College Admission and High School Integration*

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Abstract

Discrimination is an economic concern because it distorts not only the allocation, but also groups' payoffs from decisions made before the market, for instance school or neighborhood choice. Policies such as affirmative action aiming at desegregation as a response to discrimination must therefore be evaluated also in terms of their effects on earlier choice. We find that a policy only operating at a later stage, conditioning on earlier individual choice, but not on exogenous markers such as race or gender, may achieve desegregation with respect to that marker in both stages. An example for this is a college admission rule based on relative performance at school. If groups that are to be integrated are disadvantaged ex ante, this policy rewards some advantaged individuals for integrating at school. We present empirical evidence for a decrease in segregation at the high school level as an unintended consequence of introducing of the Texas Top Ten percent college admission rule.

Keywords: Matching, affirmative action, education, college admission, high school desegregation, Texas top ten percent.

JEL: C78, I23, D45, J78.

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1 Introduction

An often-voiced aim of college admission policies is to ensure diversity in higher education. A particular example of such policy is affirmative action assigning quotas based on students' race or gender. Recent court decisions have declared any college admission system using non merit based quota to be unconstitutional, thus effectively prohibiting affirmative action in higher education. In response several states in the US have devised admission rules that guarantee a top quantile of students in each high school admission to college in state schools.[1] The reasoning behind this was that as high schools are highly racially segregated such policy should admit a reasonably representative sample of the high-school population.

Yet this tacitly assumes that composition of high schools does not change in response to the policy, which appears doubtful (see Cullen et al., 2011). Indeed this paper argues that compared to an allocation under affirmative action, a college admission policy applying a top quantile rule will serve to decrease segregation at the *high school* level rather than at the *college* level, which is what we find in the data.

The theoretical argument builds on a dynamic assignment model where students are heterogenous in abilities and backgrounds. Ability can be high or low, and background privileged or underprivileged. At two stages, 1 and 2, students have the opportunity to match into schools acquiring educational attainments. After stage 2 students may apply to college without cost; acceptance will depend on their characteristics and the college admission policy in place. Payoffs are given by final educational attainment and a college wage premium that increases in attainment and ability. There are positive peer effects within schools, in that educational attainment increases in peer initial educational attainment, which in turn may depend on ability and background.

In the first stage individual ability of students is not observed, but background is. Therefore, first stage matching is in terms of background only. Educational attainment at the end of the first stage is observed, for instance in form of grades, so that second stage matching occurs in terms of first stage educational attainment, which depends on own and peers' abilities and backgrounds. That is, agents' choices are limited to first and second stage school choice. As

[1] California started admitting the top four, Florida the top twenty, and Texas the top ten percent.

a market equilibrium we use a stable allocation of students into schools of size two without monetary side payments. This could be implemented for instance through an adequate version of the Gale-Shapley algorithm (see e.g. Roth and Sotomayor, 1990).

Assignment of students to college follows one of three admission rules: Under laissez-faire the college fills its slots to exogenous capacity κ, ranking students by their final educational attainment. Under affirmative action the assignment to college has to reflect population frequencies of the different backgrounds. Under a top x percent rule admittance to colleges in a state university system is based on reaching a sufficiently high achievement rank at school. Under all three policies in the first stage students' continuation payoffs increase in first stage educational attainment. As peer effects are monotone in students' backgrounds and abilities schools segregate in backgrounds in the first stage. Under both affirmative action and laissez-faire probability of college admission and therefore obtaining the college wage premium increases in final educational attainment. Therefore in the second stage schools segregate in first stage education, which implies segregation in backgrounds.

Under a top x percent rule, however, second stage students face a trade-off. On the one hand, matching with a weaker peer increases the chance of college admission, but on the other hand this decreases absolute final educational attainment because of positive peer effects.[2] We show that when the college wage premium is low enough for low ability students and high enough for high ability students, the first effect dominates for high ability students and the second one for low ability students. That is, the policy is able to affect students' preferences over peers contingent on one attribute dimension (ability), inducing low ability students to prefer better educated peers and high ability students to prefer slightly less educated peers. As a consequence the second stage equilibrium assignment integrates as much as possible in ability and exhausts all possible matches between low and high ability students. This implies that a positive measure of schools are attended by students of different backgrounds.

When privileged background correlates to belonging to certain population groups, for instance in terms of race, the model is well suited to analyze effects of college admission policies on earlier stage behavior, such as high school choice. There is evidence of such correlation in Texas: the percentage of minority

[2]Damiano et al. (2010) find a similar trade-off when agents have a preference for both status and peer quality. They do not analyze matching rules as policy instruments.

students enrolled at a high school correlates positively with the percentage of economically disadvantaged students (Figure 1) and negatively with the high school level pass rate in TAAS[3] (Figure 2).[4] That is, a school's ethnic composition is a good predictor of socio-economic status and test score results. Then the model captures well the rematch observed by Cullen et al. (2011)

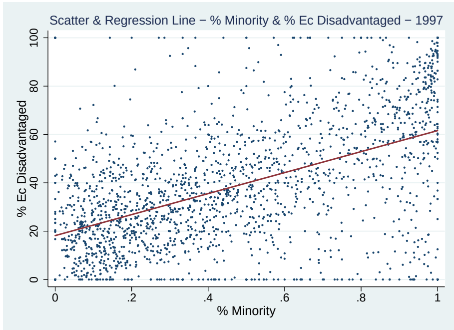

Figure 1: Proportion of minority and economically disadvantaged students. *Source*: AEIS data.

Figure 2: Proportion of minority and TAAS pass rate. *Source*: AEIS data.

after introduction of the Texas Top Ten percent policy. Moreover, due to the rematch in the second stage and the assumption that privileged students have an advantage in acquiring education, the frequency of privileged among those

[3]Texas Assessment of Academic Skills (TAAS), a standardized test for grade 10 used in Texas between 1991 and 2002.

[4]The figures use data for 1997, but look very similar for other school years. A similar exercise done with percentage of minority and average or median SAT score shows a negative correlation.

admitted to college exceeds the one under affirmative and falls short of the one induced by laissez-faire consistent with the observation for Texas and other U.S. states (Kain et al., 2005; Long, 2004).

To determine whether the college admission policy had an impact on the overall composition of high schools, consider first Figure 3. It shows a time series of the mutual information index for grades 9 and grades 12 among all Texan high schools for the years 1989 to 2007.[5] The mutual information index gives the informational content of the school's ethnic composition on the student's ethnicity and is a measure of segregation. According to the theoretical model, under the Texas Top Ten Percent law (starting in 1998) a rematch should occur in high school, reducing segregation by background. This is consistent with the visible drop in segregation for grade 12, the last grade before college admission, and the absence of such a drop for grade 9.[6] Using another measure of segregation, the Theil index, a similar picture arises, see Appendix. The time series in Figure 3 does not appear to be driven by patterns of residential segregation over time, see Figure 13 in Appendix.

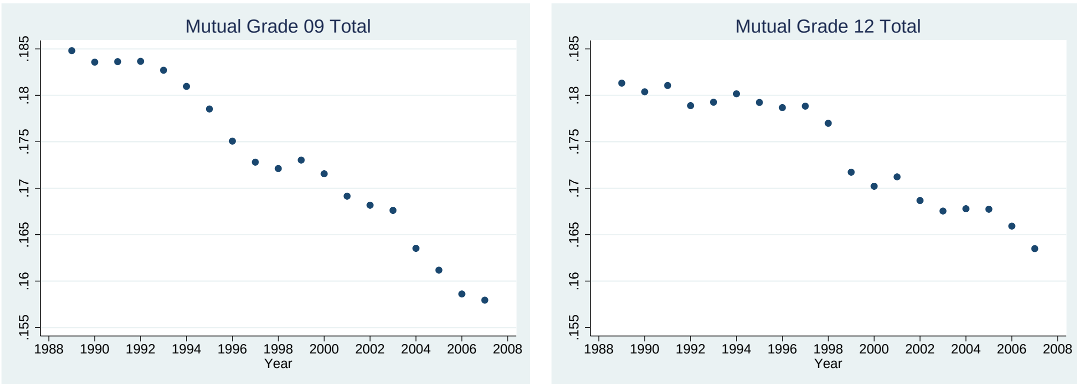

Figure 3: Time series of the mutual information index for grades 9 and 12.

The finding is corroborated using an index of local segregation at high school level and a difference in differences estimation strategy. Assuming that the policy had a differential effect on segregation measures for lower and highes grades, we test whether the difference between grade 12 and grade 9 segregation

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

[6]We test for structural breaks in the mutual information index for grades 9 to 12. The Chow test indicates a change in the trend for grade 12 in 1998 and 1999. There are no breaks in the other grades coinciding with the Texas Top Ten percent law.

at a school high changed significantly in 1998. We find this to be the case across several specifications using various types of fixed effects. Next, we examine whether the policy change is associated to a change of differences in segregation between grade 9 and 12 within the same cohort. To do so we use an index of within school district segregation and find that the difference between grade 12 and grade 9 segregation of the same cohort decreased significantly after the policy was introduced.

The contribution of this paper is threefold. First, we analyze matching policies in a dynamic matching environment with multidimensional attributes that are affected by choices (i.e. educational attainment depends on school choice; extending the model to include an explicit effort investment decision within schools is straightforward). Second, we propose a mechanism without side payments to implement earlier stage matches using later stage matches as a policy. And third, we find evidence supportive of the theoretical results in a real world college admission problems.

This paper relates to other contributions that propose later stage matching outcomes as policy instrument for early stage choices. Booth and Coles (2010) and Hoppe et al. (2009) compare market matching to random matching (see also McAfee, 2002, on coarse matching). Gall et al. (2009) is concerned with the differential effects of market matching and affirmative action policies based on achievements or background. These papers typically focus on the effects of matching policy on investments undertaken prior to the match. We look at a dynamic matching model where earlier matching decisions depend on later matching outcomes.

The paper proceeds as follows. Section 2 lays out a dynamic framework of school choice, and Section 3 evaluates effects of different college admission policies on school choice. Section 4 presents some evidence supporting the theoretical findings, and Section 5 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 of agents I endowed with unit measure. Agents are characterized by their ability a and their background b. Ability is initially unobservable and can be either *high* or *low*, that is $a \in \{\ell; h\}$. Denote the ex ante probability of having high ability by $\alpha \in (0, 1)$. Background is observable and can be either *privileged* or *underprivileged*, that is $b \in \{u; p\}$. Denote the measure of privileged agents by $\beta \in (0, 1)$. Suppose ability and background are stochastically independent. During their economic lives agents acquire education first in schools, and then in college.

Students enter schools with an educational initial endowment e that is determined by ability and background types. Suppose in particular that $e \in \{\ell u, \ell p, hu, hp\}$ and that the most able u student have higher endowment than the least able p students:

$$0 < \ell u < \ell p < hu < hp.$$

That is, privileged students begin their educational career with an advantage over underprivileged students holding ability constant. 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.[7]

2.1 Schools

For reasons of tractability schools are of size 2 and denoted by a tuple of educational endowments (e, e'). Human capital acquisition in schools depends on pupils' educational endowment at the time of enrollment only. Suppose that the final education an individual with endowment e attains in school (e, e') is given by

$$f = g(e, e')e.$$

Whether f is additive or multiplicative in $g(.)$ is not important for our results.[8] What will become very convenient, however, is that under this formulation the ranking of educational attainments is preserved within schools, i.e. $e < e'$ implies $f < f'$ in a school (e, e). This implies that advantages conveyed by a privileged background holding constant ability are persistent.[9] Suppose that

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

[8]Our argument also extends to the case where $g(.)$ depends on time, allowing early and late stage education acquisition to differ.

[9]While this seems plausible at a first glance, first order stochastic dominance should be sufficient for our results in general.

for any $e > e'$ it holds that

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

i.e. $g(.)$ obeys co-monotonicity and symmetry, although the latter may be dispensed with. Co-monotonicity means that peer effects in schools are strictly positive in the sense that any individual benefits from a better peer group. This is found for instance by Sacerdote (2001) at the college stage and by Bifulco et al. (2011) at the high school stage. Note that 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. In this sense this paper focus on a positive analysis and remains agnostic about normative implications, which may be an issue as the stable outcome may not maximize aggregate surplus when utility is not perfectly transferable (Legros and Newman, 2007).

2.2 Payoffs and College

Students' payoffs depend on their educational achievement f, and on whether they continue education in college, in which case they obtain a college wage premium $r(a)$ that strictly increases in individual ability a reflecting a student's innate potential to acquire human capital in college.[10] Going to college comes at no cost, that is $r(a)$ captures the net benefits. Denoting college enrollment by $q \in [0, 1]$, capturing possible rationing and stochastic enrollment, individual payoff is

$$\pi = f(1 + q(f)r(a)).$$

There is a representative college with an exogenous capacity of measure $\kappa > 0$ of students. Suppose that $\kappa \leq 1/2$ to avoid excessive notation. We will abstract from self-interests on the side of college and assume that it maximizes average achievement levels among the students enrolled. This is equivalent to maximizing aggregate payoff (or human capital, if the college wage premium accurately reflects this). Actual admission policies of colleges $(q(i))_{i \in I}$ may be subject to policy constraints, however. Policy can potentially condition on both students' educational achievements and backgrounds.

[10] Of course, $r(.)$ could also depend on educational achievement or background or a combination of all this. The crucial characteristic driving our results is that $r(.)$ gives an incentive to prefer weaker peers for some students, while not for others. As long as this incentive is not perfectly negatively correlated with educational attainment the thrust of our argument remains intact.

2.3 Timing

Summarizing, events unfold as follows in our economy.

0. Nature assigns backgrounds and ability, determining endowment e.

1. Agents match in schools based on educational endowment e and agents acquire education h.

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.[11] More formally, a matching equilibrium is a stable allocation of schools, such that no agent 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 prefer this to their equilibrium outcome.

2.4 Admission Regimes

This paper will examine three policy regimes for college admission in greater detail: laissez faire, affirmative action, and top x percent. These regimes closely mirror policies employed in college admission in the U.S. and elsewhere. In the following we will be concerned with their effects on the composition of colleges, and, more importantly, with repercussions on school choice.

Laissez Faire

Under laissez-faire assignment of students to colleges in the state university system is left to individual choice. The market for college places is in equilibrium when a stable allocation of students into measure κ of available colleges within the state university is reached. In our framework the colleges chooses to admit students in order to maximize aggregate surplus subject to the capacity constraint. Denoting the admission choice by the mapping $q : I \mapsto [0, 1]$, it solves

$$\max_q \int_{i \in I} (q(i)r(e) + 1)f(i)di \text{ s.t. } \int_{i \in I} q(i)di = \kappa,$$

[11]This could be implemented using a deferred acceptance algorithm, a mechanism actually employed to assign students to schools in the U.S., see for instance Pathak and Sönmez (2008).

where the integral sign indicates the Lebesgue variety. Let $\mu(.)$ denote again the Lebesgue measure of students $j \in I$ satisfying the argument. Then any solution q obeying the capacity constraint satisfies

$$q(i) = 1 \Rightarrow \mu(f(j) \leq f(i)) > (1 - \kappa) \text{ and } q(i) = 1 \Leftarrow \mu(f(j) \geq f(i)) < \kappa. \quad (1)$$

That is, quite intuitively an optimal policy admits all student above a threshold achievement level, does not admit students below that achievement level, and admits students at the threshold level with a probability to satisfy the capacity constraint. This implies q is a weakly increasing step function of f. Suppose that uniform rationing, a color-blind policy, is used to break ties.

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

$$\pi = g(e, e')e(1 + q(g(e, e')e)r(a)),$$

Since $q(f)$ weakly increases in f, individual payoff increases in f, which in turn increases in e'. Hence, any student strictly prefers a match with e over one with e' if and only if $e > e'$. Since side payments are excluded when assigning students to schools and the support of educational endowments e is finite, this co-ranking property implies that students segregate in educational endowments in the equilibrium outcome (see Legros and Newman, 2010) and all schools are of the form (e, e). Therefore an agent's educational attainment is $f = g(e, e)e$. Hence, students are admitted by their educational achievement, implying that the measure of admitted underprivileged is at most $(1-\beta)\kappa$ (if and only $\kappa = \alpha$).

Affirmative Action

Affirmative action requires background shares of students in the state university system have to match population densities of students' backgrounds. No further restrictions are placed on matches into individual colleges within the state university system. Agents are rationed uniformly if necessary.[12] Then colleges are forced to reserve exactly measure $\beta\kappa$ slots for privileged and measure $(1-\beta)\kappa$ for underprivileged agents. As colleges maximize expected educational achievement at enrollment, a similar argument as above implies that the admission policy q is now a step function of both achievement f and background b, and $q(f, p) \leq q(f, u)$ since $p > u$. That is, the threshold achievement needed for admission is higher for the privileged than that for the underprivileged.

[12]The method of rationing could be affected by policy; this instrument is left for future research, however.

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

$$\pi = g(e, e')e(1 + q(g(e, e')e, b)r(a)),$$

Again the admission probability $q(f, b)$ weakly increases in f. Therefore expected payoff increases in e', which ensures that all individuals strictly prefer to be matched to higher educational endowments. This co-ranking property again implies that school segregate in education endowment e yielding educational attainments $f = g(e, e)e$. By definition the measure of admitted underprivileged is $\beta\kappa$. The following proposition summarizes the findings so far.

Proposition 1 *Under laissez faire and affirmative action schools segregate in educational endowment and achievements are given by $f = g(e, e)e$. The measure of admitted underprivileged is never greater and, if $\kappa \neq \alpha$, strictly smaller under laissez faire.*

Top x Percent Rule

A top x percent rule sets aside measure $\bar{\kappa} \leq \kappa$ places at state university colleges for students whose achievement places them in the top half of their school. Assignment to colleges within the state university system is subject to agents' choices. The college is free to fill any remaining slots as desired. Let $\bar{\kappa}\kappa < 1/2$ to facilitate exposition (see appendix for the more general case). Suppose that schools use uniform rationing. This assumption implies that admission probability for a student with endowment e at school (e, e') is $q = 2\bar{\kappa}$ if $e > e'$, $q = \bar{\kappa}$ if $e = e'$ and $q = 0$ otherwise.

Hence, an individual with endowment e at school (e, e') has payoff

$$\pi = f(e, e')e(1 + q(e, e')r(a)).$$

If for $e' < e < e''$

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

for $e = hp, hu$ while for $e' < e < e''$

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

for $e = \ell p, \ell u$, agents with ability f prefer to match to agents with lower endowments and ℓ agents prefer higher endowment matches. Sufficient conditions for the first statement are $g(e,e) < 2g(e,\ell u)$ for $e = hp, hu$, which is trivially satisfied if $g(.)$ has weakly decreasing differences or if the support of endowments e is sufficiently small, and $r(h)$ sufficiently high. The second statement always holds if $r(\ell)$ is sufficiently close to 0. If both statements hold agents have the following preference rankings:

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

This immediately implies that there is some segregation whenever $\alpha \neq 1/2$, since hp agents match into $(hp, \ell p)$ as much as possible. This could, of course, also occur in private schools where privileged background is a necessary condition to attend. If $\alpha > 1/2$, the remaining hp agents match into $(hp, \ell u)$ schools, if $\alpha < 1/2$ the remaining ℓp agents match into $(hu, \ell p)$. The measure of admitted underprivileged depends on whether h students are abundant or not. If $\alpha > 1/2$, more hu than hp students end up in segregated schools, while all ℓ students integrate. Therefore the measure of admitted underprivileged is less than $\kappa(1-\beta)$ and more than $\kappa\alpha(1-\beta)$. If $\alpha < 1/2$, however, all h students integrate and more ℓu than ℓp students end up in segregated schools. Since some hu match into $(hu, \ell p)$ schools, the measure of admitted underprivileged is higher than $\kappa(1-\beta)$. This is summarized in the following proposition.

Proposition 2 *Let $r(h)$ be sufficiently high and $r(\ell)$ sufficiently close to 0. Suppose the support of e is sufficiently tight or $f(.)$ has weakly decreasing differences. Under a top ten percent rule h and ℓ agents match as much as possibly and a positive measure of agents integrate in backgrounds. The measure of admitted underprivileged is smaller (greater) than under affirmative action if h agents are abundant (scarce).*

2.5 Discussion

The central result of this section is that whenever the top x percent policy is a relevant entryway into college, i.e. $\kappa - \bar{\kappa}$ is small, the policy induces preference heterogeneity among students. Those with low continuation payoff from attending college prefer better peers, while students with sufficiently high continuation payoff from college prefer the best peers as long as they have lower educational attainment and do not compete for the top x percent slots. Hence, if low ability students value college education sufficiently less than high ability students this induces desegregation of high schools compared to laissez faire and affirmative action. Indeed a significant part of the college wage premium appears to be explained by sorting on an ability dimension (see Fang, 2006),

Whether the policy achieves goal of integration at college depends on whether agents who benefit little from college education are numerous. Numerous means in our context that α has to be low enough to ensure that all h agents can be distributed across schools so that they all get into the top x percent with certainty. Otherwise, if there is competition among h agents for the top x percent slots, the underprivileged have lower admission rates under a top x percent policy than under affirmative action, and possibly even less than under laissez faire.

3 Timing of Rematch

Since the Texas top ten percent policy did not require substantial minimum stay at a school in order to be eligible, in the presence of positive peer effects students should have an incentive to switch as late as possible. This section extends the basic setup to allow for this by introducing an additional school stage. The timing is now as follows.

0. Nature assigns backgrounds and ability, determining endowment e_0.
1. Agents match in schools based on educational endowment e_0 and agents acquire education e.
3. Agents may rematch into schools based on e and acquire education h.
4. Agents attend college or not, based on an admission rule, and obtain payoffs.

As above education endowments in the first stage, $e_0 \in \{\ell u; \ell p; hu; hp\}$, are characterized by $0 < \ell u < \ell p < hu < hp$. Education acquisition yields intermediate inputs e using the same technology $f(.)$ as above:

$$e = g(e_0, e_0')e_0.$$

Extending the above framework further, suppose now that neither ability nor educational endowment are observable at the time of school choice. Backgrounds are observable, however. The academic advantage enjoyed by the privileged implies that $E[e|p] > E[e|u]$. In stage 2, education is acquired in schools (e, e') as above, yielding final educational outcome $f = g(e, e')e$.

3.1 Laissez Faire

As demonstrated above students segregate in educational achievement e in stage 2 under a laissez faire regime. Therefore, an agent with educational endowment e_0 who matches into a (e_0, e_0') school in stage 1 has payoff

$$\pi = g(e, e)e(1 + q(e, e)r(a)),$$

with $e = g(e_0, e_0')e_0$. Since both $g(e, e)$ and $q(e, e)$ increase in e and e strictly increases in e_0', all agents strictly prefer to match with an endowment e_0 over an endowment e_0' if and only $e_0 > e_0'$. e_0 is not observable at the time of school choice, however. Since background is and $E[e|p] > E[e|u]$, all agents strictly prefer a privileged student as match over an underprivileged student. This immediately implies segregation in backgrounds in the first stage.

Since ability is not observable schools take the form (hp, hp), $(hp, \ell p)$, $(\ell p, \ell p)$, and similarly for the underprivileged. This generates a support of eight different intermediate education levels e. Since schools segregate in education level e at the second school stage, there will be rematch within privileged schools, and within underprivileged schools, but not across.

3.2 Affirmative Action

Since we showed above that students segregate in stage 2 based on e under an affirmative action regime, the payoff for an agent with e_0 in first stage school (e_0, e_0') is

$$\pi = g(e, e)e(1 + q(e, e, b)r(a)),$$

with $e = g(e_0, e_0')$. Therefore the same argument applies as under laissez faire and schools segregate in backgrounds under a college admission policy based on affirmative action as well.

The following proposition summarizes the equilibrium outcome under laissez faire and affirmative action allowing for rematch at school.

Proposition 3 *Suppose affirmative action or laissez faire is in place. Then in an equilibrium outcome,*

- *in stage* 1 *students segregate in backgrounds. Measures* $\beta(1-\alpha)^2$ *of* $(\ell p, \ell p)$, $\beta\alpha^2$ *of* (hp, hp), $\beta 2\alpha(1-\alpha)$ *of* $(\ell p, hp)$, $(1-\beta)(1-\alpha)^2$ *of* $(\ell u, \ell u)$, $(1-\beta)\alpha^2$ *of* (hu, hu), *and* $(1-\beta)2\alpha(1-\alpha)$ *of* $(\ell u, hu)$ *schools form,*

- *in stage* 2 *students segregate in stage* 1 *educational attainments* e.

- *A stable outcome in stage* 2 *requires rematch only between schools of the same background.*

3.3 Top x Percent

Turn now to a top x percent policy. In stage 2 a similar argument as above can be applied, so that a positive measure of schools will be integrated. Suppose again that $\bar{\kappa} = \kappa$. Note that since $hu > \ell p$ there must be at least some overlap between h and ℓ agents' achievement, i.e. $g(hu, hu)hu > g(\ell p, \ell p)\ell p$, although $g(\ell p, hp)\ell p > g(hu, hu)hu$ is possible. Since the support of educational achievement has expanded and there are now four educational outcomes for h and ℓ students each the conditions have to be slightly adjusted.

An individual with educational achievement e and ability h prefers to match with an individual of lower educational achievement e if

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

for all $e' < e$ and $e'' > e$. An individual with educational achievement e and ability ℓ prefers to match with an individual of higher educational achievement e if

$$g(e, e')(1 + 2\bar{\kappa}r(\ell)) \leq g(e, e)(1 + \bar{\kappa}r(\ell)) \leq g(e, e'') \qquad (3)$$

Assume that condition (2) holds for all education levels e such that $e = g(e_0, e_0')e_0$ for $e_0 = hp, hu$, and (3) holds for all education levels e such that $e = g(e_0, e_0')e_0$ for $e_0 = \ell p, \ell u$. Then as above h students with education e prefer to be matched to lower education levels e' over e, and e over $e'' > e$, while ℓ students prefer education levels $e'' > e$ over e, and e over $e' < e$.

Again the conditions (3) hold if $r(\ell)$ is sufficiently close to 0. The set of conditions (2) is satisfied if $r(h)$ is sufficiently high, and (i) $g(.)$ has weakly decreasing differences. i.e. $2g(e, e') \geq g(e, e) + g(e', e')$ or (ii) the support of e is sufficiently tight, i.e. $g(e_{max}, e_{max}) < 2g(e_{max}, e_{min})$ with $e_{max} = g(hp, hp)hp$ and $e_{min} = g(\ell u, \ell u)\ell u$. Note that (2) need not hold for all e such that $e = g(e_0, e_0')e_0$ for $e_0 = hp, hu$, see the example at the end of this section.

That is, whenever the college wage premium is sufficiently great for high ability types relative to the human capital gain through peer effects at schools, students have an incentive to integrate in ability. Typically integration in ability cannot be achieved unless some schools become integrated in backgrounds as well. This is stated in the following proposition.

Proposition 4 *Suppose $g(e,e) < 2g(e,e')$ for all e. An equilibrium assignment of students in period 2 exhausts all possible matches between students with $a = \ell$ and $a' = h$ and $e < e'$ in a manner positive assortative in e, and generically generates a positive measure of schools heterogenous in backgrounds if the college wage premium is sufficiently large.*

The proof can be found in the Appendix. The equilibrium matching pattern in stage 1 is determined by the continuation payoffs from matching in period 2. The following lemma ensures that continuation payoffs are monotone in e, so that pinning down the exact equilibrium allocation will not be necessary.

Lemma 1 (Monotonicity) *A student with e has higher expected payoff than a student with e' if and only if $e > e'$.*

The proof is in the Appendix and does not exploit the particular matching pattern described in Proposition 4, and thus does not rely on its assumption. Instead it relies on a revealed preference argument.

Since expected payoffs in stage 1 depend positively on own educational attainment after stage 1, e, agents maximize expected educational attainment e when deciding which school to attend in stage 1. Imperfect information on e and co-monotonicity of $g(.)$ imply then students segregate in backgrounds in period 1.

Corollary 1 *Under a top κ percent policy students segregate in backgrounds in period 1 as under affirmative action and laissez faire. There is rematch in period 2 leading to some integration in backgrounds if the college wage premium is sufficiently large.*

Essentially these results state that under plausible conditions there will be rematch of students in period 2 resulting in some integration. Conditions (2) and (3) hold for instance if the college wage premium matters more than peer effects for some students, and less for others. This seems to describe accurately the difference between middling performers (for instance with $e_1 = g(\ell p, hp)hp$)

and low performers (e.g. with $e_1 = g(\ell u, \ell u)\ell u$). This is consistent with the observation that under the Texas Top Ten Percent Law the likelihood to switch schools after grade 8 is significantly higher among students whose performance placed them not among the top ten percent at their but was high enough to guarantee a top ten percent slot elsewhere (Cullen et al., 2011).

Example

Suppose that endowments can be written as $e_0 = a_i \cdot b_i$ and let $1 < h/\ell = p/u < \sqrt{2}$, i.e. the support of the endowment distribution is sufficiently tight. Assume that $g(e, e') = \sqrt{ee'}$, and that $\bar{\kappa} = \kappa = 1/2$, $\alpha < 1/2$, while $\beta > 1/2$. That is, students with substantial payoff from attending college are scarce, and the privileged abundant. Segregation in backgrounds in stage 1 generates eight different educational attainment levels in stage 2: $\underline{\ell u} = g(\ell u, \ell u)\ell u$, $\overline{\ell u} = g(\ell u, hu)\ell u$, $\underline{\ell p} = g(\ell p, \ell p)\ell p$, and so forth. Under our parametrical assumptions, $\overline{hp} > \underline{hp} > \overline{hu} > \overline{\ell p} > \underline{hu} > \underline{\ell p} > \overline{\ell u} > \underline{\ell u}$, see Figure 4.

In stage 2 students segregate in e under laissez faire and affirmative action as shown in the top half of Figure 5. Under a top κ rule $h/\ell = p/u < \sqrt{2}$ implies that $2g(\overline{hp}, \underline{\ell p}) > g(\overline{hp}, \overline{hp})$ and $2g(\overline{hu}, \underline{\ell u}) > g(\overline{hu}, \overline{hu})$. Hence, for $r(h)$ sufficiently high and $r(\ell)$ sufficiently small, all hp students prefer to match with $\overline{\ell p}$ or $\underline{\ell p}$ students over all other alternatives, and all hu students prefer any ℓ match to any other. Since the measure of $\overline{\ell p}$ and $\underline{\ell p}$ students (equal to $\beta(1-\alpha)$) suffices to absorb all hp students, the matching equilibrium has positive measures of $(\overline{hp}, \overline{\ell p})$, $(\underline{hp}, \overline{\ell p})$, $(\underline{hp}, \underline{\ell p})$, and $(\overline{hu}, \underline{\ell p})$ schools. If $(1-\alpha)\beta \geq \alpha$, enough $\underline{\ell p}$ agents remain to absorb all $\underline{hu}$ students. If $\beta(1-2\alpha) - \alpha^2(1-\beta) \geq \alpha > (1-\alpha)\beta)$, some $\underline{hu}$ match with $\overline{\ell u}$ students, which is the case shown in the bottom half of Figure 5. Otherwise also $(\underline{\ell u}, \underline{hu})$ schools form.

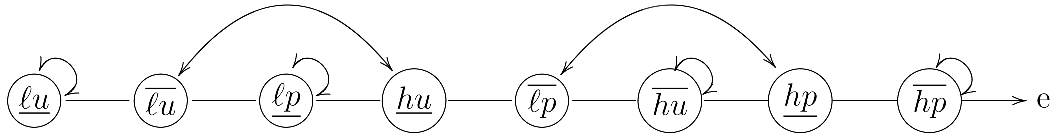

Figure 4: Matching pattern in the numerical example at the end of stage 1.

3.4 Implications

Aside from the fact that rematch will occur, the rematch will also alter the composition of high schools with respect to observable characteristics, in particular

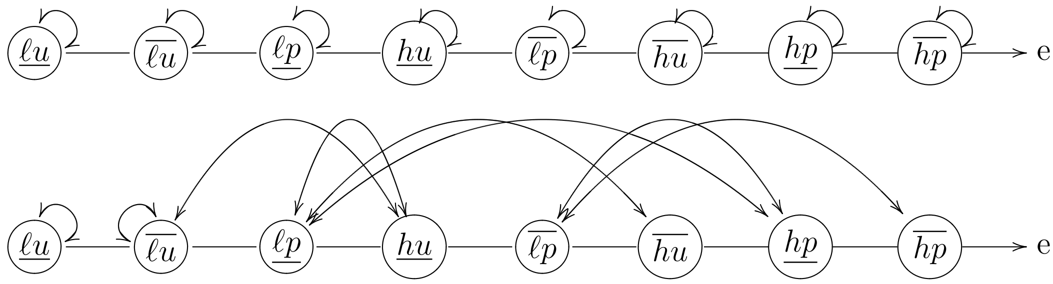

Figure 5: Stage 2 equilibrium matching pattern in the numerical example under laissez faire and affirmative action (top) and top x percent policy (bottom).

those correlated with background. Suppose that background is correlated to race in the sense that students from the ethnic majority tend to have privileged backgrounds. In stage 1 all policies yield the same equilibrium outcome, segregation in backgrounds, and on an adequately defined average, in race. Corollary 1 states that a switch from affirmative action to a top x percent policy in stage 2 induces on average a decrease in majority share in high background schools (i.e. high majority share schools), and an increase in majority share in low background schools (i.e. low majority share schools). Therefore any aggregate measure of segregation should show an increase after the policy change for grades close to college admission, but no change for lower grades, in particular middle school grades. Moreover, privileged (i.e. mainly majority) students from privileged (i.e. mainly high majority share) schools should migrate to less privileged (i.e. mainly lower majority share) schools. This amounts to a set of testable predictions that leaves us well-provisioned for a closer look at the data.

4 A Closer Look at the Data

Figure 3 in the introduction highlights two features. First, there is a downward trend in high school segregation in Texas over the period 1989-2007. Second, there appears to be a decrease in segregation in 1998 for 12th grade, but not for 9th grade, coinciding with the implementation of the Texas Top Ten Percent law. In this section we aim to determine whether this is born out by the evidence.

4.1 Data

In order to investigate the effect of the Texas Top Ten Percent law on high school segregation, we use five different sources of administrative data.

The first consists of school enrollment data obtained from the Texas Education Agency (TEA). We use data on student counts per grade and per race/ethnicity (classified into five groups: White, African American, Hispanic, Asian, and Native American) from 1995-1996 to 2001-2002. The data is provided at the school (campus) level for all ethnic groups with more than five students enrolled in school.[13] The second is the Public Elementary/Secondary School Universe Survey Data available in the Common Core of Data (CCD) database provided by the National Center for Education Statistics (NCES).[14] It contains information such as the school location, school type, etc. It also includes enrollment data, but student counts per grade and per race/ethnicity are only available starting in 1998-99. By merging the TEA enrollment counts and the CCD, we are able to characterize all the schools that were active in Texas during the period.[15]

The third is the Academic Excellence Indicator System (AEIS) available at the TEA website.[16] This database provides information on several perfor-

[13]If an ethnic group has less than five students 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 consist of replacing masked values by 0 and 2, respectively. The third strategy is to generate a random integer between 1 and 5 to replace the masked values. The results reported in this report are for the the first strategy (i.e. masked values replaced by zero), but most of the results remain unchanged when the other strategies are used.

[14]This database can be accessed at http://nces.ed.gov/ccd/pubschuniv.asp.

[15]The merge is done using the campus number (in the TEA database) and State Assigned School ID (in the NCES database).

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

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

The fourth database contains information on student mobility between 11th and 12th grades and was also obtained from the TEA. It consists of the number of students enrolled in 12th grade who attended the same school in 11th grade. The TEA has also provided the total number of transfer students (spring data) in 9th to 12th grades in Texas high schools from 1996 until 2007. The transfer data file keeps track of students who are reported to TEA with a district of residence that is different from their district of enrollment or whose campus of residence is different from their campus of enrollment.[18] Finally, we also use data on the ethnic population composition of Texas counties available from the US Census Bureau from 1990 until 1999.[19]

We use the databases above to build several variables that are used in the analysis. We now describe these variables that can be classified into segregation and mobility measures.

Segregation Measures

In the analysis, we use the mutual information index and several of its components as segregation measures. The basic component of the mutual information index is the *local segregation index.* This is an index that compares the composition of a school s to the composition of a larger unit x (e.g. state, region,

[17]The data is 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]As such, students enrolled in open-enrollment charter schools are considered to be transfer students. However, there are many other situations in which transfers are authorized, but they are subject to regulations as established in the Civil Action 5281 (available at http://ritter.tea.state.tx.us/pmi/ca5281/5281.html). In particular, 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)

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

MSA, or school district) and is defined as:[20]

$$M_s^x = \sum_{e=1}^{E} p_{es} \log\left(\frac{p_{es}}{p_{ex}}\right), \tag{4}$$

where p_{es} and p_{ex} denote the proportion of students belonging to ethnic group e in school s and in the benchmark unit x (e.g. state, region, county, MSA, or school district), respectively.

We also use two aggregated measures of segregation that are built from the local segregation index. The first, presented in the introduction, is the mutual information index.[21] It can be calculated as:

$$M = \sum_{s=1}^{S} p_s^a M_s^a,$$

where M_s^a is the local segregation index comparing school to state composition and can be obtained by setting $x = a$ in (4).

The second is a segregation measure calculated within a given unit (e.g. region, county, MSA, or school district).[22] The *within-unit x segregation index*, W^x can be calculated as:

$$W^x = \sum_{s \in X} p_{sx} M_s^x, \tag{5}$$

where p_{sx} is the proportion of students in school s in the larger unit x and M_s^x is given by (4).[23]

Mobility Measures

In order to characterize student mobility, we combine the data on the number of students enrolled in 12th grade that were in 11th grade, $GRADE1211$, in the same school with total enrollment. This allows us to calculate the proportion of students leaving 11th grade, $PLEAVE11$, and entering 12th grade, $PENTER12$, in school year t as:

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

[21] Appendix B provides more details on the mutual information index and also illustrates its decomposition properties.

[22] In the analysis, we use within-district and within-county segregation indices.

[23] Note that the mutual information index is the within-state segregation index.

$$PLEAVE11_t = \frac{GRADE11_t - GRADE1211_{t+1}}{GRADE11_t} \quad (6)$$

$$PENTER12_t = \frac{GRADE12_t - GRADE1211_t}{GRADE12_t} \quad (7)$$

4.2 Descriptive Statistics

Segregation Indices

Figure 8 shows a small decrease in the mutual information index for grade 11, but not for 10th grade. Together with Figure 3, it confirms that the decrease in segregation occurred mostly in the later grades of high school, in line with the theoretical predictions of the model. We now take a closer look at the segregation indices by decomposing the mutual information index (see Frankel and Volij, 2011, on decomposing the mutual information index with respect to regions or racial groups).

Figure 10 presents the regional decomposition of the mutual information index for 12th grade. While a considerable part of the drop in segregation in 1998-1999 is attributable to a change in between region segregation, there is also a decrease in between school districts segregation. Another possible decomposition is by ethnic groups. Following the model, we group the racial/ethnic groups in *minority* (Blacks, Hispanics and native Americans) and *majority* (White and Asian). As shown in Figure 11, a large part of the decrease in segregation can be attributed to a reduction in segregation between the majority and minority groups. Interestingly, such a pattern does not appear for other high school grades (Figure 12). The pattern for within majority and within minority has been similar for all grades.[24]

Transfers

There is substantial attrition in the transition from 11th to 12th grade, as shown in Table 1. From 1993 to 2007, around 9% of students in 12th grade were newcomers to the school. On average 17% of students in 11th grade did not return to the same school in 12th grade.[25] These proportions have been quite stable over the period. Thus, changing school in the last year of

[24]The figures are not reported here, but available from the authors.

[25]Note that these figures include those switching schools, but also depends on retention and dropout rates.

high school is not uncommon, suggesting that there is quite a lot of room for strategic switching of school.

Figure 14 shows the development of out-of-district-of-residence enrollment. The share of students attending schools out of home districts increased substantially after 1998 and approximately double over all grades. This would be consistent with the effect of the Texas Top Ten policy operating mainly through natural movement of students.

4.3 Empirical Strategy and Regression Results

4.3.1 Segregation in Backgrounds

Local Segregation Index

We now verify whether the patterns observed in the aggregate measures are observed in school level data. 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. However, some schools imposed restrictions on a minimum attendance period in order to qualify for admission under the Top Ten Percent rule. Therefore, strategic rematch may well be expected to start as soon as 10th grade in some schools, but later in others. We start by considering that the policy did not affect 9th grade, but had an impact on 12th grade. This is consistent with the analysis in Cullen et al. (2011) considering the transition from 8th to 10th grade. Then, we check the 10th and 11th grades to check for possible effects.

We use a differences-in-differences approach and start with 9th grade as the control group and 12th grade as the treatment group. The dependent variable is the local segregation index at the school level (defined in (4)). In most of the analysis, school years 1995-1996 to 1997-1998 will be our pre-treatment, while 1999-2000 to 2001-2002 correspond to post-treatment periods. Since the policy was announced in 1996 and implemented in 1998, we could expect school year 1997-1998 to be partially affected by it.[26] For $g = \{9, 12\}$, the model estimated is:

$$M^x_{gst} = c + G_g + T_t + R_r + X_{rt} + \beta_1 G12TOP_{gst} + \varepsilon_{gst},$$

[26] If we exclude both 1997-1998 and 1998-1999, we obtain similar and even stronger results. The results are also very similar when adopting the other two masking strategies, i.e. replacing the masked values by 2 or by a random integer between 1 and 5.

where G_g is a grade fixed effect, T_t is a time dummy, R_r is a region dummy, X_{rt} is a region time dummy, and $G12TOP_{gst} = 1$ if $g = 12$ and $t \geq 1998$, and 0 otherwise, and ε_{gst} is the error term. The grade fixed effect, G_g, controls for differences in segregation across grades that are common to all schools. These differences may arise since minority students tend to be under-represented in 12th with respect to 9th grade, due to larger dropout rates, for example. The time dummy, T_t, controls for the overall trend in segregation of all schools in Texas. Alternatively, we replace these time dummies by a linear time trend, $time_t$, in some specifications. The variable R_r controls for differences in segregation across regions and we allow for these differences to change over time by introducing a region time dummy, X_{rt}. This is meant to control for changes in the student population in a given region that may be caused by immigration, for instance. The coefficient of interest in this regression is β_1, indicating the change in the local segregation index in the grade and school years affected by the Top Ten Percent law.

Table 2 presents the estimation results, when school composition is compared to that of the region comparing school years 1997-1998 and 1999-2000. Columns (1) and (2) present the results for the full sample and while the coefficients are negative, they are not significant. Similar results are obtained by restricting the sample to schools located in school districts with more than one school (columns (3) and (4)) , presumably facilitating transfers to another school. Restricting the analysis to schools located in an MSA (columns (5) and (6)), we obtain slightly larger and marginally significant negative coefficients when regional dummies are not included. Tables 3 present the results for a longer time span, school years 1995-1996 to 2001-2002, using time dummies. The results remain negative but the coefficients are smaller and remain statistically insignificant.

A concern with the previous exercises is that there is much heterogeneity across schools in Texas. In order to control for time invariant school heterogeneity, we introduce school-grade fixed effects. For $g = \{9, 12\}$, the model estimated is

$$M^x_{gst} = A_{sg} + T_t + X_{rt} + \beta_1 G12POST_{gst} + \varepsilon_{gst}, \tag{8}$$

where A_{sg} is a school-grade fixed effect. The estimation results are presented in Table 4. Columns (1) and (2) show a significant decrease in school segregation when the benchmark is the region's ethnic composition. Thus, there is evidence that the Top Ten Percent law was associated with a decrease in school segregation, more pronounced in 12th grade than in 9th grade. Similar coefficient values are obtained when considering only schools located in school districts with more than one school, but the standard errors are larger and the coefficients lose statistical significance. When restricting the sample to schools located in a MSA, the coefficients increase in size and are significant (columns (5) and (6)). Table 5 considers a longer time span, three years before and three years after the reform. The results are very similar to the shorter term analysis.

Finally, we include data on 10th and 11th grades to check whether the decrease in segregation is gradual. For $g = \{9, 10, 11, 12\}$, we estimate:

$$M^x_{gst} = A_{sg} + T_t + X_{rt} + \beta_1 G12TOP_{gst} + \beta_2 G11TOP_{gst} + \beta_3 G10TOP_{gst} + \varepsilon_{gst}, \quad (9)$$

The results in Table 6 suggests that indeed there was a gradual effect that diminishes for lower high school grades. The coefficients of the interaction terms for 11th grade are smaller, but still significant. While the results remain negative for 10th grade, they are statistically insignificant in the full sample (column (1) and (2)) and MSA sample (columns (5) and (6)). Interestingly, there was a strong decrease on segregation for 10th grade, relative to 9th grade, for schools located in school districts with more than one school. The same trends are observed in longer samples (Table 7).

As a placebo, we run specification (8) for school years 1990-1991 to 1996-1997, excluding 1993-1994. Table 8 presents the results.The coefficients are positive and non significant. This indicates that the results we obtained for the Top Ten Percent law in Tables 4 and 5are not a consequence of some pre-existing trend in the data.

Within-District Segregation

Another potential concern regarding the decrease in segregation observed in 1998 is that it could be due to a cohort effect. A closer look at Figures 3 and 8 indicates a slight decrease in segregation in grades 9 to 11 in the years 1995 to 1998. Also, the fact that the larger drop has happened in between region segregation might cast some doubt on the strength of its relation to the Top Ten Percent law.

In order to further investigate these issues, we focus on the within district measure of segregation and analyze whether there was a decrease in segregation in grade 12 relative to the same cohort in grade 9. More specifically, for each school district, we calculate the within-district segregation, W^d, using (5) at the district level. This index is zero when the school composition exactly matches the district composition, implying $W^d = 0$ if a district has only one school. Therefore the analysis considers only districts with more than one school.

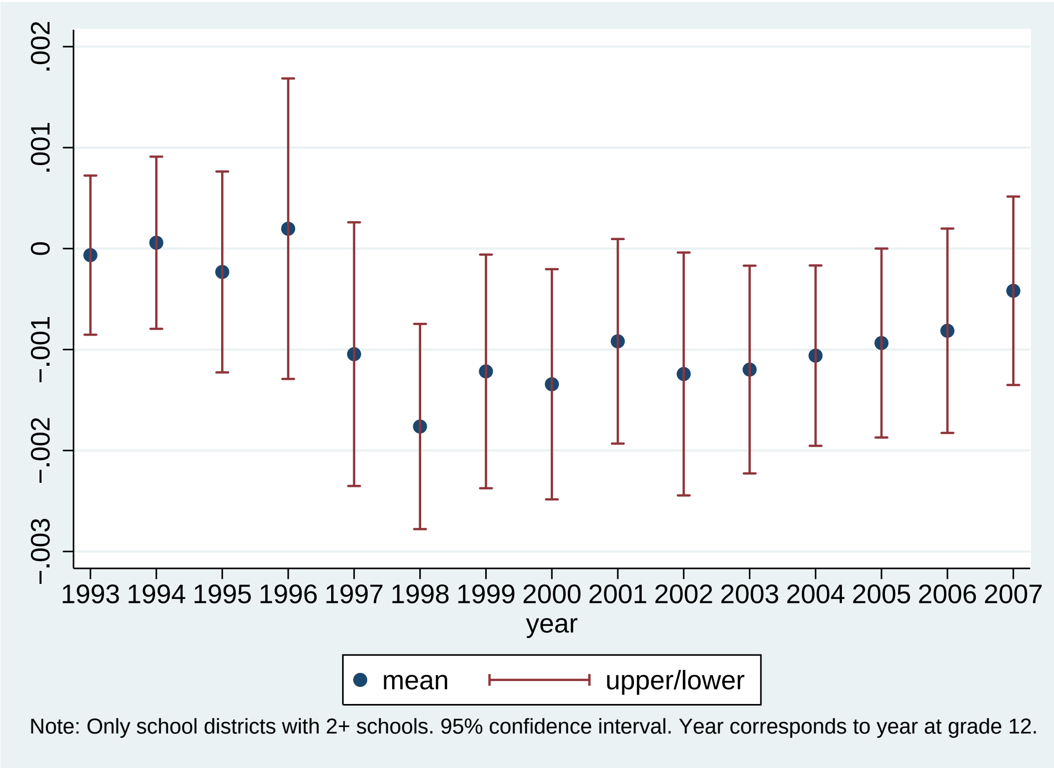

Figure 6: Within-district segregation (grade 12-grade 9), same cohort.

Figure 6 depicts the mean and the 95% confidence intervals of the difference between within-district segregation in grades 12 and 9 for the same cohort over time. Before 1998 the difference in average school district segregation between grade 9 and grade 12 was not different from zero, after 1998 this difference tends to be negative, coinciding with the introduction of the Texas Top Ten percent rule. This means that the typical increase in segregation between grade 12 and grade 9 of a cohort decreased after 1998. To verify this we estimate the following model.

$$W^d 12t - W^d 09\,(t-3) = D_d + time_t + \beta POST_{dt} + \varepsilon_{dt}, \qquad (10)$$

where $W^d gt$ is the within-school district segregation index at school district d, grade g, at time t, D_d is a school district fixed effect, $time_t$ is a linear time trend, $POST_{dt} = 1$ starting in 1998 and ε_{dt} is the error term. Table 9 presents the results using one school year before and one after the Top Ten Percent law (1997-1998 and 1999-2000) in column (1). While the coefficient is negative, it is not significant. Increasing the time span of the analysis to school years 1995-1996 to 2001-2002, we observe a drop in within-district segregation coinciding with the Top Ten Percent law (column (3)). However, the introduction of linear time trends cause a reduction in the coefficients and increase standard errors, so that coefficients become insignificant.[27]

Robustness Check: Charter Schools

The results just presented indicate a slight decrease in within-district segregation in 1998. A possible concern related to this exercise is that the decrease in within-district segregation may be due to the introduction of charter schools and not the Top Ten Percent law. Even if charter schools were introduced in 1996, their expansion started in 1998, coinciding with the Top Ten Percent law.

In Texas, there are basically two types of charter schools, open-enrollment and charter campus. The former are new schools that are created in entirely new school districts and constitute the great majority of charter schools. Before 1998, there were only 12 open-enrollment charter schools. Over the period 1996 to 2007, there were 328 open-enrollment charter schools active at some point in time. The second type of charter schools are traditional public schools that were converted into charter schools and belong to independent school districts. The first charter campus schools serving high-school in Texas were created in 2006. By 2007, there were only 16 charter campus schools.

Since most charter schools were created in new school districts, it is not possible to investigate what happened to within-district segregation before and after the introduction of charter schools. Therefore, we analyze the impact of charter schools in a larger unit, namely at the county level.

We calculate a measure of within-county segregation by using (5) and replacing $x = c$ for county. Two different indicators for charter schools are used. $CHARTER_c$ is a dummy variable equal to 1 if there is a charter school in the county in a given year. The variable $\%STUDCH_c$ is the percentage of students in a county attending a charter school and is meant to control for different intensities in charter presence. Both variables are then interacted with the indicator of the Top Ten Percent reform. A significant coefficient in any of these

[27] The results are very similar if one uses the other two unmasking strategies.

interaction terms would indicate that charter schools after the introduction of the reform were responsible for the change in within-county segregation.

Table 11 presents the results for the within-county segregation regression. While the coefficients are negative, they are not significant as before. Moreover, the existence of charter schools does not seem to reduce the within-county segregation, when one considers the presence of charter schools in a county. If instead we use the percentage of students enrolled in charter schools, the coefficients are negative but not significant, indicating that charter schools did not reduce within-county segregation.

Robustness Check: Residential Segregation

A potential concern is that a decrease in high school segregation might simply reflect residential desegregation. Using population data, we compute mutual information indices for the total population and for the group aged 15-19. The indices are calculated by comparing the composition of the population in a given county with the composition of the population of the state. Figure 13 shows on the left that residential segregation has increased over the period. If we concentrate on the age group 15-19, there was a slight decrease over the period coinciding with the reform (the right panel of Figure 13).

4.3.2 Segregation in Ability: An Introductory Analysis

We verify whether there was desegregation in abilities following the Top Ten Percent law, as predicted by the theoretical model. In this introductory analysis, we use three indicators available in the AEIS database: Percentage of students taking a college admission exam, SAT average, and ACT average.

Figure 15 shows the density of schools with respect to the percentage of students taking either the SAT or the ACT exam. While the density was very similar in 1996 and 1997, it shifted to the left in 1998.[28] This means that the students considering going to the university are more spread accross several schools, consistent with the predictions of the model. There is no difference between the densities of 1998 and 1999, indicating that the shift carried on in 1999.[29]

[28] Note that 1998 corresponds to the class graduating in the school year 1997-1998. This is the first class that enters college under the Top Ten Percent law.

[29] These results are confirmed by the Kolmogorov-Smirnov test for equality of distribution functions done for two consecutive years. Indeed, the null hypothesis that the distributions

The results for the average SAT are presented in Figure 16. For any two consecutive years, one cannot reject the null hypothesis that the two distributions are identical. Similar conclusions apply to the average ACT presented in Figure 17.

Since there was a shift in the distribution of the percentage of students taking these exams, we may wonder whether the average of these tests across different years is a good measure. An alternative is to normalize these results by assuming that the students not taking the exam would have obtained a given score, had they taken the exam. We present the results for two normalizations. In the first, we assume that students not taking the exam would score at the criterion.[30] The second assumes that these students would score half of the criterion. The results are presented in Figures 18, 19, 20, and 21. For SAT, we reject that the distributions for 1997 and 1998 are identical under the second normalization.[31] For the ACT, this is rejected for 1997 and 1998 under the first normalization at the 1% level.

5 Conclusion

To be written

A Mathematical Appendix

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

Assume that the support of e is sufficiently small, i.e. $f(hp, \ell u) > f(hp, hp)$, $r(\ell) = 0$ and $r(h)$ sufficiently high to ensure all h students prefer integration with ℓ students to segregation. Moreover, suppose that $f(hp, \ell p)hp > f(hu, hu)hu$. The other cases can be solved analogously.

Suppose the college assigns measure $\kappa - \bar{\kappa}$ of places in order to maximize aggregate human capital of entrants and $\bar{\kappa}$ to students in the top half of their school. Hence, the admission policy selects measure $\kappa - \bar{\kappa}$ of the students with highest educational achievements e who are not admitted through the top x

are identical cannot be rejected at the 1% level in 1997 and 1998, but is rejected for 1996 and 1997 and 1998 and 1999.

[30]The criterion is 24 for ACT and 1000 for SAT until 1995 and 1110 from 1996 on.

[31]These results are confirmed by the Kolmogorov-Smirnov test for equality of distribution functions and the null hypothesis is rejected at the 5% level.

percent rule. Denote by $\hat{e}$ the education level threshold such that all students with $e > \hat{e}$ enter college with certainty. It is implicitly defined by

$$\mu(i \in I : e_i \geq \hat{e}) \leq \kappa - \bar{\kappa} + \int_{i \in I: e_i > \hat{e}} \hat{q}(e_i, e')di \text{ and}$$
$$\mu(i \in I : e_i \leq \hat{e}) \geq 1 - \kappa + \bar{\kappa} - \int_{i \in I: e_i > \hat{e}} \hat{q}(e_i, e')di,$$

where $\hat{q} = 2\bar{\kappa}$ if $e_i > e'_i$, $\hat{q} = \bar{\kappa}$ if $e_i = e'_i$ and $\hat{q} = 0$ otherwise.

To ease exposition, suppose that $\kappa \leq \alpha\beta + \bar{\kappa}(1 - \alpha\beta)$. This means that the measure of places assigned by educational ranking does not suffice to guarantee a place at college to every hp student assuming all hp students segregate. The other cases can be dealt with similarly. Assume this is the case. Then $\hat{e} = f(hp, hp)hp$, and an hp student in a (hp, hp) school has payoff

$$\pi = f(hp, hp)hp \left(1 + \left(\bar{\kappa} + \frac{\kappa - \bar{\kappa}}{\alpha\beta(1 - \bar{\kappa})}\right) r(h)\right).$$

Let ν denote the measure of hp agents who segregate. An hp agent prefers segregation to matching with an ℓp student if

$$\frac{f(hp, hp)}{f(hp, \ell p)} > \frac{1 + \left(2\bar{\kappa} + \frac{\kappa - \bar{\kappa} - \min\{\nu(1-\bar{\kappa}); \kappa - \bar{\kappa}\}}{(\alpha\beta - \nu)(1 - 2\bar{\kappa})}\right) r(h)}{1 + \left(\bar{\kappa} + \frac{\kappa - \bar{\kappa}}{\max\{\nu(1-\bar{\kappa}); (\kappa - \bar{\kappa})/(1-\bar{\kappa})\}}\right) r(h)}.$$

Here we used $f(hp, \ell p)hp > f(hu, hu)hu$. For $\nu \leq (\kappa - \bar{\kappa})/(1 - \bar{\kappa})$ the condition must hold since segregated hp enter college with certainty. To have a trade-off integrated schools must offer a higher probability of being admitted to college. Hence, in equilibrium

$$\nu^* = \alpha\beta \text{ if } \frac{f(hp, hp)}{f(hp, \ell p)} > \frac{1 + 2\bar{\kappa}r(h)}{1 + (\bar{\kappa} + (\kappa - \bar{\kappa})/\alpha\beta(1 - \bar{\kappa}))r(h)},$$

and otherwise

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

With $2f(hp, \ell u) > f(hp, hp)$, $r(h)$ sufficiently high, and $r(\ell) = 0$ hu students strictly prefer to match with ℓ students, ranking them in order of their educational endowment. Hence, a matching equilibrium with $0 < \kappa - \bar{\kappa} \leq \alpha\beta(1 - \bar{\kappa})$ has measure $0 < \nu^*/2 \leq \alpha\beta/2$ of (hp, hp) schools. The remaining measure $(\alpha\beta - \nu^*)$ of hp students and all other students integrate in ability. Matching is positive assortative in educational endowment, that is, the equilibrium assignment matches first all remaining hp students given ν^*, exhausting first all

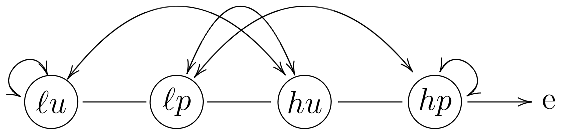

Figure 7: A possible matching pattern when $\kappa > \bar{\kappa}$.

$(hp, \ell p)$ matches, and then assign hu students to all remaining ℓ students again first exhausting potential $hu, \ell p)$ matches. (hp, hp) schools that

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 a college education our argument from above goes through and some schools will desegregate under atop x percent policy.

Proof or Proposition 4

As remarked in the text, for $r(\ell) > 0$ sufficiently close to 0, all conditions (3) are satisfied. Turn now to (2). It states that for any h agent's educational achievement e both

$$\bar{\kappa}r(h) \geq \frac{f(e, e'')}{f(e, e)} - 1 \text{ and } \bar{\kappa}r(h)(2f(e, e') - f(e, e)) \geq f(e, e) - f(e, e'),$$

for all $e' < e$ and $e'' > e$. If $2f(e, e') > f(e, e)$ for all $e > e'$ for all e associated to an agent with ability h there exists $\hat{r}$ sufficiently great to satisfy all above condition, since all get slacker as $r(h)$ increases. Since $F(.)$ increases in both arguments, a sufficient condition for $2f(e, e') > f(e, e)$ for all $e > e'$ for any e is given by $2f(e, f(\ell u, \ell u)\ell u) > f(e, e)$. Hence, under the stated assumptions all ℓ agents prefer e' over e'' whenever $e' > e''$ and all h agents with education e prefer e' over e'' if (i) $e' > e''$ and $e'' > e$, or (ii) $e' < e'\prime$ and $e \geq e'$. This immediately implies any equilibrium allocation cannot have schools heterogenous in e but homogenous in a. On the other hand, all possible schools with $a > a'$ and $e > e'$ have to form, otherwise there is a profitable deviation by a h student from a (h, h) school ((h, ℓ) school with $e < e'$ cannot have positive measure in equilibrium since ℓ agents would prefer (e, e) schools) and a ℓ student from a (ℓ, ℓ) school or a (h, ℓ) school with $e < e'$. Remaining agents segregate in (e, e) schools.

Suppose schools (e, e') and (e'', e'''), with $a = a'' = h$ and $a' = a''' = \ell$ have positive measure. Then $e > e'' \Leftrightarrow e' > e'''$, since otherwise either e and e'''

students or e' and e'' students would strictly prefer to match together instead. That is, matching across ability types is positive assortative in e.

Note that all possible gains from trade between different ability and educational attainment are exhausted, integration in ability occurs in a positive assortative manner, and $f(hp, hp)hp > f(hp, \ell p)hp, f(hu, hu)hu > f(hu, \ell u)hu$, and $f(hp, \ell p)\ell p > f(\ell p, \ell p)\ell p, f(hu, \ell u)\ell u > f(\ell u, \ell u)\ell u$. Therefore, to have measure zero of schools heterogeneous in background, at least one condition on the measure of privileged low skilled and high skilled is needed. A little bit of combinatorics show that a necessary condition depending on the order of e is either $\alpha = 1/2$, $\alpha = 1$, or $\alpha = (3 - \sqrt{5})/2$. Hence, the set of parameters α necessary for segregation in backgrounds is not dense in its domain $(0, 1)$. This establishes genericity of integration in backgrounds.

Proof of Lemma 1

Let $e > e'$ without generality. Suppose e is matched to $m(e)$ and e' to $m(e')$. Note first that if $e' = m(e)$ clearly $f(e, e')e(1+q(e, e')r(a)) > f(e, e')e'$. Therefore suppose that $e' \neq m(e)$ for the following.

Suppose now that both $e > m(e)$ and $e' > m(e')$, both $e = m(e)$ and $e' = m(e')$, or both $e < m(e)$ and $e' < m(e')$. Expected payoffs are $f(e, m(e))(1 + q(e, m(e))r(a))e$ and $f(e', m(e'))(1 + q(e', m(e'))r(a'))e'$ with $q(.) = 0, \bar{\kappa}, 2\bar{\kappa}$. Since $e > e'$, also $m(e) \geq m(e')$ by stability of the matching equilibrium. Therefore also $f(e, m(e))e(1 + q(e, m(e))r(a)) > f(e', m(e'))e'(1 + q(e', m(e'))r(a'))$.

Suppose now $e < m(e)$. Let $e' > m(e')$ first. Then stability requires $f(e, m(e'))e(1 + 2\bar{\kappa}r(a)) < f(e, m(e))e$ since $m(e') < e$. If $e' = m(e')$, stability requires that $f(e, m(e))e > f(e, e)e(1 + \bar{\kappa}r(a))$. The assumption $e > e'$ then implies $f(e, m(e))e > m(e', e')e'(1 + \bar{\kappa}r(a'))$. $a > a'$???

Let now $e = m(e)$. Suppose first that $e' > m(e')$. Then for stability $f(e, e)(1+\bar{\kappa}r(a))e > f(e, m(e'))(1+2\bar{\kappa}r(a))e$. Since $e > e'$, $f(e, e)(1+\bar{\kappa}r(a))e > f(e, m(e'))(1 + 2\bar{\kappa}r(a))e$. If $e' < m(e')$, for stability with respect to coalition (e, e') either $f(e, e)e(1 + \bar{\kappa}r(a)) > f(e, e')e(1 + 2\bar{\kappa}r(a))$, or $m(e') > e$. Suppose the latter is the case. For stability with respect to $(e, m(e'))$, either $f(e, e)e(1+\bar{\kappa}r(a)) > f(e, m(e'))e\phi$, with $\phi = 1, 1+2\bar{\kappa}r(a)$, or $m(e') < e$. Hence, $f(e, e)e(1+\bar{\kappa}r(a)) < f(e', m(e'))e'$ implies a contradiction to stability.

Finally, suppose that $e > m(e)$. Let $e' = m(e')$ first. Stability requires in particular that $f(e, m(e))e(1 + 2\bar{\kappa}r(a)) > f(e, e)e(1 + \bar{\kappa}r(a))$. Therefore $f(e, m(e))e(1 + 2\bar{\kappa}r(a)) > f(e', m(e'))e'(1 + \bar{\kappa}r(a'))$. If $e' < m(e')$ stability with respect to coalition (e, e') requires that $m(e) > e'$ or $m(e') > e$ or both. When $m(e') > e$ stability with respect to $(e, m(e'))$ requires $f(e, m(e))e(1+2\bar{\kappa}r(a)) > f(e, m(e'))e$, that is $f(e, m(e))e(1+2\bar{\kappa}r(a)) > f(e', m(e'))e'$. When $m(e') \leq e$, stability needs $m(e) > e'$, implying $f(e, m(e))e(1+2\bar{\kappa}r(a)) > f(e', m(e'))e'$.

This establishes the lemma.

B Measures of Multi-group Segregation

To examine the evolution of high school segregation among five ethnicities we use two multi-group segregation indices: the Theil Index and the Mutual Information Index. They have been singled out since they satisfy several desired properties (Reardon and Firebaugh, 2002; Frankel and Volij, 2011; Mora and Ruiz-Castillo, 2010). In what follows we compute these measure. First some notation is needed. Let e denote ethnic groups and s schools that are grouped into school district d belonging region r, and use capital letters to refer to the cardinality. A list of notation follows.

p_{es} : proportion of students of ethnic group e at school s.

p_{ed} : proportion of students of ethnic group e at school district d.

p_{er} : proportion of students of ethnic group e at region r.

p_e : proportion of state students of ethnic group e.

p_s : proportion of state students at school s.

p_d : proportion of state students in school district d.

p_r : proportion of state students in region r.

p_{dr} : proportion of students in region r in school district d.

p_{sd} : proportion of students in school district d at school s.

The Mutual Information Index

The Mutual Information Index has two distinct advantages: it can be decomposed and has a very intuitive interpretation. It reflects the informational content of a student's race contained in the information at school level. If the school's composition is identical to the state composition, the school characteristic carries no informational content and the index is zero. If each school is composed of one single race the index attains its maximum value.[32] The Mutual Information Index can be calculated as:

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

where M_s is the local segregation index at high school level comparing school composition to that of the state. It is given by

$$M_s = \sum_{e=1}^{E} p_{es} \log\left(\frac{p_{es}}{p_e}\right). \tag{11}$$

This index is easily decomposed in between region, within region, and within district measures. It also appears to capture changes in interracial context better than the Theil index (see Frankel and Volij, 2011, for details). That is,

$$M = BR + WR + WD,$$

where BR is the between-region segregation, WR is the within-region segregation, and WD is the within-district segregation measure. Between-region segregation is given by

$$BR = \sum_{r=1}^{R} p_r M_r,$$

where M_r is the local segregation index at region level comparing region composition to that of the state. It is

$$M_r = \sum_{e=1}^{E} p_{er} \log\left(\frac{p_{er}}{p_e}\right).$$

The expression for the measure of within-region segregation is

$$WR = \sum_{r=1}^{R} p_r WR_r,$$

where WR^r is the within-region segregation index corresponding to region r calculated as

$$WR_r = \sum_{d \in R} p_{dr} M_{dr},$$

[32]See Mora and Ruiz-Castillo (2010) for invariance properties of the Mutual Information Index.

where M_{dr} is the local segregation index at district level comparing district composition to that of the region, given as

$$M_{dr} = \sum_{e=1}^{E} p_{ed} \log \left(\frac{p_{ed}}{p_{er}} \right).$$

The within-district segregation index is given by

$$WD = \sum_{d=1}^{D} p_d WD_d,$$

where WD^d is the within-school district segregation of district d calculated as

$$WD_d = \sum_{s \in D} p_{sd} M_{sd},$$

where M_{sd} is the local segregation index at school level comparing school composition to that of the school district. It is given by

$$M_{sd} = \sum_{e=1}^{E} p_{es} \log \left(\frac{p_{es}}{p_{ed}} \right).$$

The Theil Information Index

The Theil index is essentially a normalized version of the Mutual Information Index. First define the *Theil's Entropy Index*, a measure of diversity.

$$T = \sum_{e=1}^{E} p_e \ln \left(\frac{1}{p_e} \right) \tag{12}$$

The Theil Information Index is then defined as:

$$H = \frac{1}{T} M = \frac{1}{T} \sum_{s=1}^{S} p_s M_s. \tag{13}$$

The index takes values in $[0, 1]$, with 1 indicating full segregation. A meaningful decomposition of the Theil index requires multiplication by T, yielding the Mutual Information Index.

C Tables and Figures

Figure 8: Time series of the mutual information index for grades 10 and 11

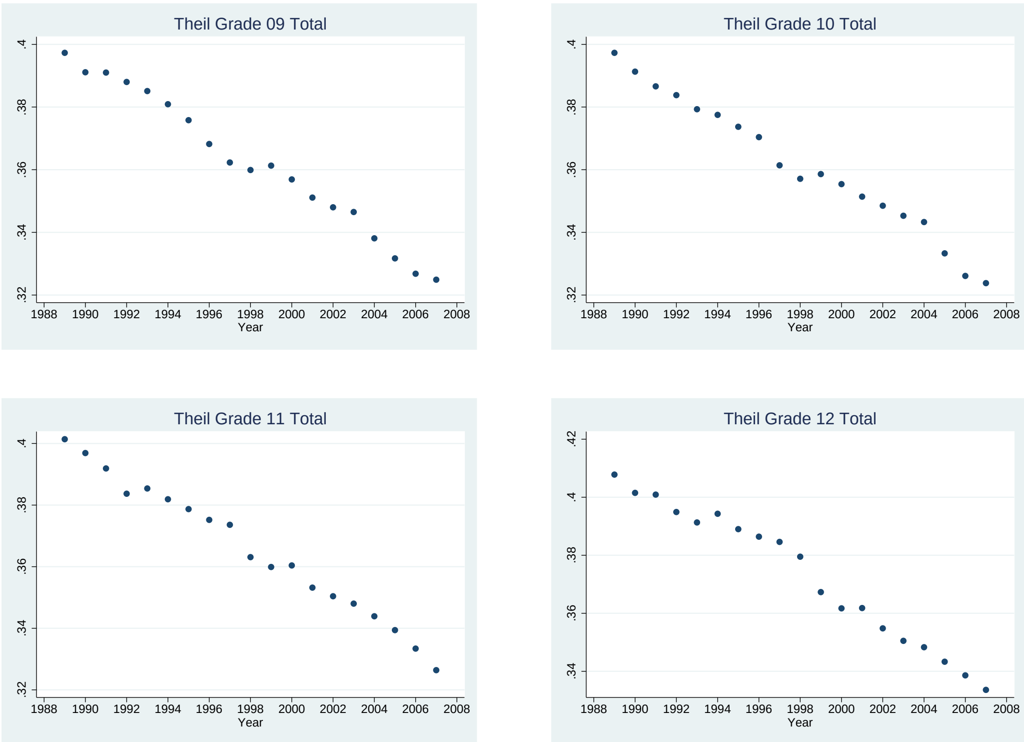

Figure 9: Time series of the Theil index for grades 09 to 12

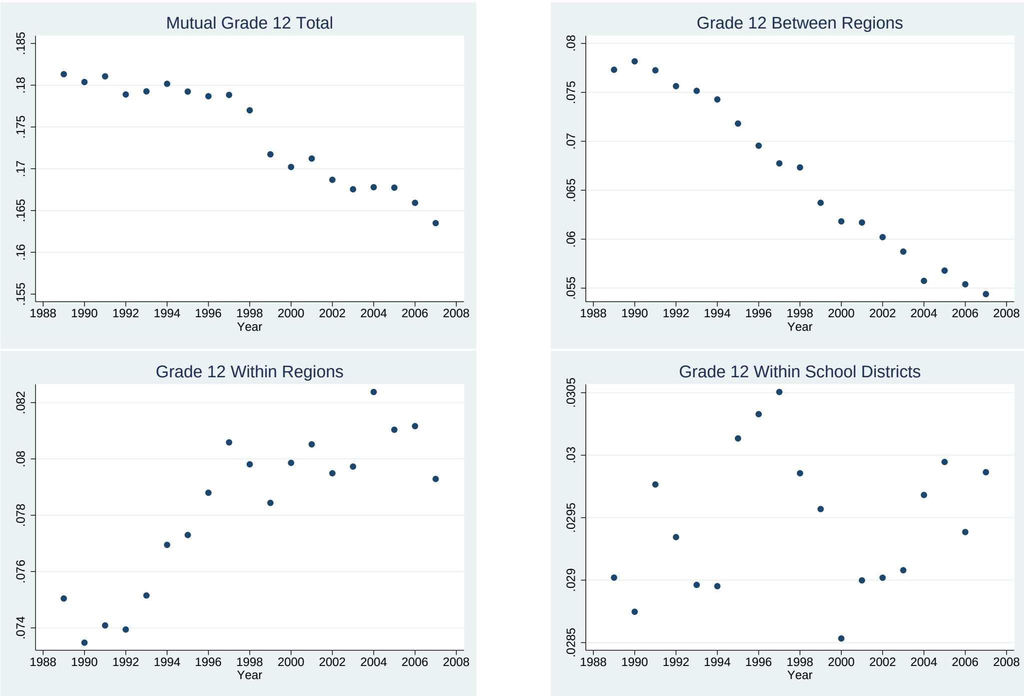

Figure 10: Mutual information index Grade 12: Decomposition by Region

Figure 11: Mutual information index Grade 12: Decomposition by Majority and Minority groups

Figure 12: M Index Grade 12: Between majority and minority Grades 9 to 12.

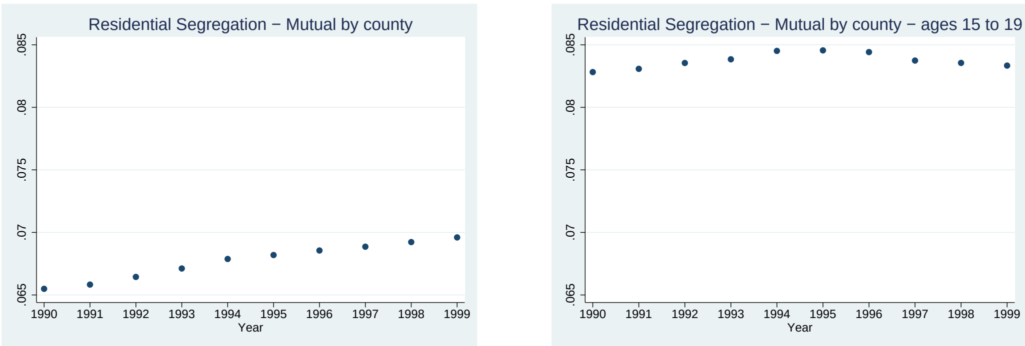

Figure 13: Residential Segregation: Total Population (left), aged 15-19 (right).

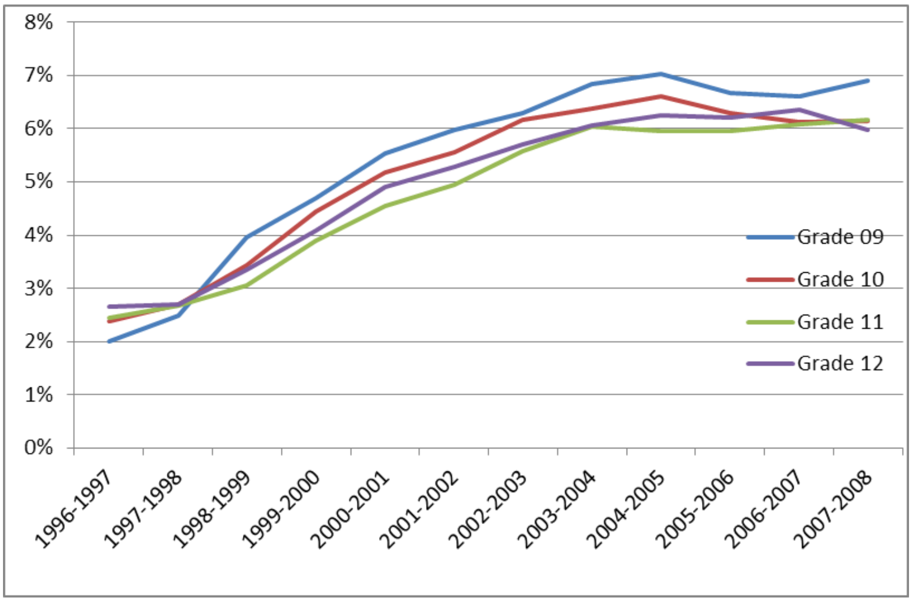

Figure 14: Share of students with a district of enrollment different from district of residence, 1996-2007

Source: TEA.

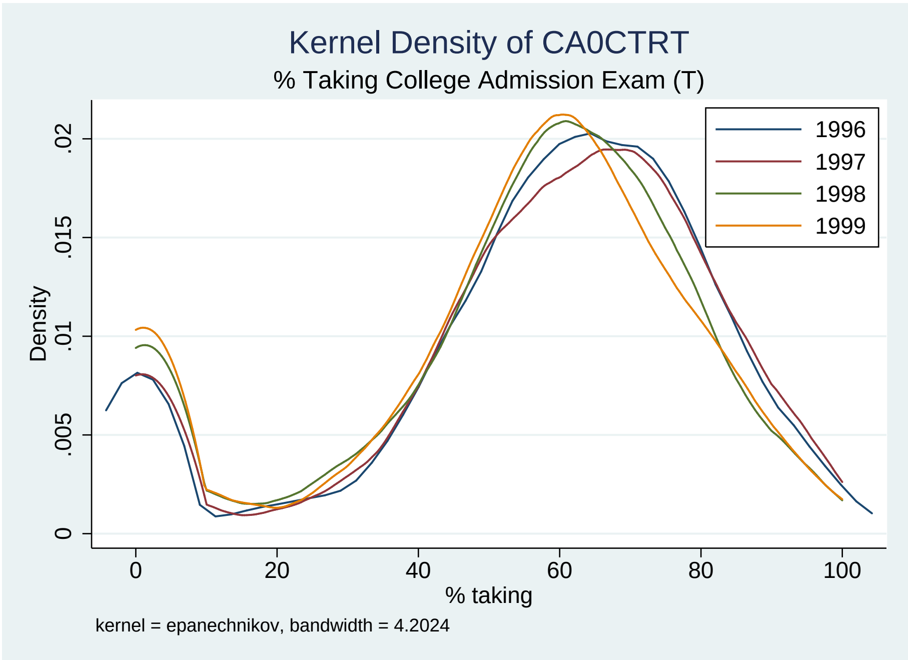

Figure 15: Percentage taking a college admission exam, 1996-1999

Source: AEIS data.

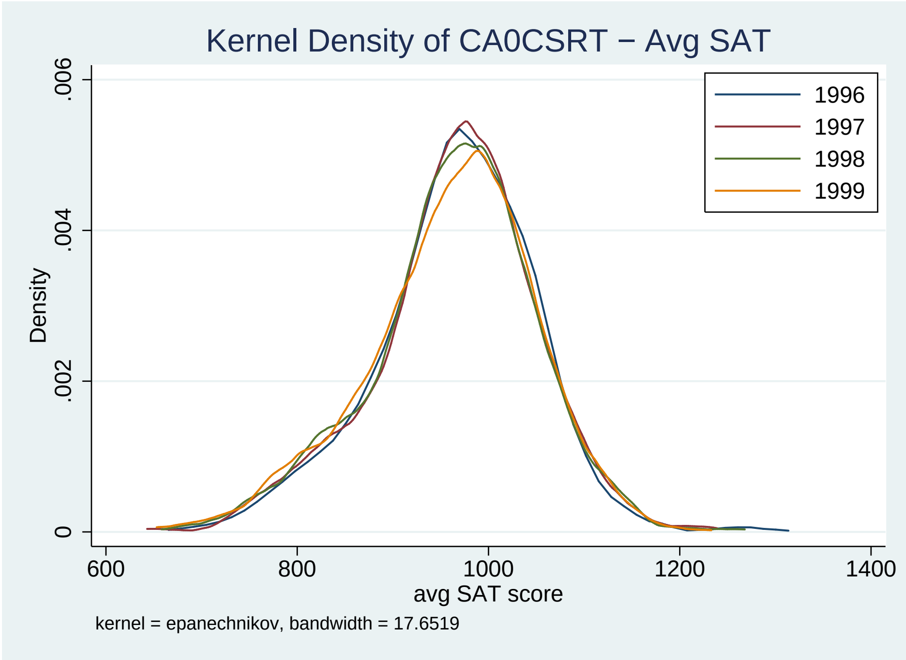

Figure 16: Average SAT, 1996-1999

Source: AEIS data.

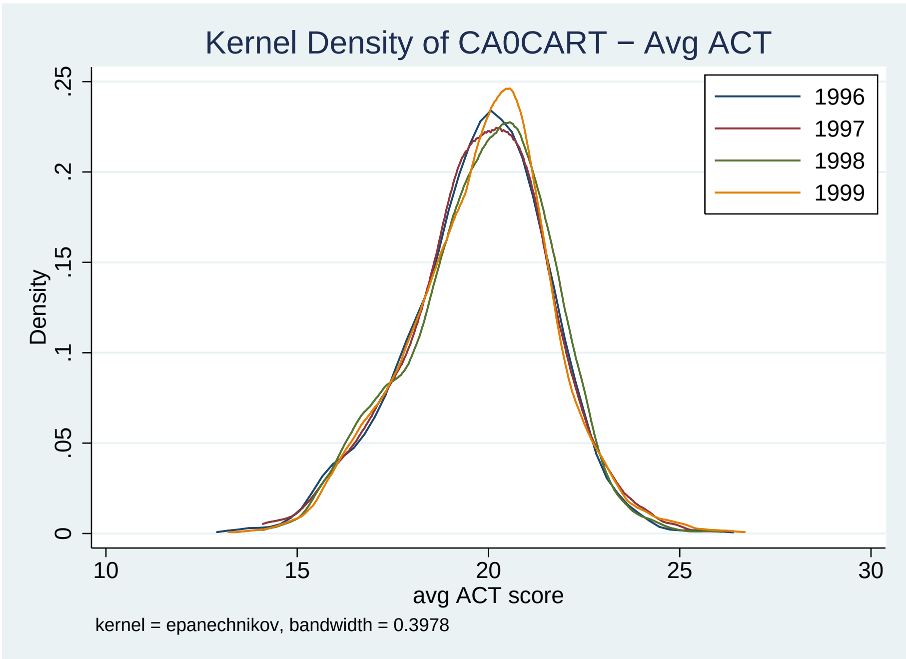

Figure 17: Average ACT, 1996-1999

Source: AEIS data.

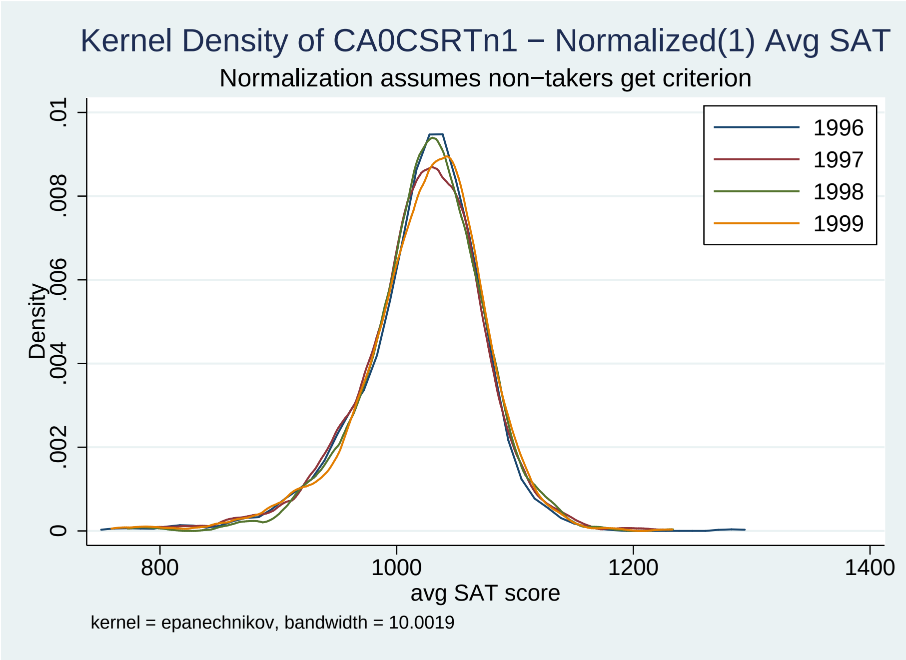

Figure 18: Average SAT, normalization 1, 1996-1999
Source: AEIS data.

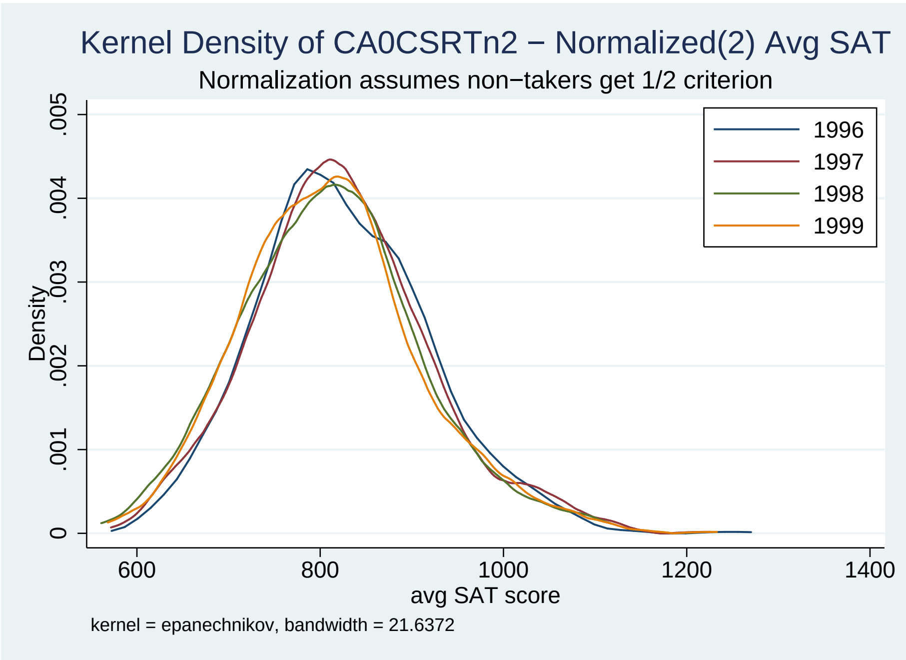

Figure 19: Average SAT, normalization 2, 1996-1999
Source: AEIS data.

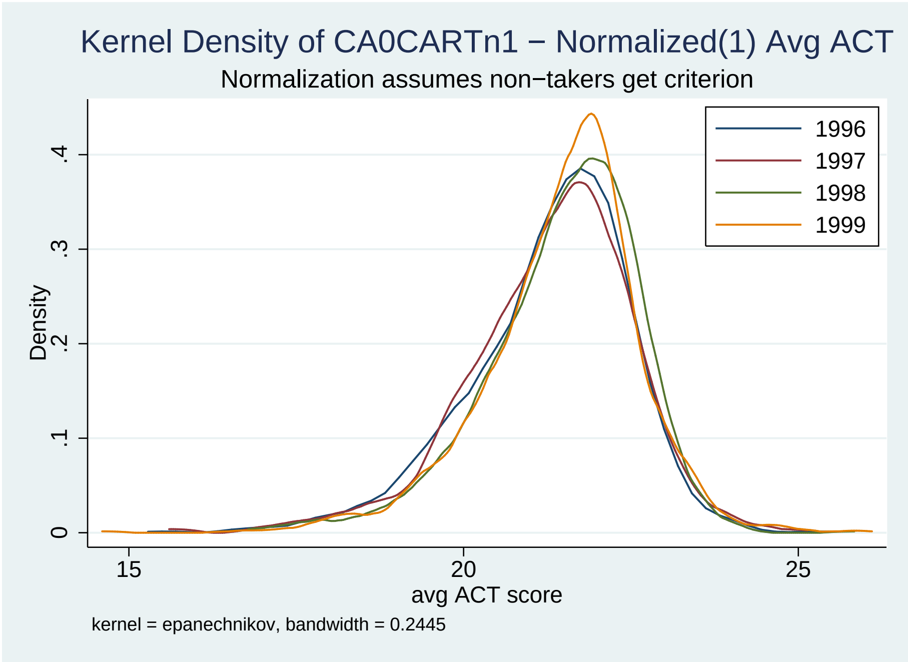

Figure 20: Average ACT, normalization 1, 1996-1999
Source: AEIS data.

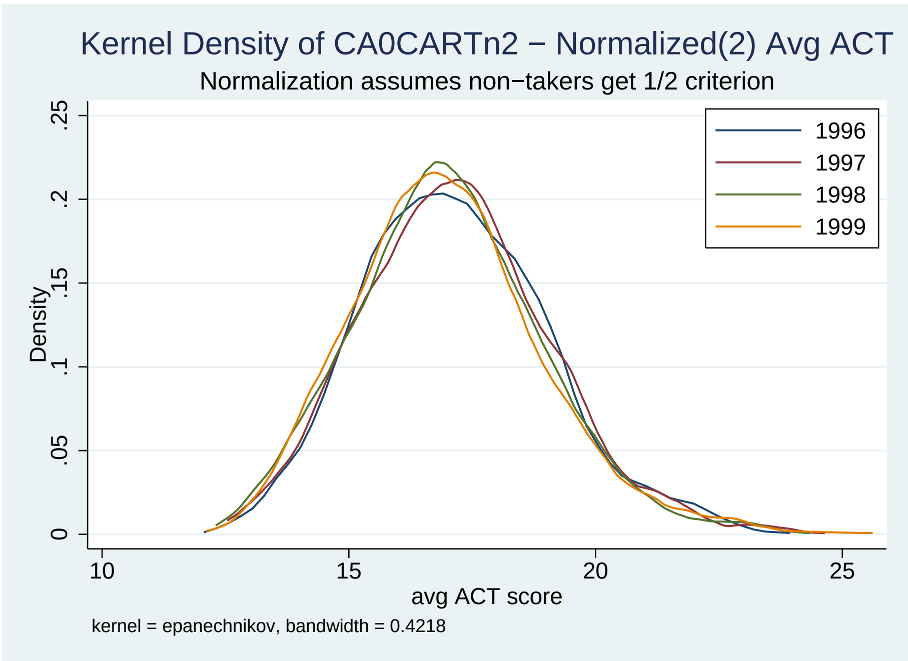

Figure 21: Average ACT, normalization 2, 1996-1999
Source: AEIS data.

Table 1: Transition Grade 11 to 12

YEAR	$PENTER12$	$PLEAVE11$
1993	0.10	0.19
1994	0.09	0.18
1995	0.10	0.19
1996	0.10	0.18
1997	0.10	0.17
1998	**0.10**	**0.19**
1999	0.09	0.18
2000	0.09	0.18
2001	0.08	0.17
2002	0.09	0.16
2003	0.08	0.15
2004	0.08	0.15
2005	0.08	0.14
2006	0.09	0.15
2007	0.09	0.14

Source: Texas Education Agency.

Table 2: Pooled estimation, grades 9 and 12, school years from 1997 to 1999 (excl. 1998)

Dep. var.:	M^r_{gs}: Local segregation index with respect to *region*					
	Full sample		Only school districts with 2+ school		Only school districts in MSA	
	(1)	(2)	(3)	(4)	(5)	(6)
$G12POST$	-0.012	-0.011	-0.014	-0.011	-0.019*	-0.016
	(0.008)	(0.007)	(0.011)	(0.010)	(0.011)	(0.010)
Constant	0.138***	0.028**	0.146***	0.029**	0.148***	0.029**
	(0.004)	(0.012)	(0.005)	(0.014)	(0.005)	(0.014)
Fixed effects:						
Grade	yes	yes	yes	yes	yes	yes
School-grade	no	no	no	no	no	no
Region	no	yes	no	yes	no	yes
Region-year	no	yes	no	yes	no	yes
Time	yes	yes	yes	yes	yes	yes
Observations	6,125	6,125	3,689	3,689	3,887	3,887
R-squared	0.004	0.115	0.004	0.117	0.006	0.129

Notes: * significant at 10%, ** significant at 5%, *** significant at 1%. Standard error in parentheses. The masked observations were converted to zero. The variable $G12POST = 1$ if $g = 12$ and $t \geq 1998$ and 0 otherwise.

Table 3: Pooled estimation, grades 9 and 12, school years from 1995 to 2001 (excl. 1998), *with time dummies*

Dep. var.:	M^r_{gs}: Local segregation index with respect to *region*					
	Full sample		Only school districts with 2+ school		Only school districts in MSA	
	(1)	(2)	(3)	(4)	(5)	(6)
$G12POST$	-0.007	-0.006	-0.004	-0.002	-0.009	-0.008
	(0.004)	(0.004)	(0.006)	(0.006)	(0.006)	(0.006)
Constant	0.133***	0.030***	0.142***	0.032**	0.141***	0.031**
	(0.003)	(0.012)	(0.005)	(0.015)	(0.004)	(0.014)
Fixed effects:						
Grade	yes	yes	yes	yes	yes	yes
School-grade	no	no	no	no	no	no
Region	no	yes	no	yes	no	yes
Region-year	no	yes	no	yes	no	yes
Time	yes	yes	yes	yes	yes	yes
Observations	18,359	18,359	10,847	10,847	11,661	11,661
R-squared	0.004	0.111	0.002	0.120	0.004	0.133

Notes: * significant at 10%, ** significant at 5%, *** significant at 1%. Standard error in parentheses. The masked observations were converted to zero. The variable $G12POST = 1$ if $g = 12$ and $t \geq 1998$ and 0 otherwise.

Table 4: Fixed effect estimation, Grades 09 and 12, school years from 1997 to 1999 (excl. 1998)

Dep. var.:	M^r_{gs}: Local segregation index with respect to *region*					
	Full sample		Only school districts with 2+ school		Only school districts in MSA	
	(1)	(2)	(3)	(4)	(5)	(6)
$G12POST$	-0.006*	-0.006*	-0.007	-0.007	-0.008**	-0.008*
	(0.003)	(0.003)	(0.005)	(0.005)	(0.004)	(0.004)
Constant	0.138***	0.138***	0.142***	0.142***	0.149***	0.149***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Fixed effects:						
Grade	no	no	no	no	no	no
School-grade	yes	yes	yes	yes	yes	yes
Region-year	no	yes	no	yes	no	yes
Year	yes	yes	yes	yes	yes	yes
Observations	6,125	6,125	3,689	3,689	3,887	3,887
School-grade	3,347	3,347	2,199	2,199	2,167	2,167
R-squared	0.004	0.012	0.006	0.013	0.006	0.014

Notes: * significant at 10%, ** significant at 5%, *** significant at 1%. Standard error in parentheses. The masked observations were converted to zero. The variable $G12POST$ = 1 if $g = 12$ and $t \geq 1998$ and 0 otherwise.

Table 5: Fixed effect estimation, Grades 09 and 12, school years from 1995 to 2001 (excl. 1998), *with time dummies*

Dep. var.:	M^{r}_{gs}: Local segregation index with respect to *region*					
	Full sample		Only school districts with 2+ school		Only school districts in MSA	
	(1)	(2)	(3)	(4)	(5)	(6)
$G12POST$	-0.007***	-0.007***	-0.004	-0.004	-0.006**	-0.006**
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Constant	0.138***	0.138***	0.144***	0.144***	0.148***	0.148***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
Fixed effects:						
Grade	no	no	no	no	no	no
School-grade	yes	yes	yes	yes	yes	yes
Region-year	no	yes	no	yes	no	yes
Year	yes	yes	yes	yes	yes	yes
Observations	18,359	18,359	10,847	10,847	11,661	11,661
School-grade	3,802	3,802	2,720	2,720	2,548	2,548
R-squared	0.003	0.011	0.002	0.016	0.002	0.013

Notes: * significant at 10%, ** significant at 5%, *** significant at 1%. Standard error in parentheses. The masked observations were converted to zero. The variable $G12POST = 1$ if $g = 12$ and $t \geq 1998$ and 0 otherwise.

Table 6: Fixed effect estimation, Grades 09 to 12, school years from 1997 to 1999 (excl. 1998)

Dep. var.:	M^r_{gs}: Local segregation index with respect to *region*					
	Full sample		Only school districts with 2+ school		Only school districts in MSA	
	(1)	(2)	(3)	(4)	(5)	(6)
$G12POST$	-0.006*	-0.006*	-0.007	-0.007	-0.008**	-0.008**
	(0.003)	(0.003)	(0.005)	(0.005)	(0.004)	(0.004)
$G11POST$	-0.005*	-0.005*	-0.007	-0.007	-0.007*	-0.006*
	(0.003)	(0.003)	(0.005)	(0.005)	(0.004)	(0.004)
$G10POST$	-0.004	-0.004	-0.012***	-0.012***	-0.005	-0.005
	(0.003)	(0.003)	(0.005)	(0.005)	(0.004)	(0.004)
Constant	0.139***	0.139***	0.145***	0.145***	0.149***	0.149***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Fixed effects:						
Grade	no	no	no	no	no	no
School-grade	yes	yes	yes	yes	yes	yes
Region-year	no	yes	no	yes	no	yes
Year	yes	yes	yes	yes	yes	yes
Observations	12,043	12,043	7,176	7,176	7,584	7,584
School-grade	6,551	6,551	4,262	4,262	4,209	4,209
R-squared	0.002	0.007	0.004	0.011	0.004	0.011

Notes: * significant at 10%, ** significant at 5%, *** significant at 1%. Standard error in parentheses. The masked observations were converted to zero. The variable $G12POST = 1$ if $g = 12$ and $t \geq 1998$ and 0 otherwise.

Table 7: Fixed effect estimation, Grades 09 to 12, school years from 1995 to 2001 (excl. 1998), *with time dummies*

Dep. var.:	M^r_{gs}: Local segregation index with respect to *region*					
	Full sample		Only school districts with 2+ school		Only school districts in MSA	
	(1)	(2)	(3)	(4)	(5)	(6)
$G12POST$	-0.007***	-0.007***	-0.004	-0.004	-0.006**	-0.006**
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
$G11POST$	-0.006***	-0.006***	-0.004	-0.004	-0.005**	-0.005**
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
$G10POST$	-0.005***	-0.005***	-0.006**	-0.006**	-0.004*	-0.004*
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Constant	0.139***	0.139***	0.146***	0.146***	0.150***	0.149***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Fixed effects:						
Grade	no	no	no	no	no	no
School-grade	yes	yes	yes	yes	yes	yes
Region-year	no	yes	no	yes	no	yes
Year	yes	yes	yes	yes	yes	yes
Observations	36,162	36,162	21,132	21,132	22,823	22,823
School-grade	7,413	7,413	5,255	5,255	4,933	4,933
R-squared	0.002	0.008	0.001	0.011	0.001	0.010

Notes: * significant at 10%, ** significant at 5%, *** significant at 1%. Standard error in parentheses. The masked observations were converted to zero. The variable $G12POST = 1$ if $g = 12$ and $t \geq 1998$ and 0 otherwise.

Table 8: Placebo analysis: Fixed effect estimation, Grades 09 and 12, school years from 1990 to 1996 (excl. 1993), *with time dummies*

Dep. var.:	M^{r}_{gs}: Local segregation index with respect to *region*					
	Full sample		Only school districts with 2+ school		Only school districts in MSA	
	(1)	(2)	(3)	(4)	(5)	(6)
$G12POST93$	0.002	0.002	0.003	0.003	0.003	0.003
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Constant	0.125***	0.126***	0.140***	0.140***	0.133***	0.133***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Fixed effects:						
Grade	no	no	no	no	no	no
School-grade	yes	yes	yes	yes	yes	yes
Region-year	no	yes	no	yes	no	yes
Year	yes	yes	yes	yes	yes	yes
Observations	16,435	16,435	8,069	8,069	10,025	10,025
School-grade	3,301	3,301	2,173	2,173	2,110	2,110
R-squared	0.001	0.012	0.002	0.022	0.001	0.018

Notes: * significant at 10%, ** significant at 5%, *** significant at 1%. Standard error in parentheses. The masked observations were converted to zero. The variable $G12POST93 = 1$ if $g = 12$ and $t \geq 1993$ and 0 otherwise.

Table 9: Fixed effect estimation, Grade 12-9, school years (excl. 1998)

Dep. var.:	Within-district segregation			
		$W^d_{t12} - W^d_{(t-3)9}$		
	(1)	(2)	(3)	(4)
	1997-1999		1995-2001	
POST	-0.0002	-0.0008*	-0.0004	-0.0004
	(0.0007)	(0.0005)	(0.0010)	(0.0010)
Constant	-0.0009*	-0.0003	0.1950	0.1940
	(0.0005)	(0.0003)	(0.5610)	(0.5610)
Fixed effects:				
Time linear trend	no	no	yes	yes
School district	yes	yes	yes	yes
Region-year	no	no	no	yes
Observations	1,172	3,521	3,521	3,521
R-squared	0.000	0.001	0.001	0.007
Number of school districts	591	600	600	600

Notes: * significant at 10%, ** significant at 5%, *** significant at 1%. Standard errors in parentheses. The masked observations were converted to zero. The variable $POST = 1$ if $t \geq 1998$ and 0 otherwise.

Table 10: Fixed effect estimation, Grade 12-9, school years from 1997 to 1999

Dep. var.:	Within-county segregation $W^c_{t12} - W^c_{(t-3)9}$		
	(1)	(2)	(3)
$POST$	-0.0011	-0.0013	-0.0012
	(0.0011)	(0.0011)	(0.0011)
$CHARTER_c$		0.00262	
		(0.0078)	
$POST * CHARTER_c$		-0.0008	
		(0.0070)	
$\%STUDCH_c$			0.2910
			(1.1690)
$POST * \%STUDCH_c$			-0.2470
			(1.1390)
Constant	-0.0003	-0.0004	-0.0003
	(0.0007)	(0.0008)	(0.0008)
County fixed effects	yes	yes	yes
Observations	504	504	504
R-squared	0.005	0.005	0.005
Number of counties	252	252	252

Notes: * significant at 10%, ** significant at 5%, *** significant at 1%. Standard errors in parentheses. The masked observations were converted to zero. The variable $POST = 1$ if $t \geq 1998$ and 0 otherwise. $CHARTER_c$ is a dummy variable equal to 1 if there is a charter school in the county and 0 otherwise. The variable $\%STUDCH_c$ is the percentage of students in a county attending a charter school.

Table 11: Fixed effect estimation, Grade 12-9, school years from 1995 to 2001 (excl 1998)

Dep. var.:	Within-county segregation $W^c_{t12} - W^c_{(t-3)9}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$POST$	-0.0005	-0.0022	-0.0007	-0.0024	-0.0010	-0.0023
	(0.0007)	(0.0017)	(0.0007)	(0.0018)	(0.0007)	(0.0017)
$CHARTER_c$			0.0014	0.0010		
			(0.0048)	(0.0048)		
$POST * CHARTER_c$			0.0005	0.0007		
			(0.0046)	(0.0046)		
$\%STUDCH_c$					0.4450	0.3880
					(0.8540)	(0.8570)
$POST * \%STUDCH_c$					-0.2930	-0.2380
					(0.8500)	(0.8530)
Constant	0.0003	-0.8540	0.00024	-0.8130	0.0002	-0.6480
	(0.0005)	(0.8040)	(0.0005)	(0.8070)	(0.0005)	(0.8040)
County fixed effects	yes	yes	yes	yes	yes	yes
Time linear trend	no	yes	no	yes	no	yes
Observations	1,512	1,512	1,512	1,512	1,512	1,512
R-squared	0.001	0.001	0.001	0.002	0.011	0.012
Number of counties	252	252	252	252	252	252

Notes: * significant at 10%, ** significant at 5%, *** significant at 1%. Standard errors in parentheses. The masked observations were converted to zero. The variable $POST = 1$ if $t \geq 1998$ and 0 otherwise. $CHARTER_c$ is a dummy variable equal to 1 if there is a charter school in the county and 0 otherwise. The variable $\%STUDCH_c$ is the percentage of students in a county attending a charter school.

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