Online Appendix for The Efficiency of Race-Neutral Alternatives to Race-Based Affirmative Action: Evidence from Chicago's Exam Schools

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A Appendix (Online)

A.1 Admissions with affirmative action

Suppose that a school system serves a heterogeneous set of students. Each student has a type vector $(\theta, \mathbf{x}, z)$, where θ describes the best curriculum for the student, $\mathbf{x}$ is a vector of student characteristics (such as race or socio-economic status), and $\mathbf{z}$ is "proxy" that may be used in assigning students to schools. Suppose that the expected educational outcome of a student of type $(\theta, \mathbf{x}, \mathbf{z})$ when assigned to school s is

$$V_s(\theta, \mathbf{x}, \mathbf{z}) = h(\theta, \mathbf{x}, \mathbf{z}) - k(\theta - c_s)^2 - d\|\overline{\mathbf{x}}_s - \mathbf{x}^*\|, \tag{1}$$

where c_s is the curriculum at school s, $\overline{\mathbf{x}}_s$ is the mean of the vector of characteristics of students in school s, and $\mathbf{x}^*$ is the composition of an optimally diverse school. The function h gives the component of a student's expected outcome which does not depend on school s. The parameter k indexes the importance of providing students with a curriculum that is matched to their type θ. The parameter d indexes the importance of losses from schools having demographics that differ from $\bar{x}_s$. This loss term might reflect the value of discussions in diverse classrooms. An optimal affirmative action plan balances curriculum matching against concerns for diversity.

Suppose that the school system operates schools indexed by $s = 1, 2, \ldots S$. Assume that the school system chooses both a student assignment function $A : \Theta \times X \times Z \to S$ and the curricula at each school $\mathbf{c} = (c_1, c_2, \ldots, c_s)$.[1] When affirmative action is unrestricted, we assume that the school system knows the distribution of student types and can choose any function $A(\theta, \mathbf{x}, \mathbf{z})$ and any curricula $\mathbf{c}$. Suppose the social welfare function aggregates student outcomes as follows:

$$W^{A,c} \equiv \sum_s \int_{\{\theta,\mathbf{x},\mathbf{z}|A(\theta,\mathbf{x},\mathbf{z})=s\}} \left(h(\theta, \mathbf{x}, \mathbf{z}) - k(\theta - c_s)^2 - d\|\overline{\mathbf{x}}_s - \mathbf{x}^*\|\right) d\mu(\theta, \mathbf{x}, \mathbf{z}), \tag{2}$$

where μ is the distribution over types. The unrestricted optimal assignment policy maximizes this objective function:

$$\{A^*(\theta, \mathbf{x}, \mathbf{z}), \mathbf{c}^*\} = \arg \max_{A(\theta,\mathbf{x},\mathbf{z}),\mathbf{c}} W^{A,c}.$$

Our utilitarian welfare function implicitly assumes that the motivation for maintaining diversity is that it affects educational outcomes of all students in the system. But our formulation could also

[1] Chan and Eyster (2003) and several subsequent papers consider a more general class of plans which may involve random assignment. The CPS plan was deterministic and we simplify the discussion that follows by only considering such plans.

capture situations where diversity benefits accrue to others, e.g. they could be realized when the current generation of students serves as role model for future students as in Chung (2000), or they could reflect the preferences of voters or politicians for diverse schools. Note also that the sum across schools of the first term of the integrals will be $\int h(\theta, \mathbf{x}, \mathbf{z}) d\mu(\theta, \mathbf{x}, \mathbf{z})$, which is independent of the plan $\{A, \mathbf{c}\}$ that is adopted. Accordingly, we will omit $h(\theta, \mathbf{x}, \mathbf{z})$ in the remainder of our discussion.

Some properties of an optimal assignment are immediate:

Proposition 1 *In any optimal assignment policy, $\{A^*(\theta, \mathbf{x}, \mathbf{z}), \mathbf{c}^*\}$, each school's curriculum c^*_s is set to the mean θ among students assigned to school s:*

$$c^*_s = E(\theta | A(\theta, \mathbf{x}, \mathbf{z}) = s), \textit{ for all } s.$$

Moreover, if $d = 0$, then each student is assigned to the school with a curriculum that is closest to the student's ideal point,

$$A^*(\theta, \mathbf{x}, \mathbf{z}) = \arg\min_{s \in S} |\theta - c^*_s|.$$

Optimal assignment rules are not as straightforward when $d > 0$. Rather than assigning all students to the closest with curriculum closest to its type, it will typically be desirable to use different cutoffs for students in different demographic groups, shifting some students to a school to which they are slightly less well matched to improve demographic balance. Our working paper, Ellison and Pathak (2016), works through a two-school version with two demographic groups as an illustration.

The social welfare function (2) can be written as a sum of school-specific welfare, $W^{A,c} = \sum_s n_s W^{A,c}_s$, where n_s is the fraction of students assigned to school s under plan $\{A, \mathbf{c}\}$ and

$$W^{A,c}_s \equiv \frac{1}{n_s} \int_{\{\theta, \mathbf{x}, \mathbf{z} | A(\theta, \mathbf{x}, \mathbf{z}) = s\}} \left(-k(\theta - c_s)^s - d\|\overline{\mathbf{x}}_s - \mathbf{x}^*\|\right) d\mu(\theta, \mathbf{x}, \mathbf{z}),$$

When the school system sets each school's curriculum optimally (which we will henceforth assume), school-specific welfare simplifies as

$$W^{A,c}_s = -k\mathrm{Var}(\theta | A(\theta, \mathbf{x}, \mathbf{z}) = s) - d\|\overline{\mathbf{x}}_s - \mathbf{x}^*\|.$$

The form of the school-specific welfare function suggests that an analysis of affirmative action plans should focus on within-school variance in the curricula to which students are best matched and demographic diversity. In our empirical work, we assume (and present some evidence in support of the assumption) that the composite scores which CPS uses to assign students to schools can be thought of as a good proxy for whether a student is well-matched to an advanced curriculum.

A useful observation about the model is that within-school variation in θ is directly related to the variation across schools in the school-mean θs.

Proposition 2 *Given any student assignment rule A,*

$$\sum_s -n_s \, Var(\theta|A(\theta,\mathbf{x},\mathbf{z})=s) = \sum_s n_s \left(E(\theta|A(\theta,\mathbf{x},\mathbf{z})=s) - E(\theta)\right)^2 - Var(\theta).$$

While the cost of student-curriculum mismatch is measured directly by the within-school variance in θ, this result shows that the school system's problem can be thought of as trying to maximize the difference across schools in school-mean θs. In a system consisting of two schools, this latter objective function is maximized by grouping all of the highest θ students together in one school and providing them with a suitably high curriculum. Our model therefore has a similar conclusion as Chan and Eyster (2003).

The optimal affirmative action plan described above will often be infeasible for two reasons: (1) schools may be legally prohibited from basing admissions decisions on some dimensions of $\mathbf{x}$ and (2) schools may not observe some dimensions of $\mathbf{x}$. An example of the former is a prohibition on using race. An example of the latter is that schools may not have data on many dimensions of disadvantage, such as family background or levels of neighborhood safety. When this occurs, school systems can only implement rules $A(\theta,\mathbf{z})$ that involve proxy-variables $\mathbf{z}$ imperfectly correlated with $\mathbf{x}$.

The previous literature has noted that some inefficiencies are inevitable when a school system is prevented from using welfare-relevant variables. Chan and Eyster (2003) consider models which can be thought of as modeling a school system that has access to no proxies for $\mathbf{x}$ beyond noisy signals of θ and note that the inefficiencies can be severe. Fryer, Loury, and Yuret (2008) explicitly include proxies and provide similar results. Ray and Sethi (2010) note that the monotonicity constraint that Chan and Eyster (2003) impose is generically binding. Dropping it will improve efficiency, but results in policies that are problematic in other ways: they seem unfair in that lower-scoring students are accepted over higher-scoring students and they can widen majority-minority score gaps.

In our model the magnitude of the welfare losses due to race-blind restrictions depend on the joint distribution of $(\theta,\mathbf{x},\mathbf{z})$. In some cases, race-neutral plans will work fairly well. In other cases, they welfare losses will be quite large even under an optimal race-neutral plan. Plans used in practice are not theoretically optimal, creating an additional source of inefficiency.

A.2 Example where race-neutral plans are counterproductive

We present here an example in which two seemingly natural race-neutral plans are counterproductive. Consider a model with two equally-sized subpopulations, $x \in \{\mathrm{o}, \mathrm{u}\}$, in which students from population u will be underrepresented at elite school under a purely θ-based admissions procedure because preparation depends both on income and x. Specificially, assume that

$$\theta_\ell = Income_\ell + 0.1\ I(x_\ell = o),$$

with income being uniformly distributed on $[0, 1]$ in population u and uniform on $[0.1, 1.1]$ in population o. As a result, θ is uniform on $[0, 1]$ in population u and uniform on $[0.2, 1.2]$ in population o.

If the school system uses a purely θ based admissions policy to assign 20% of the students to an elite school, then curriculum-matching will be optimal but there is a moderate diversity problem – one-quarter of the seats in the elite school go to the underrepresented population. The admissions cutoff is $\hat{\theta} = 0.9$. Thirty percent of population o and 10% of population u have θ's above this level.

If x can be used in assignments, the school system could increase the representation of students from group u in the elite school by giving b bonus points to members of population u. Small changes of this type will be welfare-improving – there is a first-order increase in diversity at the elite school and no first-order loss in curriculum matching from using a small bonus.[2]

If x cannot be used in the assignment process, the school system might instead use some type of income-based affirmative action plan. Several seemingly natural plans of this variety, however, will work very badly.

Example 1 *Suppose the school system implements race neutral affirmative action in either of the manners below:*

1. *Suppose school system divides the students into four equal-sized tiers on the basis of income and admits the 20% of students with the highest θ from each income tier to the elite school*
2. *Suppose the school system gives $\alpha(1-I)$ bonus points to a student of income I for some $\alpha \in [\frac{2}{3}, 1]$ and assigns the 20% of students for whom the sum of θ and the bonus is highest to the elite school.*

Then, the affirmative action plan reduces curriculum matching benefits relative to a purely θ-based policy and results in the elite school having ***no students at all*** *from population u.*

[2] The curriculum matching losses are zero to first order because the marginal added students from population u and the marginal displaced students from population o have the same θ.

The mechanics of the first example, are that the bottom tier consists of all students with incomes below 0.3: underrepresented students with incomes uniformly distributed on $[0, 0.3]$ and overrepresented students with incomes uniform on $[0.1, 0.3]$. The population u students in this tier have θ's uniform on $[0, 0.3]$. The population o students have θ's uniform on $[0.2, 0.4]$. The cutoff that selects 20% of this tier is $\hat{\theta}_1 = 0.3$. All low-income students above this cutoff are from the overrepresented group. Calculations for the other tiers are similar.

The mechanics of the second example are that the cutoff ends up being $0.8 + 0.3\alpha$. Students from population o with incomes above 0.7 all reach this cutoff. The highest-ranked student from population u (whose income is 1) fails to gain admission. Her bonus adjusted score is just 1.0 – this is her θ and she receives no income-related bonus.

While this result may seem paradoxical at first, it is just building on the insight of Chan and Eyster (2003) that adding noise to the admissions process can address underrepresentation. In this example, income is playing two roles. It is one source of disadvantage for the underrepresented population. But it can also be thought of as a source of noise that helps some underrepresented students overcome their other disadvantage. The income-based affirmative action procedures remove a source of disadvantage, but also removes a source of noise. The example is constructed so that the latter effect is more important than the former.

Many other seemingly reasonable affirmative action plans would also be counterproductive in this plan. There are other affirmative action plans that would help. For example, a highly asymmetric tier-based policy that put students with incomes in $[0, 0.1]$ in one tier and all students with incomes in $[0.1, 1.1]$ in the other would increase enrollment from population u.[3] In some cases the fully optimal plan can even be implemented, albeit via plans that seem unlikely to be politically feasible.[4] The example itself is obviously also set up to produce an extreme result. But our main motivation for presenting it is simply to highlight that inefficiencies can in theory be quite large and that suboptimal plan choice relative to constrained-optimal plan choice could be an important source of inefficiency even when plans seem reasonable.

[3] This plan, however, would be highly suboptimal in the curriculum-matching dimension because the added students from population u would have very low θs.

[4] Rather than giving bonus points to low-income students, an optimal plan would involve giving bonus points to high income students. This helps because under the purely θ based benchmark, the marginal student from population u has a higher income (0.9) than the marginal student from population o (0.8).

A.3 Predicting minority status

Each of CPS's six tract-level variables is correlated with an applicant's minority status. The first column of Table A.1 presents coefficient estimates from six OLS regressions run on the full dataset of students applying to CPS's exam schools in 2010-2012. The dependent variable in each regression is an indicator for being an underrepresented minority. Each regression has a single explanatory variable: one of the SES indicators in the current CPS formula. Each of these variables is scaled as a percentile (between 0 and 1) within Chicago's census tracts.[5] Higher percentiles correspond to what CPS regarded as being of higher SES, e.g. having higher median household income or a higher percentage of two-parent families. Five of the six variables are positively correlated with minority status because the coefficient estimates are negative and significant. The native English speaker variable is not.

The second column of Table A.1 restricts the regressions to a subsample more relevant to Payton and Northside admissions: the set of applicants with composite scores of at least 96. Here, all six variables are correlated with underrepresented minority status. Of course, whether variables are individually correlated with minority status is different from whether one would want to weight them positively in an index. The third column presents estimates from an OLS regression of the minority indicator on all six variables. The results suggest CPS's equally-weighted index may be quite different from the index that would be most aligned with minority status: there are substantial differences in the coefficients on most of the variables. Most strikingly, the coefficient on home ownership is both positive and statistically significant. This suggests that CPS's inclusion of this variable may disadvantage minority students. Chicago has some predominantly black middle class neighborhoods, such as Washington Heights, in which home ownership is high and some more affluent areas, including parts of Lakeview, the Loop, and the Near West Side, with mostly rental housing. Apparently, such examples are sufficiently common so that including home ownership on top of the other variables can disadvantage minorities.

It is unclear whether it would be legally or politically viable for CPS to adopt the predicted value from the regression in column 3 as its measure of tract SES: most obviously, the measure could be criticized for explicitly penalizing students for living in neighborhoods with lower median household

[5] For a few census tracts, CPS's version of Home Ownership Percentile does not exactly correspond to a conversion of their Home Ownership variable to percentiles. The estimates in Table A.1 are based on CPS's Percentile measure. We have re-estimated the regressions in Table A.1 by converting Home Ownership to a percentile and found very similar estimates.

incomes. Accordingly, we report in the fourth column a related regression in which we dropped the three variables that had "wrong sign" coefficient estimates in the third column. There is some loss in R^2 from making the formula immune to this criticism. The fifth column reports estimates from a regression that uses only CPS's equally weighted sum of the six tract characteristics. Note that the R^2 from this regression is yet lower, only 0.17 compared to 0.24 in the previous column. This suggests that modifying the SES index to place more weight on some demographic variables and less on others is worth exploring as a potential means to increase efficiency.

The current CPS admissions policy uses only tract-level variables. As a consequence, low-income students who qualify for FRPL receive no advantage relative to students from their census tract who do not. It seems natural that one might want to include this variable for the direct benefit of increasing the representation of low-income students. It also seems plausible that a FRPL variable might be highly correlated with minority status, so its inclusion might contribute to increased minority representation. To examine this hypothesis we added an indicator for FRPL eligibility to the regression in the sixth column of Table A.1. The estimated coefficient on the FRPL indicator is positive and significant, and increases the R^2 of the regression from 0.24 to 0.27.

	Dependent Variable: Applicant is Minority					
	Exam Applicants	Applicants with Composite Score ≥ 96				
	(1)	(2)	(3)	(4)	(5)	(6)
Median Income Perentile	-0.375	-0.657	0.124			
	(0.006)	(0.042)	(0.076)			
Adult Education Percentile	-0.380	-0.719	-0.486	-0.419		-0.240
	(0.006)	(0.040)	(0.078)	(0.043)		(0.047)
Two Parent Percentile	-0.520	-0.919	-0.728	-0.525		-0.523
	(0.006)	(0.043)	(0.081)	(0.069)		(0.068)
Native English Percentile	0.094	-0.147	-0.045			
	(0.006)	(0.056)	(0.077)			
Home Owner Percentile	-0.283	-0.339	0.351			
	(0.006)	(0.043)	(0.059)			
ISAT Percentile	-0.526	-0.760	-0.324	-0.213		-0.209
	(0.006)	(0.041)	(0.064)	(0.062)		(0.061)
Sum of Tract Characteristics					-1.101	
					(0.057)	
FRPL						0.212
						(0.024)
Observations	44962	1819	1819	1819	1819	1819
R-Squared			0.268	0.244	0.171	0.274
Misclassification			21.7%	23.1%	27.2%	22.3%

Notes: This table shows the results of regressions of minority status on the tract-level SES variables. Each of these variables is scaled as a percentile (between 0 and 1) within Chicago's census tracts. Coefficients in columns 1 and 2 are from individual models by SES variable. Column 6 adds an individual-level free or reduced-price lunch indicator.

Table A.1: Predictions of Minority Status

A.4 Additional Tables and Figures

A.4.1 Effects across all schools

In this section, we examine the effect of CPS's race-neutral affirmation action system on other exam schools. Roughly speaking, we expect CPS's policy and our benchmark policies to result in relatively small differences in the levels of diversity at other schools: both admit the same number of minority/low-income students to Payton and Northside, so the same number of minority/low-income students are available to be admitted to the other schools. Moreover, we expect that a policy that produces a higher within-school SD at Payton and Northside also produces higher within-school SD at other exam schools: the relatively low-scoring students who raise SD at Payton and Northside would have been closer to the mean at the next-tier schools, whereas high-scoring students denied entry at Payton and Northside may be higher scoring outliers at the school to which they are admitted.

To measure the effects on other exam schools, we calculate the within-school SD in composite scores at each of the other exam schools under the current tier-based policy, the purely composite score-based plan, and our race and FRPL-based benchmark. To construct the latter benchmark allocation at the other schools, we use the average of the bonus points for the minority and FRPL indicators from the Payton and Northside benchmark specifications. It is worth noting that our simulated admitted classes at less-selective exam schools may depart further from actual class composition because of lower take-up.

Figure A.1 presents histograms similar to those in Figure 4 illustrating the impact of the CPS plan on the other schools. Similar to the results for Payton and Northside, the benchmark affirmative action policy using race and FRPL results in relatively small increases in within-school heterogeneity. At all schools, the minimum scores of admitted students under the benchmark policy are at most two points lower compared to the purely score-based scheme. In contrast, the tier-based policy results in large distortions in within-school homogeneity. Most strikingly, at Young and Lane, the left tail of low-scoring students now extends 5.4 and 8.5 points further, respectively. At Lane, Jones, and Young, CPS' tier-based plan results in higher achievement gaps between majority and minority students compared to our benchmark policy, while the effect is opposite at the remaining schools.

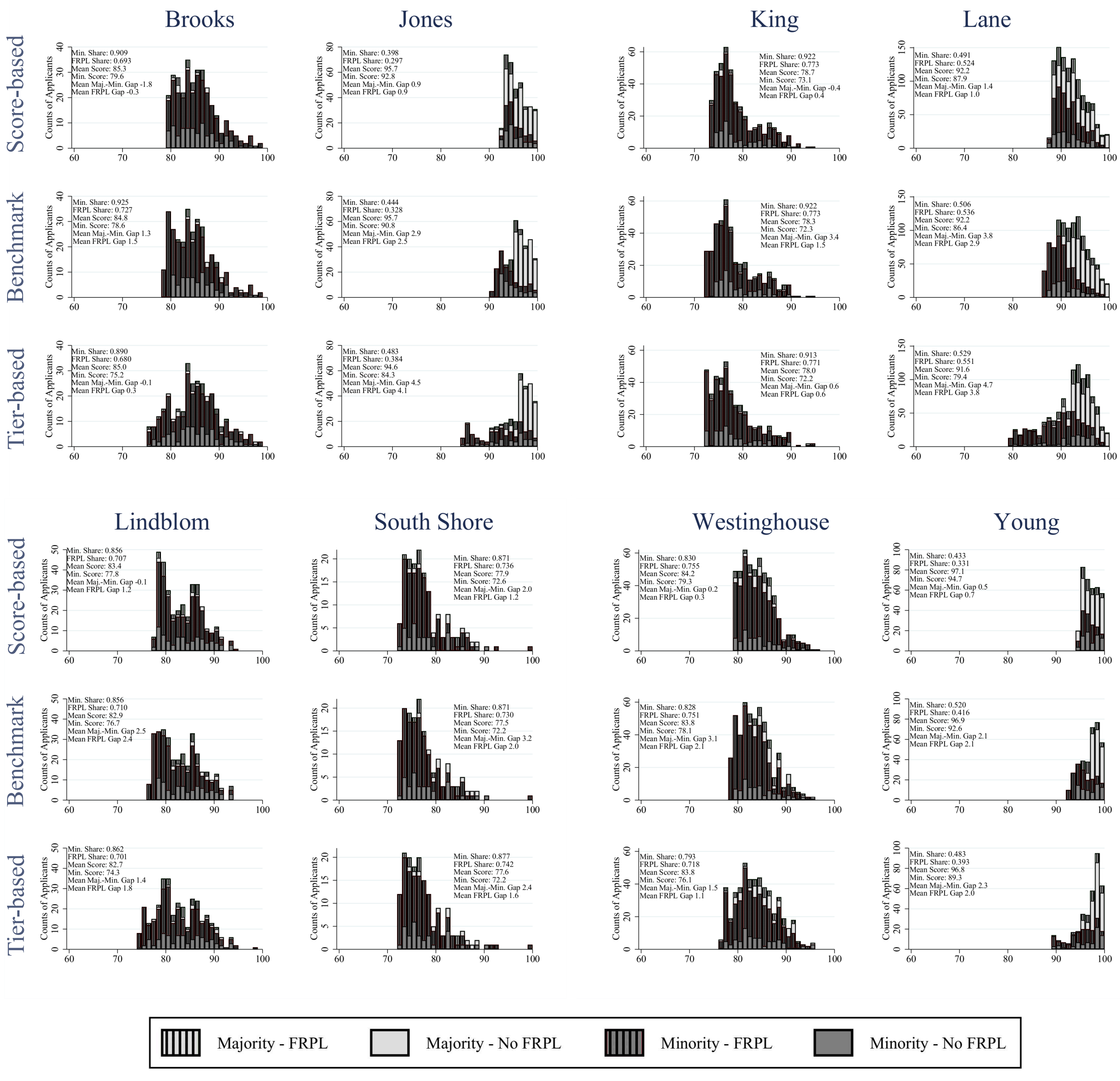
Table A.2 reports standard deviations, as well as minority and FRPL shares, quantifying the distributional effects of the three plans at all schools. In line with our intuition outlined above, CPS's tier-based plan produces a higher SD at every school relative to our benchmark. The effects are largest at Jones and Young, which are the next two schools in the selectivity hierarchy following Payton and

Northside. As expected, the allocation of minority and FRPL students changes only slightly, when comparing the benchmark and tier-based plans.

	Within School SD			Minority Share			FRPL Share		
	Score-based	Tier-based	Bench-mark	Score-based	Tier-based	Bench-mark	Score-based	Tier-based	Bench-mark
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Brooks	4.1	5.1	4.3	0.91	0.89	0.92	0.69	0.68	0.73
Jones	2.0	4.2	2.4	0.40	0.48	0.44	0.30	0.38	0.33
King	4.4	4.7	4.6	0.92	0.91	0.92	0.77	0.77	0.77
Lane	2.9	4.8	3.2	0.49	0.53	0.51	0.52	0.55	0.54
Lindblom	4.0	4.8	4.3	0.86	0.86	0.86	0.71	0.70	0.71
Northside	0.9	3.2	1.4	0.19	0.36	0.36	0.23	0.34	0.33
Payton	0.8	2.7	1.3	0.21	0.37	0.37	0.15	0.25	0.25
South Shore	4.6	4.7	4.4	0.87	0.88	0.87	0.74	0.74	0.73
Westinghouse	3.4	4.2	3.6	0.83	0.79	0.83	0.76	0.72	0.75
Young	1.5	2.7	2.0	0.43	0.48	0.52	0.33	0.39	0.42

Notes: This table shows standard deviations of composite scores, mean minority shares, and mean FRPL shares at other exam schools under three different admission schemes. Score-based refers to an admission scheme that purely admits based on composite scores. Tier-based refers to the current CPS tier policy. Benchmark refers to a plan that uses the average number of bonus points that are used under the benchmark plans that match the minority and FRPL shares under the current CPS tier plan for Payton and Northside.

Table A.2: Composite score spread and demographic representation at other exam schools

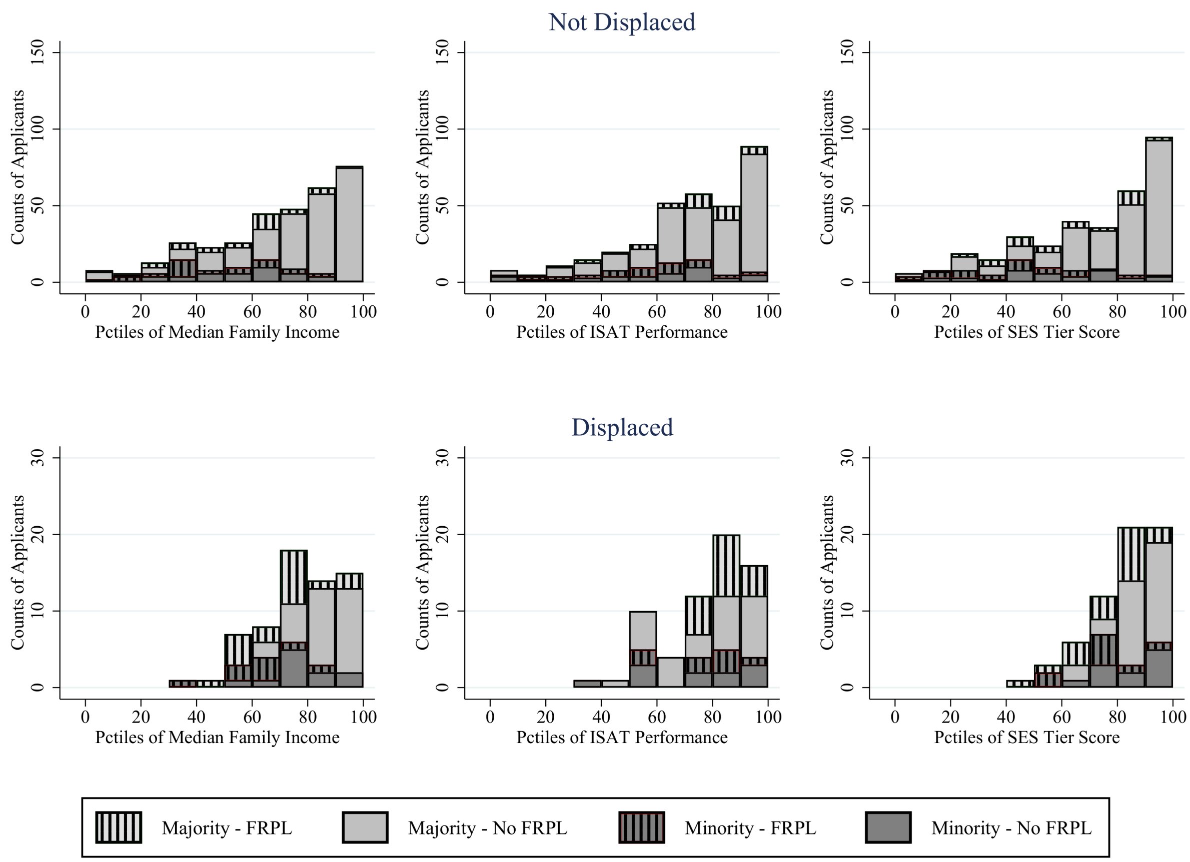


Notes: Each histogram bar is divided into four portions: the upper lighter two parts reflect the number of non-minority students and the lower darker two parts reflect the number of minority students, where the sub-portions with patterns represent FRPL students in the respective sub-portion. Score refers to the Composite Score.

Figure A.1: Within-school score distributions under alternate admissions policies at other exam schools

A.4.2 Neighborhood characteristics of displaced students

Figure A.2 reports information on the tract characteristics of students displaced under the CPS tier plan. Almost all of the displaced students come from tracts that are above the median in the CPS SES index and its income and education components. Specifically, the figure reports on the median family income, local school performance, and the percentile of the tract SES score distribution for students who are admitted to either Payton or Northside under the tier plan and the benchmark, labelled "Not Displaced", and students who are admitted under the benchmark but not the tier plan, labelled "Displaced." The histogram bars are shaded by the four strata of FRPL and minority status. Comparing the top and bottom histograms for each student characteristic, we see that Displaced students are more likely to come from census tracts with higher family income and ISAT performance. Almost none of the Displaced students are from the bottom half of the distribution of neighborhood characteristics. However, relatively more Displaced students are from the third and second decile than the top decile when compared to students who are unaffected. For example, close to 100 top decile students in the SES tier score distribution are unaffected, while 21 are displaced. In contrast, 60 students from the second decile in the SES tier score distribution are unaffected, while 21 are displaced.



Notes: Not displaced refers to applicants who are admitted to either Payton or Northside under both the current CPS tier plan and the race- and FRPL-based benchmark plan. Displaced refers to applicants who would have received an offer at either Payton or Northside under the race- and FRPL-based benchmark plan but did not get an offer for Payton and Northside under the current CPS tier plan. Each histogram bar is divided into four portions: the upper lighter two parts reflect the number of non-minority students and the lower darker two parts reflect the number of minority students, where the sub-portions with patterns represent FRPL students in the respective sub-portion.

Figure A.2: Histogram of SES percentiles of home census tracts of students displaced or not displaced by CPS tier-based plan relative to race- and free or reduced price lunch-based benchmark plan

A.4.3 Residential sorting from race-neutral affirmative action

The analysis in the paper considers admissions policies holding fixed the set of applicants and their residential location. Here we compare data on the tier of an applicant to the tier corresponding to their address in the enrollment file to examine whether residential choices respond to the tier designation. We find that applicants appear not to systematically switch tiers to increase their admissions chances.

Table A.3 tabulates the tier of exam school applicants against the tier in which they are enrolled in grade 7. An applicant who enrolled in a tier 4 school in grade 7 has an incentive to apply from a lower tier school if the tier 4 cutoff is higher than the cutoff for the lower tier. The table reports estimates for four applicant cohorts, starting with those in grade 7 in 2008 (and so they applied for an exam school in 2009) through those in grade 7 in 2011. Panel A covers all applicants, Panel B covers applicants in the highest composite score decile, Panel C covers applicants who have listed Payton and Northside, and Panel D covers applicants who would have received an offer at a higher ranked exam school if they applied from any lower. For each sample of applicants, most of the weight is on the diagonal entries of the table. This means that an applicant's tier in grade 7 is the same as the tier when they apply in grade 8. For all applicants (Panel A), movement is relatively small, since the sum of off-diagonal entries is 9% in 2008, and it is 6% for Payton and Northside applicants (Panel C). Importantly, there is no apparent trend by which applicants are enrolled in higher tiers and apply from lower tiers. For example, 19% of applicants apply from tier 1, and 2% of applicants are enrolled in a higher tier in grade 7 in Panel A in 2008. 28% of applicants apply from tier 3, and 2% of applicants are enrolled in a lower tier in grade 7, while 1% of applicants are enrolled in a higher tier. These patterns are similar each of the four samples in each Panel and also for each of the four years of our sample.

We also consider movement following assignment: do applicants apply from lower tiers and then move to higher tiers when enroll in grade 9? Table A.4 has the same format as Table A.3. It shows little evidence that applicants move to higher tiers following application. Therefore, it seems that there is relatively little residential movement due to the tier formula.

Tier in application data	Tier enrolled in Grade 7, by Application Cohort															
	2008				2009				2010				2011			
	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel A: All Applicants																
1	0.19	0.01	0.01	0.00	0.21	0.01	0.00	0.00	0.20	0.01	0.00	0.00	0.20	0.01	0.01	0.00
2	0.01	0.22	0.01	0.00	0.01	0.23	0.01	0.00	0.01	0.24	0.01	0.00	0.01	0.23	0.01	0.00
3	0.01	0.02	0.25	0.01	0.01	0.01	0.25	0.01	0.01	0.01	0.26	0.01	0.00	0.01	0.26	0.01
4	0.00	0.00	0.01	0.24	0.00	0.00	0.01	0.24	0.00	0.00	0.00	0.23	0.00	0.00	0.00	0.24
Panel B: Top Decile Applicants																
1	0.09	0.00	0.00	0.00	0.10	0.00	0.00	0.00	0.09	0.00	0.00	0.00	0.08	0.00	0.00	0.00
2	0.00	0.16	0.01	0.00	0.00	0.16	0.00	0.00	0.00	0.13	0.00	0.00	0.00	0.13	0.00	0.00
3	0.00	0.00	0.24	0.00	0.00	0.00	0.24	0.01	0.00	0.00	0.26	0.01	0.00	0.00	0.23	0.01
4	0.00	0.00	0.02	0.46	0.00	0.00	0.01	0.46	0.00	0.00	0.01	0.49	0.00	0.00	0.00	0.53
Panel C: Payton and Northside Applicants																
1	0.18	0.01	0.01	0.00	0.18	0.01	0.00	0.00	0.19	0.01	0.00	0.00	0.20	0.00	0.00	0.00
2	0.00	0.20	0.01	0.00	0.00	0.20	0.01	0.00	0.01	0.23	0.01	0.00	0.01	0.21	0.01	0.00
3	0.01	0.01	0.25	0.00	0.01	0.01	0.26	0.00	0.00	0.00	0.26	0.01	0.00	0.01	0.25	0.01
4	0.00	0.00	0.01	0.31	0.00	0.00	0.01	0.31	0.00	0.00	0.00	0.26	0.00	0.00	0.01	0.28
Panel D: Applicants with Incentive to Move to a Lower Tier																
1	0.17	0.00	0.00	0.00	0.13	0.00	0.00	0.00	0.13	0.00	0.00	0.00	0.14	0.01	0.00	0.00
2	0.01	0.20	0.01	0.00	0.00	0.18	0.01	0.00	0.00	0.19	0.01	0.00	0.00	0.16	0.00	0.00
3	0.00	0.02	0.27	0.01	0.01	0.01	0.26	0.01	0.00	0.01	0.28	0.01	0.00	0.01	0.26	0.01
4	0.00	0.00	0.01	0.28	0.00	0.00	0.01	0.37	0.00	0.00	0.00	0.35	0.00	0.00	0.00	0.38

Notes: This table tabulates tiers of applicants in the application data against tiers in the enrollment data for the sample of applicants that have same tier assigned in the enrollment data before (grade 7 and 8) and after (grade 9) applying for an exam school seat. Top Decile applicants refers to applicants that are in the highest composite score decile. Applicants with Incentive to move to a lower tier refers to applicant that would have gotten an offer at a higher ranked exam school if they would have applied from a lower tier.

Table A.3: Moving patterns of exam school applicants, I

Tier enrolled in Grade 9	Tier enrolled in Grade 7, by Application Cohort															
	2008				2009				2010				2011			
	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel A: All Applicants																
1	0.20	0.02	0.01	0.00	0.18	0.04	0.01	0.00	0.17	0.05	0.01	0.00	0.16	0.06	0.01	0.00
2	0.02	0.21	0.02	0.01	0.04	0.18	0.05	0.01	0.05	0.17	0.04	0.00	0.06	0.14	0.05	0.00
3	0.01	0.02	0.24	0.01	0.01	0.04	0.19	0.04	0.01	0.05	0.19	0.02	0.01	0.04	0.19	0.03
4	0.00	0.01	0.01	0.21	0.00	0.01	0.02	0.18	0.01	0.01	0.04	0.19	0.00	0.01	0.03	0.19
Panel B: Top Decile Applicants																
1	0.10	0.01	0.01	0.00	0.09	0.01	0.00	0.00	0.07	0.01	0.00	0.00	0.06	0.03	0.00	0.00
2	0.00	0.16	0.01	0.00	0.02	0.13	0.02	0.00	0.02	0.08	0.02	0.00	0.03	0.08	0.04	0.00
3	0.01	0.01	0.24	0.02	0.00	0.03	0.20	0.03	0.00	0.05	0.19	0.02	0.00	0.03	0.18	0.04
4	0.00	0.01	0.01	0.42	0.00	0.00	0.04	0.41	0.01	0.00	0.06	0.45	0.01	0.01	0.04	0.46
Panel C: Payton and Northside Applicants																
1	0.18	0.01	0.01	0.00	0.14	0.02	0.01	0.00	0.15	0.05	0.01	0.00	0.15	0.05	0.01	0.00
2	0.01	0.19	0.01	0.01	0.04	0.15	0.03	0.00	0.04	0.15	0.03	0.00	0.07	0.13	0.05	0.00
3	0.01	0.01	0.25	0.01	0.01	0.04	0.22	0.02	0.01	0.05	0.19	0.02	0.01	0.04	0.18	0.04
4	0.00	0.01	0.01	0.27	0.00	0.01	0.03	0.27	0.01	0.01	0.05	0.23	0.01	0.01	0.04	0.23
Panel D: Applicants with Incentive to Move to a Lower Tier																
1	0.18	0.01	0.01	0.00	0.11	0.01	0.01	0.00	0.11	0.03	0.01	0.00	0.10	0.03	0.01	0.00
2	0.01	0.19	0.02	0.00	0.03	0.13	0.03	0.01	0.03	0.12	0.03	0.00	0.05	0.11	0.04	0.00
3	0.01	0.01	0.27	0.01	0.00	0.04	0.21	0.04	0.01	0.05	0.21	0.02	0.01	0.04	0.21	0.04
4	0.00	0.01	0.01	0.26	0.00	0.00	0.03	0.33	0.01	0.01	0.05	0.31	0.01	0.01	0.03	0.32

Notes: This table tabulates applicants' tiers in the application data against tiers in grade 9, based on addresses in the enrollment data. Top Decile applicants refers to applicants that are in the highest composite score decile. Applicants with Incentive to move to a lower tier refers to applicant that would have gotten an offer at a higher ranked exam school if they would have applied from a lower tier.

Table A.4: Moving patterns of exam school applicants, II

A.4.4 LASSO regressions

To compute the LASSO results presented in this paper, we estimate a LASSO regression in R using *glmnet* on the subsample of applicants with composite scores of at least 96 with minority status as the dependent variable and both the CPS variables and our added 145 variables as potential explanatory variables. Tier variables are standardized before estimating the LASSO model. We use the most regularized model that is within 1 standard error of the minimal minimum mean cross-validated error, resulting in nine variables being picked by LASSO. We also repeated the procedure, including individual-level FRPL status as explanatory variable. The variables picked and their weight are presented in Table A.5.

We then implemented race-neutral affirmative action plans as in the main text. We treat the predicted probability of being a minority that comes out of the LASSO model as if it were an SES index and rank students on a weighted average of their composite scores and their predicted minority status. As above, we implemented two versions of each of the above plans. One uses a weight that makes the underrepresented minority share at Payton exactly match its value under the current CPS plan. The other exactly matches the current underrepresented minority share at Northside.

Variable	Weight Without FRPL (1)	 With FRPL (2)
Median value for owner occupied units	-0.720	-0.541
Fraction of foreign born from Asia	-0.422	-0.394
Fraction of foreign born from Europe	-0.397	-0.309
Free or reduced-priced lunch		0.172
Percentage of single parent households	-0.122	-0.148
Weighted Average ISAT performance at attendance area schools	-0.131	-0.142
Fraction of 45-54 year olds who did not work in the past 12 months		0.115
Fraction of children aged 3-4 in married couple households	-0.088	-0.080
Fraction of HH that are female headed, no husband, and SNAP	0.328	0.068
Household educational attainment score	0.008	

Notes: This table shows the variables picked by a LASSO regression in the subsample of applicants with composite scores of at least 96 with minority status as the dependent variable and both the CPS variables and 145 additional tier-level variables as potential explanatory variables. The first column does not include individual FRPL status and the second column does. Tier variables are standardized before estimating the LASSO model. We use the most regularized model that is within 1 standard error of the minimal minimum mean cross-validated error. SNAP refers to Supplemental Nutrition Assistance Program.

Table A.5: Demographic variables selected by LASSO

A.4.5 Additional plans

Table A.6 replicates the results from Table 3, adds estimates of efficiency defined by the mean, and considers three additional plans. To address potential concerns that the weights used in our reweighted SES bonus plan were derived from an attempt to influence racial outcomes of the school assignment plan rather than from their relative importance as components of diversity or disadvantage, we report the results for plans that use unweighted instead of weighted averages. At Payton, the unweighted SES bonus plan reaches essentially the same levels of efficiency as the reweighted version. Reweighting the three SES variables results in modest gains of 0.8 and 0.7 percentage points on overall and minority efficiency, respectively. Overall, these results suggest that the main efficiency gains relative to CPS's tier-based plan come from switching from a discrete index with four values to a continuous measure and excluding tier variables that are favor students from higher-income census tracts.

We also report results from two neighborhood-based plans more directly analogous to the Texas top 10% plan. In the first version, seats reserved for top 10% students are allocated by census tract. Each student is given a composite score tract rank defined to be their rank within the census tract of residence divided by the number of 8th grade students in that census tract. Seats are allocated to the students with the lowest composite score tract rank until the reserved seats are filled. Note that when the number of open seats is very small, students from relatively small tracts may not gain admission even if they have a perfect score.

In the second version, seats reserved for top 10% students are allocated by community area. The city of Chicago is sometimes divided into 77 community areas. We assign each student to one community area using the census tract of residence. We define each student's composite score community rank as the rank within the community divided by the number of 8th graders in the community area and again allocate seats reserved for top 10% students in order of this rank.

Both plans match the current level of minority representation at Payton and Northside under the tier-based plan. At both Payton and Northside, the community-based top-10% plans outperform the current CPS tier-based plan in our efficiency measure for minority representation. For the tract-level plan, the admission of several low-scoring applicants leads to a large increase in standard deviations at both Payton and Northside and thus a drop in efficiency. Under both plans, the share of students that qualify for FRPL is lower than under the current CPS scheme.

	Avg. Score	Within School SD	Maj.-Min. Gap	Share Minority	Share FRPL	Share Asian	% Efficiency (SD)			% Efficiency (Mean)		
							Overall	Minority Only	Income Only	Overall	Minority Only	Income Only
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A. Walter Payton College Prep												
Current CPS Plan	98.0	2.71	3.17	0.368	0.245	0.123	28.3	25.8	17.1	27.1	23.7	12.6
Reweighted SES Bonus	98.3	2.01	2.06	0.368	0.236	0.136	43.6	40.8	22.5	37.1	33.2	14.3
LASSO SES Bonus	98.3	1.87	1.97	0.368	0.236	0.109	49.0	45.9	25.3	39.0	34.9	15.0
SES Bonus with FRPL	98.4	1.80	1.93	0.368	0.286	0.127	69.8	49.0	59.6	54.1	38.0	39.8
LASSO with FRPL	98.5	1.68	1.95	0.368	0.264	0.105	73.2	56.1	57.1	61.9	47.3	39.7
Race and FRPL-based benchmark	98.8	1.34	1.77	0.368	0.245	0.100	100.0	91.1	60.4	100.0	87.7	46.6
Top-10% Communities	98.3	2.56	3.04	0.368	0.218	0.095	28.7	28.0	8.3	32.6	31.5	7.1
Top-10% Tracts	97.4	4.77	5.13	0.368	0.255	0.077	14.2	12.4	8.2	18.8	15.8	8.4
Unweighted SES Bonus	98.3	2.01	2.05	0.368	0.236	0.132	43.5	40.8	22.5	36.4	32.5	14.0
B. Northside College Prep												
Current CPS Plan	97.7	3.18	3.79	0.355	0.340	0.247	22.1	18.5	9.7	23.1	18.4	9.2
Reweighted SES Bonus	98.0	2.21	2.14	0.355	0.340	0.232	38.8	32.5	17.0	28.2	22.5	11.2
LASSO SES Bonus	98.0	2.15	2.07	0.355	0.359	0.251	45.3	34.0	21.6	31.1	22.5	13.9
SES Bonus with FRPL	98.0	2.07	1.85	0.355	0.452	0.255	76.2	36.5	62.8	59.4	22.5	46.1
LASSO with FRPL	98.0	2.08	1.88	0.355	0.429	0.243	64.9	36.1	48.4	49.7	23.9	35.9
Race and FRPL-based benchmark	98.7	1.42	1.84	0.355	0.340	0.236	100.0	83.7	43.7	100.0	79.9	39.8
Top-10% Communities	97.9	3.08	3.48	0.355	0.305	0.208	20.6	19.3	5.2	23.8	21.7	5.4
Top-10% Tracts	97.3	4.75	4.98	0.355	0.344	0.212	13.0	10.9	5.7	16.9	13.5	6.7
Unweighted SES Bonus	98.0	2.23	2.31	0.355	0.336	0.232	38.0	31.8	12.2	29.5	23.6	8.5

Notes: Unweighted SES bonus refers to a plan that uses an unweighted subset of the SES disadvantage indicators: CPS's Adult Education Index, Percentage of Single-Parent Families, and Local Elementary School ISAT Score variables. The top-10% communities plan uses weights on individual minority and FRPL status to maximize the average composite score, while matching both the minority and FRPL share achieved in the current CPS plan.

Table A.6: Results for additional admissions policies

B Supplementary Material

Data Appendix

This document describes data processing used to construct analysis files. Chicago Public Schools (CPS) is the source of the application, enrollment files, and PSAE and AP test score files (CPS 2014). This appendix describes these data sets and the procedures used to construct the sample of the main empirical analyses.

Application Data

The exam school application file contains a record for each student consisting of an application id number, CPS id number, name, gender, race, date of birth, the tier (from 2009 onwards), address, special education status, application year, preferences over nine exam schools, and the composite score for admission. Each record also includes the school where the student receives an offer (if any). The main analysis sample only includes applicants from 2013/2014. Students enroll in the fall of the following year. Cutoffs for this period were published on the CPS website; they are part of the data archive. We exclude duplicate observations, and applicants who were missing the application id number, the SES tier or the composite score, have gaps in the preference ranking or received multiple offers without clearing the relevant composite score cutoffs from the analysis.

Composite Score Tie Breaking

The composite score is based on the results from an entrance exam, standardized test scores, and 7th-grade grades, resulting in a coarse distribution of scores. CPS breaks ties among students with identical scores, using the results from the entrance exam, where the order of tie-breakers is: Core Total, Math, Reading Comprehension, Vocabulary, and Language Arts. Since the application data only provides the core total, we break remaining ties among applicants with equal composite scores and core total in the entrance exam using (i) 7th grade grades, (ii) overall standardized test results, (iii) math, and (iv) reading standardized test results, (v) and finally a unique random number that is assigned once before running the assignment mechanisms. For the analyses, we re-scale scores to a range of 0 to 100.

Enrollment Data

The CPS enrollment file spans school years 2007-2008 through 2014-2015. Each record contains a start of the school-year (October) snapshot for each student enrolled in Chicago Public Schools, with unique student identifier (the CPS ID), the student's grade and school, and demographic information. The variables of interest in the enrollment file are grade, year, date of birth, sex, race, special education (SPED), limited English proficiency (LEP) status, disability status, FRPL eligibility, and school. Students are coded as attending an exam school if their enrollment in October is at each school sector, respectively.

Outcome Data

Advanced Placement (AP) records are provided by CPS and available for 2010 through 2015. The ACT test scores come from the Prairie State Achievement Examination (PSAE) files from 2010 to 2015. PSAE is a two-day standardized test taken by all High School Juniors in the U.S. state of Illinois through 2015. On the first day, students take the ACT. On the second day, students take a WorkKeys examination and Illinois State Board of Education-developed science examination. Students were evaluated in four subjects: Math, Reading, Science, and Writing. ACT national percentiles were obtained from `https://www.act.org/`.

Tract-level Data

Data on tier assignment, the socio-economic score and the relevant tract-level variables are from Eder and Gregg (2014). The tract-level variables are included as part of the data archive. Further tract-level variables that were used in the more sophisticated plans were obtained from the census data sets. These were obtained from Census (2010). Student addresses were then geo-coded using ArcGIS and matched to the respective tract and tier.

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