JOCKEYING FOR POSITION: STRATEGIC HIGH SCHOOL CHOICE UNDER TEXAS' TOP TEN PERCENT PLAN*

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Abstract: Beginning in 1998, all students in the state of Texas who graduated in the top ten percent of their high school classes were guaranteed admission to any in-state public higher education institution, including the flagships. While the goal of this policy is to improve college access for disadvantaged and minority students, the use of a school-specific standard to determine eligibility could have unintended consequences. Students may increase their chances of being in the top ten percent by choosing a high school with lower-achieving peers. Our analysis of students' school transitions between 8th and 10th grade three years before and after the policy change reveals that this incentive influences enrollment choices in the anticipated direction. Among the subset of students with both motive and opportunity for strategic high school choice, at least 5 percent enroll in a different high school to improve the chances of being in the top ten percent. These students tend to choose the neighborhood high school in lieu of transferring to more competitive schools and, regardless of own race, typically displace minority students from the top ten percent pool. Relatively few students have both the motive and opportunity to behave strategically in the short run, so systemic effects are inherently slight. Our finding of sizable take-up in the face of costly strategizing, however, suggests that endogenous group membership may be important in the longer run and in other settings where individuals can select their peers and are then "graded on a curve."

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1. Introduction

One of the fundamental difficulties confronting the design of effective redistributive policies is targeting benefits to intended beneficiaries without attracting imitators. There is an extensive literature documenting how individuals alter their behavior to qualify for welfare programs, such as by reducing labor supply, changing living arrangements, and moving to new jurisdictions.[1] In this paper, we analyze this type of phenomenon in a novel setting where eligibility is determined by a tournament and there is scope for endogenous group membership. In particular, we explore whether students downgrade when choosing a high school, when access to a benefit—guaranteed admission to flagship universities—depends on relative position within one's class.

The policy that we consider, the Texas top ten percent plan, arose from the debate over whether universities should be allowed to consider a student's race in admissions decisions. In 1996, the Fifth Circuit Court of Appeals ruled in the case of *Hopwood v. Texas* that race could not be used as a factor at the University of Texas School of Law, and this ruling led to a ban on affirmative action at all public universities in Texas beginning in 1997.[2] In response to mounting public concern regarding the ensuing drop in minority matriculation to elite Texas public universities,[3] then Governor George W. Bush helped push through legislation guaranteeing that all seniors with grades in the top ten percent of their own high school classes gain admission to any public university within Texas. The Texas program began in the summer of 1998 and, since then, California and Florida have adopted similar plans.

The intended effect of these *x*-percent plans is to improve access to higher education for disadvantaged students by using a school-specific standard.[4] The admission guarantee ensures that students at low-achieving high schools, who tend to be disproportionately poor and minority, are equally represented among those automatically granted admission. However, these policies also change the relative attractiveness of high schools and, through this channel, might induce resorting across schools. Consider a student who would place below the top ten percent at the

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[1] See Moffitt (1992, 2002) for comprehensive reviews.
[2] Though the Supreme Court upheld the constitutionality of non-formulaic affirmative action policies in 2003 (*Grutter v. Bollinger*), voter referenda and administrative decisions in five other states (California, Florida, Michigan, Nebraska, and Washington) have also banned race-based admissions at public universities.
[3] Between 1995 and 1997, black, Hispanic and Native American students' share of enrollment fell from 20 to 16 percent at UT-Austin and from 20 to 13 percent at Texas A&M (Long, 2007). Evidence is mixed regarding how much of this response is due to changes in application behavior (e.g., Long (2004a) and Card and Krueger (2005)).
[4] Horn and Flores (2003) provide detailed descriptions of these *x*-percent plans. For simulations of the effect of *x*-percent plans on minority representation, see Long (2004b) and Howell (2010).

high school this student would have attended in the absence of the reform. This student might be able to obtain guaranteed access to a flagship by instead choosing to attend another high school with lower-achieving peers.[5] Our goal is to estimate the degree to which such would-be-eligible students are induced to choose less competitive high schools in response to the new admissions program in Texas.

Our analyses follow the high school enrollment choices of 8th graders from the 1992-93 through 1997-98 cohorts. The first three of these cohorts chose their 10th grade schools prior to the adoption of the top ten percent plan, while the latter three cohorts chose their 10th grade schools after. We characterize each high school in terms of its top ten percent threshold, defined to be the 90th percentile of achievement (on 8th grade exams) among 10th graders from our initial cohort attending that high school. First, to identify general patterns of trading down after the policy change, we examine whether students in later cohorts choose high schools with different thresholds than those chosen by similar students in the first three cohorts. Since we hold high schools' thresholds fixed at initial levels, the observed changes isolate shifts in enrollment and are not confounded by other time-varying policies that might affect the relative performance of high schools. Next, using a discrete choice model, we more explicitly examine how policy-induced changes in students' incentives influence enrollment decisions.

Both types of analyses suggest that the tournament aspect of the new college admissions policy alters sorting across high schools. Conditional on their 8th grade schools, the types of students who have the most to gain from strategizing are more likely to attend high schools with relatively lower top ten percent thresholds after the top ten percent policy is in force. This behavioral response is most apparent when we restrict the sample to students in districts served by multiple high schools. Our discrete choice analysis for this subsample reveals that at least 5 percent of students with the motivation and opportunity trade down, commonly opting for the neighborhood high school in lieu of more competitive magnet schools.

In evaluating the degree of responsiveness, it is important to note that the take-up rate we estimate is among those who engage in costly behavior in order to qualify.[6] There are also several reasons to believe our estimates are lower bounds. First, we use students' prior test

[5] The returns to attending a flagship may be substantial. Hoekstra (2009) finds that wages earned by white males ten to fifteen years after high school were 20 percent higher for those applicants who were barely accepted by a flagship institution relative to those applicants who were barely rejected.

[6] Take-up rates are far from complete even among those who are mechanically eligible for transfer and social insurance program benefits (Currie, 2006).

scores as a proxy for their ability to place in the top ten percent of a school, and students likely have more accurate perceptions of their chances than we can capture empirically.[7] Second, our incentive measures are blunted by the need to apply the first cohort's top ten percent opportunities to later cohorts for clean identification. Third, conditioning on students' middle school choices facilitates a difference-in-differences estimation strategy, but also limits the range of responses we can capture. Changes in residential and school choice at earlier grade levels, in anticipation of high school, are missed. Finally, strategic responses to the program are likely to have become even more common after our sample period, as regular admissions spaces at the flagships have been crowded out and high schools from a broader geographic area have participated in the program.

The downgrading induced by the policy could be associated with both positive and negative spillovers. Since relatively more able students attend previously undesirable schools, these transfers reduce ability stratification across high schools and might benefit students in the recipient schools. At the same time, this response crowds out some of the automatic admission slots that would have gone to disadvantaged and minority students. Regardless of own race, we find that downgrading students typically displace minority students from the top ten percent pool, so the net effect of strategic behavior is to increase white students' representation in the top ten percent pool. Thus, this form of gaming tends to undermine the top ten percent plan's goal of promoting racial diversity in university admissions. The systemic impacts on both peers and the top ten percent pool are negligible, though, due to the narrow set of students with potential to game this policy.

Finding that some families are induced to choose schools with less advantaged peers is striking in light of mounting evidence regarding the central role of peer quality as a driver of school choice.[8] This suggests that relative student evaluations, which are pervasive in education, may be a force curbing ability sorting across schools. Our findings have more general implications as well. This study uncovers evidence of behavioral responses in a context where the costs of strategizing are quite high. We would expect endogenous group membership to occur in other contexts where individuals are "graded on a curve" and have some discretion over

[7] Among sophomores surveyed in 2002 by the Texas Higher Education Opportunity Project (THEOP), 25 percent reported knowing their class rank and 92 percent were able to supply a best estimate. Within the select subsample that switched high schools by 2004, 10 percent reported having changed schools to improve class rank.
[8] See, for example, Rothstein (2006) and Hastings et al. (2009).

which group to belong to. For example, similar incentives apply for students' selection of courses and workers' selection of coworkers.

Our paper unfolds as follows: Section 2 provides background information concerning college admissions in Texas, Section 3 presents a conceptual framework for how an *x*-percent rule might influence high school enrollment decisions, and Section 4 describes our data and empirical measures of incentives. The empirical strategies for testing the hypotheses and the results are presented in Sections 5 and 6, while Section 7 concludes.

2. Background

The immediate goal of the top ten percent policy was to increase student diversity at selective universities without specifically using racial preferences in admissions. Starting in 1998, automatic admission to any of the 37 public universities in Texas was granted to students ranked in the top ten percent of their high school graduating classes, as long as they apply to college within two years of graduating. The policy pertains to both public and private high school students.

For determining eligibility, a student's class rank is based on his or her position at the end of 11^{th} grade, middle of 12^{th} grade, or at high school graduation, whichever is most recent at the college's application deadline. Application deadlines for fall matriculation to the more selective universities are generally in early February. Therefore, for students applying during their senior year, top ten percent eligibility would be based on their class rank either at the end of 11^{th} grade or in the middle of 12^{th} grade. Class rank is computed by the individual high school, and administrators have discretion regarding the formula and how to handle transfers. To avoid displacing incumbent students, school administrators typically require transferring students to attend for some period of time before qualifying as being eligible for top ten percent placement. This mitigates the scope for gain from late-term transfers during junior or senior year.

Only those students who would consider attending a selective Texas public university will be sensitive to the change in admissions policy when deciding which high school to attend. Of those freshmen attending a four-year college in the Fall of 1998 who had graduated from a Texas high school in the prior year, 66 percent went to a Texas public college, 13 percent went to a Texas private college, and 21 percent went to an out-of-state college.[9] Given that only one-

[9] These estimates are based on data from the Department of Education (DOE, 2001) and the Texas Higher Education

fourth of Texas high school students attend a four-year college, the fraction of all 10^{th} graders who enroll in a Texas public college is about 16 percent.[10] Among students in the top ten percent of their high school classes who enrolled in a Texas public college, the majority attended one of the flagships, Texas A&M (28 percent) and UT-Austin (29 percent).[11]

Nearly all applicants with high school class ranks in the top decile had been admitted to these flagships prior to the top ten percent rule. In the absence of behavioral responses, only about 0.1 percent of all 10^{th} graders would have benefited from automatic admission to one of the two flagships.[12] However, the fraction of students potentially benefiting is much larger once endogenous applications and high school enrollment choices are considered. Since the rule was introduced, there has been a dramatic rise in the number of students automatically admitted and high schools represented (Long et al., 2010). The increase in coverage has been promoted by complementary outreach efforts and scholarships that the flagships target to high-achieving students attending economically disadvantaged, traditionally underrepresented high schools.[13]

The top ten percent policy currently poses a challenge for the flagships since the majority of admissions are now automatic, limiting the role of university discretion. This issue is most pressing at UT-Austin, where the automatic admission share recently exceeded 80 percent.[14] The concern that top ten percent students are crowding out admissions slots for other meritorious students has led to a backlash from families of students attending more elite, typically suburban, high schools.[15] The incentive for strategic high school choice has clearly strengthened relative to

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Coordinating Board (THECB, 2002).

[10] This percentage is calculated as the number of enrolled students divided by an estimate of the 10^{th} grade population in 1996-97. The estimate comes from dividing the number of public school 10^{th} graders observed in our data by 0.953, the public school enrollment share (DOE, 2001).

[11] The two flagships are comparably selective and have similar enrollments. In the pre-*Hopwood* years, the average SAT score of admitted students was 1172 at Texas A&M and 1229 at UT-Austin (Long and Tienda, 2008). In 1998, 6,658 and 6,742 first-time undergraduate students enrolled at the two institutions, respectively (THECB, 2002).

[12] From 1992 to 1997, only 817 (3 percent) of in-state top ten percent applicants to UT-Austin were rejected, while only 535 (2 percent) of such applicants to Texas A&M were rejected (authors' calculations based on administrative admissions data). Thus, on an annual basis, roughly 225 in-state top ten percent applicants were rejected at one of these institutions, or 0.1 percent of Texas 10^{th} grade students in 1996.

[13] In 1999, Texas A&M and UT-Austin introduced the Century and Longhorn Opportunity Scholarship Programs, which were initially available to students at 20 and 40 high schools throughout Texas, respectively. These scholarships, which in practice are not extended to students outside the top ten percent, reinforce strategic incentives to trade down to one of the high schools selected to participate.

[14] In 2007, the state legislature's effort to cap the automatic admission share at UT-Austin to half of the admitted class failed, as lawmakers supportive of the status quo fought to protect the increased access for their constituents, particularly in rural areas (Hughes and Tresaugue, 2007). In the 2009 session, the legislature passed a less restrictive bill capping the share at 75 percent starting in 2010-11.

[15] For anecdotal evidence, see Yardley (2002) and Glater (2004).

the early years of the regime that we study, due to both this recent admission squeeze and the expansion of affiliated scholarship programs.

3. Conceptual framework for strategic high school choice

The introduction of a top ten percent policy should increase the *relative* attractiveness of communities and schools in which a child is likely to be in the top ten percent of the high school graduating class. While this prediction may seem obvious, we develop a simple theoretical framework in this section to help motivate our empirical tests and clarify the assumptions required for these tests. We presume that the decisions for families with school-aged children are partly driven by the expected impact that particular schools will have on their children's future earnings (and any other correlated outcomes). All else equal, families will prefer to send their children to schools that increase earnings capacity both directly through skills and knowledge acquisition and indirectly by improving access to institutions of higher education.

We begin by specifying an indirect utility function that each household seeks to maximize. This function is defined from the perspective of families of 8th graders making housing and schooling choices for 10th grade. Though this perspective is dictated by the structure of our data and identification strategy, schooling transitions between these grades are appropriate to study for two reasons. First, most students change campuses between middle school and high school, so may already be considering alternatives as they transition. Second, strategic transfers later than the spring of the 10th grade year may not be rewarded due to locally imposed barriers to top ten percent eligibility. This perspective misses responses from families prior to 8th grade, though these are likely to arise over a longer time span than we examine below.

For simplicity, assume that families have only one child. Define i as an index for both the family and the child, j as an index for the house/neighborhood where the family resides, and k as an index for the high school the student attends. Define $e_i(\gamma_i, Q_k, p_{ik})$ as the child's expected future earnings, which depend on the student's own ability level (γ_i), the quality of the student's high school (Q_k), and the likelihood of being accepted to a flagship conditional on applying (p_{ik}).[16] In addition to the child's expected earnings, the family considers neighborhood characteristics (N_j), housing prices inclusive of property taxes (P_j), tuition prices if school k is a

[16] The ability measure γ_i can be thought of as a combination of the student's innate ability and the amount of learning that takes place in the years preceding high school. Any effects of access to other higher education institutions are implicit in the functions of student ability and high school quality.

private school (π_k), and transportation costs from neighborhood j to school k (d_{jk}). If the family chooses to move to a new neighborhood for high school, this will involve fixed mobility costs (M_{ij}). Indirect utility is then given by the following:

$$(3.1) \qquad V_{ijk} = v_i\left(e_i\left(\gamma_i, Q_k, p_{ik}\right), N_j, P_j, \pi_k, d_{jk}, M_{ij}\right)$$

We presume the family will choose the neighborhood and high school combination that maximizes indirect utility, subject to the constraint that, depending on the schools' transferring policies, some neighborhood and school combinations will not be allowed.[17]

Given this framework, we consider some simple analytics for children who are interested in an admissions offer from a flagship (i.e., for whom $\partial e_i / \partial p_{ik} > 0$). The top ten percent plan will alter some of these children's schooling choices due to changes in p_{ik}. We assume that general equilibrium effects on housing prices, neighborhood characteristics, school quality, and tuition are likely to be small within the first years of policy implementation, attributing changes in behavior to the salient and immediate changes in flagship access.[18]

In order to formalize how access changes, we define a_{ik}^{pre} and a_{ik}^{post} to be the likelihood that student i gains admission, conditional on applying from school k, through the regular admissions process existing before and after the top ten percent plan. Define *Post* as a dummy variable, equal to one if the new policy is in place. Define τ_{ik} to be the likelihood the student would place in the top ten percent of a particular high school class, as predicted given parents' knowledge of the child's ability and expectations of the composition of that class.

A child's likelihood of being accepted at a flagship conditional on applying, is then:

$$(3.2) \qquad p_{ik} = Post \times \left[\tau_{ik} \times 1 + \left(1 - \tau_{ik}\right) \times a_{ik}^{post}\right] + \left(1 - Post\right) \times a_{ik}^{pre}$$

Before the policy change, it is simply the regular admissions policy that is relevant. Afterward, the regular admissions policy is only relevant if the child does not place in the top ten percent. The change in access can thus be expressed:

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[17] In Texas, several programs permit transfers without changes of residence. The state adopted a formal inter-district choice program in 1995, but participation in this program has been low since district participation is voluntary. On average, 2.8 percent of students in a district were nonresident transfers (Schools and Staffing Survey, 1999-00). Large districts also offer a variety of formal and informal intra-district school choice programs, such as magnet schools and programs and transfers to schools with underutilized space.

[18] The policy change should increase house prices in communities with low quality schools, since it is these schools where access to selective higher education institutions is improved the most. Broadly consistent with expectations, though also perhaps attributable to correlated school finance and accountability reforms, Cortes and Friedson (2010) find property tax values rose in previously low-performing districts. These types of capitalization effects would reduce incentives for gaming via residential relocation over time.

(3.3.1) $\Delta p_{ik} = \tau_{ik} \times \left(1 - a_{ik}^{post}\right) + \left(a_{ik}^{post} - a_{ik}^{pre}\right)$

The last term reflects the potential for newly accepted top ten percent students to displace students who would otherwise have been accepted. For simplicity, we assume that traditional college admissions decisions are independent of a student's choice of high school and are not influenced by the top ten percent plan—i.e., $a_i = a_{ik}^{pre} = a_{ik}^{post}$.[19] Abstracting from these realities of admissions policies, including the elimination of affirmative action, is not particularly problematic in our setting. These correlated shifts lead to variation in access either by cohort or by school among students of similar ability, but are not likely to have dramatic effects on differential access *across* schools by cohort the way the top ten percent plan does. With our assumption, equation 3.3.1 reduces to:

(3.3.2) $\Delta p_{ik} = \tau_{ik} \times \left(1 - a_i\right)$

The change in access varies directly with the likelihood of placing in the top ten percent, and is moderated by the likelihood of being rejected under the regular admissions process.

The robust prediction is that any child who strategically chooses a high school other than the one that would have been chosen before the policy reform should attend a school where he/she expects to have a greater chance of being in the top ten percent of the graduating class. Starting from a family's pre-reform ranking of high schools, equation 3.3.2 suggests that lower-achieving high schools offering greater top ten percent opportunities will move up in the rankings. As a result of any induced downgrading, top ten percent thresholds at relatively low-achieving schools will tend to rise and converge toward those at higher-achieving schools, dampening the scope for further gaming. If such behavior were costless, perfect arbitrage would imply that the top ten percent of each high school would include *only* students in the top decile statewide.

Trading down is associated with costs, however, and schooling choices will only change if initial gaps in net benefits are overcome. The most likely form of behavioral response would be to remain in the same home but choose an alternate school, though families moving for other reasons might choose different neighborhoods than they otherwise would have. We expect the highest rates of trading down to occur for students who would like to attend a flagship and have nearby high schools that offer quite different prospects for top ten percent placement. In our

[19] In the initial years, UT-Austin increased enrollment to accommodate top ten percent students. The admissions crowding that occurred later on would amplify the incentives to trade down to the extent that this led to a proportionate reduction in the probability of admission for students outside the top ten percent pool.

empirical analyses, we attempt to identify students with such motives and opportunities.

4. Data and empirical counterparts

The primary data source for our analysis is individual-level Texas Assessment of Academic Skills (TAAS) test score data collected by the Texas Education Agency (TEA). In the spring of each year, students are tested in math and reading in grades 3-8 and 10. Each school submits test documents for all students enrolled in every tested grade. These documents include information on students that are exempted from taking the exams due to special education and limited English proficiency status and students in the 10th grade who have passed alternative end-of-course exams and are not required to take the TAAS exams. The test score files, therefore, capture the universe of public school students in the tested grades in each year. In addition to test scores, the reports include the student's school, grade, race/ethnicity, and indicators of economic disadvantage. TEA provided us with a unique identification number for each student. This number is used to track the same student across years, as long as the student remains within the Texas public school system.[20]

We follow six cohorts as they make the transition from middle schools in 8th grade to high schools in 10th grade as revealed by the school identifiers in the test score documents, beginning with Cohort 1 (1992-93 8th graders) and ending with Cohort 6 (1997-98 8th graders). The first three cohorts attended 10th grade under the old admissions regime, while the latter three cohorts attended 10th grade after the new policy had been introduced. The first five cohorts would have chosen their 8th grade schools under the old regime, so that these locations are not endogenous to the policy change. The last cohort began 8th grade in the fall of 1997, while the new policy was signed by Governor Bush on May 20, 1997 and became effective on September 1, 1997. Thus, this cohort also had little scope or reason to adjust 8th grade school choices and we also treat these as predetermined. We rely on the early cohorts to establish the pre-policy 10th grade enrollment patterns for 8th graders from each middle school. We then explore how these patterns change for the later cohorts whose transitions are affected by the new regime.

To identify students with strategic incentives, we need to first estimate where students would

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[20] There appears to be relatively little noise in the matching process. Across our six cohorts, 71 percent of 8th graders are observed in the 10th grade data two years later. The loss can be almost entirely explained by students who are retained or who leave legitimately by dropping out, transferring to the private sector, or moving out of the state (as we can infer from information in TEA's Academic Excellence Indicator System and Snapshot School District Profiles).

place in the distribution at any given high school. The only information available to us to make this assignment is test scores, and we use these to construct a cohort-specific statewide ranking, $\hat{\gamma}_{ic}$, that can be used to estimate a student's position in any student grouping. Details on our procedure and all constructed variables described in this section are in the Appendix. For shorthand, we refer to the predicted percentile rank as the student's ability.

With $\hat{\gamma}_{ic}$ in hand, we can then calculate the minimum level of ability associated with top ten percent placement at any school *k*. For each cohort and high school, we calculate this minimum level as the 90th percentile of the distribution of $\hat{\gamma}_{ic}$ among tenth graders attending the school two years later when the majority of the cohort has progressed to this grade. We refer to this measure, $\hat{\gamma}_{kc}^{90}$, as the threshold.[21]

We then incorporate uncertainty, presuming that parents' uncertainty mirrors ours. Uncertainty about a student's ability is derived from the prediction error in the mapping from prior test scores to class ranks. Uncertainty about a high school's threshold, due to variation in the specific composition of the high school class, is simulated by repeatedly sampling from the realized composition. Given both distributions, we can then calculate the probability that the student will place in the top ten percent at high school *k*, $\hat{\tau}_{ikc}$.

Finally, we estimate the hypothetical effect of the top ten percent plan on the likelihood that student *i* would gain admission to a flagship after attending high school *k*, $\Delta\hat{p}_{ikc}$. In the conceptual framework, this term was defined to be conditional on applying. Since we cannot identify which 8th graders are interested in attending a flagship, our empirical counterpart scales $\Delta\hat{p}_{ikc}$ by an estimate of the probability that student *i* applies. In other words, we replace the probability of rejection conditional on applying, $(1-a_i)$, in equation 3.3.2 with the probability of applying and being rejected.

To calculate students' probabilities of applying to and being rejected by a flagship, we rely on additional survey and administrative data. These data are drawn from the years leading up to the policy change, and the broad patterns by ability should usefully identify the types of students

[21] Defining thresholds based on realized enrollment patterns presumes that families have perfect foresight of student sorting, including other families' strategic responses to the top ten percent plan. To avoid introducing endogeneity, our main analyses below characterize incentives based on those faced by the initial student cohort. While this instead assumes backward-looking behavior for subsequent cohorts, the practical relevance of this distinction is limited by the stability of high school thresholds over the six years of the sample period. The R-squared from an enrollment-weighted regression of high school thresholds on high school fixed effects is 0.87.

who are *a priori* most likely to value guaranteed admission. Figure 1 displays the imputed application and rejection rates by student ability. Students outside the top four statewide ability deciles (in 8th grade) almost never apply to highly selective public colleges. Among the top four statewide ability deciles, the share applying to the flagships rises monotonically with student ability from 17 to 34 percent. Rejection rates conditional on application decline dramatically with ability over this range from 48 to 5 percent, so the net result is that the probability of applying and being rejected also declines with ability in this range.

For students from our initial cohort, the average high school threshold (in an enrollment-weighted distribution) is 88. That means that the typical 8th grader attends a high school where the 10th grader positioned at the 90th percentile of his or her class achieved at the 88th percentile statewide in 8th grade. Note that the 88th percentile student in the 8th grade achievement distribution will tend to rank lower in the 10th grade achievement distribution because lower-achieving students are less likely to persist to 10th grade. The (weighted) standard deviation of high school thresholds is 8 percentile points, and the range is from 56 to 99.

Based on these patterns, we restrict our analyses to students in the top four deciles of the statewide ability distribution. This sample should include nearly all students potentially motivated to seek guaranteed admission, as well as nearly all that could feasibly place in the top ten percent at a high school. In the next sections, we analyze high school enrollment patterns among these high-ability students before and after the introduction of the top ten percent policy.

5. Analysis of thresholds at chosen high schools

Our preliminary analysis examines which types of opportunities, if any, entice students to trade down to local high schools with lower thresholds. To determine which definition of the local schooling market is most relevant, we consider four possibilities defined from the perspective of the student's middle school: i) high schools within 30 miles, ii) within 10 miles, iii) within 10 miles and within the same district, or iv) high schools that are fed by the middle school.[22] We create a dummy variable, Opp_{ic}, equal to one if there is wide variation in the likelihood that a student would place in the top ten percent across local high schools. For the results presented below, Opp_{ic} equals one if the student could increase this likelihood by at least

[22] High schools are "fed by the middle school" if they receive at least 10 percent or at least 10, whichever is less, of the middle school's graduates every year.

20 percentage points moving across local high schools.[23] Figure 2 shows the share of students with strategic opportunities for each market definition, among the subset with more than one high school within the relevant market. Not surprisingly, scope for strategizing is more common for higher-ability students and less restrictive market definitions.

To determine whether the reform led to systematic sorting to lower-achieving high schools for those with varied schooling options, we compare the choices of students with and without strategic opportunities before and after the policy change. We implement this difference-in-differences strategy within each of the top four statewide ability deciles. Looking within ability deciles helps to isolate the role of opportunities by controlling for students' motives arising from their flagship application and rejection probabilities. Define A_{ic} to be a student's statewide ability decile, and define $Post_c$ to be an indicator for whether a student's cohort attends 10th grade after implementation of the policy. Our baseline specification includes main and interaction effects for the post-policy and opportunity indicators that are allowed to differ by ability decile:

$$(5.1) \qquad \hat{\gamma}_{ikc}^{90} = \sum_{n=1}^{4}\left[\left(\lambda_{1n} \times Post_c + \lambda_{2n} \times Opp_{ic} + \lambda_{3n} \times Post_c \times Opp_{ic}\right) \times 1_{A_{ic}=n}\right] + \mathbf{X}_i\Gamma + \Theta_{A_{ic}} + \varepsilon_{ikc}$$

The vector **X** includes controls for a student's race/ethnicity and poverty status, and $\Theta_{A_{ic}}$ is a vector of high school catchment area by statewide ability decile fixed effects.[24] The catchment area is defined to be the set of middle schools that share the same "plurality high school," which is the high school that is the most common destination for the middle school's graduates. The identifying assumption for the estimated coefficient on the triple interaction term, λ_{3n}, to be interpretable as an effect of the policy change is that differences in the types of schools chosen by students with and without opportunities in the later cohorts would otherwise have been similar to the differences observed among students of similar abilities from the same catchment areas in

[23] The scope for gain is determined by calculating the difference between the students' top ten percent probabilities at the "best" and "worst" high schools in the relevant market. More accurately, to reduce sensitivity to small schools at the extremes of the distribution, we weight the high schools by enrollment and calculate the gain as the difference between the 5th and 95th percentiles of the enrollment-weighted distribution of the students' top ten percent probabilities across high schools in the relevant market. The qualitative findings hold for somewhat more and less restrictive alternatives (see columns 3 and 4 of Appendix Table B1), and the specific cut point was chosen to maintain reasonable representation of students classified with and without ready opportunities across market definitions.

[24] The results are insensitive to whether we control for interactions between ability decile and catchment area indicators or interactions between ability decile and 8th grade school indicators.

prior years.

Table 1 presents summary statistics for the estimation samples of students in the top four statewide ability deciles from the six cohorts. Because we rely on earlier cohorts to establish counterfactual enrollment patterns across local high school options, we restrict attention to high-ability students in catchment areas that have been relatively stable over the study period and that are not completely isolated.[25] The first column shows statistics for all such students, while the second column includes only those students (86 percent) that remain in the Texas public school system and progress with their cohort. These are the students for whom we can observe high school choices via the test score files. The attrition is primarily attributable to students that move to the private sector or out of the state, and comparing column 2 to column 1, it does not appear to be selective. We have tested whether 8th graders are more likely to remain in our sample after the policy change and find evidence of an increase, but this increase is generally unrelated to students' strategic opportunities within the public sector.[26]

The final three columns of Table 1 show statistics as the sample is progressively restricted to students with multiple high schools located closer to and more strongly affiliated with their middle schools. The samples are increasingly metropolitan moving across the columns. In addition to the drops in sample size, notable differences are the higher proportions of ethnic minority students and of students with plurality high schools that have feeder relationships with UT-Austin.[27] High schools in urban areas have traditionally had closer ties to the flagships.

We report the difference-in-differences estimates in Table 2. In the first column, the sample

[25] Specifically, we only include students whose middle schools are within 30 miles of more than one high school and that are assigned to the same plurality high school in all years, which eliminates 13 percent of 8th graders. We also exclude students with missing demographic information and students whose 8th grade or plurality high schools are very small (i.e., ever serve less than 20 students in a grade) or are alternative (e.g., special education or juvenile detention centers). Together these restrictions further reduce the sample by approximately 6 percent. Also, note that we assign students to the most recent 8th grade cohort if they show up more than once due to grade retention.
[26] In particular, we estimate regressions parallel to equation 5.2 (a refined version of equation 5.1 that holds high school thresholds and the student ability distribution fixed) with the dependent variable equal to an indicator for remaining in the sample. For students that have multiple within-district high schools within 10 miles, the coefficient estimate on the interaction between the opportunity and post interaction is statistically significant at the .10 level only for 2nd-decile students. These students are 1.7 percentage points more likely to remain in the sample after the policy change if they have a strategic opportunity within their own district. Thus, some of the strategic behavior that we find may reflect students opting to stay in the public sector, but much of the response appears to come from students who would have remained in the system regardless.
[27] We identify high schools that feed UT-Austin as those that sent more than 2.5 percent of their 10th graders to UT-Austin on average across the 1994-95 through the 1998-99 10th grade cohorts. We chose this cutoff since this would represent 1/10 of college-goers for the typical school. These feeder high schools are distributed widely across the state, but the suburbs of Dallas, Houston, and Austin are disproportionately represented.

and market are based on our broadest (i.e., 30-mile) definition, and the dependent variable is equal to the threshold the student faces at the chosen high school. The estimates in the bottom four rows for the coefficients on the interactions between the ability decile and post indicators suggest that the relatively less able students who do not have incentives to respond are attending high schools with higher thresholds after the reform. While this could reflect an influx of strategic movers into lower-achieving high schools, it could also be attributable to increased school accountability efforts (starting in 1993-94). By improving the scores of students in poor-performing middle schools, accountability reform could have produced the observed pattern without any changes in students' high school enrollment choices.

We conduct a placebo test to distinguish these interpretations. We replace the threshold at the chosen high school with the ability associated with the 90th percentile by catchment area and cohort. Since strategic school choice is not reflected in this measure, we should not observe any systematic patterns. The results of this placebo test, presented in column 2 of Table 2, in fact reveal a pattern very similar to that in column 1. It appears that the Texas student test score distribution was becoming more compressed across districts during our sample period for reasons unrelated to the top ten percent plan.

In order to eliminate these contaminating time series patterns and isolate the impact of changes in enrollment, we hold the ability distribution fixed based on the initial year of our sample. First, we set high school thresholds to those relevant to our initial cohort, and refer to these thresholds ($\hat{\gamma}^{90}_{ik1}$) as static thresholds. Next, we treat students analogously by assigning them the ability levels associated with the Cohort 1 students who were similarly situated within their catchment area ability distributions. For example, a student with median ability within the catchment area distribution in cohort c would be assigned the ability of the student at the median in that catchment area in Cohort 1. We refer to this adjusted ability measure, $\hat{\gamma}_{i1}$, as static ability. We also redefine students' strategic opportunities to be based on static thresholds and abilities. The revised empirical model is:

$$(5.2) \qquad \hat{\gamma}^{90}_{ik1} = \sum_{n=1}^{4}\left[\left(\lambda_{1n} \times Post_c + \lambda_{2n} \times Opp_{i1} + \lambda_{3n} \times Post_c \times Opp_{i1}\right) \times 1_{A_{i1}=n}\right] + \mathbf{X}_i\Gamma + \Theta_{A_{i1}} + \varepsilon_{ik1}$$

Estimates of equation 5.2 are displayed in columns 3 through 6 of Table 2. The sample and definition of the local market become narrower moving across the columns. Compared to behavior prior to the top ten percent plan, students with strategic opportunities moderately downgrade the quality of their high school relative to students without opportunities. The point estimates in the top four rows on the triple-interaction terms are consistently negative across these columns. While only about half of the decile-specific estimates are statistically significant, the four estimates are jointly significant at the 5 percent level in the last three columns.

The behavioral response is stronger among students with *intra-district* opportunities to strategically select their high schools (columns 5 and 6). For example, when students in the top statewide ability decile have scope for strategizing across multiple high schools fed by their middle school, they choose high schools with (static) top ten percent thresholds that are 0.43 percentage points lower in the statewide ability distribution. Our interpretation is strengthened by the fact that there is almost no change in the thresholds of high schools attended by students who lacked strategic opportunities to alter plans. The results are unaffected when we also control for the average (static) thresholds of the high schools chosen by students in the same catchment area in the bottom six statewide ability deciles.[28] The downgrading behavior of high-ability students with opportunities is thus distinct from broader trends in high school selection.

While the results in Table 2 show opportunistic downgrading is occurring, the magnitudes are difficult to interpret. That is, a drop in thresholds can indicate either many students altering high schools plans or a few students heavily downgrading. In our discrete choice analysis in the next section, we are able to separate the intensive and extensive margins.

6. Discrete choice analysis of high school enrollment decisions

6.1 Conditional logit model and estimates

For our central tests of strategic behavior, we examine students' high school enrollment choices using a conditional logit model, treating each district as a distinct market and pooling across markets. This approach allows us to more easily characterize students' opportunity sets and to estimate the implied rates at which students respond to the policy change. The results from the previous section suggest that the greatest trading down occurs among students with multiple high school options in the same district, and we thus restrict our attention to students in districts with more than one high school. There are 65 such school districts, and these serve a majority of students.

[28] The results from this and several other sensitivity tests are shown in Appendix Table B1 for the sample of students with multiple within-district high schools within 10 miles (corresponding to column 5 in Table 2).

Let S_i denote the choice set of high schools in the district where student *i* attends middle school. Table 3 displays summary statistics for students and their district-specific choice sets.[29] The first column is based on the combined sample, and the following columns divide the sample by (static) statewide ability decile and by race/ethnicity. The average student has almost six high schools to choose from in the district, and these high schools are located an average of roughly four miles from the student's middle school. Not surprisingly, plurality high schools are located much closer, at an average of just 1.6 miles away from the middle school. More than 80 percent of students choose to attend their plurality high schools, and these schools are relatively typical of district high schools in terms of size and composition. The lower-ability and minority students are more concentrated in the urban districts, so have a greater number and variety of schooling options.

We presume that the attractiveness of a school to a student is determined by characteristics that vary by student and school:

$$\begin{aligned} V_{ikc} &= \nu_{ikc} + \varepsilon_{ikc} \\ &= \alpha_k + \eta_1 Incentive_{ik1} + \eta_2\left(Incentive_{ik1} \times Post_c\right) + \mathbf{X}_{ik1}\Gamma + \varepsilon_{ikc} \end{aligned} \tag{6.1}$$

With the assumption that the error terms follow an extreme value distribution,[30] the probability the student chooses high school *k* can be expressed:

$$P_{ikc} = \frac{e^{\nu_{ikc}}}{\sum_{m \in S_i} e^{\nu_{imc}}} \tag{6.2}$$

Under the random utility interpretation of this discrete choice model, student *i* will choose to enroll in high school *k* if this provides the greatest indirect utility among high schools in the set S_i. Rather than taking this interpretation literally, we use this model primarily as a predictive tool to estimate the number of students whose high school enrollment choices are altered by the introduction of the top ten percent plan.

By limiting the choice set to high schools within students' 8th grade school districts, we capture the most relevant alternatives. The inclusion of high school fixed effects, α_k, controls for

[29] We exclude students who remain in the Texas public school system, but attend a high school outside the middle school district (3.0 percent). The great majority of these students appear to have moved residences, with the median distance to the middle school being 13.9 miles (compared to 1.3 for students staying within the district). We also exclude the 0.5 percent of remaining students attending high schools that do not serve at least 1.0 percent of the district's 10th graders in all years of our sample period.

[30] Pooling across districts relaxes the constraint on the number of high school characteristics that can be included in the control set, but assumes that the variance of the errors is the same across districts.

time-invariant differences in the relative attractiveness of alternative schools within the district, and alleviates standard concerns about the independence of irrelevant alternatives. The vector $\mathbf{X}_{ik1}$ contains the distance in miles between student *i*'s 8$^{\text{th}}$ grade school and high school *k*, an indicator for whether school *k* is the plurality high school associated with the middle school, the ratio of the fraction of students in school *k* who are nonwhite to the fraction of students who are nonwhite in the plurality high school, and a similar ratio comparing the median student ability level at these two schools. These are all set to static values from Cohort 1.

Across specifications, we set the incentive for a student to choose a given school under the top ten percent plan equal to one of three measures: the top ten percent threshold ($\hat{\gamma}_{k1}^{90}$), the probability of top ten percent placement ($\hat{\tau}_{ik1}$), or the change in the probability of flagship admission ($\Delta\hat{p}_{ik1}$). These incentive measures successively impose more of the structure suggested by our theoretical framework. We always use static incentive measures, drawing on the lessons from the prior section. That is, for students from all cohorts, $Incentive_{ik1}$ is calculated by first assigning student *i* the same statewide ability percentile as the catchment area student from Cohort 1 ranking at the same place among catchment area peers. The specifications include a main effect for the incentive term to pick up any underlying relationship between school enrollment patterns and students' absolute and relative abilities that remains conditional on the other controls. Our key coefficient of interest, η_2, captures the change in the weight placed on the opportunity offered at a high school once the top ten percent plan is in effect.

Table 4 displays the results from estimating the discrete choice model for each of the three measures of incentives. The first row displays our estimates of η_2. In all three cases, the estimate confirms our theoretical prediction and is highly statistically significant. Compared to years preceding the top ten percent plan, students prefer schools with lower top ten percent thresholds (column 1), where they have better chances of placing in the top ten percent (column 2), and where flagship university admissions probabilities were most improved (column 3). The estimated coefficients for the other control variables in the remaining rows are very similar across the three specifications. Students are more likely to choose to attend the plurality high school (tautologically), less likely to attend high schools located far from their middle school, and less likely to attend a high school with a relatively high fraction of nonwhite students. The coefficients on the relative median student ability measure are statistically insignificant, but these are highly correlated with relative racial composition.

Since the magnitudes of the estimated coefficients are not readily interpretable, the final row of Table 4 provides information to help gauge the relative importance of top ten percent incentives in determining high school enrollment decisions. We report students' apparent willingness to travel to a farther high school for a one standard deviation gain in each of the three incentive measures. Since we proxy for students' home locations using middle school locations and for incentives using a limited set of observables, these estimates should be interpreted as heuristics and not as identifying indirect utility parameters. For students in the top four statewide ability deciles, raising any one of the incentive measures by one standard deviation has a similar effect as moving a school one-fifth to one-quarter of a mile closer. To put this in perspective, note that the median difference between a student's closest high school option and his/her second-closest high school option is only 1.5 miles in this sample.

We have subjected the baseline estimates from the conditional logit model to a variety of robustness tests. One concern is that ability affects both high school enrollment choices and incentives to respond to the top ten percent policy in complex ways that may not be fully captured by our specifications. If we estimate the specifications in Table 4 separately by statewide ability decile, however, we continue to find statistically significant responses within each of the four ability deciles. Another potential concern is that coincidental changes in enrollment patterns across schools might confound our results. To explore this issue, we estimate our models with an additional control variable equal to the share of middle school classmates from the bottom six statewide ability deciles attending each school. The time-varying enrollment patterns of these lower-ability students, who are excluded from our analysis sample, are strongly predictive of those for higher-ability students, but our estimated responses to incentives among the higher-ability students hardly budge.[31] In another robustness test, we confirm that the estimated response is not mitigated when the sample is restricted to students from highly stable high school catchment areas and districts. And, finally, we find results quite similar to the baseline when we exclude Cohort 1 and add the share of Cohort 1 catchment area students attending each school and this share interacted with the post-reform indicator. This modification is meant to address both the potential endogeneity of Cohort 1's incentives to realized schooling choices and to control for shifts in enrollment that are related to the initial

[31] The results for this test and the other sensitivity tests for the pooled sample are reported in Appendix Table B2.

attractiveness of a school that might be correlated with but not attributable to top ten percent incentives.[32] Given the overall robustness of our baseline estimates, we proceed by using these estimates to calculate the rates and nature of strategic high school choice.

6.2 Implied frequency and nature of strategic behavior

We quantify the role that incentives play in altering high school choices after the reform by simulating the reallocation of students across high schools implied by the estimates. We select the roughly one-third of students from the final 1997-98 cohort who have strategic opportunities, using the same definition of strategic opportunities as in Section 5.[33] For these 12,675 students, we calculate the change in the predicted probability of enrolling in any given high school when the post-reform indicator is set to 1 rather than 0. We can then use these to impute changes in the characteristics of chosen high schools, as well as the number of students strategically altering their choices. The findings are similar across the three incentive measures, so we highlight the results for our third and most comprehensive measure, $\Delta\hat{p}_{ik1}$.

Simulations based on the estimates in column 3 of Table 4 imply that the typical student with strategic opportunities chooses a high school with a top ten percent threshold that is 0.21 percentile points lower than the high school that would have been chosen absent the reform.[34] Not surprisingly, this figure is quite similar to the average of the estimates in the first four rows of column 5 of Table 2. Since only a subset of these students is induced to enroll in alternative high schools, the implications for the schooling experiences of students who respond are much greater.[35] Students who are induced to trade down choose high schools with top ten percent

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[32] We thank an anonymous referee for suggesting this specification.

[33] We choose a single post-reform cohort solely for computational ease. A student is classified as having opportunity if there is scope for at least a 20 percentage point gain in the probability of top ten percent placement across within-district high schools within 10 miles of the middle school, where the probabilities are calculated based on static ability and thresholds.

[34] Letting ΔP_{ik} denote the predicted change in the probability that student i chooses school k, the implied average change in school characteristic C is $\Delta\overline{C} = \frac{1}{N}\sum_i \sum_{k \in S_i} \left(\Delta P_{ik} \times C_k\right)$, where N is the number of students.

[35] To estimate the average change in school characteristics for strategic students, we divide $\Delta\overline{C}$ by the estimated share of students that is induced to choose alternative schools. This share is equal to average student-level sum of the positive changes in the predicted high school choice probabilities: $\frac{1}{N}\sum_i \sum_{k \in S_i} \mathrm{Max}\left(\Delta P_{ik}, 0\right)$. Because students' predicted probabilities of attending the within-district high schools sum to one, the sum of these positive values will be of the same magnitude as the sum of the negative values and will equal the estimated probability that the student chooses a different school due to strategic incentives.

thresholds that are 19.0 percentile points lower. Further, this trading down behavior also entails choosing high schools that, on average, have greater poverty rates (21.7 percentage point increase) and higher percentages of nonwhite students (27.0 percentage point increase). Students often behave strategically by staying with their middle school peers rather than attending a more competitive magnet high school.[36] Strategic students are 16.7 percentage points *more* likely to attend their plurality high school and 26.3 percentage points *less* likely to attend a magnet.

The simulations imply that the incentives created by the top ten percent plan induced more than 140 students per cohort (within our restricted sample) to enroll in different high schools. Though negligible relative to overall enrollment across multi-high school districts, this represents a nontrivial response rate among the subset of students with the opportunity and motive to respond. The first row of Table 5 illustrates this point. Among the roughly one-third of students with strategic opportunities (column 1), 1.1 percent alter their choice of high school (column 2). Among the roughly one-quarter of the students with opportunities who are also likely to be interested in attending a flagship (column 3), the implied take-up rate is 5.2 percent (column 4).[37] This take-up rate is more impressive given the fact that the probability of these students being rejected conditional on application is only about 20 percent. Thus, dividing our take-up rate by the probability of rejection conditional on application, we find that the number of students who enroll in a different school is about one-quarter the size of the number of these students who would apply to and be rejected by a flagship (column 6).[38] We should reemphasize that these estimates are lower bounds on the actual behavioral response, due to our reliance on relatively crude proxies for individual incentives.

The next four rows of Table 5 present imputed take-up rates separately by statewide ability decile. Take-up rates conditional on having opportunities are lower for the highest ability students. On the other hand, few of these highest ability students would have been rejected from a flagship even if they failed to obtain automatic admission. The estimates in column 6 suggest

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[36] We identify magnet high schools as those that are not the plurality high school for any middle school, so do not have catchment areas and are accessible to students from a broad set of neighborhood zones.

[37] The implied take-up rate among would-be applicants is calculated by normalizing the estimated probability a student chooses a different school by the estimated likelihood the student applies to a flagship, prior to averaging across students.

[38] The rate reported in column 6 is calculated by dividing the probability a student strategically chooses a different school by the estimated likelihood that this student applies to and is rejected by a flagship. This rate should not be considered to be a proper take-up rate because students do not know at the time of their high school enrollment whether they will be rejected conditional on application.

that the numbers of would-be applicants responding in each ability decile remains about one-quarter as large as the number that would have applied to and been rejected from a flagship.

The bottom three rows of Table 5 reveal how differences in the frequency and nature of strategic opportunities lead to differences in take-up rates by race/ethnicity.[39] Black and Hispanic students are more likely to have strategic opportunities than white students (column 1), and these are also more often the types of opportunities worth taking (column 2). The largest take-up rates are among black students: more than 9 percent of would-be applicants with strategic opportunities alter their high school choices.

Given that the top ten percent plan is intended to promote racial diversity in the flagships, it is important to determine whether strategic behavior tends to undermine or enhance this goal. Although minority students trade down at higher rates, the net effect of responses to the policy is to slightly increase white students' representation in the top ten percent pool.[40] For white and minority students alike, strategic downgrading most commonly entails crowding out minority students from the top ten percent of the chosen high school. About 20 percent of strategic[41] white students end up displacing a black or Hispanic student out of the top ten percent pool. Conversely, we find that strategic minority students, on average, do not displace white students from the top ten percent pool at all. Strategic minority students rarely crowd out white students from the top ten percent of their newly chosen high schools, and they also give up small chances of a top ten percent placement at more competitive schools, which then tend to accrue to whites. Thus, any reductions in ability stratification across schools associated with strategic behavior come hand-in-hand with decreased racial diversity among those eligible for automatic admission.

7. Conclusions

Texas' top ten percent plan was instituted in 1998 after the elimination of affirmative action

[39] As with the results by ability decile, we continue to rely on the estimates in column 3 of Table 4 that impose homogenous coefficients across students by ability and race/ethnicity, so that differences in take-up rates across student groups are solely attributable to the differential nature of their opportunities (as summarized in Table 3). When we estimate the models of Table 4 allowing for heterogeneous slopes by race/ethnicity, we do not find statistically significant differences in responses to incentives across racial groups.

[40] We estimate racial displacement caused by students of various races by summing across the products of: i) the predicted change in the probability that a student chooses a particular high school due to strategic incentives, ii) the probability that the student would place in the top ten percent of that high school, and iii) the baseline-year fraction of students of the specified group at risk of being displaced from the top ten percent at the school. We estimate iii) as the initial (i.e., 1993) fraction of students in the top twenty percent of the school's 10th grade class belonging to the group in question.

[41] We use the shorthand "strategic" to refer to students who are induced to choose a lower achieving high school.

following the 1996 *Hopwood v. Texas* decision. An explicit goal of this program was to maintain minority college enrollment, particularly at Texas' selective public universities. By basing admission guarantees on school-specific standards, the policy also encourages strategic high school enrollment that might induce would-be eligible students to choose to attend lower achieving schools than they otherwise would.

In both reduced-form analyses of the peer achievement levels of the schools chosen by students before and after the policy change and discrete choice models of students' intra-district sorting across high schools, we find evidence of a meaningful behavioral response. Students with varied chances of placing in the top ten percent at nearby high schools tend to "downgrade" in peer quality by attending high schools with lower initial top ten percent thresholds. Though overall response rates are low, take-up rates are at least five percent among students with not only the opportunity but also the motive to strategically enroll in a different high school. The primary constraint on trading down among students who would value guaranteed admission to a flagship appears to be the lack of nearby high school alternatives that offer sufficiently improved top ten percent chances.

The responsiveness we find among students with sufficient scope for gain underscores the possibility that policies rewarding relative performance may reduce ability stratification across schools. In the longer run, when the policy affects how students choose districts in addition to how they choose high schools within districts, strategic high school choice is likely to be more common and have more systemic impacts. In the short-run horizon that we consider, though, the numbers of students affected is small enough that the impact on the distribution of peer quality across high schools is negligible.

We find that strategic high school choice tends to undermine the racial diversity goal of the top ten percent plan at the university access level. Though minority students have greater strategic opportunities so are more likely to trade down, the net effect of strategic behavior is to slightly increase the representation of white students in the top ten percent pool. Both white and minority students who trade down are relatively likely to displace minority students who otherwise would have placed in the top ten percent of their class. Since peer achievement and minority share are highly negatively correlated across high schools, this is almost an inevitable consequence of strategizing in this setting.

Top *x-percent* programs are likely to become increasingly important in the future. Justice

O'Connor's majority opinion in the 2003 *Grutter v. Bollinger* case stated: "We expect that 25 years from now, the use of racial preferences will no longer be necessary to further the interest approved today." In contrast, Krueger et al. (2006) find that future declines in black-white family income gaps alone are unlikely to eliminate the need for racial preferences to maintain minority enrollment in highly selective institutions. We can expect increasing court challenges to the use of affirmative action in admissions decisions juxtaposed with continued demand for substitute policies. To the extent that substitute policies equalize access across high schools, our results suggest that, in addition to the variety of direct effects of expanded access to selective institutions, lower-achieving high schools will be indirectly affected as they attract higher achieving students.

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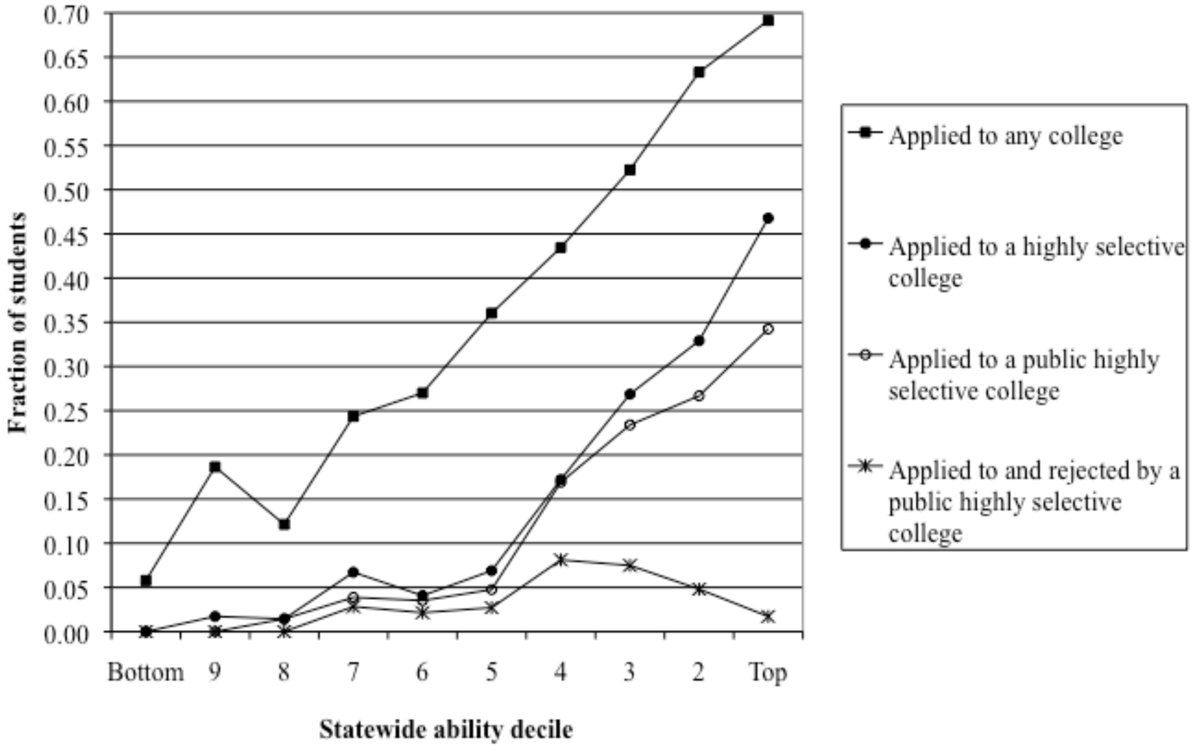
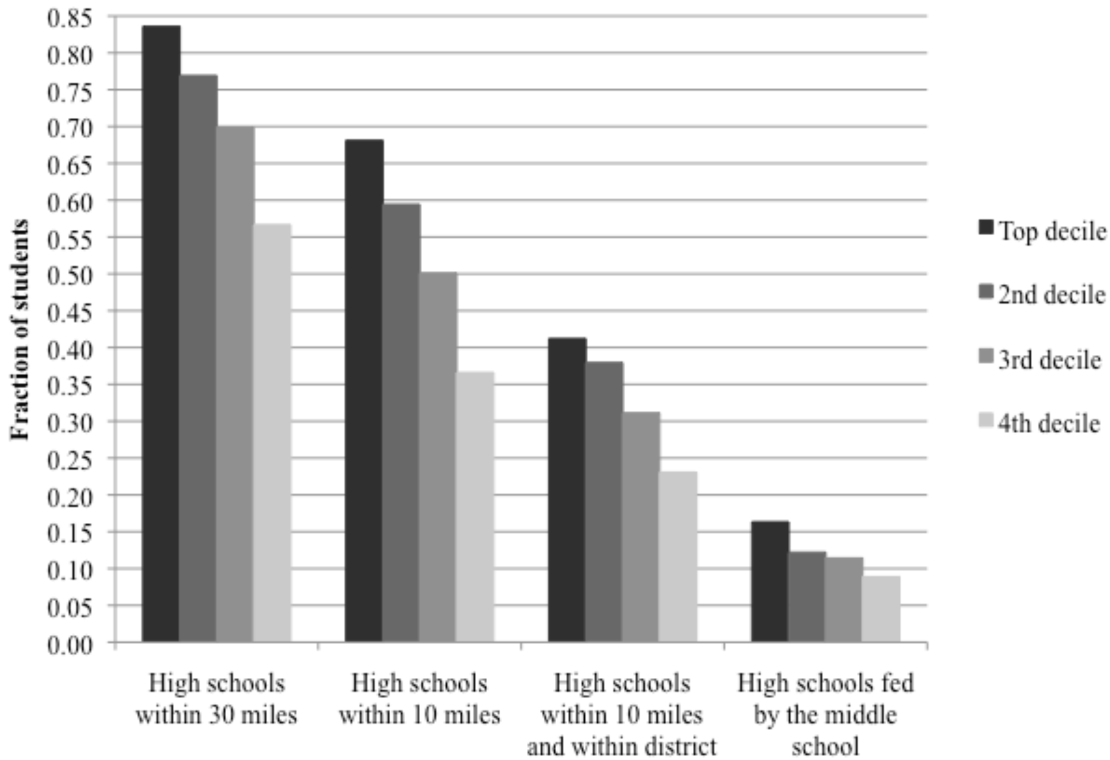
Figure 1. Application and rejection rates, by ability decile



Notes: Application and rejection rates by percentile ranks of achievement are calculated from survey and administrative data, as described in the Appendix.

Figure 2. Share with opportunity for strategic choice, by ability decile and market



Notes: The assignment to ability deciles is based on a weighted average of 8th grade math and reading cohort-specific percentile scores. The height of the bars shows the fraction of students across our six cohorts classified as having an opportunity to exercise strategic choice, conditional on having multiple high schools within the set of high schools indicated beneath. Those classified as having opportunity could increase the probability of top ten percent placement by at least 20 percentage points across high schools within the relevant market.

Table 1. Summary statistics for students in the top four statewide ability deciles in 8th grade

	Subsample with multiple high schools …				
	within 30 miles	within 30 miles	within 10 miles	within 10 miles & within district	fed by the middle school
	(1)	(2)	(3)	(4)	(5)
Student characteristics					
Black	0.073	0.071	0.077	0.095	0.135
Hispanic	0.201	0.197	0.196	0.236	0.267
Poor	0.221	0.209	0.203	0.221	0.257
Has opportunity for strategic choice	0.673	0.674	0.499	0.314	0.178
Statewide percentile rank ($\hat{\gamma}_{ic}$)	79.7	80.1	80.2	80.3	79.7
	(12.4)	(12.3)	(12.2)	(12.2)	(12.4)
Probability of applying to a flagship	0.242	0.246	0.246	0.247	0.242
	(0.099)	(0.099)	(0.099)	(0.099)	(0.099)
Prob. of applying and being rejected	0.048	0.048	0.048	0.048	0.048
	(0.015)	(0.016)	(0.016)	(0.016)	(0.015)
Plurality high school feeds UT-Austin	0.328	0.326	0.359	0.487	0.427
Characteristics of chosen high school					
Plurality high school	n.a.	0.837	0.822	0.756	0.579
Threshold for top 10% placement ($\hat{\gamma}^{90}_{ikc}$)	n.a.	90.4	90.5	90.2	89.0
		(5.9)	(6.0)	(6.7)	(7.0)
Probability of top 10% placement ($\hat{\tau}_{ikc}$)	n.a.	0.206	0.206	0.207	0.219
		(0.121)	(0.121)	(0.125)	(0.129)
Restricted to students who progress to 10th grade with their cohort?	No	Yes	Yes	Yes	Yes
Number of students	549,134	473,314	409,184	245,795	90,217
Number of 8th grade schools	1,055	1,055	821	404	158
Number of plurality high schools	861	861	630	240	123
Number of districts	683	683	454	65	46

Notes: Each column presents means (standard deviations in parentheses) for 8th grade students from the 1992-93 through 1997-98 TX cohorts. The data include only 8th grade students who were in the top 40 percent of the cohort-specific statewide ability distribution. The first column includes 8th grade students excluded from our regression sample because they do not appear in the 10th grade Texas public school data two years later. The remaining columns exclude these students. Columns 2 through 5 progressively restrict the sample to students that have multiple high school options located closer to and more strongly affiliated with their middle schools. A high school is "fed by the middle school" if it receives at least 10 percent of graduates every year. The plurality high school is the high school that receives the greatest share of the middle school's graduates. A student is defined as having a strategic opportunity if the student could increase the probability of top ten percent placement by at least 20 percentage points across high schools in the relevant market.

Table 2. Impact of the policy on the threshold of the high school attended, by student ability

Independent variable	Top 10% threshold used for the dependent variable:					
	Chosen HS	Catchment area	Chosen HS			
	Actual	Actual	Static	Static	Static	Static
	(1)	(2)	(3)	(4)	(5)	(6)
Top decile × post × has opp.	-0.203	-0.186	-0.073*	-0.084*	-0.090	-0.426*
	(0.180)	(0.216)	(0.038)	(0.047)	(0.108)	(0.250)
2nd decile × post × has opp.	-0.076	-0.169	-0.057	-0.068	-0.250**	-0.320
	(0.180)	(0.212)	(0.049)	(0.057)	(0.124)	(0.372)
3rd decile × post × has opp.	0.055	-0.012	-0.044	-0.118**	-0.317***	-0.809**
	(0.177)	(0.206)	(0.040)	(0.053)	(0.115)	(0.325)
4th decile × post × has opp.	-0.317*	-0.516***	-0.017	-0.087	-0.280	-0.204
	(0.168)	(0.186)	(0.050)	(0.076)	(0.175)	(0.548)
Top decile × post	0.160	0.080	0.005	0.002	-0.028	-0.002
	(0.160)	(0.189)	(0.019)	(0.016)	(0.036)	(0.114)
2nd decile × post	0.210	0.212	0.001	-0.002	0.050	-0.000
	(0.146)	(0.169)	(0.032)	(0.025)	(0.040)	(0.096)
3rd decile × post	0.207	0.188	0.005	0.034	0.058	0.041
	(0.132)	(0.150)	(0.021)	(0.023)	(0.038)	(0.082)
4th decile × post	0.481***	0.532***	-0.008	0.023	0.070*	-0.072
	(0.127)	(0.144)	(0.026)	(0.025)	(0.039)	(0.096)
Joint significance of the 3-way interactions, p-value	0.277	0.400	0.162	0.027	0.005	0.042
Subsample with multiple high schools ...	within 30 miles	within 30 miles	within 30 miles	within 10 miles	within 10 miles & within district	fed by the middle school
Observations	467,206	467,206	473,314	409,184	245,795	90,217

Notes: Each column corresponds to a separate OLS regression on the sample of high-ability students who progress with their cohort between 8th and 10th grade and who reside in relatively stable high school catchment areas. The dependent variable and the criteria for sample inclusion vary across columns. The dependent variable is the actual time-varying threshold at the high school attended in column 1, the equivalent concept for the high school catchment area in column 2, and the static threshold (from Cohort 1) at the high school attended in columns 3 through 6. All specifications control for catchment area × ability decile fixed effects and indicators for student race/ethnicity and poverty status. The indicator variable "has opportunity" equals one if the set of high schools within the local market indicated offers considerable variation (i.e., at least a 20 percentage point difference) in the probability of top ten percent placement for that student. Ability deciles and the presence of strategic opportunities are assigned based on own statewide rank and cohort-specific high school thresholds in columns 1 and 2, and on the static measures described in the text in the remaining columns. Robust standard errors allowing for clustering at the level of the fixed effects are reported in parentheses.
***Significant at the 1% level; **5% level; *10% level.

Table 3. Summary statistics for the discrete choice analysis sample

Characteristics	Overall sample	Statewide ability decile				Race/ethnicity		
		Top	2nd	3rd	4th	White	Black	Hispanic
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Student								
Black	0.092	0.044	0.077	0.112	0.145	0	1	0
Hispanic	0.235	0.134	0.214	0.278	0.339	0	0	1
Poor	0.216	0.114	0.191	0.259	0.324	0.082	0.356	0.546
Number of high school options	5.83	5.49	5.61	6.02	6.29	4.80	10.07	7.13
	(6.08)	(5.74)	(5.80)	(6.29)	(6.53)	(4.71)	(9.31)	(6.94)
Average high sch.								
Miles from middle to high school	4.07	3.98	4.05	4.11	4.15	3.92	4.99	4.14
	(1.95)	(1.81)	(1.93)	(2.01)	(2.04)	(1.75)	(2.39)	(2.17)
Fraction nonwhite	0.445	0.395	0.430	0.466	0.500	0.355	0.571	0.652
	(0.252)	(0.233)	(0.247)	(0.257)	(0.263)	(0.202)	(0.234)	(0.247)
Median ability	0.584	0.608	0.591	0.573	0.559	0.619	0.530	0.506
	(0.109)	(0.104)	(0.107)	(0.109)	(0.110)	(0.095)	(0.103)	(0.100)
10th grade enrollment	530	542	535	524	515	551	476	488
	(124)	(121)	(123)	(126)	(127)	(119)	(137)	(117)
Plurality high sch.								
Miles from middle to high school	1.58	1.59	1.58	1.59	1.54	1.60	1.77	1.46
	(1.29)	(1.28)	(1.30)	(1.32)	(1.26)	(1.24)	(1.42)	(1.37)
Fraction nonwhite	0.416	0.348	0.398	0.446	0.489	0.306	0.585	0.664
	(0.276)	(0.243)	(0.268)	(0.282)	(0.294)	(0.201)	(0.271)	(0.269)
Median ability	0.601	0.639	0.610	0.583	0.563	0.687	0.524	0.500
	(0.134)	(0.125)	(0.131)	(0.133)	(0.135)	(0.112)	(0.132)	(0.120)
10th grade enrollment	567	583	574	560	549	586	529	527
	(157)	(152)	(155)	(157)	(161)	(152)	(176)	(153)
Chosen high sch.								
Plurality high school	0.823	0.834	0.830	0.817	0.810	0.859	0.637	0.781
Miles from middle to high school	1.92	1.91	1.90	1.95	1.92	1.81	2.71	1.91
	(1.77)	(1.71)	(1.75)	(1.82)	(1.81)	(1.54)	(2.48)	(1.97)
Fraction nonwhite	0.413	0.343	0.395	0.444	0.488	0.301	0.594	0.664
	(0.276)	(0.241)	(0.268)	(0.283)	(0.295)	(0.198)	(0.274)	(0.269)
Median ability	0.607	0.646	0.616	0.589	0.567	0.651	0.536	0.509
	(0.132)	(0.121)	(0.129)	(0.132)	(0.134)	(0.110)	(0.133)	(0.124)
10th grade enrollment	560	576	566	553	543	582	505	519
	(163)	(161)	(162)	(163)	(166)	(155)	(190)	(162)
Number of students	226,873	63,122	57,521	54,990	51,240	152,670	20,798	53,405

Notes: The columns present means (standard deviations in parentheses) for the overall discrete choice analysis sample, and the sample broken down by statewide ability decile and student race/ethnicity. These are students who have multiple high schools within the same district as their 8th grade schools, and who enroll in one of these in 10th grade two years later. All high school characteristics are assigned Cohort 1 values, and students are assigned to ability deciles based on an analogous static measure. "Average high school characteristics" are based on student-level means, derived by first averaging the characteristics of the high schools in each student's choice set.

Table 4. Conditional logit estimates of within-district high school enrollment choices

Independent variable	Incentive Measure: Top 10% Threshold ($\hat{\gamma}_{k1}^{90}$)	Top 10% probability ($\hat{\tau}_{ik1}$)	Change in flagship admission probability ($\Delta\hat{p}_{ik1}$)
	(1)	(2)	(3)
Incentive × post	-0.75***	0.59***	12.07***
	(0.25)	(0.24)	(4.30)
Indicator for plurality high school	1.88***	1.89***	1.88***
	(0.16)	(0.16)	(0.16)
Miles from middle school to high school	-0.41***	-0.41***	-0.41***
	(0.05)	(0.05)	(0.05)
Fraction nonwhite at high school relative to at plurality high school	-0.77**	-0.77**	-0.77**
	(0.38)	(0.38)	(0.38)
Median ability at high school relative to at plurality high school	-0.04	0.31	-0.02
	(0.48)	(0.57)	(0.50)
Additional miles willing to travel for a one std. dev. improvement in the incentive	0.21	0.26	0.22

Notes: Each column corresponds to a separate conditional logit model of 8th grade students' choices among high schools. There are 226,873 students from the top four statewide ability deciles combined choosing within 65 multi-high school districts, and a total of 1,322,569 student-high school combinations. The school characteristics and incentive measures are the static versions described in the text. In addition to the control variables shown, the specifications include high school fixed effects, as well as main effects for the incentives measures for columns 2 and 3. Including high school fixed effects precludes estimating a coefficient for the main effect of the incentive measure in column 1, since the static threshold is constant for any given high school. We report robust standard errors (in parentheses below each estimated coefficient) that allow for clustering at the district level. The value shown in the final row in column 1 is equal to the product of the estimated coefficient on (Incentive × post) and the standard deviation of the incentive measure, divided by the distance variable's estimated coefficient. The values shown in the final row of columns 2 and 3 are the same, except multiplied by –1.
***Significant at the 1% level; **5% level; *10% level.

Table 5. Implied conditional rates of strategic behavior

	Students with strategic opportunity		Would-be applicants with strategic opportunity		Would-be rejected applicants with strategic opportunity	
	Fraction	Take-up Rate	Fraction	Take-up Rate	Fraction	"Take-up Rate"
	(1)	(2)	(3)	(4)	(5)	(6)
Overall	0.332	1.1%	0.091	5.2%	0.015	24.5%
By ability decile						
Top decile	0.400	0.6%	0.151	1.6%	0.010	23.6%
2nd decile	0.375	1.2%	0.107	4.4%	0.019	24.5%
3rd decile	0.310	1.6%	0.062	7.9%	0.019	25.7%
4th decile	0.225	1.5%	0.030	11.0%	0.013	24.9%
By race/ethnicity						
White	0.280	0.7%	0.085	2.9%	0.011	18.3%
Black	0.439	1.8%	0.101	9.4%	0.023	35.3%
Hispanic	0.423	1.5%	0.104	7.5%	0.021	30.7%

Notes: The first row shows results for students in the final 1997-98 8th grade cohort from the top four statewide ability deciles combined, while the remaining rows are for the subsample of these students indicated in the row heading. The first column shows the fraction of students with strategic opportunities (i.e., scope for at least a 20 percentage point gain in the probability of top ten percent placement across within-district high schools within 10 miles, based on static ability and thresholds). The third column shows the fraction that has opportunity and is predicted to apply to a flagship. The fifth column shows the fraction that has opportunity and is predicted to apply to and be rejected by a flagship. The take-up rates are calculated based on the parameter estimates in column 3 of Table 4, so that differences across subgroups arise from differences in the distribution of ability and nature of schooling opportunities and not differences in estimated responsiveness.

Appendix A. Data sources and construction of variables

Data sources

Table A1. Variables by data source

Data	Source	Variables
Administrative student-level test score documents	Data for fiscal years 1993 to 2000 were provided on request by the Communications and Student Assessment Divisions of the Texas Education Agency	Unique student ID; math, reading, and writing test scores; exemption status; LEP status; special education status; free and reduced-price lunch status; ethnicity; grade; school and district identifiers
Administrative annual school-level data	Texas Academic Excellence Indicator System (AEIS)	School identification number; enrollment by grade and program (e.g., special education); charter school status; alternative school status
School geographic coordinates	NCES Common Core of Data for the years 1992 to 2002	Location and mailing addresses for each school are available all years; for schools with missing latitude and longitude data (available starting 2000), we used EZ-Locate (www.geocode.com)
UT Austin Texas feeder high schools	UT Austin Office of Admissions annual "Texas Feeder Schools" report for the years 1996 to 2000	Number of graduates entering the freshman class from each public high school in the state

Imputing missing test scores

In all of our analysis years, students were tested through the Texas Assessment of Academic Skills (TAAS). We use the math and reading Texas Learning Index (TLI) scores which are designed to assess learning progress. These scores describe how far a student's performance is above or below the passing standard (70), and range from approximately 0 to 100. Receiving the same score in the following grade indicates the student has demonstrated one year's typical progress, regardless of where the student is on the scale. The TLI is not available for writing, since this exam is not administered in consecutive grades, so we use the writing scale score. This score ranges from approximately 400 to 2400, with 1500 representing minimum expectations. It is designed to allow comparisons across years within a grade, adjusting for differences in test difficulty. The Texas Education Agency Technical Digest (1998-99) describes in detail how the math and reading TLI scores and the writing scale scores are created.

In order to rank students, we require 8^{th} grade test scores for all students in our 8^{th} grade cohorts, as well as for students who attend 10^{th} grade with these cohorts. We start by combining the sample of all 8th graders in 1993 to 1998 and the sample of all 10th graders in 1995 to 2000, linking observations from students that are in both 8th and 10th grades with their cohort.

Approximately 16 percent of 8^{th} graders are missing math and/or reading scores. We impute these using linear regressions on the best available subset of alternative 8^{th} grade exams, including writing. Scores on the alternative exams are entered as cubics. For those students with no available scores, we assign the average across students with similar test code patterns on the other two 8^{th} grade exams (i.e., absent or exempt for the same set of exams). Those exempt due to special education or limited English proficient (LEP) classification are assigned the minimum test score for that exam. We are able to use alternative test scores in the imputation for 34 percent of students with missing test scores. We do not use any information on future test scores, since these could be endogenous to choices about which high school to attend.

Nearly one-third of 10^{th} graders is missing either math or reading scores from two years prior, meaning they were either not in 8^{th} grade with their cohort or did not have their exams scored. However, only one-quarter of these cases (primarily special education exempt students) have no current or prior test score information to aid in the imputation. For those students with missing scores who have alternative 8^{th} or 10^{th} grade scores available, we use linear regressions on the best available subset to impute values. Included in the control set are cubics in 8^{th} and 10^{th} grade math, reading, and writing scores, as well as indicators for students credited with automatic passes on the 10^{th} grade TAAS due to their scores on the end-of-year course examinations. For non-special education students with no available 8^{th} or 10^{th} grade scores, we assign the average score for students with the same missing test score patterns for all but the exam in question. For special education exempt students with no prior scores, we assign the minimum test score for that exam. No students are LEP exempt in 10^{th} grade.

Predicting students' class ranks

Since we have multiple scores, we attempt to combine them in a way that is as informative as possible about a student's potential class rank. We therefore define student *i*'s predicted statewide percentile rank within his/her cohort *c*, $\hat{\gamma}_{ic}$, based on a weighted average of the student's 8^{th} grade math and reading percentile test scores. The math and reading percentile scores are assigned weights of 0.69 and 0.31, respectively. These weights reflect relative power in predicting high school class rank observed in the National Education Longitudinal Study (NELS), which has both 8th grade test scores and high school class rank. The higher relative importance of math scores is consistent with prior studies' findings. For example, Hanushek et al. (1996) find math scores are three times as important in predicting the probability that sophomores continue in high school to 12th grade.

We turned to the second follow-up of the NELS for choosing weights since we cannot link 8th grade test scores to students' actual high school class rank (either in the high school they attend or in other possible high schools) in our main data set. The NELS surveyed a nationally representative sample of 8th grade students in 1988. These students were then followed as they progressed to 10th and 12th grade in 1990 and 1992. Students were tested in math and reading in the base survey, and class rank and class size are reported in the student's senior year (or terminal year for dropout and alternative completers) allowing us to compute a student's percentile class rank.

Prior to analyzing the relationships between class rank and test scores, we first also convert the NELS math and reading aptitude scores to percentile ranks and then downgrade their quality to match that of the TAAS scores. In calculating the percentile test score ranks, we use the longitudinal weights provided by NCES that are meant to adjust for unequal probabilities of selection into the sample and non-response. The TAAS tests have many fewer distinct scores (approximately 65 vs. a nearly continuous distribution on the NELS exams), and distinguish better among lower than higher performers. We merge neighboring percentiles in the NELS data where the TAAS cumulative distribution is flat, yielding an equally clumpy distribution.

Our prediction equations relate a student's percentile class rank to the student's adjusted math and reading percentile ranks, with all percentiles computed to range from a low of zero to a high of one. In order to address the fact that class rank is relative to the ability level of one's peers, the specifications also include high school fixed effects. We estimate the models using ordinary least squares with observations weighted by the appropriate longitudinal sample weight, and report robust standard errors.

Table A2 shows the results for both a Texas-only and a nationally representative sample. For both the nation as a whole and for Texas, math and reading test scores explain slightly more than one third of the variation in class rank within schools. The implied relative weight on math is quite similar in Texas and the whole nation (0.69 vs. 0.65). Though we found some evidence for nonlinearities in the underlying relationships, specifications that included squared and interacted test score terms had only marginally greater explanatory power than our chosen specification. In particular, allowing for nonlinearities does not improve our ability to accurately predict whether a given student places in the top ten percent of his or her class.

Table A2. Predicting high school percentile class rank

Independent variable	NELS longitudinal 2nd follow-up sample	
	Texas	Nation
	(1)	(2)
8th grade math percentile rank	0.493	0.466
	(0.043)	(0.014)
8th grade reading percentile rank	0.226	0.251
	(0.047)	(0.013)
Number of observations	787	10,918
R-squared	0.384	0.361
Correlation between math and reading percentile ranks	0.701	0.680
Implied math relative weight	0.686	0.650

Notes: Each column reports the results from a separate ordinary least squares regression based on the sample indicated. The dependent variable is the student's percentile high school class rank, and ranges from 0 to 1. In addition to the variables shown, the specifications also include high school fixed effects. Robust standard errors are shown in parentheses. The R-squared is based on within-high school variation. The implied math relative weight is the ratio of the estimated coefficient for the math test score measure to the sum of the coefficients for math and reading.

In order to calculate predicted ranks for students from the Texas administrative data, we convert 8th grade math and reading TAAS scores (or predicted scores if these are missing) into percentile scores by cohort. We then calculate predicted percentile class ranks by applying the coefficients for the Texas-only sample in Table A2. As a final adjustment, we rescale the predictions to range from 0 to 1 within each cohort by replacing each predicted value with its percentile within the cohort-specific distribution, to yield $\hat{\gamma}_{ic}$.

Predicting students' likelihoods of placing in the top ten percent at any given high school

To determine how likely a student is to place in the top ten percent at any given high school, we incorporate uncertainty both about a student's statewide percentile rank and the distribution of school peers' percentile ranks. To account for uncertainty arising from the mapping from test scores to class ranks, we assume that a student's expected statewide rank is distributed normally, with a common variance determined by the variance of our prediction error (from the regression in column 1 in Table A2). We assume the error distribution is normal and that the overall standard deviation of the estimation error describes the distribution of the predicted rank for each student (prior to the final adjustment). Although applying ordinary least squares ignores the special nature of the dependent variable (which is uniformly distributed with unequal intervals, i.e., the distance between 0.50 and 0.51 is not the same as between .90 and .91), we find that the errors are approximately normally distributed and homoskedastic when the test score variables used as controls are also specified as percentile ranks. So, our assumption of a common degree of uncertainty across the distribution is not at odds with our estimation strategy.

To account for variation in the specific composition of the high school class, which is particularly important for smaller schools, we simulate the variances of the thresholds. In each of 1000 rounds, we calculate the threshold by drawing with replacement a class of the same size as the observed size and assigning each 10th grader a random draw from his/her predicted ability distribution. Under joint normality, we can then calculate the probability that the student will place in the top ten percent at high school *k*, $\hat{\tau}_{ikc}$.

Predicting students' likelihoods of applying to and being rejected by a flagship university

We again turn to the NELS to estimate how flagship application rates depend on a measure comparable to $\hat{\gamma}_{ic}$, and we then apply this estimated relationship to our sample. We use the sample of students in the third follow-up with non-missing 8th grade test scores. The survey provides information on two application schools, the two the student believed he/she was most likely to attend. We then identify which of the applications were to selective public four-year institutions, using the 1992 Barron's Guide to assign selectivity. We use probit specifications to estimate the probability of application conditional on predicted class rank, calculated using the strategy described above.

Though the NELS also reports the outcomes of applications, these data appear to be contaminated by the wording of the question. Rejection rates conditional on applying are non-monotonic across the achievement distribution, and in particular, implausibly low toward the bottom. Therefore, we instead rely on administrative data from the Texas Higher Education Opportunity Project (THEOP) to map rejection rates conditional on application to $\hat{\gamma}_{ic}$ using applicants' SAT test score percentiles. For the Texas flagship institutions, we have information on the outcome of applications for several pre-*Hopwood* years (THEOP, 1992-1996). We apply the coefficients from column 1 in Table A2 to verbal and quantitative SAT percentile scores to rank applicants, in order to determine how the likelihood of rejection at one of the flagships evolves across the applicant-only achievement distribution. Assuming this same pattern applies, we impute rejection rates conditional on applying for the NELS and then our Texas students.

Appendix B. Robustness tests

Table B1. Impact of the policy on the threshold of the high school attended, by student ability

	Dependent variable: Static top 10% threshold at chosen high school					
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
Top decile × post × has opp.	-0.090 (0.108)	-0.091 (0.102)	-0.186** (0.080)	-0.120 (0.125)	-0.086 (0.099)	-0.105 (0.109)
2nd decile × post × has opp.	-0.250** (0.124)	-0.245** (0.118)	-0.225** (0.105)	-0.231 (0.155)	-0.366*** (0.141)	-0.393** (0.155)
3rd decile × post × has opp.	-0.317*** (0.115)	-0.324*** (0.110)	-0.250*** (0.091)	-0.363*** (0.129)	-0.283** (0.130)	-0.293** (0.137)
4th decile × post × has opp.	-0.280 (0.175)	-0.296* (0.170)	-0.220 (0.140)	-0.334 (0.234)	-0.196 (0.206)	-0.176 (0.212)
Top decile × post	-0.028 (0.036)	-0.031 (0.033)	0.046* (0.025)	-0.024 (0.036)	-0.039 (0.043)	-0.056 (0.053)
2nd decile × post	0.050 (0.040)	0.047 (0.039)	0.065 (0.044)	0.021 (0.041)	0.052 (0.045)	0.032 (0.052)
3rd decile × post	0.058 (0.038)	0.057 (0.037)	0.067* (0.036)	0.050 (0.039)	0.036 (0.045)	0.026 (0.046)
4th decile × post	0.070* (0.039)	0.069* (0.037)	0.077** (0.035)	0.056 (0.042)	0.037 (0.046)	0.014 (0.051)
Joint significance of the 3-way interactions, p-value	0.005	0.002	0.001	0.011	0.011	0.014
Fraction with opportunity	0.330	0.338	0.460	0.252	0.331	0.351
Variation	Baseline	Secular controls	Less restrictive opp. def.	More restrictive opp. def.	Only very stable catchment areas	Only very stable districts
Observations	245,795	245,795	245,795	245,795	189,077	162,700

Notes: Each column corresponds to a separate OLS regression. In all cases, the sample is restricted to students with multiple within-district high schools within 10 miles and the dependent variable is the static threshold at the high school attended. The results in column 1 correspond to column 5 in Table 2, and the remaining columns present results from variations of this baseline specification. Column 2 adds the average static threshold at high schools attended by students in the bottom six ability deciles from the same catchment area and year to the control set. In columns 3 and 4, the "has opportunity" variable indicates whether the student can realize at least a 15 and at least a 25 percentage point gain, respectively, in the probability of top ten percent placement across high schools in the local market—as compared to the baseline of at least a 20 percentage point gain. The final two columns impose additional restrictions on the stability of catchment areas and districts included. In column 5, students attending catchment areas in which more than 20 percent of any cohort attends middle schools that enter, exit, or are reassigned to different plurality high schools are dropped. Column 6 furthers exclude students from districts if more than 20 percent of any cohort is assigned to plurality high schools that enter or exit. Note that the students newly dropped are those indirectly affected, since we have already excluded those directly affected by these reassignments. ***Significant at the 1% level; **5% level; *10% level.

Table B2. Conditional logit estimates of within-district high school enrollment choices

Specification		Incentive Measure: Top 10% Threshold ($\hat{\gamma}_{k1}^{90}$)	Incentive Measure: Top 10% probability ($\hat{\tau}_{ik1}$)	Incentive Measure: Change in flagship admission probability ($\Delta\hat{p}_{ik1}$)
		(1)	(2)	(3)
Baseline (Table 4)	Incentive × post	-0.75*** (0.25)	0.59*** (0.24)	12.07*** (4.30)
	Additional miles willing to travel	0.21	0.26	0.22
Controlling for share of low-ability catchment area students attending the high school each year	Incentive × post	-0.76*** (0.23)	0.55** (0.22)	11.59*** (4.11)
	Additional miles willing to travel	0.35	0.39	0.35
Including only very stable catchment areas	Incentive × post	-0.92*** (0.34)	0.71** (0.33)	14.13** (6.15)
	Additional miles willing to travel	0.28	0.32	0.28
Including only very stable catchment areas and districts	Incentive × post	-0.98*** (0.33)	0.76** (0.33)	15.04** (6.15)
	Additional miles willing to travel	0.30	0.36	0.30
Excluding Year 1	Incentive × post	-0.62** (0.24)	0.49** (0.23)	10.12** (4.31)
	Additional miles willing to travel	0.18	0.21	0.19
Excluding Year 1 and controlling for share of high-ability catchment area students attending the high school in Year 1 and this variable × post	Incentive × post	-0.57** (0.23)	0.47** (0.22)	9.55** (4.13)
	Additional miles willing to travel	0.20	0.25	0.21

Notes: Each cell corresponds to a separate conditional logit model of 8th grade students' choices among high schools. What varies across columns is the incentive measure that is included in the control set. The specifications are variations of the baseline specifications presented in Table 4, as indicated in the row headings. In each case, we report only the estimates for the coefficient and robust standard error for (Incentive × post) and the implied additional miles willing to travel for a one standard deviation improvement in the incentive, calculated as described in the notes to Table 4. "Very stable" catchment areas and districts are defined in the notes to Table B1.
***Significant at the 1% level; **5% level; *10% level.