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 12^{th} 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.

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In the space of several months I had made desperate attempts, with this and that professor, to enter as a degree student. Some, with twisted mouth, or even rudely, had responded that the racial laws prohibited it; others had had recourse to vague and flimsy pretexts. One night, having politely absorbed the fourth or fifth rejection, I was going home on my bicycle ... The passersby were few and hurried, and then one of them caught my attention ... He was the Assistant [Professor at the Institute for Experimental Physics]. ... I thought that I risked nothing but another rejection, and asked straight out if it would be possible to be accepted for experimental research work in his institute. The Assistant looked at me in surprise, and, in place of the long speech that I would have expected, he answered with two words of the Gospel: "Follow me." ∼Primo Levi, The Periodic Table

1 Introduction

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 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

[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.

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 4 and 8 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

[3] As I discuss below, ELC was indeed "expanded" in 2012 to the top 9 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.

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 1, 2, and up to the top 9 percent of applicants from each California high school. The simulations show that top percent policies are indeed "access-oriented": the 9 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

[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.

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]

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[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% 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.

2.1 Prior Literature

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

[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).

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: thirty-one 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

[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.

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.

[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 cross-walk. 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.

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% and 2.8% 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 US 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 US 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 5 percent. About 55 percent of applicants in the sample have positive wages in each of 7-9 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

[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 4 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% of cases.

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).

3.1 Summary Statistics

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

[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 takeup of Texas's top percent policy among students from less-competitive schools.

applicants is:

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

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:

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

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 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 ($\mathbb{1}_{GPA_i \geq 0}$).

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

[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.

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 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 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,

[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.

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:

- Random assignment to ELC eligibility. This follows from the regression discontinuity setting.
- Monotonicity: $Absorb_i(1) - Absorb_i(0) \geq 0 \quad \forall i \ s.t. \ |GPA_i| < \epsilon$, 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

[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.

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 8 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 5^{th} 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 Educational and Labor Market Outcomes

5.1 Reduced Form Estimates

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

[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.

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 3-5 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 7 and 9 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 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:

[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

$$Y_{it} = \sum_{c \in Abs} \Big(\beta_c E\hat{N}R_{ic} + f_c(GPA_i) \times Dist_{ic} \Big) + \delta X_i + \gamma_t + \epsilon_{it} \tag{3}$$

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 $E\hat{N}R_{ic}$ enrollment indicators are instrumented by $(\mathbb{1}_{GPA_i \geq 0} \times Dist_{ic})$, 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 UCSB 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 UCSB 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]

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

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

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.

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 reestimate 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.

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

[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.

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 $j \in 1, ..., J, CC, CSU$, 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 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, $\nu_{ij} \sim N(0, \sigma_{\nu_j}^2)$ 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

$$U_{iB} = \log\Big(\sum_{j \in B} \exp(\delta_j + x_{ij}\beta_j^x + \nu_{ij})\Big)$$

[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^x 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.

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

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

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:

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

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 $\pi_{ij} > \underline{\pi}_j$.

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

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

[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.

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

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

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

$$\sigma_s^2(w_i) = \log(1 + \exp(w_i \gamma^s))$$

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

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

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

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

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

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 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 $\theta = \{\beta_j^x, \beta_j^z, \gamma^c, \gamma^s, \gamma^{q|s}, \delta_j, \sigma^2_{\nu_j}, \underline{\pi}_j\} \in \Theta \subset R^{99}$ 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 fifteen possible combinations), and all students are also able to enroll at either community college or CSU (each modeled as a single institution).

In order to compare admission and enrollment outcomes in the presence and absence of ELC, I restrict

[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.

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:

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

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:

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

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

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

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

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 (π_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, and applicants generally had strong knowledge of their caliber. Finally, it shows that the magnitudes of students' taste shocks are relatively large across institutions ($\sigma^2_{\nu_j}$ 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.

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

[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).

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 π_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 π_j parameters adjust as expected: the Unimpacted and Dispersing campuses' admissions thresholds hardly adjust, while π_{Abs1} and π_{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

[55] I set $\beta^{ELC}_{Unimp} = \beta^{ELC}_{Disp} = 0$ 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 π_{Abs1} and π_{Abs2} adjust).

[58] The reduced-form estimates report a somewhat higher relative share coming from the Dispersing UC campuses.

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 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 1, 2, and down to top 9 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 1 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 4 and 8 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

[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

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.

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

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.

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

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

(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

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

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-

[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.

selective institutions. I estimate these models for two outcomes: five-year degree attainment and early-career wages (7-8 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 1 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 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 en-

[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.

rollment 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 7 to 9 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 12^{th} 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 4 and 8 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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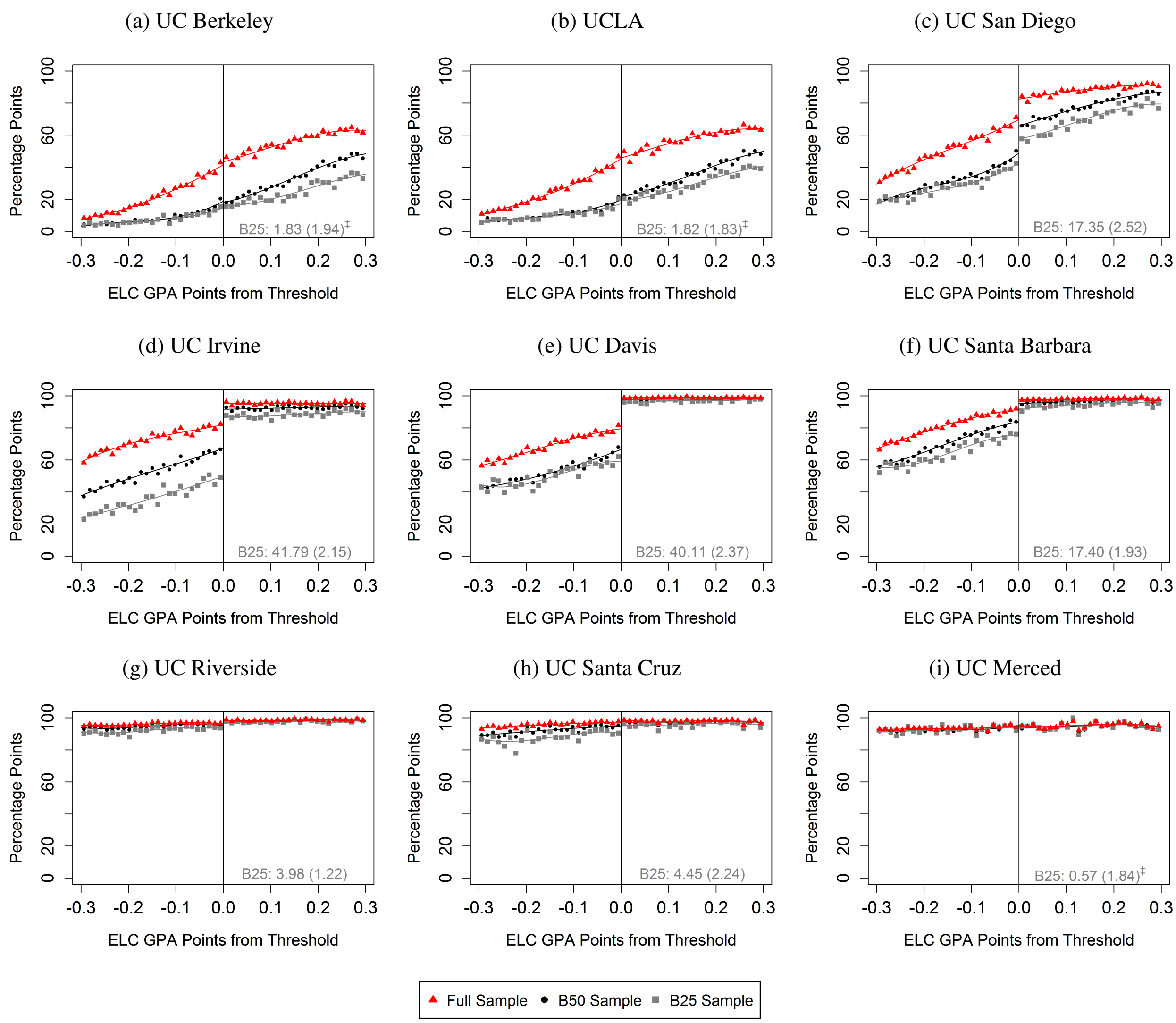
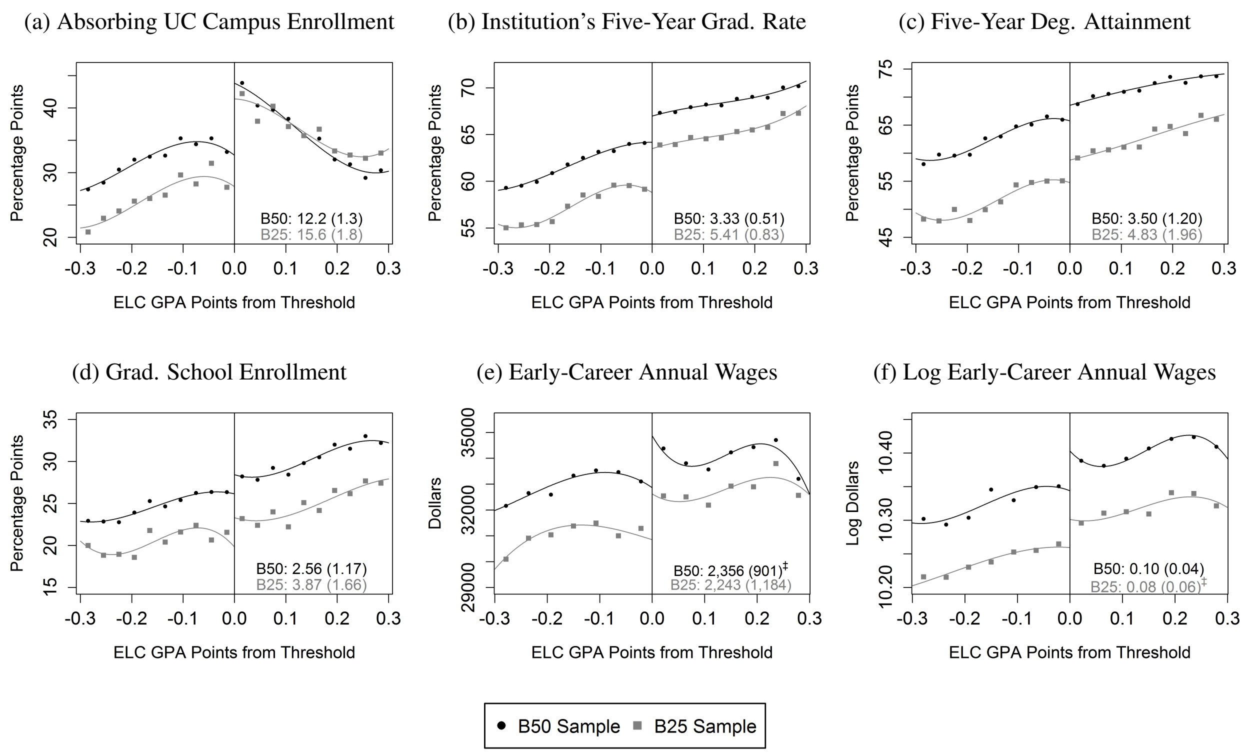
Figure 1: Local Effect of ELC Eligibility on Applicants' Likelihood of Admission to each UC Campus



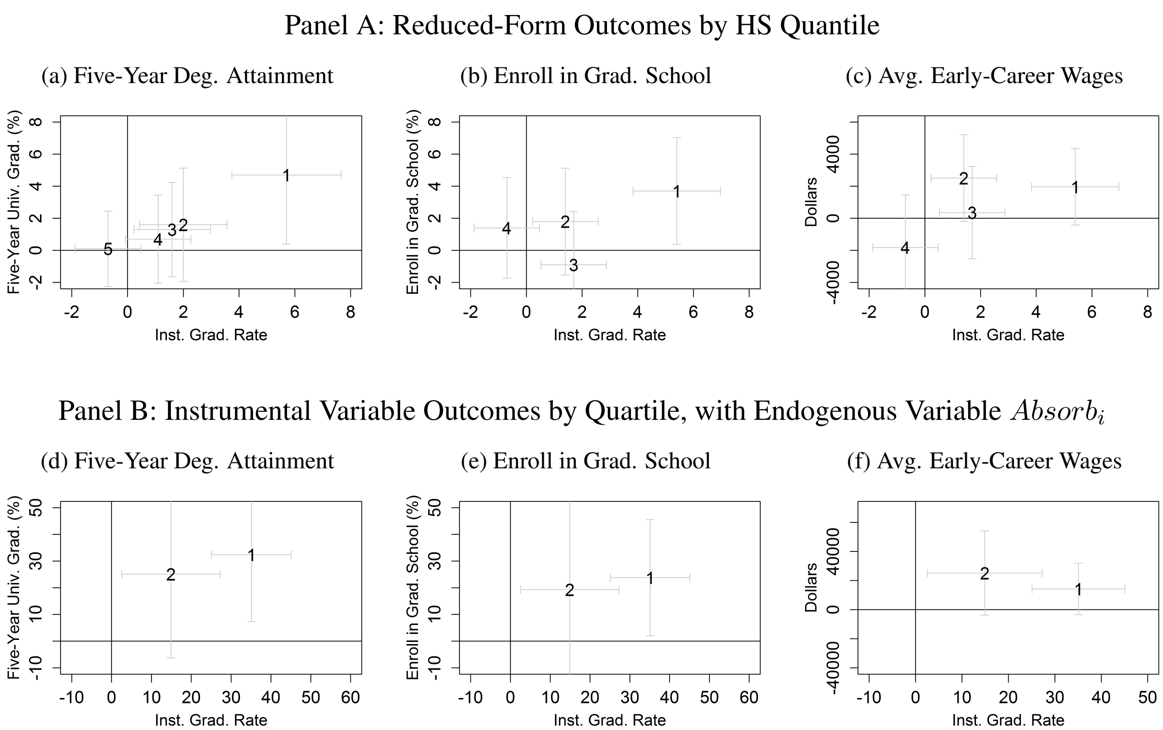
Note: Applicants' likelihood of admission to each UC campus by ELC GPA distance from their high school's ELC eligibility threshold, among all applicants and those from the bottom half (B50) or quartile (B25) of California high schools by SAT. Points are binned averages; lines are cubic fits. Beta estimates 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.

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).

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).

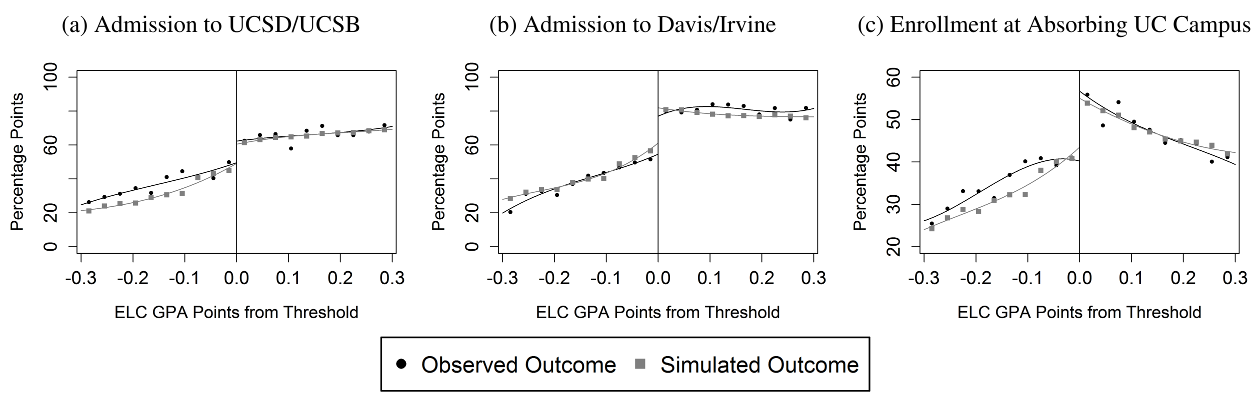
Figure 4: 2002 Admissions Protocol used by UC Davis

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 11^{th} grade	0 or 1	250	250
TOTAL REVIEW			13,000

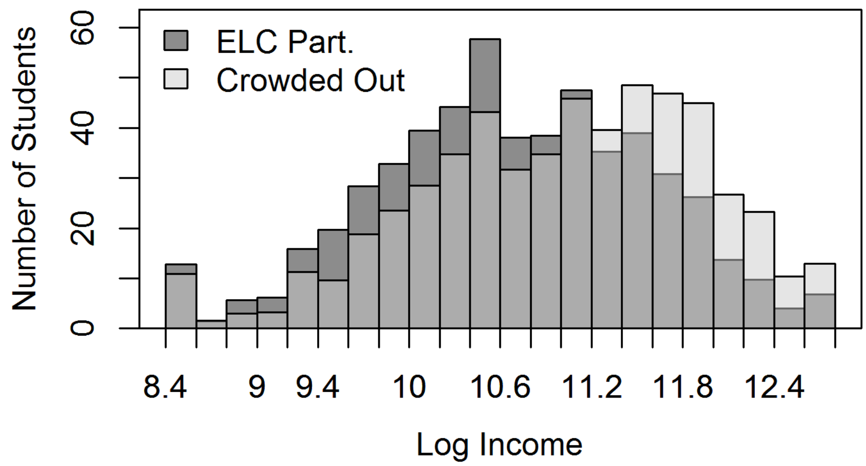
Note: This photograph shows an internal archival UC Davis admissions document visualizing Davis's 2002 freshman admissions protocol. Students were assigned points on the basis of applicant characteristics, and those with scores above a designated threshold were admitted to the campus. Source: Archives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

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



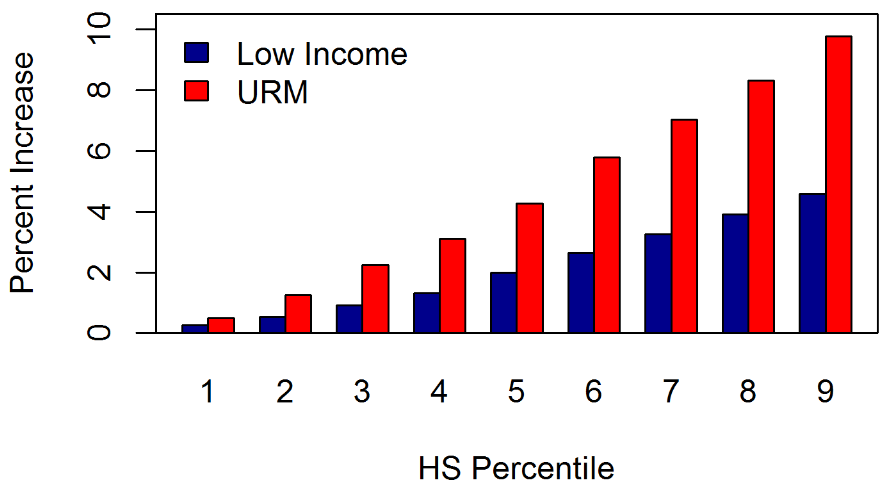
Note: Binned scatterplots and third-order polynomial best-fit lines of 2010-2011 UC applicants' (black) unconditional admission or enrollment at each set of UC campuses and (gray) simulated likelihoods of unconditional admission or enrollment at each set of UC campuses using the estimated parameters 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.

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



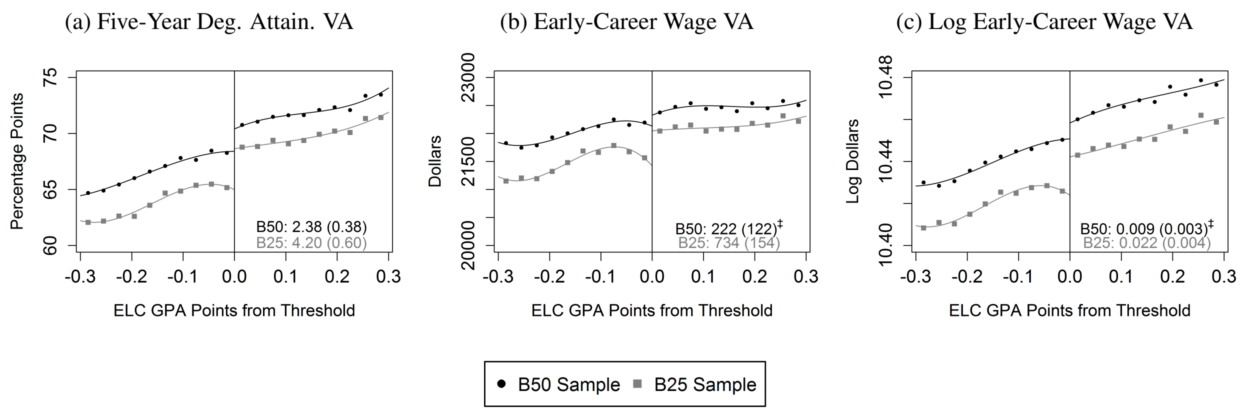
Note: Distribution of family incomes of annual ELC participants and crowded-out students under a simulation (employing the estimated parameters of the model described in Equation 7) in which 2010-2011 UC applicants were no longer provided an admissions advantage at the Absorbing UC campuses ($\beta^{ELC}_{Abs1} = \beta^{ELC}_{Abs2} = 0$). 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.

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.

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).

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

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 $p \nless 0.05$ (*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.

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.

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).

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	0.26	0.19	0.06	0.20	-0.12
	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.004)
Female	-0.42	-0.03	0.02	0.00	0.11	0.10
	(0.06)	(0.03)	(0.03)	(0.03)	(0.03)	(0.01)
Asian	0.93	-0.18	-0.31	0.02	-0.02	0.23
	(0.09)	(0.05)	(0.05)	(0.04)	(0.03)	(0.01)
URM	2.55	1.00	1.82	0.28	-0.23	0.04
	(0.08)	(0.04)	(0.04)	(0.04)	(0.03)	(0.01)
SAT	1.07	0.50	-0.11	-0.19	-0.18	0.53
	(0.05)	(0.02)	(0.02)	(0.02)	(0.02)	(0.005)
HS GPA	-0.87	-0.81	-0.79	-1.02	0.27	1.15
	(0.07)	(0.03)	(0.03)	(0.02)	(0.01)	(0.01)
CC VA	-0.01	-0.04	-0.02	-0.32	-0.13	-0.04
	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.003)
δ_j	4.97	2.18	2.13	-0.47	0.76	
	(0.10)	(0.04)	(0.04)	(0.04)	(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.

Table 6: ELC and Admissions Model Parameters

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

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.

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 $\times$ 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 $\times$ 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).

Online Appendix: Top Percent Policies and the Return to Postsecondary Selectivity

Zachary Bleemer

Appendix A: The Impact of ELC on UC Admissions after 2012

In 2011, the University of California "expanded" its Eligibility in the Local Context program to the top nine percent of graduates from each California high school. It also began calculating each high school's GPA thresholds at each percentile from first to ninth, instead of only the fourth percentile, and each UC campus was directly provided with its applicants' ELC percentiles for admissions purposes.[64] As a result, campuses were subsequently able to provide admissions advantages to their choice of applicant GPA centile.

I analyze the post-2011 impact of ELC eligibility on UC admissions and enrollment by employing the same regression discontinuity research design described in the main text to estimate the effect of barely achieving each GPA centile threshold on admission and enrollment at each UC campus. I follow Equation

Table AA-1: The 2012-2017 Impact of ELC Percentile on Admission to Each UC Campus

	UCB	UCLA	UCSB	UCD	UCSD	UCI	UCR	UCSC	UCM
First Centile	-4.19	-1.94	-0.83	-0.08	3.44 *	1.12	-1.66	-3.35	-2.60
Second Centile	1.36	0.32	-2.70	0.19	5.69 **	1.45	-1.85	1.04	0.85
Third Centile	1.44	2.30	-1.56	-1.58	0.59	-1.98	-1.75	2.80	0.96
Fourth Centile	-0.63	-0.30	0.72	1.48	-0.71	4.05 †	1.57	-0.65	-0.07
Fifth Centile	0.38	0.87	0.22	-0.26	3.78	0.62	-0.62	-0.07	2.04
Sixth Centile	-1.01	-0.07	0.35	-1.86	-1.84	-1.49	-1.00	0.74	-0.04
Seventh Centile	0.51	1.45	0.42	2.57	2.04	0.10	0.71	0.21	1.11
Eighth Centile	-0.77	0.46	0.36	1.76	1.27	0.04	-1.22	-0.61	0.38
Ninth Centile	-0.19	0.44	1.00	0.89	0.44	1.18	-4.83 *	1.47	10.54 **

Note: This table shows that achieving post-2011 ELC eligibility or any of the first to ninth centiles of (within-high-school) ELC GPA rank provided negligible admissions advantages at all UC campuses except for UC Merced, which provided a small admissions advantage to ELC-eligible students. Estimated $\hat{\beta}$ (treatment) coefficients on applicants' likelihood of admission to each UC campus (conditional on application) at each 2012-2017 ELC GPA centile threshold from local linear regression discontinuity estimation, with indicated statistical significance (from 0) estimated by bias-corrected cluster-robust standard errors by school-year (Calonico et al., 2019) following Equation 2. Sample restricted to applicants from the bottom half of California high schools by SAT (B50). Applicants from high schools with ELC eligibility thresholds between 3.96 and 4.00 are omitted. Statistical significance: † 10 percent, * 5 percent, ** 1 percent. Source: UC Corporate Student System

[64] UC also ceased calculating special "ELC GPA"s, instead relying on high-school-provided grade point averages, and switched to only updating each schools' centile thresholds every three years. It also ceased informing students of their ELC eligibility prior to UC application.

Table AA-2: The 2012-2017 Impact of ELC Percentile on Enrollment at Each UC Campus

	UCB	UCLA	UCSB	UCD	UCSD	UCI	UCR	UCSC	UCM
First Centile	-1.60	-0.83	2.25 **	1.46	2.18	-1.31	0.79	-0.16	-0.64
Second Centile	-0.51	-1.14	0.66	-3.07 *	0.26	0.93	0.73	0.20	-0.58
Third Centile	-0.35	0.68	-0.31	-1.27	-0.58	-0.31	0.21	-0.66	0.20
Fourth Centile	-0.02	-0.70	-0.13	0.41	-1.58 †	0.58	0.40	0.16	-0.02
Fifth Centile	0.67	0.26	-0.13	0.37	-0.33	-0.26	0.64	0.16	0.14
Sixth Centile	0.29	0.06	-0.39	-2.40 †	0.51	1.20	-0.07	0.15	0.43
Seventh Centile	0.09	0.47	0.85	0.14	0.50	-0.47	0.51	0.17	0.60
Eighth Centile	-0.15	0.52	0.71	0.08	1.31 *	0.40	-0.16	-0.48	-0.71
Ninth Centile	-0.10	0.00	-0.23	0.78	-0.04	0.51	-0.10	0.45	-0.03

Note: This table shows that achieving post-2011 ELC eligibility or any of the first to ninth centiles of (within-high-school) ELC GPA rank caused no meaningful measurable changes in students' likelihood of enrollment at any UC campus, including UC Merced. Estimated $\hat{\beta}$ (treatment) coefficients on applicants' unconditional likelihood of enrollment at each UC campus at each 2012-2017 ELC GPA centile threshold from local linear regression discontinuity estimation, with indicated statistical significance (from 0) estimated by bias-corrected cluster-robust standard errors by school-year (Calonico et al., 2019) following Equation 2. Sample restricted to applicants from the bottom half of California high schools by SAT (B50). Applicants from high schools with ELC eligibility thresholds between 3.96 and 4.00 are omitted. Statistical significance: † 10 percent, * 5 percent, ** 1 percent. Source: UC Corporate Student System

2 and employ the conservative local linear running variable specification with bias-corrected cluster-robust standard errors (Calonico et al., 2019).[65] The data cover UC admissions from 2012 to 2017 and are restricted to students from the bottom half of California high schools by SAT (B50).

Between 2001 and 2011, the four Absorbing UC campuses provided admissions advantages to the top four percent of B50 graduates from each high school of between 12 and 33 percentage points, leading to 3-5 percentage point enrollment increases at Davis, San Diego, and Irvine (see Table A-2). After 2012, the impact of ELC eligibility on campus admissions was far smaller. Table AA-1 shows that only UC's least-selective Merced campus provided an estimable admissions advantage to ELC-eligible students, with eligible students becoming about 10 percentage points more likely to be admitted. There is further evidence that Irvine provided a small (4 p.p.) advantage to students in the top four percent of their graduating class, and perhaps some evidence that San Diego provided an advantage to applicants from the top 1 or 2 percent of their classes. In short, ELC ceased providing meaningful admissions advantages to any campus other than UC Merced.

As a result of these inestimably small admissions advantages provided by ELC eligibility after 2012, ELC ceased substantially shifting near-threshold applicants' UC enrollment decisions. Table AA-2 replicates the structure of the previous table, replacing each outcome with unconditional enrollment by centile and UC campus. It shows no evidence of any enrollment increases at any UC campus among barely ELC-

[65] I calculate each of the annual centile thresholds for each high school using the same minimum-error method described in the main text.

eligible applicants or applicants barely in the top four percent of their graduating classes. There is not even a measurable enrollment increase at UC Merced among ELC-eligible applicants, despite its small admissions advantage for ELC-eligible applicants. Estimating Equation 2 for enrollment at *any* Absorbing UC campus between 2012 and 2017 results in a $\hat{\beta}$ of 1.1 p.p. (s.e. 1.4 p.p.) — and a coefficient of 0.4 (s.e. 1.3) at the fourth percentile threshold — rejecting any ELC-generated enrollment increase that is even a third of the magnitude of the pre-2012 policy's; in fact, the post-2011 policy appears no larger than one-tenth the size of its predecessor in terms of spurring more-selective university enrollment.

As a result of these findings, I assume that ELC played no substantial role in post-2011 UC admissions when constructing the structural model of university decision-making in Section 6 above.

Appendix B: Robustness of Regression Discontinuity Design

This appendix discusses several tests of the key smoothness assumption justifying the regression discontinuity design presented in the main text.

B.1 Sample Selection Bias

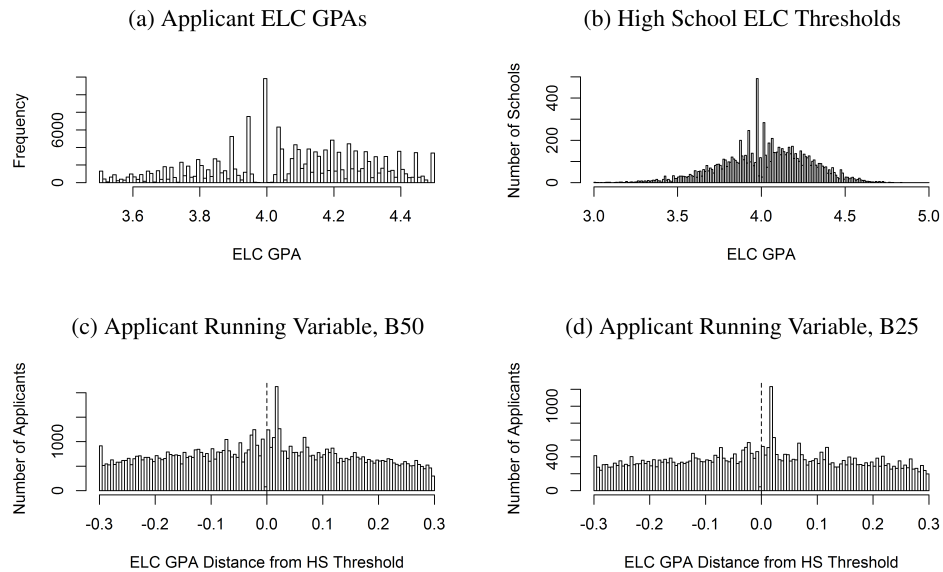
The most common sample selection concern in regression discontinuity settings arises from individuals observing their running variable value and changing their position to end up across the threshold. In the present setting, such "cheating" would involve high school students inflating their grades — for example, by studying harder for certain exams — in order to end up above their school's ELC eligibility threshold. However, ELC's centrally-organized policy structure makes such behavior impossible. Thresholds were recalculated every year using special centrally-calculated ELC GPAs, so students would have been unable to know their own or their peers' UC-calculated ELC GPA ranks prior to being informed of their eligibility. Indeed, even students who strategically switched high schools in order to achieve ELC eligibility (as some students appear to have done in Texas (Cullen, Long, and Reback, 2013)) could not have known where they would fall on the ELC GPA running variable, for which reason their presence is not a threat to the research design as presented.

However, the observed data do not contain every ELC-eligible or -ineligible California high school student, but are instead limited to students who apply to at least one of the nine undergraduate UC campuses. There is good reason to think that all students within 0.3 GPA points of their high schools' thresholds — the relevant sample in this study — would apply to at least one UC campus whether or not they were ELC eligible. These are students in the top $\sim$5% of their high school classes, and by 2000 over 14 percent of the average California high school's graduates applied to at least one UC campus. Even bottom-quartile schools by SAT score had an average UC application rate of 9.4 percent, and 9.5 percent of the average school's URM graduates applied to UC.

Moreover, nearly all of the sample's students would be virtually guaranteed to be admitted to several highly-regarded UC campuses. For example, Appendix Table A-2 shows that barely ELC-ineligible students had admissions rates of 91.9 percent at UC Santa Barbara, 98.0 percent at Santa Cruz, and 96.6 percent at Riverside, which had US News & World Report national rankings of 44^{th}, 79^{th}, and 96^{th} in 2008. Even at bottom-quartile (B25) high schools, the admissions rates would be 77.3 percent, 93.0 percent, and 94.1 percent; among URM students, 83.5 percent at Santa Barbara, 94.6 percent at Santa Cruz, and 93.1 percent at Riverside. There are no public research universities in California outside the UC system; students' next-best alternative paying in-state tuition (which in 2008 was $6,200, a small fraction of the cost of comparable alternatives) would be local comprehensive universities in the California State University system.

Also, though ELC-eligible students received letters notifying them that they would be guaranteed admission to at least one UC campus if they applied, 94.5 percent of ELC-ineligible students within 0.3 ELC

Figure BB-1: Distribution of ELC GPAs, Overall and Around High School Thresholds



Note: This figure shows that the uneven discrete nature of the ELC GPA running variable combines with UC's GPA threshold selection rule (providing ELC eligibility to GPA 'ties') to cause a discrete mass of applicants with running variables exactly 0.02 GPA points above their high schools' thresholds, but there is no other evidence of applicants bunching above the eligibility threshold. (a) Discrete distribution of observed ELC GPAs by hundredth across years. ELC GPAs only observed for California high school seniors in the top 10 percent of their class who did not allow their ELC-participating high school to share their transcript with UC, and who applied to at least one UC campus. (b) Discrete distribution of high schools' estimated ELC eligibility thresholds (see the Data section for estimation details). (c and d) Discrete distribution of the running variable (difference between high school threshold and own ELC GPA), within 0.3 GPA of the threshold, for applicants from the bottom half and quartile of California high schools by SAT (see Footnote 28 for definition of SAT quartiles). Source: UC Corporate Student System.

GPA points of their high schools' thresholds received similar letters notifying them that they too would likely be guaranteed admission to at least one UC campus under UC's "Eligibility in the Statewide Context" program, which guaranteed admission to students in the top 12.5% of California high school graduates by a publicly-available linear combination of GPA and SAT score.[66] There is thus little reason to expect that the ELC eligibility letter would cause barely above-threshold students to become meaningfully more likely to apply to UC relative to below-threshold students.

However, a peculiarity of the University of California's ELC eligibility threshold-setting rule interferes the clearest test of the presence of selection into application, the McCrary (2008) test of distributional discontinuity at the eligibility boundary. Because ELC eligibility was determined using ELC GPAs rounded to the nearest hundredth, any students who 'tied' for the 4th percentile GPA were also deemed ELC-eligible. Moreover, because the distribution of ELC GPAs is highly lumpy — see Panel (a) in Figure BB-1 — popular ELC GPAs were likely to be chosen as the fourth-percentile threshold, which algorithmically generates a particular 'bunching' pattern immediately above the ELC eligibility threshold. The distribution of thresholds across high schools is shown in Panel (b) of Figure BB-1. Note that these figures are not histograms, but complete reflections of the counts of the discrete running variable.[67]

[66] The letter to ELC-ineligible students was somewhat speculative, because UC administrators could not yet observe the students' SAT scores.

[67] In the 1.3% of high-school-years when the estimated ELC eligibility thresholds are not in these discrete bins, as a result of noise in eligibility reporting around the threshold discussed in the Data section above, I round to the nearest 0.005 for Figure BB-1.

As a result, Panel (c) of Figure BB-1 shows a discrete mass of B50 applicants exactly 0.02 GPA points above the eligibility threshold. There is no evidence of bunching at any other level of the running variable, nor evidence of a decline in the number of applicants below the threshold (a tell-tale pattern of selection); indeed, there appears to be slightly elevated numbers of applicants just below the threshold as well, another artifact of the threshold determination rule (which usually selects the mean between the lowest eligible ELC GPA and the highest ineligible ELC GPA). Panel (d) shows an even more extreme pattern among B25 applicants, since those schools tend to have fewer honors- and AP-level courses available and thus coarser grade point averages. The 0.02 mass point largely reflects schools with minimum eligible ELC GPAs at exactly 3.94, 4.0, and 4.06 (with the next-highest GPA exactly 0.04 points lower). There is no other evidence of distributional discontinuity in the sample.

While both of these distributions fail the McCrary test, it appears unlikely that they do so as a result of selection into UC application among ELC-eligible students, which would generate a more distributed pattern of increased applications just above high schools' thresholds. Sample selection bias would also likely lead to different observable student characteristics across the eligibility threshold, of which no evidence can be seen in the baseline coefficient estimates presented in Table A-1 despite substantial power and highly-detailed observed demographics.

B.1.1 Difference-in-Difference Comparison with Comparable Post-2011 Applicants

I conduct one further test of selection into application, investigating whether the characteristics of UC applicants in the top four percent of the graduating classes change after the ELC program's admissions advantages ceased in 2012 (see Appendix A). While UC continued to identify the fourth percentile of applicants from each school-year, though it made a number of changes after 2011: (a) eligibility was determined using grades submitted by applicants on their UC applications instead of being calculated from high school records, including ninth grade grades; (b) applicants were no longer informed by letter of their eligibility; and (c) GPAs were no longer rounded to the nearest hundredth, and thresholds were only calculated every three years.[68] Nevertheless, if being notified of ELC eligibility encouraged UC application, then the identification of a group of fourth-percentile applicants who did *not* receive notification suggests a test of whether the informed applicants differ from the non-informed on detailed observables. I restrict the sample to 2010-2013 applicants within 0.1 ELC GPA points of their schools' fourth percentile threshold and estimate difference-in-difference regressions of the form:

$$Y_{iy} = \alpha_{h_i} + \gamma_y + \beta_1 Above_i + \beta_2 Above_i Pre_y + \gamma_{1y} GPA_{iy} Above_i + \gamma_{2y} GPA_{iy}(1 - Above_i) + \epsilon_{iy} \quad (9)$$

where Y_{iy} is an observed permanent characteristic of individual i who applied to UC in y, $Above_i$ indicates having an ELC GPA above the fourth percentile threshold, Pre_y indicates $y \in (2010, 2011)$, and GPA_{iy} is that year's ELC GPA.[69] Standard errors are clustered by school-year.

Table BB-1 shows estimates of Equation 9's β_2 for the highly detailed set of observable characteristics described above. Estimates are shown for the full sample and for B50 and B25 applicants. Despite substantial precision (e.g. standard errors of 2 percentage points for gender and 6 points for the SAT), the only estimate with a t-statistic greater than 1.5 suggests that under the ELC program, above-threshold B25 applicants had somewhat-*lower* average SAT scores by about 35 points, or 0.15 standard deviations. As in the main text, I construct predicted measures of degree attainment and early-career earnings and find that the estimates of predicted income are precisely estimated 0's, while those of college graduation suggest slight

[68] Because of the change in GPA and threshold calculations implemented by policy-makers, the distributions of students around the ELC eligibility thresholds also changes somewhat, prohibiting direct tests of running-variable distributional similarity.

[69] I allow the γ terms to differ before and after 2011 in order to account for the 2012 change in GPA calculation.

Table BB-1: Baseline Balance Versus Post-2011 Applicants within 0.1 GPA Points of 4th Percentile Threshold

	Pre-Treatment Dependent Variable						Predicted Values[2]	
	Female (%)	URM (%)	Max. Parent Ed. (Index)[1]	Log Fam. Income	Missing Inc. (%)	SAT Score	Graduation Rate (%)	California Earnings ($)
All	0.55	-0.06	-0.12	-0.072	-1.13	-8.80	-0.32	86.44
	(1.92)	(1.47)	(0.07)	(0.055)	(1.36)	(6.36)	(0.29)	(411)
B50	0.84	1.26	-0.01	-0.030	-0.11	-15.41	-0.22	160
	(3.21)	(2.72)	(0.14)	(0.088)	(1.75)	(12.04)	(0.52)	(566)
B25	3.24	2.50	-0.34	0.051	-3.16	-35.06	-0.88	-75.66
	(4.35)	(3.73)	(0.20)	(0.123)	(2.00)	(17.10)	(0.70)	(706)

Note: Reported coefficients are from difference-in-difference balance estimates of permanent applicant characteristics on an indicator for pre-2012 and above the 4th percentile ELC eligibility threshold, among 2010-2013 UC applicants within 0.1 ELC GPA points of their high schools' ELC eligibility threshold. Sample covers all students and applicants and applicants from the bottom half (B50) or quartile (B25) of California high schools by SAT. Covariates include interactions between a pre-2012 indicator, a 4th percentile indicator, and the running variable (applicants' ELC GPA distance from their high school's threshold), along with high school and year fixed effects. Standard errors (in parentheses) are clustered by school-year. [1]Integer index of reported maximum parental education (across two parents), from 1 (no high school) to 7 (graduate degree). [2]Dependent variable is 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 either five-year NSC graduation or 6-to-8 year average California covered wages (see text for definitions) on gender by ethnicity indicators, maximum parental education indicators (7 categories), family income, missing income indicator, SAT score, and year indicators. UC Corporate Student System.

negative selection, with pre-2012 above-threshold B25 applicants having lower expected likelihoods of graduation by 0.9 (s.e. 0.7) percentage points. These evidence suggest that the composition of near-threshold UC applicants did not change after ELC's letter-sending and admissions advantages ceased.

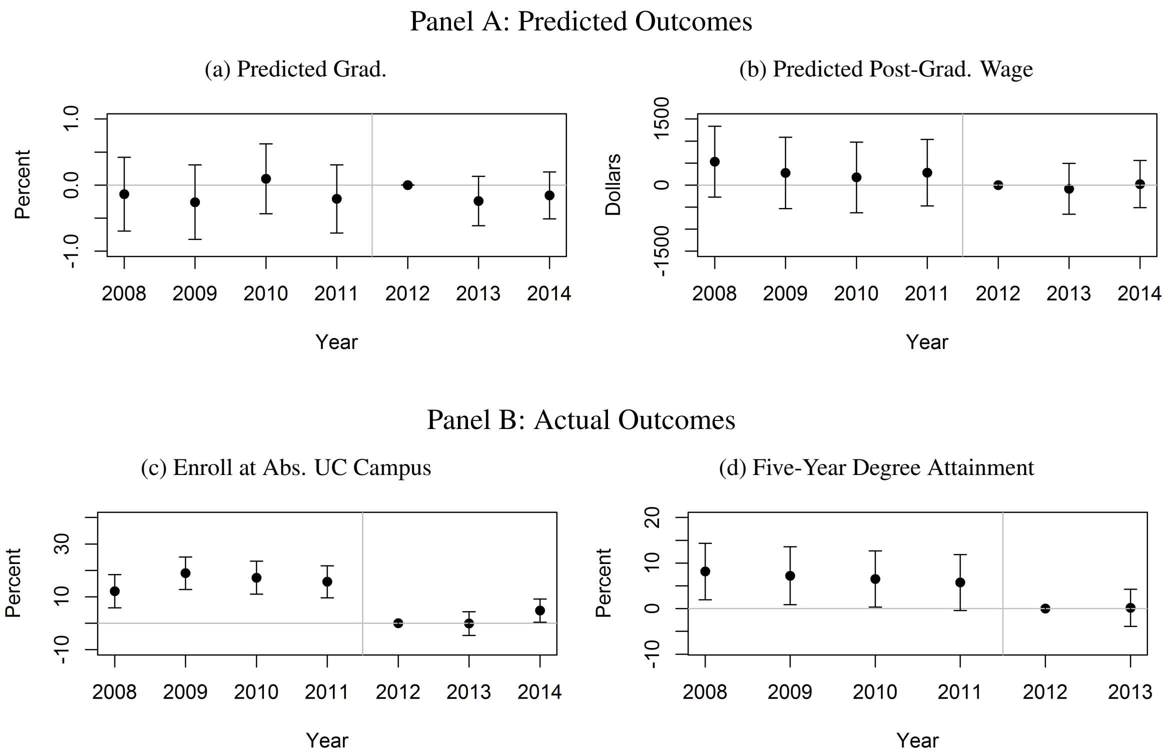
The first panel of Figure BB-2 estimates Equation 9 annually relative to 2012, adding the covariates used in the main analysis: gender-ethnicity indicators and a quadratic of SAT score. It suggests that there is little evidence of a meaningful change in near-threshold applicant characteristics around the ELC eligibility threshold, providing important evidence against sample selection driving the present study's main reduced-form findings. Indeed, the small degree of selection appears to be negative selection, suggesting that those estimates may be slightly conservative.

Panel B provides an additional robustness check on the study's findings by replacing Y_{iy} in Equation 9 with indicators for enrolling at an Absorbing UC campus and five-year degree attainment. It shows that despite no evidence of differential selection, above-threshold applicants prior to 2012 were significantly and substantially more likely than their post-2011 peers to enroll at Absorbing campuses and earn college degrees (though the latter estimates are somewhat noisy). The estimated coefficients are slightly larger than the regression discontinuity results, though the two are statistically indistinguishable. In short, these difference-in-difference findings provide additional support for a causal interpretation of the study's main reduced-form findings.

B.2 Alternative Discontinuities in the Running Variable

The distribution of ELC GPAs shown in Figure BB-1 also suggests a second possible threat to the research design resulting from the apparent non-continuity of the running variable as a measure of student preparedness. The large mass point at 4.00 GPA, for example, could indicate that students at that GPA level are qualitatively different academic performers than those with slightly lower GPAs, perhaps because GPAs above 4.00 are effectively top-censored for students not taking honors-level classes (since even the best students are unable to earn more than 4.00 GPA points in such courses). Similar (though lesser) concerns

Figure BB-2: Difference-in-Difference Estimates after 2011 for Near-Threshold B50 Applicants



Note: This table replicates the main reduced-form findings in the study in a difference-in-difference design following the end of admissions advantages for top-four-percent applicants after 2011, showing that above-threshold B50 applicants were of similar socioeconomic composition but faced declines in Absorbing UC campus enrollment and degree attainment as would have been anticipated by the regression-discontinuity estimates. Difference-in-difference estimates of applicant characteristics and outcomes on annual indicators interacted with an indicator for being above the 4th percentile ELC eligibility threshold, among 2008-2014 UC applicants within 0.1 ELC GPA points of their high schools' ELC eligibility threshold. Sample restricted to applicants from the bottom half of California high schools by SAT (B50). Covariates include interactions between pre-2012 indicator, a 4th percentile indicator, and the running variable (applicants' ELC GPA distance from their high school's threshold), along with high school and year fixed effects, gender-ethnicity indicators, and a quadratic in SAT score. Predicted graduation rate and wages from an OLS regression (across the full sample of 1995-2013 UC freshman California-resident applicants, excluding the study's primary sample) of either five-year NSC graduation or 6-to-8 year average California covered wages on gender by ethnicity indicators, maximum parental education indicators (7 categories), family income, missing income indicator, SAT score, and year indicators. Absorbing UC Campus enrollment includes San Diego, Davis, Irvine, and Santa Barbara, and is measured from National Student Clearinghouse, as is whether the student has earned a college degree within five years of high school graduation. Degree attainment for the 2014 cohort is not yet observed. Standard errors (in parentheses) are clustered by school-year. Source: UC Corporate Student System, National Student Clearinghouse, and the California Employment Development Department (Bleemer, 2018).

may be present at other GPA mass points. Because UC's ELC eligibility threshold-setting rule tended to set thresholds just below these mass points — since greater mass at a given GPA leads to a greater likelihood of the fourth-percentile student having that GPA — these qualitative differences could positively bias the study's main reduced-form results: GPA mass points tend to be censored from above, suggesting that students at mass points are higher-performing than their GPA evinces.

These arguments justify the removal of high schools with ELC eligibility thresholds at 4.00, which I omit from all reduced-form analysis.[70] Having removed those schools, the clearest test of the presence of

[70] In particular, I omit high schools with estimated ELC eligibility thresholds between 3.96 and 4.00. Estimates are highly similar — with no important changes to estimate magnitude or significance — when those schools are included.

Table BB-2: Caetano (2015) Endogeneity Test Coefficients at 4.0 ELC GPA

	SAT	Predicted Values Grad. Rate	Predicted Values Earnings	Abs. UC Enr.	Five-Year Grad. Rate	Grad. In Five Years	Early-Career CA Earnings
All	-9.3	-0.01	-17.68	-0.39	0.39	1.42	-2,085
	(0.66)	(0.01)	(31.99)	(0.19)	(0.08)	(0.15)	(419)
B25	12.24	0.06	-243.32	0.52	1.05	2.05	-2,336
	(1.47)	(0.02)	(53.12)	(0.40)	(0.19)	(0.37)	(764)
Bandwidth	0.09	0.09	0.09	0.08	0.07	0.09	0.07

Note: This table shows the potential for small upward biases in reduced-form estimates of barely-eligible applicants' degree attainment resulting from a possible potential-outcome discontinuity in applicants' GPA running variable at exactly 4.0, though as the text explains, the actual biases resulting from such discontinuities is far smaller than those shown in this table (which assume that *every* ELC eligibility threshold is set at exactly 4.0, whereas in fact all such applicants are removed from the main estimation sample). Reported coefficients are endogeneity test coefficients estimated by two-step procedure described in Caetano (2015) around a 4.0 ELC GPA on various outcomes defined in previous tables, with same controls as main specification (indicator for above ELC eligibility threshold, polynomial in distance from threshold, polynomial in SAT, gender/URM indicators, and high school and year FEs), for the full sample and for students from the bottom SAT quartile of high schools. Coefficients are normally distributed with standard errors in parentheses; statistical significance rejects the null hypothesis that the outcome is conditionally continuous at GPA 4.0. Coefficients can be interpreted as the bias induced by endogeneity in the running variable at 4.0. Bandwidths are optimally chosen following Calonico, Cattaneo, and Titiunik (2014), and range from 0.07 to 0.09 GPA points. B25 applicants are those from the bottom quartile of high schools by SAT score. Source: UC Corporate Student System, National Student Clearinghouse, and CA Employment Development Department.

running variable discontinuities at the eligibility threshold is the baseline estimates presented in Table A-1, along with the covariate comparisons with post-2011 applicants (for whom mechanical threshold-bunching no longer occurred) presented in Appendix Table BB-1. These estimates suggest the absence of positive selection just above the eligibility threshold on detailed demographic and socioeconomic characteristics.

The binned scatterplots in Figure 2 provide additional evidence that running variable discontinuities are not biasing the estimates; a discontinuity just above the threshold would lead the fit line to spike upwards approaching the threshold from above, but there is no such pattern in any of the figures.

I further test the continuity of applicant preparedness along the running variable at the 4.00 mass point using the test presented by Caetano (2015), directly estimating the degree of mass-point non-continuity by comparing conditional regression estimates at the mass point to those of local linear regressions around the mass point. The tests include the same covariates as in Equation 2, with third-order polynomials in distance to the ELC eligibility threshold, and provide bounds on the bias induced by the running variable's non-continuities. Bandwidths are optimally chosen following Calonico, Cattaneo, and Titiunik (2014) as in the local linear estimates presented above, and range from 0.07 to 0.09 GPA points.

4.00 is chosen because it is almost-certainly the mass point with the largest type-discontinuity in the running variable; students with 4.00 GPAs might have been able to perform better if grades above A were available to be earned, and thus may be qualitatively different from students just below that GPA. As a result, the generated estimates are not only upper bounds for the possible degree of bias caused by type discontinuities at the eligibility threshold, but would be expected to be *far* higher than the true observed bias, since high schools with 4.00 eligibility thresholds are omitted from the analysis and most high schools' thresholds are not located at similar discontinuities.

Table BB-2 shows the resulting estimates. Unsurprisingly, 4.00 students in the bottom SAT quartile of high schools have significantly upwardly biased SAT scores and predicted likelihoods of graduation, though their expected postgraduate wages are substantially negatively biased. These estimates suggest that if type-discontinuities were driving the observed results, we would expect to observe them in discontinuous student characteristics at the eligibility threshold, though no such differences are observed (see Table A-1).

The remaining columns suggest the possibility for modest bias in enrollment behavior, graduation rate, and early-career California wages, the latter of which appears to be negatively biased. The most-troubling of these results is the possible two percentage-point upward bias in five-year graduation rates. However, consider a worst-case scenario in which half of students' high schools' eligibility thresholds were set at type discontinuities just as biased as the 4.00 bias (an extremely unlikely scenario). In this case, we would expect a 1 percentage point upward bias in our estimate of the impact of ELC eligibility on graduation. In fact, Table A-10 shows that the comparable local-linear estimate of the increase in five-year graduation rate for bottom-quartile applicants is 6.29 p.p. This implies a maximum possible upward bias of 16 percent. In fact, there is good reason to think that the bias is substantially smaller:

1. Bias of such magnitude would be observable in the detailed characteristics observed for each applicant, but there is no evidence of positive selection on observables (if anything, there is slight evidence of negative selection on SAT score).

2. Most type discontinuities are likely to impose less bias than the discontinuity at 4.00, which is omitted from the sample.

3. Most high schools' thresholds are likely *not* set at meaningfully discontinuous points in the running variable.

As a result of these estimates and others described in the text, I report uncorrected estimates and assume that type discontinuities play a very minor (if any) role in driving this study's results.

Appendix C: National Student Clearinghouse Data Quality

The National Student Clearinghouse's StudentTracker database contains enrollment and graduation records for nearly all two- and four-year postsecondary institutions in the United States. A nonprofit and non-governmental organization founded in 1993, NSC collects postsecondary student records and provides degree verification and other services back to contributing universities. Participating universities, including the University of California, are permitted to match their applicants and enrollees by name and date of birth (using NSC's proprietary match algorithm) in order to observe those students' enrollment and degrees at other institutions.[71]

Individual students' enrollment or graduation records may fail to match in the NSC for three reasons: (1) because the student's institution does not report records to NSC; (2) because the student has blocked their record from being shared through NSC; or (3) the student's name and date of birth fail to match using the NSC's match algorithm. NSC reports that about 4 percent of records are censored due to student- or institution-requested blocks for privacy concerns (National Student Clearinghouse Research Center, 2017), and that the only public university in California with censorship greater than 10 percent is UC Berkeley. Dynarski, Hemelt, and Hyman (2015) compare aggregate NSC enrollment to aggregate enrollment reported in the federal Integrated Postsecondary Education Data System (IPEDS) and find that enrollment coverage has been greater than 90 percent in California since at least 2003, the first year of data used in the present study, and is near-comprehensive for public institutions. Coverage is shown to generally be poorest at for-profit institutions.

I directly test the quality of NSC coverage for the institutions at which UC applicants tend to enroll in two ways. Using the complete linked UC-NSC database since 1994, I measure institution's NSC participation by identifying the first recorded year in which each institution appears in the NSC records. Table CC-1 presents a complete list of California public four-year universities along with all private California four-year universities with at least 500 enrolled students in 1998. The largest institution that still fails to report

[71] For additional documentation, see NSC's "StudentTracker for Systems of Institutions User Manual": https://studentclearinghouse.info/onestop/wp-content/uploads/STSOI_User_Manual.pdf.

Table CC-1: Maximum Years that Four-Year Universities in California Began Contributing to National Student Clearinghouse

Institution	1998 Enroll.	In NSC Data Enroll.	In NSC Data Grad.	Univ.	1998 Enroll.	In NSC Data Enroll.	In NSC Data Grad.
University of California							
UC Los Angeles	24,101	1995	1995	UC Irvine	14,336	1995	1995
UC Berkeley	22,259	1995	1996	UC Santa Cruz	9,921	1995	1996
UC Davis	19,258	1995	1995	UC Riverside	9,125	**2000**	1996
UC Santa Barbara	17,048	1996	1995	UC Merced (2005)		2008	2006
UC San Diego	15,818	1995	1995				
California State University							
San Diego State Univ.	25,773	1995	1996	CSU San Bernardino	9,636	1995	1996
CSU Long Beach	22,868	1995	1996	CSU East Bay	9,626	1996	1996
CSU Fullerton	21,279	1996	1997	CSU Dominguez Hills	7,834	1996	1996
San Francisco State Univ.	21,044	1994	1995	Humboldt State Univ.	6,534	1995	1997
CSU Northridge	20,955	1995	1995	Sonoma State Univ.	5,856	**1998**	1996
San Jose State Univ.	20,681	1995	1996	CSU Stanislaus	4,992	1997	1995
CSU Sacramento	18,702	1995	1995	CSU Bakersfield	4,223	**2003**	1996
CA State Poly. Univ.	15,351	1996	1995	CSU San Marcos	4,103	1995	1996
CA Poly. State Univ.	15,347	1995	1996	CSU Monterey Bay	1,716	1995	1997
CSU Fresno	14,518	1995	1996	CA State Univ. Maritime Academy	436	**2006**	1998
CSU Los Angeles	13,935	**2003**	1996	CSU Channel Islands (2002)		2006	2003
CSU Chico	13,196	1996	1997				
Private Universities in California (Undergraduate enrollment $\geq$ 500 in 1998)							
Univ. of Southern CA	15,218	1995	1996	Golden Gate Univ.	1,235	**1998**	1996
Stanford Univ.	6,391	1994	1996	Vanguard Univ. of Southern CA	1,180	**2003**	1996
Univ. of San Francisco	4,570	1995	1996	La Sierra Univ.	1,148	1997	1997
Univ. of San Diego	4,439	**2007**	1997	Loma Linda Univ.	1,137	1995	1998
National Univ.	4,393	1995	1997	Claremont McKenna College	1,024	1996	1996
Loyola Marymount Univ.	4,327	1995	1996	Simpson Univ.	1,021	1996	**2003**
Santa Clara Univ.	4,311	**1999**	1997	CA College of the Arts	1,004	**2006**	1997
Academy of Art Univ.	4,023	1997	1998	Notre Dame de Namur Univ.	983	1997	1996
Saint Mary's College of CA	3,234	1996	1997	The Master's Univ. and Seminary	959	1997	1999
Pepperdine Univ.	3,233	1995	1996	Dominican Univ. of CA	946	**2001**	1998
Univ. of La Verne	3,168	**2005**	1995	Woodbury Univ.	931	1996	1998
Univ. of the Pacific	2,802	1996	1996	Marymount CA Univ.	923	**1998**	1995
Azusa Pacific Univ.	2,795	1996	1996	CA Institute of Technology	901	**2004**	1997
Univ. of Redlands	2,737	1997	1997	Pitzer College	880	1997	1997
Chapman Univ.	2,486	**2001**	1996	CA Institute of the Arts	777	1998	1997
Biola Univ.	2,341	1996	1997	Scripps College	776	1996	1997
Point Loma Nazarene Univ.	2,301	1996	1997	Otis College of Art and Design	763	**2004**	1998
Brandman Univ.	2,125	**2011**	**2003**	Fresno Pacific Univ.	754	1997	1997
CA Lutheran Univ.	1,750	1996	1996	Mills College	741	1996	1997
Mount Saint Mary's Univ.	1,687	1996	1996	Hope International Univ.	706	**1998**	1997
CA Baptist Univ.	1,653	1995	1997	Harvey Mudd College	705	1996	1997
Pomona College	1,571	1996	1995	Concordia Univ.	694	1996	1999
Pacific Union College	1,554	1997	1997	San Diego Christian College	648	**2015**	**2015**
Occidental College	1,529	**1999**	1995	Musicians Institute	559	**2011**	**2011**
Art Center College of Design	1,308	**2008**	1998	Ashford Univ.	555	**2000**	**2001**
Westmont College	1,304	1997	1998	Menlo College	534	**2015**	1997
Whittier College	1,279	1995	1996				

Note: This table shows that all public California universities were reporting enrollment and degree attainment throughout the ELC study period. The largest private California university that did not report degree attainment by the beginning of the study period was the 648-student San Diego Christian College. For all four-year public and private (with more than 500 students in 1998) higher education institutions in California, the earliest year in which any 1995-2016 applicant to any UC campus was recorded in the National Student Clearinghouse as being enrolled at that university or having graduated from that university. Years that might interfere with inference in a study of 1996 (or later) UC enrollees — that is, any years that suggest uniformly missing enrollment records after 1997 or missing graduation records after or in 1996+4=2000 — are in bold. Source: UC Corporate Student System and National Student Clearinghouse

enrollment to NSC in 2003 was the private 4,400-student University of San Diego, but all California public universities were reporting both enrollment and degree attainment by that year. The largest university to begin reporting degree attainment after 2007, the first year of degree receipience for the first cohort in the present study, was the 648-student San Diego Christian College.

Table CC-2 shows similar statistics for the California Community Colleges. As with the private universities, many community colleges did not begin reporting enrollment until the late 1990s or early 2000s,

Table CC-2: Maximum Years that California Community Colleges Began Contributing to National Student Clearinghouse

Institution	1998 Enroll.	In NSC Data Enroll.	In NSC Data Grad.	Univ.	1998 Enroll.	In NSC Data Enroll.	In NSC Data Grad.
California Community Colleges							
Pasadena City College	16272	**1998**	1995	West Valley College	4952	**2001**	1995
Orange Coast College	15759	**2000**	1995	Mt San Jacinto C.C. District	4805	1997	1995
Cerritos College	15703	1995	1997	Irvine Valley College	4793	1995	1995
Mt San Antonio College	15073	1996	1995	College of the Desert	4768	1996	1998
San Diego Mesa College	14527	**1998**	2004	Skyline College	4687	1996	1995
City College of San Francisco	13679	**2001**	1995	Ohlone College	4667	1997	1996
Riverside City College	13542	1996	1995	Merced College	4601	**1999**	1995
El Camino C.C. District	13379	1997	1995	Allan Hancock College	4593	1995	1995
American River College	13031	**1999**	1995	MiraCosta College	4307	1996	1995
Santa Monica College	12801	1996	1995	Coastline C.C.	4157	**2000**	2001
Fullerton College	12390	**1998**	1995	Imperial Valley College	4103	**2001**	1995
Palomar College	12338	**1998**	1995	Hartnell College	4093	1995	1997
Diablo Valley College	12229	1997	1995	Mission College	3963	**2001**	1995
De Anza College	11919	1995	1995	San Diego Miramar College	3905	**1998**	2004
Santa Rosa Junior College	11727	**1998**	1995	Victor Valley College	3680	**2001**	1998
Fresno City College	11491	**1998**	1995	Los Medanos College	3632	**2000**	1995
Long Beach City College	11247	1995	1995	Las Positas College	3508	1996	1995
Grossmont College	10976	**1999**	1998	Cuyamaca College	3463	**1999**	2003
Sacramento City College	10273	**1999**	1995	College of the Redwoods	3445	**2000**	1995
Sierra College	10113	1996	1995	Los Angeles Harbor College	3375	**1999**	1995
Modesto Junior College	9790	**2000**	1996	Los Angeles Trade Tech. College	3362	**1999**	1995
Southwestern College	9620	**2001**	1995	Contra Costa College	3237	**2001**	1995
San Diego City College	9574	**1998**	2004	Copper Mountain C.C.	2942	**1999**	2000
Chaffey College	9408	1997	1995	West Los Angeles College	2929	**1999**	1995
Citrus College	9317	**2000**	1995	Monterey Peninsula College	2913	**1998**	2002
Glendale C.C.	8672	**2001**	2001	Napa Valley College	2886	**1998**	1995
San Joaquin Delta College	8432	**1998**	1995	College of Marin	2881	**2000**	1995
Chabot College	8418	1996	1995	Oxnard College	2728	1996	1995
Rio Hondo College	8146	**2001**	1995	Crafton Hills College	2514	1995	1995
Cosumnes River College	7843	**1999**	1995	College of Alameda	2246	1997	1995
College of the Sequoias	7788	**2006**	1995	Los Angeles Southwest College	2112	**1999**	1995
Bakersfield College	7762	**2000**	1995	Los Angeles Mission College	2097	**1999**	1995
Cypress College	7718	**1998**	1995	Canada College	2094	1996	1995
Santa Barbara City College	7689	**1998**	1995	West Hills College	2086	**2001**	1995
Saddleback College	7673	1995	1995	Merritt College	1969	1997	1997
Santa Ana College	7629	1996	1995	Cerro Coso C.C.	1889	**2000**	1998
Moorpark College	7414	1996	1995	Porterville College	1692	**2000**	1998
East Los Angeles College	7151	**1999**	1995	Gavilan College	1650	**2010**	1995
Los Angeles Pierce College	6984	**1999**	1995	Mendocino College	1647	**1998**	1997
Golden West College	6961	**2000**	1997	Berkeley City College	1528	1997	2000
Butte College	6804	**1998**	2000	Barstow C.C.	1434	**1998**	1995
Los Angeles City College	6772	**1999**	1995	Columbia College	1328	**2000**	1997
Cuesta College	6644	1995	1995	College of the Siskiyous	991	**1998**	1998
Evergreen Valley College	6461	**2002**	1998	Lake Tahoe C.C.	910	**2001**	1995
College of San Mateo	6349	1996	1995	Lassen C.C.	837	**1998**	1995
Los Angeles Valley College	6337	**1999**	1995	College of the Canyons	637	**1998**	1995
San Jose City College	6230	**2002**	1995	Taft College	578	**2012**	1995
Foothill College	5836	1996	1995	Feather River C.C. District	486	**1998**	1995
Cabrillo College	5820	1996	1995	Palo Verde College	370	**2009**	2010
Solano C.C.	5602	**1998**	1995	Santiago Canyon College (2001)		2009	2001
Shasta College	5462	**1999**	1997	Folsom Lake College (2004)		2005	2004
Yuba College	5358	**2001**	1995	West Hills College (2006)		2007	2006
Antelope Valley College	5156	**1998**	1998	Woodland C.C. (2009)		2010	2009
Reedley College	5004	**1998**	1995	Moreno Valley College (2010)		2011	2010
Ventura College	4980	1996	1995	Norco College (2010)		2011	2010
Laney College	4978	1997	1997	Clovis C.C. (2016)		2016	2016
San Bernardino Valley College	4968	1995	1996				

Note: This table shows that nearly all California Community Colleges were reporting enrollment to NSC by the start of the study period. For all community colleges in California, the earliest year in which any 1995-2016 applicant to any UC campus was recorded in the National Student Clearinghouse as being enrolled at that college or having graduated from that college. Years that might interfere with inference in a study of 1996 (or later) UC enrollees — that is, any years that suggest uniformly missing enrollment records after 1997 or missing graduation records after or in 1996+4=2000 — are in bold. Source: UC Corporate Student System and National Student Clearinghouse

though they reported degree attainment in earlier years. However, by 2003 nearly-all extant schools were reporting enrollment.

Unfortunately, because I only observe enrollment for UC applicants, I cannot directly measure the pro-

Table CC-3: National Student Clearinghouse Degree Data Quality for UC Graduates

Year	UCB	UCD	UCLA	UCR	UCSD	UCSC	UCSB	UCI	UCM
1995	1.3	1.9	5.0	11.6	1.5	79.1	1.7	3.5	
1996	2.5	2.3	6.0	13.1	1.5	78.1	1.6	2.8	
1997	0.9	1.7	6.1	8.2	1.1	74.4	1.6	2.4	
1998	1.5	2.0	6.1	5.2	1.9	69.1	1.4	2.2	
1999	1.2	1.3	5.9	7.3	2.1	70.1	1.2	1.9	
2000	1.4	1.5	7.8	8.6	1.9	55.9	1.1	1.8	
2001	1.2	1.9	6.8	9.2	1.3	5.7	0.9	2.6	
2002	1.1	1.6	6.7	10.5	1.6	2.1	1.8	2.6	
2003	0.3	1.8	6.7	9.9	1.8	2.8	1.9	1.7	
2004	0.8	2.7	6.0	9.5	1.9	2.9	1.7	1.9	
2005	1.2	2.2	6.6	9.0	2.0	2.1	2.5	2.1	1.5
2006	1.4	2.2	8.4	8.5	2.0	3.5	2.4	1.8	0.5
2007	1.1	2.6	8.9	8.7	2.1	3.4	2.0	1.6	3.0
2008	1.1	2.8	7.6	9.4	2.8	3.0	2.2	1.9	1.3
2009	1.2	3.2	7.7	8.1	2.0	3.5	2.9	2.4	1.5
2010	1.5	2.7	8.1	7.6	2.6	2.7	3.1	2.4	1.4
2011	2.4	2.7	6.5	9.7	2.8	3.3	3.5	2.4	0.9
2012	0.4	2.1	4.4	7.3	1.7	2.0	2.5	2.2	1.6

Note: This table shows low levels of missing NSC degree attainment records for UC graduates identified in administrative data throughout the study period. The proportion of UC graduates (within five years of first enrollment), among freshman California-resident enrollees, who are not recorded as having graduated within five years of graduating in their matched National Student Clearinghouse record, by UC campus and year of first enrollment. Source: UC Corporate Student System and National Student Clearinghouse

portion of enrollees at each California university that appear in the NSC. However, I *can* estimate NSC's data quality for the UC campuses themselves. I first focus on degree attainment, measuring the proportion of UC graduates by campus who are observed as such in the NSC records. The most likely reason for match failure is students' decision to censor their records, as permitted under federal FERPA guidelines, though universities may also choose to censor student records. Table CC-3 presents type 2 error rates (that is, false negative rates) by campus and application year. Censorship rates are persistently highest at UCLA and UC Riverside, which had NSC error rates around 5-10 percent annually between 1995 and 2012. The only school to face large non-reporting bias is UC Santa Cruz, which had error rates between 50 and 80 percent from 1995 until the 2000 entering class, suggesting substantial censorship of degrees from that campus. Interestingly, it does not appear that coverage rates are improving over time — indeed, several campuses' error rates were higher in 2012 than in 1995 — nor does it appear that more-selective campuses systematically have lower error rates than less-selective campuses. In general, however, failure rates are very low at most campuses for the 2003-2011 cohorts.

Finally, I conduct a similar exercise for STEM major choice, conditional on being recorded as having earned a degree in both the NSC and UC records. Students are defined as studying STEM if their stated major is included on a federally designated list of 278 "fields involving research, innovation, or development of new technologies using engineering, mathematics, computer science, or natural sciences (including physical, biological, and agricultural sciences)" (US Department of Homeland Security, 2016). While six-digit CIP codes are available for UC majors, permitting direct matching to the STEM list, the frequent absence of CIP codes in the NSC required hand-coding of each observed major in the NSC dataset (omitting majors ever earned by fewer than 20 UC applicants). A complete crosswalk is available from the author.

Table CC-4 shows the Type 1 and Type 2 error rates in STEM major attainment for each UC graduate by campus and application year. Type 1 errors tend to occur because the UC campus records a major in NSC that was not recorded as STEM, but its CIP code recorded by UC *is* designated as STEM; these cases are very rare at most campuses. Type 2 errors tend to occur because either no major is recorded in the NSC file or a different major is recorded; this appears most prevalent among double-majors, with sometimes only a single major reported to NSC (although NSC allows multiple fields for major reporting). UC Berkeley has remarkably low error rates, never higher than 0.4 percent, while most campuses have Type 2 error rates around 1-5 percent. As in the case of degrees, these very low error rates serve to increase confidence in the

Table CC-4: National Student Clearinghouse STEM Major Data Quality for UC Graduates

Year	UCB		UCD		UCLA		UCR		UCSD		UCSC		UCSB		UCI		UCM	
Err. Type:	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2
1996	0.2	0.0	0.7	6.3	1.2	3.2	3.0	1.7	3.0	2.7	11.7	2.0	2.6	2.8	1.3	3.1		
1997	0.4	0.1	1.6	5.6	0.4	2.5	3.1	2.2	2.0	4.0	6.8	2.1	1.9	3.5	1.5	3.4		
1998	0.3	0.4	0.9	5.8	0.4	3.0	5.8	2.4	1.6	3.1	8.1	0.5	2.3	2.9	0.7	2.7		
1999	0.1	0.1	0.6	6.0	0.2	2.8	3.7	1.4	1.6	2.9	5.3	2.2	2.8	1.8	0.6	2.1		
2000	0.3	0.2	1.2	6.9	0.4	2.4	6.0	1.6	1.0	4.6	10.1	5.1	2.3	2.4	0.9	2.9		
2001	0.2	0.2	0.9	4.7	0.3	2.6	6.2	1.1	1.7	4.4	6.6	4.9	2.3	1.2	1.7	1.8		
2002	0.1	0.2	0.8	5.2	0.3	2.2	3.8	1.7	1.1	3.5	6.3	6.3	1.7	2.0	1.4	2.7		
2003	0.1	0.0	1.1	5.2	0.3	2.7	5.0	1.1	1.0	4.2	4.2	11.5	1.7	1.9	1.2	1.9		
2004	0.2	0.2	1.1	4.7	0.3	2.5	3.7	1.3	1.0	3.3	5.9	15.3	1.9	1.9	1.2	2.5		
2005	0.1	0.2	1.5	4.5	0.7	2.6	6.4	1.1	1.3	4.0	5.2	8.3	2.5	2.7	1.4	2.5	4.8	0.6
2006	0.0	0.1	1.0	4.5	0.4	2.2	5.0	0.5	1.9	3.1	4.3	7.1	2.4	1.7	0.8	2.5	5.9	0.0
2007	0.2	0.0	1.0	2.9	0.1	2.6	3.8	0.7	1.1	4.4	2.9	6.1	1.9	2.0	1.1	2.6	11.0	0.0
2008	0.1	0.1	0.7	4.0	0.3	2.0	4.0	0.8	0.8	3.0	3.7	5.8	1.5	2.0	1.1	2.2	2.6	0.5
2009	0.0	0.1	0.5	3.7	0.1	2.4	3.9	1.0	0.8	2.9	2.5	2.8	1.5	2.2	1.0	2.4	4.1	0.3
2010	0.1	0.1	0.2	3.2	0.1	1.6	4.0	0.4	0.7	2.2	3.5	2.5	1.5	1.1	0.6	2.0	2.7	0.2
2011	0.1	0.3	0.6	2.5	0.1	1.7	2.7	0.5	0.9	2.1	2.3	2.0	0.8	1.8	1.0	2.7	2.7	0.9
2012	0.1	0.7	0.2	4.1	0.2	2.9	3.3	0.9	0.5	1.8	2.3	1.6	1.4	2.9	0.8	2.9	4.4	1.1

Note: This table shows NSC's very low error rates in identifying UC students who earned STEM degrees throughout the study period. The Type 1 and Type 2 error rate in measurement of STEM major (among students denoted as graduates in base-truth UC records and linked to NSC degree records within five years of first enrollment) among freshman California-resident enrollees. Type 1 error (false positive) indicates non-STEM graduates listed with STEM majors in NSC; Type 2 error (false negative) indicates STEM graduates listed without STEM majors in NSC. STEM defined in US Department of Homeland Security (2016), with NSC majors hand-coded in the absence of CIP codes. Source: UC Corporate Student System and National Student Clearinghouse

reliability of the major-specific estimates reported in the study.

Appendix D: NSC-Estimated Five-Year Graduation Rates

This appendix describes the novel institutional five-year graduation rate and average SAT score statistics produced to index colleges' and universities' selectivity in this study. As discussed in the text, these statistics are calculated for all two- and four-year postsecondary institutions at which at least 100 UC applicants first enroll, making them a much more useful proxy than many alternative selectivity statistics that are unavailable for community colleges (or fail to account for many students' transferring from those colleges after two years). Specifically, I restrict the sample to 2001-2011 California-resident freshman UC applicants outside this study's primary sample — that is, applicants without ELC GPAs or with ELC GPAs more than 0.3 GPA points from their high schools' eligibility threshold — which leaves 618,116 applicants. I assign each applicant to their institution of first enrollment using NSC enrollment records from July of their year of high school graduation to six years later.[72]. I then define each institution's average SAT score as the average SAT score of assigned applicants, and its five-year graduation rate as the percent of assigned applicants who are reported to have earned a degree in the NSC within five years of high school graduation. 3.0 percent of applicants in this study's sample do not have any enrollment institution reported within six years of high school graduation, and another 3.0 percent enroll at institutions that fewer than 100 applicants from the full sample had enrolled at in the sample period, for which reason they are omitted (since the university characteristics are noisily estimated).

This appendix contains five tables, covering UC, CSU, California community colleges, and the top and bottom half of private (and out-of-state) universities. Each table presents each in-sample institution's 'NSC-measured' graduation rate and average SAT score, along with the same measures from 2008 IPEDS where available. These rates differ for three primary reasons: the UC applicant pool is positively selected relative to other California public institutions (though perhaps negatively selected at some highly-selective private

[72]If an applicant enrolls at a two-year institution but has changed enrollment to a four-year institution within six months, I assign them to the latter institution

Table DD-1: University of California Campuses

Institution	NSC 5-Yr. G.R.	NSC Avg. SAT	IPEDS 5-Yr. G.R.	IPEDS Avg. SAT	Institution	NSC 5-Yr. G.R.	NSC Avg. SAT	IPEDS 5-Yr. G.R.	IPEDS Avg. SAT
UC Berkeley	82.3	1941	87	1995	UC Davis	74.3	1756	77	1740
UCLA	80.2	1886	88	1928	UC Santa Cruz	72.7	1715	68	1702
UC San Diego	79.4	1884	80	1868	UC Riverside	63.7	1586	60	1568
UC Irvine	79.3	1773	78	1755	UC Merced	58.0	1547		1568
UC Santa Barbara	78.5	1791	76	1778					

Note: This table presents selectivity statistics for the nine undergraduate University of California campuses, showing that the Absorbing UC campuses fall relatively in between the most-selective Berkeley and UCLA campuses and the less-selective Santa Cruz, Riverside, and Merced campuses. University of California estimated graduation rates and average SAT scores. 'NSC' statistics measured from 2001-2011 UC freshman California-resident applicants assigned by first institution of enrollment (using National Student Clearinghouse data), with '5-Yr. G.R.' measuring the percent of those applicants who had earned a Bachelor's degree within five years of high school graduation (according to NSC records) and 'Avg. SAT' measuring their average SAT score. 'IPEDS' presents statistics as publicly reported in 2008. Institutions are ordered by NSC graduation rate. Source: National Student Clearinghouse, UC Corporate Student System, and Integrated Postsecondary Education Data System (IPEDS).

institutions), the NSC-measured graduation rates include degrees obtained at other institutions (following transfer), and they do not include degrees censored from NSC by the institutions. The most notable feature of these new statistics is their inclusion of community colleges, which have NSC-measured graduation rates ranging from 6.6 to over 40 percent.

Table DD-1 shows the estimated selectivity statistics for the nine undergraduate University of California campuses, ordered by their NSC-calculated graduation rates. The third and fourth columns show 2008 IPEDS measures of the campuses' average SAT score and five-year graduation rates. The most-selective UC campuses had published graduation rates over 80 percent and average SAT scores over 1900 on the 2400 scale, more than a standard deviation above the median SAT test-taker. The least-selective UC campuses have substantially lower SAT scores and graduation rates, with UC Riverside and Merced each reporting average SAT scores of 1568.[73]

These statistics are relatively closely mirrored in the NSC-calculated statistics shown in the first and second columns. Average SAT scores run from 1942 at UC Berkeley down to 1548 at UC Merced, and graduation rates run from 87.0 to 64.9. The Absorbing UC campuses have five-year graduation rates between 74 and 79 percent.

Table DD-2 shows an even greater degree of variation variation in average SAT scores and graduation rates among the California State Universities, California's public comprehensive university system. According to IPEDS, the two institutions with the strongest statistics are the CSU Maritime Academy and California Polytechnic State University in San Luis Obispo (Cal Poly), with average SAT scores between 1575 and 1780 and five-year graduation rates above 55 percent. That graduation rate is on par with the UC Riverside and UC Merced campuses, though Cal Poly's SAT scores are closer to those of the middle UC campuses. Meanwhile, the CSU Los Angeles and Dominguez Hills campuses have far lower measured statistics, with average SAT scores under 1300 and five-year graduation rates around 25 percent.

The institutional quality measures estimated from the UC-applicant NSC database are generally higher than those available from IPEDS, likely as a result of selection into UC application: the CSU enrollees who had also chosen to apply to at least one University of California campus tend to have higher SAT scores and were otherwise more likely to ultimately earn a college degree. Graduation rates are also higher because of high transfer rates between and out of the CSU system, such that more students who first enroll at a given institution end up earning a college degree than the number of students who earn degrees from that particular

[73]Since UC Merced was founded in 2005, it did not yet report a five-year graduation rate in 2008.

Table DD-2: California State University Campuses

Institution	NSC 5-Yr. G.R.	NSC Avg. SAT	IPEDS 5-Yr. G.R.	IPEDS Avg. SAT	Institution	NSC 5-Yr. G.R.	NSC Avg. SAT	IPEDS 5-Yr. G.R.	IPEDS Avg. SAT
CA State Univ. Maritime Academy	73.2	1673	57	1575	CSU Fullerton	44.0	1531	38	1470
CA Poly. State Univ.	67.4	1796	60	1778	CA State Poly. Univ.	42.1	1590	38	1530
Sonoma State Univ.	63.0	1611	43	1522	CSU Northridge	39.9	1463	29	1410
San Diego State Univ.	62.4	1627	53	1575	San Jose State Univ.	39.0	1549	26	1492
CSU Chico	59.1	1607	45	1515	CSU East Bay	38.7	1433	35	1365
CSU Monterey Bay	51.4	1519	30	1470	Humboldt State Univ.	38.1	1595	32	1552
CSU San Marcos	47.7	1503	34	1455	CSU Sacramento	37.4	1489	30	1440
CSU Long Beach	47.6	1570	40	1515	CSU San Bernardino	37.2	1393	34	1328
CSU Fresno	46.9	1480	37	1388	CSU Bakersfield	36.7	1427	33	1380
San Francisco State Univ.	45.6	1541	32	1500	CSU LA	30.6	1373	23	1298
CSU Stanislaus	45.3	1464	45	1425	CSU Dominguez Hills	30.1	1340	24	1222
CSU Channel Islands	44.1	1509							

Note: This table presents selectivity statistics for the California State University system, showing that the campuses range in selectivity from schools that look similar to the least-selective UC campuses to schools that have considerably lower graduation rates. California State University estimated graduation rates and average SAT scores. ‘NSC’ statistics measured from 2001-2011 UC freshman California-resident applicants assigned by first institution of enrollment (using National Student Clearinghouse data), with ‘5-Yr. G.R.’ measuring the percent of those applicants who had earned a Bachelor’s degree within five years of high school graduation (according to NSC records) and ‘Avg. SAT’ measuring their average SAT score. ‘IPEDS’ presents statistics as publicly reported in 2008. Institutions are ordered by NSC graduation rate. Source: National Student Clearinghouse, UC Corporate Student System, and Integrated Postsecondary Education Data System (IPEDS).

university. Average SAT scores are only modestly higher, by between 20 and 120 points, but graduation rates exceed IPEDS-reported rates by as much as 20 percentage points (at Sonoma State University).

As a result, the five-year graduation rates observed at a few top CSU institutions are comparable to those of the middle-selectivity University of California campuses, with a 73 percent graduation rate at the small CSU Maritime Academy and graduation rates above 60 percent at Cal Poly, Sonoma State, and San Diego State. The median CSU campus had a five-year graduation rate around 44 percent, while the least-selective CSU campuses had graduation rates just above 30 percent.

Table DD-3 does not present IPEDS statistics for the California Community Colleges because graduation rates and average SAT scores are unavailable for two-year institutions. The first two columns show the average SAT score and five-year graduation rates of enrollees at each California Community College, omitting colleges with fewer than 100 UC-applicant enrollees in the sample period. As in the case of the CSU system, these statistics are likely upward-biased snapshots of the actual student body of each college, since CC enrollees who chose to apply to a UC campus after graduating high school were likely positively selected relative to the average CC enrollee. Nevertheless, these selectivity statistics are relevant for the UC applicants who comprise the main estimation sample in this study.

UC-applicant enrollees at many California community colleges are strikingly prepared for university enrollment. About half of all community colleges have measured average SAT scores that are higher than the average SAT score of enrollees at UC Riverside or UC Merced. The college with the highest average observed SAT score is the Foothill College (in California’s high-income Silicon Valley), which has an average SAT score among UC applicants of 1739, higher than all but one CSU institution and approximately equal to the average SAT score of enrollees at UC Davis. Indeed, more than a quarter of the 93 observable community colleges have average SAT scores above 1600 among UC applicants, higher than nearly all CSU campuses.

Moreover, the community colleges have relatively high five-year college graduation rates, despite their not awarding Bachelor’s degrees themselves. Seventeen community colleges have graduation rates above 35 percent, comparable to the bottom quartile of CSU institutions. One college — Moorpark College, near the Simi Valley outside of Los Angeles — has a graduation rate of almost 45 percent. While some colleges’

Table DD-3: CA Community Colleges

Institution	NSC 5-Yr. G.R.	NSC Avg. SAT	IPEDS 5-Yr. G.R.	IPEDS Avg. SAT	Institution	NSC 5-Yr. G.R.	NSC Avg. SAT	IPEDS 5-Yr. G.R.	IPEDS Avg. SAT
Moorpark C.	43.5	1674	-	-	Cuesta C.	25.1	1678	-	-
Saddleback C.	41.0	1689	-	-	Cuyamaca C.	25.0	1545	-	-
Las Positas C.	40.1	1677	-	-	Reedley C.	24.9	1512	-	-
C. of San Mateo	40.1	1623	-	-	Berkeley City C.	24.9	1673	-	-
Ohlone C.	39.8	1644	-	-	El Camino C.	24.8	1511	-	-
Folsom Lake C.	38.6	1718	-	-	Yuba C.	24.8	1508	-	-
C. of Marin	38.5	1723	-	-	San Joaquin Delta C.	24.6	1499	-	-
Diablo Valley C.	37.9	1651	-	-	Cabrillo C.	23.9	1628	-	-
Santa Barbara City C.	37.7	1637	-	-	Mission C.	23.7	1592	-	-
De Anza C.	37.4	1660	-	-	San Jose City C.	22.9	1545	-	-
Shasta C.	37.0	1652	-	-	C. of the Redwoods	22.6	1665	-	-
Skyline C.	36.8	1563	-	-	LA Valley C.	22.5	1515	-	-
MiraCosta C.	36.7	1683	-	-	Laney C.	22.5	1495	-	-
Irvine Valley C.	36.4	1678	-	-	Merritt C.	22.4	1467	-	-
Foothill C.	36.1	1739	-	-	Los Medanos C.	22.3	1497	-	-
Glendale C.C.	35.7	1568	-	-	Bakersfield C.	22.0	1557	-	-
West Valley C.	35.0	1698	-	-	Cosumnes River C.	21.9	1531	-	-
Orange Coast C.	34.5	1624	-	-	Coastline C.C.	21.8	1613	-	-
Sierra C.	34.0	1663	-	-	Antelope Valley C.	21.5	1511	-	-
Canada C.	32.2	1633	-	-	Modesto Junior C.	21.2	1554	-	-
Santa Rosa Junior C.	31.7	1703	-	-	Citrus C.	20.6	1505	-	-
Palomar C.	31.7	1642	-	-	Long Beach City C.	20.0	1499	-	-
C. of the Canyons	30.9	1599	-	-	Allan Hancock C.	19.5	1543	-	-
City C. of San Francisco	30.5	1573	-	-	Grossmont C.	19.2	1557	-	-
Butte C.	30.2	1616	-	-	LA Mission C.	19.0	1430	-	-
Santa Monica C.	30.0	1583	-	-	Crafton Hills C.	18.5	1522	-	-
Sacramento City C.	30.0	1562	-	-	Oxnard C.	18.5	1439	-	-
Santiago Canyon C.	29.8	1652	-	-	C. of the Sequoias	17.9	1448	-	-
Contra Costa C.	29.8	1464	-	-	LA Harbor C.	16.5	1465	-	-
Golden West C.	29.2	1594	-	-	West Hills C.	16.5	1400	-	-
LA Pierce C.	29.2	1585	-	-	Cerritos C.	16.2	1460	-	-
San Diego Miramar C.	29.2	1623	-	-	Imperial Valley C.	16.1	1401	-	-
Napa Valley C.	28.2	1571	-	-	San Diego City C.	15.8	1449	-	-
American River C.	28.1	1608	-	-	Hartnell C.	15.6	1477	-	-
Solano C.C.	28.1	1574	-	-	Chaffey C.	15.5	1489	-	-
San Diego Mesa C.	27.9	1587	-	-	Southwestern C.	15.2	1443	-	-
Ventura C.	27.7	1554	-	-	Merced C.	15.2	1422	-	-
Pasadena City C.	27.4	1586	-	-	Rio Hondo C.	14.8	1463	-	-
Chabot C.	27.3	1519	-	-	Mt San Jacinto C.C.	14.3	1500	-	-
C. of Alameda	27.0	1440	-	-	Victor Valley C.	13.5	1473	-	-
Fullerton C.	26.8	1619	-	-	West LA C.	13.5	1479	-	-
Evergreen Valley C.	26.5	1526	-	-	C. of the Desert	13.3	1430	-	-
Mt San Antonio C.	26.4	1559	-	-	Riverside City C.	12.5	1452	-	-
Santa Ana C.	26.0	1533	-	-	East LA C.	11.7	1401	-	-
Fresno City C.	25.5	1494	-	-	LA City C.	11.1	1463	-	-
Monterey Peninsula C.	25.5	1632	-	-	LA Trade Tech. C.	7.1	1293	-	-
Cypress C.	25.4	1610	-	-	San Bernardino Valley C.	6.6	1422	-	-

Note: This table presents selectivity statistics for the California Community College system, showing that many community colleges have average SAT scores comparable to middle-selective public universities, though their five-year graduation rates tend to be comparable only to the least-selective universities. California Community College estimated (Bachelor's) graduation rates and average SAT scores, among colleges with at least 100 enrollees among applicants in the NSC sample. 'NSC' statistics measured from 2001-2011 UC California-resident freshman applicants assigned by first institution of enrollment (using National Student Clearinghouse data), with '5-Yr. G.R.' measuring the percent of those applicants who had earned a Bachelor's degree within five years of high school graduation (according to NSC records) and 'Avg. SAT' measuring their average SAT score. 'IPEDS' statistics unavailable for community colleges. Institutions are ordered by NSC graduation rate. Source: National Student Clearinghouse, UC Corporate Student System, and Integrated Postsecondary Education Data System (IPEDS).

graduation rates are low, some even below 10 percent, these calculations suggests that large numbers of UC applicants who choose to enroll at community colleges ultimately earn college degrees, making some colleges of comparable selectivity to lower-tier public universities.

Finally, Tables DD-4 and DD-5 presents statistics for the 200 private and out-of-state univerities with at least 100 UC-applicant enrollees. The schools with the highest graduation rates tend to be private institutions on the East Coast with graduates rates (over 93) and average SAT scores (2000+) considerably higher than the most-selective UC campuses. The median private or out-of-state university in the sample has a graduation rate and average SAT scores comparable to the middle-selectivity UC campuses.

Table DD-4: Top Half of Private and Out-of-State Universities (by Grad. Rate)

	NSC		IPEDS			NSC		IPEDS	
Institution	5-Yr. G.R.	Avg. SAT	5-Yr. G.R.	Avg. SAT	Institution	5-Yr. G.R.	Avg. SAT	5-Yr. G.R.	Avg. SAT
Bates C.	96.7	1893	89		Santa Clara Univ.	87.1	1819	84	1822
Swarthmore C.	95.4	2103	91	2152	Kenyon C.	87.0	1965	88	2002
Williams C.	94.7	2085	95	2130	Univ. of San Diego	86.8	1798	74	1785
Bowdoin C.	94.4	2017	89	2108	Macalester C.	86.8	2015	87	2040
Haverford C.	94.3	2061	94	2085	Univ. of Portland	86.3	1794	70	1792
Northwestern Univ.	93.6	2110	93	2152	Whitworth Univ.	86.3	1804	75	1808
Claremont McKenna C.	93.5	2002	94	2100	Johns Hopkins Univ.	86.0	2085	88	2100
Pomona C.	93.1	2099	94	2212	Univ. of Southern CA	85.9	1961	86	2055
Princeton Univ.	93.0	2167	95	2228	Univ. of North Carolina at Chapel Hill	85.4	2003	83	1958
Wesleyan Univ.	92.6	2063	92	2092	Stanford Univ.	85.4	2142	92	2152
Middlebury C.	92.6	2036	93	2092	Univ. of Virginia	84.9	2019	92	1995
Carleton C.	92.4	2052	92	2100	Bryn Mawr C.	84.4	1944	85	1958
Brown Univ.	92.4	2098	92	2145	Colorado C.	84.3	1966	86	1972
Yale Univ.	92.4	2180	95	2242	Pepperdine Univ.	84.1	1816	80	1860
Tufts Univ.	92.3	2068	91	2130	Seattle Univ.	84.0	1796	68	1718
Duke Univ.	92.3	2127	88	2160	Southern Methodist Univ.	84.0	1854	72	1868
Amherst C.	92.2	2093	93	2130	New York Univ.	83.9	1992	83	2018
Colby C.	92.0	1981	90	2032	Brandeis Univ.	83.6	1991	88	2055
Univ. of Pennsylvania	91.6	2126	94	2138	Miami Univ.	83.5	1787	40	1770
Wellesley C.	91.3	2062	90	2051	Lehigh Univ.	83.2	1922	83	1972
Dartmouth C.	91.2	2099	94	2160	Boston Univ.	83.0	1894	79	1905
Wheaton C.	90.9	1792	81		Brite Divinity School	83.0	1769	67	1748
Connecticut C.	90.5	1870	87	1988	Clark Univ.	83.0	1830	72	1800
Georgetown Univ.	90.4	2050	92	2032	Loyola Marymount Univ.	82.7	1749	78	1755
Skidmore C.	90.4	1882	81	1890	Trinity Univ.	82.6	1886	80	1935
Whitman C.	90.4	2006	91	1980	George Washington Univ.	82.4	1932	80	1935
Davidson C.	90.2	2022	93	2046	Univ. of Wisconsin Extension	82.0	1842	78	1905
Univ. of Chicago	90.2	2115	91	2130	Point Loma Nazarene Univ.	81.8	1726	69	1680
Villanova Univ.	90.2	1881	88	1958	Grinnell C.	81.8	1929	85	2010
Washington Univ. in St Louis	90.2	2131	92	2190	Univ. of Denver	81.6	1790	72	1792
Vanderbilt Univ.	90.1	2038	89	2122	Baylor Univ.	81.1	1819	71	1808
Boston C.	89.7	1988	90	2010	American Univ.	81.1	1907	75	1890
CA Inst. of Tech.	89.6	2219	87	2272	Indiana Univ.	81.0	1813	69	1725
Rice Univ.	89.5	2111	92	2138	Seattle Pacific Univ.	81.0	1774	61	1725
Oberlin C.	89.2	2021	82	2032	Tulane Univ. of Louisiana	80.9	1969	73	2010
Bucknell Univ.	89.1	1932	88	1965	Sarah Lawrence C.	80.8	1872	71	
Harvey Mudd C.	89.0	2144	89	2242	Emerson C.	80.7	1864	75	1838
Univ. of Michigan	88.7	1952	85	1988	Univ. of Puget Sound	80.3	1883	75	1860
Rhode Island School of Design	88.5	1903	85	1838	Willamette Univ.	80.3	1860	69	1838
Wake Forest Univ.	88.4	1962	88	1980	Carnegie Mellon Univ.	80.1	2047	84	2092
Scripps C.	88.4	1994	82	2025	Syracuse Univ.	80.0	1781	79	1755
Barnard C.	88.3	2066	88	2018	Fordham Univ.	79.5	1879	78	1838
Massachusetts Inst. of Tech.	88.2	2161	92	2205	Lewis & Clark C.	79.4	1891	70	1965
Smith C.	88.1	1905	88	1920	Case Western Reserve Univ.	79.3	1992	78	1965
Columbia Univ.	88.1	2096	92	2152	Univ. of Vermont	79.2	1829	69	1785
Dickinson C.	88.0	1720	84	1935	Univ. of Maryland	79.1	1944	80	1912
Wheaton C.	87.9	2004	83	1950	Marquette Univ.	79.0	1766	74	1755
Occidental C.	87.5	1868	85	1912	Brandman Univ.	78.9	1789	62	1837
Gonzaga Univ.	87.2	1790	78	1770	Univ. of Washington	77.9	1865	73	1608
Emory Univ.	87.2	2009	87	2078	Univ. of Miami	77.7	1870	75	1928

Note: This table presents selectivity statistics for the top half of private and out-of-state universities, showing that many of these schools tend to be even more selective than the most-selective UC campuses. Estimated graduation rates and average SAT scores of the private and out-of-state universities with at least 100 enrollees among applicants in the UC-NSC sample. 'NSC' statistics measured from 2001-2011 UC freshman California-resident applicants assigned by first institution of enrollment (using National Student Clearinghouse data), with '5-Yr. G.R.' measuring the percent of those applicants who had earned a Bachelor's degree within five years of high school graduation (according to NSC records) and 'Avg. SAT' measuring their average SAT score. 'IPEDS' presents statistics as publicly reported in 2008. Institutions are ordered by NSC graduation rate. Source: National Student Clearinghouse, UC Corporate Student System, and Integrated Postsecondary Education Data System (IPEDS).

The less-selective private and out-of-state universities, however, shows a small set of outliers — including Harvard University and Mount Holyoke College — that appear to have extremely low graduation rates. These institutions likely do not report degree attainment to National Student Clearinghouse, such that the only reported degrees earned by their enrolled students are from students who transferred and earned degrees elsewhere. While this could be concerning for the graduation rate measures discussed in this study, none of the impacted schools enroll more than a tiny handful of students near their high schools' ELC eligibility thresholds, and (as shown in Table 2) their enrollment is unimpacted by (and largely irrelevant to) ELC eligibility. The other schools that actually have the lowest reported graduation rates include out-of-state public universities and several for-profits (like the University of Phoenix and DeVry University), and have SAT

Table DD-5: Bottom Half of Private and Out-of-State Universities (by Grad. Rate)

	NSC		IPEDS			NSC		IPEDS	
Institution	5-Yr. G.R.	Avg. SAT	5-Yr. G.R.	Avg. SAT	Institution	5-Yr. G.R.	Avg. SAT	5-Yr. G.R.	Avg. SAT
The Univ. of Texas at Austin	77.0	1924	73	1838	Oregon State Univ.	63.5	1715	57	1605
Univ. of Oregon	76.4	1736	61	1635	Notre Dame de Namur Univ.	63.0	1507	53	1446
Rensselaer at Hartford	76.2	1958	81	2002	The Evergreen State C.	62.6	1790	59	1695
Spelman C.	75.8	1618	0	1605	Arizona State Univ.	62.5	1659	50	1612
Vassar C.	75.7	2029	91	2070	Concordia Univ.	62.0	1555	59	1740
Pitzer C.	75.7	1822	69		Univ. of the Pacific	61.8	1769	62	1740
Univ. of Rochester	75.6	1918	82	1980	Colgate Univ.	61.5	1986	91	2048
Univ. of Illinois at Urbana	75.0	1943	80	1942	Hofstra Univ.	61.5	1769	52	1762
Saint Mary's C. of CA	75.0	1646	63	1612	Pacific Union C.	61.2	1706	36	1492
Univ. of Redlands	75.0	1686	73	1725	Pace Univ.	60.8	1725	53	1605
Reed C.	74.7	2059	76	2070	Washington State Univ.	60.5	1705	62	1665
CA Lutheran Univ.	74.5	1671	68	1642	St John's Univ.	59.4	1667	50	1605
Univ. of Missouri	74.4	1892	65	1792	Rutgers Univ.	59.3	1807	56	1660
Ithaca C.	74.3	1803	77	1778	Dominican Univ. of CA	59.2	1583	46	1538
CA C. of the Arts	74.2	1694	56		Univ. of Iowa	58.8	1778	0	1808
Whittier C.	74.0	1614	54	1568	Northern Arizona Univ.	58.4	1647	48	1582
Ohio State Univ. Ag. Tech. Inst.	73.7	1828	35	1845	George Mason Univ.	58.0	1754	55	1672
Creighton Univ.	72.5	1778	75	1755	Morehouse C.	57.9	1589	62	1530
Arizona Board of Regents	72.0	1690	52	1650	Saint Louis Univ.	57.3	1849	73	1800
Hampshire C.	71.8	1884	0	1882	Univ. of Hawaii at Manoa	55.9	1649	40	1635
Pennsylvania State Univ.	71.4	1771	48	1463	Clark Atlanta Univ.	53.3	1362	42	1350
Virginia Poly. Inst. and State Univ.	71.4	1771	75	1808	Yeshiva Univ.	53.3	1925	69	1815
Biola Univ.	71.3	1723	68	1680	Embry	52.4	1699	53	1631
Azusa Pacific Univ.	70.3	1681	60	1605	Univ. of Minnesota	52.1	1842	61	1868
Texas A & M Univ.	70.0	1872	73	1785	Art Center C. of Design	52.1	1731	86	
Drexel Univ.	69.6	1853	56	1800	Boise State Univ.	51.7	1580	19	1545
Loyola Univ. Chicago	69.6	1771	64	1768	CA Inst. of the Arts	50.9	1739	61	
Univ. of Pittsburgh	69.3	1900	56	1557	Univ. of Nevada	48.8	1660	39	1575
Mills C.	69.2	1693	61	1688	Rochester Inst. of Tech.	48.3	1854	54	1800
Univ. of Colorado Boulder	69.1	1755	62	1762	Holy Names Univ.	46.9	1399	11	1397
Univ. of San Francisco	68.8	1682	65	1718	Univ. of New Mexico	46.7	1658	35	1598
Univ. of Massachusetts	68.4	1770	67	1732	Univ. of Utah	46.4	1706	39	1661
The New School	68.0	1780	60	1665	Marymount CA Univ.	45.3	1497		
Vanguard Univ. of Southern CA	67.8	1523	51	1455	Univ. of Nevada	42.0	1546	31	1522
Pratt Inst.	67.6	1772	45	1725	La Sierra Univ.	41.5	1496	25	1478
Northeastern Univ.	67.5	1925	64	1905	Tuskegee Univ.	41.4	1362	39	1312
DePaul Univ.	67.3	1748	60	1702	Southern Oregon Univ.	40.7	1686	33	1500
Purdue Univ.	66.8	1811	66	1725	Fresno Pacific Univ.	38.1	1549	60	1522
Loyola Univ. New Orleans	66.7	1781	61	1778	DeVry Univ.	36.6	1402		
Howard Univ.	66.4	1587	61	1710	Portland State Univ.	35.7	1711	27	1568
Hampton Univ.	66.2	1475	48	1589	Brigham Young Univ.	34.0	1859	53	1845
Georgia Inst. of Tech.	66.1	1982	70	1995	Brigham Young Univ.	33.3	1579	39	1635
Univ. of Notre Dame	66.0	2019	96	2115	Academy of Art Univ.	28.9	1596	24	
Michigan State Univ.	66.0	1756	72	1725	Woodbury Univ.	27.0	1472	54	1395
Western Washington Univ.	65.9	1767	63	1672	Univ. of Phoenix	12.1	1529	4	
Otis C. of Art and Design	65.8	1652	52	1545	Mount Holyoke C.	10.2	1819	82	
Univ. of La Verne	65.5	1514	57	1470	Westmont C.	8.6	1809	78	1822
Colorado State Univ.	64.8	1729	58	1680	Harvard Univ.	5.7	2186	96	2228
Mount Saint Mary's Univ.	64.0	1429	57	1380	CA Baptist Univ.	4.5	1492	45	1574
Cornell Univ.	63.5	2065	92	2100	Soka Univ. of America	2.3	1773	93	1750

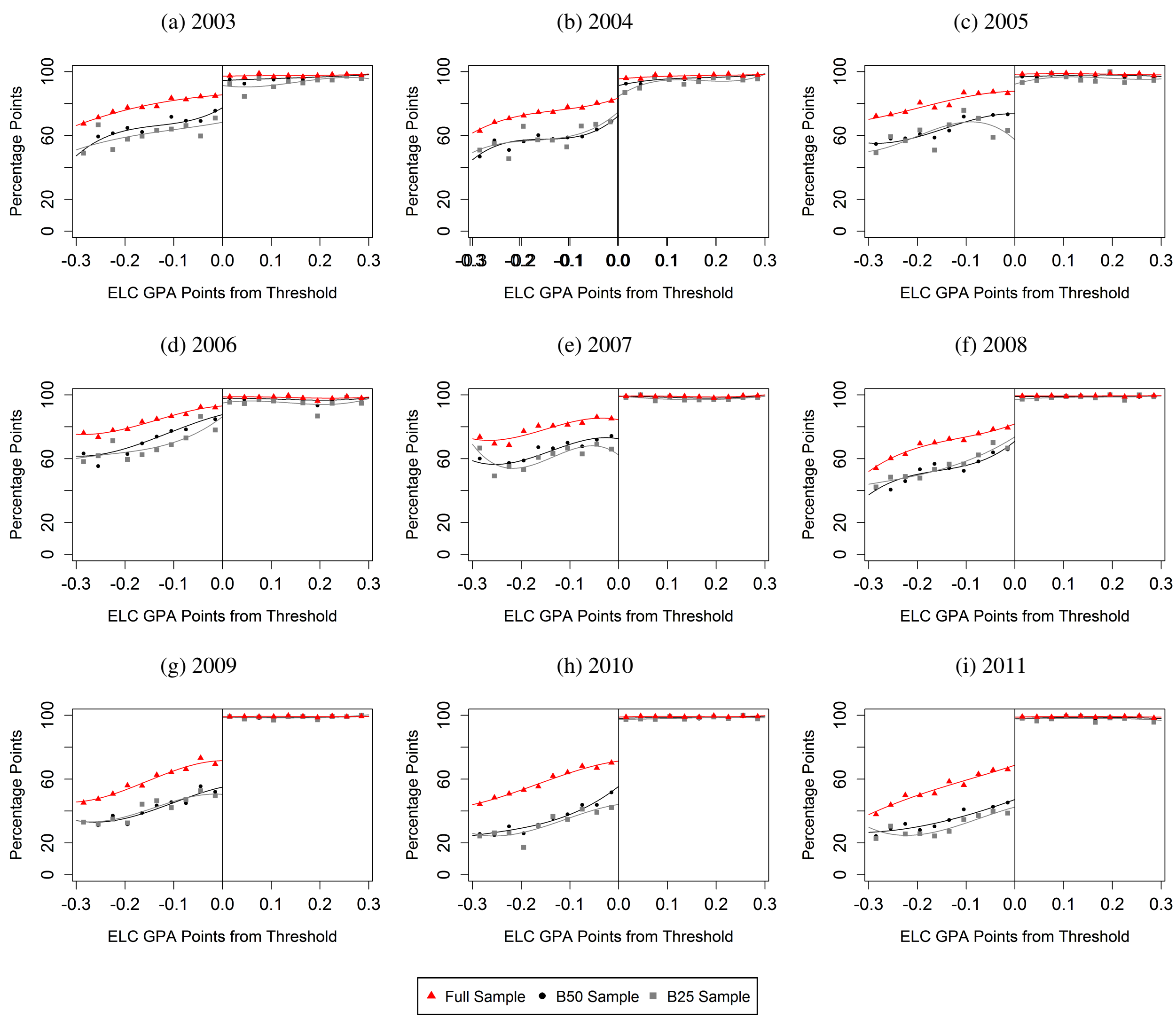
Note: This table presents selectivity statistics for the bottom half of private and out-of-state universities, showing that these schools exhibit a comparable selectivity range to the CSU system, though there are a small number of universities that have erroneously-low NSC graduation rates as a result of non-reporting. Estimated graduation rates and average SAT scores of the private and out-of-state universities with at least 100 enrollees among applicants in the UC-NSC sample. 'NSC' statistics measured from 2001-2011 UC freshman California-resident applicants assigned by first institution of enrollment (using National Student Clearinghouse data), with '5-Yr. G.R.' measuring the percent of those applicants who had earned a Bachelor's degree within five years of high school graduation (according to NSC records) and 'Avg. SAT' measuring their average SAT score. 'IPEDS' presents statistics as publicly reported in 2008. Institutions are ordered by NSC graduation rate. Source: National Student Clearinghouse, UC Corporate Student System, and Integrated Postsecondary Education Data System (IPEDS).

scores comparable to the lower-tier CSU campuses. As a result of these outliers (and also because of the other differences discussed above), the correlation between IPEDS and NSC-measured graduation rates is only about 0.56, while the correlation between average SAT scores is over 0.95.

Appendix E: NSC-Estimated Five-Year Graduation Rates

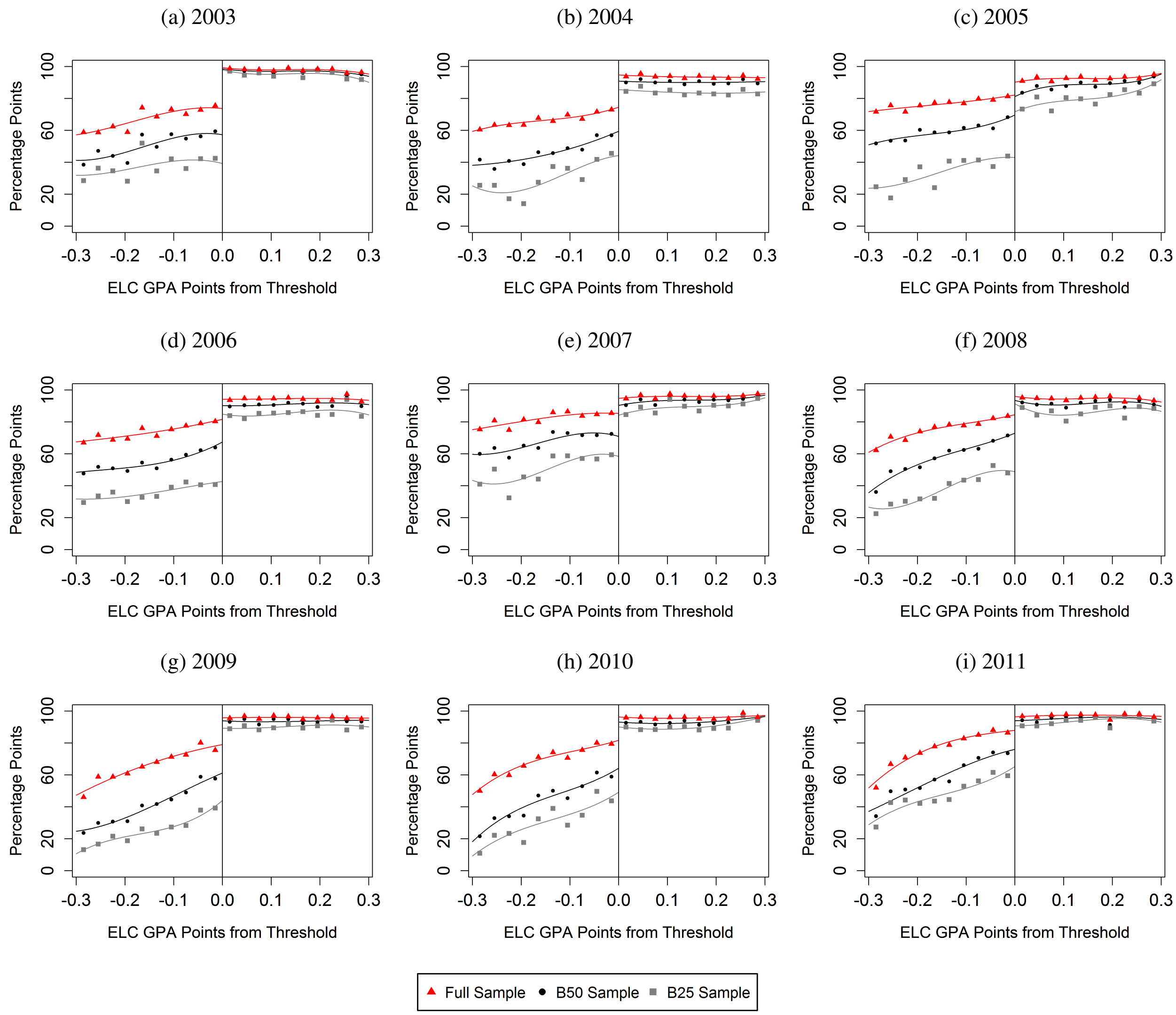
Figures EE-1 to EE-9 show annual break-outs of the effect of ELC eligibility on applicants' likelihood of admission to each campus. They show that the general admissions patterns remain highly persistent across the nine observed years: applicants receive large admissions advantages in most years at the Absorbing UC campuses and negligible admissions advantages at the other UC campuses. Some Absorbing UC campuses' admissions advantages grow somewhat over time, largely driven by the campuses' increasing selectivity in the period (decreasing near-threshold applicants' admissions likelihood through non-ELC admissions).

Figure EE-1: Local Effect of ELC Eligibility on Applicants' Likelihood of Admission to UC Davis



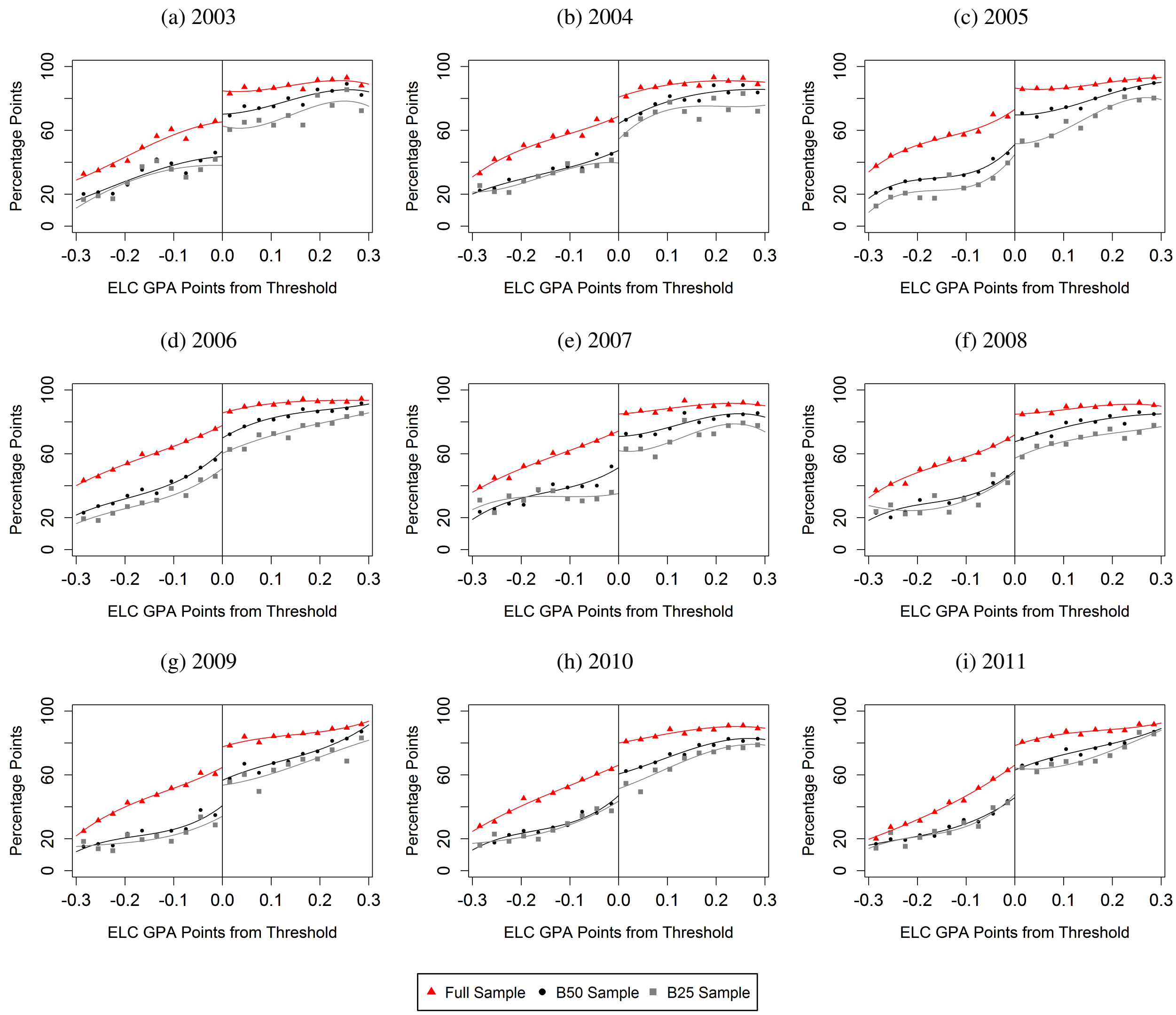
Note: Applicants' annual likelihood of admission to UC Davis by ELC GPA distance from their high school's ELC eligibility threshold, among all applicants and those from the bottom half (B50) or quartile (B25) of California high schools by SAT. Points are binned averages; lines are cubic fits. Each panel conditions on applying to that UC campus in that year. Applicants from high schools with approximated ELC eligibility thresholds between 3.96 and 4.00 are omitted. Source: UC Corporate Student System.

Figure EE-2: Local Effect of ELC Eligibility on Applicants' Likelihood of Admission to UC Irvine



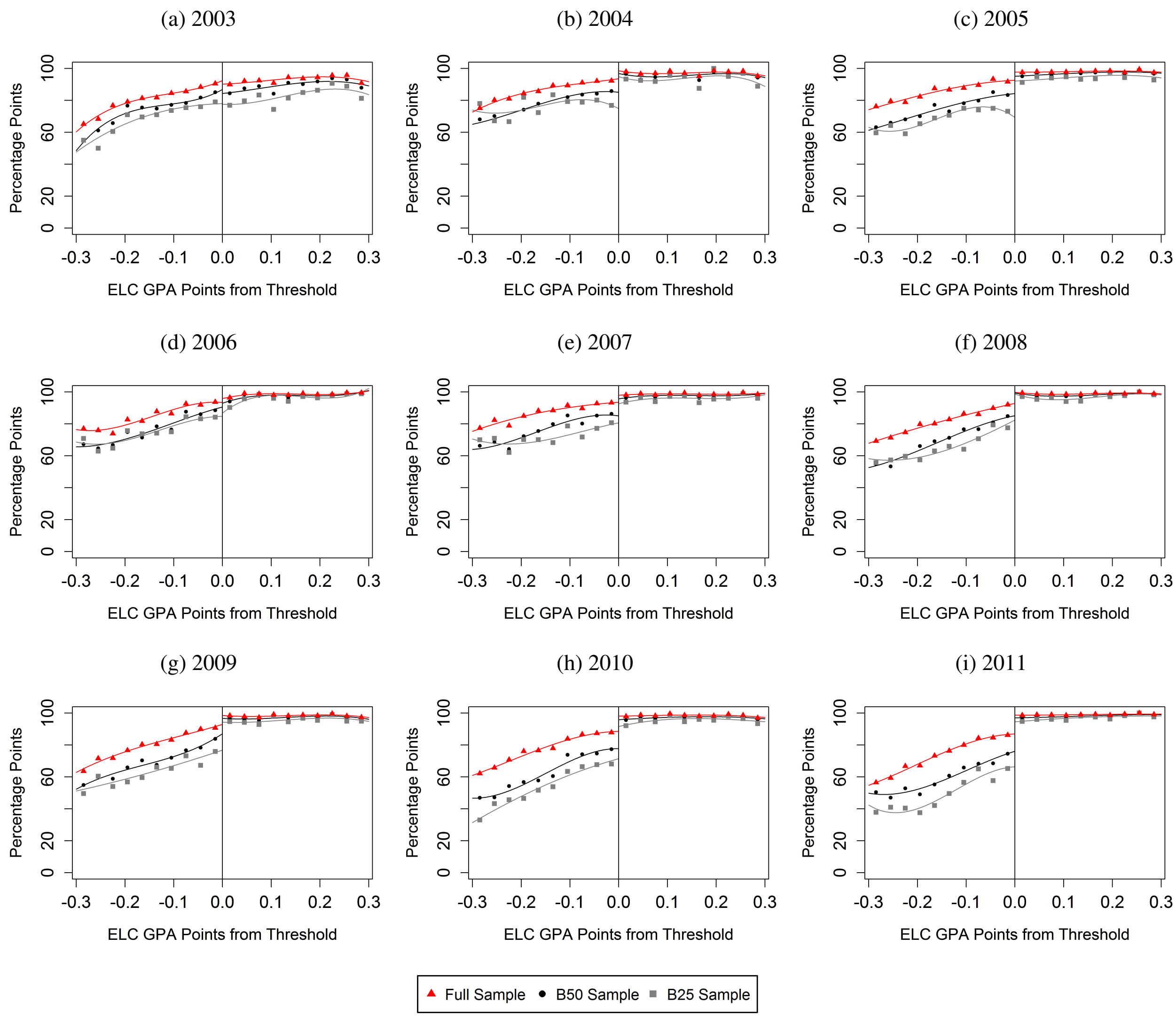
Note: Applicants' annual likelihood of admission to UC Irvine by ELC GPA distance from their high school's ELC eligibility threshold, among all applicants and those from the bottom half (B50) or quartile (B25) of California high schools by SAT. Points are binned averages; lines are cubic fits. Each panel conditions on applying to that UC campus in that year. Applicants from high schools with approximated ELC eligibility thresholds between 3.96 and 4.00 are omitted. Source: UC Corporate Student System.

Figure EE-3: Local Effect of ELC Eligibility on Applicants' Likelihood of Admission to UC San Diego



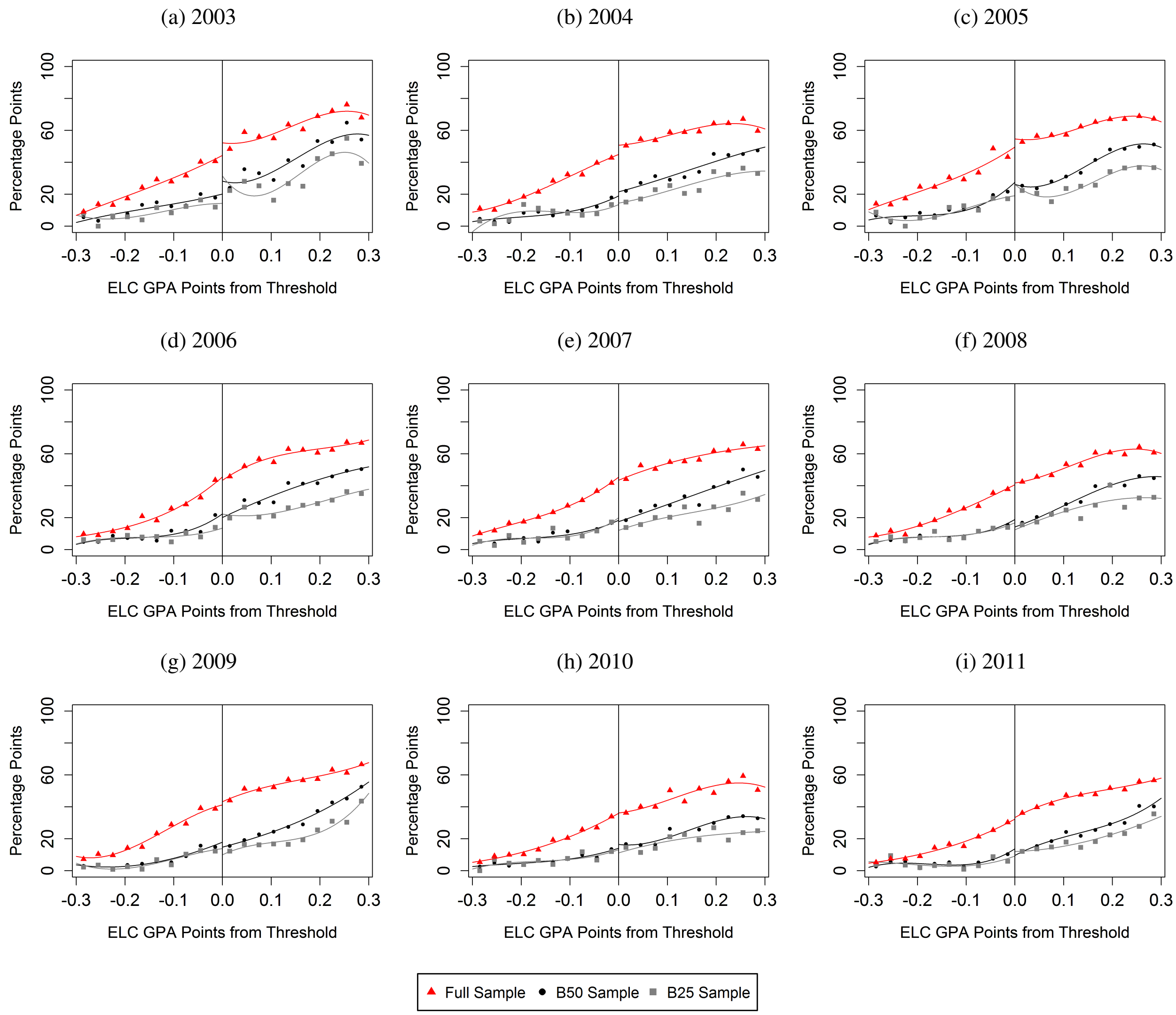
Note: Applicants' annual likelihood of admission to UC San Diego by ELC GPA distance from their high school's ELC eligibility threshold, among all applicants and those from the bottom half (B50) or quartile (B25) of California high schools by SAT. Points are binned averages; lines are cubic fits. Each panel conditions on applying to that UC campus in that year. Applicants from high schools with approximated ELC eligibility thresholds between 3.96 and 4.00 are omitted. Source: UC Corporate Student System.

Figure EE-4: Local Effect of ELC Eligibility on Applicants' Likelihood of Admission to UC Santa Barbara



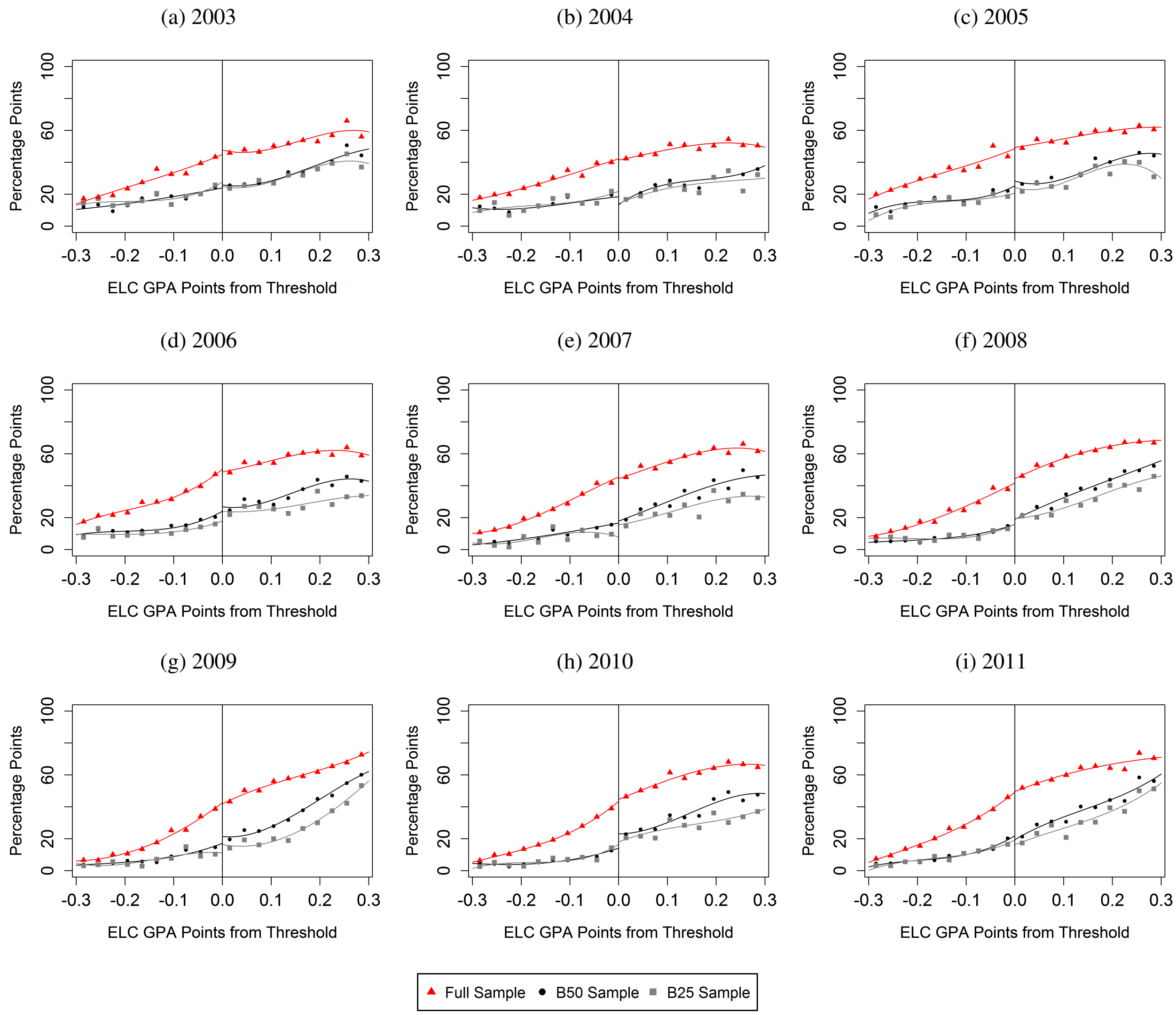
Note: Applicants' annual likelihood of admission to UC Santa Barbara by ELC GPA distance from their high school's ELC eligibility threshold, among all applicants and those from the bottom half (B50) or quartile (B25) of California high schools by SAT. Points are binned averages; lines are cubic fits. Each panel conditions on applying to that UC campus in that year. Applicants from high schools with approximated ELC eligibility thresholds between 3.96 and 4.00 are omitted. Source: UC Corporate Student System.

Figure EE-5: Local Effect of ELC Eligibility on Applicants' Likelihood of Admission to UC Berkeley



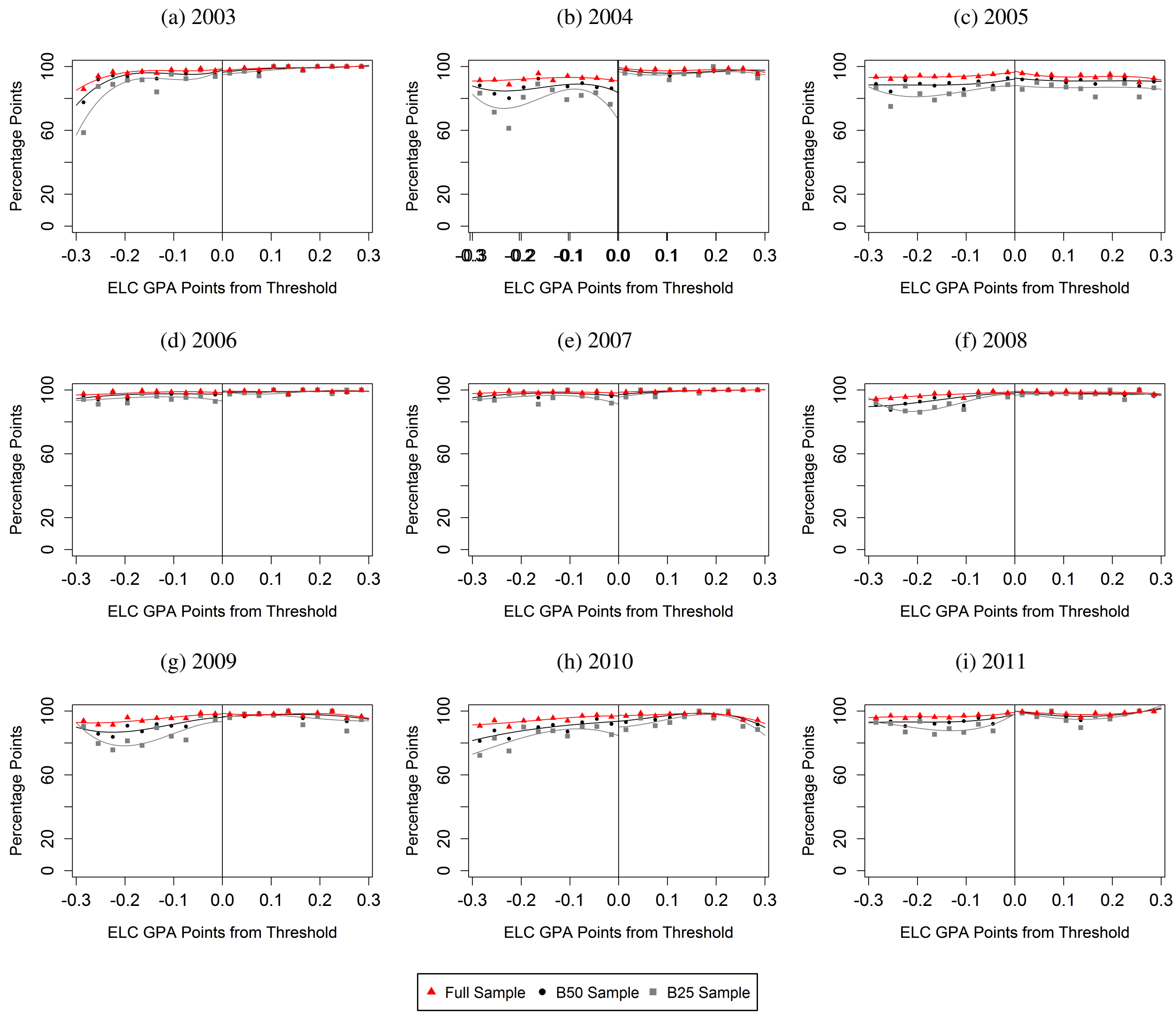
Note: Applicants' annual likelihood of admission to UC Berkeley by ELC GPA distance from their high school's ELC eligibility threshold, among all applicants and those from the bottom half (B50) or quartile (B25) of California high schools by SAT. Points are binned averages; lines are cubic fits. Each panel conditions on applying to that UC campus in that year. Applicants from high schools with approximated ELC eligibility thresholds between 3.96 and 4.00 are omitted. Source: UC Corporate Student System.

Figure EE-6: Local Effect of ELC Eligibility on Applicants' Likelihood of Admission to UCLA



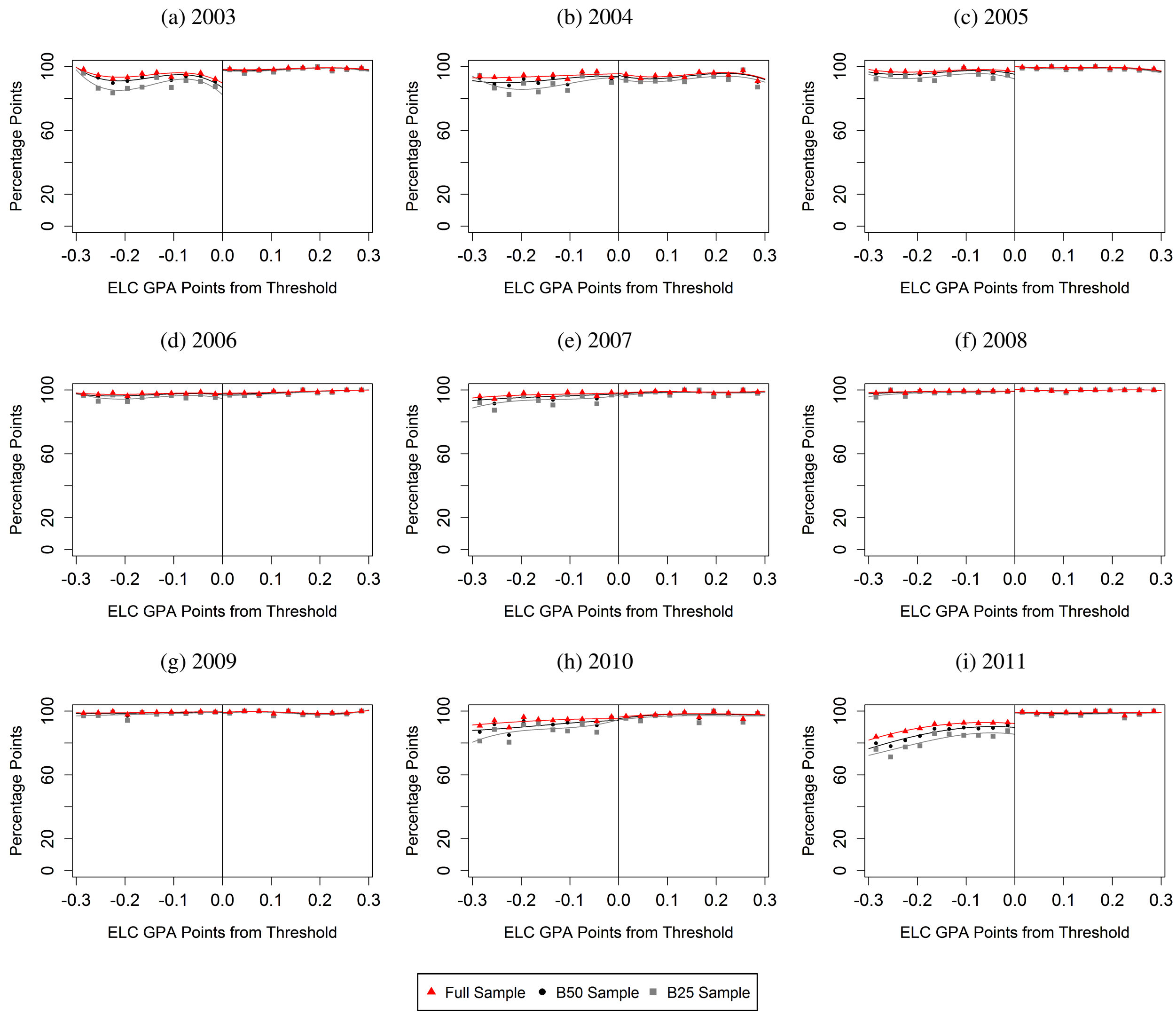
Note: Applicants' annual likelihood of admission to UCLA by ELC GPA distance from their high school's ELC eligibility threshold, among all applicants and those from the bottom half (B50) or quartile (B25) of California high schools by SAT. Points are binned averages; lines are cubic fits. Each panel conditions on applying to that UC campus in that year. Applicants from high schools with approximated ELC eligibility thresholds between 3.96 and 4.00 are omitted. Source: UC Corporate Student System.

Figure EE-7: Local Effect of ELC Eligibility on Applicants' Likelihood of Admission to UC Santa Cruz



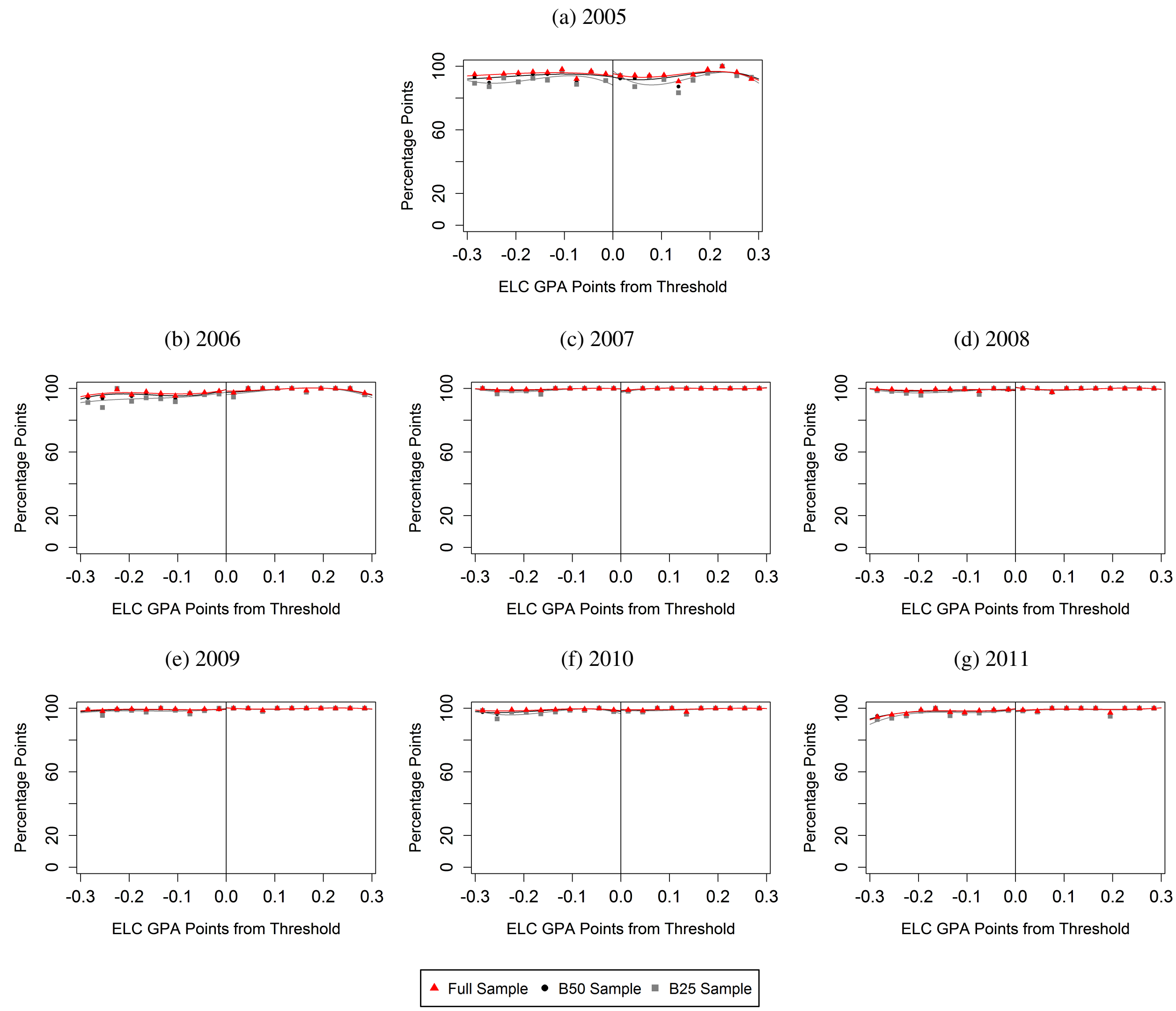
Note: Applicants' annual likelihood of admission to UC Santa Cruz by ELC GPA distance from their high school's ELC eligibility threshold, among all applicants and those from the bottom half (B50) or quartile (B25) of California high schools by SAT. Points are binned averages; lines are cubic fits. Each panel conditions on applying to that UC campus in that year. Applicants from high schools with approximated ELC eligibility thresholds between 3.96 and 4.00 are omitted. Source: UC Corporate Student System.

Figure EE-8: Local Effect of ELC Eligibility on Applicants' Likelihood of Admission to UC Riverside



Note: Applicants' annual likelihood of admission to UC Riverside 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. Each panel conditions on applying to that UC campus in that year. Applicants from high schools with approximated ELC eligibility thresholds between 3.96 and 4.00 are omitted. Source: UC Corporate Student System.

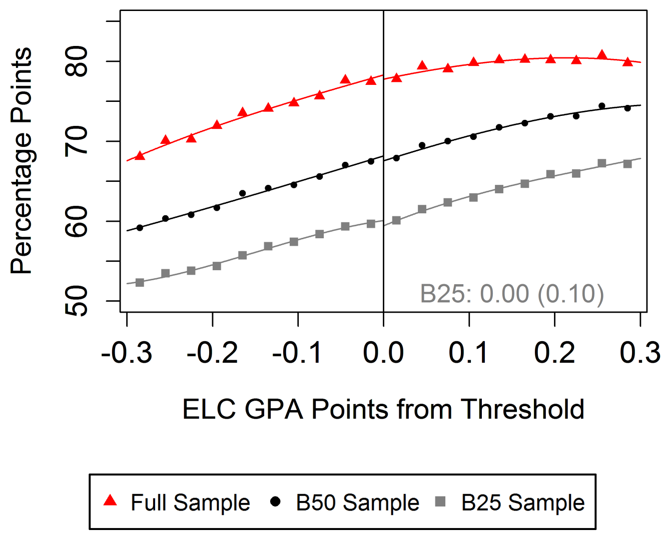
Figure EE-9: Local Effect of ELC Eligibility on Applicants' Likelihood of Admission to UC Merced



Note: Applicants' annual likelihood of admission to UC Merced 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. Each panel conditions on applying to that UC campus in that year. Applicants from high schools with approximated ELC eligibility thresholds between 3.96 and 4.00 are omitted. Source: UC Corporate Student System.

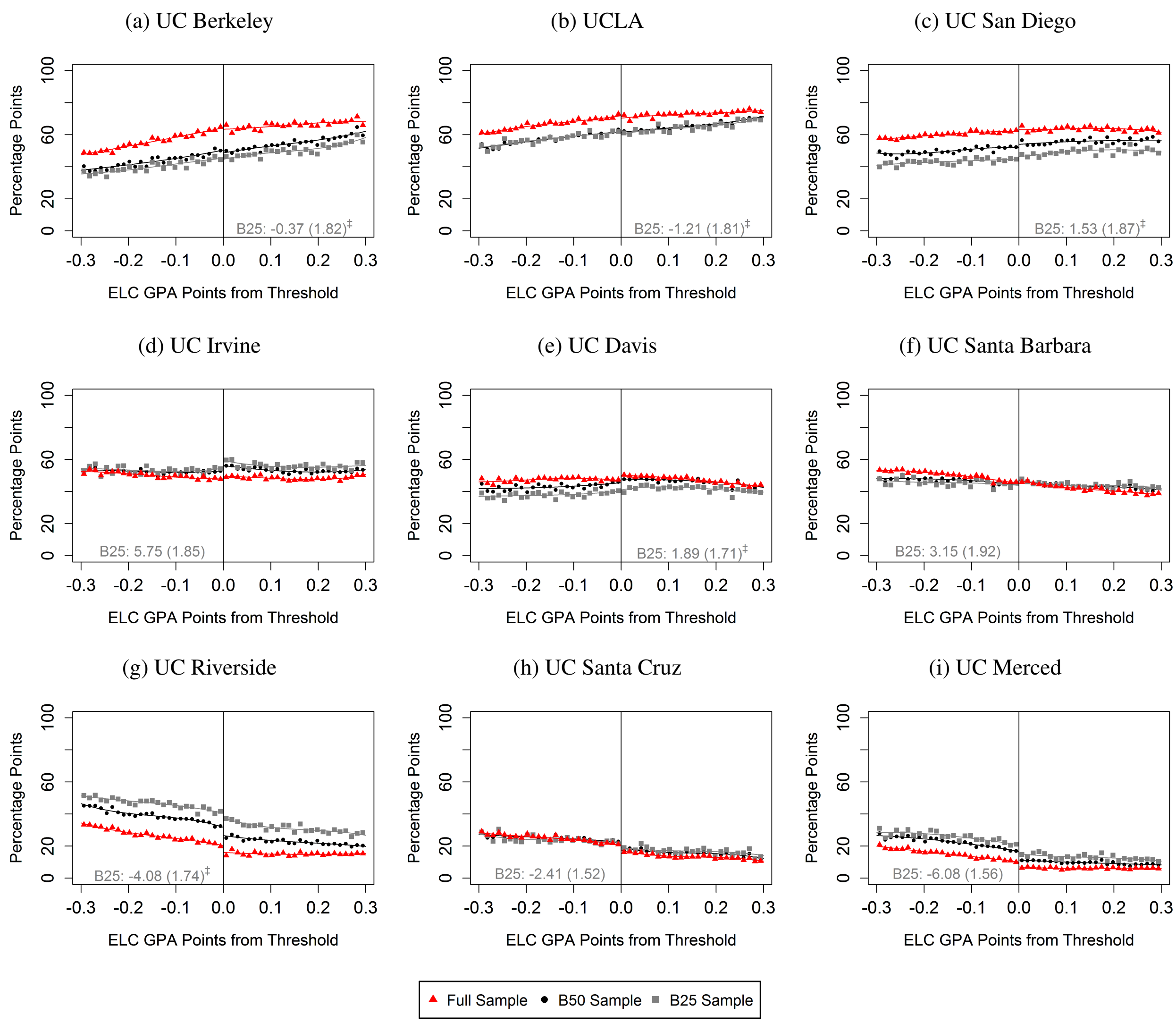
Other Appendix Figures and Tables

Figure A-1: Socioeconomic-Predicted Five-Year Degree Attainment



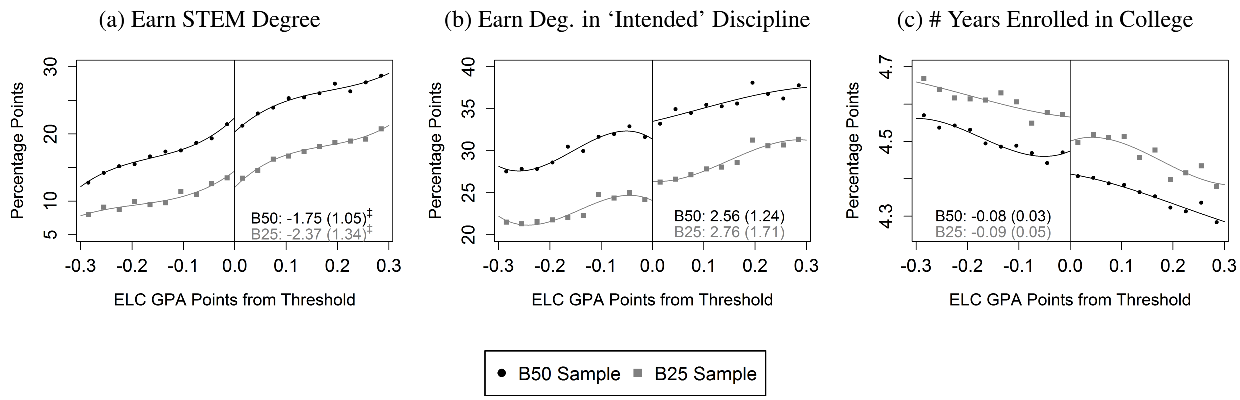
Note: This figure summarizes baseline sample balance across the ELC eligibility threshold using applicants' predicted five-year degree attainment (on the basis of socioeconomic characteristics). Regression discontinuity plot of applicants' predicted likelihood of five-year degree attainment by ELC GPA distance from their high school's ELC eligibility threshold, among all applicants or applicants from the bottom half or quartile of California high schools by SAT. Points are binned averages; lines are unconditional cubics. Beta estimate from cubic parameterization of Equation 2 for the B50 sample, with standard error clustered by school-year in parentheses. Predicted graduation from an OLS regression (across 1995-2013 UC freshman California-resident applicants outside the study's primary sample) of five-year NSC degree-attainment on gender-ethnicity indicators, maximum parental education indicators (7 categories), family income, missing income indicator, SAT score, high school GPA, and year indicators. Applicants from high schools with ELC eligibility thresholds between 3.96 and 4.00 are omitted. Source: UC Corporate Student System and National Student Clearinghouse.

Figure A-2: Local Effect of ELC Eligibility on Applicants' Likelihood of Application to each UC Campus



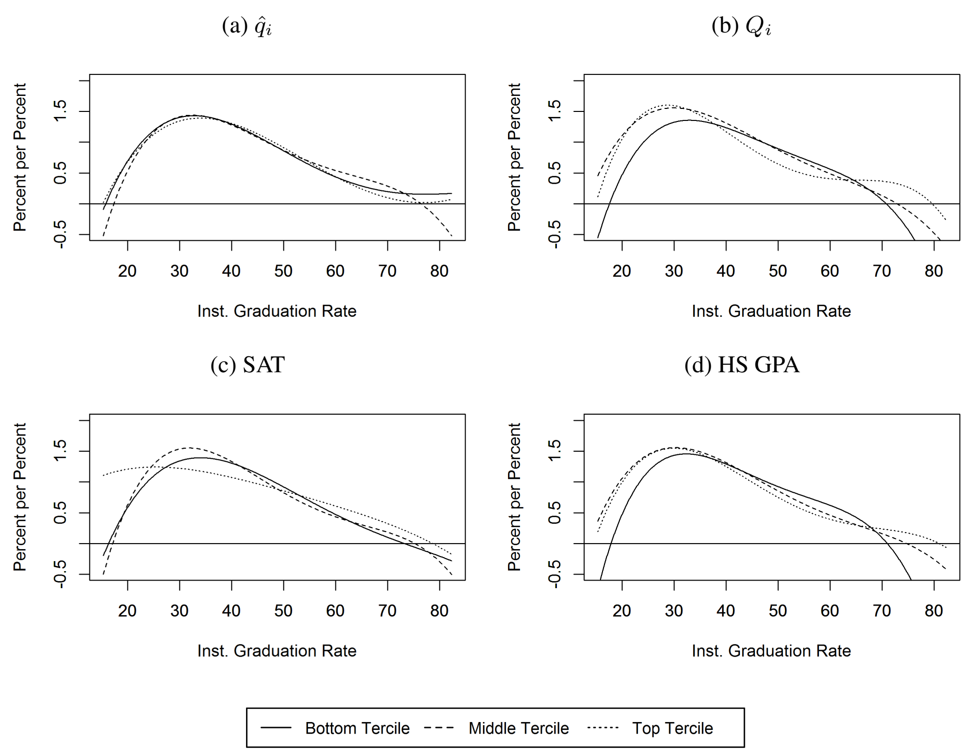
Note: This figure shows that barely ELC-eligible applicants responded to their Absorbing UC campus admissions advantages by becoming slightly more likely to apply to those campuses and slightly less likely to apply to the Dispersing campuses, though the magnitudes are far smaller than the shifts in those applicants' admissions likelihoods. UC applicants' likelihood of application to each UC campus by ELC GPA distance from their high school's ELC eligibility threshold, among all UC 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.

Figure A-3: Local Effect of ELC Eligibility on UC Applicants' Other Education 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. Degree attainment by discipline is unconditional on overall attainment. See footnote 22 for definitions of STEM and other disciplines; intended discipline is applicants' most-selected prospective major discipline reported to UC campuses. Number of years enrolled in college is the number of academic years within seven years of high school graduation in which the applicant is observed enrolled at a postsecondary institution but has not yet earned a Bachelor's degree. 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 and National Student Clearinghouse.

Figure A-4: Estimated Return per Inst. Grad Rate for Applicants by q_i, Q_i, and SAT Tercile



Note: This figure shows that the return to more-selective university enrollment (per one point of graduation rate) for universities in the support of the data (which is strongest from about 30 to 75) is similar for top-, middle-, and bottom-tercile UC applicants by model-defined caliber (q_i), application merit (Q_i), SAT score, or high school GPA, where returns are measured by five-year degree attainment. Estimated change in applicants' likelihood of five-year degree attainment per additional percentage point in institutional graduation rate, by tercile of $\hat{q}_i$, $\hat{Q}_i$, SAT score, or high school GPA. Estimates from an extension of equation 8 in which GR_i is a fifth-order polynomial in institutional graduation rate and $\hat{q}_i$ is replaced by tercile indicators, omitting the constant term; the plot shows the *derivative* of the resulting estimated polynomials. Applicants' $\hat{q}_i$ estimated using the posterior distribution of q_i's resulting from the model parameters described in the text, and $\hat{Q}_i = z_i \hat{\beta}^z + \hat{q}_i$. 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, as well as admissions portfolio indicators for every combination of UC campuses to which the applicant applies and UC campuses to which they are admitted. See Appendix D for definition of institutional graduation rates. Source: UC Corporate Student System and the National Student Clearinghouse.

Table A-1: Baseline Characteristic Balance at ELC GPA Threshold, 2003-2011

	Permanent Applicant Characteristics						Predicted Values[2]	
	Female (%)	URM (%)	Max. Parent Ed. (Index)[1]	Log Fam. Income	Missing Inc. (%)	SAT Score	Graduation Rate (%)	California Earnings ($)
All	0.0	1.0	-0.022	0.02	-0.0	-5.7	0.06	83.5
	(0.8)	(0.6)‡	(0.030)	(0.02)	(0.7)	(2.9)‡	(0.06)	(63.2)
URM	-0.6	-	-0.061	-0.04	-0.1	-2.0	-0.07	-105.2
	(1.8)	-	(0.078)	(0.05)	(1.1)	(6.6)	(0.20)	(111.5)
High School Quartiles by SAT Score								
Top Quartile	0.6	0.2	-0.017	0.05	0.9	-0.6	0.00	188.1
	(1.6)	(0.8)	(0.038)	(0.05)	(1.5)	(4.1)	(0.12)	(136.3)
Third Quartile	0.5	2.1	-0.020	0.06	-0.2	-10.6	0.16	61.7
	(1.6)	(1.1)‡	(0.055)	(0.04)	(1.5)	(5.3)	(0.12)	(121.3)
Second Quartile	-0.6	0.7	0.014	-0.01	-1.5	-5.9	0.04	129.0
	(1.7)	(1.4)	(0.068)	(0.04)	(1.3)	(6.1)	(0.11)	(117.0)
Bottom Quartile	-1.4	0.8	-0.085	-0.01	0.4	-3.3	0.05	-126.6
	(1.9)	(1.6)	(0.082)	(0.05)	(1.0)	(7.4)	(0.10)	(105.3)
Male[3]	-	1.0	-0.221	0.00	2.3	-7.2	-0.01	-200.8
	-	(2.7)	(0.146)	(0.09)	(1.8)	(13.0)	(0.26)	(218.4)
Female[3]	-	0.2	0.060	0.00	-0.1	-0.3	0.01	-376.9
	-	(2.1)	(0.111)	(0.06)	(1.2)	(9.1)	(0.16)	(151.1)
Baseline[4]	60.5	21.9	5.15	11.01	22.7	1877	75.6	87,477

Note: This table shows baseline sample balance across the ELC eligibility threshold. Reported coefficients are estimated changes in various applicant characteristics across the ELC eligibility threshold. Estimates from 2SLS cubic fuzzy regression discontinuity models, with standard errors in parentheses clustered by high-school-year. Additional covariates (where not colinear with the outcome variable) include gender-ethnicity indicators and a quadratic term in SAT score, along with year and high school fixed effects. Coefficients estimated overall, for URM (Black, Hispanic, and Native American) applicants, by high school SAT quartiles (see the text for definition), and for male and female applicants (among applicants from the bottom two high school SAT quartiles). SAT score on a 2400 point scale; converted from ACT score or 1600-point SAT score if otherwise unavailable. Family income is not reported by 12 percent of applicants. Applicants from high schools with ELC eligibility thresholds between 3.96 and 4.00 are omitted. ‡ 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). [1]Integer index of reported maximum parental education (across two parents), from 1 (no high school) to 7 (graduate degree). [2]Dependent variable is 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 either five-year NSC graduation or 6-to-8 year average California covered wages (see text for definitions) on gender-ethnicity indicators, maximum parental education indicators (7 categories), family income, missing income indicator, SAT score, and year indicators. [3]Conditional on graduating from the bottom two SAT high school quartiles. [4]The estimated baseline (ELC-ineligible) mean characteristic of barely below-threshold UC applicants, estimated following Abadie (2002).

Source: UC Corporate Student System.

Table A-2: Impact of ELC on Admissions and Enrollment for Barely ELC-Eligible Applicants by Campus

	Admission (%)				Enrollment (%)			
	All		B25[1]		All		B25[1]	
	Baseline	β	Baseline	β	Baseline	β	Baseline	β
Unimpacted Campuses								
Berkeley	42.6	2.0	15.7	1.8	13.5	0.8	4.8	0.9
		(0.9)‡		(1.9)		(0.6)		(0.8)
UCLA	46.0	1.3	17.4	1.8	12.5	-0.6	6.7	0.2
		(0.8)		(1.8)		(0.5)		(1.0)
Absorbing Campuses								
Davis	79.6	19.8	57.9	40.1	6.6	2.7	7.9	4.3
		(0.8)		(2.4)		(0.5)		(1.1)
San Diego	70.1	13.9	42.7	17.3	7.3	2.8	5.2	2.7
		(0.8)		(2.5)		(0.5)		(0.9)
Santa Barbara	91.9	6.7	77.3	17.4	6.1	-0.5	8.0	1.2
		(0.6)		(1.9)		(0.4)		(1.1)
Irvine	81.9	14.9	49.1	41.8	5.9	0.9	6.8	7.4
		(0.8)		(2.1)		(0.4)‡		(1.1)
Dispersing Campuses								
Riverside	96.5	2.4	94.1	4.0	2.5	-0.9	8.5	-2.5
		(0.6)		(1.2)‡		(0.2)		(1.0)‡
Santa Cruz	98.0	1.4	93.0	4.5	1.7	-0.4	2.7	-1.7
		(0.6)‡		(2.2)‡		(0.2)		(0.6)
Merced	95.6	0.4	95.5	0.6	0.7	-0.4	1.7	-0.8
		(1.3)		(1.8)		(0.1)		(0.5)

Note: This table presents the impact of near-threshold ELC eligibility on each UC campus's admissions and enrollment, showing that the Absorbing UC campuses provided large admissions advantages to eligible students (especially those from less-competitive high schools) that translated into increased likelihood of enrollment. Reported coefficients are the estimated baseline (ELC-ineligible) proportion of below-threshold students at their high school's ELC eligibility threshold admitted or enrolled at each UC campus 2003-2011, and the estimated change in admission or enrollment for barely ELC-eligible applicants (β), overall and for students from the bottom SAT quartile of high schools. Values in percentages. Estimates from 2SLS cubic fuzzy regression discontinuity models; standard errors are clustered by school-year, and omitted for baseline estimates (which are estimated following Abadie (2002)). Additional covariates include gender-ethnicity indicators and a quadratic term in SAT score, along with year and high school fixed effects. 'Admission' estimates are conditional on applying to that campus; 'Enrollment' estimates are conditional on applying to *at least one* UC campus. Applicants from high schools with ELC eligibility thresholds between 3.96 and 4.00 are omitted. ‡ 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).
[1] Bottom quartile of high schools by SAT scores of students within 0.3 GPA points of the ELC eligibility threshold.

Source: UC Corporate Student System and National Student Clearinghouse.

Table A-3: Local Effect of ELC Eligibility on Application to Each UC Campus

	UCB	UCLA	UCSD	UCI	UCD	UCSB	UCSC	UCR	UCM
Panel A: Baseline Application Likelihood (%)									
All	64.6	72.2	62.4	47.8	47.0	45.5	20.0	20.4	9.9
B50	50.3	62.0	52.4	53.2	45.9	44.5	31.8	21.6	16.6
B25	45.1	61.7	44.8	55.0	39.9	43.4	40.9	20.4	20.7
Panel B: Local Change in App. Likelihood Caused by ELC Eligibility (p.p.)									
All	-0.2	-0.9	1.7	1.9	3.3	1.0	-4.9	-3.8	-3.5
	(0.8)	(0.7)	(0.8)	(0.8)	(0.8)	(0.9)	(0.6)	(0.7)	(0.5)
B50	-1.0	0.4	2.5	4.2	2.6	2.4	-6.2	-3.7	-6.1
	(1.2)	(1.2)	(1.2)	(1.3)	(1.2)‡	(1.3)‡	(1.1)	(1.0)	(1.0)
B25	-0.4	-1.2	1.5	5.8	1.9	3.1	-4.1	-2.4	-6.1
	(1.8)	(1.8)	(1.9)	(1.8)	(1.7)	(1.9)	(1.7)‡	(1.5)	(1.6)

Note: This table shows that barely ELC-eligible applicants responded to their Absorbing UC campus admissions advantages by becoming slightly more likely to apply to those campuses and slightly less likely to apply to the Dispersing campuses, though the magnitudes are far smaller than the shifts in those applicants' admissions likelihoods. Reported coefficients are the estimated baseline (ELC-ineligible) proportion of near-threshold UC applicants who apply to each UC campus, and the estimated change in application likelihood 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.

Table A-4: Change in Characteristics of ELC-Eligible Students' University of First Enrollment

Sample:	First Four-Year Inst.			First Two- or Four-Year Institution[1]				
	Admit Rate	Avg. SAT	Four-Year Grad. Rate	Five-Year Grad. Rate	Avg. SAT	Med. Fam. Income	Sticker Price	Est. Net Price[2]
Overall								
Baseline	43.0	1,820.9	55.4	1,821.0	75.0	111,874.0	29,977.7	18,601.7
β	-0.70 (0.35)‡	15.46 (3.17)	1.58 (0.35)	12.66 (2.27)	1.63 (0.32)	766.79 (393.49)‡	225.61 (238.18)	113.65 (231.97)
IV: Enroll Abs. UC	-9.9 (5.4)	208.4 (47.3)	21.8 (5.1)	209.6 (43.6)	27.1 (5.4)	12,313.4 (6,414.6)	3,297.3 (3,609.6)	1,672.0 (3,444.8)
Bottom High School Quartile (B25)								
Baseline	52.8	1,678.6	42.3	1,682.0	64.2	95,371.0	26,794.2	11,536.9
β	-2.17 (0.85)	36.71 (8.33)	5.59 (0.90)	39.46 (5.68)	5.24 (0.83)	2,612.37 (906.39)	902.14 (417.07)‡	305.00 (382.89)
IV: Enroll Abs. UC	-12.2 (4.8)	201.9 (41.9)	30.8 (4.4)	249.1 (35.4)	33.1 (4.8)	15,285.5 (4,964.1)	4,259.2 (2,003.7)	1,505.8 (1,903.4)
Source:	IPEDS	IPEDS	IPEDS	NSC	NSC	OI	IPEDS	IPEDS

Note: This table shows that ELC caused barely-eligible applicants to enroll at more-selective universities using a host of selectivity measures, and but those universities had similar net prices for students with their family incomes. Reported coefficients are the estimated characteristics of applicants' first-enrollment university or post-secondary institution at the barely ELC-ineligible baseline, the change in those characteristics across the ELC eligibility threshold (β), and the estimated change in those characteristics for Absorbing-UC-campus compliers estimated using ELC eligibility as an instrumental variable. Estimates from 2SLS cubic fuzzy regression discontinuity models; standard errors are clustered by school-year, and omitted for baseline estimates (which are estimated following Abadie (2002)). Additional covariates include gender-ethnicity indicators and a quadratic term in SAT score, along with year and high school fixed effects. Enrollment measured as first four-year (columns 1-3) or two- or four-year (columns 4-8) college or university of enrollment between July following high school graduation and six years later. IPEDS and Opportunity Insights (OI) data linked by OPE ID (and year in IPEDS case) to NSC enrollment. NSC-measured average SAT scores and five-year graduation measured only for 2001-2011 UC applicants (excluding applicants within 0.3 GPA points of their high school's ELC eligibility threshold) and are time-invariant; see the text for the definition. Also see the text for definition of high school quartiles. IPEDS Average SAT score calculated for each school as the sum of the mean of the 25th and 75th percentiles of each SAT section, converting scores from 1600 scale to 2400 scale when necessary. Sticker price is defined using on-campus residency unless unavailable, in which case it is defined using off-campus non-family residency. IPEDS admission rate unavailable prior to 2005, and price information unavailable prior to 2008. Applicants from high schools with ELC eligibility thresholds between 3.96 and 4.00 are omitted. ‡ Indicates reduced-form 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). [1]If the applicant enrolls at a community college but then enrolls at a four-year university within 6 months, the latter is defined as her first institution of enrollment. [2]Net price includes tuition and fees, expected room and board, books and supplies, and other expenses net of federal, state, local, or institutional grant aid. Calculated as the IPEDS average net price for Title-IV-aid-awarded enrollees in the applicant's family income bin, where the observed bins are \$0-30,000, \$30,000-48,000, \$48,000-75,000, \$75,000-110,000, and above \$110,000. Applicants with unobserved family incomes are omitted, and likely paid the sticker price (as they did not apply for federal financial aid, including loans).

Source: UC Corporate Student System, National Student Clearinghouse, the Integrated Postsecondary Education Data System (IPEDS), and Opportunity Insights (Chetty et al., 2020).

Table A-5: Change in Characteristics of ELC-Eligible Students' Degree-Providing Universities

Sample:	First Four-Year Inst.			First Two- or Four-Year Institution[1]				
	Admit Rate	Avg. SAT	Four-Year Grad. Rate	Five-Year Grad. Rate	Avg. SAT	Med. Fam. Income	Sticker Price	Est. Net Price[2]
Overall								
Baseline	42.5	1,826.7	56.2	80.0	1,840.2	113,380.8	29,974.5	18,801.1
β	-0.56 (0.38)	16.26 (3.39)	1.53 (0.37)	0.93 (0.21)	10.13 (2.28)	623.98 (400.77)	325.98 (249.42)	364.73 (246.87)
IV: Enroll Abs. UC	-8.9 (6.4)	247.7 (61.3)	23.9 (6.3)	17.2 (4.1)	187.5 (50.7)	11,556.1 (7,608.6)	4,877.1 (3,996.2)	5,886.1 (4,258.6)
Bottom High School Quartile (B25)								
Baseline	52.9	1,687.7	44.0	1,704.0	70.6	97,577.2	26,812.8	11,526.0
β	-2.05 (0.99)	33.56 (10.13)	4.43 (1.05)	35.26 (7.03)	3.87 (0.76)	2,172.27 (971.84)	991.20 (473.61)‡	570.78 (436.75)
IV: Enroll Abs. UC	-12.4 (6.1)	200.5 (56.2)	26.2 (5.7)	222.6 (44.6)	24.4 (4.6)	13,830.3 (5,876.4)	5,058.3 (2,521.4)	3,165.8 (2,495.1)
Source:	IPEDS	IPEDS	IPEDS	NSC	NSC	OI	IPEDS	IPEDS

Note: This table shows that ELC caused barely-eligible applicants to earn degrees from more-selective institutions using a host of selectivity measures (conditional on degree attainment). Reported coefficients are the estimated characteristics of applicants' Bachelor's graduation university or post-secondary institution (conditional on BA graduation) at the barely ELC-ineligible baseline, the change in those characteristics across the ELC eligibility threshold (β), and the estimated change in those characteristics for Absorbing-UC-campus compliers using an IV estimator instrumenting with ELC eligibility. Estimates from instrumental variable 2SLS cubic fuzzy regression discontinuity models; standard errors are clustered by school-year, and omitted for baseline estimates (which are estimated following Abadie (2002)). Graduation measured as first Bachelor's degree earned between July following high school graduation and six years later. IPEDS and Opportunity Insights (OI) data linked by OPE ID (and year in IPEDS case) to NSC enrollment. NSC-measured average SAT scores and five-year graduation measured only for 2001-2011 UC applicants (excluding applicants within 0.3 GPA points of their high school's ELC eligibility threshold) and are time-invariant; see the text for the definition. Also see the text for definition of high school quartiles. IPEDS Average SAT score calculated for each school as the sum of the mean of the 25th and 75th percentiles of each SAT section, converting scores from 1600 scale to 2400 scale when necessary. Sticker price is defined using on-campus residency unless unavailable, in which case it is defined using off-campus non-family residency. IPEDS admission rate unavailable prior to 2005, and price information unavailable prior to 2008. Applicants from high schools with ELC eligibility thresholds between 3.96 and 4.00 are omitted. ‡ Indicates reduced-form 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). [1]If the applicant enrolls at a community college but then enrolls at a four-year university within 6 months, the latter is defined as her first institution of enrollment. [2]Net price includes tuition and fees, expected room and board, books and supplies, and other expenses net of federal, state, local, or institutional grant aid. Calculated as the IPEDS average net price for Title-IV-aid-awarded enrollees in the applicant's family income bin, where the observed bins are $0-30,000, $30,000-48,000, $48,000-75,000, $75,000-110,000, and above $110,000. Applicants with unobserved family incomes are omitted, and likely paid the sticker price (as they did not apply for federal financial aid, including loans).

Source: UC Corporate Student System, National Student Clearinghouse, the Integrated Postsecondary Education Data System (IPEDS), and Opportunity Insights (Chetty et al., 2020).

Table A-6: Instrumental Variable Estimates of Near-Threshold ELC Eligibility Outcomes by Campus, with Unadjusted Log-Distance Instrumental Variables

	UCD	UCSD	UCSB	UCI	F^1
Predicted Grad.[2]	-0.32	-0.45	1.46	-0.50	0.583
	(0.54)	(0.78)	(1.61)	(0.64)	
Institution's 5-Year Grad. Rate	24.0	33.6	38.3	23.4	0.266
	(4.94)	(7.21)	(14.8)	(6.20)	
Grad. Within 5 Years (%)	32.48	27.40	53.47	27.75	0.817
	(11.89)	(17.44)	(35.76)	(14.90)	
Earn STEM Degree (%)	-9.06	-5.27	-71.07	-19.63	0.100
	(11.71)	(17.87)	(35.29)	(14.52)	
Enr. At Grad School within 7 Yrs. (%)	31.88	18.24	83.13	37.06	0.413
	(12.85)	(18.58)	(40.46)	(16.08)	
Num. Yrs. Pos. CA Wages[3]	0.33	0.19	-0.14	0.43	0.898
	(0.35)	(0.48)	(1.01)	(0.45)	
Avg. Early-Career Wages[3]	24,819	16,095	1,555	7,788	0.049
	(10,581)	(13,836)	(28,973)	(12,635)	
Avg. Early-Career Log Wages[3]	0.71	0.13	-0.87	0.19	0.006
	(0.31)	(0.48)	(0.86)	(0.33)	
First Stage F	107.1	12.8	7.2	61.8	
Conditional F	41.6	51.7	16.1	46.4	

Note: This table replicates Table 4 without adjusting the UCSB distance-to-campus instrument, showing that the reduction in that instruments' predictive power does not substantially change the main presented results. Estimates of the effect of Absorbing UC campus enrollment on educational and labor market outcomes for near-threshold ELC-eligible students following Equation 3. Log distance to Santa Barbara is unadjusted, resulting in poor instrument strength; see Table 4 for adjusted 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 6 and 8 years after high school graduation in which the applicant has positive covered California wages, and the applicants' unconditional average annual wages in the period.

Source: UC Corporate Student System, National Student Clearinghouse, and the California Employment Development Department (Bleemer, 2018).

Table A-7: First-Stage IV Estimates of Near-Threshold ELC Eligibility Outcomes by Campus

	UCD	UCSD	UCSB	UCI
Log Distance to UC Davis × ELC Elig.	-0.063	0.021	0.016	0.021
	(0.003)	(0.004)	(0.003)	(0.003)
Log Distance to UC San Diego × ELC Elig.	0.018	-0.055	0.001	0.049
	(0.005)	(0.011)	(0.006)	(0.008)
Log Distance to UC Santa Barbara × ELC Elig.	0.019	0.009	-0.034	0.017
	(0.004)	(0.004)	(0.004)	(0.004)
Log Distance to UC Irvine × ELC Elig.	0.043	0.034	0.014	-0.091
	(0.005)	(0.010)	(0.006)	(0.008)

Note: This table shows first-stage OLS regression coefficients for the four instrumental variables used in the IV specifications in Table 4, showing that near-threshold enrollment at each UC campus is much more strongly predicted by distance to that campus as by distance to the other campuses. Estimates of the effect of the interaction between ELC eligibility and log distance to each Absorbing UC campus on enrollment at each of those campuses, representing the four first-stage regressions implied by instrumental variable OLS estimation of Equation 3. Each column presents estimates from a separate OLS regression predicting enrollment at the stated Absorbing UC campus; covariate coefficients are not reported. Log distance to Santa Barbara is set to 0 after 2010 to increase instrument strength. Applicants from high schools with ELC eligibility thresholds between 3.96 and 4.00 are omitted.

Source: UC Corporate Student System and National Student Clearinghouse.

Table A-8: Baseline Changes in Intended Major Selection

	Undec.	Art	Hum.	Soc. Sci.	Nat. Sci.	Engin.	Profess.	Bus.	STEM[1]
B50 Sample									
Baseline	14.9	-1.4	8.4	2.6	52.0	16.2	11.8	10.0	69.4
$\hat{\beta}$	-0.1	-0.1	-0.3	2.1	-2.1	0.8	-0.4	0.1	-1.3
	(1.0)	(0.5)	(0.8)	(1.0)	(1.3)	(1.0)	(0.6)	(0.7)	(1.3)
B25 Sample									
Baseline	19.5	-2.4	4.9	6.4	56.4	17.5	10.7	6.7	73.7
$\hat{\beta}$	0.0	-0.4	-0.4	1.6	-2.6	0.3	0.2	1.2	-2.0
	(1.5)	(0.6)	(1.2)	(1.6)	(1.9)	(1.5)	(0.9)	(1.1)	(2.0)

Note: This table shows that barely ELC-eligible applicants were somewhat less likely to report intended majors in natural science and broader STEM fields, with some switching toward social science, potentially suggesting that eligible students felt less pressure to earn lucrative majors if they attended more-selective universities. Reported coefficients are the estimated distribution of intended majors reported on UC applications at the barely ELC-ineligible baseline (estimated following Abadie (2002) with Absorbing UC campus enrollment as the endogenous variable), and the change in those characteristics across the ELC eligibility threshold ($\hat{\beta}$) estimated following Equation 2. Estimates from 2SLS cubic fuzzy regression discontinuity models; standard errors are clustered by school-year. Applicants from high schools with ELC eligibility thresholds between 3.96 and 4.00 are omitted. Statistical significance: † 10 percent, * 5 percent, ** 1 percent. [1]STEM includes all Natural Science and Engineering majors as well as some Professional majors (e.g. Agriculture and Architecture); see US Department of Homeland Security (2016).

Source: UC Corporate Student System.

Table A-9: ELC Impact on Intended Major to Earned Major Transitions, B50 Sample

	No Degree	Art	Human.	Soc. Sci.	Nat. Sci.	Engin.	Profess.	Bus.	STEM[1]
Undeclared	-2.5	0.5	1.2	4.5	-4.3*	-0.2	0	4.2*	-3.5
Hum.	-1.4	-4.5*	1.8	2.8	1.9	0.1	-1.8	0.6	0.6
Soc. Sci.	-8.6**	0.6	-0.2	10**	-0.7	0.2	0.1	-1	-2.8
Nat. Sci.	-2.9	0.2	-1.2	5.3**	0.6	-2**	0.3	-0.6	-1.9
Engin.	0.4	0.7	-0.1	-0.6	0	-2.7	1.1	2	-1.8
Profess.	-10.1**	0.6	-4†	5.9	0.3	-0.9	4.9	2.1	1.1
Bus.	-5.9	-0.5	-0.2	1.9	3	-1.2	3.5	-1.9	1.2
STEM	-2	0.2	-1.4†	3.8**	-0.3	-1.2	0.5	0.4	-1.7

Note: This table shows that barely ELC-eligible intended STEM majors tended to switch into social science majors, though the estimates are too noisy to precisely estimate intended STEM majors' transition out of STEM fields. Reported coefficients are the estimated change in likelihood for barely ELC-eligible applicants ($\hat{\beta}$) to earn a major by discipline conditional on their intended major's discipline, among applicants from the bottom half of California high schools by SAT. Estimates from polynomial specification of Equation 2; hypothesis tests (from 0) conducted with standard errors clustered by school-year. Degree attainment measured five years after initial enrollment. Applicants from high schools with ELC eligibility thresholds between 3.96 and 4.00 are omitted. [1]STEM includes all Natural Science and Engineering majors as well as some Professional majors (e.g. Agriculture and Architecture); see US Department of Homeland Security (2016).

Source: UC Corporate Student System and National Student Clearinghouse

Table A-10: Impact of ELC Eligibility on Schooling and Labor Market Outcomes

	B50 Sample						B25 Sample					
	Reduced Form			Abs. UC	Potential Out.		Reduced Form			Abs. UC	Potential Out.	
	Base.	CCT	Min. GPA	IV	Below	Above	Base.	CCT	Min. GPA	IV	Below	Above
Inst. Five-Year	3.33	3.05	3.57	26.78	49.89	76.68	5.41	5.27	5.74	34.14	44.51	78.65
Grad. Rate (%)	(0.51)	(0.75)	(0.51)	(3.83)	(3.67)	(1.15)	(0.83)	(0.94)	(0.81)	(4.84)	(4.51)	(1.52)
Grad. within	3.50	4.50	2.66	28.59	46.41	75.00	4.83	6.29	3.13	31.00	34.98	65.98
Five Years (%)	(1.20)	(1.59)	(1.19)	(9.92)	(8.27)	(5.82)	(1.96)	(2.55)	(1.91)	(12.63)	(10.51)	(7.13)
Number of	-0.08	-0.12	-0.08	-0.62	4.99	4.37	-0.09	-0.12	-0.07	-0.55	4.96	4.41
Year Enrolled	(0.03)	(0.04)	(0.03)	(0.24)	(0.20)	(0.14)	(0.05)	(0.06)	(0.05)	(0.31)	(0.26)	(0.17)
STEM	-1.75	-1.27	-1.14	-14.28	37.32	23.04	-2.37	-1.80	-1.44	-15.22	26.46	11.24
Degree (%)	(1.05)	(1.23)	(1.04)	(8.81)	(6.52)	(6.05)	(1.34)	(1.56)	(1.29)	(8.95)	(6.46)	(6.03)
Deg. in Intended	2.56	3.60	3.24	20.92	25.08	46.00	2.76	4.31	3.28	17.68	7.89	25.57
Field of Study (%)	(1.24)	(1.47)	(1.24)	(10.20)	(7.73)	(6.65)	(1.71)	(2.12)	(1.66)	(11.01)	(8.71)	(7.13)
Enr. Grad. School	2.56	3.87	1.76	20.94	4.00	24.94	3.87	3.77	2.13	24.82	-1.27	23.54
Within 7 Years	(1.17)	(1.65)	(1.17)	(9.78)	(7.91)	(6.27)	(1.66)	(1.83)	(1.62)	(11.02)	(9.02)	(6.48)
# Early-Career	0.05	0.04	0.05	0.47	2.17	2.64	0.07	0.05	0.03	0.47	2.21	2.68
Years Employed	(0.03)	(0.04)	(0.03)	(0.30)	(0.24)	(0.18)	(0.05)	(0.05)	(0.05)	(0.35)	(0.30)	(0.20)
Average Early-Career	2,356	1,253	2,254	20,341	27,351	47,692	2,243	2,227	1,400	16,205	27,145	43,350
Covered Earnings	(901)	(1,206)	(865)	(8,199)	(6,322)	(4,891)	(1,184)	(1,262)	(1,139)	(8,884)	(7,164)	(5,231)
Average Early-Career	0.10	0.08	0.06	0.76	10.04	10.81	0.08	0.06	0.03	0.56	10.19	10.75
Log Covered Earnings	(0.04)	(0.05)	(0.03)	(0.33)	(0.25)	(0.21)	(0.06)	(0.06)	(0.04)	(0.39)	(0.32)	(0.25)

Note: This table summarizes a series of robustness checks and extensions of the main regression discontinuity findings, showing that they are generally robust to alternative specifications and also highlighting the changes in potential outcomes resulting from Absorbing UC campus enrollment because of ELC eligibility. Reported coefficients are the estimated change in various outcome measures for barely ELC-eligible applicants estimated by Equation 2: reduced-form 2SLS polynomial and 'CCT' local linear (Calonico, Cattaneo, and Titiunik, 2014) regression discontinuity models; reduced-form polynomial regression discontinuity model using an alternative measurement of each high school's ELC eligibility threshold (just below the lowest ELC-eligible applicant's ELC GPA); polynomial models with Absorbing UC campus enrollment ($\mathbb{1}_{Abs.}$) as the endogenous variable; and estimated average potential outcomes for barely ELC-ineligible and barely ELC-eligible Absorbing UC campus compliers (following Abadie (2002)). Standard errors in parentheses are clustered by high-school-year. Coefficients estimated for applicants from the bottom half (B50) and quartile (B25) of California high schools by SAT; see text for details, and for definitions of the outcome variables. Early-career employment outcomes for 7-9 years after high school graduation. See Appendix Table A-13 for annual specifications 6-10 years after high school graduation. 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).

Table A-11: Impact of ELC Eligibility on Schooling and Labor Market Outcomes by Subgroup

	Reduced-Form Polynomial Estimates						Five-Year Graduation Rate IV Estimates					
	B50	B25	Female	Male	URM	Non-URM	B50	B25	Female	Male	URM	Non-URM
Inst. Five-Year Grad. Rate (%)	3.33	5.41	3.97	2.27	3.59	3.03						
	(0.51)	(0.83)	(0.67)	(0.82)	(0.93)	(0.62)						
Grad. within Five Years (%)	3.50	4.83	3.45	3.89	3.97	3.08	1.01	0.85	0.89	1.57	1.08	0.98
	(1.20)	(1.96)	(1.49)	(2.05)	(2.12)	(1.45)	(0.35)	(0.34)	(0.35)	(0.93)	(0.57)	(0.46)
Number of Year Enrolled	-0.078	-0.092	-0.058	-0.120	-0.103	-0.070	-0.024	-0.018	-0.016	-0.048	-0.030	-0.022
	(0.030)	(0.050)	(0.037)	(0.051)	(0.055)	(0.035)	(0.010)	(0.010)	(0.010)	(0.025)	(0.016)	(0.012)
STEM Degree (%)	-1.75	-2.37	-3.74	0.54	-1.96	-1.61	-0.52	-0.44	-0.87	0.11	-0.55	-0.50
	(1.05)	(1.34)	(1.25)	(1.90)	(1.45)	(1.48)	(0.33)	(0.27)	(0.36)	(0.84)	(0.44)	(0.52)
Deg. in Intended Field of Study (%)	2.56	2.76	1.49	4.09	3.06	2.19	0.79	0.54	0.42	1.85	0.89	0.78
	(1.24)	(1.71)	(1.60)	(2.08)	(1.93)	(1.62)	(0.38)	(0.32)	(0.40)	(1.06)	(0.55)	(0.53)
Enr. Grad. School Within 7 Years	2.56	3.87	3.63	1.06	4.15	1.47	0.77	0.63	0.94	0.43	1.12	0.48
	(1.17)	(1.66)	(1.58)	(1.81)	(1.90)	(1.51)	(0.36)	(0.31)	(0.41)	(0.81)	(0.58)	(0.50)
# Early-Career Years Employed	0.054	0.065	0.053	0.055	0.012	0.074	0.016	0.014	0.014	0.023	-0.003	0.025
	(0.034)	(0.048)	(0.042)	(0.057)	(0.056)	(0.044)	(0.011)	(0.010)	(0.011)	(0.030)	(0.020)	(0.014)
Average Early-Career Covered Earnings	2,356	2,243	2,422	2,575	704	3,392	728	478	670	1,082	104	1,111
	(901)	(1,184)	(1,079)	(1,616)	(1,349)	(1,207)	(310)	(258)	(298)	(938)	(488)	(437)
Average Early-Career Log Covered Earnings	0.100	0.083	0.080	0.146	-0.008	0.176	0.033	0.021	0.018	0.146	0.000	0.063
	(0.04)	(0.06)	(0.05)	(0.07)	(0.06)	(0.05)	(0.02)	(0.01)	(0.01)	(0.17)	(0.02)	(0.03)

Note: This table summarizes heterogeneity in the estimated relative return to university selectivity for near-threshold ELC-eligible participants, generally suggesting similar treatment effect magnitudes for male, female, URM, and non-URM applicants. Reported coefficients are the estimated change in various outcome measures for barely ELC-eligible applicants from the polynomial specification of Equation 2, with the IV estimates replacing the endogenous variable with applicant's first institution's five-year graduation rate. Sample is restricted to the bottom half (B50) of California high schools by SAT; second column is further restricted to bottom quartile (B25) of high schools, and other columns are restricted to female, male, URM, or non-URM applicants. Standard errors in parentheses are clustered by high-school-year. URM includes black, Hispanic, and Native American applicants. See the text for definition of high school SAT quartiles and the outcome variables. Applicants from high schools with ELC eligibility thresholds between 3.96 and 4.00 are omitted. Early-career employment outcomes are for 7-9 years after high school graduation.

Source: UC Corporate Student System, National Student Clearinghouse, and the California Employment Development Department (Bleemer, 2018).

Table A-12: Tests of Treatment Effect Linearity in University Graduation Rate

	Number of HS Quantiles				
	2	4	6	8	10
Panel A: 2SLS Over-ID Tests on Graduation Rate					
IV β	1.05	0.88	1.04	1.04	1.16
	(0.35)	(0.33)	(0.33)	(0.32)	(0.31)
Sargan's S	0.15	1.89	1.85	2.58	2.31
p	0.698	0.595	0.870	0.921	0.986
Panel B: LIML Estimates on Graduation Rate					
IV β	1.06	0.95	1.21	1.33	1.47
	(0.36)	(0.57)	(0.53)	(0.67)	(0.59)
Panel C: 2SLS Estimates of Quadratic in Grad. Rate					
GR^2 β	0.369	0.326	0.091	0.091	0.052
	(1.332)	(0.336)	(0.063)	(0.056)	(0.039)

Note: This table reports the results of three series of tests of whether the changes in outcomes caused by barely ELC-eligible students' Absorbing UC campus enrollment could be usefully projected onto their change in university selectivity (indexed by five-year graduation rates). Interacting ELC eligibility and the running variable terms with applicants' high school quantiles, Panel A shows that over-id tests cannot reject linear returns to selectivity; Panel B shows that the LIML IV estimates do not shrink as the number of instruments increase; and Panel C shows that a quadratic term in graduation rate is not statistically significantly different from 0. Reported coefficients are coefficient estimates and test statistics from regressions of an indicator for applicants' five-year university graduation on their institution of first enrollment's NSC-calculated five-year graduation rate, instrumented by ELC eligibility interacted with high school SAT quantile indicators. Sample restricted to UC applicants in the bottom half of California high schools by near-threshold SAT score, and regressions include third-order polynomials in the ELC running variable interacted with quantile dummies along with high school and year fixed effects, gender-ethnicity indicators, and a quadratic in SAT score. Standard errors in parentheses clustered by high-school-year. **Panel A:** Coefficients and statistics from 2SLS regression estimation. Reported "IV β" is the second-stage term on five-year graduation rates; Sargan's S tests for over-identification and is distributed χ^2 with degrees of freedom equal to the number of high school quantiles minus 1 (p estimates model's likelihood under the null hypothesis). **Panel B:** Coefficients on graduation rate from Limited Information Maximum Likelihood estimation. **Panel C:** Coefficients on the square of graduation rate when both linear and squared rates are instrumented by ELC-interactions.

Source: UC Corporate Student System and National Student Clearinghouse

Table A-13: Impact of ELC Eligibility on Observed Annual California Wages

	B50 Sample						B25 Sample					
# Years after HS Grad:	6	7	8	9	10	11	6	7	8	9	10	11
Non-Zero Wage Indicator	1.65 (1.15)	1.34 (1.18)	1.81 (1.28)	1.82 (1.39)	1.76 (1.53)	2.13 (1.70)	2.55 (1.66)	2.23 (1.69)	1.52 (1.79)	1.53 (1.99)	0.53 (2.20)	1.25 (2.42)
Average Wages	734 (690)	1,758 (814)	2,150 (964)	2,068 (1,154)	2,237 (1,383)	2,063 (1,637)	1,341 (917)	1,637 (1,059)	2,062 (1,261)	1,652 (1,554)	1,249 (1,897)	2,597 (2,248)
Average Log Wages	0.017 (0.037)	0.083 (0.038)	0.070 (0.038)	0.042 (0.040)	0.040 (0.042)	-0.005 (0.048)	0.061 (0.052)	0.053 (0.050)	0.052 (0.054)	0.036 (0.056)	0.059 (0.060)	0.082 (0.069)
Latest Year Inc.[1]	2011	2011	2011	2010	2009	2008	2011	2011	2011	2010	2009	2008
Number of Observations	85,725	85,725	85,725	75,334	65,462	54,811	42,904	42,904	42,904	37,435	32,121	26,669
Percent of Total[1]	100	100	100	87.9	76.4	63.9	100	100	100	87.3	74.9	62.2

Note: This table shows that ELC eligibility appears to persistently increase wages for barely-eligible applicants as they age (from about age 24 to 29, though the number of observations declines in years further from high school graduation), suggesting that the main estimates are unlikely to be short-lived in applicants' very early careers. Estimated reduced-form changes ($\hat{\beta}$) in annual covered California employment and covered California wages and log wages 6-11 years after high school graduation caused by near-threshold ELC eligibility. Estimates from polynomial specification of Equation 2, restricting the sample to the bottom half (B50) or quartile (B50) of California high schools by SAT (see text for details); standard errors are clustered by school-year. Covered wages exclude wages not covered by unemployment insurance, including federal and self-employment. Applicants from high schools with ELC eligibility thresholds between 3.96 and 4.00 are omitted. [1]The latest observed high school cohort is 2011, and the latest observed wages are 2019. As a result, every year more than 8 years following high school graduation requires dropping one cohort of applicants from the estimation sample. These figures show the latest cohort included in estimation, the number of within-sample applicants in those cohorts, and the percent of all in-sample applicants in available cohorts.

Source: UC Corporate Student System and the California Employment Development Department. (Bleemer, 2018).

Table A-14: Other Model Parameters

Parameter	Value	Parameter	Value	Parameter	Value
$\sigma^2_{\nu_{CSU}}$	1.54 (0.71)	γ^s_{Const}	-0.59 (0.04)	β^x_{Dist}	-0.37 (0.02)
$\sigma^2_{\nu_{Unimp}}$	3.05 (0.76)	γ^s_{LogInc}	-0.11 (0.02)	$\beta^x_{Dist^2}$	0.02 (0.01)
$\sigma^2_{\nu_{Abs1}}$	1.58 (0.72)	γ^s_{Female}	-0.14 (0.04)	$\beta^x_{Dist \times LogInc}$	0.08 (0.01)
$\sigma^2_{\nu_{Abs2}}$	1.78 (0.71)	γ^s_{Asian}	0.13 (0.05)	$\beta^x_{Dist \times Female}$	0.02 (0.01)
$\sigma^2_{\nu_{Disp}}$	2.22 (0.71)	γ^s_{URM}	-0.61 (0.06)	$\beta^x_{Dist \times Asian}$	-0.10 (0.02)
				$\beta^x_{Dist \times URM}$	-0.03 (0.02)
γ^c_{Const}	0.05 (0.001)	$\gamma^{q\|s}_{Const}$	-2.58 (0.72)		
γ^c_{LogInc}	0.02 (0.001)	$\gamma^{q\|s}_{LogInc}$	0.03 (0.31)		
γ^c_{Female}	0.00 (0.001)	$\gamma^{q\|s}_{Female}$	-0.55 (0.66)		
γ^c_{Asian}	-0.03 (0.001)	$\gamma^{q\|s}_{Asian}$	0.13 (0.65)		
γ^c_{URM}	-0.02 (0.001)	$\gamma^{q\|s}_{URM}$	-0.53 (1.06)		

Note: This table presents estimates of the remaining structural model parameters not presented in the main tables; see text for details. Parameter estimates from maximum simulated likelihood (maximized by the BFGS Quasi-Newton algorithm) of Equation 7. Reported standard errors from the inverse of the empirical Hessian matrix. Missing family incomes are imputed; see footnote 50. Continuous variables are standardized in-sample. 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.

Table A-15: Adjusted Admissions Thresholds in in Counterfactual Simulations

	Unimpacted	UCSD/UCSB	UCD/UCI	Dispersing
Baseline π_j's	1.95	0.46	0.15	-1.63
Counterfactual 1: Setting $\beta_{Abs1}^{ELC} = \beta_{Abs2}^{ELC} = 0$ before 2012				
	1.95	0.41	0.07	-1.64
Counterfactual 2: Setting $ELC = 1$ above threshold after 2011				
Threshold:				
1	1.95	0.48	0.17	-1.63
2	1.94	0.50	0.20	-1.62
3	1.94	0.52	0.23	-1.62
4	1.94	0.54	0.27	-1.62
5	1.94	0.57	0.32	-1.62
6	1.94	0.60	0.38	-1.61
7	1.94	0.63	0.46	-1.61
8	1.94	0.67	0.54	-1.61
9	1.94	0.70	0.63	-1.61

Note: This table shows how each UC campus's π_j admissions threshold adjusts to preserve expected enrollment in the counterfactual presence or absence of a top percent admissions policy; the Absorbing UC campuses' thresholds relax (tighten) when the top percent policy is removed (added), reflecting their trade-off between admitting students through regular admissions or the top percent policy. Parameter estimates from maximum simulated likelihood (maximized by the BFGS Quasi-Newton algorithm) minimizing changes in each UC campus's expected enrollment in counterfactual exercises removing the ELC policy before or adding the policy after 2011 (providing admissions advantages to students at or above the specified GPA rank admissions threshold). Standard errors are omitted. Sample restricted to 2010-2013 UC freshman California-resident applicants who enroll at a public California institution in the fall after high school graduation. See text for details on the counterfactual exercises.

Source: UC Corporate Student System and the National Student Clearinghouse.