79.4 percent — this implies that each campus's enrollees' counterfactual enrollment would have been strikingly similar, with mean graduation rates around 50 percent. Between 46 and 54 percent of enrollees would have otherwise enrolled at CSU campuses and 21 to 28 percent would have enrolled at community colleges, depending on the Absorbing UC campus, with the remainder coming from the Dispersing UC campuses.

The same is true for applicants' own likelihood of graduation, which uniformly increases by between 30 and 34 percentage points (*F*-stat $p = 0.99$). Though the Santa Barbara estimate is somewhat noisy, these coefficients' apparent equality suggests that the four campuses had highly similar attainment treatment effects for ELC participants, with the magnitude of the effect mirroring that of the change in institutional graduation rates. There is some evidence that Santa Barbara caused a relatively greater decline in ELC participants' likelihood of earning a STEM degree than the other UC campuses, but their treatment effects on graduate school enrollment are also similar across institutions.[43]

The bottom half of Table 4 shows campus-specific instrumental variable estimates of the effect of ELC participation on early-career labor market outcomes. There is no evidence that enrollment at any of the campuses changed the number of years in which ELC participants are employed in California, and there is some heterogeneity in the wage effects across Absorbing campuses: there is clear evidence that UC Davis increased its students' annual early-career wages by about \$25,000, but the estimated coefficients are positive but imprecise for the other three Absorbing campuses, ranging from \$2,000 to \$16,000.

In total, this evidence suggests that ELC participants were very substantially benefited by enrolling at Absorbing UC campuses instead of less-selective universities.[44] The next section further analyzes effect heterogeneity by comparing outcomes for students from more- or less-competitive California high schools.

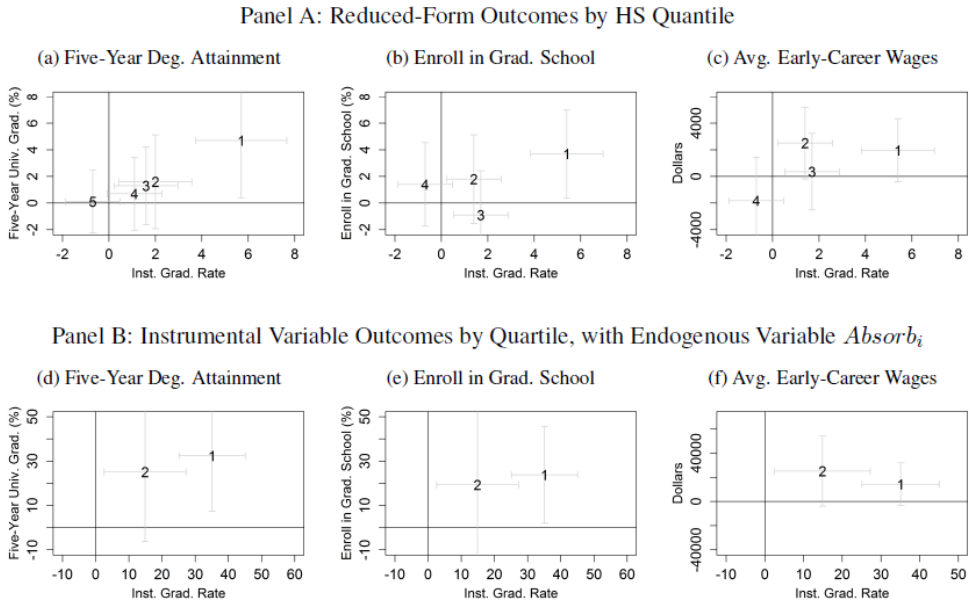
5.3 Outcome Heterogeneity by Applicant Characteristics

The efficiency of the ELC policy requires that ELC not only provide substantial benefits to targeted participants, but also that those benefits be comparable in magnitude (or larger than) the benefits that would have been derived from Absorbing UC campus enrollment by the "crowded-out" applicants who would have enrolled at those campuses absent the ELC policy. The next section turns to a structural model of university application, admissions, and enrollment in order to characterize those students and their return to more-selective enrollment. Before doing so, this section presents reduced-form evidence on how the return to Absorbing UC campus enrollment differs for different subgroups of near-threshold ELC participants.

Panel A of Figure 3 graphs reduced-form estimates of the impact of ELC eligibility on near-threshold applicants' university selectivity (measured by institutional graduation rate) and on three measured outcomes for applicants from different quantiles of California high school. The figures show that students from lower high school quantiles tended to experience larger increases in university selectivity across the eligibility threshold and also tended to face larger increases in educational and labor market outcomes in the following years. These figures reiterate that the ELC policy's benefits almost exclusively obtained for applicants from California's least-competitive high schools.

This pattern of increasing returns may just reflect the higher number of near-threshold ELC participants at less-competitive California high schools. In order to isolate the relative effects of ELC eligibility for different ELC participants, I restrict the sample to the bottom half of California high schools and re-estimate Equation 2 separately for each quartile, replacing the endogenous variable with an indicator for Absorbing UC campus enrollment ($Absorb_i$).[45] Panel B shows that second-quartile near-threshold ELC participants faced a smaller increase in university graduation rate (15 percentage points) than first-quartile participants (35 percentage points). Despite this tremendous institutional shift — the average bottom-quartile applicant switched from an average local comprehensive university (or above-average community college) into a top-ranked public research university — the return to Absorbing UC campus enrollment for those applicants was nearly as large or slightly larger than the return for the second-quartile students who switched, on average, from somewhat less-selective public universities. The standard errors on these estimates are quite large, challenging clean parameterization of the relationship between counterfactual enrollment and the return to university selectivity, but this evidence strongly suggests that the value of more-selective university enrollment remains large (and perhaps growing in institutional selectivity) even for students who would have enrolled at non-selective institutions absent the ELC policy. I will return to this relationship below in the context of the structural model.

Figure 3: Local Effect of ELC Eligibility on UC Applicants' Outcomes by High School Quantile



Note: Estimates of $\hat{\beta}$ from Equation 2 (Panel A) and replacing the endogenous variable with Absorbing UC campus enrollment (Panel B) by high school SAT quantile (where 1 indexes the lowest quantile). The x-axis plots estimates for enrollment institution's graduation rate; the y-axis plots five-year degree attainment, enrollment in graduate school within seven years of UC application, and average California covered wages 7-9 years after high school graduation, winsorizing wages at 5 percent. Confidence intervals are clustered by school-year and are estimated independently by axis. Panel B restricts the sample to the bottom two quartiles. Applicants from high schools with ELC eligibility thresholds between 3.96 and 4.00 are omitted. Source: UC Corporate Student System, National Student Clearinghouse, and the California Employment Development Department (Bleemer, 2018).

Appendix Table A-11 provides additional estimates of heterogeneity in the return to more-selective university enrollment under ELC, treating first enrollment institutions' graduation rates as an alternative endogenous variable in Equation 2 (a linear projection as in, e.g., Kling (2001)).[46] It shows that the returns to more-selective university enrollment appear statistically and substantively indistinguishable for URM and non-URM students and for male and female students, though many of the estimates have relatively large confidence intervals.

6 Structural Model of University Enrollment

More-selective university enrollment substantially benefits the low-testing high-GPA students targeted by ELC. However, while the reduced form analysis above showed that near-threshold ELC participants were lower-income and from less-competitive high schools than their Absorbing UC campus peers, its focus on partial equilibrium outcomes may ignore important general equilibrium effects like universities' dynamic admissions responses to ELC admissions advantages. As a result, the previous analysis cannot characterize compositional or outcome differences between the average "winners" or "losers" of the ELC policy — that is, the students who enrolled at Absorbing UC campuses as a result of ELC and those who were "crowded out" by ELC but otherwise would have enrolled at Absorbing UC campuses.[47] These characterizations — as well as characterizations of the "winners" and "losers" of counterfactual top percent policies with alternative eligibility thresholds — are central to the determination of top percent policies' efficiency, but require estimation of how the policies broadly shift applicants' and universities' decisions.

I analyze those decisions by constructing a three-period model of university applications, admissions, and enrollment adapted from Kapor (2020). First, California-resident high school seniors apply to a portfolio of universities (A_i), including at least one UC campus. Second, each university observes its applicant pool and determines which students to admit. Third, applicants observe which institutions have admitted them (B_i), as well as previously unobserved preference shocks, and choose where to enroll (C_i).

The model spans colleges $j \in 1, \ldots, J, CC, CSU$, where CC is the California community college system and CSU the California State University system. I assume that all students apply and are admitted to CC and CSU. Each college is characterized by

Figure 4: 2002 Admissions Protocol used by UC Davis

POINT RANGES & WEIGHTS FOR SELECTION CRITERIA

Criteria	Point range	Weight	Total possible score
HS GPA	2.8–4.0	1000	4000
5 Exams (SAT I/ACT & 3 SAT II)	200–800 each	1	4000
ELC (Eligibility in the Local Context)	0 or 1	1000	1000
Number of "a-f" courses beyond minimum	0–5	100	500
Individual Initiative	0 or 1	500	500
EOP (Educational Opportunity Program)	0 or 1	500	500
Pre-collegiate motivational program	0 or 1	500	500
First-generation university attendance	0 or 1	250	250
Non-traditional	0 or 1	250	250
Veteran/ROTC Scholarship	0 or 1	250	250
Significant Disability	0 or 1	250	250
Leadership	0 or 1	250	250
Special Talent	0 or 1	250	250
Perseverance	0 or 1	250	250
Marked improvement in 11th grade	0 or 1	250	250
TOTAL REVIEW			13,000

Note: This photograph shows an internal archival UC Davis admissions document visualizing Davis's 2002 freshman admissions protocol. Students were assigned points on the basis of applicant characteristics, and those with scores above a designated threshold were admitted to the campus. Source: Archives and Special Collections, UC Davis — Shields Library.

average quality δ_j, with δ_{CC} normalized to 0. The following subsections explain the model by proceeding backward, from enrollment to admission to application.

6.1 Student Preferences

After receiving admissions offers, student $i \in I$ chooses to enroll at her most-preferred university j. Her utility of enrolling at j is given by

$$U_{ij} = \delta_j + x_{ij}\beta_j^x + \nu_{ij} + \epsilon_{ij} \tag{4}$$

where x_{ij} are student characteristics, $\nu_{ij} \sim N\left(0, \sigma_{\nu_j}^2\right)$ are *i.i.d.* preference shocks always observed by students, and ϵ_{ij} is a previously unobserved idiosyncratic preference shock modeled by the Type I extreme value distribution (perhaps resulting from post-admission campus visits).[48] Student i enrolls at

$$C_i = \max_{j \in B_i} U_{ij}$$

after being admitted B_i. Following from the distribution of ϵ_{ij} (Train, 2003), i's expected utility from being admitted to B_i is given by

$$U_{iB} = \log\left(\sum\nolimits_{j \in B} exp\left(\delta_j + x_{ij}\beta_j^x + \nu_{ij}\right)\right)$$

and her conditional likelihood of enrolling at C after being admitted to B is

$$P(C_i = C|B) = \frac{\exp(\delta_C + x_{iC}\beta_C^x + \nu_{ic})}{\sum_{j \in B}\exp\left(\delta_j + x_{ij}\beta_j^x + \nu_{ij}\right)}$$

6.2 University Preferences

Selective universities prefer to enroll the highest-quality class of students, defining students' quality by

$$\pi_{ij} = z_i\beta_j^z + q_i + \mu_{ij}^{Admit} \tag{5}$$

where z_i is a vector of student characteristics, q_i is a caliber characteristic of student i unobserved by the student, and μ_{ij}^{Admit} is a normally-distributed error term capturing preference variation across application readers and other factors. Universities admit students $B(j)$ to maximize the quality of their enrollment class:

$$B(j) = \max_{B \subset A} \sum_{i \in B} E\left[1_{\{C_i = j\}} \pi_{ij}\right] = \max_{B \subset A} \sum_{i \in B} P(C_i = j | B_i) \pi_{ij} \quad s.t. \quad \sum_{i \in B} P(C_i = j | B_i) \leq k_j$$

where universities' expected enrollment is capped at k_j.[49] Kapor (2020) shows that, under technical assumptions limiting universities' strategic behavior, this results in each university choosing an admissions threshold $\underline{\pi}_j$ such that it admits all applicants with $\pi_{ij} \leq \underline{\pi}_j$.

Figure 4 presents an internal 2002 UC Davis admissions document explaining their admissions protocols. It shows how closely the presented model maps to the actual admissions practices of most UC campuses during the sample period: Davis assigned each applicant a score based on their characteristics, including a large boost for ELC eligibility, and then admitted all applicants with scores above a threshold determined on the basis of expected enrollment.

6.3 University Applications

When students choose which universities to apply to, they do not observe ϵ_{ij}, the post-admissions preference shock; μ_{ij}^{Admit}, universities' preference shocks over students; or q_i, a measure of students' own 'caliber' only observed by universities. Instead of directly observing q_i, students observe a signal of their caliber denoted s_i, which is jointly normally distributed with q_i (independently across applicants) by

$$\begin{pmatrix} q_i \\ s_i \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_q^2(w_i) & \\ \sigma_s^2(w_i) & \sigma_s^2(w_i) \end{pmatrix}\right)$$

where $\sigma_s^2(w_i)$ is the variance of students' signals, $\sigma_q^2(w_i)$ is the variance of students' actual q_i, and $w_i \subset z_i$are i's sociodemographic characteristics. As in Kapor (2020), the covariance between s_i and q_i is normalized (without loss of generality) to equal $\sigma_s^2(w_i)$ in order to decompose q_i into two interpretable components, one known by students (s_i) and the other unobserved. This allows the marginal distribution of $q_i|s_i$, the information known by students at the time of application, to be written as

$$q_i | s_i \sim N\left(s_i, \sigma_{q|s}^2(w_i)\right)$$

where $\sigma_{q|s}^2(w_i) = \sigma_q^2(w_i) - \sigma_s^2(w_i)$. These variances are parameterized as

$$\sigma_s^2 = \log(1 + exp(w_i \gamma^s))$$
$$\sigma_{q|s}^2 = \log\left(1 + exp\left(w_i \gamma^{q|s}\right)\right)$$

to constrain them to positive values.

Instead of interpreting q_i as a latent student 'ability' feature, it is best understood as an index of universities' preference for certain students that is unobserved by the econometrician and only partly observed by students. For example, students' applications might contain information — like athletics participation, extracurricular leadership positions, and essay-writing style — the value of which in university admissions is unknown to them. High-q_i students are those who submit unobserved application components that are valued in university admissions. Low-$\sigma_s^2(w_i)$ students are those with strong knowledge of the value of their unobserved application components.

Applicants expect benefits of applying to each university that are proportional to their likelihood of admission to the university and the utility of their being admitted to it, but face costs associated with applying to each additional university. As a result, their maximization problem can be stated as

$$\max_{A \subset J} V_i(A) = \left(\textstyle\sum_{B \subset A} P_i(B_i = B | A) U_{iB}\right) - |A| w_i \gamma^c \tag{6}$$

where $P_i(B_i = B|A)$ is i's perceived likelihood of admission to university set B given application set A and γ^c parameterizes i's cost of applying to $|A|$ universities. Following from the distribution of μ_{ij}^{Admit}, i's perceived probability of admission to B is

$$P_i(B_i = B|A) = \int \prod_{j \in B} \left(\Phi\left(z_i \beta_j^z + q_i - \underline{\pi}_j\right)\right) \prod_{j \in A \setminus B} \left(1 - \Phi\left(z_i \beta_j^z + q_i - \underline{\pi}_j\right)\right) \phi\left(q_i | s_i; \sigma_{q|s}^2\right) dq_i$$

6.4 Estimation

I define each of the covariate sets x_{ij}, z_i, and w_i to include a female gender indicator, three ethnicity indicators (Asian, URM, and other), and log family income.[50] Student preferences (x_{ij}) and university preferences (z_i) also include SAT score, high school

Table 5: Main Applicant and University Preference Model Parameters

	Applicant Preferences (β_j^x), Relative to CC					Univ. Pref. (β_j^z)
	Unimp. UC	UCSD/UCSB	UCD/UCI	Disp. UC	CSU	All UC
Log Inc.	0.15 (0.03)	0.26 (0.02)	0.19 (0.02)	0.06 (0.02)	0.20 (0.01)	-0.12 (0.004)
Female	-0.42 (0.06)	-0.03 (0.03)	0.02 (0.03)	0.00 (0.03)	0.11 (0.03)	0.10 (0.01)
Asian	0.93 (0.09)	-0.18 (0.05)	-0.31 (0.05)	0.02 (0.04)	-0.02 (0.03)	0.23 (0.01)
URM	2.55 (0.08)	1.00 (0.04)	1.82 (0.04)	0.28 (0.04)	-0.23 (0.03)	0.04 (0.01)
SAT	1.07 (0.05)	0.50 (0.02)	-0.11 (0.02)	-0.19 (0.02)	-0.18 (0.02)	0.53 (0.005)
HS GPA	-0.87 (0.07)	-0.81 (0.03)	-0.79 (0.03)	-1.02 (0.02)	0.27 (0.01)	1.15 (0.01)
CC VA	-0.01 (0.03)	-0.04 (0.02)	-0.02 (0.02)	-0.32 (0.02)	-0.13 (0.01)	-0.04 (0.003)
δ_j	4.97 (0.10)	2.18 (0.04)	2.13 (0.04)	-0.47 (0.04)	0.76 (0.03)	

Note: Parameter estimates from maximum simulated likelihood (maximized by the BFGS Quasi-Newton algorithm) of Equation 7. Parameters measure applicant preferences for each set of universities (see Equation 4) and universities' preferences for applicants (see Equation 5). Continuous variables are standardized in-sample. 'CC VA' is the estimated value-added of the nearest community college to applicants' home address, estimated following Chetty et al. (2020); see Appendix G.1 of Bleemer (2020). Reported standard errors from the inverse of the empirical Hessian matrix. Missing family incomes are imputed; see footnote 50. Sample restricted to 2010-2013 UC freshman California-resident applicants who enroll at a public California institution in the fall after high school graduation. Source: UC Corporate Student System and the National Student Clearinghouse.

GPA, and the estimated value-added of the closest community college as a measure of the quality of students' regional educational availability.[51] Universities' preferences over students also vary by a set of ELC covariates, including an ELC eligibility indicator, the ELC GPA running variable interacted with ELC eligibility (within a narrow bandwidth), and indicators for having a running variable above or below the bandwidth and for whether the ELC program is operative in that year. Finally, students' preferences also vary by a set of distance-to-university covariates — including the distance and squared distance between i's home and j as well as distance interacted with the covariates in w_i — which allow students to have heterogeneous preferences over enrolling at more-distant institutions. I assume that ELC covariates enter into university admissions decisions but not students' preferences over institutions, while (following a long literature) distance covariates enter into students' preferences but not university admissions decisions, each of which helps to separately identify student and university preferences. A Constant term is absorbed in the specifications of x_{ij} and z_i but is included in w_i.

I allow β_j^x to vary for each j for most covariates, but model the effects of distance and its interactions uniformly across universities. I allow separate β_j^z terms for each of the ELC covariates, but otherwise treat university preferences as uniform. All coefficients are deterministic. The socioeconomic covariates w_i enter into students' application costs (γ^c), the variance of their informational signal about their caliber (γ^s), and the variance of the gap between their signal and their true caliber ($\gamma^{q|s}$).

I estimate model parameters $\theta = \left\{\beta_j^x, \beta_j^z, \gamma^c, \gamma^s, \gamma^{q|s}, \delta_j, \sigma_{v_j}^2, \underline{\pi}_j\right\} \in \Theta \subset R^{99}$ by simulated maximum likelihood using the quasi-Newton method.[52] Following the reduced-form findings on the function of the ELC policy, I group UC campuses into four sets: two sets of Absorbing UC campuses (UCD/UCI and UCSD/UCSB, allowing their different ELC admissions advantage magnitudes), the Unimpacted campuses (UCB and UCLA), and the Dispersing campuses (UCSC, UCR, and UCM). Because enrollment at private and out-of-state universities is observably unchanged as a result of ELC, and because I do not observe application or enrollment to those institutions, I omit those institutions from the model and restrict the estimation sample to UC applicants who enroll at a public California institution. Students can apply to any combination of the four combined UC universities (with 15 possible combinations), and all students are also able to enroll at either community college or CSU (each modeled as a single institution).

Table 6: ELC and Admissions Model Parameters

	Unimpacted	UCSD/UCSB	UCD/UCI	Dispersing
ELC Eligibility	0.15 (0.06)	0.80 (0.08)	1.69 (0.08)	0.40 (0.17)
ELC GPA × Above	0.60 (0.87)	-0.53 (1.47)	0	0
ELC GPA × Below	1.39 (0.92)	0.79 (1.14)	1.09 (1.16)	-0.69 (2.83)
Above Bandwidth	0.23 (0.04)	-0.08 (0.07)	-0.47 (0.08)	-0.19 (0.17)
Below Bandwidth	-0.14 (0.04)	-0.28 (0.05)	-0.31 (0.05)	0.10 (0.13)
No ELC	-0.18 (0.04)	-0.28 (0.05)	-0.33 (0.05)	-0.51 (0.13)
$\underline{\pi}_j$	1.95 (0.04)	0.46 (0.05)	0.15 (0.05)	-1.63 (0.13)

Note: Parameter estimates from maximum simulated likelihood (maximized by the BFGS Quasi-Newton algorithm) of Equation 7. Parameters measure universities' preferences for applicants (see Equation 5) with regard to their ELC GPAs and eligibility. 'ELC GPA' running variable is set to zero outside a 0.08 GPA bandwidth from the eligibility threshold; 'above' and 'below' bandwidth indicates applicants with ELC GPAs outside that bandwidth above or below the threshold, with 'below bandwidth' including all applicant without ELC GPAs. 'No ELC' indicates students who applied to UC after 2011; all other ELC variables are 0 after 2011. The 'ELC GPA×Above' coefficients for UCD/UCI and Dispersing campuses are set to 0 since those schools admit nearly all above-threshold applicants. Reported standard errors from the inverse of the empirical Hessian matrix. Sample restricted to 2010-2013 UC freshman California-resident applicants who enroll at a public California institution in the fall after high school graduation. Source: UC Corporate Student System and the National Student Clearinghouse.

In order to compare admission and enrollment outcomes in the presence and absence of ELC, I restrict the sample to 2010-2013 UC applicants, the final two years of the ELC policy and the first two years of its absence (see Appendix A). It is useful to include non-ELC years both for parameter identification and because UC identified the within-school GPA centile (from first to ninth) of each applicant starting in 2012, permitting counterfactual analysis of alternative top percent thresholds. The resulting estimation sample includes 219,876 applicants.

6.5 Likelihood

For each student *i*, the likelihood of all observables in the data is:

$$l_i(\theta) = \int_s \int_{\nu_i} l_i^A(\theta, \nu_i, s) l_i^{B|A}(\theta, \nu_i) l_i^{C|B}(\theta, \nu_i) dF_i(s;\theta) dG_i(\nu_i;\theta) \tag{7}$$

where l_i^A is the likelihood of i applying to A_i, $l_i^{B|A}$ is her likelihood of being admitted to B_i if she applied to A_i, and $l_i^{C|B}$ is her likelihood of enrolling at C_i after being admitted to B_i. Following the structural assumptions described above, these terms take the following forms:

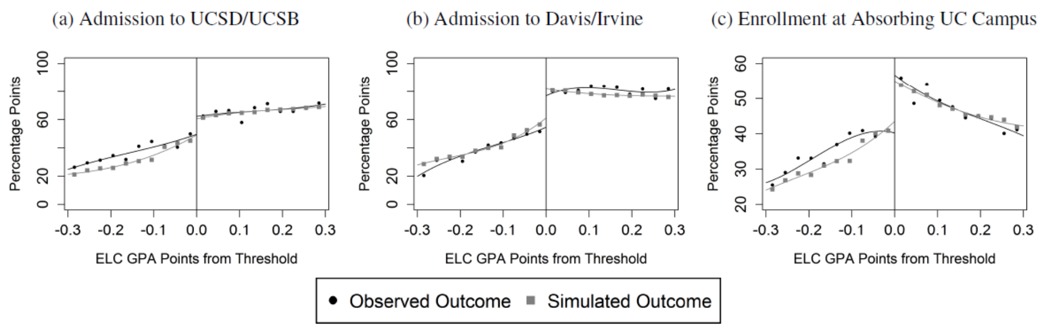
$$l_i^{C|B}(\theta, \nu_i) = \frac{\exp(\delta_C + x_{iC}\beta_C^x + \nu_{iC})}{\sum_{j\in B} \exp(\delta_j + x_{ij}\beta_j^x + \nu_{ij})}$$

$$l_i^{B|A}(\theta, s) = \int \prod_{j\in B} \left(\Phi(\mathrm{z_i}\beta_j^z + q_i - \underline{\pi}_j)\right) \prod_{j\in A\setminus B} \left(1 - \Phi(\mathrm{z_i}\beta_j^z + q_i - \underline{\pi}_j)\right) \phi(q_i | s_i; \sigma_{q|s}^2) dq_i$$

$$l_i^A(\theta, \nu_i, s) = \frac{\exp \frac{1}{\lambda} V_i(A)}{\sum_{A' \subset J} \exp \frac{1}{\lambda} V_i(A')}$$

where the smoothing parameter λ is set to 0.1 (see Train (2003)).

Figure 5: True and Simulated UC Admission and Enrollment for Near-Threshold B50 UC Applicants



Note: Binned scatterplots and third-order polynomial best-fit lines of 2010-2011 UC applicants' (black) unconditional admission or enrollment at each set of UC campuses and (gray) simulated likelihoods of unconditional admission or enrollment at each set of UC campuses using the estimated parameters from Equation 7, by their ELC GPA distance from their high schools' ELC eligibility threshold. Sample restricted to 2010-2011 UC freshman California-resident applicants who (1) enroll at a public California institution in the fall after high school graduation, (2) who have ELC GPAs within 0.3 of their high school's eligibility threshold, and (3) graduated from the bottom half (B50) of high schools by SAT. Source: UC Corporate Student System and the National Student Clearinghouse.

6.6 Estimated Parameters

Tables 5, 6, and A-14 present the model's estimated equilibrium parameters, with standard errors from the inverse of the empirical Hessian matrix. The β_j^x and δ_j parameters shown in Table 5 are scaled relative to students' preferences for community college; all continuous variables are standardized, so the baseline applicant is a white male with mean attributes. Higher-income students prefer against community college enrollment. While high-SAT applicants have strong preferences for UC's most-selective campuses, high-GPA low-SAT students show a preference for CSU enrollment. Applicants' average preferences align with the UC campuses' selectivity — applicants generally prefer to enroll at more-selective schools — though the average applicant prefers CSU or CC enrollment to enrollment at the Dispersing UC campuses.

The final column in Table 5 shows that universities strongly prefer applicants with higher GPAs and SAT scores. With applicants' socioeconomic characteristics proxying other unobserved application components, the UC campuses appear to slightly prefer lower-income, female, Asian, and URM applicants. All of the applicant and university preference parameters are estimated with high precision.

Table 6 shows how ELC is embedded into the estimated UC admissions model.[53] As in the reduced-form analysis, the Davis and Irvine campuses provided the largest admissions advantage to ELC-eligible students, followed by the San Diego and Santa Barbara campuses. The Dispersing and Unimpacted campuses are precisely estimated to have only provided very small admissions advantages to ELC-eligible students.

The final row of Table 6 shows the model estimates of campuses' admissions thresholds ($\underline{\pi}_j$). The thresholds align with campuses' actual selectivity during the period; the Unimpacted campuses have the highest admissions threshold, followed by UCSD/UCSB, then UCD/UCI, and finally the Dispersing campuses.[54]

Appendix Table A-14 reports the remaining model parameters. Applicants faced positive costs for each additional application, and applicants preferred to enroll at less-distant institutions (with smaller distance costs for higher-income applicants). Lower-income and URM students had substantially more-negative signals of their unobserved caliber q_i, and applicants generally had strong knowledge of their caliber. Finally, it shows that the magnitudes of students' taste shocks are relatively large across institutions ($\sigma_{\nu_j}^2$) between 1.5 and 4, with standard errors around 0.75), especially for the Unimpacted UC campuses.

6.7 Model Validation

The previous subsection showed that the model parameters match widely-held beliefs about the direction and relative magnitude of relationships between observed applicant characteristics and their preferences and admissions outcomes. I further validate the model by testing the success with which it replicates the effects of near-threshold ELC eligibility on applicants' admissions and enrollment outcomes. I restrict the sample to 2010-2011 applicants in the model sample and use the model to estimate each applicant's unconditional likelihood of admission and enrollment at each set of UC campuses. I then compare the binned averages of those likelihoods with the binned averages of those applicants' actual admissions and enrollment outcomes among near-threshold applicants.

Table 7: Simulated Counterfactual UC Enrollment with and without ELC Admissions

	Remove ELC, '10-11		Add ELC, '12-13			
	ELC Part.	Crowded Out	ELC Part.	Crowded Out		
Annual Enr.						
Absorbing UC	-549	549	717	-717		
Unimpacted UC	30	-30	77	-77		
Dispersing UC	98	-98	-124	124		
CSU	277	-254	-443	405		
CC	143	-166	-227	265	LATE Compliers	Absorbing UC Average
URM	44.1	27.2	46.9	32.8	43.9	20.1
Family Income	62,900	85,200	63,100	83,200	66,900	87,300
SAT	1625	1729	1627	1693	1524	1796
HS GPA	3.98	3.66	4.01	3.66	3.87	3.80

Note: Characteristics of applicants who become more likely (ELC participants) or less likely (crowded out) to enroll at the Absorbing UC campuses as a result of those campuses' implementation of ELC, on the basis of two counterfactual simulations employing the estimated parameters of the model described in Equation 7. The first simulation restricts the sample to pre-2012 and sets $\beta^{ELC}_{Abs1} = \beta^{ELC}_{Abs2} = 0$, eliminating the Absorbing UC campuses' ELC admissions advantage; the second simulation restricts the sample to post-2011 and assigns ELC eligibility to the top four percent of applicants from each high school. Applicants are weighted by half of their net change in Absorbing UC enrollment likelihood to scale annually. Complier characteristics and Absorbing UC student averages from Table 3 are presented for comparison. Missing family incomes are imputed; see footnote 50. Sample restricted to 2010-2013 UC freshman California-resident applicants who enroll at a public California institution in the fall after high school graduation. Source: UC Corporate Student System and the National Student Clearinghouse.

These comparisons are visualized in Figure 5. While the information provided to the model only includes the ELC GPA running variable within a narrow bandwidth on either side of the threshold, the figures show remarkable alignment between near-threshold applicants' simulated and actual admissions and enrollment outcomes, though applicants' admission to the San Diego and Santa Barbara campuses is underestimated for lower-GPA applicants. The estimated effects of ELC eligibility on UC admission at the eligibility threshold are closely matched by the model, while the effect of ELC eligibility on Absorbing UC campus enrollment is slightly under-predicted by the model. In general, the model effectively simulates the near-threshold effects of ELC relative to reduced-form estimates.

7 The Impact of Top Percent Policies on UC Enrollment Composition

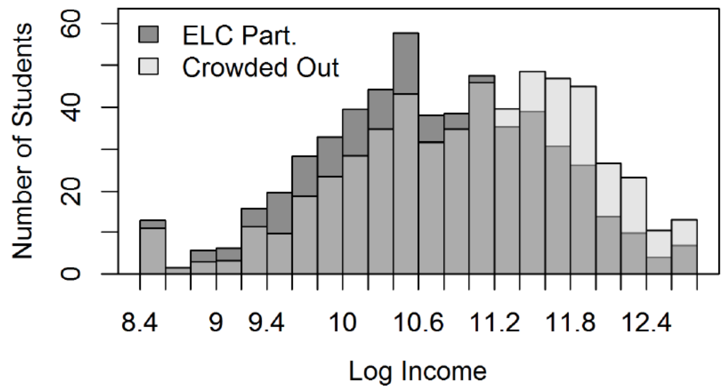
7.1 "Winners" and "Losers" of ELC Implementation

In this section, I employ the previous section's model to quantify top percent policies' economic mobility potential by estimating the net effects of top percent policies on selective universities' enrollment composition, focusing on the net enrollment of socioeconomically-disadvantaged students. First, I estimate how the students who enrolled at Absorbing UC campuses because of ELC ("ELC participants") differed from the crowded-out students who were unable to enroll at those universities as a result of the ELC policy. I conduct this counterfactual enrollment exercise in two ways: by eliminating ELC from 2010-2011 admissions in the model (by setting $\beta^{ELC}_{Abs1} = \beta^{ELC}_{Abs2} = 0$) and by adding ELC to 2012-2013 admissions (by setting $ELC = 1$ for applicants in the top four percent of their high school class).[55] I then allow universities to adjust their admissions thresholds $\underline{\pi}_j$ so that their annual expected enrollment remains unchanged, assuming that each Absorbing campus would fill the same number of enrollment seats in one of two ways: through ELC or through their regular freshman admissions process.[56]

In both of these counterfactual exercises, the $\underline{\pi}_j$ parameters adjust as expected: the Unimpacted and Dispersing campuses' admissions thresholds hardly adjust, while $\underline{\pi}_{Abs1}$ and $\underline{\pi}_{Abs2}$ decrease in the former exercise (to expand enrollment absent ELC) and increases in the latter exercise (to shrink non-ELC enrollment); see Appendix Figure A-15. Moreover, the two counterfactual exercises provide very similar estimates for the impact of ELC. The first and third columns of Table 7 show that ELC shifted Absorbing UC campus enrollment by about 600 students per year: there are about 600 annual ELC participants and 600 annual crowded-out students.[57] ELC participants' counterfactual enrollments look very similar to the counterfactual enrollments of near-threshold participants estimated above: about half would have otherwise enrolled at CSU, with the remainder split between the Dispersing UC campuses and community colleges.[58]A comparison between the characteristics of simulated ELC participants and those of the estimated local compliers (replicated in column 5 from Table 3) shows near-identical URM shares (44-47 percent) and average family incomes ($63,000-$67,000). The average simulated ELC participants had somewhat higher SAT scores and high school GPAs than the barely above-threshold compliers.

The second and fourth columns of Table 7 show that the characteristics of the students crowded out by ELC appear more similar to the average Absorbing UC campus student, though they are also somewhat negatively-selected (as a result of their being the first students to be rejected in the presence of the ELC policy). Their household incomes were slightly lower than the Absorbing

Figure 6: Log Family Incomes of Simulated ELC Participants and Crowded Out Students



Note: Distribution of family incomes of annual ELC participants and crowded-out students under a simulation (employing the estimated parameters of the model described in Equation 7) in which 2010-2011 UC applicants were no longer provided an admissions advantage at the Absorbing UC campuses ($\beta^{ELC}_{Abs1} = \beta^{ELC}_{Abs2} = 0$). ELC participants are defined as applicants whose simulated likelihood of Absorbing UC campus enrollment increases, and crowded-out applicants those whose likelihood decreases; applicants are weighted by their net change in likelihood and halved to scale annually. Missing family incomes are imputed — see footnote 50 — and incomes are winsorized at 8.4 and 12.6. Sample restricted to 2010-2011 UC freshman California-resident applicants who enroll at a public California institution in the fall after high school graduation. Source: UC Corporate Student System and the National Student Clearinghouse.

UC average, and about 30 percent were URM (compared to 20 percent overall). While the crowded-out students had below-average SAT scores and high school GPAs, their average SAT scores remained substantially higher than ELC participants'.

Figure 6 compares the family income distributions of ELC winners and losers. It shows that the ELC policy increased annual Absorbing UC net enrollment among students with log family incomes between 9 and 11 and decreased annual net enrollment among students with log family incomes over 11.2. However, it also shows substantial overlap between the two distributions; by increasing selective university enrollment among top students from less-competitive California high schools, ELC increased lower-income enrollment at Absorbing UC campuses but also decreased many other lower-income applicants' likelihood of Absorbing UC enrollment through regular admissions channels.

7.2 Top Percent Policies and University Enrollment Composition

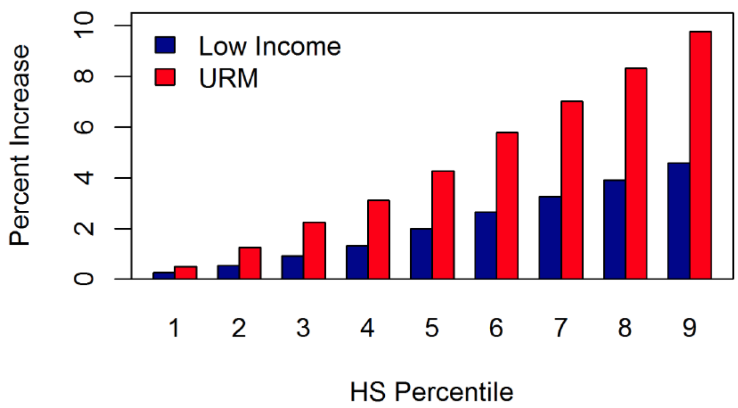
Next, I estimate how top percent policies with alternative percentile thresholds would impact the composition of the Absorbing UC campuses. As discussed above, 2012 and 2013 applicants were categorized by UC as being in the top one, two, and down to top nine percent of their high school classes, but UC campuses generally provided negligible admissions advantages to students using these class ranks. I simulate counterfactual enrollments as if the Absorbing UC campuses had provided the same admissions advantage to 2012-2013 applicants with GPAs above each rank-specific threshold that they had provided to ELC-eligible students prior to 2012. I estimate these simulations by setting *ELC* = 1 for applicants above each alternative rank-specific threshold and then allowing for $\underline{\pi}_j$ adjustments to equalize expected enrollment.

In 2012-2013, lower-income (URM) students made up about 9,500 (4,700) of the 17,200 freshman California-resident enrollees at the Absorbing UC campuses. Figure 7 shows that these net enrollments would increase by about one and 2.5 percent (respectively) if the campuses had continued providing similar-magnitude admissions advantages to the top four percent of each high school's graduates after 2011. However, those impacts would have been much larger — about five and ten percent, respectively — if the Absorbing campuses had provided parallel admissions advantages to the top nine percent of each high school's graduates.[59] In sum, these simulations show that top percent policies can substantively increase universities' net enrollment of socioeconomically-disadvantaged students, with larger increases from lower thresholds.

8 Discussion: Who Benefits Most from More-Selective Enrollment?

Having shown that top percent policies can meaningfully increase selective universities' net enrollment of disadvantaged students, I conclude by discussing reduced-form and structural evidence on the relative return to more-selective university enrollment for applicants with higher or lower traditional meritocratic rank.

Figure 7: Simulated Changes in Absorbing UC Enrollment under Counterfactual Top Percent Policies



Note: Estimated percent changes in the number of low-income and URM Absorbing UC campus students under top percent policies in which those campuses provide their estimated ELC admissions advantage to the top x percent of graduates from each high school, with x ranging from 1 to 9, relative to no top percent policy. Estimates from simulations employing the estimated parameters of the model described in Equation 7. Each simulation assigns ELC eligibility to the top x percent of each high school's graduates; Absorbing campus enrollment characteristics are determined by weighting each applicant by their estimated likelihood of enrolling at those campuses. Missing family incomes are imputed — see footnote 50 — and low income is defined as applicants with family incomes below the California median. The sample is restricted to 2012-2013 UC freshman California-resident applicants who enroll at a public California institution in the fall after high school graduation. Source: UC Corporate Student System and the National Student Clearinghouse.

8.1 Reduced-Form Evidence

Section 5.3 presents reduced-form evidence showing that the benefits of selective university enrollment remain large even for students who would have otherwise enrolled at very low-selectivity institutions. While the reduced-form setting prohibits direct comparison of the return to university selectivity for students crowded out by ELC, I employ estimated "value-added" statistics for each college and university to conduct an alternative comparison: how does the effect of Absorbing UC enrollment for barely-eligible ELC participants compare to those institutions' *average* treatment effect for their enrolled students?

I estimate three measures of institutional value-added: the degree to which each institution tends to increase enrollees' five-year degree attainment, early-career wages, and early-career log wages. Value-added statistics are estimated using 2003-2011 UC applicants (holding out the main estimation sample) in a fixed effect specification following Chetty et al. (2020), controlling for applicant ethnicity and fifth-order polynomials in SAT score and family income.[60]

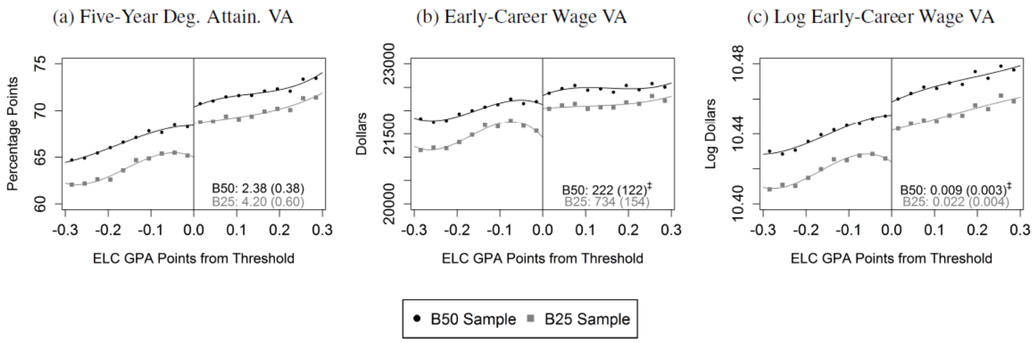
Figure 8 shows how applicants' first enrollment institutions' estimated value-added varies near the ELC eligibility threshold. Panel (a) shows that the change in five-year degree attainment value-added at the eligibility threshold closely matches the change in applicants' actual five-year degree attainment (see Figure 2), suggesting that ELC applicants' educational value derived from the Absorbing UC campuses matched the value derived by average UC students. Panels (b) and (c), however, show that ELC participants' increase in institutional wage value-added is far smaller than the increases in early-career wages observed in Figure 2: Barely above-threshold B25 applicants enrolled at universities with $730 (0.02) higher (log) wage value-added but actually earned higher annual wages by about $2,200 (0.08) in their early careers. While the estimates on wages and wage value-added are not all statistically distinguishable, this suggests that the wage return to Absorbing UC campus enrollment for ELC participants may (substantially) exceed the average return to enrolling at those universities.

8.2 Structural Evidence

The structural model estimated above facilitates a more direct test of whether deviations from selective universities' regular meritocratic admissions procedures generate inefficiencies by admitting students who benefit relatively less from selective university enrollment, abstracting from the particulars of UC's ELC policy. Consider applicants' q_i caliber terms observed by UC campuses in the model. As described above, q_i indexes the latent characteristics of applicants that are valued by UC admissions offices but are unobserved by the econometrician; applicants with high q_i are those whose admissions outcomes are stronger than what would be expected given their test scores, grades, and other characteristics. Similarly, we can define

$$Q_i = z_i\beta^z + q_i$$

Figure 8: Local Effect of ELC Eligibility on UC Applicants' First Institutions' Estimated Value-Added



Note: Regression discontinuity plots of the estimated value-added of applicants' initial enrollment institution (within 6 years of high school graduation) by ELC GPA distance from their high school's ELC eligibility threshold, among applicants from the bottom half (B50) or quartile (B25) of California high schools by SAT. Points are binned averages; lines are cubic fits. Beta estimates are from cubic regression discontinuity models following Equation 2, with standard errors in parentheses clustered by high-school-year. Institutional value-added estimated for degree attainment and wages and log wages (averaged 7-9 years after graduating high school, omitting zeros in the log and winsorizing at 5 percent) using 2003-2011 UC applicants (holding out applicants in the main estimation sample) conditional on ethnicity and fifth-order polynomials in family income and SAT score following Chetty et al. (2020). Applicants from high schools with approximated ELC eligibility thresholds between 3.96 and 4.00 are omitted. ‡ indicates reduced-form estimates with $p > 0.1$ for the null hypothesis ($\hat{\beta} = 0$) when estimated using a local linear model with bias-corrected and cluster-robust confidence intervals following Calonico et al. (2019). Source: UC Corporate Student System, National Student Clearinghouse, and the California Employment Development Department (Bleemer, 2018).

(omitting the ELC terms) as the application 'merit' of applicant *i* as observed by UC campuses. By selecting high-Q_i or high-q_i applicants, are universities admitting students who are generally better able to benefit from their admission? Using a similar selection-on-observables methodology to Dale and Krueger (2002) and Dillon and Smith (2020), I investigate this question by estimating a series of linear regression models relating applicant outcomes to the interaction between university selectivity and either $\hat{Q}_i$ or $\hat{q}_i$.

Among the model sample of applicants — that is, 2010-2013 freshman California-resident UC applicants who first enroll at a public California institution — I estimate each applicant's $\hat{q}_i$ from the posterior distribution implied by the estimated structural model parameters.[61] The estimated $\hat{q}_i$ statistics are normally distributed with mean 0 and standard deviation 0.15. I then estimate $\hat{Q}_i = z_i\hat{\beta}^z + \hat{q}_i$, excluding the ELC terms, and standardize $\hat{Q}_i$ for interpretability. I estimate linear regressions of the form

$$Y_i = \beta_1 GR_i + \beta_2 \hat{Q}_i + \beta_3 \left(GR_i \times \hat{Q}_i\right) + \gamma X_i + \epsilon_i \tag{8}$$

where GR_i is i's first enrollment institution's five-year graduation rate and X_i takes one of three forms: (1) null; (2) includes detailed covariates, including gender-ethnicity indicators, SAT score, HS GPA, log income, parental education and occupation indicators, ELC eligibility, and high school, Zip code, and year fixed effects; and (3) those same covariates in addition to fixed effects for every portfolio of UC applications and admissions across campuses (as in, e.g., Mountjoy and Hickman (2020)). These covariate sets are intended to absorb selection bias arising from applicants' non-random enrollment across more- or less-selective institutions. I estimate these models for two outcomes: five-year degree attainment and early-career wages (seven to eight years after high school graduation), with the latter models restricted to pre-2012 applicants (since wages for later applicants are not yet observed). I also estimate similar models replacing $\hat{Q}_i$ with either $\hat{q}_i$ or (standardized) SAT score and high school GPA, as well as models that allow GR_i to be a polynomial expansion of institutional graduation rate. The robust standard errors assume $\hat{Q}_i$ and $\hat{q}_i$ to be accurate.

Table 8 shows that enrolling at an institution with a higher graduation rate by one percentage point increases applicants' own five-year degree attainment by about 0.8 percentage points, matching the reduced-form relationship estimated for ELC participants. Applicants' measured $\hat{Q}_i$ is also strongly associated with positive outcomes: applicants with a 1 standard deviation higher $\hat{Q}_i$ tend to have higher five-year degree attainment by 16 percentage points and have higher early-career wages by \$10,000. However, there is no evidence that the return to more-selective university enrollment is larger for high-$\hat{Q}_i$ applicants; instead low-$\hat{Q}_i$ applicants benefit slightly *more* from enrolling at more-selective institutions. In the most restrictive specifications — comparing applicants at different institutions with highly similar socioeconomic and academic backgrounds who had identical UC application and admission outcomes — enrolling at a more-selective institution provides broadly similar attainment and wage benefits to higher- or lower-$\hat{Q}_i$ applicants. Replacing $\hat{Q}_i$ with $\hat{q}_i$ results in smaller but still-negative $\hat{\beta}_3$ estimates, suggesting that the component of universities' applicant preferences orthogonal to socioeconomic and academic characteristics also does not identify higher-value-add students. Including interactions with both SAT score and HS GPA again results in negative interaction terms between

Table 8: Estimated Relationship between Student 'Merit' and Return to University Selectivity

Var:	$\hat{Q}$			$\hat{Q}$			$\hat{q}$		SAT	
Y_i:	Five-Year Deg. Attain.			Early Wages (7-8 Yr.)			Deg.	Wages	Deg.	Wages
Inst. Grad. Rate	0.77 (0.01)	0.77 (0.01)	0.81 (0.01)	220 (15)	199 (17)	207 (20)	0.81 (0.01)	207 (20)	0.80 (0.01)	206 (20)
Var	15.68 (0.40)	-3.80 (1.63)	-0.39 (2.33)	9851 (789)	3060 (3337)	1788 (4936)	2.23 (0.47)	334 (985)	2.66 (0.49)	1423 (1033)
Var × Inst. Grad. Rate	-0.11 (0.01)	-0.10 (0.01)	-0.05 (0.01)	-116 (13)	-98 (14)	-63 (18)	-0.04 (0.01)	-6 (15)	-0.05 (0.01)	-29 (16)
HS GPA									9.73 (0.48)	6537 (1036)
HS GPA × Inst. Grad. Rate									-0.01 (0.01)	-40 (19)
Det. Covariates		X	X		X	X	X	X	X	X
Adm. Portfol.			X			X	X	X	X	X
Observations	110,114	107,300	107,300	51,144	49,339	49,339	107,300	49,339	107,300	49,339

Note: Estimates of Equation 8 for 2010-2013 freshman California-resident UC applicants who first enroll at a public California institution. Institutions' graduation rates are defined for each applicant's institution of first enrollment (within six years after graduating high school); see Appendix D for details. Applicants' university-observed caliber $\hat{q}_i$ — a latent index of universities' preferences for certain applicants on the basis of unobservables — is estimated using the posterior distribution of q_i's resulting from the structural model parameters described above, and applicant summed admissions merit $\hat{Q}_i$ is estimated by $z_i\hat{\beta}^z + \hat{q}_i$, excluding the ELC covariates. $\hat{q}_i$, $\hat{Q}_i$, SAT, and HSGPA are standardized. Detailed covariates include gender-ethnicity indicators, SAT score, HS GPA, log income, parental education and occupation indicators, ELC eligibility, and high school, zip code, and year fixed effects; admissions portfolios include indicators for every combination of UC campuses to which the applicant applies and UC campuses to which they are admitted. Five-year degree attainment indicates earning a college degree within five years of high school graduation. Early-career wages are measured as average observed wages 7-8 years after high school graduation; wages are winsorized at 5 percent and are unobserved for post-2011 applicants. Robust standard errors in parentheses assume that $\hat{q}_i$ and $\hat{Q}_i$ are accurately measured. Source: UC Corporate Student System, the National Student Clearinghouse, and the California Employment Development Department (Bleemer, 2018).

university selectivity and each measure of college preparedness (with GPA correlating much more strongly with applicant outcomes than SAT).[62,63]

Taken together, these findings leverage the advantages of the structural model of public California university enrollment to provide evidence against the claim that traditional meritocratic admissions procedures identify the selective university applicants who would most benefit from that education. Instead, the kinds of students admitted under ELC or alternative access-oriented admission policies appear likely to obtain as high or higher benefits of selective university enrollment.

9 Conclusion

This study uses a novel comprehensive database of university applications linked to educational and wage outcomes to provide the first quasi-experimental estimates of the impact of more-selective university enrollment on the lives of the high-GPA low-SAT students targeted by top percent policies and other policies that curtail the influence of standardized test scores in university admissions. The University of California's 2001-2011 Eligibility in the Local Context program provided substantial UC admissions advantages to graduates in the top four percent of their high school class. Implementing a regression discontinuity design across high schools' eligibility thresholds, I find that ELC shifted university enrollment among barely-eligible applicants from much less-selective California public colleges and universities into four highly-selective UC campuses. As a result of this shift, barely ELC-eligible applicants became more than 30 percentage points more likely to earn a college degree within five years, graduate school enrollment increased by about 20 percentage points, and early-career annual wages (between seven to nine years following high school graduation) increased by as much as $25,000.

The study then turns to the general equilibrium effects of top percent policies like ELC, estimating a structural model of university application, admission, and enrollment for California public universities. The 600 ELC participants each year were well-characterized by the policy's near-threshold participants: about 65 percent came from families with below-median household incomes, almost half were Black or Hispanic, and their average SAT scores were at the 12th percentile of their Absorbing UC peers. Compared to the "crowded-out" students replaced by ELC participants, the participants were about 15 percentage points more likely to be underrepresented minorities (URM) and had lower average family incomes by 0.3 log points. A potential expansion of the ELC policy to the top nine percent of UC applicants from each California high school is estimated to increase lower-income and URM Absorbing UC enrollment by five and ten percent, respectively (each about 350 students per year). Finally, both reduced-form and structural evidence are brought to bear on the efficiency of top percent policies, with both suggesting that the returns to more-selective enrollment experienced by the targeted disadvantaged applicants are no lower — and may be considerably higher — than they would have been for the regular-admissions students who would have otherwise enrolled in their place.

This study presents the first quasi-experimental analysis of the medium-run impact of selective university admission under an access-oriented admission policy, finding that broadening selective university access is an impactful and potentially-efficient economic mobility lever available to policymakers. It also provides unique analysis of how high-GPA low-SAT students perform at selective research universities that typically would have rejected them because of their poor standardized test scores, showing that the students likely to be advantaged by test-optional or no-test admissions policies would be substantially benefited (though selective universities' graduation rates may decline as they enroll more-disadvantaged students). Finally, this study challenges a central tenet supporting test-based meritocratic university admissions policies — that the policies efficiently allocate educational resources to students who will best be able to take advantage of them — by identifying a group of low-testing (perhaps high-noncognitive-skill) and low-opportunity applicants who appear to earn greater benefits from selective university enrollment than the higher-testing applicants who are typically admitted in their place.

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[1] Until surging demand for postsecondary education made open access impossible in the late 1950s, public universities provided low-cost education to any student who satisfactorily completed high school (Douglass, 2007; Goldin and Katz, 2008).

[2] Top percent policies have been implemented in Texas, Florida, and Georgia, and have been considered in several other states.

[3] As I discuss below, ELC was indeed "expanded" in 2012 to the top nine percent of applicants from each high school, but Appendix A shows that every selective UC campus ceased providing admissions advantages to ELC-eligible students, *de facto* ending the policy's effects on the composition of UC enrollment.

[4] EDD employment records are maintained for state unemployment insurance provision and exclude out-of-state, federal, and self-employment. Appendix C demonstrates the relative comprehensiveness of the relevant NSC records in this period.

[5] One previous study, Bertrand, Hanna, and Mullainathan (2010), estimates a positive wage return to caste-based affirmative action programs at engineering colleges in India, though that context is very different from the present study. Subsequent to this study, Bleemer (2020) and Black, Denning, and Rothstein (2020) find similar reduced-form returns to a race-based affirmative action policy in California and a top percent policy in Texas, but neither paper is amenable to an instrumental variable strategy that identifies effects for policy compliers. I discuss the latter paper in greater detail below.

[6] Zimmerman (2014) and Smith, Goodman, and Hurwitz (2020) show substantial positive returns to less- or non-selective university enrollment for students at those institutions' admissions thresholds. Dale and Krueger (2002, 2014) show evidence of positive returns for disadvantaged students enrolling at highly-selective institutions instead of other selective institutions, and Cohodes and Goodman (2014) show that more-selective enrollment improves students' degree attainment.

[7] Cullen, Long, and Reback (2013) find that only a small number of students switched high schools in order to "game" this kind of high-school-percentile admissions policy after Texas implemented a similar top percent policy.

[8] See Atkinson and Pelfrey (2004). The courses included two years of English and Mathematics, one year of History, Lab Science, a Non-English Language, and four other UC-approved courses. Students or their parents could opt out of their high school's providing their transcript to UC at their discretion. This centralized ELC administration importantly differs from Texas's program, where high schools were directly responsible for identifying the top ten percent of students; some high schools purposefully extended "Top Ten" eligibility to a greater proportion of students (Golden, 2000).

[9] UC's "Eligibility in the State-Wide Context" policy provided a *de jure* similar admissions guarantee for the top 12.5 percent of California seniors based on a publicly available linear combination of high school GPA and SAT scores. In practice, most UC campuses provided substantially larger admissions benefits to ELC-eligible students than to those eligible in the state-wide context. It is unknown whether UC applicants were aware of the difference.

[10] Appendix B exploits this abrupt ELC cessation to replicate the main reduced-form results presented below using a difference-in-difference design after 2011.

[11] A related literature uses quasi-experimental research designs to examine heterogeneity in the return to higher education by field of study (e.g. Kirkeboen, Leuven, and Mogstad, 2016; Hastings, Nielsen, and Zimmerman, 2018; Bleemer and Mehta, 2020).

[12] Hastings, Nielsen, and Zimmerman (2018) exploit minimum score admissions thresholds in Chile to identify positive wage returns to more-selective university enrollment. Zimmerman (2019) shows that disadvantaged Chilean students are no more likely to become top earners if they are barely admitted to top business schools. Others use similar research designs to examine on-the-margin students choosing between community colleges and less-selective four-year universities, finding that enrolling at the four-year universities appears to increase students' likelihood of earning a college degree (Reynolds, 2012; Angrist et al., 2016; Goodman, Hurwitz, and Smith, 2017) and medium-run wages (Mountjoy, 2019; Smith, Goodman, and Hurwitz, 2020). Abdulkadiroglu, Angrist, and Pathak (2014) show that on-the-margin access to selective high schools does not improve U.S. students' standardized test scores or university selectivity.

[13] Ge, Isaac, and Miller (2018) follow the research design of Dale and Krueger (2002) but find that attending more-selective universities improves female students' postgraduate labor market outcomes. Griffith (2010) shows that observably similar students at more-selective universities are less likely to earn STEM degrees. An earlier generation of literature shows a positive correlation between university selectivity and wages (Wales, 1973; Morgan and Duncan, 1979; James et al., 1989; Behnman, Rosenzweig, and Taubman, 1996).

[14] The same is true of affirmative action policies in India (Bertrand, Hanna, and Mullainathan, 2010; Bagde, Epple, and Taylor, 2016) and Brazil (Francis and Tannuri-Pianto, 2012).

[15] Bertrand, Hanna, and Mullainathan (2010) find that affirmative action increases impacted students' medium-run wages in the Indian contexts. Cestau et al. (2020) show that Black students at West Point have lower test scores but similar postgraduate achievement as their white peers. Arcidiacono (2005) estimates a structural model suggesting that the U.S. wage effect is small. The contentious affirmative action literature is reviewed by Arcidiacono and Lovenheim (2016) and Arcidiacono, Lovenheim, and Zhu (2015), with an earlier literature reviewed by Holzer and Neumark (2006). A related literature examines whether attending a more-selective law school under an access-oriented admission policy has negative educational and labor market repercussions (Sander, 2004; Rothstein and Yoon, 2008), coming to

contradictory conclusions, though there is general agreement that race-based affirmative action increases targeted students' likelihood of more-selective law school enrollment (Yagan, 2016).
[16] Daugherty, Martorell, and McFarlin Jr. (2014) show that enrollees from one large urban school district would have otherwise enrolled at similarly-selective private universities. Cortes and Lincove (2019) show that TTT encourages public flagship university enrollment among high-performing low-income high school graduates.
[17] Furstenberg (2010) argues that TTT decreased targeted students' likelihood of degree attainment, but that study has substantial limitations: outcomes are only observed for enrollees at public universities, the only observed graduation rate is four-year (and it is only observed for a single cohort, the first that TTT was implemented), and transfers between universities are treated as non-graduation, all of which is compounded with technical limitations like a coarse discrete running variable.
[18] Seven percent of applicants' addresses cannot be geolocated. Parental education is observed as an index of maximum parental education for both parents. ACT scores or SAT scores on the 1600 scale are converted to the 2400 SAT scale using a standard crosswalk. Family income is not reported by 12 percent of applicants. Intended majors are non-binding, and about one-third of applicants select 'Undeclared'. I assign to each applicant the intended discipline(s) that they most frequently report across campuses.
[19] When multiple thresholds minimize eligibility in the latter case, I take their average.
[20] In particular, it contains semesterly enrollment records and graduation records (including degrees, majors earned, and year of graduation) for all degree-granting institutions that accept federal Title IV funding. Records are linked by first and last name, middle initial, and birth date, allowing for common nicknames and typos.
[21] NSC reports that about four percent of records are censored due to student- or institution-requested blocks for privacy concerns (National Student Clearinghouse Research Center, 2017). Enrollment is near-comprehensive for California public institutions (Dynarski, Hemelt, and Hyman, 2015). Appendix C shows that nearly all California colleges and universities were reporting to NSC by 2003 and that a comparison between UC and NSC records reveals very low degree attainment and major censorship rates.
[22] STEM includes the 278 "fields involving research, innovation, or development of new technologies using engineering, mathematics, computer science, or natural sciences (including physical, biological, and agricultural sciences)" identified by CIP code. Not all NSC majors have CIP codes; I assign each major to its modal CIP code (in the full observed NSC database) for categorization. Disciplines are also partitioned into arts, humanities, social sciences, natural sciences, engineering, professional, and business by hand-coding from NSC records; the discipline coding is available from the author.
[23] The most recent wages available are 2019, so every year more than eight years after graduation omits one class of ELC students from the observed sample. All wage statistics were originally estimated as institutional research (see Bleemer (2018)).
[24] Social security numbers on UC applications are not verified unless the student enrolls at a UC campus. Among enrollees, the verified social security number differs from that reported on their application in fewer than 0.25 percent of cases.
[25] See the CDE Public Schools and Districts Data Files, the CDE's Private School Directory, and the NCES's School Locale Definitions. Rural schools are outside of any Census Urbanized Area; urban schools are inside a Census Principal City.
[26] The main sample is restricted to 2003-2011 because ELC GPAs are not observed until 2003.
[27] Because the number of Black applicants near the ELC eligibility threshold is so low, most of the estimates below group Hispanic and Black applicants as "underrepresented minorities", or "URM" along with Native American applicants.
[28] For the purpose of calculating quartiles, high-school-years are ranked by the average SAT score of applicants within 0.3 ELC GPA points of their school's ELC eligibility threshold in the given year and then weighted by their number of applicants within the 0.3 GPA band, resulting in quartiles with approximately the same number of *students*, not high schools. All results below are robust to using leave-one-out average SAT scores to measure high school quartiles, but the aggregate high school averages are used so that each school-year is in a single quartile.
[29] Cortes and Lincove (2019) find greater take-up of Texas's top percent policy among students from less-competitive schools.
[30] Controls are omitted when they are collinear with the outcome variable, as when Y_{it} is the applicant's SAT score. Nearly all of the results presented below are quantitatively and statistically unchanged if these controls are selectively or completely omitted, or if high school fixed effects are omitted.
[31] Because the number of running variable values on each side of the threshold is relatively large, I cluster by treatment level instead of running variable bin following Kolesar and Rothe (2018).
[32] OLS estimation was conducted using the *felm* command in R's *lfe* package. Local linear regressions were estimated using the *rdrobust* package in R (Calonico, Cattaneo, and Titiunik, 2015). The latter does not permit fixed effects; instead, I include indicator variables for all high schools with more than 50 applicants in the sample as controls.
[33] Five-year degree attainment is predicted by OLS using gender-ethnicity indicators, family income, max parental education indicators, year indicators, SAT score, and high school GPA using the full 1995-2013 sample of UC freshman California-resident applicants, excluding the estimation sample.
[34] Appendix E shows that ELC eligibility had generally consistent effects on admissions at each UC campus in each year between 2003 and 2011. ELC eligibility also shifted UC applicants' relative likelihoods of applying to each campus, with barely-eligible applicants becoming slightly more likely to apply to campuses that provided ELC admissions advantages and slightly less likely to apply to the less-selective campuses. However, the application effects are an order of magnitude smaller than the changes in admissions likelihood, suggesting that the latter largely account for the resulting enrollment shifts (an interpretation confirmed by the structural model estimates below). See Figure A-2 and Table A-3.
[35] Coefficients are estimated using Equation 2 for enrollment in the fall semester following UC application. Baseline estimates are estimated following Abadie (2002), which requires the monotonicity assumption that no near-threshold ELC-eligible student became *less* likely to enroll at the Absorbing UC campuses. Non-UC institutions could not observe or infer applicants' ELC eligibility, implying that any enrollment changes at non-UC institutions resulted from changes in applicants' UC admission.
[36] Appendix Table A-2 presents estimated changes in admission and enrollment at each UC campus for barely above-threshold applicants, showing that these aggregated changes at the threshold are mirrored at each of the respective campuses.
[37] There is statistically insignificant evidence of a small above-threshold decline in non-enrollment. Students who take gap years

following high school are categorized here as non-enrollees, as are students or institutions with masked records; see Appendix C.

[38] Graduation rates are defined by linking all UC applicants to their first enrollment institution and measuring their five-year Bachelor's degree attainment from any institution, even if they transfer elsewhere. See Appendix D.

[39] Appendix Table A-5 shows similar conditional differences across the ELC eligibility threshold in the selectivity of the institutions where degree-attainers earn their undergraduate degrees.

[40] Average log wages omit years in which no California wages were earned.

[41] This research design relies on the plausible exogeneity of which Absorbing campus each near-threshold UC applicant lives closest to. For example, it requires that the potential outcomes of near-threshold applicants who will attend Davis (iff they are ELC-eligible) because they live near to Davis must be equivalent to those of the near-threshold applicants who will attend Irvine (iff they are ELC-eligible) because they live near to Irvine. This assumption is testable on observables: the first row of Table 4 shows that there is no observable cross-campus difference in the observed academic preparedness of the students who enroll at one campus instead of another, measuring preparedness by their predicted likelihood of college graduation. The research design also assumes constant treatment effects in the relationship between students' outcomes and their Absorbing UC campus enrollment caused by their distances to each of the four UC campuses, though Table A-7 shows that enrollment at each campus is largely predicted by their log distance to *that* campus, not their distances to the other campuses.

[42] The last two rows of Table 4 show that the instrumental variables easily satisfy weak-instrument tests; the first-stage *F*-statistics range from 13 to 107 (Stock and Yogo, 2002), and the conditional first-stage *F*-statistics (Sanderson and Windmeijer, 2016) range from 33.6 to 104.1, all far above suggested minima. To improve the instrument's strength, I interact the Santa Barbara distance measure with an indicator for $t < 2011$, exploiting Santa Barbara's increasing popularity among applicants over time (it rose over the sample period from the lowest- to highest-ranked of the Absorbing UC campuses in the US News & World Report rankings). Appendix Table A-6 shows the unadjusted estimates.

[43] There are at least two possible explanations for this decline in STEM major selection at the ELC eligibility threshold. The first, put forward by Sander and Taylor (2012), argues that less-prepared students likely earn lower grades in introductory science courses when their peers as a result of their peers' stronger academic preparation, discouraging them and leading them to less-challenging majors in other disciplines. However, Bleemer (2020) shows that a natural experiment that led disadvantaged students to enroll in introductory STEM courses with less academically-prepared peers did not improve their performance or persistence in those courses. Alternatively, students who might have otherwise been pressured to earn STEM degrees (perhaps by parents or others advocating for higher-average-wage degrees) could face less (external or internal) pressure after enrolling in a more-selective university, leading them to earn non-STEM degrees. Indeed, Appendix Table A-8 shows noisy reduced-form evidence suggests that barely ELC-eligible students may have been less likely to report the intention of earning a Natural Science or STEM degree on their UC application. ELC-eligible applicants also because substantially more likely to earn a degree in their "intended" discipline (as reported on their UC applications), which increases in the reduced-form among B50 applicants by 2.6 percentage points (s.e. 1.2). Finally, additional speculative evidence can be found in Appendix Table A-9, which presents a 'transition table' showing reduced-form estimates of barely-eligible applicants' major choice changes by intended field of study (as reported on the UC application). The table shows that the largest observable cross-discipline switches among barely ELC-eligible applicants were of intended social science and STEM majors switching into social science degrees and undeclared majors switching from the natural sciences into business degrees, with clear evidence of intended STEM majors switching out of STEM degrees.

[44] Appendix Table A-10 presents estimates from alternative specifications of these regression discontinuity and instrumental variable outcome models, including (1) showing reduced-form coefficients from local linear specifications following Calonico et al. (2019) and with an alternative definition of high school eligibility thresholds, and (2) exploiting the assumptions justifying treating Absorbing UC campus enrollment as the endogenous variable in order to estimate potential outcomes for barely below- and above-threshold ELC compliers. It shows, for example, that ELC eligibility increased B50 ELC participants' enrollment institution's graduation rate (likelihood of graduating within five years) from 50 (46) to 77 (75) percent.

[45] This instrumental variable strategy requires the exogeneity assumption that the only reason that applicant outcomes shift across the eligibility threshold is as a result of their Absorbing UC campus enrollment, which in turn requires that either applicants did not switch *between* Absorbing UC campuses across the threshold or that those applicants who did switch would have obtained similar outcomes at either of those campuses, with Table 4 providing some evidence for the latter claim.

[46] Appendix Table A-12 performs a series of linearity tests that provide suggestive evidence favoring this instrumental variable design, which imposes a linear relationship between university selectivity and applicant outcomes.

[47] I borrow this "winners" and "losers" terminology from Black, Denning, and Rothstein (2020).

[48] While the relationship between U_{ij} and the financial return to i enrolling at j is not explicitly modeled, the β_j terms can be understood as potentially partially capturing student-university match effects on observable characteristics, with students of a particular type preferring enrollment at j because of their relatively large return to enrollment.

[49] This model excludes universities from "balancing" their classes to maintain quotas of certain student types. Balancing classes by gender and/or ethnicity was legally prohibited at public California institutions throughout the study period.

[50] For applicants without observed family income, I predict income using high school and Zip code fixed effects, gender-ethnicity indicators, parental education and occupation indicators, and SAT and HS GPA.

[51] See section 8.1 for a discussion of these value-added statistics.

[52] Estimation is conducted using MATLAB's *fminunc* function with the BFGS algorithm and default parameterization.

[53] Because Davis, Irvine, and the Dispersing UC campuses admit nearly all above-threshold applicants, the slope of their above-threshold running variable is only weakly identified. I assume those parameters to be 0.

[54] In 2011, the UC campuses' admissions rates were 21 and 26 (Berkeley and UCLA), 38 and 45 (San Diego and Santa Barbara), 46 and 45 (Davis and Irvine), and 64, 76, and 89 (Santa Cruz, Riverside, and Merced).

[55] I set $\beta_{Abs1}^{ELC} = \beta_{Abs2}^{ELC} = 0$ in the latter exercise to isolate the admissions effects at the Absorbing UC campuses.

[56] In the counterfactual compositions presented below, I characterize ELC participants as anyone whose likelihood of Absorbing UC enrollment increases in the presence of ELC (and crowded-out applicants as anyone whose likelihood of Absorbing UC enrollment declines), weighted by their change in enrollment likelihood.
[57] That is, the sum of the differences in applicants' enrollment likelihoods in the presence or absence of ELC, conditional on those differences being positive, is 550 in the first simulation and 720 in the second. The sum of the negative differences is the same by construction (after $\underline{\pi}_{Abs1}$ and $\underline{\pi}_{Abs2}$ adjust).
[58] The reduced-form estimates report a somewhat higher relative share coming from the Dispersing UC campuses.
[59] This equates to increases of lower-income and URM enrollment by about 2 percentage points each. Note that it is not obvious *a priori* whether top percent policies with lower percentile thresholds will have the same, larger, or smaller proportional effects on the proportion of lower-income or URM students at a selective university. On the one hand, as the policy provides admissions advantages to students with lower high school GPAs, those students are more likely to be disadvantaged, and as the number of policy losers increases the on-the-margin student is also less likely to be disadvantaged. On the other hand, the on-the-margin student will be coming from a more-advantaged high school (since broadening a top percent policy will increase the number of schools where students will want to take advantage of that policy), which may imply that they will be less likely to be lower-income or URM. However, Figure 7 shows that the former trends are dominant: the net effect is that the percentage point gap between the lower-income and/or URM share of ELC winners and losers grows as the policy's admissions threshold declines.

[60] For details on value-added estimation for each institution, see Appendix G.1 of Bleemer (2020). Chetty et al. (2020) argue that about 80 percent in the variation of these value-added statistics is 'causal,' implying that differences in the presented value-added statistics may *overstate* differences in institutions' average treatment effects.

[61] In particular, I draw 1,000 sets of preference shocks, s_i's, and $q_i|s_i$ values, calculate each applicant's q_i and the likelihood of those values given the estimated parameters for each set, and then take the likelihood-weighted average of the resulting q_i's.
[62] All results are very similar in direction and magnitude when replacing (winsorized) income with log income. Estimates are presented in dollars for interpretability.
[63] Appendix Figure A-4 visualizes estimates from an alternative version of Equation 8, with fifth-order polynomials in GR_i interacted with in-sample tercile indicators for q_i, SAT, and HSGPA. Plots of the derivatives of the resulting polynomials (which represent the gains in degree attainment associated with the increase in GR_i at each GR_i) show substantial uniformity across most of the distribution of GR_i where each of the terciles has support in the data.