College Admission and High School Integration*

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Abstract

We investigate whether a policy that bases college admission on relative performance at high school could modify in the aggregate the degree of segregation in schools, by inducing some students to relocate to schools that offer weaker competition. In a theoretical model, such high school arbitrage will occur in equilibrium and typically result in desegregating high schools, if schools are segregated with regards to socio-economic characteristics that are correlated with academic performance and race. This is supported by empirical evidence on the effects of the Texas Top Ten Percent Law, indicating that a policy designed to support diversity at the college level in fact achieved high school desegregation, unintentionally generating incentives for some students to choose schools strategically.

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

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1 Introduction

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

In recent years, several U.S. states, including three of the largest (California, Texas, and Florida) have passed "top-x percent" laws, guaranteeing university admission to every high school student who graduates in the top X percent of his or her class.[1] We argue that an unintended consequence of this kind of policy is to increase diversity in the high schools. Using a rich data set constructed using a combination of multiple administrative and Census data from Texas, we find there was a drop in high school racial segregation in the years immediately following the introduction of the policy there.

Following court decisions in the 1990s, the use of quotas to maintain racial or ethnic balance in higher education was discontinued. The top-x percent laws were adopted in response: since high schools are highly racially segregated, the expectation was to draw a representative sample of the high school population, guaranteeing diversity on campus.

Though widely used[2] the policy could not replicate the level of campus diversity seen under the abandoned affirmative action quota system: representation of minority students on University of Texas flagship campuses, which had dropped by one third after removing affirmative action, was still down by a quarter four years into the new policy.[3] Despite criticism on equity as well as efficacy grounds, and much controversy, the top-x percent policies are still in use.

Our study examines an argument that seems to have been absent from the policy debate. Under a top-x percent policy students in good schools who almost qualify for admission have an incentive to move to another school, where they are more likely to meet the criterion (indeed Cullen et al., 2013, present evidence for some strategic behavior at an individual level). We take this argument a step further and note that since school quality, ethnic background,

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

[2] In 2009, 81% of the first year students at University of Texas at Austin were admitted under its top-10-percent plan (UT OISPA, 2010).

[3] We calculated over- and under-presentation of backgrounds in University of Texas at Austin and Texas A&M with respect to the previous year's high school population using data from Kain et al. (2005) and TEA.

and student achievement are correlated, such "school arbitrage" will indeed tend to desegregate the high schools. For example, some students from more privileged socio-economic background will have incentives to move to a school with less-privileged students. This is crucial not only for assessing the functioning of college admission rules, but also for informing the adequate design of desegregation policies in the future. Moreover, the top-x percent policies use only class rank in the final years of high school. Therefore students who value attending good schools will delay a school change as long as possible. Hence, any effects of the policy will be more pronounced for later grade levels.

We use enrollment data for all Texas high schools to compute a number of segregation measures, and find evidence of a reduction in the state-wide segregation at the 11th and 12th grade levels, when students are applying to college, as compared to 9th grade coinciding with the policy change. We also find that the number of transfer students doubled and students who were not economically disadvantaged were more inclined to move to worse performing schools after the policy was introduced. This effect was stronger for higher grades, as predicted by our theory.

The theoretical argument is best highlighted in a simple model of location choice, where students differ in educational endowments. Students attend one of two schools, which may differ in their attractiveness for students. Students can move from one school to another at a positive cost. After attending high school a student has reached an education level that depends on individual educational endowment. Students apply to a state university with exogenous capacity and are accepted depending on the admission rule in place, and obtain a college education premium.

When the university admits the students with the best education levels either unconditional, or conditional on race, an allocation with one high school dominating the other in terms of average educational endowment of its pupils is perfectly consistent with an absence of any incentive for strategic rematch. This is no longer true, however, when considering a policy that admits the best $x\%$ students of each high school: students in the better high school will need a higher educational level to qualify for college admission than in the worse school. This induces an incentive for students at the better school that are close to but below the necessary education level to switch to the worse school.[4] If the college education premium is high relative to movement costs

[4] Damiano et al. (2010) examine a similar trade-off when agents have a preference for both

the strategic rematch will completely undo the policy, in that the set of students admitted to the university remains the same under new policy. This implies that the share of underprivileged among those admitted to college under a top-x percent policy falls short of the one under affirmative action when places at college are scarce and not all high ability students can obtain a place. This appears consistent with observations for Texas and other U.S. states (Kain et al., 2005; Long, 2004).

If educational endowments correlate with socioeconomic background such as race this will also imply that a top $x\%$ policy will desegregate high schools. There is evidence of such correlation in Texas: the share of minority students at a high school correlates positively with the share of economically disadvantaged students and negatively with the high school level pass rate in the Texas Assessment of Academic Skills (TAAS).[5] If students have some benefit from attending the better school the strategic movement will be delayed until higher grades. This observation will be useful for our identification strategy. Moreover, when students prefer better peers ceteris paribus, the top $x\%$ policy will induce mutual gains from trade and students who switch from a better to a worse school are acceptable to the majority of students of the receiving schools. Hence, school transfers that require the consent of the receiving school should increase when the top ten persent rule is introduced.

To assess our argument in light of the empirical evidence, consider first Figure 1. It shows a time series of the mutual information index for 9th and 12th grades of all Texan high schools from 1990 to 2007.[6] The mutual information index is a measure of segregation, 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.[7] Trends in residential segregation do not explain the pattern in Figure 1, see Figure 3 in the Appendix.

This observation is corroborated at the high school level using a difference-

status and peer quality. They do not analyze matching rules as policy instruments.

[5]A standardized test for 10th grade used in Texas between 1991 and 2002.

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

[7]See appendix for further graphs corresponding to 10th and 11th grades. Using the Theil index as a measure of segregation instead yields similar pictures. The policy was announced in 1996, signed into law in early 1997, and did not take effect before fall 1998.

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

in-differences estimation strategy on an index of local segregation. In line with the theory, we test for a significant change in the difference between the degree of segregation in 12th and 9th grades after 1998. This is indeed the case across several specifications, controlling for school-grade unobserved heterogeneity. Next, we examine whether the policy change affected the behavior of high school segregation over time within a cohort. Indeed we find that the difference in within-county segregation between 12th and 9th grades of the same cohort has decreased significantly after the introduction of the policy. This suggests that moves between schools have led to the decrease in segregation. We also show that this phenomenon does not seem to be associated with the establishment of charter schools in Texas around the same period. Finally, using 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, lower SAT average, lower TAAS pass rate, and less Asian and White students. In fact these effects are stronger for students who were not economically disadvantaged and arguably are more likely to benefit from strategic school choice.

Empirical evidence for strategic rematch as a response to the arbitrage incentives generated by the policy has been presented by Cullen et al. (2013) and Cortes and Friedson (2010). Cullen et al. (2013) use individual data to consider school transitions from 8th to 10th grade. They find that around 5% of students who could potentially benefit from selecting a high school strategically chose a neighborhood school instead of a competitive high school. This amounts to about 200 students (i.e., less than 0.1%) per cohort. Cortes and Friedson (2010) use a similar identification strategy and report differential changes in property prices in districts with low and high performing schools, which is consistent with the arbitrage argument.

Our approach focuses instead on using school level data to evaluate whether a top-x percent policy has succeeded in achieving high school desegregation at an aggregate level as predicted by a dynamic matching theory. Composition effects as a consequence of strategic behavior have received little attention in the literature and in the policy debate.

The paper proceeds as follows. Section 2 lays out a simple model of school choice. Its theoretical predictions are discussed in Section 3, and taken to the data in Section 4. Section 5 concludes. All tables and figures omitted from the text can be found in the Appendix.

2 A Simple Framework

The economy is populated by a continuum of students, characterized by their educational endowment $e \in \mathcal{R}$. By going to school, a student with educational endowment e obtains an education level e, for reasons of tractability.

Students are distributed across two schools (districts, counties, etc.), $\mathcal{A}$ and $\mathcal{B}$. Denote the distribution of educational endowments of students in school $\mathcal{A}$ by $A(e)$ and the one in school $\mathcal{B}$ by $B(e)$. Let $n_{\mathcal{A}} \equiv A(\infty), n_{\mathcal{B}} \equiv B(\infty)$, be the mass of students in each school.

Moving from one district to another is possible at a cost of c. The cost c captures actual moving costs, which may be heterogenous due to occupational shocks or wealth constraints, as well as psychic cost stemming, e.g., from moving away for a network of friends.[8]

Moreover, students have preferences over the schools: students has payoff $v(\mathcal{A})$ from attending school $\mathcal{A}$ and $v(\mathcal{B})$ from attending $\mathcal{B}$. The difference $v(\mathcal{A}) - v(\mathcal{B})$ captures the difference in perceived school qualities. The total cost of moving can thus be summed up by a cost $c_{\mathcal{AB}}$ for going from school $\mathcal{A}$ to $\mathcal{B}$, and $c_{\mathcal{BA}}$ for moving from school $\mathcal{B}$ to $\mathcal{A}$ costs $c_{\mathcal{BA}}$. Supposing that

$$v(\mathcal{A}) - v_i(\mathcal{B}) < c \text{ for } \mathcal{B} \text{ and } v_i(\mathcal{B}) - v_i(\mathcal{A}) < c \text{ for } \mathcal{A} \text{ students,} \qquad (1)$$

ensures that $c_{\mathcal{AB}} > 0$ and $c_{\mathcal{BA}} > 0$.

[8] Letting c vary stochastically is a straightforward extension that preserve our results qualitatively, while inducing for some movement of students for non-strategic reasons, such as parental employment shocks.

After school a student can attend the University of Texas if accepted, yielding a college premium of r, while the outside option gives a payoff of $w < r$.[9]

The state university has a capacity of $K < n_{\mathcal{A}} + n_{\mathcal{B}}$, and selects students purely on the basis of education level, and sets a minimum education level e^* for admission. This is indeed an optimal policy for a university that aims to maximise the average education level of its new students.

Suppose that for exogenous, historical reasons the schools differ systematically in the distribution of educational endowments of their students: The distribution $A(e)$ is stochastically dominated in the first order by the distribution $B(e)$. We therefore assume that:

$$\forall e, \frac{A(e)}{n_{\mathcal{A}}} \geq \frac{B(e)}{n_{\mathcal{B}}} \tag{2}$$

Note that under Condition (1) no student has an incentive to move from one school to another, as moving cost are positive and the probability of obtaining a place at the state university does only depend on e.

The capacity constraint K implies that the cutoff value of education e^* must satisfy:

$$n_{\mathcal{A}} - A(e^*) + n_{\mathcal{B}} - B(e^*) = K. \tag{3}$$

By (2) there are proportionally more students from the school $\mathcal{B}$ who are admitted to college than students from school $\mathcal{A}$.

Lemma 1.

$$\frac{n_{\mathcal{A}} - A(e^*)}{n_{\mathcal{A}}} < \frac{K}{n_{\mathcal{A}} + n_{\mathcal{B}}} < \frac{n_{\mathcal{B}} - B(e^*)}{n_{\mathcal{B}}}$$

Proof. The capacity constraint can be rewritten

$$\frac{n_{\mathcal{A}}}{n_{\mathcal{A}} + n_{\mathcal{B}}} \frac{n_{\mathcal{A}} - A(e^*)}{n_{\mathcal{A}}} + \frac{n_{\mathcal{B}}}{n_{\mathcal{A}} + n_{\mathcal{B}}} \frac{n_{\mathcal{B}} - B(e^*)}{n_{\mathcal{B}}} = \frac{K}{n_{\mathcal{A}} + n_{\mathcal{B}}}$$

Since (2) is equivalent to $\frac{n_{\mathcal{A}} - A(e^*)}{n_{\mathcal{A}}} < \frac{n_{\mathcal{B}} - B(e^*)}{n_{\mathcal{B}}}$, the result follows □

[9] The value v_i could depend on the composition of each school to capture peer effects, and both r and w could be a function of the type of the student, without changing our analysis. w can be thought either as a competitive wage or the benefit of going to an out-of-state university.

A top κ% policy

Consider now an admission rule that selects the

$$\kappa \equiv \frac{K}{n_{\mathcal{A}} + n_{\mathcal{B}}}$$

percent of students with the highest education level students in each school. From the lemma, it follows that some students in school $\mathcal{B}$ with education level greater than e^* will not be admitted to college unless they move. We will show that mobility happens for strategic reasons only from $\mathcal{B}$ to $\mathcal{A}$.

Moving strategies are choices $\mu_{\mathcal{A}}(e) \in \{0, 1\}$ and $\mu_{\mathcal{B}}(e) \in \{0, 1\}$ for each student of type e from school $\mathcal{A}, \mathcal{B}$ respectively. Let $m_{\mathcal{B}} \equiv \int \mu_{\mathcal{B}}(e)dB(e)$ denote the mass of students moving from $\mathcal{B}$ to $\mathcal{A}$ and $m_{\mathcal{A}} \equiv \int \mu_{\mathcal{A}}(e)dA(e)$ the mass of students moving from $\mathcal{A}$ to $\mathcal{B}$. Then the final mass of students in schools $\mathcal{A}, \mathcal{B}$ are respectively:

$$\hat{n}_{\mathcal{A}} = n_{\mathcal{A}} + m_{\mathcal{B}} - m_{\mathcal{A}};\ \hat{n}_{\mathcal{B}} = n_{\mathcal{B}} + m_{\mathcal{A}} - m_b,$$

and the distributions of types in each school are:

$$\hat{A}(e) \equiv A(e) + \int_{x \le e} \mu_{\mathcal{B}}(x)dB(x) - \int_{x \le e} \mu_{\mathcal{A}}(x)dA(x)$$
$$\hat{B}(e) \equiv B(e) + \int_{x \le e} \mu_{\mathcal{A}}(x)dA(x) - \int_{x \le e} \mu_{\mathcal{B}}(x)dB(x).$$

The top κ% rule implies that there are $e_{\mathcal{A}}$ and $e_{\mathcal{B}}$ such that only students with type greater than $e_{\mathcal{A}}$ in school $\mathcal{A}$ and greater than $e_{\mathcal{B}}$ in school $\mathcal{B}$ will go to the state university:

$$\frac{\hat{n}_{\mathcal{A}} - \hat{A}(e_{\mathcal{A}})}{\hat{n}_{\mathcal{A}}} = \frac{\hat{n}_{\mathcal{B}} - \hat{B}(e_{\mathcal{B}})}{\hat{n}_{\mathcal{B}}} = \kappa. \tag{4}$$

Because moving is costly, students with $e > e_{\mathcal{A}}$ have a best-response $\mu_{\mathcal{A}}(e) = 0$ and students with $e > e_{\mathcal{B}}$ have a best response $\mu_{\mathcal{B}}(e) = 0$. Hence only students with types less than $e_{\mathcal{A}}$ could have an incentive to move away from $\mathcal{A}$, and only students with types less than $e_{\mathcal{B}}$ could have an incentive to move away from $\mathcal{B}$.

We show first that there is mobility from $\mathcal{B}$ to $\mathcal{A}$ only.

Suppose that $e_{\mathcal{B}} < e_{\mathcal{A}}$. Then, by our previous remark, only $m_{\mathcal{A}}$ students from school $\mathcal{A}$ move to the other school $\mathcal{B}$, and these students have types in $[e_{\mathcal{B}}, e_{\mathcal{A}}]$. Hence, $\hat{n}_{\mathcal{A}} = n_{\mathcal{A}} - m_{\mathcal{A}}, \hat{n}_{\mathcal{B}} = n_{\mathcal{B}} + m_{\mathcal{A}}$, $\hat{A}(e_A) = A(e_A) - m_{\mathcal{A}}$ and

$\hat{B}(e_{\mathcal{B}}) = B(e_{\mathcal{B}})$. Now, (4) and Lemma 1 imply:

$$\begin{aligned}\frac{n_{\mathcal{A}} - A(e^*)}{n_{\mathcal{A}}} < \kappa = & \frac{n_{\mathcal{A}} - m_{\mathcal{A}} - A(e)}{n_{\mathcal{A}} - m_{\mathcal{A}}} \\ \Rightarrow & A(e^*) > \frac{n_{\mathcal{A}}}{n_{\mathcal{A}} - m_{\mathcal{A}}} A(e_{\mathcal{A}}) \\ \Rightarrow & e^* > e_{\mathcal{A}}.\end{aligned}$$

Similarly,

$$\begin{aligned}\frac{n_{\mathcal{B}} - B(e^*)}{n_{\mathcal{B}}} > \kappa = & \frac{n_{\mathcal{B}} + m_{\mathcal{B}} - B(e_b)}{n_{\mathcal{B}} + m_{\mathcal{A}}} \\ \Rightarrow & B(e^*) < \frac{n_{\mathcal{B}}}{n_{\mathcal{B}} + m_{\mathcal{A}}} B(e_{\mathcal{B}}) \\ \Rightarrow & e^* < e_{\mathcal{B}}.\end{aligned}$$

But then $e_{\mathcal{A}} < e_{\mathcal{B}}$, contradicting our assumption.

If $e_{\mathcal{A}} \leq e_{\mathcal{B}}$, only students from $\mathcal{B}$ move, implying that $\hat{n}_{\mathcal{A}} = n_{\mathcal{A}} + m_{\mathcal{B}}$, $\hat{n}_{\mathcal{B}} = n_{\mathcal{B}} - m_{\mathcal{B}}$, $\hat{A}(e_{\mathcal{A}}) = A(e_{\mathcal{A}})$ and $\hat{B}(e_{\mathcal{B}}) = B(e_{\mathcal{B}}) - m_{\mathcal{B}}$. Replicating the previous arguments, it follows that $e_{\mathcal{A}} \leq e^* \leq e_b$. This proves the following proposition.

Proposition 1. *In equilibrium, only students from school $\mathcal{B}$ move to school $\mathcal{A}$ and $e_{\mathcal{A}} \leq e^* \leq e_{\mathcal{B}}$.*

Because students from $\mathcal{B}$ with type greater than $e_{\mathcal{B}}$ get a place at the state university, only students with types $e \in [e_{\mathcal{A}}, e_{\mathcal{B}}]$ have a strategic reason to move to school $\mathcal{A}$. If the cost of moving is smaller than the college premium for *all* the types greater than e^*, we obtain the striking result that the *same* students will be eventually admitted to college.

Proposition 2. *Suppose that $\max_{e \geq e^*} r - w$ is greater than $c_{\mathcal{B}\mathcal{A}}$, then $e_{\mathcal{A}} = e_{\mathcal{B}} = e^*$ and $m_{\mathcal{B}} = n_b - B(e^*) - \kappa$. Hence the set of students going to college is not affected by the policy.*

Proof. Proposition 1 implies that a measure $m_{\mathcal{B}}$ of students with education level greater than e^* move from school $\mathcal{B}$ to school $\mathcal{A}$, while other students stay put. With our assumption on cost, all students with type $e \geq e^*$ would benefit from moving to $\mathcal{A}$ in order to get $r - c_{\mathcal{B}\mathcal{A}}$ rather than taking their outside option w. In equilibrium it must be the case that these two measures represent κ% of their respective schools, hence that:

$$\frac{n_{\mathcal{A}} - A(e^*) + m_{\mathcal{B}}}{n_{\mathcal{A}} + m_{\mathcal{B}}} = \frac{n_{\mathcal{B}} - B(e^*) - m_{\mathcal{B}}}{n_{\mathcal{B}} - m_{\mathcal{B}}} \tag{5}$$

Since the left hand side is increasing and the right hand side is decreasing in $m_{\mathcal{B}}$, Lemma 1 implies that there exists a unique $m_{\mathcal{B}} > 0$ solving the equality. Clearly the common value of the fractions in (3) is κ since the total measure of students going to college is $n_{\mathcal{A}} - A(e^*) + n_{\mathcal{B}} - B(e^*) = K$. $\square$

Note that the students who move are those whose education level is the interval $[e^*, e_m]$, where $B(e_m) - B(e^*) = m_{\mathcal{B}}$, and $m_{\mathcal{B}}$ solves (5).

This leads to our main observation: *Mobility takes the form of going from a school with higher education level on average to a school with lower education level on average.*

Suppose now that the education level is imperfectly positively correlated with the socio-economic group g a student belongs to (like race, parents' income). That is, students from a privileged background have an advantage in terms of educational endowments over underprivileged students. This is best interpreted as background capturing differential parental investment in their children, endowing pupils from privileged backgrounds with a greater set of skills already before starting school.[10] To simplify, suppose that the variable capturing background is binary and let p_{gs} denote the share of students from group g at school s, and p_g the share of students from group g in the entire student population. Segregation is measured by the mutual information index for school s:

$$M_s = p_{0s} \log\left(\frac{p_{0s}}{p_0}\right) + p_{1s} \log\left(\frac{p_{1s}}{p_1}\right).$$

If, say, $p_{0s} > p_0$ then the segregation index will decrease as p_{0s} decreases. Supposing that e and g are correlated positively, $p_{0\mathcal{A}} > p_0 > p_{0\mathcal{B}}$ and $p_{1\mathcal{A}} < p_1 < p_{1\mathcal{B}}$. Hence, if a policy induces some movement of students between schools that increases $p_{1\mathcal{A}}$ and decreases $p_{1\mathcal{B}}$, both $M_{\mathcal{A}}$ and $M_{\mathcal{B}}$ must decrease, i.e., both schools become more integrated with respect to g.

Denote the conditional probability of g given e by $P(g|e)$. Then the new shares p'_{gs} are given by

$$p'_{1\mathcal{B}} = \frac{p_{1\mathcal{B}} n_{\mathcal{B}} - m_{\mathcal{B}} \int_{e_m}^{e^*} B(e) P(1|e) de}{n_{\mathcal{B}} - m_{\mathcal{B}}},$$

and

$$p'_{1\mathcal{A}} = \frac{p_{1\mathcal{A}} n_{\mathcal{A}} + m_{\mathcal{B}} \int_{e_m}^{e^*} B(e) P(1|e) de}{n_{\mathcal{A}} + m_{\mathcal{B}}}.$$

[10] For instance Heckman (2008) summarizes findings where differential parental early childhood investments explain school performance gaps between children with different social backgrounds.

Hence, the policy change decreases $p_{1\mathcal{B}}$ and increases $p_{1\mathcal{A}}$ if

$$\frac{\int_{e_m}^{e^*} B(e)P(1|e)de}{m_{\mathcal{B}}} > p_{1\mathcal{B}} \text{ and } \frac{\int_{e_m}^{e^*} B(e)P(1|e)de}{m_{\mathcal{B}}} > p_{1\mathcal{A}}.$$

Note that the first condition implies the second. The condition for a decrease in measured segregation with respect to socioeconomic groups g is thus

$$P(1|e_m < e < e^*) > p_{1\mathcal{B}}.$$

This means that the share of $g = 1$ students is required to be greater among movers than among the entire school $\mathcal{B}$ population. This is satisfied if, e.g., e and g correlate positively, and e_m is greater than the average educational level, which is the case when, say, $\kappa = .1$.

3 Discussion and Extensions

The results in the previous section show that if schools are segregated with respect to socioeconomic background such as race or SES, a top κ% policy will 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 a move to school profitable that would not have been chosen without the policy. That is, a top κ% policy will in effect assist some schools to attract students with high educational endowment who would otherwise not have considered to attend that school. In this sense the policy can be understood as subsidising less than elite schools that nevertheless offer a viable pathway to university education.

In our setting one school stochastically dominates another in terms of students' educational outcomes and this is positively correlated with socioeconomic background. Under our assumptions this is a stable outcome in the sense that no student has incentive move absent a top κ% policy. Indeed students from the ethnic majority tend to have privileged backgrounds in Texas, as shown in Figure 2: the percentage of minority students enrolled at a high school correlates positively with the percentage of economically disadvantaged students and negatively with the high school pass rate in TAAS.[11] That is, a

[11]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.

school's ethnic composition is a good predictor of socio-economic status and test score results.

Figure 2: Share of minority and economically disadvantaged students (left) and share of minority and TAAS pass rate (right). *Source*: AEIS data.

The model can be extended in different directions and we consider some of the possibilities below. The first one, using multiple years of schooling, inspires our empirical strategy; assessing the consequences of the others empirically is difficult given the nature of our data.

3.1 Multiple Years of Schooling and Rematch

If the top $\kappa\%$ policy does not require a minimum stay at a school in order to be eligible, students effectively have the opportunity to choose whether to move between schools both at an earlier and a later stage. A student who has a purely strategic motive to move from school $\mathcal{B}$ to $\mathcal{A}$ in order to secure access to college, while preferring the original school $\mathcal{B}$ to $\mathcal{A}$, i.e. $v(\mathcal{B}) > v(\mathcal{A})$, will, of course, prefer to make the move at a later stage, to enjoy the preferred school for longer. Hence, students who move for strategic reasons will do so mainly in later grades, suggesting that the effect on segregation should be small in early grades and more pronounced in later grades.

The theoretical implication of late rematch is a useful guide for empirical work. While Cullen et al. (2013) present evidence for strategic rematch between 8th and 10th grades under a top-x percent policy, it is not clear whether this effect is large enough to change substantially the degree of high school segregation in Texas. Our model suggests that strategic rematch is more likely to occur later, between 9th and 12th grades, as high ability students would prefer to enjoy peer effects in segregated schools for as long as possible, and also that there may be significant aggregate consequences for high school composition.

3.2 Quota-based Affirmative Action

Extending the analysis above to allow for quota based affirmative action that sets aside capacity K_g for each group $g = 0, 1$ of students is straightforward. A university that maximizes average educational quality of its new students will thus admit all students from a group g who have at least $e \geq e^*_g$, so that the mass of admitted students from group g equals K_g. Since the threshold education level e^*_g does not depend on the school that a student is attending the analysis above carries over and there is no strategic incentive for students to move to another school.

3.3 Peer Effects and Mutual Gains from Trade

Suppose that the quality of a school depends positively on its students' abilities, for instance in form of average educational endowment. Then a move of a student from school $\mathcal{B}$ to $\mathcal{A}$ for strategic reasons will result in an increase of average ability in school $\mathcal{A}$ and decrease average ability in school $\mathcal{B}$. Hence, if students derive utility from the quality of a school then all students in school $\mathcal{A}$, except for the one who loses access to college as a consequence of the new arrival, will strictly prefer the new student to join the school. That is, with positive peer effects the policy will induce mutual gains from switching schools, both the mover and most of the receivers will have higher payoff as a result of the move.

3.4 Predictions

In conclusion, the theoretical results predict a decrease of segregation in background, in particular with respect to race, after introducing the Texas top ten policy. The decrease will be more pronounced for higher grades at high school than for lower grades. The introduction of the policy will also be associated with movement of students with medium to high educational endowment to schools with lower average educational endowment. An increase in students' strategic movement will be partly in form of changes of schools that require agreement by the new school; in Texas this mainly takes the form of so called transfers.

4 A Closer Look at the Data

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

4.1 Data and Descriptive Statistics

To do so 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 enrolment data. We use data on student counts per grade and per race/ethnicity (classified into five groups: White, African American, Hispanic, Asian, and Native American).[12] The data are provided at the school (campus) level for all ethnic groups with more than five students enrolled in school.[13] We use this data to compute the segregation measures that will be explained below.

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

[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.

10th grade used in Texas between 1991 and 2002, and several indicators such as dropouts, school composition, and attendance.

The third database contains individual-level data for students enrolled in 8th and 12th grades in a public school.[16] For each student, we observe the grade and school they are enrolled in, whether they are a transfer student,[17] and their ethnic group and economic disadvantaged status. Each record is assigned a unique student ID, allowing us to track students as they change schools, as long as they remain in the Texas education system. The 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, 2010). 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]

$$M_s^x = \sum_{g=1}^{G} p_{gs} \log\left(\frac{p_{gs}}{p_{gx}}\right), \tag{6}$$

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

[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)

[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 mutual information index. It can be calculated as:

$$M = \sum_{s=1}^{S} p_s M_s^{Texas}, \tag{7}$$

where M_s^{Texas} is the local segregation index comparing school to state composition and can be obtained by using (6), and p_s is the share of Texan students who attend school s.

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

$$W^c = \sum_{s \in C} p_{sc} M_s^c, \tag{8}$$

where p_{sc} is the share of students attending school s in county c, and M_s^c is given by (6) using the county as a benchmark unit. Note that the mutual information index defined in (7) is the within-Texas segregation index.

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

4.2 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

[19] We use the county, not the school district, as the relevant unit, since many school districts contain only one school, so that within-school district segregation is zero by definition.

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

Local Segregation Index

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

The dependent variable of interest in our difference-in-difference approach is the local segregation index M^r_{yst} (defined in (6)) for grade level y in school s at time t, where the benchmark unit is the region r to which the school belongs.[20] We consider school years 1994-1995 to 1996-1997 to be pre-treatment, while 1998-1999 to 2000-2001 correspond to post-treatment periods.[21] Since the policy was signed in 1997 and implemented in 1998, school year 1997-1998 may be partially affected by the reform and is therefore excluded from the analysis. For grade levels $y = \{9; 12\}$ we estimate the model:

$$M^r_{yst} = \beta_1 \left(G12_{ys} \times TOP_t\right) + \boldsymbol{\delta}'\mathbf{T} + u_{ys} + \varepsilon_{yst}, \tag{9}$$

where $G12_{ys} = 1$ if $y = 12$, $TOP_t = 1$ 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

[20] 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.

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

also allow these trends to be region-specific to control for changes in the student population in a given region that may be caused by immigration, for example. The coefficient of interest in this regression is β_1 and it indicates the relative change in the local segregation index in the grade and school years affected by the top ten percent law.

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

$$\begin{aligned} M^r_{yst} =& \beta_1(G12_{ys} \times TOP_t) + \beta_2(G11_{ys} \times TOP_t) + \beta_3(G10_{ys} \times TOP_t) \\ &+ \boldsymbol{\delta}'\mathbf{T} + u_{ys} + \varepsilon_{yst}, \end{aligned} \tag{10}$$

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

A possible concern with the results presented in Table 2 is that they may reflect pre-existing trends in the local segregation indices. As a placebo, we run equations (9) and (10) 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 4 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 (8). Using the within-county segregation measure instead of the local segregation index allows us to capture some of the movement of students across schools between these grades, a relatively common phenomenon in the Texas high school system.[22]

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

$$W^c_{12t} - W^c_{09(t-3)} = \beta TOP_t + \delta t + u_c + \varepsilon_{ct}, \tag{11}$$

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

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. As

[22]Focusing on within school district segregation instead yields similar results. The drawback of using districts is that many districts contain only one school as mentioned above.

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

mentioned above, the decrease in segregation does not appear to be related to more school choice, as the effect is not stronger for schools located in larger school districts or in MSAs. The magnitude of the movement of students necessary to bring about the decrease can be explained by the natural fluctuation of students between high schools in Texas.[24] Indeed, changing schools is a relatively common phenomenon in Texas. 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). Nevertheless it seems desirable to shed some light on the specific mechanism through which strategic moves may have taken place.

The time series of the number of transfer students in Texas offers some indicative evidence. Transfer students are students whose district of residence is not the same as the school district they attend. Indeed, as shown in Figure 5, the number of transfer students has more than doubled since 1998, even when one discounts charter school students, which is in line with our expectations.[25]

To examine the hypothesis that at least some students who changed schools did so strategically, be it by applying for a transfer or in the course of natural fluctuation, we will use student level individual data. That is, our hypothesis is that students who change schools will prefer schools where they are more likely to be in the top ten percent of their class, similar to the one examined by Cullen et al. (2013). While they use the available choice set (i.e., the presence of suitable schools in the vicinity) for identification of a student's likelihood to move, our identification strategy relies instead on the differential effect of the policy for different grades, conditional on a student moving schools.

We are interested in whether the introduction of the top ten percent policy was associated to a change in the characteristics of target schools of moving students, and whether the change differed between in lower and higher grades. Specifically, we examine whether after the introduction of the policy movers in 11th and 12th grades were more likely to move to schools with less college bound students, lower SAT average, lower TAAS pass rate, and less majority students (i.e., Asians and Whites) than their school of origin compared to 9th and 10th grade movers. These variables are plausible indicators of a

[24]Simulations show that strategic movement of about 3000 students (1.5% of the student population) would suffice to generate the effect; the actual annual movement rate is 10%.

[25]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.

move to an academically worse school. We therefore estimate equations with a dependent variable Y_{it} that takes the value 1 if this is indeed the case (e.g., school of destination has less college-bound students than school of origin) and 0 otherwise:

$$Y_{it} = \beta_1 (G12_i \times TOP_t) + \beta_2 (G11_i \times TOP_t) + \boldsymbol{\gamma}'\mathbf{G_i} + \boldsymbol{\rho}'\mathbf{X_i} + \boldsymbol{\delta}'\mathbf{T} + \varepsilon_{it}, \quad (12)$$

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. After running the regressions for the full sample, we estimate (12) separately for economically disadvantaged students and non-economically disadvantaged students (excluding economic disadvantage status as a control variable).[26]

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

The results are presented in Tables 5 to 8. Table 5 shows that the probability of moving to a school with less college bound students than the previous school increases for movers in the 11th and 12th grades by 2.8 and 6.4 percentage points, respectively. This is amplified with the top ten percent rule, by 2.5 and 3.1 percentage points for 11th and 12th grades, respectively. This corresponds to an increase of 4.7% and 5.9%, respectively. Note that this effect is driven mainly by students who are not economically disadvantaged. The coefficient estimates for economically disadvantaged students are positive, but not statistically significant. That is, under the top ten percent rule relatively well-off students in higher grades were significantly more likely to move to academically worse schools, unlike economically disadvantaged students.

Table 6 shows a similar pattern for SAT averages. Considering the transition from 11th to 12th grade, the probability of moving to a school with lower SAT average than the school of origin increases by 3.2 percentage points for non-economically disadvantaged students. This corresponds to a 7.4% increase,

[26]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.

given that the sample mean of the dependent variable is 0.431. The same effect is almost zero and not statistically significant for economically disadvantaged students. While well-off students tend to move down in terms of the academic quality measured by average SAT score after the top ten percent policy has been introduced, economically disadvantaged student tend to move up, if anything.

When considering TAAS pass rates a similar picture emerges, see Table 7. Both economically disadvantaged and well-off students are more likely to choose a school with lower TAAS pass rate than their previous school after the introduction of the top ten percent plan. The effect is much weaker for the economically disadvantaged students, however: the probability increases by 7.0% for economically disadvantaged students, compared to a 14.3% increase for other students in 12th grade, for instance.

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

Taken together, these results very strongly suggest that students who have moved schools in 11th and 12th grades were more likely to choose their new school strategically than students in lower grades after the introduction of the top ten percent policy. In particular, the data are consistent with students targeting schools with a lower proportion of college bound students, lower SAT average, lower TAAS pass rates, and less Asian and White students, and with the fact that this is particularly pronounced for students who were not economically disadvantaged, who arguably tend to benefit more from university education and are likely to profit more from the top ten percent rule in expectation.

Robustness Check: Charter Schools

The results presented above indicate a decrease in within-county segregation that took place after the top ten percent policy was introduced in 1998. An obvious concern is that other changes affecting the segregation at lower and higher grades differentially may have occurred at the same time. The only other major policy that could potentially have had a similar aggregate effect and occurred contemporaneously was the introduction of charter schools. Indeed, the first charter schools were starting in 1996, but the first wave of expansion began in 1998, coinciding with the introduction of the top ten percent law. Charter schools accept students from multiple school districts, and thus their proliferation could contribute to a decrease in segregation, mechanically through redistricting or by allowing students a possibility to strategically relocate.[27]

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

Table 9 presents the results of the within-county segregation regression. The coefficients for the top ten percent policy are negative and significant as before. Moreover, the existence of charter schools does not seem to reduce within-county segregation, as the coefficient estimates are statistically indistinguishable from zero at conventional levels, both when one considers the presence of charter schools in a county and when one uses the percentage of students enrolled in charter schools.[28]

Robustness Check: Residential Segregation

Another potential concern is that the decrease in high school segregation might simply reflect residential desegregation, given that students usually attend schools in their district of residence. Using population data, we compute mutual information indices for the total population and for the group aged 15-19.

[27]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.

[28]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.

The indices are calculated by comparing the composition of the population in a given county with the composition of the population of the state. For comparison we also plot the mutual information index for 9th to 12th grades with the county as the unit of observation. Figure 3 shows that, if anything, residential segregation has increased over the period 1990 to 1999[29] and cannot explain the decrease in segregation among the student population over the period.

5 Conclusion

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

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

[29]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.

A Appendix: Tables and Figures

Figure 3: Residential versus School System Segregation

Figure 4: Time series of the mutual information index for 10th and 11th grades

Figure 5: 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
lower TAAS pass rate	0.417	0.493	97,968	0.357	0.479	112,381
less Asian and White students	0.592	0.492	679,962	0.585	0.493	784,266

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)
$G12 \times TOP$	-0.004*	-0.004*	-0.004*	-0.004*
	(0.002)	(0.002)	(0.002)	(0.002)
$G11 \times TOP$			-0.004*	-0.004*
			(0.002)	(0.002)
$G10 \times TOP$			-0.003	-0.003
			(0.002)	(0.002)
Constant	0.135***	0.135***	0.136***	0.136***
	(0.001)	(0.001)	(0.001)	(0.001)
Fixed effects:				
School-grade	yes	yes	yes	yes
region-year	no	yes	no	yes
Year	yes	no	yes	no
Mean of Dep. Var.	0.137	0.137	0.138	0.138
Observations	17,984	17,984	35,384	35,384
School-grade	3,722	3,722	7,274	7,274
r-squared (within)	0.002	0.011	0.001	0.008

Notes: * significant at 10%, ** significant at 5%, *** significant at 1%. robust standard errors in parentheses. The masked observations were converted to zero. The variable $Gy \times TOP = 1$ if $y = \{10, 11, 12\}$ and $t \geq 1997$ 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)
TOP	-0.001**	-0.004**
	(0.001)	(0.002)
Constant	0.000	-1.020
	(0.000)	(0.778)
County fixed effect	yes	yes
Linear time trend	no	yes
Mean of Dep. Var.	-0.001	-0.001
Observations	1,512	1,512
r-squared (within)	0.004	0.006
Number of school districts	252	252

Notes: * significant at 10%, ** significant at 5%, *** significant at 1%. Standard errors in parentheses. The masked observations were converted to zero, but results are similar using the other unmasking strategies. The variable $TOP = 1$ if $t \geq 1997$ 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		
		If student changing schools is Economic Disadvantage Status	
	Full Sample	No	Yes
	(1)	(2)	(3)
$G11$	0.028***	0.021***	0.044***
	(0.004)	(0.005)	(0.008)
$G12$	0.064***	0.060***	0.073***
	(0.005)	(0.006)	(0.010)
$G11 \times TOP$	0.025***	0.026***	0.015
	(0.006)	(0.007)	(0.011)
$G12 \times TOP$	0.031***	0.039***	0.004
	(0.007)	(0.008)	(0.013)
Constant	0.454***	0.452***	0.467***
	(0.005)	(0.006)	(0.008)
Mean of Dep. Var.	0.530	0.527	0.539
Observations	151,038	106,756	44,282
r-squared	0.007	0.007	0.011

Notes: * significant at 10%, ** significant at 5%, *** significant at 1%. Standard errors in parentheses. The control variables are year, ethnic group, eco disad, grade, grade offered.

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

Dep. Var.:	Probability of moving to a school with **lower SAT average** than school of origin		
		If student changing schools is Economic Disadvantage Status	
	Full Sample	No	Yes
	(1)	(2)	(3)
$G11$	0.016***	0.010**	0.028***
	(0.004)	(0.005)	(0.008)
$G12$	0.020***	0.014**	0.035***
	(0.005)	(0.006)	(0.010)
$G11 \times TOP$	-0.013**	-0.006	-0.028**
	(0.006)	(0.007)	(0.011)
$G12 \times TOP$	0.023***	0.032***	0.004
	(0.007)	(0.008)	(0.014)
Constant	0.501***	0.508***	0.507***
	(0.005)	(0.006)	(0.009)
Mean of Dep. Var.	0.435	0.431	0.446
Observations	131,811	94,259	37,552
r-squared	0.082	0.087	0.068

Notes: * significant at 10%, ** significant at 5%, *** significant at 1%. robust standard errors in parentheses. The control variables are year, ethnic group, eco disad, grade, grade offered.

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

Dep. Var.:	Probability of moving to a school with **lower TAAS pass rate** than school of origin		
		If student changing schools is Economic Disadvantage Status	
	Full Sample	No	Yes
	(1)	(2)	(3)
$G11$	-0.015***	-0.030***	0.038***
	(0.003)	(0.004)	(0.007)
$G12$	0.057***	0.054***	0.063***
	(0.004)	(0.005)	(0.009)
$G11 \times TOP$	0.065***	0.071***	0.036***
	(0.005)	(0.006)	(0.009)
$G12 \times TOP$	0.047***	0.055***	0.027**
	(0.006)	(0.007)	(0.012)
Constant	0.488***	0.503***	0.447***
	(0.004)	(0.005)	(0.007)
Mean of Dep. Var.	0.385	0.384	0.388
Observations	210,349	148,682	61,667
r-squared	0.037	0.039	0.038

Notes: * significant at 10%, ** significant at 5%, *** significant at 1%. robust standard errors in parentheses. The control variables are year, ethnic group, economic disadvantaged status, grade, and grade offered.

Table 8: 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 Asian and White** students than school of origin		
		If student changing schools is Economic Disadvantage Status	
	Full Sample	No	Yes
	(1)	(2)	(3)
$G11$	-0.076***	-0.084***	-0.020***
	(0.003)	(0.003)	(0.006)
$G12$	-0.049***	-0.050***	0.004
	(0.004)	(0.004)	(0.008)
$G11 \times TOP$	0.055***	0.049***	0.045***
	(0.004)	(0.004)	(0.008)
$G12 \times TOP$	0.015***	0.011**	-0.003
	(0.005)	(0.006)	(0.010)
Constant	0.503***	0.453***	0.521***
	(0.002)	(0.002)	(0.003)
Mean of Dep. Var.	0.588	0.623	0.517
Observations	1,464,228	987,573	476,655
r-squared	0.025	0.022	0.008

Notes: * significant at 10%, ** significant at 5%, *** significant at 1%. robust standard errors in parentheses. The control variables are year, ethnic group, eco disad, grade, grade offered.

Table 9: 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)
TOP	-0.004**	-0.004**	-0.004**
	(0.002)	(0.002)	(0.002)
CHA		-0.000	
		(0.006)	
$TOP * CHA$		0.002	
		(0.006)	
$\%STUDCH$			-0.126
			(1.342)
$TOP * \%STUDCH$			0.234
			(1.339)
Constant	-1.020	-0.982	-0.889
	(0.773)	(0.780)	(0.778)
County fixed effect	yes	yes	yes
Linear time trend	yes	yes	yes
Mean of Dep. Var.	-0.001	-0.001	-0.001
Observations	1,512	1,512	1,512
r-squared (within)	0.034	0.034	0.038
Counties	252	252	252

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

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