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College Admission and High School Integration

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The Top-Ten Way to Integrate High Schools*

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Abstract

We investigate how "top-N percent" policies in college admission affect diversity at the high-school level. It is well understood that these policies produce incentives for students to relocate to schools with weaker competition. We show theoretically that such school arbitrage can neutralize the policy at the college level but may partially desegregate high schools. 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. Thus top-N percent policies may provide a new instrument for the long sought goal of achieving high school integration.

Keywords: Matching, affirmative action, education, college admission, high school desegregation, Texas Top Ten Percent.

JEL: C78, I23, D45, J78.

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1 Introduction

Could a law designed to maintain racial diversity in a state's universities help to integrate its high schools instead? Based on a theoretical and empirical analysis of the effects of such a policy 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.

Assessment of these policies has been devoted almost exclusively to their efficacy at achieving diversity in the universities; the consensus is that in this dimension, they have fallen rather short. But top-n laws have another potential impact, which is to increase diversity in the *high schools*. It is this largely-ignored effect that is the subject of the present paper. Our theory and evidence serve as a first step in understanding the effects of policies like top-n on high school composition and as a proof-of-concept for novel instruments to integrate high schools, a long-sought policy goal with a controversial history of implementation.

The chief economic force at work in our analysis is an arbitrage incentive that top-n laws create: students who fall short of the admission requirement of being in the top N% of their current high school class could benefit from moving to a lower-quality school, where they are more likely to meet the criterion. The observation that arbitrage might occur is not new, but for lack of a theoretical framework, there is as yet no systematic understanding of what it implies.

We provide a formal model that analyzes arbitrage following top-n laws and derive from it two types of consequences. First, it can explain some of the established facts about top-n policies, including their disappointing performance at achieving ethnic integration of the universities. Second, the movement of

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

arbitrageurs across schools has the potential to blend the ethnic composition of all high schools.

These implications are contained in two general results provided by the theory. First, the Top-N Percent Neutrality Theorem states that if the private cost of moving across high schools is lower than the benefit of attending a flagship university, then the equilibrium sets of admitted students in university with and without a top-n policy are identical. Second, our Unbiased Mixing Theorem shows that arbitrage *must* reduce the overall level of ethnic segregation at the high school level, as conventionally measured by most indexes of segregation, if the flow of students between any pair of schools is ethnically representative of their origin schools.

The conditions in these two theorems are sufficient for the policy to increase high school integration while leaving university enrollment unchanged. We show via examples that some violations of unbiasedness leave the conclusion of the mixing theorem unchanged. But other violations may not lead to an increase in the high school integration.

Thus, whether changes in segregation at the high school level are consistent with our conditions is an empirical question. 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.

Beyond the increase in integration at the high school level, we can characterize theoretically the equilibrium flow of students when schools are ordered on the basis of the distribution of performance of their students, and when the cost of moving is a function of the distance implied by this order between schools. We obtain two additional theoretical insights.

First, there is a *cascading effect* where students from higher ranked schools move to lower rank schools. Second, since Texas's top-n policies condition only on class rank in the final years of high school, students who value attending their initial school will delay a school change as long as possible if the cost of moving away from one's school is decreasing in the time spent in that school (for instance if students want to keep in touch as long as possible with their friends.) Hence, effects of the policy will be more pronounced for later grade levels.

A Preview of the Data

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.[2] 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.[3] 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 difference-in-differences estimation strategy on an index of local segregation. In line with

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

[3]Using alternate measures of segregation, such as the Theil index, yield similar pictures. See appendix for further graphs corresponding to 10th and 11th grades. The policy was announced in 1996, signed into law in early 1997, and took effect with 1998-99 school year. While the observed drop in segregation for 10th grade in 1997 may also be related to the policy, we exclude 1997 from our estimations to avoid capturing confounding effects. In the analysis, we also perform a within-cohort exercise to ensure that we are not capturing cohort effects.

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 and, 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 individual-level data we document a change in the pattern of school moves taking place during 11th and 12th grades. After the introduction of the policy, students became more likely to move to schools with less college-bound students and lower SAT average and these effects are significant for moves taking place within school districts. The fact that student movement also appears to be unbiased lends credibility to the mechanism highlighted by our theory.

Literature

The idea that top-n laws may induce students to move among high schools is familiar to economists and has already been spelled out in the context of educational policies. In their survey of affirmative action, Fryer and Loury (2005) suggest that "color-blind" policies, of which top-n is an example, may induce students to move schools or to choose less challenging courses in order to increase their chances of benefiting from the policy. Cullen et al. (2013) find empirically that in Texas there is a positive, albeit small, aggregate response to the Top Ten Percent Law in the form of movement across high schools. Cortes and Friedson (2014) suggest that there are above-trend real-estate price increases in neighborhoods that could be "natural" targets for students who try to arbitrage the top-n laws.

The literature is silent on how this arbitrage opportunity will affect the degree of segregation in high schools. In addition to guiding us toward uncovering new empirical regularities on the effects of top-n policies, our model provides a unifying framework for a number of existing and separate findings in the empirical literature on the effects of the Texas Top-n law: that racial integration in flagship universities in Texas was not much affected by the law (Horn and Flores, 2003; Kain et al., 2005; Long and Tienda, 2008); that top-n-induced strategic school enrollment choices of 8th graders have only minimal aggregate effects (Cullen et al., 2013); and that, following the law, more high schools send students to the flagship universities (Long et al., 2010).

Finally, high school integration has been a goal of policy makers at least since the 1950's. Durlauf (1996) makes the broad case for the social benefits of intervention in matching markets ("associational redistribution") such as schools or communities. Overwhelmingly, most policies that have been implemented have tried to impose diversity at the high school level *directly*; by contrast, the top-n laws provide *indirect* inducements. Lutz (2011) summarizes the history of court-ordered high school integration in the USA, as well as the resulting political tensions these orders created. In England, France and other countries, diversity in public high schools is encouraged either via quotas or priority levels in matching algorithms. Because these policies *impose* mobility costs on most students, they could induce students who are not able to go to their preferred high school to shift to private high schools, potentially creating a countervailing effect to integration. By contrast top-n policies induce mobility of students among high schools without the unintended consequence of increasing the flow into private high schools.

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 Conceptual Framework

2.1 The Basic Model

The economy is populated by a unit-measure continuum of students, each characterized by an educational achievement $a \in [0, \overline{a}]$.[4] 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

[4]We 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.

of achievements $F_s(a)$, which has support $[0, \bar{a}]$. The aggregate distribution is $F(a) = \sum_{s=1}^{S} q_s F_s(a)$.

Prior to admission to college, each student initially in a school s may *(re)-locate* by selecting a school s' at a cost $c(s, s') \geq 0$; remaining in one's initial school is costless ($c(s, s) = 0$). It will simplify matters to suppose that from any initial school, the relocation costs among all target schools are unique: for each s, $c(s, s') \neq c(s, s'')$ whenever $s' \neq s''$.

Note that this model can accommodate an interpretation in which there are positive effects of school characteristics on human capital. For instance, advance placement courses or inspiring teachers will increase the set of skills needed to perform well at the university or in the labor market, in which case student i has a total skill $a_i + r_i(s)$ for future performance, where a_i is the ability we use in the model and $r_i(s)$ is this future return from attending school s. The difference $r_i(s) - r_i(s')$ is part of the cost $c(s, s')$.

Location decisions are made simultaneously after the admission policy is announced, and we consider Nash equilibria in location 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.[5]

Upon graduation, students can either go to the university U or pursue an alternative option, denoted u, which could be moving to another, less prestigious, state university, or moving to an out-of-state university, or entering in the labor market. 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 $U(a) - c(s, s')$

[5]In 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.

(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

$$F(a^*) = 1 - k. \tag{1}$$

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 location 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.[6]

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

[6]Since 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.

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 ($a \geq a^*$) 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.

Theorem 1. (The Top-N Percent Neutrality Theorem). *If $c(s, s') < U(a) - u(a)$ for all students with $a \geq a^*$, 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.[7] In particular, movement of students induced by the top-n 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 consider indexes 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 $H(p_s) = \sum_g p_s^g \log(p_s^g)$ is the entropy of p_s, $A_1(p) = H(p)$ the entropy of p, and

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

$A_2(p) \equiv 1$, in which case $\mathcal{I}(p, \{p_s\})$ is the mutual information index (MMI). 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).

Intuitively, the mutual information index, which features in our empirical analysis, is a measure of how much information the knowledge of the school a student attends conveys on the student's race, and vice versa. For instance, if all schools have exactly the same racial composition as the state, then the mutual information index is zero, as knowing a student's school does not allow any inference on the student's race. Conversely, a larger index value reflects that more information is gained on students' race by learning about their school.

2.2 Effects of Movement

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

$$\hat{\mathcal{I}} = A_1(p) - A_2(p)\left[(q_1 - m)H(p_1) + (q_2 + m)H(\hat{p}_2) + q_3 H(p_3))\right].$$

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

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

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 distribution among those who move from s to any target school s'. Formally, if $p_{s,s'}$ is the group distribution among the movers from school s to school s', we have $p_{s,s'} = p_s$ for all s'.

Theorem 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.*

Of course, unbiasedness is only sufficient for reducing segregation, not necessary. To illustrate this point, we revisit the case of two groups and three schools. Suppose initial proportions are $p_1^1 = 0.9$, $p_2^1 = 0.5$, and $p_3^1 = 0.1$ of the first group, with equal masses of students in each school, $q_1 = q_2 = q_3 = 1/3$. The overall degree of segregation (using the MMI) is approximately 0.107.

Suppose a tenth of school 1 students move out, with half of these targeting each of the other two schools. If movement is unbiased, the new proportions are $\hat{p}_1^1 = 0.9$, $\hat{p}_2^1 = 0.52$, and $\hat{p}_3^1 = 0.14$. In this case the Theorem applies, and segregation decreases to 0.092. But even if there is biased sampling, for instance with 0.7 instead of 0.9 of the movers being from group 1, the new proportions $\hat{p}_1^1 = 0.92$, $\hat{p}_2^1 = 0.51$, and $\hat{p}_3^1 = 0.13$ yield a segregation index of 0.102.

Finally, unbiased sampling might be accompanied by biased targeting and yet still generate a decrease in segregation: suppose an unbiased sample from school 1 splits along group lines, with all of the group 1 students targeting school 2 and all the group 2 students targeting school 3. Then the final proportions are $\hat{p}_1^1 = 0.9$, $\hat{p}_2^1 = 0.54$, and $\hat{p}_3^1 = 0.099$. Even in this extreme case of biased targeting, the MMI falls, to 0.103.

2.3 Equilibrium Flows

Putting additional structure on the achievement distributions and moving costs allows one to characterize the location 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 cost $c(s, s')$ strictly increases in the "distance" between schools, captured by the absolute difference in their indexes $|s - s'|$.[8] 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 quality or reputation. Finally, assume that at least one school s satisfies the movement condition in Footnote 7, 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 1. *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 $\{\hat{a}_s, s = 1, \ldots, S\}$, 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.

[8] Even 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.

Hence in equilibrium 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., $1 - F_s(a^*) \geq n$ 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. 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.

As mentioned in the Introduction, there is evidence that the number of schools sending students to the University of Texas increased after the introduction of the Top Ten Percent Law. This is easy to see with the aid of the present model: if, say, school 3 initially had no one above the threshold a^*, then after the policy change, this school will have an inflow of above-a^* students. Now some students will attend the U from a school that previously had sent no one. As the other two schools continue to send some students, the number of sending schools has increased. This is a general result: all schools that sent students to the U continue to do so under the top-n policy, and some that did not before do so now. The set of sending schools cannot become smaller and in general will increase. But the set of students who attend the U does not change.

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 Theorem 2 tells us, group unbiasedness is sufficient to assure his outcome.

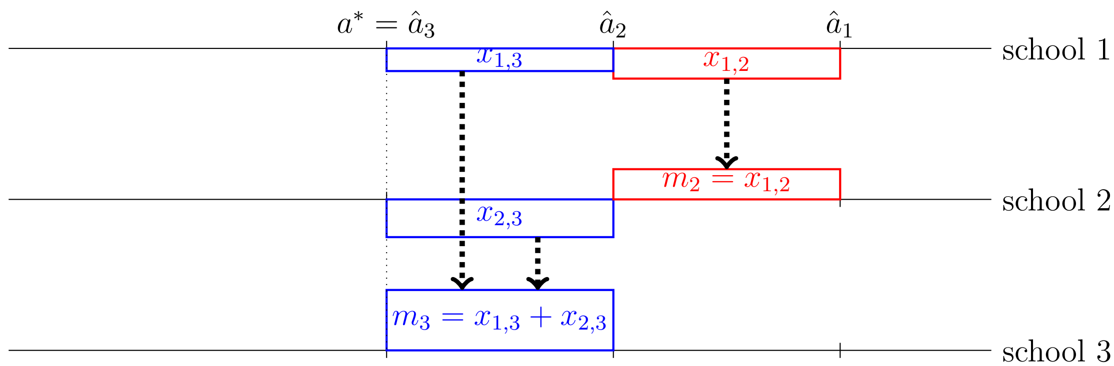


Figure 2: Post-policy flows with three schools

One situation in which unbiasedness is satisfied is where every school's ethnic composition is *independent* of a: within a school, it is the same for all a, though 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.

To see how this works, denote these attributes α and suppose they take S values $s \in \{1, \dots, S\}$ with the frequencies q_s in the population. Different ethnic groups g have different distributions p^g ($p^g_s \neq p^{g'}_s$ for at least some s) over the attributes, and $q_s = \sum_g p^g_s$. In this case, 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 $F_s(a) = \mathcal{F}(a|s)$.

The distributions $F_s(a)$ will be stochastically decreasing in s. Moreover, the fraction of group g in school s will be p^g_s, 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'. In this case the unbiasedness conditions of Theorem 2 are satisfied by the flows depicted in Proposition 1 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.[9] 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. As a group, 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. More saliently, 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* preference for ethnic groups motivating movement.

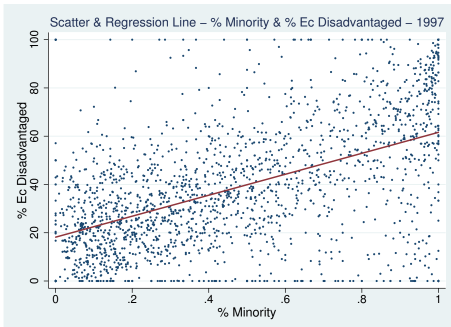
This case is rather extreme in the degree of bias. As we suggested above, for more moderate departures from unbiasedness, the Unbiased Mixing Theorem suggests that top$-n$ policies will decrease segregation. Ultimately, whether they do or not is an empirical question.

2.4 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 the Proposition is stochastically increasing in socio-economic status or higher for some ethnic groups than others. Texas high-schools 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

[9] The 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.

with the high school pass rate in TAAS.[10] That is, a school's ethnic composition is a good predictor of socio-economic status and test score results. Our 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.



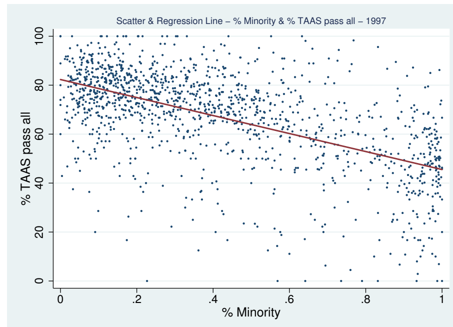


Figure 3: Share of minority and economically disadvantaged students (left) and share of minority and TAAS pass rate (right). *Source*: AEIS data.

Under the top-n policy, students have the opportunity to choose not only whether to move between schools but also when to move, conditional on eligibility rules.[11] Supposing therefore that students can choose the date at which to move, the time spent in the initial school will affect the cost of moving. Moving early from one's initial school is often costly: it is more difficult to make long-lasting friends in the new school since existing students have already created their social network; the initial school had been chosen because it was the best at the time and moving early means spending more time in a less preferred environment. An example is a simple modification of the cost function used in Proposition 1, namely

$$c(s, s', t) = F - t + |s - s'|,$$

where F is a fixed cost of moving. Since the cost function satisfies the distance property: $\forall s, s', s'', \forall T, \forall t < T, c(s, s', t) + c(s', s'', T - t) \geq c(s, s'', T)$, students will choose to move only once.

[10]The 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.

[11]As will be discussed later, the Texas Top Ten Percent Policy did not impose a minimum stay period in order to be eligible and we could not find any evidence that school districts enforced a minimum stay rule.

Corollary 1. *For cost functions $c(s, s', t)$ decreasing in t and satisfying the distance property, students move as late as possible from their initial school and move directly to their final school.*

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.

2.5 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.

P.1 Arbitrage by students leads to lower segregation index for high schools. Hence the information index should decrease following the policy.

P.2 Students who arbitrage "move down": they move from schools with higher average educational achievement to schools with lower average educational achievement.

P.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 in 12th grade, but not in 9th grade, from 1998 onwards, which coincides with the start of the Texas Top Ten Percent policy. In this section we will 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]

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]

[12]We 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.

[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.

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

[15]The 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.

[16]Like the other databases these data are subject to masking based on FERPA regulations.

[17]Transfer 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)

and their ethnic group and economic disadvantaged status. Each record is assigned a unique student ID, allowing us to track students as they change 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). As discussed above it measures the degree of segregation in terms of the information that can be gained from the sorting of groups into schools, with higher segregation corresponding to higher index values. Moreover, this index is one of the few that is defined for multiple groups and can be aggregated over several organizational layers such as school district, region, etc.

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 $g = 1, ..., G$ in 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.

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

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

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

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.[20] 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 that, after the Top Ten Percent Law, moving students were more likely to move to schools with less college bound students and lower SAT average.

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, middle of 12th, or end of 12th grade. Therefore strategic rematch may well have taken place as late as between 11th and 12th grades for some schools, and we will focus on all possible rematch occurring between 9th and 12th grades. Using 9th grade as the reference point means

[19] We 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.

[20] Using a placebo exercise, we show that the parallel trend assumption needed for our differences-in-differences strategy holds, see Table 3.

losing any strategic rematch having occurred earlier in students' careers, which will again bias the estimates downwards.

The Texas Top Ten Percent rule did not impose a minimum period at school in order to be eligible for the policy, but allowed school districts to define rules regarding that matter. We could not find any evidence that districts imposed minimum attendance rules in order to qualify for the Top Ten Percent rule.[21] Moreover, even if some did, this would bias our 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^r_{yst} (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.[22] We consider school years 1994-1995 to 1996-1997 to be pre-treatment, while 1998-1999 to 2000-2001 correspond to post-treatment periods.[23] 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:

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

where $G12_{ys} = 1$ if $y = 12$, $POST_t = 1$ if $t \geq 1997$, $\mathbf{T}$ 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, $\mathbf{T}$, 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

[21]For instance, we contacted three large school districts by phone and none of them had any such rule in place.

[22]We 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.

[23]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.

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 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:

$$\begin{aligned} M^r_{yst} = &\beta_1(G12_{ys} \times POST_t) + \beta_2(G11_{ys} \times POST_t) + \beta_3(G10_{ys} \times POST_t) \\ &+ \boldsymbol{\delta}'\mathbf{T} + u_{ys} + \varepsilon_{yst}, \end{aligned} \tag{7}$$

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 indexes. 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 6 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.[24]

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

$$W^c_{12t} - W^c_{09(t-3)} = \beta POST_t + \delta t + u_c + \varepsilon_{ct}, \tag{8}$$

where W^c_{yt} is the within-county segregation index at county c, grade y, at time t, $POST_t = 1$ 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.[25]

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.

[24]Focusing 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 zero, as mentioned above.

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

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.

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 7, 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.[26]

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. 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.

We examine prediction P.2 that after the introduction of the policy movers in 11th and 12th grades were more likely to move to schools with less college bound students and lower SAT average.[27] These variables are plausible indicators of a move to an academically worse school.

We use the characteristics of schools in the year that the student transferred to them, consistent with rational expectations. The results remain qualitatively unchanged if we use instead school characteristics in the year before the move.

[26]Students 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.

[27]Note that universities in Texas require SAT scores even for Top Ten Percent applications, so that the policy would not affect the probability of taking SAT exams, which were also required by out-of-state universities.

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:

$$Y_{it} = \beta_1 (G12_i \times POST_t) + \beta_2 (G11_i \times POST_t) + \boldsymbol{\gamma}'\mathbf{G_i} + \boldsymbol{\rho}'\mathbf{X_i} + \boldsymbol{\delta}'\mathbf{T} + \varepsilon_{it}, \quad (9)$$

where $\mathbf{G_i}$ is a vector of grade dummies, $\mathbf{X_i}$ 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. We cluster the standard errors at the school of origin level.

Because students move strategically if the benefits of moving outweigh its cost, strategic movements should be particularly salient for 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 that occur within and across districts, and expect that treatment effects are greater for within district moves.[28]

The results are presented in Table 5. Columns (1) to (3) show 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, consistent with prediction P.3. 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. This effect is driven mainly by moves within districts. That is, under the Top Ten Percent rule students in higher grades were significantly more likely to move to academically worse schools within the same district. Columns (4) to (6) show 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 2.3 percentage points for non-economically disadvantaged students. This corresponds to a 5.3% increase, given that the sample mean of the dependent variable is 0.435. The effect is only significant for moves that occur within districts.

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

[28] Numbers 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.

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 and lower SAT average. As expected, these strategic moves tend to occur within the school districts, where moving costs would tend to be minimized.

Evidence on Unbiasedness of Flows

Our theory suggests that the decrease in Texas school segregation following the introduction of the Top Ten Percent Law can be explained by arbitrage behavior of students moving to schools that enhance their chances of graduating in the top decile of their class. However, the theoretical argument rests on the assumption of sufficient unbiasedness in the flows: moving students should be close to ethnically representative of their schools and should be close to ethnically neutral in targeting destinations. This raises the question of whether actual movements in Texas displays this sort of unbiasedness.

To address this question we first test for biased sampling using a linear probability model that regresses an indicator of whether a student moving from school s to school s' at time t is from the majority (white + Asian) on the share of the majority among the sending school's students:

$$MAJ_{it} = \beta_0 + \beta_1 MAJ_{st} + \beta_2 \left(MAJ_{st} \times POST_t \right) + \boldsymbol{\gamma}' \mathbf{G_i} + \boldsymbol{\delta}' \mathbf{T} + \varepsilon_{it}, \tag{10}$$

where the dependent variable MAJ_{it} takes the value 1 if a moving student is from the majority and 0 otherwise; MAJ_{st} is the share of majority students in i's school of origin s, and the other variables are defined as above. We cluster the standard errors at the school of origin level. If the sampling of school leavers is in fact unbiased under the policy, then that probability will exactly reflect the school majority share and we would expect the sum of the coefficients β_1 and β_2 to equal one.

Table 6 presents the result. In column (1), we show the correlation between majority status of moving student and the proportion of majority in school of origin without any additional controls. The estimated coefficient is very close to 1, consistent with unbiased sampling. The introduction of year and grade fixed effects yields very similar results (column (2)). In column (4), we also allow for this correlation to have changed after the implementation of the Top Ten Percent Law. While we cannot rule out that majority students were slightly oversampled after 1997, the coefficient of the interaction term is very close to zero.

To test for unbiased targeting, we regress the residuals of equation (10) on the majority share in the receiving school s':

$$MAJ_{it} - \widehat{MAJ_{it}} = \beta_1 MAJ_{s't} + \beta_2 \left(MAJ_{s't} \times POST_t\right) + \varepsilon_{it}, \tag{11}$$

where the dependent variable $MAJ_{it} - \widehat{MAJ_{it}}$ is the residual of regression (10) and $MAJ_{s't}$ is the share of majority students in i's target school. Under unbiased targeting we expect the coefficient to be zero, because the target school composition will not affect the composition of incoming students conditional on their origin school composition.[29]

Columns (3) and (5) in Table 6 present the results. While the estimated coefficients are statistically significant, they are very close to zero. The introduction of the policy was not associated with a change of biasedness. To interpret the coefficients we used actual student movements of 11th graders in 1998 to compute the effect of biased sampling and targeting on the regression coefficients. Unbiased flows would produce coefficients of 1 and 0 in regressions (10) and (11). Assuming a very small oversampling of majority students going to majority schools, by setting the majority share among moving students to $MAJ_{st} + 0.03MAJ_{s't}$, produced coefficients (1.006 and 0.020) that are very close to the ones we observe.

This appears rather small and in line with the assumption of our theory, in particular when recalling our examples accompanying Theorem 2. If the case of biased targeting coupled with biased sampling considered there had generated the data, we would by contrast obtain coefficients of 1 and 0.5, yet still have observed reduced segregation.

As a robustness check we also run specification (10) including fixed effects for pairs of origin and destination schools. Thus controlling for the association between the actual flows and the share of majority students we would again expect the coefficient β_1 to equal 1 if there was no bias in sampling or targeting. For computational purposes we have to restrict our analysis to samples of pairs

[29] Based on our theory we would expect some correlation between the ethnic composition of sending and targeted schools: Proposition 1 predicts that the expected quality of target schools increases with the quality of sending schools. If in turn ethnic composition is correlated with quality along the lines of the discussion following the Proposition, then when i moves from s to s', MAJ_{st} and $MAJ_{s't}$ are correlated, so we cannot simply add $MAJ_{s't}$ as a control to equation (10).

of schools, with enough movement between them. The results in Table 7 yield coefficients close to 1, suggesting low bias, which is consistent with the results obtained from our preferred specification.

Overall, the evidence suggests that school migration in Texas displayed remarkably little ethnic bias, a finding that helps support the view that the Unbiased Mixing Theorem can account for the reduction in segregation trends in Texas high schools following the introduction of its Top Ten Percent Law.

3.3 Robustness Checks

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.[30]

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.

[30] In 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.

Table 8 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.[31]

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 indexes for the total population and for the group aged 15-19. The indexes 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 1999[32] and cannot explain the decrease in segregation among the student population over the period.

Dropout rates

A change in dropout rates could potentially be a confounding effect. Possible differences in the dropout rates between majority and minority students are taken care of by our differences-in-differences approach. A possible concern is that the trends were significantly different between ethnic groups in 9th and 12th grades. Unfortunately, the data do not allow us to compute grade specific dropout rates. However, Figure 5 shows that dropout rates for 7th to 12th graders in Texas are low and the trends are very similar for different ethnic groups. Thus it seems unlikely that dropout rates drive the reduction in segregation we observe in the data.

[31]The 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 observed decrease in segregation.

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

4 Conclusion

Theory and evidence show that a policy intended to achieve integration at the college level may actually have contributed to achieving it in the high schools. By basing admission on relative performance at high school, the Texas Top Ten Percent policy appears to have induced some near-threshold students to move to lower quality schools. Coupled with evidently low differences in the ethnic composition of movers relative to their origin schools and low ethnic bias in targeting behavior, the result is a reduction in high-school ethnic segregation.

It is worth asking whether the movements of students needed to account for the observed change in high school segregation following the introduction of the Top Ten Percent Law are enough to account for oft-noted the diversity shortfalls in the University of Texas system. A numerical simulation shows that the observed drop in segregation could have been generated by strategic movement by as little as 1,500 students (of about 20,000) per year per grade. On the other hand, comparing post-policy admission numbers at the UT campuses at Austin, Dallas, and A & M to those expected if the minority share had remained equal to the one under affirmative action, produces a shortfall of around 650 minority students.

The apparent excess of movement can be accounted for if one realizes that in practice the effects of an individual arbitrage decision are uncertain. For at the time a decision to move has to be made, it is likely that one is unsure 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, someone just above the percentile threshold might move as insurance against the possibility of falling below it.

The experience of apparently unintended consequences in Texas suggests that top-N percent policies may be an effective tool for achieving broader social goals than was previously understood: they offer a novel way to integrate high schools. As it happens, similar policies are being rolled out around the world. For instance, Sciences Po in France uses preferential admission based on zip codes; the University of Bristol in the UK offers lower entry standards for applicants from lower-performing schools; and Brazilian state universities set aside places for students who come from public schools. Although differing in detail from top-n policies, all of these "school-based" policies generate similar incentives for some high school students to move and will therefore affect high school integration.

A natural question that arises concerns the optimal design of school-based policies if the intent is to accomplish school integration.[33] Since policies such as those at Sciences Po and Bristol are likely too small to have much impact, and an increase in the number of universities participating in such schemes would be required. This corresponds to increases the policy threshold n in our model: given the capacity k, increasing n increases cross-school flows, so as long as movement is unbiased, segregation falls with participation.

Increasing the capacity of the university system need not have the same effects: since movement is bounded by the capacity, there is clearly a range of (low) capacities where increasing capacity (and n to keep up) increases movement. At the other extreme, when capacity is equal to the entire population, there is no movement incentive, so the relationship between capacity and movement is non-monotonic.

Finally, analysis of optimal policy needs to acknowledge the timing of desegregation. As our analysis shows, in the absence of lengthy residency requirements, students tend to delay their movements to the later grades. Policies that lengthen these requirements in order to increase exposure during high school among students of differing backgrounds must contend with the evident increase in moving costs, which would tend to reduce flows.

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[33]Obviously we are abstracting from the weighing of moving costs against the ostensible benefits of integration, as well as constraints to policy emanating from limited capacities of target high schools.

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Appendix 1: Proofs

Neutrality Theorem: Proof of Existence of an Equilibrium

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 characterized 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 A. *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 $a \geq \hat{a}_s$.

(ii) Define $\underline{a} = \min_s\{\hat{a}_s\}$. Then, $\sigma(a, s, s) = 1$ if $a < \underline{a}$, or $a \geq \hat{a}_s$.

(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 $a \geq \hat{a}_s$ can be admitted in her initial school; hence $\sigma(a, s, s) = 1$ is a strict best response for such a student.

(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 $\sum_{s' \neq s} \sigma(a, s, s') = 1$. $\square$

Under neutrality only students with $a \geq a^*$ 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 A 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 A 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:

$$
\begin{aligned}
& q_s(1 - F_s(\hat{a}_s^N)) + \sum_{s'} \mathbb{M}_{s'}^s(\hat{a})(F_{s'}(\min\{\hat{a}_{s'}^N, \hat{a}^L\}) - F_{s'}(\hat{a}_s^N)) \\
& \quad = n q_s(1 - F_s(\hat{a}_s^N)) + n \sum_{s'} [\mathbb{M}_{s'}^s(\hat{a})(F_{s'}(\min\{\hat{a}_{s'}^N, \hat{a}^L\}) - F_{s'}(\hat{a}_s^N))] \\
& \qquad + n q_s \max\{F_s(\hat{a}_s^N) - F_s(\hat{a}^L), 0\} + n q_s F_s(a^*).
\end{aligned}
$$

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 $\omega_s \equiv \frac{n}{1-n} q_s F_s(a^*)$ and $\hat{a} = (\hat{a}_1^N, \ldots, \hat{a}_S^N, \hat{a}^L)$ we can rewrite this condition as the requirement that the "excess demand" in school s be zero:

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

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

$$\begin{aligned} &B_s(a) = \max[\min(z_s(a) + a_s, \overline{a}), a^*] \text{ for } s = 1, \ldots, S \text{ and} \\ &B_{S+1}(a) = \max[\min(z_{S+1}(a) + a_{S+1}, \overline{a}), a^*]. \end{aligned}$$

$B(\cdot)$ 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 $z_s(\hat{a}) + a^* \geq a^*$, 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

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

Since $z_{S+1}(\hat{a})$ can be written as $\sum_{s:\hat{a}_s^N \geq \hat{a}^L} q_s[F_s(\hat{a}_s^N) - F_s(\hat{a}^L)] - (k - n)$, 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 $0 > \sum_{s \leq S} z_s(\hat{a}) = 0$, a contradiction. We conclude that $z_s(\hat{a}) = 0$. □

Proof of The Unbiased Mixing Theorem

Let $x_{s,s'}$ be 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. Since moving decisions depend only on ability and distance between schools but not on group, 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

$$
m_s = \sum_{s'} x_{s',s} \quad \text{and} \quad \sum_s x_s = \sum_s m_s. \tag{12}
$$

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

$$\hat{p}_s^g = \frac{(q_s - x_s)p_s^g + \sum_{s'} m_{s,s'} p_{s'}^g}{q_s - x_s + m_s}. \tag{13}$$

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

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

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 (12). Hence we have $\hat{\mathcal{I}} - \mathcal{I} < 0$ as claimed. □

Proof of the Proposition

As shown in lemma A, the 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 $a \geq \hat{a}_s^N$ 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

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

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 $a \geq \hat{a}_{[1]}$, 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

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

or

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

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 $\hat{a}^L$ and derive then cutoffs $\hat{a}_s$ for $s > \bar{s}$ constructively. From the proof of Theorem we know that the equilibrium cutoff $\hat{a}^L$ satisfies

$$\sum_{s \in L} q_s(F_s(\hat{a}_s^N) - F_s(\hat{a}^L)) = k - n. \tag{14}$$

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

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

Therefore $F_s(\hat{a}_s^N) = 1 - n(1 - F_s(\hat{a}^L) + F_s(a^*))$ and (14) becomes

$$\sum_{L} q_s((1-n)(1 - F_s(\hat{a}^L)) - nF_s(a^*)) = k - n, \tag{15}$$

The left hand side of (15) 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 $\hat{a}^L = a^*$, 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 (15) whenever $n < k$ (if $n = k$ there is a continuum of solutions $[\hat{a}_1^N, \overline{a}]$, where

$1 - F_1(\hat{a}_1^N) = \frac{n}{1-n} F_1(a^*)$; 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

$$1 - F_s(\hat{a}_s) + \frac{m_s}{q_s} = \frac{n}{1-n} F_s(a^*). \tag{16}$$

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 (16) can therefore be written

$$1 - \sum_{s' \leq s} \frac{q_{s'}}{q_s} F_{s'}(\hat{a}_s) + \sum_{s' \leq s-1} \frac{q_{s'}}{q_s} F_{s'}(\hat{a}_{s-1}) = \frac{n}{1-n} F_s(a^*). \tag{17}$$

Since the LHS of (17) 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 $\{\hat{a}_s\}$. $\square$

Appendix 2: Tables and Figures

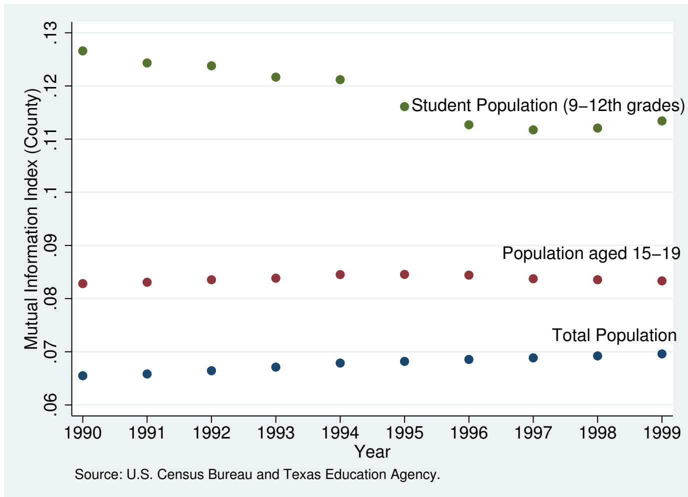

Figure 4: Residential versus School System Segregation

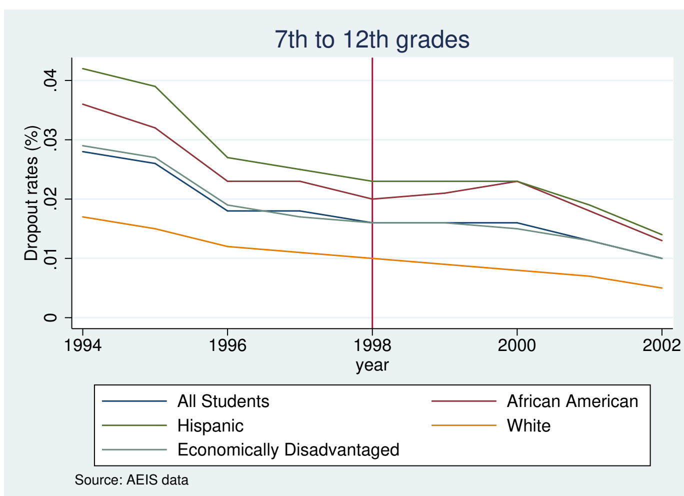

Figure 5: Dropout Rates

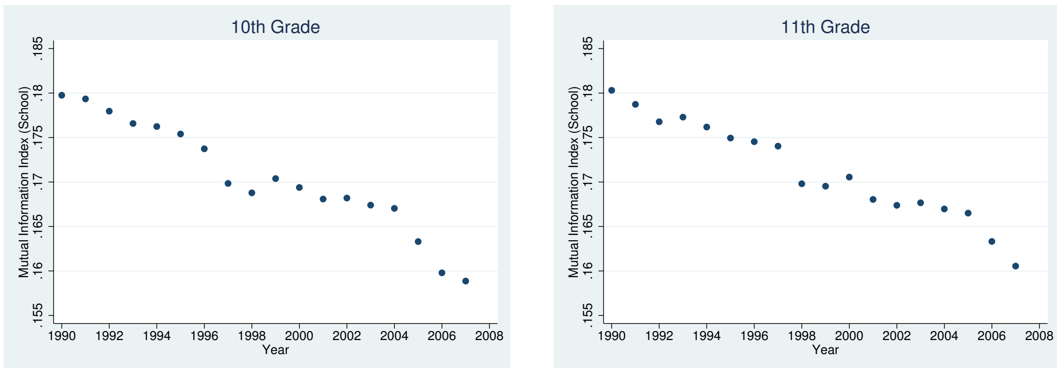

Figure 6: Time series of the mutual information index for 10th and 11th grades

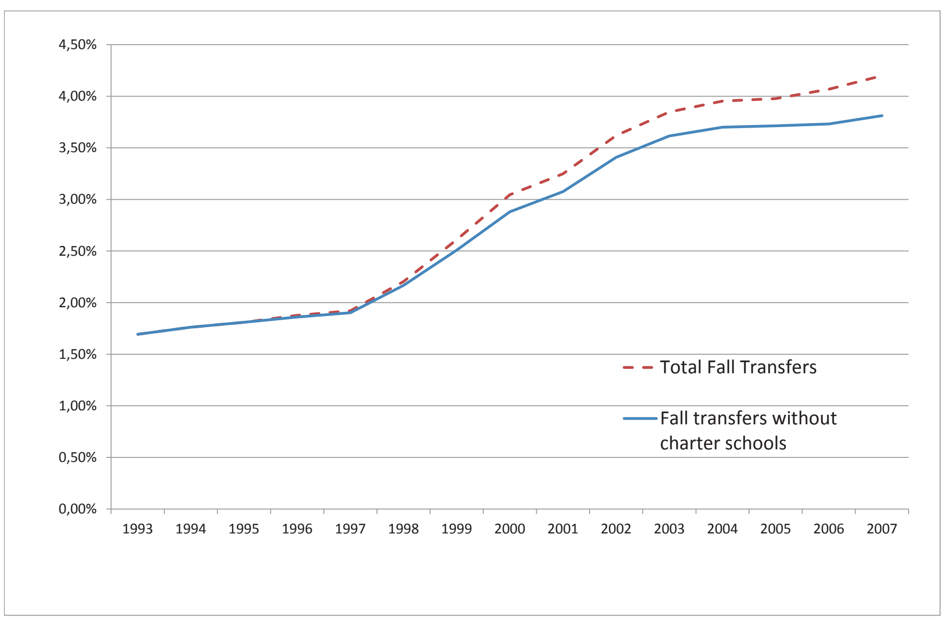

Figure 7: Share of students in 8th to 12th grades with a district of enrollment different from district of residence, 1993-2007. The dashed line corresponds to the total number, while the solid corresponds to all students except for those attending charter schools. *Source*: TEA.

Table 1: Descriptive Statistics

	Before (1994-1996)			**After (1998-2000)**		
	Mean	**Std. Dev.**	**N**	**Mean**	**Std. Dev.**	**N**
A. School Level Data						
A.1. Local segregation index with respect to region						
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. Probabiliy of moving to a school with ... than school of 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

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.

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

Dep. Var.: M^{r}_{ys}: Local segregation index with respect to *region*				
	(1)	(2)	(3)	(4)
$G12 \times POST$	-0.004*	-0.004*	-0.004*	-0.004*
	(0.002)	(0.002)	(0.002)	(0.002)
$G11 \times POST$			-0.004*	-0.004*
			(0.002)	(0.002)
$G10 \times POST$			-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

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

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

Dep. Var.: M^r_{ys}: Local segregation index with respect to *region*				
	(1)	(2)	(3)	(4)
$G12 \times T93$	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

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 $t \geq 1993$ and 0 otherwise.

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

Dep. Var.:	Within-county segregation $W^c_{12t} - W^c_{9(t-3)}$	
	(1)	(2)
POST	-0.001**	-0.004**
	(0.001)	(0.002)
Constant	0.000	-1.020
	(0.000)	(0.773)
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

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 $POST = 1$ if $t \geq 1997$ and 0 otherwise.

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

Dep. Var.:	Probability of moving to a school with **less college bound** students than school of origin			Probability of moving to a school with **lower SAT average** than school of origin		
	Full Sample	Within Districts	Across Districts	Full Sample	Within Districts	Across Districts
	(1)	(2)	(3)	(4)	(5)	(6)
$G11$	0.028***	0.079***	0.008	0.016**	0.023	0.012**
	(0.005)	(0.014)	(0.005)	(0.006)	(0.020)	(0.005)
$G12$	0.064***	0.148***	0.024***	0.020***	0.026*	0.019***
	(0.006)	(0.016)	(0.006)	(0.005)	(0.015)	(0.006)
$G11 \times POST$	0.025**	0.074**	0.004	-0.013	-0.048	0.000
	(0.012)	(0.031)	(0.007)	(0.015)	(0.052)	(0.007)
$G12 \times POST$	0.031***	0.067***	0.009	0.023***	0.066***	0.010
	(0.008)	(0.021)	(0.008)	(0.008)	(0.023)	(0.008)
Constant	0.454***	0.462***	0.446***	0.501***	0.552***	0.475***
	(0.010)	(0.024)	(0.009)	(0.011)	(0.026)	(0.010)
Mean Dep. Var.	0.530	0.611	0.502	0.435	0.488	0.418
Observations	151,038	39,341	111,697	131,811	32,072	99,739
R-squared	0.007	0.036	0.003	0.082	0.117	0.068

Notes: * significant at 10%, ** significant at 5%, *** significant at 1%. Robust standard errors clustered at the school of origin level in parentheses. The control variables are year, ethnic group, eco disad, grade, grade offered.

Table 6: Testing the unbiasedness assumption

Dep. Var.:	MAJ_i	MAJ_i	$MAJ_i - \widehat{MAJ}_i$	MAJ_i	$MAJ_i - \widehat{MAJ}_i$
	(1)	(2)	(3)	(4)	(5)
MAJ_s	0.996***	0.996***		0.994***	
	(0.002)	(0.002)		(0.002)	
$MAJ_{s'}$			0.026***		0.025***
			(0.002)		(0.002)
$MAJ_s \times POST$				0.004**	
				(0.002)	
$MAJ_{s'} \times POST$					0.001
					(0.001)
Constant	0.024***	0.026***		0.028***	
	(0.001)	(0.002)		(0.002)	
Fixed effects					
Year	no	yes	no	yes	no
Grade	no	yes	no	yes	no
Observations	1,464,216	1,464,216	1,464,216	1,464,216	1,464,216

Notes: * significant at 10%, ** significant at 5%, *** significant at 1%. The dependent variable MAJ_i is equal to 1 if student moving from school s to s' is from majority group (i.e., white or Asian) and 0 otherwise. The dependent variable $MAJ_i - \widehat{MAJ}_i$ corresponds to the residuals from the previous column. Robust standard errors clustered at the school of origin level in parentheses.

Table 7: Robustness checks: unbiasedness assumption

Dep. Var.:	MAJ_i: Majority status of student moving from school s to s'					
	(1)	(2)	(3)	(4)	(5)	(6)
MAJ_s	1.004***	0.945***	1.005***	0.950***	1.007***	0.951***
	(0.002)	(0.012)	(0.002)	(0.012)	(0.002)	(0.013)
Constant	0.019***	0.053***	0.019***	0.048***	0.019***	0.048***
	(0.002)	(0.011)	(0.002)	(0.012)	(0.002)	(0.012)
Fixed effects						
Year	yes	yes	yes	yes	yes	yes
Grade	yes	yes	yes	yes	yes	yes
Origin-destination school	no	yes	no	yes	no	yes
Observations	1,253,180	1,253,180	1,214,427	1,214,427	1,181,042	1,181,042
Sample restriction	Only pairs of schools with 20+ movers		Only pairs of schools with 50+ movers		Only pairs of schools with 100+ movers	

Notes: * significant at 10%, ** significant at 5%, *** significant at 1%. Robust standard errors clustered at the school of origin level in parentheses.

Table 8: Fixed effect estimation, 12th-9th grade, school years 1994 to 2000

Dep. var.:	Within-county segregation $W^c_{t12} - W^c_{(t-3)9}$		
	(1)	(2)	(3)
$POST$	-0.004**	-0.004**	-0.004**
	(0.002)	(0.002)	(0.002)
CHA		-0.000	
		(0.006)	
$POST * CHA$		0.002	
		(0.006)	
$\%STUDCH$			-0.126
			(1.342)
$POST * \%STUDCH$			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

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 $POST = 1$ if $t \geq 1997$ 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.