Department of Economics- FEA/USP

College Admission and High School Integration

Fernanda Estevan
Thomas Gall
Patrick Legros
Andrew F. Newman

Working Paper Series Nº 2014-26

DEPARTMENT OF ECONOMICS, FEA-USP
WORKING PAPER Nº 2014-26

College Admission and High School Integration

Fernanda Estevan (festevan@usp.br)
Thomas Gall (t.gall@soton.ac.uk)
Patrick Legros (plegros@ulb.ac.be)
Andrew F. Newman (afnewman@bu.edu)

Abstract:

This paper examines possible effects of college admission policy on general equilibrium outcomes at the high school stage. Specifically, 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 matching 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.

JEL Codes: C78; I23; D45; J78.

College Admission and High School Integration*

Fernanda Estevan[†], Thomas Gall[‡], Patrick Legros[§], Andrew F. Newman[¶]

Abstract

This paper examines possible effects of college admission policy on general equilibrium outcomes at the high school stage. Specifically, 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 matching 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.

JEL: C78, I23, D45, J78.

*The authors are grateful for valuable comments and discussion to Matteo Bobba, Louis-Philippe Morin, and participants of NEUDC 2010, ThreD meeting 2011, CEA Meeting 2012, and seminars at University of Essex, IZA, University of Mannheim, UQAM, University of Ottawa, Wilfrid Laurier University, FEA-USP, and FEA-RP. Gall thanks DFG for financial support (Grant GA-1499) and BU for its hospitality. Legros has benefitted from the financial support of a 2010 grant FNRS *Crédit aux chercheurs* entitled "The Dynamic Effects of Matching Policies under Nontransferabilities." Chaker El Mostafa and Deborah Goldschmidt provided excellent research assistance during this project.

†Department of Economics, University of Sao Paulo, Avenida Professor Luciano Gualberto, 908 - Cidade Universitária - São Paulo - SP - Brazil - CEP: 05508-01; email: festevan@usp.br

‡University of Southampton, Southampton, SO17 1BJ, UK; email: t.gall@soton.ac.uk.

§ECARES, Université Libre de Bruxelles and CEPR.

¶Boston University and CEPR.

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, and student achievement are correlated, such "school arbitrage" will indeed

[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.

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 builds on a dynamic assignment model where students differ in abilities and backgrounds. Ability can be high or low, and background privileged or underprivileged. A cohort of students matches into high schools and acquires education in several periods. There are positive peer effects within schools, in that educational attainment increases in peer educational endowment, which in turn depends on educational attainment in the last period, and on ability and background in the first period of schooling. After completing high school, students apply to a college with exogenous capacity and are accepted depending on the admission rule in place. We consider three admission rules: Under laissez-faire the college admits students ranking them by their final educational attainment. Affirmative action induces a side constraint: admission has to reflect population frequencies of the backgrounds. A top-x percent rule admits the top X percent students at each school. Payoffs are given by final educational attainment and a college wage premium that increases in attainment and ability. As a market equilibrium we use a stable allocation of students into schools without monetary side payments.

Under both affirmative action policies and laissez-faire a student's admission probability increases in the final grade (e.g., test score), which in turn increases with peer quality. Therefore students segregate in the last period under both policies. Under a top-x percent rule, however, final period students face a trade-off: a higher quality peer augments education acquisition and thus expected wages, but competes for college admission, decreasing the admission probability.[4] When the students differ sufficiently in their college wage premium, the first effect dominates for low ability students and the second one for high ability students. Therefore, in the final all possible matches between low and high ability students in schools are exhausted. This implies that a positive measure of schools are attended by students of different backgrounds. In earlier stages students' continuation valuations increase in peer quality under all three policies, implying full segregation. Hence, the theory predicts a rematch in the final stages of high school resulting in some background integration for a top-x percent rule, but not for the other regimes.

When background correlates with race, the model predicts racial desegregation of high schools as a consequence of the policy. 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] Strategic rematch 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).

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 4 in the Appendix.

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

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 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 Liberty Global (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

Liberty Global (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, Sections 3 and 4 evaluate different college admission policies and derive theoretical predictions that are taken to the data in Section 5. Section 6 concludes. The more cumbersome proofs as well as tables and figures can be found in the Appendix.

2 A Simple Framework

The economy is populated by a continuum with unit measure of students I. Students are characterized by ability a and background b. We assume that ability is observable, an assumption without much loss of generality; see Section 4 for a discussion. Ability can be either *high* or *low*, that is, $a \in \{h, \ell\}$. Denote the ex ante probability of having high ability by $\alpha \in (0, 1)$. Background is also observable and can be either *privileged* or *underprivileged*, $b \in \{p, u\}$. Denote the share of privileged agents by $\pi \in (0, 1)$. Suppose innate ability and background are stochastically independent.

Students acquire education, first at school, and then in college. They enter school with an educational initial endowment e that is determined by ability and background type. Because there are two levels of ability and two background types, there are four possible levels of endowments that we index by the one-dimensional variable $e \in \{\ell u, \ell p, hu, hp\}$. We suppose that the most able u student has higher endowment than the least able p student:

$$0 < \ell u < \ell p < hu < hp. \tag{1}$$

Hence privileged students begin their educational career with an advantage over underprivileged students, for a given ability. 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.[8]

Schools

Education acquisition occurs in schools, which we assume for simplicity to be of size two. A school is thus a tuple of educational endowments (e, e'). The human capital acquired by a student with endowment e in school (e, e') is summarized by the final grade $g(e, e')$. We assume that $g(e, e')$ is a weighted average of own and peer attributes and gives a measure of absolute performance:

$$g(e, e') = ((1 - \lambda)e + \lambda e')^{\gamma},$$

where $\lambda \in (0, 1/2)$ denotes the intensity of peer effects and $\gamma > 0$ determines whether peer effects have decreasing ($\gamma < 1$), constant ($\gamma = 1$), or increasing differences ($\gamma > 1$). This formulation implies that the ranking of educational attainments is preserved within schools and advantages conveyed by a privileged background for a given ability are persistent. Indeed, $e < e'$ implies $g(e, e') < g(e', e)$ in a school (e, e').[9]

Furthermore, we note that for any $e > e'$:

$$g(e, e) > g(e, e') > g(e', e) > g(e', e'), \tag{CM}$$

i.e., peer effects in schools are strictly positive in the sense that any individual benefits from a better peer group.[10] This assumption does not pin down the surplus efficient allocation, which will depend on whether low or high attribute students benefit more from peer effects, i.e., whether γ is lower or greater than 1. In this paper we focus on a positive analysis and remain agnostic about normative implications, which may become an issue as the stable outcome may not maximize aggregate surplus when utility is not perfectly transferable (see Legros and Newman, 2007).

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

[9] Though plausible at a first glance this assumption is made for convenience and first order stochastic dominance suffices to generate our results.

[10] For recent evidence that college achievement increases in peers' high school grades see for instance Stinebrickner and Stinebrickner (2006), or Kremer and Levy (2008). Bifulco et al. (2011) report that better peers increase the probability of attending college.

Payoffs and College

After attending school students either begin to work or move on to college. In any event individuals' payoffs are determined by the wage they receive after education, which depends on educational achievements. Assume for simplicity that the wage of high school graduates without college education equals the final grade $g(e, e')$.

A college graduate additionally obtains a college wage premium. A significant part of the college wage premium appears to be explained by sorting on an ability dimension (see Fang, 2006), suggesting that students of different abilities differ in their continuation valuation of attending college. We assume that the college wage premium is an increasing function $r(e)$ of educational endowment, and thus also of a and b. Of course, the college premium could also depend only on ability a, or background b, or a combination of all these. The crucial property driving our results is that the college premium gives only some students an incentive to prefer weaker peers. If this incentive is not perfectly negatively correlated with educational attainment our argument remains valid.

Individual expected payoff from attending a school (e, e') is

$$v(e, e') = g(e, e')(1 + qr(e)),$$

where $q \in [0, 1]$ denotes the probability an individual attends college. This probability will play a crucial role in shaping the composition of schools and will be affected by the policy put in place for screening students in college.

There is a representative college with an exogenous capacity of measure $\kappa > 0$ of students. To avoid excessive notation, we suppose that $\kappa \leq 1/2$. We shall abstract from self-interests on the side of college and assume that its admission rule maximizes the students' aggregate surplus (or human capital, if accurately reflected by wage). This will result in maximizing average educational achievement among enrolled students. Actual admission policies of colleges may be subject to policy constraints.

Timing

Summarizing, events unfold as follows in the economy.

0. Nature assigns background and ability, determining endowments e_i.

1. Agents match in schools and acquire education resulting in a grade; $g(e_i, e_j)$ is the grade of individual i who is in school with individual j.

2. Agents attend college or not, based on an admission rule, and obtain payoffs.

As a solution concept we use a stable match of students into schools without side payments. Formally, a matching equilibrium is a stable assignment of students into schools of size two, such that no student matched into a school finds it strictly more profitable to stay solitary, and there is no pair of agents not matched into the same school that would both strictly gain by matching together. Hence, in equilibrium all students at a school must find matching with their current peers profitable. This well describes settings where parents can influence a school's administration with discretion over admission.

3 College Admission Regimes and Matching in High Schools

In the following we will examine three policies of college admission in greater detail: laissez faire, affirmative action, and top-x percent. These regimes closely mirror the different policies that have been in place in Texas during the time covered by our data. We shall be concerned with their effects on the composition of colleges, and, more importantly, oh high schools. All three policies can base admission on an individual i's final grade g_i, and will therefore imply different probabilities of accessing college as a function of a given match. We denote the policies by a superscript taking values $P = L, A, X$ for laissez-faire, affirmative action and top-x percent respectively.

3.1 Laissez Faire

Under laissez-faire the college chooses an admission rule $q^L : I \mapsto [0, 1]$ to admit students in order to maximize aggregate surplus subject to the capacity constraint. That is, the college solves

$$\max_{q^L} \int_{i \in I} (1 + q^L(i) r(e_i)) g_i di \text{ s.t. } \int_{i \in I} q^L(i) di = \kappa.$$

Let $\mu(i \in I : g_i \leq g)$ denote the Lebesgue measure of students with grade $g_i \leq g$. Since $hu > \ell p$, any solution q^L obeying the capacity constraint satisfies

$$\begin{aligned} q^L(i) &= 1 \text{ if } \mu(j \in I : g_i \geq g_j) < \kappa \text{ and} \\ q^L(i) &= 0 \text{ if } \mu(j \in I : g_i \leq g_j) < 1 - \kappa. \end{aligned} \tag{2}$$

That is, an optimal policy admits all student above a threshold achievement level, does not admit students below that level, and admits students at the threshold level with a probability to satisfy the capacity constraint. Suppose that uniform rationing is used to break ties.

By (2) an optimal admission policy $q^L(i)$ depends only on a student's final grade g_i and weakly increases in g_i. For these reasons we can ignore individual subscripts and express payoffs and probability of accessing the university as a function of the endowment e, and the grade $g(e, e')$, where e' is the equilibrium match of e. In particular, we will write $q^L(g(e, e'))$ for the probability of accessing college for an agent with endowment e who is in school (e, e').

A student with endowment e who attends a school (e, e') has therefore payoff

$$v^L(e, e') = g(e, e') \left(1 + q^L(g(e, e'))r(e)\right).$$

Since $q^L(g(e, e'))$ weakly increases and $g(e, e')$ strictly increases in e', students' payoffs strictly increase in their matches' educational endowments,

$$v^L(e, e') > v^L(e, e'') \Leftrightarrow e' > e''.$$

That is, all students prefer better peers. This co-ranking property implies that students segregate in endowments in a stable match, as monetary side payments are excluded and the support of endowments e is finite (see Legros and Newman, 2010). Therefore a student's educational attainment is $g(e, e) = e^{\gamma}$, and the probability of college admission $q^L(g(e, e))$ increases in own educational endowment e. This in turn implies that the measure of admitted privileged exceeds $\pi\kappa$ if the share of high ability students does not exactly match the capacity of the college, $\alpha \neq \kappa$. The following statement summarizes these observations.

Fact 1. *Under laissez faire all students prefer a match with individuals with higher educational endowment. In a stable match students segregate in endowments, i.e. all schools are of the form (e, e). The share of privileged among* *admitted students strictly exceeds their population share if $\kappa \neq \alpha$.*

3.2 Affirmative Action

Affirmative action requires the background distribution of students admitted to college to match the population distribution of backgrounds. No further restrictions are placed on the admission rule. That is, the college reserves measure $\pi\kappa$ slots for privileged and measure $(1-\pi)\kappa$ for underprivileged agents. The college's optimization problem under this additional side constraint is

$$\max_{q^A} \int_{i \in I} (1 + q^A(i) r(e_i)) g_i di \text{ s.t.} \int_{i \in I : b_i = p} q^A(i) di = \pi\kappa \text{ and } \int_{i \in I : b_i = u} q^A(i) di = (1-\pi)\kappa.$$

As above the optimal admission rule takes the form of a cutoff: there exist values g^p and g^u such that for each $b = u, p$, $q^A(i) = 1$ if $b_i = b$ and $g_i > g^b$ and $q^A(i) = 0$ if $b_i = b$ and $g_i < g^b$. That is, every privileged student with $g_i > g^p$ and every underprivileged student with $g_i > g^u$ is admitted with probability 1. Suppose again that uniform rationing is used to break ties. As before we can now express payoffs as a function of endowments and the probability of admission as a function of the grade.

This means the admission probability of a student with background b and endowment e who attends a school (e, e') depends on both background and grade, and can be rewritten, with some abuse of notation, as $q_b^A(g(e, e'))$. The student has payoff

$$v^A(e, e') = g(e, e')(1 + q_b^A(g(e, e'))r(e)).$$

As the admission probability $q_b^A(g(e, e'))$ given background b weakly increases in e', a student's expected payoff strictly increases in e'. As above this implies that a stable results in segregation of students in educational achievement e. Therefore educational attainment is $g(e, e) = e^\gamma$, which means that $g^p > g^u$. By definition the measure of admitted underprivileged is $\pi\kappa$. The following statement summarizes these findings.

Fact 2. *Under affirmative action all students prefer a match with individuals with higher educational endowment. In a stable match students segregate in endowments, i.e. all schools are of the form (e, e). The share of privileged among admitted students equals their population share.*

3.3 Top-x Percent Rule

A top-x percent rule sets aside measure $\bar{\kappa} \leq \kappa$ of places at the college for students whose achievement places them in the top half of their school. The college is free to fill any remaining slots as desired. Here also, we ignore individual indexes and focus on endowments and grades.

Let $\bar{\kappa} = \kappa$ to facilitate exposition (see the appendix for the more general case). The college uses uniform rationing to break ties. Since there is a measure 1/2 of schools, the probability of admission for a student with endowment e at school (e, e') is $q^T = 2\bar{\kappa}$ if $e > e'$, $q^T = \bar{\kappa}$ if $e = e'$ and $q^T = 0$ otherwise. Hence, a student with endowment e at school (e, e') has expected payoff:

$$v^X(e, e') = \begin{cases} g(e, e')(1 + 2\kappa r(e)) & \text{if } e > e' \\ g(e, e')(1 + \kappa r(e)) & \text{if } e = e' \\ g(e, e') & \text{if } e < e'. \end{cases} \tag{3}$$

That is, the policy introduces a trade-off between the probability of access to college and the level of college return: a better peer increases the final grade $g(e, e')$ and thus wage income, but also may decrease the probability q^T of college admission and obtaining the college wage premium. Since the wage premium depends on individual characteristics, a different effect may dominate for different types of students. The first effect ("wage") dominates for students who have little to gain from college, i.e., low endowment students. For those who expect a high college wage premium, i.e., high ability students, the second effect ("access") may dominate: increasing the probability to obtain that premium outweighs the cost of having worse peers.

To study the induced preferences for peers depending on own type, consider a student with endowment e. This student prefers a match $e' < e$ to e if

$$g(e, e')(1 + 2\bar{\kappa} r(e)) \geq g(e, e)(1 + \bar{\kappa} r(e)),$$

which is equivalent to

$$e' \geq \frac{1}{\lambda} \left(\left(\frac{1 + \bar{\kappa} r(e)}{1 + 2\bar{\kappa} r(e)} \right)^{\frac{1}{\gamma}} - (1 - \lambda) \right) e \equiv \underline{m}(e). \tag{4}$$

That is, an agent with endowment e prefers to match with an agent of lower endowment e' only if e' is not too low: the loss in peer effects must be compensated by the increase in the probability of being among the top-x percent. Note that $\underline{m}(e)$ is not necessarily monotonic in e, but that for any $r(e) > 0$, $\underline{m}(e) < e$.

Similarly, a student with endowment e prefers a match $e' > e$ to e if the loss in the probability of being in the top-x percent is compensated by the peer effect, that is if e' is large enough. Indeed,

$$g(e, e') \geq g(e, e)(1 + \bar{\kappa} r(e)),$$

implies that:

$$e' \geq \frac{1}{\lambda} \left((1 + \bar{\kappa} r(e))^{\frac{1}{\gamma}} - (1 - \lambda) \right) e \equiv \overline{m}(e). \tag{5}$$

$\overline{m}(e)$ increases in e and $\overline{m}(e) > e$ for any $r(e) > 0$.

Since higher endowment schoolmates increase the peer effect, conditional on being the highest (or the lowest) endowment in the school, an individual prefers schoolmates with as high as possible an endowment. However, the previous observations suggest that heterogeneous matches can arise as long as the endowment levels are *not too close*. Indeed, e will match with a lower endowment individual only if $e - e' > e - \underline{m}(e)$ and will match with a higher endowment individual only if $e' - e > \overline{m}(e) - e$, which are both bounded away from 0 when $r(e)$ is positive.

Lemma 1. *Under a top-x percent rule, equilibrium matching is consistent with heterogenous matches if, and only if there exist $e' < e$ such that $e' \geq \underline{m}(e)$ and $e \geq \overline{m}(e')$.*

Lemma 1 reveals two important differences of a top-x percent rule to affirmative action and laissez faire: first, students strictly prefer weaker, but not too weak, peers (those with $e' \in (\underline{m}(e), e)$), to peers that have the same type e. Second, students strictly prefer only peers who are substantially stronger (those with $e'' > \overline{m}(e)$) to peers of the same type. This may introduce mutual gains from trade between heterogeneous individuals, as high ability students may prefer to match downwards and low ability students to match upwards.

To demonstrate that heterogenous matches can be mutually beneficial, suppose that $r(\ell p) = 0$. Because $r(e)$ is increasing in e, it is also the case that $r(\ell u) = 0$; then for $e = \ell u, \ell p$, $\underline{m}(e) = \overline{m}(e) = e$, and students of ability ℓ strictly prefer to match with students who have higher educational endowment $e'' > e$. As $v^X(e, e'')$ strictly increases in $e'' > e$ (since in this case the probability of accessing college is equal to zero), ℓu and ℓp agents have the same preference ordering on potential matches, which, by continuity, will also be the case if $r(\ell p)$ is sufficiently small:

$$\ell p : hp \succ hu \succ \ell p \succ \ell u, \text{ and } \ell u : hp \succ hu \succ \ell p \succ \ell u.$$

On the contrary, for students of high ability h, whenever $2(1-\lambda)^\gamma > 1$ there is always $r(hu)$ sufficiently large[11] such that $\underline{m}(e) \leq 0$ and $\overline{m}(e) > hp$. Then hu, hp agents rank peers differently:

$$hp : hu \succ \ell p \succ \ell u \succ hp, \text{ and } hu : \ell p \succ \ell u \succ hu \succ hp.$$

This means that hp agents match into $(hp, \ell p)$ schools as much as possible.If $\alpha > 1/2$, the remaining hp agents match into $(hp, \ell u)$ schools, if $\alpha < 1/2$ the remaining ℓp agents match into $(hu, \ell p)$ schools. Therefore the outcome under a top-x percent policy results in some integration of backgrounds u and p whenever $\alpha \neq 1/2$.

The measure of admitted underprivileged depends on whether all h students can become eligible for the top-x percent policy by ranking among the top x percent of their school. Since schools have size 2, if $\alpha > 1/2$, all ℓ students obtain an h match, but some h segregate. Since hp students are the first choice of all ℓ students, more hu students will segregate than hp students, and the number of admitted underprivileged is $[2\alpha(1-\pi) - \min\{2\alpha - 1, \alpha(1-\pi)\}]\,\kappa$, which is lower than the population share, i.e. $\kappa(1-\pi)$. If there are more top ranks than h students, i.e., if $\alpha < 1/2$, all h students obtain an ℓ match, but some ℓ students segregate. Since necessarily some ℓp students match with hu students and some $(\ell u, \ell u)$ schools form, the measure of admitted underprivileged is higher than $\kappa(1-\pi)$, exceeding the population share. Using (4) and (5), the following proposition summarizes our results on the top-x percent policy.

Proposition 1. *Suppose $\lambda < 1 - (1/2)^{1/\gamma}$. There exist $r(hu)$ large enough and $r(\ell p)$ low enough such that under a top-x percent rule all matches of h and ℓ agents are exhausted and a positive measure of agents integrate in backgrounds. If not all h students can enter the college through the top-x percent policy, the measure of admitted underprivileged is smaller than under affirmative action.*

[11] Precisely, $r(hu) \geq (1-(1-\lambda)^\gamma)/((2(1-\lambda)^\gamma - 1)\bar{\kappa})$, implying that $r(hp)$ is also greater than this bound by monotonicity of $r(e)$.

That is, if the strength of peer effects λ is sufficiently low compared to the "returns to scale" of peer effects γ, there will be types ℓ and h that find it mutually profitable to integrate in high school, inducing background integration but potentially a lower access to college of underprivileged than under an affirmative action policy.

4 Discussion and Extensions

The results in the previous section show that if the top-x percent policy is a relevant entryway into college, i.e. $\kappa - \bar{\kappa}$ is small, it generates substantial heterogeneity in the ranking of potential peers among students. In contrast to laissez faire and affirmative action, which induce all students to rank potential peers the same, by their endowments, under the top-x percent policy students' rankings depend on their continuation valuation from attending college: those with low continuation payoff from college rank peers according to their educational endowment, but those with sufficiently high continuation payoff from college rank peers highest that have slightly less educational endowment, but do not compete for the top-x percent slots. Hence, the policy induces mutual gains from trade between students with high and low continuation values, even when there are no monetary transfers.[12]

If some low ability students value college education sufficiently less than some high ability students, low and high ability students will exploit mutual gains from trade resulting in integration of students of different abilities. Typically, this necessitates some integration in backgrounds, even when ability and background do not correlate. Hence, a top-x percent policy will generate racial desegregation in high schools compared to laissez faire and affirmative action if privileged background correlates with race.

The model can be extended in different directions beyond this important observation, 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.

[12]Note that a top-x percent policy does not require the social planner to have any information about agents' characteristics, if agents do. The policy then induces self-selection into pairs of agents with heterogenous continuation valuation, similar to self-selection of borrowers with different credit risks in the group-lending model of Ghatak (1999), although there the aim is segregation in terms of risk types.

4.1 Multiple Years of Schooling and Rematch

If peer effects are positive and a top-x percent policy does not require a minimum stay at a school in order to be eligible, the question of timing arises: high ability students would prefer to remain in good schools for as long as possible before switching to worse schools to increase the likelihood of college admission. To account for this possibility we need to extend the basic setup by adding other stages of schooling.

Suppose therefore that students go to school for T years indexed by $t = 1, 2, \ldots, T$. In the first year individuals have an endowment e_1, and like in the basic model, choose to go to a school $(e_1, m_1(e_1))$. Let $m_1(.)$ denote the first year match of e_1. We link periods by assuming that an individual's endowment in period 2 is $e_2 = g(e_1, m_1(e_1))$, and recursively, an individual with endowment e_{t-1} who is in a school $(e_{t-1}, m_{t-1}(e_{t-1}))$ in year $t-1$ will have endowment $e_t \equiv g(e_{t-1}, m_{t-1}(e_{t-1}))$ in year t.

For laissez-faire and affirmative action, college admission depends only on the grades obtained at the end of year T, that is $g(e_T, m_T(e_T))$ and, for affirmative action, on the background of the agent. Because a student's grade increases in own endowment and that of his match, all individuals prefer peers with higher educational endowment in year T. Hence, there will be segregation by endowment at time T. Since a student's expected payoff $v^P(e_T, e_T)$ increases in e_T, also in year $T-1$ the student will prefer to match into the school that yields the highest grade at the end of that year, leading to segregation in year $T-1$. Replicating this argument yields segregation in all years.

The case of the top-x percent rule is a bit more subtle, because students trade off a higher grade and a possibly lower probability of accessing college, see (3). It is therefore not immediate, for instance, that the equilibrium expected payoff $v^X(e, m_T(e))$ increases in e. Nevertheless this will be the case, as we show in the Appendix. Using the same recursive argument as above, in each year $t \leq T-1$ students segregate in school by their endowment, but may integrate in the final year T.

Proposition 2. *Both laissez-faire and affirmative action result in segregation in educational endowment in each year. A top-x percent policy yields segregation in each year $t \leq T-1$ and re-match in year T of previously segregated students, following the characterization of Proposition 1.*

The previous specification assumed that there is only one cohort of students and that the college admission policy is a function of the grade obtained in the last period of schooling. Changing these assumptions may lead to rematching before period $T-1$. For instance, with different generations of students, the composition of schools at a given time will already reflect the matching decisions of previous generations. The previous results extend to this framework if the peer effects are operative only within a given cohort, but not across cohorts (i.e., a privileged senior does not affect underprivileged juniors). However, if this is not the case, and peer effects operate across cohorts, students' opportunity cost of re-matching may not be as high, as schools are already heterogeneous and re-matching may occur earlier than in the final year. Similarly, if the strength of peer effects is a function of the duration of interaction of peers, re-matching may have to happen earlier: a privileged student who only remains briefly in a school populated largely by underprivileged will not generate sufficient positive externalities to compensate incumbent students for the decrease in probability of accessing college, implying that early re-matching is needed for stability.

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.

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

The rematch will alter the composition of high schools with respect to observable characteristics that are correlated with background. 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.[13] That is, a school's ethnic composition is a good predictor of socio-economic status and test score results. Therefore an aggregate measure of ethnic segregation should show a decrease after the policy change for grades close to college admission compared to that for lower grades, in particular middle school grades.

4.2 Other Extensions

We conclude by discussing two natural extensions of the model that may be useful if richer data sets become available: greater school sizes and incomplete information. Allowing for school sizes greater than 2 is potentially interesting because the nature of peer effects may reflect the internal organization or internal 'social networks' in schools, and will in turn define the level of the peer effects that are generated.

The model can be extended in a straightforward way along these lines, but we need to assume a specific map linking the composition within a school and the type dependent peer effects. If, for instance, a student is equally likely to interact with any other student, the grade g of a student of type e could be a function of the average type in the school.

Another extension is to incomplete information about the ability a, hence about the endowment of the individuals, even if background is known by all individuals at the time of matching. In this case, segregation can be only on the basis of background and rematching may be on the basis of background or ability, once abilities become known or information about them is revealed (e.g., through grades).

This extension enriches the possibilities of rematching. Indeed, let us revisit the multi-year extension above and assume to simplify two years of schooling. Suppose that while in year 1 students do not know their ability, they do so at the end of this year, e.g., through grades. Since future payoffs are increasing in year 2 endowments, students will *segregate by background* in year 1. Note that at the beginning of year 2 the support of endowments in year 2 has now eight

[13] 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.

elements rather than four as before. Indeed, the grades at the end of year 1 take values $g(ab, a'b)$, where a, a' are either ℓ or h. This implies that now, while top-x percent rules will still generate some re-matching across backgrounds, under laissez-faire and affirmative action policies learning will generate re-matching across abilities *within* a given background.

5 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.

5.1 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 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).[14] The data are provided at the school (campus) level for all ethnic groups with more than five students enrolled in school.[15] We use this data to compute the segregation measures that will be explained below.

The second one is the Academic Excellence Indicator System (AEIS).[16] 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

[14]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.

[15]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.

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

taking ACT or SAT, of students above criterion, and of students completing advanced courses.[17] Additionally, this database provides information on the Texas Assessment of Academic Skills (TAAS), a standardized test taken in 10th grade used in Texas between 1991 and 2002, and several indicators such as dropouts, school composition, and attendance.

The third database contains individual-level data for students enrolled in 8th and 12th grades in a public school.[18] For each student, we observe the grade and school they are enrolled in, whether they are a transfer student,[19] 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):[20]

$$M_s^x = \sum_{e=1}^{E} p_{es} \log\left(\frac{p_{es}}{p_{ex}}\right), \tag{6}$$

where p_{es} and p_{ex} denote the share of students of an ethnic group e 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.

[17] 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.

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

[19] 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)

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

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:

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

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.[21] 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.

[21] 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.

5.2 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 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.[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:

$$M^r_{yst} = \pi_1 \left(G12_{ys} \times TOP_t\right) + \boldsymbol{\delta}'\mathbf{T} + u_{ys} + \varepsilon_{yst}, \tag{9}$$

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}

[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.

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 population in a given region that may be caused by immigration, for example. The coefficient of interest in this regression is π_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:

$$\begin{aligned} M^r_{yst} =& \pi_1(G12_{ys} \times TOP_t) + \pi_2(G11_{ys} \times TOP_t) + \pi_3(G10_{ys} \times TOP_t) \\ &+ \boldsymbol{\delta}'\mathbf{T} + u_{ys} + \varepsilon_{yst}, \end{aligned} \tag{10}$$

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 5 indicates a slight decrease in segregation in 9th to 11th grades in the years 1995 to 1998.

In order to investigate this issue we focus on the within county measure of segregation to analyze whether there was a decrease in segregation in 12th grade relative to 9th grade of the same cohort (i.e., three years before). That is, we compute the within-county segregation coefficient W^c for each county c, using (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.[24]

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

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

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, π, 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]

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

[24]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.

[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.

same cohort, coinciding with the introduction of the top ten percent law. As mentioned above, the decrease in segregation does not appear to be related to more school choice, as the effect is not stronger for schools located in larger school districts or in MSAs. 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.[26] 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 6, the number of transfer students has more than doubled since 1998, even when one discounts charter school students.[27]

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

[26]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%.

[27]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.

to 9th and 10th grade movers. These variables are plausible indicators of a move to an academically worse school. We therefore estimate equations with a dependent variable Y_{it} that takes the value 1 if this is indeed the case (e.g., school of destination has less college-bound students than school of origin) and 0 otherwise:

$$Y_{it} = \pi_1 \left(G12_i \times TOP_t \right) + \pi_2 \left(G11_i \times TOP_t \right) + \boldsymbol{\gamma}' \mathbf{G_i} + \boldsymbol{\rho}' \mathbf{X_i} + \boldsymbol{\delta}' \mathbf{T} + \varepsilon_{it}, \quad (12)$$

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).[28]

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-

[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.

economically disadvantaged students. This corresponds to a 7.4% increase, given that the sample mean of the dependent variable is 0.431. The same effect is almost zero and not statistically significant for economically disadvantaged students. 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.[29]

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.[30]

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.

[29] 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.

[30] 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 4 shows that, if anything, residential segregation has increased over the period 1990 to 1999[31] and cannot explain the decrease in segregation among the student population over the period.

6 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.

[31]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

Top x Percent Policy with $\kappa > \bar{\kappa}$

Suppose the condition of Lemma 1 holds, i.e. $\lambda < 1 - (1/2)^{1/\gamma}$, and for the moment that $(1-\lambda)hp + \lambda \ell p > hu$, i.e. the ranking of educational attaining of hu and hp students is preserved.

Suppose the college assigns first measure $\bar{\kappa}$ of places to students in the top half of their school, and then the remaining measure $\kappa - \bar{\kappa}$ to maximize aggregate human capital of entrants. This procedure admits measure $\kappa - \bar{\kappa}$ of the students with highest educational achievements e not already admitted through the top x percent rule.

Several cases are possible, depending on whether all hp (and hu) types are admitted with certainty if they segregate. Focus on the one where $\kappa - \bar{\kappa}$ is sufficiently small so that under full segregation of hp types not every hp type will be admitted with certainty (the other cases are similar and therefore omitted). This case occurs if

$$\kappa \leq \alpha\pi + \bar{\kappa}(1 - \alpha\pi).$$

Denote by ν the measure of hp agents who segregate. Then an hp student in an (hp, hp) school has payoff

$$v = g(hp, hp)\left(1 + \left(\bar{\kappa} + (1-\bar{\kappa})\max\{\frac{\kappa - \bar{\kappa}}{\nu(1-\bar{\kappa})}, 1\}\right) r(hp)\right).$$

If $(1-\lambda)hp + \lambda \ell p > hu$, an hp student in an $(hp, \ell p)$ school will have higher attainment than an hu student in an (hu, hu) school. An hp student prefers segregation to matching with an ℓp student if

$$\frac{g(hp, hp)}{g(hp, \ell p)} > \frac{1 + \left(2\bar{\kappa} + \min\{\frac{\kappa - \bar{\kappa} - \min\{\nu(1-\bar{\kappa}), \kappa - \bar{\kappa}\}}{(\alpha\pi - \nu)}, 1 - 2\bar{\kappa}\}\right) r(hp)}{1 + \left(\bar{\kappa} + \frac{(1-\bar{\kappa})(\kappa - \bar{\kappa})}{\max\{\nu(1-\bar{\kappa}), \kappa - \bar{\kappa}\}}\right) r(hp)}.$$

For $\nu \leq (\kappa - \bar{\kappa})/(1 - \bar{\kappa})$ the condition must hold, since segregated hp students enter college with certainty. Hence, $\nu > (\kappa - \bar{\kappa})/(1 - \bar{\kappa})$ as otherwise all hp students strictly prefer segregation. This means that if $\pi(2\alpha - 1) \leq (\kappa - \bar{\kappa})/(1 - \bar{\kappa})$ the measure of ℓp students is sufficient to absorb all remaining hp students.

Therefore in equilibrium,

$$\nu^* = \alpha\pi \text{ if } \frac{g(hp,hp)}{g(hp,\ell p)} \geq \frac{1 + 2\bar{\kappa}r(hp)}{1 + (\bar{\kappa} + (\kappa - \bar{\kappa})/(\alpha\pi))r(hp)},$$

and otherwise

$$\nu^* = \frac{r(hp)(\kappa - \bar{\kappa})}{\frac{g(hp,\ell p)}{g(hp,hp)}(1 + 2\bar{\kappa}r(hp)) - (1 + \bar{\kappa}r(hp))}.$$

Notice that these expressions are true also when $(1-\lambda)hp + \lambda\ell p \leq hu$, since hp students take up all $\kappa - \bar{\kappa}$ slots anyway.

hu students are only admitted to college by way of the top-x percent rule. Using Lemma 1, for $r(\ell p)$ sufficiently small and $r(\ell h)$ sufficiently large, hu students strictly prefer to match with ℓ students, ranking them in order of their educational endowment, and ℓ types will prefer matching with h types over segregation.

Hence, if $\lambda < 1 - (1/2)^{1/\gamma}$ and for $r(\ell p)$ sufficiently small and $r(hu)$ sufficiently large, the matching equilibrium with $0 < \kappa - \bar{\kappa} \leq \alpha\pi(1 - \bar{\kappa})$, and $\pi(2\alpha - 1) \leq (\kappa - \bar{\kappa})/(1 - \bar{\kappa})$ has measure $0 < \nu^*/2 \leq \alpha\pi/2$ of (hp, hp) schools. The remaining measure $(\alpha\pi - \nu^*)$ of hp students and all other students integrate in ability. ν^* decreases in ℓp and $\bar{\kappa}$. Matching is positive assortative in educational endowment, that is, the equilibrium assignment matches first all remaining hp students given ν^*, exhausting first all $(hp, \ell p)$ matches, and then assigns hu students to all remaining ℓ students again first exhausting potential $(hu, \ell p)$ matches.

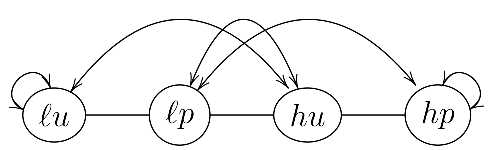

Figure 3: A possible matching pattern when $\kappa > \bar{\kappa}$.

In essence a policy with $\kappa > \bar{\kappa}$ gives students with the highest education level an incentive to segregate. As long as the quota $\kappa - \bar{\kappa}$ does not suffice for all students with substantial private returns to college education our argument from above goes through and some schools will desegregate under a top-x percent policy.

Proof of Proposition 2

Note that the equilibrium matching may require individuals of the same endowment to be matched to individuals with different endowments, that is there there may be a matching correspondence for endowments. Figure 3 above is an illustration of this.

The following lemma establishes that for general distributions of endowments (e.g., having a support greater than four), in a model with one period, the equilibrium expected payoffs are increasing in the endowment of a student.

Lemma 2. *Consider the top-x percent rule, any distribution of endowments and an equilibrium matching correspondence M in period T. Then for any selection m of M, $e' > e$ implies that $v^X(e', m(e')) \geq v^X(e, m(e))$.*

Proof. Suppose, contrary to the claim that there exists a selection m violating the condition, that is:

$$e' > e \text{ but } v^X(e, m(e)) > v^X(e', m(e')). \tag{13}$$

There are three cases of interest.

(i) If $e > m(e)$, we show a contradiction to stability since a school $(e', m(e))$ could form and make each student strictly better off than under the matching m. Indeed, since $e > m(e)$, $m(e)$ has a zero probability of accessing college and $v^X(m(e), e) = g(m(e), e)$ which is strictly inferior to $g(m(e), e')$. Similarly, since e' accesses college with the same probability as e when matching with $m(e)$, we have $v^X(e', m(e)) > v^X(e, m(e)) > v^X(e', m(e'))$. Hence, e' and $m(e)$ are indeed strictly better off by being in a school $(e', m(e))$.

(ii) If $e = m(e)$, we have a contradiction since $v^X(e, e) < v^X(e', e') \leq v^X(e', m(e'))$: the first inequality is by direct inspection of the segregation payoffs in (3), the second inequality is by revealed preferences of students with endowment e'.

(iii) If $e < m(e)$, then e does not go to college and we have:

$$\begin{aligned} v^X(e, m(e)) &= g(e, m(e)) \\ &> v^X(e', m(e')) \\ &\geq g(e', e'). \end{aligned}$$

The first inequality is (13), and the second is revealed preference of e'. Because g is increasing in both arguments and $e' > e$, it must be the case that $m(e) > e'$.

But then, using monotonicity of g together with monotonicity of $v^X(a,b)$ in $b < a$ we have:

$$v^X(e', m(e)) > v^X(e, m(e)) > v^X(e', m(e'))$$
$$\text{and } v^X(m(e), e') > v^X(m(e), e).$$

This implies that a school $(e', m(e))$ could form and make both students strictly better off, contradicting stability.

Hence (13) cannot hold in an equilibrium, and payoffs $v^X(e, m(e))$ are increasing in e for any selection from the equilibrium correspondence M. $\square$

Since the expected payoffs at T are increasing in the endowment at the beginning of time T, students will match in earlier periods in order to achieve the highest possible endowment at time T, implying by the argument in the text segregation in these earlier periods. It follows that there are only four endowment levels in equilibrium at time T, and we can use Proposition 1 to characterize the equilibrium rematching.

B Tables and Figures

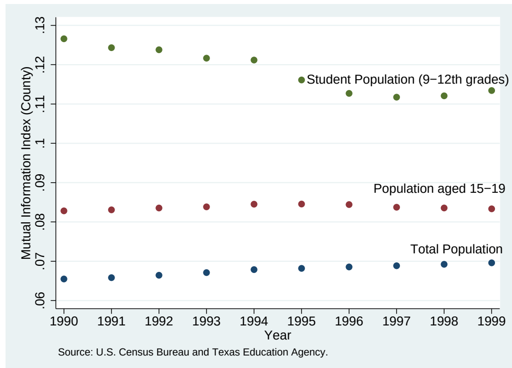

Figure 4: Residential versus School System Segregation

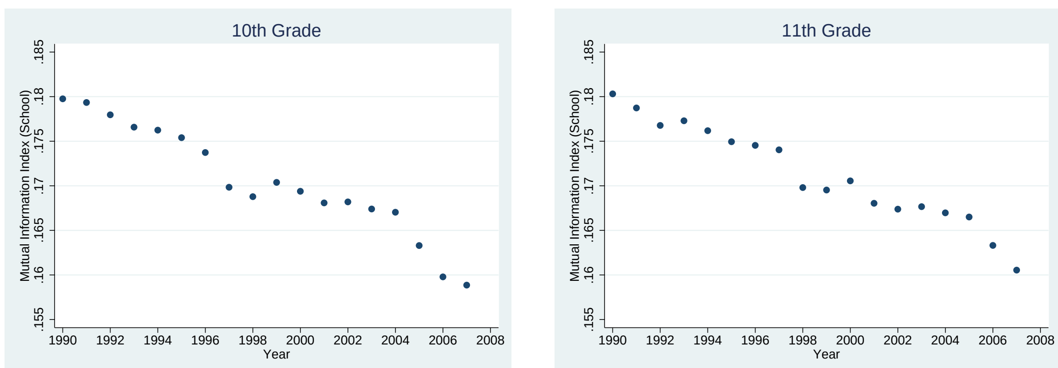

Figure 5: Time series of the mutual information index for 10th and 11th grades

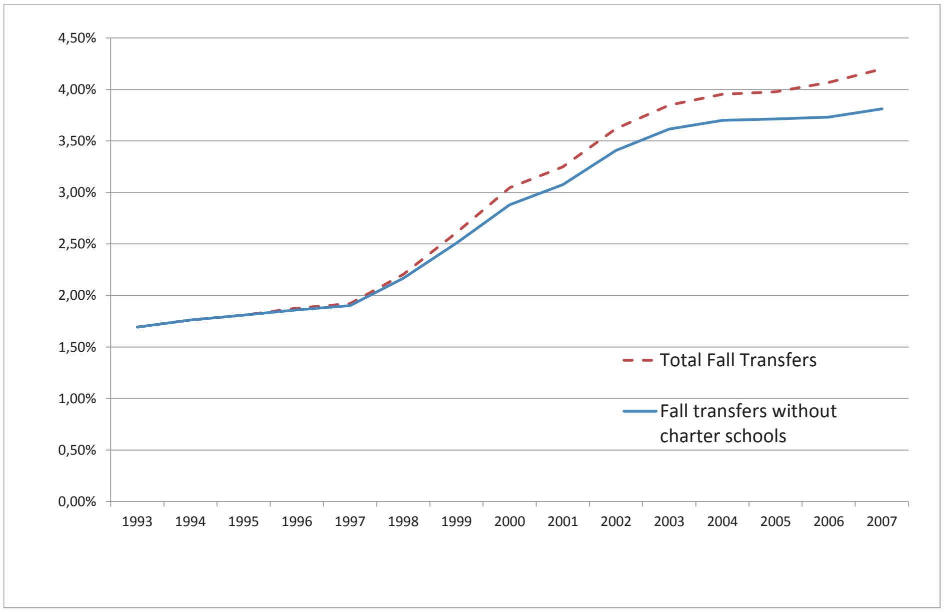

Figure 6: Share of students in 8th to 12th grades with a district of enrollment different from district of residence, 1993-2007. The dashed line corresponds to the total number, while the solid corresponds to all students except for those attending charter schools. *Source*: TEA.

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.

References

Bifulco, R., J. M. Fletcher, and S. L. Ross: 2011, 'The Effect of Classmate Characteristics on Post-Secondary Outcomes: Evidence from the Add Health'. *AEJ:Economic Policy* **3**(1), 25–53.

Cortes, K. E., and A. I. Friedson: 2010, 'Ranking Up by Moving Out: The Effect of the Texas Top 10% Plan on Property Values'. *IZA Discussion Paper* No. 5026.

Cullen, J. B., M. C. Long, and R. Reback: 2013, 'Jockeying for position: Strategic high school choice under Texas' top ten percent plan'. *Journal of Public Economics* **97**, 32–48.

Damiano, E., H. Li, and W. Suen: 2010, 'First in Village or Second in rome?'. *International Economic review* **51**(1), 263–288.

Fang, H.: 2006, 'Disentangling the College Wage Premium: Estimating a Model with Endogenous Education Choices'. *International Economic review* **47**(4), 1151–1185.

Frankel, D. M. and O. Volij: 2011, 'Measuring School Segregation'. *Journal of Economic Theory* **146**(1), 1–38.

Ghatak, M.: 1999, 'Group Lending, Local Information and Peer Selection'. *Journal of Development Economics* **60**(1), 27–50.

Heckman, J. J.: 2008, 'Schools, Skills, and Synapses'. *Economic Inquiry* **46**(3), 289–324.

Kain, J. F., D. M. O'Brien, and P. A. Jargowsky: 2005, 'Hopwood and the Top 10 Percent Law: How They Have Affected the College Enrollment Decisions of Texas High School Graduates'. *mimeo University of Texas at Dallas*.

Kremer, M. and D. Levy: 2008, 'Peer Effects and Alcohol Use Among College Students'. *Journal of Economic Perspectives* **22**(3), 189–206.

Legros, P. and A. F. Newman: 2007, 'Beauty Is a Beast, Frog Is a Prince: Assortative Matching with Nontransferabilities'. *Econometrica* **75**(4), 1073–1102.

Legros, P. and A. F. Newman: 2010, 'Co-ranking Mates: Assortative Matching in Marriage Markets'. *Economics Letters* **106**(3), 177–179.

Long, M. C.: 2004, 'Race and College Admissions: An Alternative to Affirmative Action?'. *review of Economics and Statistics* **86**(4), 1020–1033.

Mora, R. and J. Ruiz-Castillo: 2010, 'The Invariance Properties of the Mutual Information Index of Multigroup Segregation'. *research on Economic Inequality (forthcoming)*.

Reardon, S. F. and G. Firebaugh: 2002, 'Measures of Multigroup Segregation'. *Sociological Methodology* **32**, 33–67.

Stinebrickner, R. and T. R. Stinebrickner: 2006, 'What can be Learned About Peer Effects Using College Roommates? Evidence from New Survey Data and Students from Disadvantaged Backgrounds'. *Journal of Public Economics* **90**(8-9), 1435–1454.

University of Texas Office of Institutional Studies and Policy Analysis: 2010, *Facts and Trends 2010*. University of Texas System, Austin.