College Admission and High School Integration^{*}

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Abstract

We investigate whether a policy that bases college admission on relative performance can modify the degree of racial or ethnic segregation in high schools by inducing students to relocate to schools with weaker competition. Theoretically, such school arbitrage will neutralize the admissions policy at the college level. It will result in partial desegregation of the high schools if flows are sufficiently unbiased. These predictions are supported by empirical evidence on the effects of the Texas Top Ten Percent Law, indicating that a policy intended to support diversity at the college level actually helped achieve it in the high schools.

Keywords: Matching, affirmative action, education, college admission, high school desegregation, Texas Top Ten Percent. JEL: C78, I23, D45, J78.

1 Introduction

Could a policy designed to maintain racial diversity in a state's universities help to integrate its high schools instead? Based on a theoretical and empirical

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analysis of the effects of such a law implemented in the state of Texas, we show that it can.

In recent years, several U.S. states, including three of the largest (California, Texas, and Florida) have passed "top-N percent" laws, guaranteeing university admission to every high school student who graduates in the top N percent of his or her class.¹ Following court decisions in the 1990s, the use of affirmative action policies to maintain racial or ethnic balance in higher education was discontinued. The top-N percent laws (or top-n laws for short) were adopted in response: since high schools were highly racially segregated, the expectation was to draw a representative sample of the statewide high school population, guaranteeing diversity on campus. Despite their breadth – in 2009, 81% of first year students enrolling at the University of Texas at Austin were admitted under its top-10-percent plan (UT OISPA, 2010) – the new policies did not replicate the level of campus diversity seen under the abandoned affirmative action system: representation of minority students on University of Texas flagship campuses, which had dropped by one third after removing affirmative action, was still down by a quarter four years into the new policy.²

A possible explanation for this seeming policy ineffectiveness is an arbitrage incentive it creates: under the law, students who fall just short of the admission requirement of being in the top 10% of their current high school class could move to a lower quality school, where they are more likely to meet the criterion. Indeed, this arbitrage opportunity was not lost on economists after the policy was enacted (Cullen et al., 2013; Cortes and Friedson, 2014); and, as their evidence indicates, neither was it missed by at least a few Texans. If the moving students are disproportionately non-minority, then their movement will undermine the policy's ability to integrate the university.

We begin our analysis by taking this observation a step further with the Top-N Percent Neutrality Theorem: if the private cost of moving across high schools is sufficiently low, then in equilibrium, the set of admitted students in university with and without a top-n policy is identical. This result can help explain why the hoped-for diversity in the university was not achieved.

Our paper's focus is on a corollary effect that appears to have gone un-

¹California started admitting the top four, Florida the top twenty, and Texas the top ten percent performing students of every high school.

²These calculations of over- and under-presentation of backgrounds in University of Texas at Austin and Texas A&M with respect to the previous year's high school population use data from Kain et al. (2005) and Texas Education Authority.

noticed in the policy debate, and concerns how top-n laws may affect high schools. In general, the movement of arbitrageurs across schools has the potential to blend the ethnic composition of all high schools. As we show theoretically, there are cases in which this blending must reduce the overall level of segregation, as conventionally measured. Indeed, our Unbiased Mixing Theorem states that any movement across schools that is ethnically unbiased, in the sense that arbitrageurs are both ethnically representative of their original schools and effectively ignore ethnic composition in targeting schools, will reduce the mutual information index and several other commonly-used measures of ethnic segregation. We then go on to establish sufficient conditions under which the top-n policy leads to ethnically unbiased relocations. It follows from our two results that these conditions are sufficient for the policy to increase high school integration while leaving university enrollment unchanged.

Of course such conditions may not pertain in practice. Using a rich data set constructed using a combination of multiple administrative and Census data from Texas, we find that there was indeed a drop in high school racial segregation in the years immediately following the introduction of the policy there. Thus a policy instrument that may appear to have yielded disappointing results with respect to integrating universities, may nonetheless be a powerful tool for achieving integration in high schools. More generally, our results show that integration at lower educational tiers can be achieved by rewarding relative performance without the need to force integration or to condition on race.

Texas's top-n policies condition only on class rank in the final year of high school. Therefore students who value attending their initial school will delay a school change as long as possible. Hence, any effects of the policy will be more pronounced for later grade levels. Using enrollment data for all Texas high schools, we compute a number of segregation measures, and find evidence of a reduction in the state-wide segregation at the 11th and 12th grade levels, when students are applying to college, as compared to 9th grade. We also find that the number of transfer students doubled and students who were not economically disadvantaged were more inclined to move to worse performing schools after the policy was introduced. This effect was stronger for higher grades, as predicted by theory.

Figure 1 provides a first glance at the evidence. It shows a time series of high school segregation – measured by the mutual information index – for 9th

and 12th grades of all Texas high schools from 1990 to 2007.³ The mutual information index measures segregation by indicating how well information about a student's high school predicts that student's ethnicity. Consistent with our reasoning above, a substantial drop in segregation coincides with the introduction of the policy in 1998 for 12th grade but not for 9th grade.⁴ Trends in residential segregation do not explain the pattern in Figure 1, see Figure 4 in the Appendix.

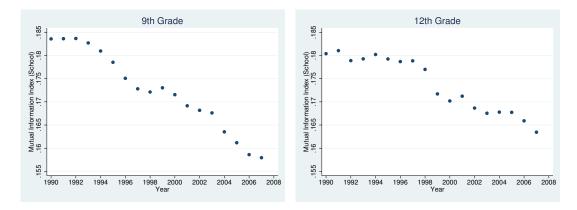


Figure 1: Time series of the mutual information index for 9th and 12th grades.

This observation is corroborated at the high school level using a differencein-differences estimation strategy on an index of local segregation. In line with the theory, we test for a significant change in the difference between the degree of segregation in 12th and 9th grades after 1998. This is indeed the case across several specifications, controlling for school-grade unobserved heterogeneity. Next, we examine whether the policy change affected the behavior of high school segregation over time within a cohort. Indeed we find that the difference in within-county segregation between 12th and 9th grades of the same cohort has decreased significantly after the introduction of the policy. This suggests that moves between schools have led to the decrease in segregation. We also show that this phenomenon does not seem to be associated with the establishment of charter schools in Texas around the same period. Finally, using individuallevel data we document a change in the pattern of school moves taking place

³One school is excluded from the analysis due to an atypical large number of students with Native American origins in 1998.

⁴See appendix for further graphs corresponding to 10th and 11th grades. Using alternate measures of segregation, such as the Theil index, yield similar pictures. The policy was announced in 1996, signed into law in early 1997, and took effect with 1998-99 school year.

during 11th and 12th grades. After the introduction of the policy, students became more likely to move to schools with less college-bound students, lower SAT average, lower TAAS pass rate, and less Asian and White students. In fact these effects are stronger for students who were not economically disadvantaged and arguably are more likely to benefit from strategic school choice.

In the next section of the paper, we present the Top-N Percent Neutrality Theorem and lay out a simple model of school choice that generates testable predictions about flows across schools and their effects on segregation. Then, in Section 3, we confront the data. Finally we offer some remarks about the possibility of broadening top-n laws in order to increase high school integration. All tables and figures omitted from the text can be found in the Appendix.

2 Theoretical Framework

2.1 The Basic Model

The economy is populated by a unit-measure continuum of students, each characterized by an educational achievement $a \in [0, \overline{a}]$.⁵ Each student is initially enrolled in one of a finite set of high schools $s \in \{1, ..., S\}$. School *s* has measure q_s of students, with $\sum_{s=1}^{S} q_s = 1$ and is characterized by its distribution of achievements $F_s(a)$, which has support $[0, \overline{a}]$. The aggregate distribution is $F(a) = \sum_{s=1}^{S} q_s F_s(a)$.

Prior to admission to college, each student may *relocate* by selecting a school s' different from her initial school s at a cost $c(s, s') \ge 0$. It will simplify matters somewhat to suppose that from any initial school, the relocation costs among all target schools are unique: for instance, for each s, $c(s, s') \ne c(s, s'')$ whenever $s' \ne s''$. Relocation decisions are made simultaneously after the admission policy is announced, and we consider Nash equilibria in relocation choice. Schools have no say in the location decisions; as is the situation in most public schools in the US, any student becomes eligible to attend a high school simply by moving into its geographic catchment.⁶

⁵We abstract here from peer effects within schools that could bear on achievement. Thus a is best interpreted as capturing parental or community investment in students in early childhood or primary and middle school.

⁶In practice, students sometimes can gain admission to local schools at even lower cost, e.g. by claiming to live with a relative in the catchment or having a parent rent a small dwelling there.

Upon graduation, students can either go to the university U or pursue an alternative option, denoted u. A policy maker controls admission to the U, which has fixed capacity k < 1. U is more desirable than u for all students in the population – students for whom u is preferred to U will not be competing for spots in the U under any policy, and so can be ignored for the purposes of this analysis. Specifically, for a student of achievement a, the return to attending the U is U(a), which strictly exceeds u(a), the return to attending u. The notation signifies that returns may vary across education levels, as may the interpretation of the opportunity cost u(a) of attending the U: for some levels it might mean the value of attending another university than U, while for others it might be the value of immediate entry into the labor market. A student of type a who moves from s to s' and enters the U (resp. u) receives payoff U(a) - c(s, s') (resp. u(a) - c(s, s')).

We will be comparing an initial admission policy selecting the top achievers in the state, (hence a "school-blind" policy), against a top-n law that admits the top N percent in each high school; if there is a residual capacity, the rest of the places in the U are covered by the school-blind policy.

Under a school-blind policy, the university U admits all students with the highest endowments, up to capacity. Since all students admitted strictly prefer the U, they will attend, and the marginal student achievement a^* satisfies

$$F(a^*) = 1 - k. (1)$$

Since location is irrelevant to attending the U under the school-blind policy, no one has any incentive to relocate (and if there is any cost to moving, a strict incentive not to).

Now consider a top-*n* policy. In this case, every student in the top *n* percentile of his high school class is admitted to the *U*, and the residual capacity k-n is allocated on to the highest-achieving students in the state who have not already been admitted. Because students may decide to move across schools as a result of the policy, there will be new distributions $\hat{F}_s(a)$ in each school.

Formally, the policy induces a relocation game in which students simultaneously choose *moving strategies*, i.e., maps $\sigma(a, s, s') \in [0, 1]$ indicating the probability that a student of achievement *a* moves from initial school *s* to school *s'*; thus, $\sum_{s'} \sigma(a, s, s') = 1$. An equilibrium is a profile σ of moving strategies $(\sigma(a, s, s') \in \{0, 1\})$ such that for almost all *a* and associated *s*, $\sigma(a, s, \cdot)$ is a best response to σ .⁷

Our neutrality theorem states that as long as the cost of moving to any school is less than the benefit U(a)-u(a) of attending the U, the set of admitted students is the same as when the policy was not in place.

The logic behind why equilibria with and without the top-*n* policy must have the same *U* enrollments is very simple. Suppose an equilibrium of the relocation game induced by the top-*n* policy has a set of admitted students that differs from that of the school-blind policy. Then somewhere in the state, there is a "winner" $a_w < a^*$ who is admitted, as well as a "loser" $a_\ell > a^*$ who is rejected (more precisely, there is a positive measure of winning achievement levels, and because of the capacity constraint, an equal measure of losing levels). Now, a_w must be admitted as a member of the top *n* of his school and a_ℓ and a_w must be in different schools, else a_ℓ would also have been admitted under the top-*n* rule. But now, a_ℓ can secure admission to the *U*, and strictly gains from doing so, simply by relocating from his school to a_w 's school. Thus we are not looking at an equilibrium.

In the appendix we show an equilibrium always exists and is characterized by a set of cutoffs, one for each school, weakly exceeding a^* and such that each student below his initial school's cutoff and above a^* moves to another school, while all others remain.

Notice that the only types that might engage in arbitrage are the potential losers $(a \ge a^*)$ from the top-*n* policy. Thus only their costs need to be compared with the benefit of attending the U in order to reach the neutrality conclusion.

Proposition 1. (The Top-N Percent Neutrality Theorem). If c(s, s') < U(a) - u(a) for all students with $a \ge a^*$, university enrollments under the top-n and school-blind admission policies are identical.

Thus, with low moving costs, the top-n law will have no impact on enrollment in the University. As a result, there can be no change in the ethnic, socio-economic, gender, or racial composition of the student body there.

However, all of this movement is *not* neutral with respect to the composition of the high schools.⁸ In particular, movement of students induced by the top-n

⁷Since a student is admitted with probability 1 or 0 from his destination school and there is never indifference between schools because moving costs are distinct, it suffices to consider pure strategy equilibria.

⁸ Necessary and sufficient condition for some movement of students to occur is that there is a school s such that $1 - F_s(a^*) < n$. Then, absent any movement, the top-n policy would

law may reduce segregation by ethnic group or socio-economic status.

Let $g \in G$ be a student's ethnic or socioeconomic group, where G is some finite set. Denote by $p_s^g \in p_s = (p_s^1, ..., p_s^{|G|})$ the population share of group g in school s and by $p^g \in p = (p^1, ..., p^{|G|}) g$'s share in the aggregate population. To measure the degree of segregation we use an index of the form:

$$\mathcal{I}(p, \{p_s\}) \equiv A_1(p) - A_2(p) \sum_s q_s H(p_s),$$

where $A_1(p)$ and $A_2(p) \neq 0$ are functions of the aggregate distribution of groups $p, H(p_s)$ is a concave function of the distribution of groups at school s, and q_s the measure of students in school s, with $\sum_s q_s = 1$. A leading example is when $H(p_s) = \sum_g p_s^g \log(1/p_s^g)$ is the entropy of $p_s, A_1(p) = H(p)$ the entropy of p, and $A_2(p) \equiv 1$, in which case $\mathcal{I}(p, \{p_s\})$ is the mutual information index. If $H(\cdot)$ is the entropy, $A_1(p) = 1, A_2(p) = 1/H(p)$, then $\mathcal{I}(p, \{p_s\})$ is Theil's information index (Theil, 1972; Theil and Finizza, 1971). Other segregation indexes that are consistent with our formulation are the variance ratio index (James and Taeuber, 1985) or the Bell-Robinson Index (Kremer and Maskin, 1996).

To illustrate the effect of relocation, consider the case of two groups and three schools, which have initial proportions $p_1^1 = 1$, $p_2^1 = 1/2$, and $p_3^1 = 0$ of the first group and equal masses of students, $q_1 = q_2 = q_3 = 1/3$. Suppose that the policy induces a random sample of students with mass m > 0 from school 1 to move to school 2. This movement makes school 2 more segregated, as the proportion of the first group there moves away from the population average 1/2. Schools 1 and 3 do not become less segregated either since the proportions of the first group remains 1 in school 1 and 0 in school 3. Nevertheless the segregation index $\mathcal{I}(p)$ will decrease! This is because, after students have moved, the population weight of the fully segregated school 1 decreases and the weight of the now marginally segregated school 2 increases. The aggregate effect is to decrease segregation, as concavity of $H(p_s)$ ensures that the increase in population weight of the less segregated school 2 overcompensates the increase in segregation in school 2.

To show this denote equilibrium quantities by hats. Then the new segregation index is

$$\hat{\mathcal{I}} = A_1(p) - A_2(p) \left[(q_1 - m)H(p_1) + (q_2 + m)H(\hat{p}_2) + q_3H(p_3). \right]$$

allow some students in s with $a < a^*$ to enter the U, which contradicts neutrality.

Because students move only from one school to another, not into or out of the system as whole, $A_1(p)$ and $A_2(p)$ remain unchanged, so

$$\hat{\mathcal{I}} - \mathcal{I} \propto mH(p_1) - (q_2 + m)H(\hat{p}_2) + q_2H(p_2).$$
 (2)

Since we can write $\hat{p}_2 = \frac{m}{m+q_2}p_1 + \frac{q_2}{m+q_2}p_2$, concavity of H and $p_1 \neq p_2$, imply that

$$H(\hat{p}_2) > \frac{m}{m+q_2}H(p_1) + \frac{q_2}{m+q_2}H(p_2).$$

Substituting this inequality into the right hand side of (2), we have $\hat{\mathcal{I}} - \mathcal{I} < 0$. Indeed, this establishes that whenever two schools have different proportions of the two groups, the segregation index will decrease after a move of a random sample students from one school to another, because more students will be in less segregated schools after the move.

The result and the mechanism at work in the example can be generalized (see appendix) to any number of schools or groups, so long as the system as a whole remains closed (no student exits and no new student enters) and movement is (group) *unbiased*: the initial group distribution p_s in school s is equal to the group distribution among those who exit school s and among those who target school s' from school s.

Proposition 2. (The Unbiased Mixing Theorem). Suppose the school system is closed, that schools initially have different proportions of groups, and that movement of students is group unbiased. Then the segregation index \mathcal{I} falls following movement.

Putting additional structure on the achievement distributions and moving costs allows one to characterize the relocation equilibrium and the associated flows of students more precisely. Assume that schools are ordered by quality: if s < s', $F_s(a)$ strictly first order stochastically dominates $F_{s'}(a)$. That is, for any $a \in (0, \overline{a})$, $F_s(a) < F_{s'}(a)$. The moving costs c(s, s') strictly increases in the "distance" between schools, captured by the absolute difference in their indices |s - s'|.⁹ In addition to geographic distance, this preference might reflect horizontal differentiation of schools, or, perhaps more importantly, fixed school characteristics that are correlated with quality, such as teacher or facility

⁹Even though distance measured in this way admits the possibility that c(s, s') = c(s, s''), where s' > s > s'', it turns out with this construction, target schools always have index higher than s, so that costs remain unique among targets.

quality or reputation. Finally, assume that at least one school s satisfies the movement condition in Footnote 8, i.e. that $1 - F_s(a^*) < n$, so that there will be movement in equilibrium.

Under these conditions, we can show (see appendix) that there exists a unique equilibrium outcome that is characterized by two properties.

Proposition 3. Suppose that $F_s(a)$ strictly first order stochastically dominates $F_{s'}(a)$ if s < s', and that the cost of moving from s to $s' \neq s$ is an increasing function of the distance |s - s'|. In the unique equilibrium outcome,

- (i) There is a sequence of cutoffs $\{\hat{a}_s, s = 1, ..., S\}$, with \hat{a}_s weakly decreasing in s, and $\hat{a}_1 > a^* = \hat{a}_s$. Only students with ability greater than \hat{a}_s are admitted from school s.
- (ii) In school $s \leq S 1$, students with ability in $[\hat{a}_{s'}, \hat{a}_{s'-1})$ move to school $s' \geq s + 1$; students in $[\hat{a}_s, \overline{a}]$ and $[0, a^*)$ do not move.

That is, students who would not get into the U from their original school will move to the closest school that will enable them to obtain a place at the U. Since schools are stochastically ordered, movement is always to ex-ante lower quality schools, and to the best (nearest) school that will allow a to be among the top n.

If n < k, then some students are admitted at large. The proof shows that they are all drawn from the highest-quality (lowest index) schools, which share a common threshold \hat{a}^L that exceeds the threshold for all other schools. There is no movement into those schools. In the trivial case that n is very small (i.e., $1 - F_s(a^*) \ge n$ for all s), the policy has no bite, all schools have some at-large admission with $\hat{a}^L = a^*$, and there is no movement at all.

Figure 2 gives a graphical illustration of these flows in the case n = k. Students from school 1 with achievement closely below the cutoff \hat{a}_1 (with mass $x_{1,2}$ in the figure) will move to neighboring school 2, while their counterparts with achievements closely above a^* (with mass $x_{1,3}$) need to move further to school 3 in order to ensure admission to the U. School 2 students with achievements between a^* and school 2's cutoff (with mass $x_{2,3}$) move to school 3. Notice also that "cascades" may be part of the equilibrium allocation: school 2 students with achievements closely below \hat{a}_2 are crowded out by the competition of incoming, high achieving students from school 1 (m_2), inducing them to move to school 3. The flows described in this case will tend to equalize average achievement across schools: this is an easy consequence of our characterization if the mean achievement in school 1 (and therefore all other schools) is below a^* . Mean achievement falls in schools that are net exporters (schools with the initially highest distributions), and rises in schools that are net importers (initially lowest). However, further assumptions need to be maintained if these flows are to result in decreased ethnic segregation as portrayed in Proposition 2.

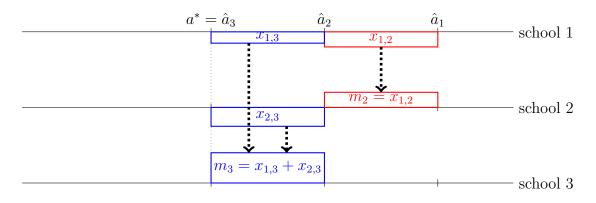


Figure 2: Post-policy flows with three schools

Suppose that ethnic composition *independent* of a: it is the same for all a within a school, but it differs across schools. This situation could arise from a process similar to the one in which public schools are chosen in the US and some other nations: parents choose communities and the schools therein on the basis of their own achievement, aspirations for their children, or other attributes correlated with their children's achievement. Denote these attributes α and suppose they take S values $1, \ldots, S$ with the frequencies q_s in the population. Different ethnic groups g have different distributions p^g ($p_s^g \neq p_s^{g'}$ for at least some s) over the attributes, and $q_s = \sum_g p_s^g$.

A student's achievement is the realization of a random variable with distribution $\mathcal{F}(a|\alpha)$, a continuous distribution with support $[0, \overline{a}]$ that is stochastically decreasing in α . If parents sort perfectly into communities by the attribute α , then their children's school achievement distributions will be $F_s(a) = \mathcal{F}(a|s)$, and the $F_s(a)$ will be stochastically decreasing in s. Moreover, the fraction of group g in school s will be p_s^g , and the achievement distribution will be the same $F_s(a)$ for each for each group in school s. Any sample of students exiting school s will have the same distribution of groups, as will any subsample entering another school s'. Thus, in this case the unbiasedness conditions of Proposition 2 are satisfied by the flows depicted in Proposition 3, and it follows that the top-n policy not only equalizes mean achievements across schools but also reduces segregation.

To get some appreciation of the role played by independence for unbiasedness, consider the following example. Suppose that of the schools in Figure 2, Schools 1 and 2 are initially slightly integrated: they are populated by red students, except for those in the interval $[a^*, \hat{a}_2]$, who are all blue. School 3 is entirely blue.¹⁰ Once the policy is implemented, students in $[\hat{a}_2, \hat{a}_1)$, who are all red, move from school 1 to school 2. Students in $[a^*, \hat{a}_2)$, who are all blue, move out of schools 1 and 2 into school 3. Thus after the policy, schools 1 and 2 are entirely red, while school 3 remains entirely blue: the outcome is now perfect segregation, and integration has therefore decreased.

This example violates unbiasedness because the ethnic mix among movers depends on the achievement level. In particular, the movers from school 1 are ethnically diverse, more so than the school as a whole; the movers from school 2 are entirely blue but come from a largely red school. In neither case are the emigrants ethnically representative of the school. Moreover, the targeting is also biased: red movers target the overwhelmingly red school 2, while blue movers target the entirely blue school 3. Notice this biased targeting occurs even though there is no e preference for ethnic groups motivating movement.

This case is rather extreme in the degree of bias. For more moderate departures from unbiasedness, Proposition 2 suggests that top-n policies will decrease segregation Ultimately, whether they do or not is an empirical question.

2.2 First Steps toward Bringing the Theory to the Data

A plausible hypothesis is that the distribution of ex-ante achievement referred to in the discussion following Proposition 3 is stochastically increasing in socioeconomic status or higher for some ethnic groups than others. Texas highschools display some signs of student sorting, as shown in Figure 3: the percentage of minority students enrolled at a high school correlates positively with the percentage of economically disadvantaged students and negatively with the

¹⁰The initial situation might arise if blue parents take advantage of a metropolitan-area busing program that sends inner-city blues to largely red suburban schools.

high school pass rate in TAAS.¹¹ That is, a school's ethnic composition is a good predictor of socio-economic status and test score results. Out results would then suggest that the policy would induce student flows from better (i.e. majority) to worse (i.e. minority) schools, and that these flows tend to consist proportionally of majority students, which in turn would reduce segregation.

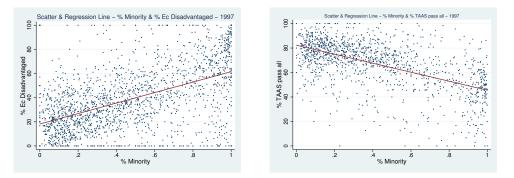


Figure 3: Share of minority and economically disadvantaged students (left) and share of minority and TAAS pass rate (right). *Source*: AEIS data.

If the top-n policy does not require a minimum stay at a school in order to be eligible, students have the opportunity to choose not only whether to move between schools but also when to move. If we suppose that the moving cost can be decomposed into a fixed component (e.g. the cost of moving house) and a flow component (e.g. peer effects, reduced quality of teachers at the new school, reduced contact with one's original network of friends) that accrues with the time spent in the new school, a student who has a purely strategic motive to move in order to secure access to college, will prefer to make the move at a later stage. Hence, students who move for strategic reasons will do so mainly in later grades, suggesting that the effect on segregation should be small in early grades and more pronounced in later grades.

The theoretical implication of late relocation is a useful guide for empirical work. While Cullen et al. (2013) present evidence for strategic rematch between 8th and 10th grades under a top-n policy, it is not clear whether this effect is large enough to change substantially the degree of high school segregation in Texas. Our model suggests that strategic rematch is more likely to occur later, between 9th and 12th grades, as high ability students would prefer to enjoy

¹¹The figures use data for 1997, but the picture looks very similar for other school years. A similar exercise using percentage of minority and average or median SAT score shows a negative correlation.

peer effects in segregated schools for as long as possible, and also that there may be significant aggregate consequences for high school composition.

2.3 Predictions

The results in the previous section show that if schools are segregated with respect to socioeconomic background such as race or SES, a top-*n* policy may induce some desegregation in background, if socioeconomic background correlates positively with education levels. This is because the policy can change individuals' ranking of different schools, making it profitable to move to a school that would not have been chosen without the policy.

There are three results from the theoretical analysis that we will be able to test in our empirical analysis.

- (1) Arbitrage by students leads to lower segregation index in aggregate. Hence the information index should decrease following the policy.
- (2) Students who arbitrage "move down": they move from schools with higher average educational achievement to schools with lower average educational achievement.
- (3) Arbitrage should be more pronounced for students in the later grades.

3 A Closer Look at the Data

Figure 1 in the introduction suggests there was a persistent decrease in segregation from 1998 onwards in 12th grade, but not in 9th grade, which coincides with the start of the Texas Top Ten Percent policy. In this section we shall investigate whether this is verified using school-level data and whether that is consistent with strategic rematch using individual data.

3.1 Data and Descriptive Statistics

We use three databases for the school years 1994-1995 to 2000-2001 obtained from the Texas Education Agency (TEA).

The first database contains school-level enrollment data. We use data on student counts per grade and per race/ethnicity (classified into five groups:

White, African American, Hispanic, Asian, and Native American).¹² The data are provided at the school (campus) level for all ethnic groups with more than five students enrolled in school.¹³ We use this data to compute the segregation measures that will be explained below.

The second one is the Academic Excellence Indicator System (AEIS).¹⁴ This database provides information on several performance indicators at the school level, e.g. average and median SAT and ACT scores, the share of students taking ACT or SAT, of students above criterion, and of students completing advanced courses.¹⁵ Additionally, this database provides information on the Texas Assessment of Academic Skills (TAAS), a standardized test taken in 10th grade used in Texas between 1991 and 2002, and several indicators such as dropouts, school composition, and attendance.

The third database contains individual-level data for students enrolled in 8th and 12th grades in a public school.¹⁶ For each student, we observe the grade and school they are enrolled in, whether they are a transfer student,¹⁷ and their ethnic group and economic disadvantaged status. Each record is assigned a unique student ID, allowing us to track students as they change

 13 If less than five students belong to an ethnic group in a given grade, the TEA masks the data in compliance with the *Family Educational Rights and Privacy Act* (FERPA) of 1974. We use three different strategies to deal with masking: the first and the second replace masked values by 0 and 2, respectively, and the third one replaces the masked value by a random integer between 1 and 5. The results we report use the first strategy, but results remain largely unchanged for the other strategies.

¹⁴The data can be accessed at http://ritter.tea.state.tx.us/perfreport/aeis/.

¹⁵The data are based on students graduating in the spring of a given year. For instance, the data for 1998-99 provides information on students graduating in the spring 1998.

¹⁶Like the other databases these data are subject to masking based on FERPA regulations. ¹⁷Transfer students are students whose district of residence is different from their district of enrollment, or whose campus of residence is different from their campus of enrollment. Transfers are authorized by the school subject to regulations (Civil Action 5281, available at http://ritter.tea.state.tx.us/pmi/ca5281/5281.html), giving schools some discretion. For instance, transfer requests may be denied if "they will change the majority or minority percentage of the school population by more than one percent (1%), in either the home or the receiving district or the home or the receiving school." (Civil Action 5281, A.3.b)

¹²We merge the school-level enrollment data with the Public Elementary/Secondary School Universe Survey Data from the Common Core of Data (CCD) dataset of the National Center for Education Statistics (NCES), accessible at http://nces.ed.gov/ccd/pubschuniv.asp. It contains information such as school location and school type. By merging the TEA enrollment counts and the CCD, using campus number (TEA) and state assigned school ID (NCES) as unique identifiers, we have information on all schools that were active in Texas.

schools, as long as they remain in the Texas education system. We restrict the sample to students who switched schools at least once. These last two databases enable us to identify patterns of students' movements between schools.

Segregation Measures

To measure the degree of segregation empirically we use the mutual information index and some of its components (for a discussion of this measure, see Reardon and Firebaugh, 2002; Frankel and Volij, 2011; Mora and Ruiz-Castillo, 2009). The basic component of the mutual information index is the *local segregation index*. It compares the composition of a school s to the composition of a larger unit x (e.g., state, region, county, MSA, or school district):¹⁸

$$M_s^x = \sum_{g=1}^G p_{gs} \log\left(\frac{p_{gs}}{p_{gx}}\right),\tag{3}$$

where p_{gs} and p_{gx} denote the share of students of an ethnic group g = 1, ..., Gin school s and in the benchmark unit x (e.g., state, region, county, MSA, or school district), respectively. In our regressions the benchmark unit is the region.

We also use two aggregate measures of segregation that are constructed from the local segregation index. The first, presented in the introduction, is the mutual information index. It can be calculated as:

$$M = \sum_{s=1}^{S} p_s M_s^{Texas},\tag{4}$$

where M_s^{Texas} is the local segregation index comparing school to state composition and can be obtained by using (3), and p_s is the share of Texan students who attend school s.

The second aggregate measure of segregation is calculated within the county.¹⁹ The within-county segregation index, W^c , can be calculated as:

$$W^c = \sum_{s \in C} p_{sc} M_s^c, \tag{5}$$

¹⁸Note that these measures are calculated for a given grade in a given year. We omit the subscripts here in order to simplify notation.

¹⁹We use the county, not the school district, as the relevant unit, since within-school district segregation is zero by definition in school districts containing only one school.

where p_{sc} is the share of students attending school s in county c, and M_s^c is given by (3) using the county as a benchmark unit. Note that the mutual information index defined in (4) is the within-Texas segregation index.

Table 1 provides summary statistics for the main variables used in the regressions. While the mean of the local segregation index (using the region as a benchmark) has increased between the periods 1994-1996 and 1998-2000, the increase seems to be less pronounced for 12th than for 9th grade. This is consistent with a decrease in the difference of within-county segregation between 9th and 12th grades. The data also show that charter schools were established in the post-treatment period (1998-2000). While only 0.8% of counties had a charter school in the pre-treatment years, that proportion increased to 9.5% after 1998. However, the average proportion of students attending a charter school is still very small (0.2%), but see below for a discussion of the role of charter schools. The summary statistics of individual level data show a mixed picture. After the Top Ten Percent Law, moving students were more likely to move to schools with less college bound students and lower SAT average, but less likely to move to schools with lower TAAS pass rates and less Asian and White students.

3.2 Empirical Strategy and Regression Results

We now verify whether the differential change in segregation observed in the aggregate for the whole of Texas is observed as well at the school and county level, i.e., whether segregation of individual schools and counties has changed differentially. Under the Texas Top Ten Percent rule admission was granted based on the class rank at the end of 11th grade, middle of 12th grade, or end of 12th grade. Only some schools imposed restrictions on a minimum attendance period in order to qualify for the Top Ten Percent rule. Therefore, strategic rematch may well be expected to take place as late as between 11th and 12th grades for some schools, and we shall be interested in the possible rematch occurring between 9th and 12th grades. Using 9th grade as the reference point implies losing any strategic rematch that may have occurred earlier in students' careers, which will tend to bias the estimates of the policy effects downwards.

Local Segregation Index

We use a differences-in-differences approach and start with 9th grade as the control group and 12th grade as the treatment group. Below we also introduce 10th and 11th grades to check for effects of the policy on these grades.

The dependent variable of interest in our difference-in-difference approach is the local segregation index M_{yst}^r (defined in (3)) for grade level y in school s at time t, where the benchmark unit is the region r to which the school belongs.²⁰ We consider school years 1994-1995 to 1996-1997 to be pre-treatment, while 1998-1999 to 2000-2001 correspond to post-treatment periods.²¹ Since the policy was signed in 1997 and implemented in 1998, school year 1997-1998 may be partially affected by the reform and is therefore excluded from the analysis. For grade levels $y = \{9; 12\}$ we estimate the model:

$$M_{yst}^r = \beta_1 \left(G12_{ys} \times TOP_t \right) + \boldsymbol{\delta}' \mathbf{T} + u_{ys} + \varepsilon_{yst}, \tag{6}$$

where $G12_{ys} = 1$ if y = 12, $TOP_t = 1$ if $t \ge 1997$, **T** is a vector of year dummies (or region-year dummies), u_{ys} is a school-grade fixed effect, and ε_{yst} is the error term. The school-grade fixed effect allows for time invariant school heterogeneity that may vary by grade. The vector of year dummies, **T**, controls for the overall trend in segregation of all schools in Texas. Some specifications also allow these trends to be region-specific to control for changes in the student population in a given region that may be caused by immigration, for example. The coefficient of interest in this regression is β_1 and it indicates the relative change in the local segregation index in the grade and school years affected by the Top Ten Percent Law.

The estimation results are presented in Table 2. Columns (1) and (2) show a significant decrease in school segregation for 12th grade as compared to 9th grade coinciding with the Top Ten Percent Law. The relative reduction in 12th grade corresponds to about 3% of a standard deviation in the local segregation index. Interestingly, additional regression results (available from the authors) indicate that this effect is not driven by schools located in larger school districts or in MSAs. Thus, the effect we find seems not to operate through greater

²⁰We adopt the Texas Educational Agency's classification, which divides Texas into 20 regions. Each of these regions contains an Educational Service Center (ESC) and provides support to the school districts under their responsibility.

 $^{^{21}}$ The results are very similar when using different masking strategies (i.e., replacing masked observations by 2 or a random integer between 1 and 5). If we add or exclude one school year on the pre- and post-treatment, the results also remain the same.

school choice in the neighborhood, but rather through strategic choice of students who move house and school district, possibly for exogenous reasons such as a parental job change. We will return to this issue below.

Finally, we include data on 10th and 11th grades to detect in which grade the decrease in segregation took place. For $y = \{9, 10, 11, 12\}$, we estimate:

$$M_{yst}^{r} = \beta_{1}(G12_{ys} \times TOP_{t}) + \beta_{2}(G11_{ys} \times TOP_{t}) + \beta_{3}(G10_{ys} \times TOP_{t}) + \boldsymbol{\delta}'\mathbf{T} + u_{ys} + \varepsilon_{yst},$$

$$(7)$$

The results are presented in columns (3) and (4). In both specifications, we cannot reject that the magnitudes of the coefficient estimates are identical. However, the estimates for the 10th grade are not statistically significant at conventional levels. That is, while some of the decrease in segregation may have already happened by 10th grade, a significant change occurs only beginning with 11th grade. There seems to be little action between 11th and 12th grade in terms of a change in segregation.

A possible concern with the results presented in Table 2 is that they may reflect pre-existing trends in the local segregation indices. As a placebo, we run equations (6) and (7) for school years 1990-1991 to 1996-1997, excluding 1993-1994. Table 3 presents the results. The coefficient estimates are positive and not statistically significant. This indicates that our results for the Top Ten Percent Law in Table 2 are not driven by pre-existing trends in the data.

Within-County Segregation

Another potential concern is that the observed relative decrease in segregation after 1998 could be due to a cohort effect. In principle, there could be some idiosyncrasies in later or earlier cohorts that generate the observed decrease in segregation. A closer look at Figures 1 and 5 indicates a slight decrease in segregation in 9th to 11th grades in the years 1995 to 1998.

In order to investigate this issue we focus on the within county measure of segregation to analyze whether there was a decrease in segregation in 12th grade relative to 9th grade of the same cohort (i.e., three years before). That is, we compute the within-county segregation coefficient W^c for each county c, using (5). Using the within-county segregation measure instead of the local segregation index allows us to capture some of the movement of students across schools between these grades, a relatively common phenomenon in the Texas high school system.²²

We estimate the following model, controlling for county (time-invariant) heterogeneity:

$$W_{12t}^c - W_{09(t-3)}^c = \beta TOP_t + \delta t + u_c + \varepsilon_{ct}, \tag{8}$$

where $W^c yt$ is the within-county segregation index at county c, grade y, at time t, $TOP_t = 1$ starting in 1997, t is a linear time trend, u_c is a county fixed effect, and ε_{ct} is the error term. Table 4 presents the results, again for school years 1994-1995 to 2000-2001 excluding 1997-1998. The coefficient associated with the Top Ten Percent policy, β , is negative and significant. The magnitude of the coefficient estimate increases when controlling for a linear time trend. The Top Ten Percent policy is associated with a reduction in the within-county segregation index in 12th grade compared to 9th grade of the same cohort of 10.4% of one standard deviation.²³

Strategic Movement of Students

The evidence presented so far suggests a decrease in high school segregation in 12th grade relative to that in 9th grade both within the same year and the same cohort, coinciding with the introduction of the Top Ten Percent Law. Our theoretical model in Section 2 would imply that this decrease was induced by strategic movement of students across schools.

Changing schools is a relatively common phenomenon in Texas, however. The fluctuation of students between high schools in Texas is high, at more than 10% of the student population per year before and after the policy change. Almost 50% of Texan students will change schools between the 8th and 12th grades, the great majority of them because the following school grade is not offered in their school (92% of moves). Indeed, the strategic movement of students necessary to bring about the decrease in segregation could have been simply part of the natural fluctuation (a simulation shows that strategic movement of about 1.5% of the student population would easily suffice to generate the effect). That is, students who have to move schools for an exogenous reason could have simply done so strategically.

²²Focusing on within school district segregation instead yields similar results. The drawback of using districts is that many districts contain only one school and the within-district segregation measure would be by definition one, as mentioned above.

²³Shortening the time span and losing observations decreases the significance level, but the coefficient remains negative. Using different unmasking strategies yields very similar results.

Another indicator for strategic movements may be the use of transfers: transfer students are students whose district of residence is not the same as the school district they attend. Indeed, as shown in Figure 6, the number of transfer students has more than doubled since 1998, which is in line with our expectations, even when one discounts charter school students.²⁴

To examine the hypothesis that at least some students who changed schools did so strategically, be it by applying for a transfer or in the course of natural fluctuation, we will use student level individual data. That is, our hypothesis is that students who change schools will prefer schools where they are more likely to be in the top ten percent of their class. We are interested in whether the introduction of the Top Ten Percent policy was associated with a change in the characteristics of target schools of moving students, and whether the change differed between lower and higher grades. Moreover, according to the predictions of our theoretical model, strategic movements are to be expected specifically by students who "move down", from schools with higher educational endowment to schools with lower average educational endowment. Therefore we examine possible differences in the policy effects on poor and non-poor students, measured by whether they qualify for a free school meal. Finally, in the model students move strategically if the benefits of moving outweigh its cost. Therefore we would expect that strategic movements are particularly pertinent among moves within the same school district, and less so among moves across school districts. To test this prediction we split the sample of student moves into those occuring within and those across districts. We would expect that treatment effects are greater for within district moves.

Our approach differs from the one by Cullen et al. (2013) who use students' available choice sets (i.e., the presence of suitable schools in the vicinity) for identification of a student's likelihood to move, because our identification strategy relies instead on the differential effect of the policy for different grades, different students and different moving cost, conditional on a student moving schools. Moreover, as mentioned above, the decrease in segregation does not appear to be related to more school choice, as the effect is not stronger for schools located in larger school districts or in MSAs.

Specifically, we examine whether after the introduction of the policy movers

²⁴Students attending a charter schools are usually considered to be transfer students. The role of introducing charter schools in explaining the decrease in segregation appears rather limited, see the robustness checks below.

in 11th and 12th grades were more likely to move to schools with less college bound students, lower SAT average, lower TAAS pass rate, and less majority students (i.e., Asians and Whites) than their school of origin compared to 9th and 10th grade movers. These variables are plausible indicators of a move to an academically worse school. We therefore estimate equations with a dependent variable Y_{it} that takes the value 1 if this is indeed the case (e.g., school of destination has less college-bound students than school of origin) and 0 otherwise:

$$Y_{it} = \beta_1 \left(G12_i \times TOP_t \right) + \beta_2 \left(G11_i \times TOP_t \right) + \boldsymbol{\gamma}' \mathbf{G}_i + \boldsymbol{\rho}' \mathbf{X}_i + \boldsymbol{\delta}' \mathbf{T} + \varepsilon_{it}, \quad (9)$$

where $\mathbf{G}_{\mathbf{i}}$ is a vector of grade dummies, $\mathbf{X}_{\mathbf{i}}$ is a vector of individual and school controls including ethnic group, economic disadvantage status, a dummy for grade not offered, and a constant; the other variables are defined as above. After running the regressions for the full sample, we estimate (9) separately for economically disadvantaged students and non-economically disadvantaged students (excluding economic disadvantage status as a control variable), and we also split the sample between within and across district moves.²⁵

Our hypothesis is that economically disadvantaged (i.e. poor) students have less incentive to strategically match into academically worse schools, both because they tend to be less likely to be among the top ten percent in a new school and because they may have less to gain from attending college, consistent with the theory presented above.

The results are presented in Tables 5 to 8. Table 5 shows that the probability of moving to a school with less college bound students than the previous school increases for movers in the 11th and 12th grades by 2.8 and 6.4 percentage points, respectively. This is amplified under the Top Ten Percent rule, by 2.5 and 3.1 percentage points for 11th and 12th grades, respectively. This corresponds to an increase of 4.7% and 5.9%, respectively. Note that this effect is driven mainly by non-poor students and by moves within districts. The coefficient estimates for economically disadvantaged students and moves across districts are positive, but not statistically significant. That is, under the Top Ten Percent rule relatively well-off students in higher grades were significantly

²⁵Numbers of observations differ across regressions depending on the dependent variable used, as not all variables are available for every school. For example, if students move from a school without 12th grade, the information on the share of college bound students is not available for that school, so that data for these students will be missing.

more likely to move to academically worse schools within the same district, unlike economically disadvantaged students.

Table 6 shows a similar pattern for SAT averages. Considering the transition from 11th to 12th grade, the probability of moving to a school with lower SAT average than the school of origin increases by 3.2 percentage points for noneconomically disadvantaged students. This corresponds to a 7.4% increase, given that the sample mean of the dependent variable is 0.431. The same effect is almost zero and not statistically significant for economically disadvantaged students. The effect is also much stronger for moves that occur within districts. While well-off students tend to move down in terms of the academic quality measured by average SAT score after the Top Ten Percent policy has been introduced, economically disadvantaged student tend to move up, if anything.

A similar picture emerges for TAAS pass rates in Table 7. Both poor and well-off students are more likely to choose a school with lower TAAS pass rate than their previous school within the same district after the introduction of the Top Ten Percent plan. The effect is much weaker for the economically disadvantaged students, however: their probability increases by 7.0% compared to a 14.3% increase for non-poor students in 12th grade, for instance.

Finally, students are typically less likely to move to schools with less Asian and White students in the 11th and 12th grades (i.e., regression coefficient estimates are negative). After the introduction of the Top Ten Percent Law, however, the likelihood of moving to a school with less Asian and White students increased for both grades. As before, this effect is mainly driven by non-poor students and by moves within districts. Under the Top Ten Percent Law non-poor students were 7.9% and 1.8% more likely to move to a school with less Asians and Whites in 11th and 12th grades, respectively.

Taken together, these results very strongly suggest that students who have moved schools in 11th and 12th grades were more likely to choose their new school strategically than students in lower grades after the introduction of the Top Ten Percent policy. In particular, the data are consistent with students targeting schools with a lower proportion of college bound students, lower SAT average, lower TAAS pass rates, and less Asian and White students, and with the fact that this is particularly pronounced for students who were not economically disadvantaged, who arguably tend to benefit more from university education and profit more from switching schools under the Top Ten Percent rule. Moreover, these strategic moves tend to occur within the school districts, as predicted by our theoretical model.

Robustness Check: Charter Schools

The results presented above indicate a decrease in within-county segregation that took place after the Top Ten Percent policy was introduced in 1998. An obvious concern is that other changes affecting the segregation at lower and higher grades differentially may have occurred at the same time. The only other major policy that could potentially have had a similar aggregate effect and occurred contemporaneously was the introduction of charter schools. Indeed, the first charter schools were starting in 1996, but the first wave of expansion began in 1998, coinciding with the introduction of the Top Ten Percent Law. Charter schools accept students from multiple school districts, and thus their proliferation could contribute to a decrease in segregation, mechanically through redistricting or by allowing students a possibility to strategically relocate.²⁶

To test for a possible effect of charter schools on segregation we use two different indicators for charter school prevalence. CHA_c is a dummy variable equal to 1 if there is a charter school in a county c in a given year. The variable $\% STUDCH_c$ is the percentage of students in a county c attending a charter school, which accounts for the intensity in charter school prevalence. We interact both variables with the indicator of the Top Ten Percent reform. A significant coefficient estimate in any of these interaction terms would indicate that charter schools were contributing to the within-county desegregation effect associated with the Top Ten Percent reform.

Table 9 presents the results of the within-county segregation regression. The coefficients for the Top Ten Percent policy are negative and significant as before. Moreover, the existence of charter schools does not seem to reduce within-county segregation, as the coefficient estimates are statistically indistinguishable from zero at conventional levels, both when one considers the presence of charter schools in a county and when one uses the percentage of students enrolled in charter schools.²⁷

²⁶In Texas there are two types of charter schools. The great majority of charter schools are open-enrollment. These are new schools that were assigned their own, new school district. Before 1998 there were only 12 open-enrollment charter schools, but during the years 1996 to 2007 there were 328 open-enrollment charter schools active at some time. The second type are charter campus high schools, which were created only in 2006, numbering 16 in 2007.

²⁷The reduced number of charter schools generates large standard errors associated with the estimates, but it also makes it unlikely that charter schools are responsible for the ob-

Robustness Check: Residential Segregation

Another potential concern is that the decrease in high school segregation might simply reflect residential desegregation, given that students usually attend schools in their district of residence. Using population data, we compute mutual information indices for the total population and for the group aged 15-19. The indices are calculated by comparing the composition of the population in a given county with the composition of the population of the state. For comparison we also plot the mutual information index for 9th to 12th grades with the county as the unit of observation. Figure 4 shows that, if anything, residential segregation has increased over the period 1990 to 1999²⁸ and cannot explain the decrease in segregation among the student population over the period.

4 Conclusion

Theory as well as evidence show that a policy intended to achieve integration at the college level may actually have achieved it in high schools. By basing admission on relative performance at high school, the Texas Top Ten Percent policy can induce students with high continuation value from attending college to match into low quality schools, thereby eliminating competition. When educational attainment at earlier stages correlate with ethnicity, top-n percent laws will achieve some integration in ethnic backgrounds in high schools. If students value high quality peers, strategic movement will be delayed as long as possible, however. Using enrollment data for all Texas high schools this is precisely what we find: after the policy was introduced segregation decreases, more so for higher grades.

A numerical simulation taking into account the actual school composition shows that in order to generate a drop of around 0.6 in the coefficient of segregation for the whole of Texas, it would suffice that at least around 1,500 students moved schools strategically (of about 20,000 students switching school each year in each grade). On the other hand, from 1998 onwards the number of residence preserving transfer students in grades 8-12 increased by an additional 3,000 students per year, see Figure 6. At least part of this movement could have led to successful crowding out of minority students in admission to the UT

served decrease in segregation.

²⁸Starting in 2000, individuals were able to choose more than one race/ethnicity. Therefore, we had to limit the analysis to the period 1990-1999.

flagship campuses at Austin and Dallas, as well as A & M: comparing actual admission numbers in 1999 and 2000 to expected admission numbers supposing that the minority share under the Top Ten Percent Law would equal the one under affirmative action up to 1996 produces a shortfall of around 650 minority students per vear (although this ignores both demographic trends, increasing the number of minority students in the population over time amplifying the effect, and possible high school composition effects, since top deciles of high quality high school tend to consist over proportionally of majority students, mitigating the effect of the Top Ten Percent policy). These numbers appear consistent since (i) some of the moving students are from minorities and (ii) the mere opportunity to increase one's probability to access a flagship campus may suffice to induce a move of schools, so that each successful strategic move resulting in crowding a minority student may be accompanied be several unsuccessful ones. For at the time a decision to move has to be made, it is likely that there is still some uncertainty about one's final performance that will be used to determine admission. Then one might contemplate a move of schools even if one is below the threshold for eligibility in both schools, as there is a chance to get over the bar, and a better chance in a worse school. By the same token, even someone fairly high up in the achievement distribution might move as insurance.

That is, top-N percent policies may be more effective for achieving broader social goals than was previously understood. This is relevant in particular as current court decisions (for instance, the Supreme Court ruling on Fisher vs. University of Texas in 2013) emphasize the use of markers other than race as a base for affirmative action. While in our case desegregation in high schools was limited to higher grades and our measured effect on segregation levels is small, our results suggest that a properly designed top-n policy could be used to achieve desegregation both in earlier and later stages. How incentives for students to acquire education at high school and in college can be affected optimally by such policies is an interesting question for future research.

The optimal design of a policy is beyond the scope of this paper, but we can provide some insights from our analysis. By the neutrality theorem, if the cost of moving is lower than the incremental value of being admitted at the university, the only effective way to increase diversity at the university level is to increase the capacity k of the university. This will have two effects; first it will decrease a^* and second it will reduce movement of students, hence integration

in high schools. There is therefore a substitution between integration at the college level and integration at the high school level when the regulator adjusts the capacity of the university for the same top-N percent policy.

If n increases, keeping the capacity k fixed, there is more movement of students among schools. Hence if the goal is also to increase diversity in high schools, n and k should covary positively; in fact n = k will maximize movement at the school level. However the benefit of reduced segregation at the school level should probably be contrasted with the increased moving costs borne by students who arbitrage against the top-n policy, suggestion that n < k may be optimal.

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Appendix 1: Proofs

Proof of Proposition 1

In the text we have established that any equilibrium must satisfy neutrality. To ensure this is not a vacuous result, the following provides a proof of existence. First, we establish that all equilibria are characterised by cutoff values \hat{a}_s in each school s that determine which students move out. Using this structure we then establish existence of an equilibrium satisfying neutrality.

Lemma 1. Any equilibrium has cutoff values \hat{a}_s , one for each school s such that:

- (i) a student in school s is admitted to the U if $a \ge \hat{a}_s$.
- (ii) Define $\underline{a} = \min_{s} \{\hat{a}_{s}\}$. Then, $\sigma(a, s, s) = 1$ if $a < \underline{a}$, or $a \ge \hat{a}_{s}$.
- (iii) $\sum_{s'\neq s} \sigma(a, s, s') = 1$ if $a \in [\underline{a}, \hat{a}_s)$.

Proof. (i) For a given strategy profile σ , there are new distributions $\hat{F}_s(a)$ and new masses \hat{q}_s of students. Given these, if a student with a in school s is admitted to the U (either through the top-n policy or through at-large admission) then a student with a' > a in school s is admitted to the U as well. Define by \hat{a}_s the minimal ability such that a student in school s is admitted to the U.

(ii) By construction a student $a < \underline{a}$ cannot be admitted in any school s', hence $\sigma(a, s, s) = 1$ is a strict best response for such students, because moving is costly. A student from school s with $a \ge \hat{a}_s$ can be admitted in her initial school; hence $\sigma(a, s, s) = 1$ is a strict best response for such a student since moving is costly.

(iii) Students from school s in $a \in [\underline{a}, \hat{a}_s)$ are not admitted if they stay and get admitted in another school if they move; since the cost of moving is smaller than the benefit of being admitted, they should move to another school with a cutoff less that their ability; hence $\sum_{s' \neq s} \sigma(a, s, s') = 1$.

Under neutrality only students with $a \ge a^*$ are admitted to the U. This implies that $\underline{a} = a^*$. Since any equilibrium satisfies neutrality, cutoffs lie in the interval $[a^*, \overline{a}]$.

Lemma 1 states that any equilibrium entails a set of thresholds $\{\hat{a}_1, \ldots, \hat{a}_S\}$. In each school, the set of students who attend the U are natives with attainment above the threshold plus any "immigrants"; other students may leave. By Lemma 1 and neutrality all students below a^* remain in their initial school.

Denote by \hat{a}_s^N the lowest achievement admitted in equilibrium via the top-n rule: $1 - \hat{F}_s(\hat{a}_s^N) = n$. In case n < k, some students are admitted at large. Let \hat{a}_s^L be the lowest such student from school s. In equilibrium, we must have $\hat{a}_s^L = \hat{a}_{s'}^L$ for any two schools s, s' admitting students at large; if instead $\hat{a}_s^L < \hat{a}_{s'}^L < \hat{a}_{s'}^N$, there are students in s who are admitted at large, while higher attainment students originally in s' (those in $(\hat{a}_s^L, \hat{a}_{s'}^L)$ could also have been admitted at large simply by staying put). Thus we write \hat{a}^L for the common at large threshold, and $\hat{a}_s = \min\{\hat{a}_s^N, \hat{a}^L\}$. Note that $\sum_s \hat{q}_s \hat{F}_s(\hat{a}_s^N) = \sum_s q_s F_s(\hat{a}_s^N) = 1 - n$ and $\sum_s q_s F_s(a^*) = 1 - k$.

Immigrants to s consist of those who, given the threshold in their own school s', find s to be the cheapest school to move to with a threshold below their attainment. Thus the measure of students who migrate from s' to s is $q_{s'}(F_{s'}(\hat{a}_{s'}) - F_{s'}(\hat{a}_{s}))$ if $\hat{a}_{s'} > \hat{a}_s$ and $s = \arg\min_{\{s''|\hat{a}_{s'}>\hat{a}_{s''}\}} c(s', s'')$ (since $c(s'', s) \neq c(s''s')$ for all s, s' the minimum is unique). Define $\mathbb{M}_{s'}^{s}(\hat{a}) = q_{s'}$ if $\hat{a}_{s'} > \hat{a}_s$ and $s = \arg\min_{\{s''|\hat{a}_{s'}>\hat{a}_{s''}\}} c(s', s'')$, and 0 otherwise.

The threshold to be admitted in equilibrium through the top-*n* rule, \hat{a}_s^N , has to satisfy:

$$q_{s}(1 - F_{s}(\hat{a}_{s}^{N})) + \sum_{s'} \mathbb{M}_{s'}^{s}(\hat{a})(F_{s'}(\min\{\hat{a}_{s'}^{N}, \hat{a}^{L}\}) - F_{s'}(\hat{a}_{s}^{N}))$$

$$= nq_{s}(1 - F_{s}(\hat{a}_{s}^{N})) + n\sum_{s'} [\mathbb{M}_{s'}^{s}(\hat{a})(F_{s'}(\min\{\hat{a}_{s'}^{N}, \hat{a}^{L}\}) - F_{s'}(\hat{a}_{s}^{N}))]$$

$$+ nq_{s}\max\{F_{s}(\hat{a}_{s}^{N}) - F_{s}(\hat{a}^{L}), 0\} + nq_{s}F_{s}(a^{*}).$$

That is, in each school s the natives above the top-n threshold plus the immigrants (who only move in if they are admitted through the top-n rule) constitute N percent of the equilibrium population, which consists of natives and immigrants admitted through the top-n rule, natives admitted at large and natives who are not admitted to the U. The last two terms on the right hand side denote those admitted at large, if any, and those who are not admitted at all. Letting $\omega_s \equiv \frac{n}{1-n}q_sF_s(a^*)$ and $\hat{a} = (\hat{a}_1^N, \dots, \hat{a}_S^N, \hat{a}^L)$ we can rewrite this condition as the requirement that the "excess demand" in school s be zero:

$$z_s(\hat{a}) \equiv q_s(1 - F_s(\hat{a}_s^N)) + \sum_{s'} [\mathbb{M}_{s'}^s(\hat{a})(F_{s'}(\min\{\hat{a}_{s'}^N, \hat{a}^L\}) - F_{s'}(\hat{a}_s^N))] - \frac{n}{1 - n} q_s \max\{F_s(\hat{a}_s^N) - F_s(\hat{a}^L), 0\} - \omega_s = 0.$$

The common threshold for at-large admission \hat{a}^L has to satisfy the capacity constraint; thus

$$z_{S+1}(\hat{a}) \equiv \sum_{s} q_s \max\{F_s(\hat{a}_s^N) - F_s(\hat{a}^L), 0\} - (k-n) = 0.$$

Let $a = (a_1, \ldots, a_{S+1}) \in [a^*, \overline{a}]^{S+1}$. Note that continuity of the c.d.f's $\{F_s\}$ implies $z(a) = (z_1(a), \ldots, z_{S+1}(a))$ is continuous. Define a map $B : [a^*, \overline{a}]^{S+1} \to [a^*, \overline{a}]^{S+1}$ by

$$B_{s}(a) = \max[\min(z_{s}(a) + a_{s}, \overline{a}), a^{*}] \text{ for } s = 1, \dots, S \text{ and}$$
$$B_{S+1}(a) = \max[\min(z_{S+1}(a) + a_{S+1}, \overline{a}), a^{*}].$$

 $B(\cdot)$ is continuous and therefore by Brouwer's theorem has a fixed point $\hat{a} = (\hat{a}_1^N, \ldots, \hat{a}_S^N, \hat{a}^L) \in [a^*, \overline{a}]^{S+1}$. We claim that \hat{a} is an equilibrium for our model, i.e., that $z(\hat{a}) = 0$.

Start with $z_{S+1}(\hat{a})$. First, $\hat{a}^L \neq \overline{a}$ for k > n; if instead $\hat{a}^L = \overline{a}$, we would have $B_{S+1}(\hat{a}) = \max\{\overline{a} - (k - n), a^*\} < \overline{a}$, a contradiction. But for k = n, $z_{S+1}(\hat{a}) = 0$ when $\hat{a}^L = \overline{a}$.

Second, if $\hat{a}^L \in (a^*, \overline{a})$, then $z_{S+1}(\hat{a}) + \hat{a}^L \in (a^*, \overline{a})$ as well; assuming otherwise leads to a contradiction: if $z_{S+1}(\hat{a}) + \hat{a}^L \geq \overline{a}$ then $B_{S+1}(\hat{a}) = \overline{a} \neq a^L$. Similarly, supposing that $z_{S+1}(\hat{a}) + a^* \leq a^*$ would imply $B_{S+1}(\hat{a}) = a^* \neq a^L$. Therefore $z_{S+1}(\hat{a}) = 0$, as desired.

Third, if $\hat{a}^{L} = a^{*}$, then $z_{S+1}(\hat{a}) = 0$, because $\max\{F_{s}(\hat{a}_{s}^{N}) - F_{s}(a^{*}), 0\} = F_{s}(\hat{a}_{s}^{N}) - F_{s}(\hat{a}^{*})$, so $\sum_{s} q_{s}(F_{s}(\hat{a}_{s}^{N}) - F_{s}(\hat{a}^{*})) = k - n$ by definition (since $\sum_{s} q_{s}F_{s}(a^{*}) = 1 - k$ and $1 - n = \sum_{s} \hat{q}_{s}\hat{F}_{s}(\hat{a}_{s}^{N}) = \sum_{s} q_{s}F_{s}(\hat{a}_{s}^{N})$).

Hence, for any fixed point \hat{a} we have that $z_{S+1}(\hat{a}) = 0$.

Turning to $z_s(\hat{a}^N)$, note first that $\hat{a}_s^N \neq \overline{a}$ for any s; if instead $\hat{a}_s^N = \overline{a}$, we would have $B_s(\hat{a}) = \max\{\overline{a} - \frac{n}{1-n}q_s(1 - F_s(\hat{a}^L)) - \omega_s, a^*\} < \overline{a}$, a contradiction.

Second, if $\hat{a}_s^N \in (a^*, \overline{a})$, then, to the case of \hat{a}^L above, $B_s(\hat{a}) = z_s(\hat{a}) + \hat{a}_s^N$, which implies $z_s(\hat{a}) = 0$.

Third, if $\hat{a}_s^N = a^*$, then $z_s(\hat{a}) + a^* < \overline{a}$, else $B_s(\hat{a}) = \overline{a} > a^*$, a contradiction. Thus if $z_s(\hat{a}) + a^* \ge a^*$, then $B_s(\hat{a}) = z_s(\hat{a}) + a^* = a^*$, so $z_s(\hat{a}) = 0$, as desired. The final possibility is that $z_s(\hat{a}) + a^* < a^*$, but this implies $z_s(\hat{a}) < 0$, which we now show leads to a contradiction.

We have shown $z_s(\hat{a}) \leq 0$ for all $s = 1, \ldots, S$; if $z_s(\hat{a}) < 0$ for some s, which can only happen if $\hat{a}_s = a^*$, then $\sum_{s \leq S} z_s(\hat{a}) < 0$. Denote by $M_s = \sum_{s'} [\mathbb{M}_{s'}^s(\hat{a})(F_{s'}(\min\{\hat{a}_{s'}^N, \hat{a}^L\}) - F_{s'}(a^*))]$ the mass of immigrants into s. The mass of "emigrants" $X_{s'}$ from s' is $q_{s'}(F_{s'}(\min\{\hat{a}_{s'}^N, \hat{a}^L\}) - F_{s'}(a^*))$ (recall we are supposing $\hat{a}_s^N = a^*$). Since the system is closed, $\sum_s M_s = \sum_s X_s$. Then

$$\begin{split} 0 &> \sum_{s \leq S} z_s(\hat{a}) = \sum_{s \leq S} [q_s(1 - F_s(\hat{a}_s^N)) + M_s - \frac{n}{1 - n} q_s \left(\max\{F_s(\hat{a}_s^N) - F_s(\hat{a}^L), 0\} + F_s(a^*) \right)] \\ &= \sum_{s \leq S} [q_s(1 - F_s(\hat{a}_s^N)) + X_s - \frac{n}{1 - n} q_s \left(\max\{F_s(\hat{a}_s^N) - F_s(\hat{a}^L), 0\} + F_s(a^*) \right)] \\ &= \sum_{s \leq S} [q_s(1 - F_s(\hat{a}_s^N)) + q_s(F_s(\min\{\hat{a}_s^N, \hat{a}^L\}) - F_s(a^*)) \\ &- \frac{n}{1 - n} q_s \max\{F_s(\hat{a}_s^N) - F_s(\hat{a}^L), 0\} - \frac{n}{1 - n} q_s F_s(a^*)] \\ &= \sum_{s \leq S} q_s \left[1 - \frac{1}{1 - n} F_s(a^*) \right] - \sum_{s:\hat{a}_s^N \geq \hat{a}^L} q_s \frac{F_s(\hat{a}_s^N) - F_s(\hat{a}^L)}{1 - n} \end{split}$$

Since $z_{S+1}(\hat{a})$ can be written as $\sum_{s:\hat{a}_s^N \ge \hat{a}^L} q_s [F_s(\hat{a}_s^N) - F_s(\hat{a}^L)] - (k-n)$, and we have established that $z_{S+1}(\hat{a}) = 0$, using $\sum_s q_s F_s(a^*) = 1 - k$, the last line vanishes, and we obtain $0 > \sum_{s \le S} z_s(\hat{a}) = 0$, a contradiction. We conclude that $z_s(\hat{a}) = 0$.

Proof of Proposition 2

Let us denote by $x_{s,s'}$ the mass of students from school s who move to school s', $m_{s,s'}$ the mass of students entering school s from school s'; x_s the mass of students leaving school s; m_s the mass of students entering school s. Note the importance of our assumption that moving decisions depends only on ability: it implies that the ratios of the masses of students from different groups in school s' entering school s from school s' are equal to the ratios of their initial proportions in school s'. That is, the proportion of group g among students moving to s from s' is $p_{s'}^g$ and among students who stay at s by p_s^g .

The flows must balance, that is

$$m_s = \sum_{s'} x_{s',s} \quad \text{and} \quad \sum_s x_s = \sum_s m_s. \tag{10}$$

In equilibrium, accounting for the equilibrium movement of students, we have new proportions of groups within school s:

$$\hat{p}_{s}^{g} = \frac{(q_{s} - x_{s})p_{s}^{g} + \sum_{s'} m_{s,s'} p_{s'}^{g}}{q_{s} - x_{s} + m_{s}}.$$
(11)

where $q_s - x_s + m_s$ is the equilibrium mass of students in school s. The new segregation index is

$$\hat{\mathcal{I}} = A_1(p) - A_2(p) \sum_s (q_s - x_s + m_s) H(\hat{p}_s).$$

Hence the change in segregation indexes $\hat{\mathcal{I}} - \mathcal{I}$ is proportional to

$$\sum_{s} (q_s H(p_s) - (q_s - x_s + m_s)H(\hat{p}_s))$$

The new proportion of students of background g can be written as,

$$\hat{p}_{s}^{g} = \frac{q_{s} - x_{s}}{q_{s} - x_{s} + m_{s}} p_{s}^{g} + \sum_{s'} \frac{m_{s,s'}}{q_{s} - x_{s} + m_{s}} p_{s'}^{g},$$

concavity of H(p) and the fact that the weights are independent of g imply that

$$H(\hat{p}_s) \ge \frac{q_s - x_s}{q_s - x_s + m_s} H(p_s) + \sum_{s'} \frac{m_{s,s'}}{q_s - x_s + m_s} H(p_{s'}).$$

where the inequality is strict if $m_s \neq 0$ since $p_s \neq p_{s'}$. Hence, we have

$$\begin{aligned} \hat{\mathcal{I}} - \mathcal{I} &< \sum_{s} \left(x_{s} H(p_{s}) - \sum_{s'} m_{s,s'} H(p_{s'}) \right) \\ &= \sum_{s} x_{s} H(p_{s}) - \sum_{s} \sum_{s'} m_{s,s'} H(p_{s'}) \\ &= \sum_{s} x_{s} H(p_{s}) - \sum_{s'} \left(\sum_{s} m_{s,s'} \right) H(p_{s'}) \\ &= 0 \end{aligned}$$

where the strict inequality is due to the assumption that a positive mass of students move (hence $m_s \neq 0$ for some s), and that $p_s \neq p_{s'}$ for all schools s, s'. The last equality follows (10). Hence we have $\hat{\mathcal{I}} - \mathcal{I} < 0$ as claimed. \Box

Proof of Proposition 3

As shown in the proof of Proposition 1, equilibrium is characterized by a set of thresholds $\{\hat{a}_1^N, \ldots, \hat{a}_s^N, \hat{a}^L\}$. Students in school *s* with $a \ge \hat{a}_s^N$ are admitted through the top-*n* policy; if n < k there will be students admitted at large with achievement $a \in [\hat{a}^L, \hat{a}_s^N)$. Hence, the cutoff for admission to the *U* in school *s* is $\hat{a}_s = \min\{\hat{a}^L, \hat{a}_s^N\}$ and cutoffs are at most equal to \hat{a}^L .

Note that all schools s with cutoff $\hat{a}_s = \hat{a}^L$ cannot have students moving in: any student who would be admitted to the U through s would also have been admitted in their initial school and, because of the moving cost, would have strictly preferred to stay there. The population of students admitted from such a school is therefore $q_s(1 - F_s(\hat{a}^L))$, and its equilibrium population is $q_s(1 - F_s(\hat{a}^L)) + q_s F_s(a^*)$, since all students in $[a^*, \hat{a}^L]$ have incentives to move elsewhere.

For schools that have students admitted at large, with $\hat{a}_s^N \geq \hat{a}^L$, it must be that

$$\frac{q_s(1 - F_s(\hat{a}^L))}{q_s(1 - F_s(\hat{a}^L) + q_s F_s(a^*))} \ge n,$$

i.e., a student at the at-large threshold must be outside the top N percent.

Denote the set of schools that admit students at large by L; given \hat{a}^L a school $s \in L$ if $1 - F_s(\hat{a}^L) \geq \frac{n}{1-n}F_s(a^*)$. Note that $s \in L$ implies that $s' \in L$ if s' < s, since by hypothesis $1 - F_{s'}(\hat{a}^L) > 1 - F_s(\hat{a}^L) \geq \frac{n}{1-n}F_s(a^*)$. Therefore there is an index \bar{s} such that $s \in L$ if $s \leq \bar{s}$, and all $s \leq \bar{s}$ have $\hat{a}_s = \hat{a}^L$.

The complementary set T of schools $s > \bar{s}$ have thresholds $\hat{a}_s = \hat{a}_s^N < \hat{a}^L$ and admit students only through the top-n policy. Denote by [1] the school in T that has the highest equilibrium threshold, and assume it is not school $\bar{s} + 1$. The only students who would like to move to school [1] are students $a \ge \hat{a}_{[1]}$, but below the cutoff in their own school; the only candidates are students from schools in L. However, since $[1] > \bar{s} + 1$, students in schools in L with ability in $[\hat{a}_{[1]}, \hat{a}^L)$ prefer to move to school $\bar{s} + 1$, since this also ensures admission but does so at lower cost. Hence, [1] receives no new students, while school $\bar{s} + 1$ may have new students; denote them by $m_{\bar{s}+1}$. Then

$$\frac{1 - F_{\bar{s}+1}(\hat{a}_{\bar{s}+1}) + m_{\bar{s}+1}}{1 - F_{\bar{s}+1}(\hat{a}_{\bar{s}+1}) + m_{\bar{s}+1} + F_{\bar{s}+1}(a^*)} = \frac{1 - F_{[1]}(\hat{a}_{[1]})}{1 - F_{[1]}(\hat{a}_{[1]}) + F_{[1]}(a^*)} = n$$

Cross multiply and cancel terms to get to get

$$F_{[1]}(a^*)(1 - F_{\bar{s}+1}(\hat{a}_{\bar{s}+1})) + F_{[1]}(a^*)m_{\bar{s}+1} = F_{\bar{s}+1}(a^*)(1 - F_{[1]}(\hat{a}_{[1]}))$$

$$\frac{1 - F_{\bar{s}+1}(\hat{a}_{\bar{s}+1}) + m_{\bar{s}+1}}{1 - F_{[1]}(\hat{a}_{[1]})} = \frac{F_{\bar{s}+1}(a^*)}{F_{[1]}(a^*)}$$

The right hand side is less than 1 by FOSD. The left side weakly exceeds $\frac{1-F_{\bar{s}+1}(\hat{a}_{\bar{s}+1})}{1-F_{[1]}(a_{[1]})}$, since $m_{\bar{s}+1} \geq 0$. Thus, $\frac{1-F_{\bar{s}+1}(\hat{a}_{\bar{s}+1})}{1-F_{[1]}(a_{[1]})} < 1$, implying

$$F_{\bar{s}+1}(\hat{a}_{\bar{s}+1}) > F_{[1]}(\hat{a}_{[1]})$$

But $\hat{a}_{[1]} > \hat{a}_{\bar{s}+1}$ implies

$$F_{\bar{s}+1}(\hat{a}_{[1]}) > F_{\bar{s}+1}(\hat{a}_{\bar{s}+1}) > F_{[1]}(\hat{a}_{[1]}),$$

which contradicts FOSD.

The above argument can be repeated for schools greater than $\bar{s} + 1$: supposing that school $[2] \in T$ is not school $\bar{s} + 2$ leads to a similar contradiction, and so on through school S.

Monotonicity in \hat{a}_s and students' preference for moving to the closest school proves (ii).

For uniqueness, start with a^L and derive then cutoffs \hat{a}_s for $s > \bar{s}$ constructively. From the proof of Proposition 1 we know that the equilibrium cutoff a^L satisfies

$$\sum_{s \in L} q_s (F_s(\hat{a}_s^N) - F_s(\hat{a}^L)) = k - n.$$
(12)

The thresholds for admission through the top-*n* rule in schools $s \in L$ are:

$$\frac{q_s(1 - F_s(\hat{a}_s^N))}{q_s(1 - F_s(\hat{a}^L) + q_sF_s(a^*))} = n.$$

Therefore $F_s(\hat{a}_s^N) = 1 - n(1 - F_s(\hat{a}^L) - F_s(a^*))$ and (12) becomes

$$\sum_{L} q_s((1-n)(1-F_s(\hat{a}^L) - nF_s(a^*)) = k - n,$$
(13)

The LHS is decreasing in \hat{a}^L because both the set $L = \{s : 1 - F_s(\hat{a}^L) \geq \frac{n}{1-n}F_s(a^*)\}$ is non-increasing and the summands are positive and decreasing in \hat{a}^L . For $\hat{a}^L = \hat{a}^*$, the LHS is strictly greater than k-n since there is at least one school s with $1 - F_s(a^*) < n$. On the other hand, at $\hat{a}^L = \overline{a}$ the set L is empty so the LHS is zero. Hence, there is a unique \hat{a}^L solving (13) whenever n < k (if n = k there is a continuum of solutions $[\hat{a}_1^N, \overline{a}]$, where $1 - F_1(\hat{a}_1^N) = \frac{n}{1-n}F_1(a^*)$;

or

set $\hat{a}^L = \hat{a}_1^N$ in this case). Given the solution \hat{a}^L , the set L is defined (possibly comprising only school 1), and $\hat{a}_s = \hat{a}^L$ for $s \in L$.

For $s \in T$, admission is through the top-*n* rule so that cutoffs are defined by:

$$\frac{q_s(1 - F_s(\hat{a}_s)) + m_s}{q_s(1 - F_s(\hat{a}_s)) + m_s + q_s F_s(a^*)} = n$$

which is equivalent to

$$1 - F_s(\hat{a}_s) + \frac{m_s}{q_s} = \frac{n}{1 - n} F_s(a^*).$$
(14)

Proceeding recursively, given \hat{a}_{s-1} , note that $m_s = \sum_{s' \leq s-1} q_{s'} [F_{s'}(\hat{a}_{s-1}) - F_{s'}(\hat{a}_s)]$ from part (ii), and (14) can therefore be written

$$1 - \sum_{s' \le s} \frac{q_{s'}}{q_s} F_{s'}(\hat{a}_s) + \sum_{s' \le s-1} \frac{q_{s'}}{q_s} F_{s'}(\hat{a}_{s-1}) = \frac{n}{1-n} F_s(a^*).$$

Since the LHS is strictly decreasing in \hat{a}_s , the solution \hat{a}_s is unique given \hat{a}_{s-1} , which establishes uniqueness of the sequence $\{\hat{a}_s\}$.

Appendix 2: Tables and Figures

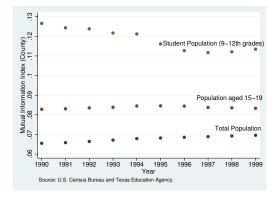


Figure 4: Residential versus School System Segregation

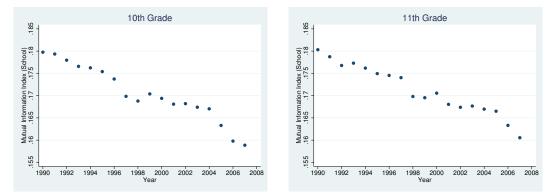


Figure 5: Time series of the mutual information index for 10th and 11th grades

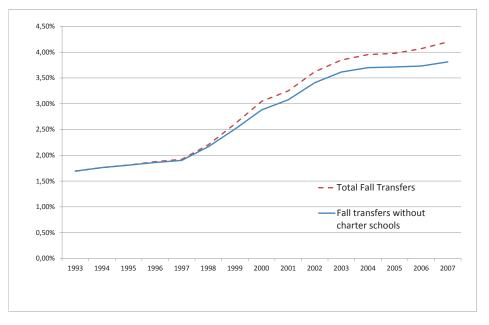


Figure 6: Share of students in 8th to 12th grades with a district of enrollment different from district of residence, 1993-2007. The dashed line corresponds to the total number, while the solid corresponds to all students except for those attending charter schools. *Source*: TEA.

	Befor	e (1994	-1996)	After	r (1998	-2000)
	Mean	Std.	\mathbf{N}	Mean	Std.	\mathbf{N}
		Dev.			Dev.	
A. School Level Data						
A.1. Local segregation index with	th respect	t to regio	on			
9th grade	0.134	0.132	4,563	0.150	0.151	$5,\!000$
10th grade	0.134	0.142	4,253	0.149	0.160	$4,\!633$
11th grade	0.128	0.139	4,103	0.140	0.153	4,411
12th grade	0.127	0.138	4,086	0.136	0.150	4,335
9th to 12th grades	0.131	0.138	$17,\!005$	0.144	0.154	$18,\!379$
9th and 12th grades	0.130	0.135	8,649	0.144	0.151	$9,\!335$
B. County Level Data						
B.1. Within-county segregation	index					
12th - 9th grade	0.000	0.012	756	-0.001	0.016	756
B.2. Charter schools						
Presence	0.008	0.089	756	0.095	0.294	756
Percentage of students	0.000	0.000	756	0.002	0.011	756
C. Individual Level Data						
C.1. Probability of moving to a	school wi	th th	an school o	f origin		
less college bound students	0.514	0.500	72,749	0.546	0.498	78,289
lower SAT average	0.377	0.485	64,714	0.491	0.500	67,097
lower TAAS pass rate	0.417	0.493	97,968	0.357	0.479	112,38
less Asian and White students	0.592	0.492	679,962	0.585	0.493	784,26

 Table 1: Descriptive Statistics

Notes: All the differences between the before and after means are statistically significant at the 1% level, apart from the within-county segregation index that is statistically significant at the 5% level.

Dep. Var.: M_{ys}^r : Loca	al segregati	on index wi	th respect	to <i>region</i>
	(1)	(2)	(3)	(4)
$G12 \times TOP$	-0.004*	-0.004*	-0.004*	-0.004*
	(0.002)	(0.002)	(0.002)	(0.002)
$G11 \times TOP$			-0.004*	-0.004*
			(0.002)	(0.002)
$G10 \times TOP$			-0.003	-0.003
			(0.002)	(0.002)
Constant	0.135^{***}	0.135^{***}	0.136^{***}	0.136^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Fixed effects:				
School-grade	yes	yes	yes	yes
region-year	no	yes	no	yes
Year	yes	no	yes	no
Mean of Dep. Var.	0.137	0.137	0.138	0.138
Observations	$17,\!984$	$17,\!984$	$35,\!384$	$35,\!384$
School-grade	3,722	3,722	$7,\!274$	$7,\!274$
r-squared (within)	0.002	0.011	0.001	0.008

Table 2: Fixed effect estimation, 9th to 12th grades, school years from 1994 to 2000 (excl. 1997)

Notes: * significant at 10%, ** significant at 5%, *** significant at 1%. robust standard errors in parentheses. The masked observations were converted to zero. The variable $Gy \times TOP = 1$ if $y = \{10, 11, 12\}$ and $t \ge 1997$ and 0 otherwise.

Dep. Var.: M_{ys}^r : Loca	al segregati	on index wi	th respect	to <i>region</i>
	(1)	(2)	(3)	(4)
G12 imes T93	0.002	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
$G11 \times T93$			0.001	0.001
			(0.002)	(0.002)
$G10 \times T93$			0.001	0.001
			(0.002)	(0.002)
Constant	0.125^{***}	0.126^{***}	0.127***	0.127***
	(0.001)	(0.001)	(0.001)	(0.001)
Fixed effects:				
School-grade	yes	yes	yes	yes
region-year	no	yes	no	yes
Year	yes	no	yes	no
Mean of Dep. Var.	0.127	0.127	0.128	0.128
Observations	$16,\!435$	$16,\!435$	$32,\!441$	32,441
School-grade	$3,\!301$	$3,\!301$	$6,\!454$	$6,\!454$
r-squared (within)	0.001	0.012	0.000	0.008

Table 3: Placebo analysis: Fixed effect estimation, 9th to 12th grades, school years from 1990 to 1996 (excl. 1993)

Notes: * significant at 10%, ** significant at 5%, *** significant at 1%. robust standard errors in parentheses. The masked observations were converted to zero. The variable $Gy \times T93 = 1$ if $y = \{10, 11, 12\}$ and $t \ge 1993$ and 0 otherwise.

Dep. Var.:	Within-cou	nty segregation
	W^c_{12t}	$-W^{c}_{9(t-3)}$
	(1)	(2)
ТОР	-0.001**	-0.004**
	(0.001)	(0.002)
Constant	0.000	-1.020
	(0.000)	(0.778)
County fixed effect	yes	yes
Linear time trend	no	yes
Mean of Dep. Var.	-0.001	-0.001
Observations	1,512	1,512
r-squared (within)	0.004	0.006
Number of school districts	252	252

Table 4: Fixed effect estimation, 12th-9th grade, school years from 1994 to 2000

Notes: * significant at 10%, ** significant at 5%, *** significant at 1%. Standard errors in parentheses. The masked observations were converted to zero, but results are similar using the other unmasking strategies. The variable TOP = 1 if $t \ge 1997$ and 0 otherwise.

		Full Sample			Within Districts	S		Across Districts	
		Student from Economic	n Economic		Student from Economic	Economic		Student from Economic	Economic
		Disadvantaged Status	ged Status		Disadvantaged Status	ed Status		Disadvantaged Status	d Status
	All Students	No	\mathbf{Yes}	All Students	No	Yes	All Students	N_{O}	Yes
	(1)	(2)	(3)	(4)	(5)	(9)	(2)	(8)	(6)
G11	0.028^{***}	0.021^{***}	0.044^{***}	0.079^{***}	0.067^{***}	0.100^{***}	0.008	0.005	0.014
	(0.004)	(0.005)	(0.008)	(0.009)	(0.011)	(0.014)	(0.005)	(0.006)	(0.010)
G12	0.064^{***}	0.060^{***}	0.073^{***}	0.148^{***}	0.147^{***}	0.148^{***}	0.024^{***}	0.023^{***}	0.021^{*}
	(0.005)	(0.006)	(0.010)	(0.009)	(0.011)	(0.016)	(0.006)	(0.006)	(0.012)
$G11 \times TOP$	0.025^{***}	0.026^{***}	0.015	0.074^{***}	0.095^{***}	0.030	0.004	0.003	0.005
	(0.006)	(0.007)	(0.011)	(0.012)	(0.015)	(0.019)	(0.007)	(0.008)	(0.013)
G12 imes TOP	0.031^{***}	0.039^{***}	0.004	0.067^{***}	0.093^{***}	0.015	0.009	0.013	0.002
	(0.007)	(0.008)	(0.013)	(0.012)	(0.015)	(0.021)	(0.008)	(0.00)	(0.016)
Constant	0.454^{***}	0.452^{***}	0.467^{***}	0.462^{***}	0.456^{***}	0.467^{***}	0.446^{***}	0.445^{***}	0.461^{***}
	(0.005)	(0.006)	(0.008)	(0.009)	(0.011)	(0.014)	(0.006)	(0.001)	(0.011)
Mean Dep. Var.	0.530	0.527	0.539	0.611	0.624	0.589	0.502	0.499	0.512
Observations	151,038	106,756	44,282	39, 341	24,085	$15,\!256$	111,697	82,671	29,026
R-squared	0.007	0.007	0.011	0.036	0.043	0.030	0.003	0.003	0.004

Table 5: Linear Probability Model, 9th to 12th grades, school years from 1994 to 2000 (excl. 1997)

		Full Sample			Within Districts	S	•	Across Districts	70
		Student from Economic	n Economic		Student from Economic	Economic		Student from Economic	Economic
	All Students (1)	Disarvanuaged Statuts No Yes (2) (3)	ged Diatus Yes (3)	All Students (4)	Disadvalluaged Jualus No Yes (5) (6)	Yes (6)	All Students (7)	Disativalluaged Statuls No Yes (8) (9)	Yes (9)
G11	0.016^{***}	0.010^{**}	0.028^{***}	0.023^{***}	0.029^{***}	0.008	0.012^{***}	0.004	0.038^{***}
	(0.004)	(0.005)	(0.008)	(0.008)	(0.011)	(0.014)	(0.005)	(0.005)	(0.010)
G12	0.020^{***}	0.014^{***}	0.035^{***}	0.026^{**}	0.022^{*}	0.027	0.019^{***}	0.013^{**}	0.040^{***}
	(0.005)	(0.005)	(0.010)	(0.010)	(0.013)	(0.017)	(0.005)	(0.006)	(0.012)
$G11 \times TOP$	-0.013^{**}	-0.006	-0.028**	-0.048***	-0.046^{***}	-0.034*	0.000	0.008	-0.024^{*}
	(0.006)	(0.007)	(0.011)	(0.012)	(0.015)	(0.019)	(0.007)	(0.008)	(0.014)
G12 imes TOP	0.023^{***}	0.032^{***}	0.004	0.066^{***}	0.091^{***}	0.037	0.010	0.017*	-0.011
	(0.007)	(0.008)	(0.014)	(0.015)	(0.019)	(0.024)	(0.008)	(0.00)	(0.017)
Constant	0.501^{***}	0.508^{***}	0.507^{***}	0.552^{***}	0.540^{***}	0.578^{***}	0.475^{***}	0.491^{***}	0.457^{***}
	(0.005)	(0.006)	(0.00)	(0.009)	(0.012)	(0.014)	(0.006)	(0.007)	(0.011)
Mean Dep. Var.	0.435	0.431	0.446	0.488	0.499	0.471	0.418	0.413	0.433
Observations	131,811	94,259	37,552	32,072	19,735	12,337	99,739	74,524	25,215
R-squared	0.082	0.087	0.068	0.117	0.136	0.088	0.068	0.071	0.062

Table 6: Linear Probability Model, 9th to 12th grades, school years from 1994 to 2000 (excl. 1997)

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		Full Sample			Within Districts	Ñ	·	Across Districts	
		Student from Economic Disadvantaged Status	n Economic red Status		Student from Economic Disadvantaged Status	Economic ed Status		Student from Economic Disadvantaged Status	Economic 3d Status
	All Students (1)	No (2)	Yes (3)	All Students (4)	No (5)	$\mathbf{Y}_{\mathbf{es}}$ (6)	All Students (7)	No (8)	Yes (9)
G11	-0.015***	-0.030***	0.038^{***}	-0.044***	-0.071***	0.072^{***}	0.007	0.001	0.025^{**}
(412)	(0.003) 0.057***	(0.004) 0.054***	(0.007)	(0.005) 0 130***	(0.006) 0 138***	(0.011) 0 111***	(0.005) 0.036***	(0.005) 0.035^{***}	(0.010) 0 0.34**
	(0.004)	(0.005)	(0.00)	(0.008)	(0.010)	(0.014)	(0.005)	(0.006)	(0.012)
G11 x TOP	0.065^{***}	0.071^{***}	0.036^{***}	0.137^{***}	0.151^{***}	0.066^{***}	0.004	0.010	-0.010
	(0.005)	(0.005)	(0.00)	(0.007)	(0.008)	(0.014)	(0.006)	(0.007)	(0.013)
$G12 \times TOP$	0.047^{***}	0.055^{***}	0.027^{**}	0.104^{***}	0.120^{***}	0.074^{***}	-0.000	0.007	-0.016
	(0.006)	(0.007)	(0.012)	(0.011)	(0.013)	(0.019)	(0.008)	(0.00)	(0.016)
Constant	0.488^{***}	0.503^{***}	0.447^{***}	0.513^{***}	0.550^{***}	0.413^{***}	0.465^{***}	0.468^{***}	0.465^{***}
	(0.004)	(0.005)	(0.007)	(0.006)	(0.007)	(0.010)	(0.006)	(0.007)	(0.010)
Mean Dep. Var.	0.385	0.384	0.388	0.358	0.354	0.365	0.405	0.404	0.410
Observations	210, 349	148,682	61,667	90,769	60,242	30,527	119,580	88,440	31,140
R-squared	0.037	0.039	0.038	0.084	0.094	0.093	0.016	0.018	0.012

Table 7: Linear Probability Model. 9th to 12th grades. school vears from 1994 to 2000 (excl. 1997)

		Full Sample			Within Districts	S		Across Districts	ζ Ω
		Student from Economic Disadvanta and Status	a Economic		Student from Economic Disadvantaged Status	Economic ed Status		Student from Economic Disadvantaged Status	Economic ed Status
	All Students (1)	No (2)	Yes (3)	All Students (4)	No (5)	Yes (6)	All Students (7)	No (8)	www.res
G11	-0.076***	-0.084**	-0.020***	-0.118***	-0.135***	-0.042***	0.004	0.001	0.019^{**}
	(0.003)	(0.003)	(0.006)	(0.004)	(0.005)	(0.010)	(0.004)	(0.005)	(0.000)
G12	-0.049^{***}	-0.050***	0.004	-0.105^{***}	-0.130^{***}	-0.012	0.031^{***}	0.032^{***}	0.035^{***}
	(0.004)	(0.004)	(0.008)	(0.007)	(0.008)	(0.012)	(0.005)	(0.006)	(0.011)
$G11 \times TOP$	0.055^{***}	0.049^{***}	0.045^{***}	0.090^{***}	0.084^{***}	0.084^{***}	0.006	0.008	-0.004
	(0.004)	(0.004)	(0.008)	(0.005)	(0.006)	(0.011)	(0.005)	(0.006)	(0.011)
G12 imes TOP	0.015^{***}	0.011^{*}	-0.003	-0.002	0.006	-0.039^{**}	0.014^{**}	0.011	0.019
	(0.005)	(0.006)	(0.010)	(0.008)	(0.010)	(0.015)	(0.007)	(0.008)	(0.015)
Constant	0.503^{***}	0.453^{***}	0.521^{***}	0.569^{***}	0.518^{***}	0.562^{***}	0.451^{***}	0.448^{***}	0.473^{***}
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.004)	(0.004)	(0.005)	(0.007)
Mean Dep. Var.	0.588	0.623	0.517	0.613	0.655	0.526	0.445	0.442	0.452
Observations	1,464,216	987,561	476,655	1,251,428	836,697	414, 731	212,788	150,864	61,924
R-squared	0.025	0.022	0.008	0.026	0.014	0.011	0.002	0.002	0.002

Table 8: Linear Probability Model. 9th to 12th grades. school years from 1994 to 2000 (excl. 1997)

Dep. var.:	Within-co	ounty segrega	tion $W_{t12}^c - W_{(t-3)9}^c$
_	(1)	(2)	(3)
TOP	-0.004**	-0.004**	-0.004**
	(0.002)	(0.002)	(0.002)
CHA		-0.000	
		(0.006)	
TOP * CHA		0.002	
		(0.006)	
% STUDCH			-0.126
			(1.342)
TOP*%STUDCH			0.234
			(1.339)
Constant	-1.020	-0.982	-0.889
	(0.773)	(0.780)	(0.778)
County fixed effect	yes	yes	yes
Linear time trend	yes	yes	yes
Mean of Dep. Var.	-0.001	-0.001	-0.001
Observations	1,512	1,512	1,512
r-squared (within)	0.034	0.034	0.038
Counties	252	252	252

Table 9: Fixed effect estimation, 12th-9th grade, school years 1994 to 2000

Notes: * significant at 10%, ** significant at 5%, *** significant at 1%. robust standard errors in parentheses. The masked observations were converted to zero, but results are similar using the other unmasking strategies. The variable TOP = 1 if $t \ge 1997$ and 0 otherwise. CHA is a dummy variable equal to 1 if there is a charter school in the county and 0 otherwise. The variable % STUDCH is the percentage of students in a county attending a charter school.