Analyzing Integration in Charter Schools: A Comparative Analysis of California and Texas

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May 11, 2023

Abstract

Numerous studies have discovered relationships between charter schools and the extent of segregation within student bodies, but few have offered evidence to suggest a causal mechanism for these relationships. This paper attempts to 1) analyze the relationship between charter schools and integration, and 2) pinpoint a potential policies that may be the cause of this relationship. Using multi-level regression models and a novel multi-group measure of relative integration that does not consider pre-defined geographic boundaries such as school districts, I compare school integration in Texas and California along dimensions of race and socio-economic status. While I find evidence that charter schools are positively associated with socio-economic integration, I find no evidence of differences between California and Texas charter schools with respect to integration despite their different policies as to who receives priority in enrollment. I conclude that cross-district enrollment is likely not the core causal factor driving differences in integration, though more research into this topic is needed.

Introduction

In the early 1990s, charter school laws burst onto the scene with the promise of choice for parents and academic success for students. The expansion of school choice also brought a new means for the advancement of racial integration of American public education, with some school choice advocates deeming the expansion of school choice for minority communities the "unfinished task of the civil right movement" (Holt 1999). Unlike Traditional Public Schools, most charter schools are able to enroll students from a broad geographic area, unconstrained from school district lines often drawn in ways that entrench segregation (Holt 1999). This circumvention of district boundaries, in theory, leads us to expect more integration in charter schools than in traditional public schools (Potter 2019). Meanwhile, others have theorized that the self-selection process inherent to charter schools serves to exacerbate segregation as parents of similar ethnic groups send their children to the same schools (Cobb and Glass 1999).

Apart from the sociological benefits arising out of children gaining exposure to persons of different skin color and socio-economic status (Wells, Fox, and Cordova-Cobo 2016), the composition of a school's student body stands as the single most significant school factor in student achievement (Coleman and Others 1966).¹ Some research suggests that the socioeconomic composition of schools plays a significant role in student academic achievement

^{1.} To quote Coleman directly: "The social composition of the student body is more highly rated to achievement, independently of the student's own social background, than is any school factor."

and not racial composition (Rumberger and Palardy 2005), while others come to the opposite finding — racial composition of schools is associated with higher academic achievement and not SES (Caldas and Bankston 1998; Armor, Marks, and Malatinszky 2018). In either case, the consensus remains strong that the composition of schools affects student academic achievement.

In light of the social and academic impacts that racial and socio-economic integration hold on American students and the potential for cross-district admissions to aid in integration, this paper aims to continue research into the effects of charter schools on school integration. I pose the question:

To what extent do state charter school policies restricting across-district enrollment affect segregation of student populations?

I analyze charter schools in California, a state that discourages cross-district charter enrollment, and charter schools in Texas, a state that does not discourage cross-district charter enrollment. I find evidence that 1) Charter schools are not correlated with racial integration in California and Texas and 2) That charter schools are positively correlated with SES integration in California and Texas. I do not find any evidence that the relationship between Charter schools and integration differs between California and Texas.

Literature Review

Early research into school segregation within charter schools provided negative results. Casey Dobbs' 1999 study of schools in Arizona — the state with more charter schools than any other state — found that charter schools, on average, enrolled 20% more white students compared to their traditional public school counterparts (Cobb and Glass 1999). A nationwide study from 2000 found that, while charter schools on the whole contained higher proportions of minority students, minority ethnic groups were more likely to be clustered in individual charter schools relative to traditional public schools, providing evidence that charter schools worsened segregation (Frankenberg and Lee 2003). More recent research suggests that parents of white children residing in school districts with highly integrated schools are more likely than parents of minority children to apply for a place in a charter school, thereby avoiding the possibility that their children attend an integrated school (Denice 2022).

Other research has offered more mixed results on the matter. A 2016 study found that charter schools in Little Rock Arkansas not only demonstrated slightly higher levels of integration, but also that the presence of charter schools aided integration in nearby traditional public schools (Ritter et al. 2016). The Urban Institute has offered the most comprehensive nationwide analysis of the issue in 2020, when it utilized a interrupted time series analysis design by measuring the change in school compositions following a charter school's opening. It found that, compared to traditional public schools, charter schools had significantly higher rates of segregation within school districts, though they significantly improved integration across district boundaries (Monarrez, Kisida, and Chingos 2020). This finding supports the theory that charter schools promote segregation by ignoring school district boundaries. The study by The Urban Institute possesses strengths in its longitudinal data and its interrupted time series analysis, though there also exists weaknesses that this paper seeks to address.

I identify three weaknesses in the research conducted by The Urban Institute, some of which are shared by other, similar studies. (1) The nationwide scope of the analysis does not account for the fact that charter laws differ greatly between states. Some states, such as South Carolina, mandate that charter schools' student populations reflect the racial composition of the surrounding area. The Urban Institute study does reference this problem in a footnote, but does not, as far as I can tell, take any steps to counteract this fact in developing its conclusions. An analysis tailored to a specific state's charter policies would be more effective in making predictions about charter schools in that state or other states with similar policies. (2) The measure of segregation used in the study only compares two groups: white students and underrepresented minority students. This measure does not take into account the distinctions between Black, Hispanic, and Asian students, for instance. Some studies (Fiel 2013) utilize an entropy measure that does account for multigroup segregation, but such a measure requires that segregation be measured within school districts, which relates to problem three. (3) Every study I have found treats school districts as the geographic region in which to measure segregation.² Treating school districts as geographic units for studying demographics sidesteps completely the primary hypothesized vehicle by which charter schools promote integration: their ability to enroll students from across district lines. There also exists evidence that school districts can reflect and/or create demographic divisions in communities. (Holt 1999; Monarrez and Chien, n.d.).

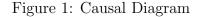
To address these weaknesses, my study (1) focuses exclusively on Texas and California, and documents the differences in their charter admissions policies, (2) uses a generalized dissimilarity index to measure segregation between more than two groups, and (3) measures segregation with respect to the communities surrounding schools, not with respect to the

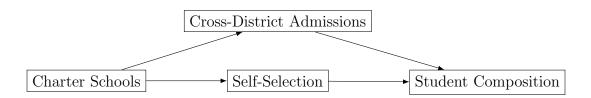
^{2.} The Urban Institute study attempts to account for this problem by analyzing across-district effects on segregation.

(often arbitrary) borders of a school district.

Theoretical Framework

Charter schools are hypothesized to affect student racial and socio-economic composition in two ways.





The first causal mechanism arises from the fact that families must apply to attend charter schools. ³ If we assume that the racial and/or socio-economic composition of families applying to charter schools does not match the racial and/or socio-economic composition of the set of families eligible to apply to charter schools, then the self-selection of charter school families will result in charter schools possessing different student compositions relative to traditional public schools, in which no such self-selection occurs. This causal mechanism gives reason to believe that charter schools may hold an independent effect on integration of the student body across the country, as the self-selection property is definitional to charter schools.⁴

The second causal mechanism by which the composition of charter student bodies may differ from those of traditional public school (TPS) student bodies, and the one that this paper focuses on, is the ability of charter schools to admit students from across school districts and TPS enrollment zones. Consider the example in Figure 2, which displays school districts (red) in the San Antonio area. A darker shade of blue coloring the census tracts represents a higher proportion of the underlying population that holds an income above 200% of the poverty line. As is evident in the figure, certain districts — Alamo Heights ISD, For Sam

^{3.} If a charter school received more applications that it has places, almost all states specify that a random draw determines the ultimate enrollees, with some negligible exceptions such as children of charter school staff receiving priority.

^{4.} see Monarrez, Kisida, and Chingos 2020; "On the one hand, choice entails decoupling school assignments from residential neighborhoods, many of which are already segregated, which by itself may generate changes in enrollment that impact stratification. On the other, greater choice may lead to segregation if parents have strong peer preferences..."

Houston ISD, and Lackland ISD — are drawn such that they encompass relatively wealthy areas. Given that traditional public schools within those districts can only draw their student populations from the relatively wealthy families within the district, those schools are very unlikely to represent the SES composition of the broader community.

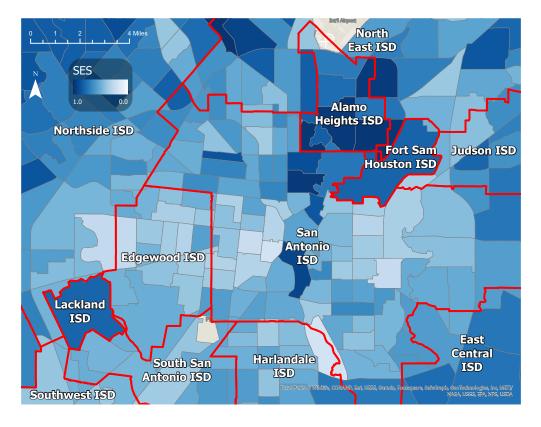


Figure 2: School District SES Grouping Example

The district-blind enrollment policies of charter schools are not universal, however.⁵ Some states, such as California, give enrollment priority to students within the school districts charter schools reside in.⁶ Though California schools are still capable of admitting students across multiple school districts, this scenario will occur with less frequency than in states such as Texas, in which no-such district priority is given to students.

In addition to state policies influencing the effectiveness of charter school integration, I also hypothesize that academic performance may wield influence. I assume that if a charter

^{5.} Technically speaking, even states that allow for extensive cross-district enrollment for charter schools still have enrollment zones based on school districts, so they are not strictly "district-blind." These district zones, in the case of Texas at least, are expansive, often incorporating many school districts.

^{6.} Cal. Educ. Code § 47605.3: "Preference shall be extended to pupils currently attending the charter school and pupils who reside in the school district."

school is more desirable to families by virtue of its above-average academic performance, then more families from more distant areas will apply to the school, thus improving its representation of the surrounding community. Put explicitly, my hypotheses are as follows:

- 1. Charter Schools in Texas will display a positive independent effect on school integration relative to traditional public schools, while charter schools in California will not.
- 2. Among charter schools, academic performance will be positively correlated with integration.

Methods

Given that Texas and California share many descriptive similarities — namely, being populous states that also include rural areas as well as being home to a significant population of minority racial groups — they stand as ideal candidates for a comparative analysis of Charter school effectiveness. With a unit of analysis of schools, I calculate integration indices for every school in Texas and California during the 2018-19 school year and build multi-level regression models to estimate the effect of charter schools on the integration indices.

Measuring Integration

There exist two general classes of segregation measures: absolute measures and relative measures (Clotfelter et al. 2018). Absolute measures, such as an isolation index or entropy index, measure the distribution of groups within a population irrespective of the contextual demographics, while relative measures measure the extent to which a population represents a larger population. For instance, an absolute measure of segregation would find a school that is 95% white and 5% black to be rather segregated, whereas a relative measure might find this same school perfectly integrated if the surrounding population of the school is also 95% white and 5% black. While absolute measures have their useful applications, this study uses a relative measure. In other words, I am interested in the extent to which the population of a school represents the community surrounding a school.

Since the concept of "community surrounding a school" is vague, I calculate three different representation indices that define the community surrounding a school as being different arbitrary sizes. I consider the community defined as the region within a 2mi, 5mi, and 10mi radius of school. I calculate these regions around each school in GIS software and then summarize the census demographic data that it overlaps. If the circle surrounding a school

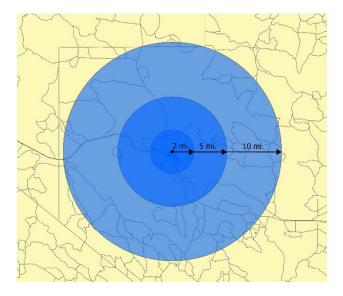


Figure 3: Defining a School's Community

only partially overlaps a census region, then that data within that region is summarized in proportion to the area of the region that the circle covers.⁷

While relative measures of integration such as Theil's Information Theory Index (H) and Variance Ratio (η^2) offer unique advantages over a dissimilarity index (D), such as decomposability, these measures assume that schools are grouped within regions (usually school districts) such that integration for each school is measured relative to the region that the school resides in (Reardon and Firebaugh 2002; Mora and Ruiz-Castillo 2011; Monarrez, Kisida, and Chingos 2020). This fact poses a problem for my analysis, as I draw a region around every individual school such that the integration measure for each school cannot be decomposed to reveal within and between district integration. As such, I utilize a dissimilarity index, which measures the ratio of a population that must change groups in order for the group composition of the population to match the group composition of a broader population (Sakoda 1981; Reardon and Firebaugh 2002). For example, consider a school with 50% white students and 50% black students residing in a community with 75% white students and 25% black students. In this case, the index of dissimilarity of the school would be .25, since 25% of the school's population would have to change racial groups in order for the school's population to match that of the community.⁸ This paper utilizes a gener-

^{7.} Demographic information was gathered at the smallest granularity publicly available. Racial demographic information was gathered at the granularity of census blocks, and income economic data was gathered at the granularity of census tracts.

^{8.} Note that in this example, the *absolute* measure of integration according to a normalized entropy index would be 1, since the school is evenly divided between students.

alized dissimilarity index, which allows for the measurement of dissimilarity between more than two groups while maintaining the same descriptive definition of dissimilarity indices (Sakoda 1981; Reardon and Firebaugh 2002). For the sake of simplifying the interpretation of results, I reverse the dissimilarity index to produce a similarity index, which is a measure of integration rather than segregation. The equation for a generalized similarity index is as follows:

$$S = 1 - \frac{1}{2} \sum_{i} |p_i - P_i|$$
(1)

where p_i is the proportion of group *i* in the school, and P_i is the proportion of group *i* in the area surrounding the school. The equation assumes that $\sum_i p_i = 1$ and $\sum_i P_i = 1$.

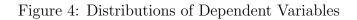
I used the following five racial groups in my analysis: White alone, Black alone, Hispanic alone, Asian alone, and all other races. These five groups are measured in California school data, Texas school data, and census data, making them suitable for analysis. As for socioeconomic status, populations are divided into two groups, roughly corresponding to those with a family income greater than 185% of the poverty line and those with a family income less than 185% of the poverty line.⁹ While more income groups are available in census data, schools only report students eligible for free or reduced lunches and those not eligible (the eligibility threshold is family income 185% of the poverty line), forcing me into using only two income groups (TEA 2022)

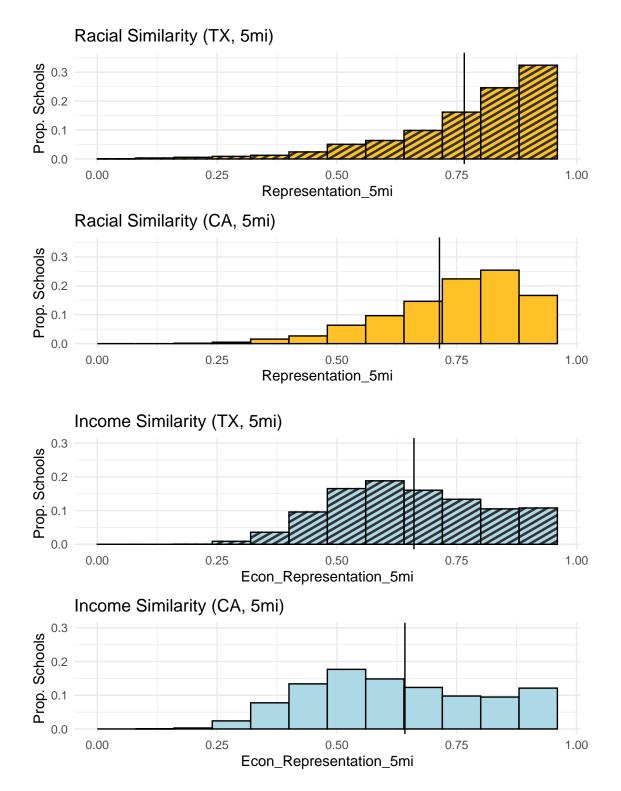
Schools Included in Analysis

Only K-12 traditional in-person public schools in the academic year 2018-2019 are considered in this analysis. This filtering excludes magnet schools, special education schools, adult schools, and virtual schools. This set of schools, along with private school, were considered when calculating the total number of schools within a district. An additional restriction of schools with total enrollments greater than or equal to 50 was added to filter schools serving as units of analysis. This additional filter was included because very small schools create problems in the similarity index calculation, as they lack the number of students needed to adequately represent a broader community even in an ideal situation — a school of ten students cannot possibly represent its broader community in any detail.

Among schools in California and Texas matching the above criteria, 11.7% had to be

^{9.} Census data does not record family income groups based on a 185% poverty line threshold, thus I use the next closest threshold of 200% the poverty line in the similarity index measurement.





discarded due to insufficient data.

Table 1: 2018-2019TX/CA School Summary Statistics (Used in Analysis)

	Ν	Total_Enrollment
TPS	13,611	9,593,676
Charter	1,566	810, 370

Regression Models

For both California and Texas I create three models for racial and socio-economic integration, one at each level of school community size — the areas two miles, five miles, and ten miles around each school.

A full list of variables, their sources, their descriptions, and their distributions can be found the in the appendix. For the sake of understanding regression coefficients, I will describe in this section the variables that I transformed either to aid in the regression or to aid in interpret-ability.

Total school enrollment is measured in 100s of students. Population density is measured in 1000s of persons per square mile and describes the average population density of the area within 5mi of a school. Academic Performance is a normalized measure of state test scores, such that a value of 0 indicates an average test score in the state, and a value of 1 indicates a test score one standard deviation higher than average.

In addition to school-level variables, I also consider two district-level variables that might affect school integration: the number of traditional public schools in a district, and the number of alternative schools (charter and private schools) in a district. Even though this analysis ignores school districts as a matter of determining relative measures of school integration, these district level measures remain important because the number of schools within a district can greatly affect the fragmentation of a district's population among traditional public schools within the district, which in turn affects the demographic compositions of schools relative to their communities. Given the nested nature of the school level data within the district level data, I can take advantage of hierarchical linear modeling techniques. Specifically, I my HLM models Specify random intercepts within school districts as well as random slopes for the variables "Charter" and "Academic_Performance". The models not utilizing HLM are presented in the appendices. I use beta regression models in this analysis because the response variable — representation index — is a proportion within the range [0,1] and follows a beta distribution.¹⁰ I interact the charter dummy variable with academic performance to test hypothesis 2. I also interact the charter variable with population density to account for the possibility that charter schools only affect the integration of urban or rural charter schools.

Outlier observations were removed from the models according to the guidelines of running beta regressions (Geissinger et al. 2022). This process was not straightforward, and is detailed in the appendices. Regression models without outliers removed can also be found in the appendices.

Results

Tables 2 and 3 display the model results for racial and income similarity, respectively. After correcting for both school-level and district-level variables, the models predict that the status of a school being a charter school rather than a TPS yields no independent effect on racial integration in both Texas and California.¹¹ The interaction of the charter variable and the population density variable is significant across all of the California integration measures and one of the Texas measures, though this effect is not especially large: for every increase of 1000 persons per square mile in the area around a school, the model predicts that integration decreases by at most 6.3% on average. Given that the mean population density around charter schools in Texas and California is 3.7 thousand per square mile, the interaction does indicate a significant and somewhat substantial effect that population density yields on racial integration, at least in California. Additionally, the model predicts that California charter schools become significantly more integrated when the academic performance of the school is higher than the California average, though not when integration is measured relative to the area only 2mi surrounding the school. This provides some evidence against my hypothesis that Texas charter schools with higher academic performance would display higher levels of integration.

Given that other research into the effects of charter schools on racial integration have produced conflicting results, it is not particularly surprising to find in my models no or very small significant associations between charter schools and racial integration.

^{10.} Since packages for beta regression in R do not allow 0 or 1 inflation on multilevel beta regression models, I adjusted all values of 1 to be 0.999 and all values of 0 to be 0.001.

^{11.} A non-HLM model finds significant negative "Charter" coefficients for California and no significant coefficients for Texas. See Appendix, Table 7.

The models measuring socio-economic integration reveal significant correlations between the Charter parameter and integration levels, though these correlations are shared between both Texas and California, indicating that the two states' different charter policies do not yield different results with regard to SES integration. The models predict that charter schools, on average, independently correlate with substantially higher socio-economic integration measures relative to all three community areas — two miles, five miles, and ten miles. The fact that the effect sizes increase as the community region becomes smaller could indicate that charter schools do an especially better job than traditional public schools at integrating their immediate communities.

The interaction between the "Charter" and "Academic Performance" variables is also significant and substantially negative across all three community sizes and across both states. These negative coefficients indicate that charter schools performing above average academically on average have less integration than similarly performing traditional public schools. This finding serves as evidence for the opposite of what I predicted in hypothesis 2: that academic performance of charter schools would improve their integration levels. Interestingly, academic performance held a significant and substantial independent positive effect on SES integration across all the models.

The interaction between the "Pop_Dens" and "Charter" parameters is negative as well, and, as Figure 5 shows, this negative interaction coefficient is large enough for California that it erases the positive relationship between "Charter" and SES integration when the school resides in a high population density area.

Overall, the models provide no evidence for charter schools correlating with higher racial integration, though they do provide evidence that charter schools are positively correlated with SES integration, contingent on the population density surrounding the school and its academic performance. Because the models indicate essentially the same charter school effects for both California and Texas, the findings provide no insight into the causal mechanism driving charter schools' positive correlation with SES integration. This does suggest, however, that the differences in charter school policies between California and Texas are not particularly significant to school integration.

		Texas			California	
	10mi	5mi	2mi	10mi	5mi	2mi
Charter Effects						
Charter	-0.147	-0.142	-0.055	-0.053	-0.064	-0.007
Charter:Academic_Performance	(0.082) -0.019	$(0.083) \\ -0.050$	$(0.079) \\ -0.032$	(0.041) 0.060 **	(0.041) 0.045^*	$(0.044) \\ 0.018$
Charter:Pop_Dens	(0.031) 0.012	(0.032) 0.006	(0.029) - 0.063 *	(0.018) - 0.020 **	(0.020) - 0.023 **	(0.023) -0.034***
Level 1 Controls	(0.026)	(0.027)	(0.025)	(0.008)	(0.008)	(0.010)
Academic_Performance	-0.000 (0.018)	0.025 (0.018)	0.066 *** (0.016)	-0.008 (0.015)	-0.003 (0.016)	0.022 (0.019)
Dual_Language	-0.011 (0.048)	-0.006 (0.052)	-0.039 (0.046)	-0.045 (0.059)	-0.083 (0.066)	-0.088 (0.075)
Total_Enrollment	0.003	0.003	0.004	0.005***	0.007***	0.007***
Pop_Dens	(0.002) 0.030 ***	$(0.002) \\ 0.004$	(0.002) - 0.082 ***	(0.002) 0.017^{***}	(0.002) 0.025 ***	(0.002) 0.018 **
Econ_Dis	$(0.009) - 0.012^{***}$	$(0.009) - 0.011^{***}$	$(0.008) \\ -0.007^{***}$	$(0.005) - 1.164^{***}$	$(0.005) - 1.179^{***}$	$(0.006) - 0.851^{***}$
ELL	(0.001) - 0.760 ***	$(0.001) -0.640^{***}$	$(0.001) - 0.378^{***}$	$(0.048) -1.257^{***}$	$(0.054) -1.136^{***}$	(0.060) -0.716***
KIPP	$(0.064) \\ 0.068$	(0.069) 0.213	(0.062) 0.447 ***	(0.054) 0.062	(0.061) 0.164	(0.070) 0.290 **
School_TypeElementaryHighMiddle	$(0.126) \\ -0.009$	$(0.136) \\ -0.063$	(0.127) - 0.231 ***	(0.085) 0.006	(0.095) 0.057	(0.112) 0.087
School_TypeLiementaryHighMiddle	(0.063)	(0.064)	(0.057)	(0.000)	(0.057)	(0.087)
${\it School_TypeElementaryMiddle}$	0.018 (0.048)	-0.004 (0.051)	-0.109^{*} (0.046)	-0.022 (0.017)	-0.001 (0.019)	-0.001 (0.022)
School_TypeHigh	-0.075^{*} (0.030)	(0.032) (0.032)	-0.074^{*} (0.029)	-0.174^{***} (0.030)	-0.175^{***} (0.034)	(0.032) -0.162^{***} (0.039)
School_TypeHighMiddle	-0.062	-0.038	-0.035	-0.178^{***}	-0.213^{***}	-0.186^{***}
School_TypeMiddle	$(0.056) \\ -0.007$	$(0.059) \\ 0.003$	$(0.053) \\ -0.033$	(0.039) - 0.096 ***	(0.043) - 0.098 ***	$(0.050) - 0.112^{***}$
Level 2 Controls	(0.020)	(0.021)	(0.019)	(0.022)	(0.024)	(0.028)
Num_TPS_in_District	-0.004^{*}	-0.006**	-0.004^{*}	-0.009**	-0.007^{*}	-0.006*
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)
Num_Alt_Schools_in_District	$0.006 \\ (0.010)$	$\begin{array}{c} 0.013 \\ (0.009) \end{array}$	$0.005 \\ (0.008)$	$0.005 \\ (0.003)$	$\begin{array}{c} 0.003 \\ (0.002) \end{array}$	0.003 (0.002)
(Intercept)	2.303***	2.401^{***}	2.532^{***}	2.230***	2.289***	2.086***
· · ·	(0.051)	(0.052)	(0.046)	(0.041)	(0.041)	(0.040)
AIC	-11995.281	-12343.932	-16905.206	-15945.398	-15543.827	-14662.503
Log Likelihood	6022.641	6196.966	8477.603	7997.699	7796.914	7356.251
Num. obs.	7147	7147	7144	7675	7675	7675
Num. groups: District	958	958	957	658	658	658
Var: District (Intercept)	0.311	0.272	0.213	0.406	0.359	0.270
Var: District Charter	0.133	0.086	0.133	0.147	0.119	0.115
Var: District Academic_Performance	0.042	0.026	0.021	0.010	0.013	0.019

Table 2: Racial Integration Models

 $^{***}p < 0.001; \ ^{**}p < 0.01; \ ^{*}p < 0.05$

		Texas		California			
	10mi	5mi	2mi	10mi	5mi	2mi	
Charter Effects							
Charter	0.191 ** (0.070)	0.290 *** (0.071)	0.418^{***} (0.075)	0.191 *** (0.044)	0.245^{***} (0.044)	0.294^{***} (0.047)	
Charter:Academic_Performance	(0.070) -0.264^{***} (0.025)	(0.071) -0.250^{***} (0.025)	(0.073) -0.222^{***} (0.027)	(0.044) -0.127^{***} (0.022)	(0.044) -0.129^{***} (0.022)	(0.047) -0.129^{***} (0.023)	
Charter:Pop_Dens	(0.025) -0.035 (0.020)	(0.023) -0.051^{*} (0.020)	(0.027) -0.081^{***} (0.023)	(0.022) -0.027^{**} (0.009)	(0.022) -0.024^{**} (0.009)	(0.023) -0.012 (0.009)	
Level 1 Controls	(0.020)	(0.020)	(0.025)	(0.003)	(0.003)	(0.003)	
Academic_Performance	0.307 *** (0.018)	0.314^{***} (0.017)	0.289 *** (0.017)	0.501^{***} (0.018)	0.503 *** (0.018)	0.499 *** (0.018)	
Dual_Language	0.074 * (0.038)	(0.017) 0.056 (0.039)	(0.017) -0.005 (0.041)	0.157 * (0.068)	0.245 *** (0.068)	0.221^{**} (0.070)	
Total_Enrollment	0.012 *** (0.002)	0.010 *** (0.002)	0.006 *** (0.002)	0.004 * (0.002)	0.005 * (0.002)	0.006 ** (0.002)	
Pop_Dens	(0.002) -0.002 (0.007)	(0.002) -0.007 (0.007)	(0.002) -0.005 (0.007)	0.027 *** (0.005)	0.058 *** (0.006)	0.063 *** (0.006)	
White_pct	0.021 *** (0.001)	0.017 *** (0.001)	0.014 *** (0.001)	0.025 *** (0.001)	0.024 *** (0.001)	0.021 *** (0.001)	
ELL	(0.001) -0.950^{***} (0.048)	(0.001) -0.798^{***} (0.048)	(0.001) -0.412^{***} (0.051)	(0.001) -1.620^{***} (0.065)	(0.001) -1.440^{***} (0.066)	-0.836^{***} (0.067)	
KIPP	(0.040) -0.242^{*} (0.101)	(0.040) -0.240^{*} (0.102)	(0.031) -0.132 (0.109)	(0.003) -0.415^{***} (0.102)	(0.000) -0.379^{***} (0.103)	-0.360^{**} (0.106)	
$School_TypeElementaryHighMiddle$	(0.101) -0.118^{*} (0.053)	(0.102) -0.077 (0.051)	(0.109) -0.189^{***} (0.052)	(0.102) -0.490^{***} (0.054)	(0.105) -0.468^{***} (0.054)	(0.100) -0.342^{***} (0.057)	
$School_TypeElementaryMiddle$	0.151 *** (0.036)	0.134^{***} (0.037)	0.093 * (0.039)	(0.034) -0.167^{***} (0.020)	(0.034) -0.170^{***} (0.020)	(0.037) -0.173^{***} (0.021)	
School_TypeHigh	0.106 *** (0.024)	0.134 *** (0.024)	0.213 *** (0.025)	(0.020) -1.020^{***} (0.035)	(0.020) -1.003^{***} (0.035)	(0.021) -0.924^{**} (0.035)	
School_TypeHighMiddle	(0.024) -0.005 (0.044)	(0.024) 0.013 (0.045)	0.025 0.114^{*} (0.047)	(0.035) -0.752^{***} (0.046)	(0.035) -0.753^{***} (0.047)	(0.033) -0.741^{***} (0.048)	
School_TypeMiddle	(0.044) 0.094 *** (0.015)	(0.043) 0.084^{***} (0.015)	0.105 *** (0.016)	(0.040) -0.714^{***} (0.024)	(0.047) -0.703^{***} (0.025)	(0.048) -0.650^{***} (0.025)	
Level 2 Controls	(0.013)	(0.013)	(0.010)	(0.024)	(0.023)	(0.025)	
Num_TPS_in_District	0.010 *** (0.002)	0.007 *** (0.002)	0.006 *** (0.002)	$\begin{array}{c} 0.011^{***} \\ (0.003) \end{array}$	0.008 ** (0.003)	$0.005 \\ (0.003)$	
Num_Alt_Schools_in_District	(0.002) -0.021^{*} (0.010)	(0.002) -0.013 (0.008)	(0.002) -0.010 (0.007)	(0.003) -0.010^{***} (0.003)	(0.003) -0.007^{**} (0.003)	(0.003) -0.005^{*} (0.002)	
(Intercept)	-0.133^{**} (0.050)	$0.064 \\ (0.046)$	$\begin{array}{c} 0.131^{**} \\ (0.043) \end{array}$	0.593 *** (0.056)	$\begin{array}{c} 0.583^{***} \\ (0.054) \end{array}$	$\begin{array}{c} 0.525^{***} \\ (0.053) \end{array}$	
AIC	-13100.111	-12942.309	-12266.786	-14220.095	-14020.216	-13400.72	
Log Likelihood	6575.055	6496.155	6158.393	7135.047	7035.108	6725.363	
Num. obs.	6996 051	6996 051	6996 051	7591 654	7591 654	7591 654	
Num. groups: District	951 0.205	951 0.221	951 0.107	654	654	654	
Var: District (Intercept)	0.295	0.221	0.197	0.460	0.418	0.351	
Var: District Charter Var: District Academic_Performance	$0.096 \\ 0.072$	$0.103 \\ 0.076$	$0.160 \\ 0.072$	$0.130 \\ 0.032$	$0.123 \\ 0.032$	$0.176 \\ 0.032$	

Table 3: SES Integration Models

 $^{***}p < 0.001; \ ^{**}p < 0.01; \ ^{*}p < 0.05$

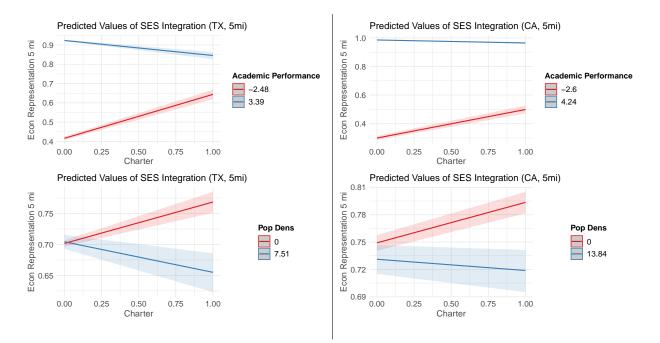


Figure 5: Charter Interactions for SES Integration

Conclusion

By using a unique multi-group measure of relative integration that compares a school's demographics to the demographics of its surrounding community, multi-level beta regression models found compelling evidence that charter schools hold a significant positive independent correlation with socio-economic integration. I found no strong evidence that a school's status as a charter school or traditional public school explains variation in school racial integration. Additionally, the models found no difference in the effects of charter schools between the state of California and Texas, indicating that charter policies encouraging within-district enrollment do not function as the causal mechanism driving a relationship between charter schools and integration.

Future research could provide more insight into the causal mechanisms behind the integration effects of charter schools by comparing more states with similar charter policies against each other. More complex analyses that utilize interrupted time series models could better isolate the independent effects of charter schools over time as well as the effects charter schools have on TPS integration. As far as data collection, future studies with access to more granular school-level income data could measure SES integration far better then the current noisy two-group method available for this study. Additionally, while decomposable segregation measures such as Theil's H are often superior to the older dissimilarity index, I believe that future research into school segregation should at least consider a district-blind measurement of segregation for robustness checks.

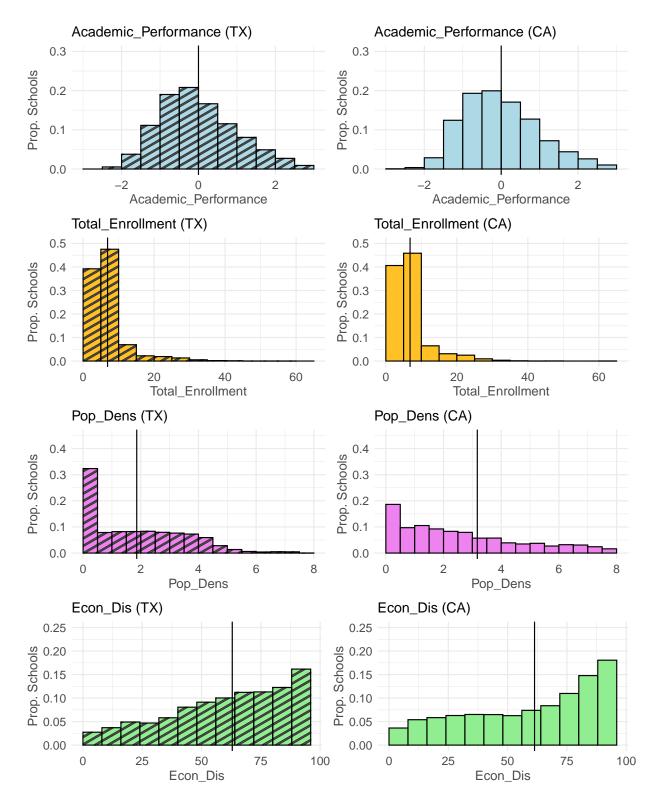
Families and policymakers will continue to judge the effectiveness of charter schools by various measures, and one such criteria for success will continue to be a school's ability to integrate communities. While many studies, including this one, have found relationships between charter schools and demographic integration, few have offered satisfying causal explanations for why these relationships exist. This paper attempted to leverage the vast differences in charter school policies between states to determine if more restrictive charter enrollment policies exacerbated segregation. This paper found no evidence for such a causal mechanism, though future studies utilizing more robust methods and data could very well build on this approach of comparing state policies and come to firmer conclusions on the kinds of policies associated with better, more integrated schools.

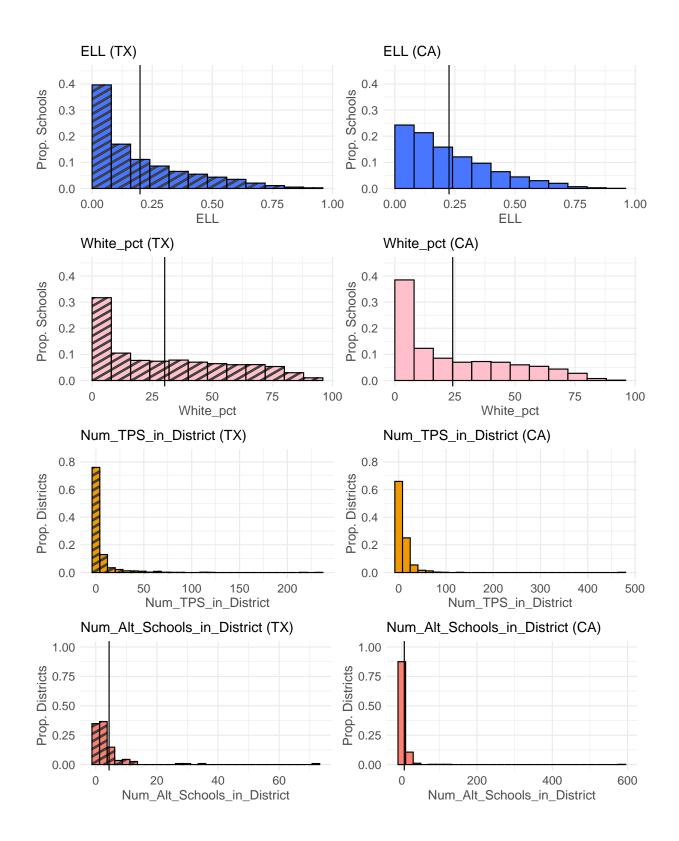
Appendix

Independent Variables

Variable	Description
Charter	Dummy variable denoting whether a school is a charter school or traditional public school.
Academic_Performance	A normalized measure of academic performance within a given state. A value of one indicates a school that scores one standard deviation higher than average of exams relative to other schools in the state. For Texas, the variable measures score from a school's average STAAR exam scores for reading and math. For California the variable measures a school's average score on the CAASPP. is normalized for ease of model interpretation.
Dual_Language	Dummy variable denoting whether a school offers dual-language programs. These include two-way (bilingual), one-way language immersion programs.
Total_Enrollment	The total enrollment of a school measured in 100s of students.
Pop_Dens	The population density in the 5mi surrounding a school, measured in 1000s of persons per square mile.
Econ_Dis	The proportion of economically disadvantaged students at a school. An economically disadvantaged student is defined as a student who is eligible to receive free or reduced lunch. This means that the student's family earns an income below 1859 of the poverty threshold.
ELL	The proportion of a student body who are designated as English language learners
KIPP	A dummy variable denoting whether or not a school is part of the Knowledge Power Program (KIPP) national network of charter schools, which targets primaril low-income students.
School_Type	A factor variable denoting the grade range a school serves. A school may be code as elementary, middle, high, or any combination of the three.
White_pct	The percentage of white students attending a school, ranging from 0-100.
Num_TPS_in_District	The number of traditional public schools in each district during the 2018-19 school year.
Num_Alt_Schools_in_District	The number of charter and private public schools in each district during the 2018 19 school year. California private schools were geocoded with data from the C. Department of Education. Texas private schools were geocoded with data from the Texas Private School Accreditation Commission.

Variable Distributions





	California	Texas
TPS	6,971	6,792
Charter	1,140	578

Table 4: # TPS/Charter by State

Coding School_Type

A school could be coded as an elementary school, middle school, high school, elementary/middle school, middle/high school, and elementary/middle/high school. The grade range for elementary schools was K-5; for middle schools, 6-8; for high schools, 9-12. Schools that served grades overlapping these grade ranges were coded as a combination school type.

Identifying Outliers

Given that there exists no current method for calculating Cook's Distance for glmTMBB multilevel models (glmTMBB being the R package I utilized to perform multilevel beta regressions), I resorted to running a separate set of OLS multilevel models using the lme4 package and calculating Cook's D for each of these models. An outlier observation was defined as one that produced a Cook's D greater than three times the average of all Cook's D in the model (Thieme 2021). I proceeded to only remove observations that the 10mi, 5mi, and 2mi models all "agreed" were influential outliers.

$\begin{array}{c} 5 \text{mi} \\ & -0.112 \\ (0.081) \\ & -0.049 \\ (0.032) \\ & -0.004 \\ (0.026) \\ \end{array} \\ \begin{array}{c} 0.025 \\ (0.018) \\ 0.002 \\ (0.052) \\ 0.003 \\ (0.002) \\ 0.006 \\ (0.009) \\ & -\textbf{0.011}^{***} \\ (0.001) \\ & -\textbf{0.645}^{***} \\ (0.069) \\ 0.201 \\ (0.132) \\ & -0.065 \\ (0.064) \\ & -0.012 \\ (0.051) \\ & -0.026 \end{array}$	$\begin{array}{r} 2 \text{mi} \\ & -0.024 \\ (0.079) \\ & -0.029 \\ (0.028) \\ & -\textbf{0.073}^{**} \\ (0.024) \\ \end{array} \\ \begin{array}{r} \textbf{0.068}^{***} \\ (0.024) \\ \hline \textbf{0.0016} \\ & -0.021 \\ (0.046) \\ & 0.004 \\ (0.002) \\ & -\textbf{0.083}^{***} \\ (0.008) \\ \hline \textbf{-0.007}^{***} \\ (0.008) \\ \hline \textbf{-0.007}^{***} \\ (0.001) \\ & -\textbf{0.375}^{***} \\ (0.062) \\ \hline \textbf{0.469}^{***} \\ (0.125) \\ & -\textbf{0.235}^{***} \\ (0.057) \\ & -\textbf{0.120}^{**} \\ (0.046) \\ \end{array}$	$\begin{array}{r} 10 \text{mi} \\ \hline \\ -0.065 \\ (0.040) \\ \textbf{0.055}^{**} \\ (0.018) \\ \textbf{-0.021}^{**} \\ (0.007) \\ \hline \\ -0.009 \\ (0.014) \\ \textbf{-0.044} \\ (0.058) \\ \textbf{0.005}^{***} \\ (0.001) \\ \textbf{0.018}^{***} \\ (0.005) \\ \textbf{-0.012}^{***} \\ (0.005) \\ \textbf{-1.249}^{***} \\ (0.054) \\ 0.033 \\ (0.078) \\ 0.024 \\ (0.046) \\ \end{array}$	$\begin{array}{c} 5 \text{mi} \\ & -0.076 \\ (0.040) \\ \textbf{0.042}^* \\ (0.020) \\ -\textbf{0.022}^{**} \\ (0.008) \\ \end{array} \\ \begin{array}{c} -0.003 \\ (0.016) \\ -0.086 \\ (0.065) \\ \textbf{0.007}^{***} \\ (0.002) \\ \textbf{0.026}^{***} \\ (0.005) \\ \textbf{-0.012}^{***} \\ (0.001) \\ -\textbf{1.141}^{***} \\ (0.061) \\ 0.153 \\ (0.088) \\ 0.083 \\ (0.051) \end{array}$	2mi -0.012 (0.043) 0.013 (0.023) -0.033*** (0.009) 0.027 (0.018) -0.096 (0.074) 0.006** (0.002) 0.019** (0.006) -0.008*** (0.001) -0.710*** (0.069) 0.306** (0.103) 0.104 (0.057)
$\begin{array}{c} (0.081) \\ -0.049 \\ (0.032) \\ -0.004 \\ (0.026) \end{array}$ $\begin{array}{c} 0.025 \\ (0.018) \\ 0.002 \\ (0.052) \\ 0.003 \\ (0.002) \\ 0.006 \\ (0.009) \end{array}$ $\begin{array}{c} -0.011^{***} \\ (0.001) \\ -0.645^{***} \\ (0.069) \\ 0.201 \\ (0.132) \\ -0.065 \\ (0.064) \\ -0.012 \\ (0.051) \end{array}$	$\begin{array}{c} (0.079) \\ -0.029 \\ (0.028) \\ - 0.073^{**} \\ (0.024) \\ \end{array}$ $\begin{array}{c} 0.068^{***} \\ (0.016) \\ -0.021 \\ (0.046) \\ 0.004 \\ (0.002) \\ - 0.083^{***} \\ (0.008) \\ - 0.007^{***} \\ (0.001) \\ - 0.375^{***} \\ (0.062) \\ 0.469^{***} \\ (0.125) \\ - 0.235^{***} \\ (0.057) \\ - 0.120^{**} \end{array}$	$\begin{array}{c} (0.040)\\ \textbf{0.055}^{**}\\ (0.018)\\ \textbf{-0.021}^{**}\\ (0.007)\\ \end{array}\\ \begin{array}{c} -0.009\\ (0.014)\\ -0.044\\ (0.058)\\ \textbf{0.005}^{***}\\ (0.001)\\ \textbf{0.018}^{***}\\ (0.005)\\ \textbf{-0.012}^{***}\\ (0.000)\\ \textbf{-1.249}^{***}\\ (0.054)\\ 0.033\\ (0.078)\\ 0.024\\ (0.046)\\ \end{array}$	$\begin{array}{c} (0.040)\\ \textbf{0.042}^{*}\\ (0.020)\\ \textbf{-0.022}^{**}\\ (0.008)\\ \end{array}\\ \begin{array}{c} -0.003\\ (0.016)\\ -0.086\\ (0.065)\\ \textbf{0.007}^{***}\\ (0.002)\\ \textbf{0.026}^{***}\\ (0.005)\\ \textbf{-0.012}^{***}\\ (0.001)\\ \textbf{-1.141}^{***}\\ (0.061)\\ 0.153\\ (0.088)\\ 0.083\\ \end{array}$	$\begin{array}{c} (0.043)\\ 0.013\\ (0.023)\\ -0.033^{***}\\ (0.009)\\ \end{array}\\\\ \begin{array}{c} 0.027\\ (0.018)\\ -0.096\\ (0.074)\\ \textbf{0.006}^{**}\\ (0.002)\\ \textbf{0.019^{**}}\\ (0.006)\\ -\textbf{0.008^{****}}\\ (0.001)\\ -\textbf{0.710^{***}}\\ (0.069)\\ \textbf{0.306^{**}}\\ (0.103)\\ 0.104\\ \end{array}$
$\begin{array}{c} (0.081) \\ -0.049 \\ (0.032) \\ -0.004 \\ (0.026) \end{array}$ $\begin{array}{c} 0.025 \\ (0.018) \\ 0.002 \\ (0.052) \\ 0.003 \\ (0.002) \\ 0.006 \\ (0.009) \end{array}$ $\begin{array}{c} -0.011^{***} \\ (0.001) \\ -0.645^{***} \\ (0.069) \\ 0.201 \\ (0.132) \\ -0.065 \\ (0.064) \\ -0.012 \\ (0.051) \end{array}$	$\begin{array}{c} (0.079) \\ -0.029 \\ (0.028) \\ - 0.073^{**} \\ (0.024) \\ \end{array}$ $\begin{array}{c} 0.068^{***} \\ (0.016) \\ -0.021 \\ (0.046) \\ 0.004 \\ (0.002) \\ - 0.083^{***} \\ (0.008) \\ - 0.007^{***} \\ (0.001) \\ - 0.375^{***} \\ (0.062) \\ 0.469^{***} \\ (0.125) \\ - 0.235^{***} \\ (0.057) \\ - 0.120^{**} \end{array}$	$\begin{array}{c} (0.040)\\ \textbf{0.055}^{**}\\ (0.018)\\ \textbf{-0.021}^{**}\\ (0.007)\\ \end{array}\\ \begin{array}{c} -0.009\\ (0.014)\\ -0.044\\ (0.058)\\ \textbf{0.005}^{***}\\ (0.001)\\ \textbf{0.018}^{***}\\ (0.005)\\ \textbf{-0.012}^{***}\\ (0.000)\\ \textbf{-1.249}^{***}\\ (0.054)\\ 0.033\\ (0.078)\\ 0.024\\ (0.046)\\ \end{array}$	$\begin{array}{c} (0.040)\\ \textbf{0.042}^{*}\\ (0.020)\\ \textbf{-0.022}^{**}\\ (0.008)\\ \end{array}\\ \begin{array}{c} -0.003\\ (0.016)\\ -0.086\\ (0.065)\\ \textbf{0.007}^{***}\\ (0.002)\\ \textbf{0.026}^{***}\\ (0.005)\\ \textbf{-0.012}^{***}\\ (0.001)\\ \textbf{-1.141}^{***}\\ (0.061)\\ 0.153\\ (0.088)\\ 0.083\\ \end{array}$	$\begin{array}{c} (0.043)\\ 0.013\\ (0.023)\\ -0.033^{***}\\ (0.009)\\ \end{array}\\\\ \begin{array}{c} 0.027\\ (0.018)\\ -0.096\\ (0.074)\\ \textbf{0.006}^{**}\\ (0.002)\\ \textbf{0.019^{**}}\\ (0.006)\\ -\textbf{0.008^{****}}\\ (0.001)\\ -\textbf{0.710^{***}}\\ (0.069)\\ \textbf{0.306^{**}}\\ (0.103)\\ 0.104\\ \end{array}$
$\begin{array}{c} -0.049\\ (0.032)\\ -0.004\\ (0.026)\\\\ \end{array}$ $\begin{array}{c} 0.025\\ (0.018)\\ 0.002\\ (0.052)\\ 0.003\\ (0.002)\\ 0.006\\ (0.009)\\ -\textbf{0.011}^{***}\\ (0.001)\\ -\textbf{0.645}^{***}\\ (0.069)\\ 0.201\\ (0.132)\\ -0.065\\ (0.064)\\ -0.012\\ (0.051)\\ \end{array}$	$\begin{array}{c} -0.029\\ (0.028)\\ -0.073^{**}\\ (0.024)\\ \end{array}\\ \begin{array}{c} 0.068^{***}\\ (0.016)\\ -0.021\\ (0.046)\\ 0.004\\ (0.002)\\ -0.083^{***}\\ (0.008)\\ -0.007^{***}\\ (0.001)\\ -0.375^{***}\\ (0.062)\\ 0.469^{***}\\ (0.125)\\ -0.235^{***}\\ (0.057)\\ -0.120^{**}\\ \end{array}$	0.055^{**} (0.018) -0.021^{**} (0.007) (0.014) -0.044 (0.058) 0.005^{***} (0.001) 0.018^{***} (0.005) -0.012^{***} (0.000) -1.249^{***} (0.054) 0.033 (0.078) 0.024 (0.046)	$\begin{array}{c} \mathbf{0.042^{*}} \\ (0.020) \\ -\mathbf{0.022^{**}} \\ (0.008) \\ \end{array}$ $\begin{array}{c} -0.003 \\ (0.016) \\ -0.086 \\ (0.065) \\ \mathbf{0.007^{***}} \\ (0.002) \\ \mathbf{0.026^{***}} \\ (0.005) \\ -\mathbf{0.012^{***}} \\ (0.001) \\ -\mathbf{1.141^{***}} \\ (0.061) \\ 0.153 \\ (0.088) \\ 0.083 \\ \end{array}$	$\begin{array}{c} 0.013\\ (0.023)\\ -0.033^{***}\\ (0.009)\\ \end{array}\\ \begin{array}{c} 0.027\\ (0.018)\\ -0.096\\ (0.074)\\ \textbf{0.006}^{**}\\ (0.002)\\ \textbf{0.019^{**}}\\ (0.006)\\ -\textbf{0.008^{****}}\\ (0.001)\\ -\textbf{0.710^{***}}\\ (0.069)\\ \textbf{0.306^{**}}\\ (0.103)\\ 0.104\\ \end{array}$
$\begin{array}{c} -0.004\\ (0.026)\\ \end{array}\\ \begin{array}{c} 0.025\\ (0.018)\\ 0.002\\ (0.052)\\ 0.003\\ (0.002)\\ 0.006\\ (0.009)\\ -\textbf{0.011}^{***}\\ (0.001)\\ -\textbf{0.645}^{***}\\ (0.069)\\ 0.201\\ (0.132)\\ -0.065\\ (0.064)\\ -0.012\\ (0.051)\\ \end{array}$	$\begin{array}{c} \textbf{-0.073}^{**} \\ (0.024) \\ \hline \textbf{0.068}^{***} \\ (0.016) \\ -0.021 \\ (0.046) \\ 0.004 \\ (0.002) \\ \textbf{-0.083}^{***} \\ (0.008) \\ \textbf{-0.007}^{***} \\ (0.001) \\ \textbf{-0.375}^{***} \\ (0.062) \\ \textbf{0.469}^{***} \\ (0.125) \\ \textbf{-0.235}^{***} \\ (0.057) \\ \textbf{-0.120}^{**} \end{array}$	$\begin{array}{c} -0.021^{**} \\ (0.007) \\ \end{array}$ $\begin{array}{c} -0.009 \\ (0.014) \\ -0.044 \\ (0.058) \\ \textbf{0.005}^{***} \\ (0.001) \\ \textbf{0.018}^{***} \\ (0.005) \\ \textbf{-0.012}^{***} \\ (0.000) \\ \textbf{-1.249}^{***} \\ (0.054) \\ 0.033 \\ (0.078) \\ 0.024 \\ (0.046) \end{array}$	$\begin{array}{c} -0.022^{**} \\ (0.008) \\ \end{array}$ $\begin{array}{c} -0.003 \\ (0.016) \\ -0.086 \\ (0.065) \\ \textbf{0.007}^{***} \\ (0.002) \\ \textbf{0.026}^{***} \\ (0.005) \\ \textbf{-0.012}^{***} \\ (0.001) \\ \textbf{-1.141}^{***} \\ (0.061) \\ 0.153 \\ (0.088) \\ 0.083 \end{array}$	$\begin{array}{c} -0.033^{***}\\ (0.009) \\ \end{array}$
$\begin{array}{c} (0.026) \\ 0.025 \\ (0.018) \\ 0.002 \\ (0.052) \\ 0.003 \\ (0.002) \\ 0.006 \\ (0.009) \\ - 0.011^{***} \\ (0.001) \\ - 0.645^{***} \\ (0.069) \\ 0.201 \\ (0.132) \\ - 0.065 \\ (0.064) \\ - 0.012 \\ (0.051) \end{array}$	$\begin{array}{c} (0.024) \\ \textbf{0.068}^{***} \\ (0.016) \\ -0.021 \\ (0.046) \\ 0.004 \\ (0.002) \\ \textbf{-0.083}^{***} \\ (0.008) \\ \textbf{-0.007}^{***} \\ (0.001) \\ \textbf{-0.375}^{***} \\ (0.062) \\ \textbf{0.469}^{***} \\ (0.125) \\ \textbf{-0.235}^{***} \\ (0.057) \\ \textbf{-0.120}^{**} \end{array}$	$\begin{array}{c} (0.007) \\ -0.009 \\ (0.014) \\ -0.044 \\ (0.058) \\ \textbf{0.005}^{***} \\ (0.001) \\ \textbf{0.018}^{***} \\ (0.005) \\ -\textbf{0.012}^{***} \\ (0.000) \\ -\textbf{1.249}^{***} \\ (0.054) \\ 0.033 \\ (0.078) \\ 0.024 \\ (0.046) \end{array}$	$\begin{array}{c} (0.008) \\ -0.003 \\ (0.016) \\ -0.086 \\ (0.065) \\ \textbf{0.007}^{***} \\ (0.002) \\ \textbf{0.026}^{***} \\ (0.005) \\ -\textbf{0.012}^{***} \\ (0.001) \\ -\textbf{1.141}^{***} \\ (0.061) \\ 0.153 \\ (0.088) \\ 0.083 \end{array}$	$\begin{array}{c} (0.009) \\ \hline 0.027 \\ (0.018) \\ -0.096 \\ (0.074) \\ \hline 0.006^{**} \\ (0.002) \\ \hline 0.019^{**} \\ (0.006) \\ -0.008^{***} \\ (0.001) \\ -0.710^{***} \\ (0.069) \\ \hline 0.306^{**} \\ (0.103) \\ 0.104 \end{array}$
$\begin{array}{c} (0.018)\\ 0.002\\ (0.052)\\ 0.003\\ (0.002)\\ 0.006\\ (0.009)\\ -\textbf{0.011}^{***}\\ (0.001)\\ -\textbf{0.645}^{***}\\ (0.069)\\ 0.201\\ (0.132)\\ -0.065\\ (0.064)\\ -0.012\\ (0.051)\\ \end{array}$	$\begin{array}{c} (0.016) \\ -0.021 \\ (0.046) \\ 0.004 \\ (0.002) \\ \textbf{-0.083}^{***} \\ (0.008) \\ \textbf{-0.007}^{***} \\ (0.001) \\ \textbf{-0.375}^{***} \\ (0.062) \\ \textbf{0.469}^{***} \\ (0.125) \\ \textbf{-0.235}^{***} \\ (0.057) \\ \textbf{-0.120}^{**} \end{array}$	$\begin{array}{c} (0.014) \\ -0.044 \\ (0.058) \\ \textbf{0.005}^{***} \\ (0.001) \\ \textbf{0.018}^{***} \\ (0.005) \\ -\textbf{0.012}^{***} \\ (0.000) \\ -\textbf{1.249}^{***} \\ (0.054) \\ 0.033 \\ (0.078) \\ 0.024 \\ (0.046) \end{array}$	$\begin{array}{c} (0.016) \\ -0.086 \\ (0.065) \\ \textbf{0.007}^{***} \\ (0.002) \\ \textbf{0.026}^{***} \\ (0.005) \\ -\textbf{0.012}^{***} \\ (0.001) \\ -\textbf{1.141}^{***} \\ (0.061) \\ 0.153 \\ (0.088) \\ 0.083 \end{array}$	$\begin{array}{c} (0.018) \\ -0.096 \\ (0.074) \\ \textbf{0.006}^{**} \\ (0.002) \\ \textbf{0.019}^{**} \\ (0.006) \\ -\textbf{0.008}^{***} \\ (0.001) \\ -\textbf{0.710}^{***} \\ (0.069) \\ \textbf{0.306}^{**} \\ (0.103) \\ 0.104 \end{array}$
$\begin{array}{c} (0.018)\\ 0.002\\ (0.052)\\ 0.003\\ (0.002)\\ 0.006\\ (0.009)\\ -\textbf{0.011}^{***}\\ (0.001)\\ -\textbf{0.645}^{***}\\ (0.069)\\ 0.201\\ (0.132)\\ -0.065\\ (0.064)\\ -0.012\\ (0.051)\\ \end{array}$	$\begin{array}{c} (0.016) \\ -0.021 \\ (0.046) \\ 0.004 \\ (0.002) \\ \textbf{-0.083}^{***} \\ (0.008) \\ \textbf{-0.007}^{***} \\ (0.001) \\ \textbf{-0.375}^{***} \\ (0.062) \\ \textbf{0.469}^{***} \\ (0.125) \\ \textbf{-0.235}^{***} \\ (0.057) \\ \textbf{-0.120}^{**} \end{array}$	$\begin{array}{c} (0.014) \\ -0.044 \\ (0.058) \\ \textbf{0.005}^{***} \\ (0.001) \\ \textbf{0.018}^{***} \\ (0.005) \\ -\textbf{0.012}^{***} \\ (0.000) \\ -\textbf{1.249}^{***} \\ (0.054) \\ 0.033 \\ (0.078) \\ 0.024 \\ (0.046) \end{array}$	$\begin{array}{c} (0.016) \\ -0.086 \\ (0.065) \\ \textbf{0.007}^{***} \\ (0.002) \\ \textbf{0.026}^{***} \\ (0.005) \\ -\textbf{0.012}^{***} \\ (0.001) \\ -\textbf{1.141}^{***} \\ (0.061) \\ 0.153 \\ (0.088) \\ 0.083 \end{array}$	$\begin{array}{c} (0.018) \\ -0.096 \\ (0.074) \\ \textbf{0.006}^{**} \\ (0.002) \\ \textbf{0.019}^{**} \\ (0.006) \\ -\textbf{0.008}^{***} \\ (0.001) \\ -\textbf{0.710}^{***} \\ (0.069) \\ \textbf{0.306}^{**} \\ (0.103) \\ 0.104 \end{array}$
$\begin{array}{c} 0.002\\ (0.052)\\ 0.003\\ (0.002)\\ 0.006\\ (0.009)\\ -\textbf{0.011}^{***}\\ (0.001)\\ -\textbf{0.645}^{***}\\ (0.069)\\ 0.201\\ (0.132)\\ -0.065\\ (0.064)\\ -0.012\\ (0.051)\\ \end{array}$	$\begin{array}{c} -0.021\\ (0.046)\\ 0.004\\ (0.002)\\ -\textbf{0.083}^{***}\\ (0.008)\\ -\textbf{0.007}^{***}\\ (0.001)\\ -\textbf{0.375}^{***}\\ (0.062)\\ \textbf{0.469}^{***}\\ (0.125)\\ -\textbf{0.235}^{***}\\ (0.057)\\ -\textbf{0.120}^{**} \end{array}$	$\begin{array}{c} -0.044\\ (0.058)\\ \textbf{0.005}^{***}\\ (0.001)\\ \textbf{0.018}^{***}\\ (0.005)\\ \textbf{-0.012}^{***}\\ (0.000)\\ \textbf{-1.249}^{***}\\ (0.054)\\ 0.033\\ (0.078)\\ 0.024\\ (0.046)\\ \end{array}$	$\begin{array}{c} -0.086\\ (0.065)\\ \textbf{0.007}^{***}\\ (0.002)\\ \textbf{0.026}^{***}\\ (0.005)\\ \textbf{-0.012}^{***}\\ (0.001)\\ \textbf{-1.141}^{***}\\ (0.061)\\ 0.153\\ (0.088)\\ 0.083\\ \end{array}$	 -0.096 (0.074) 0.006** (0.002) 0.019** (0.006) -0.008**** (0.001) -0.710**** (0.069) 0.306*** (0.103) 0.104
$\begin{array}{c} 0.003\\ (0.002)\\ 0.006\\ (0.009)\\ \textbf{-0.011}^{***}\\ (0.001)\\ \textbf{-0.645}^{***}\\ (0.069)\\ 0.201\\ (0.132)\\ \textbf{-0.065}\\ (0.064)\\ \textbf{-0.012}\\ (0.051)\\ \end{array}$	$\begin{array}{c} 0.004\\ (0.002)\\ -0.083^{***}\\ (0.008)\\ -0.007^{***}\\ (0.001)\\ -0.375^{***}\\ (0.062)\\ 0.469^{***}\\ (0.125)\\ -0.235^{***}\\ (0.057)\\ -0.120^{**} \end{array}$	$\begin{array}{c} \textbf{0.005}^{***} \\ (0.001) \\ \textbf{0.018}^{***} \\ (0.005) \\ \textbf{-0.012}^{***} \\ (0.000) \\ \textbf{-1.249}^{***} \\ (0.054) \\ 0.033 \\ (0.078) \\ 0.024 \\ (0.046) \end{array}$	$\begin{array}{c} \textbf{0.007}^{***} \\ (0.002) \\ \textbf{0.026}^{***} \\ (0.005) \\ \textbf{-0.012}^{***} \\ (0.001) \\ \textbf{-1.141}^{***} \\ (0.061) \\ 0.153 \\ (0.088) \\ 0.083 \end{array}$	0.006** (0.002) 0.019** (0.006) -0.008*** (0.001) -0.710*** (0.069) 0.306** (0.103) 0.104
$\begin{array}{c} 0.006\\ (0.009)\\ -0.011^{***}\\ (0.001)\\ -0.645^{***}\\ (0.069)\\ 0.201\\ (0.132)\\ -0.065\\ (0.064)\\ -0.012\\ (0.051)\\ \end{array}$	$\begin{array}{c} \textbf{-0.083}^{***} \\ (0.008) \\ \textbf{-0.007}^{***} \\ (0.001) \\ \textbf{-0.375}^{***} \\ (0.062) \\ \textbf{0.469}^{***} \\ (0.125) \\ \textbf{-0.235}^{***} \\ (0.057) \\ \textbf{-0.120}^{**} \end{array}$	$\begin{array}{c} \textbf{0.018}^{***} \\ (0.005) \\ \textbf{-0.012}^{***} \\ (0.000) \\ \textbf{-1.249}^{***} \\ (0.054) \\ 0.033 \\ (0.078) \\ 0.024 \\ (0.046) \end{array}$	$\begin{array}{c} \textbf{0.026}^{***} \\ (0.005) \\ \textbf{-0.012}^{***} \\ (0.001) \\ \textbf{-1.141}^{***} \\ (0.061) \\ 0.153 \\ (0.088) \\ 0.083 \end{array}$	0.019** (0.006) -0.008*** (0.001) -0.710*** (0.069) 0.306** (0.103) 0.104
$\begin{array}{c} -0.011^{***}\\ (0.001)\\ -0.645^{***}\\ (0.069)\\ 0.201\\ (0.132)\\ -0.065\\ (0.064)\\ -0.012\\ (0.051) \end{array}$	$\begin{array}{c} -0.007^{***}\\ (0.001)\\ -0.375^{***}\\ (0.062)\\ 0.469^{***}\\ (0.125)\\ -0.235^{***}\\ (0.057)\\ -0.120^{**} \end{array}$	$\begin{array}{c} -0.012^{***}\\ (0.000)\\ -1.249^{***}\\ (0.054)\\ 0.033\\ (0.078)\\ 0.024\\ (0.046) \end{array}$	$\begin{array}{c} -0.012^{***}\\ (0.001)\\ -1.141^{***}\\ (0.061)\\ 0.153\\ (0.088)\\ 0.083\end{array}$	-0.008**** (0.001) -0.710*** (0.069) 0.306** (0.103) 0.104
$\begin{array}{c} -0.645^{***}\\ (0.069)\\ 0.201\\ (0.132)\\ -0.065\\ (0.064)\\ -0.012\\ (0.051) \end{array}$	$\begin{array}{c} -0.375^{***}\\ (0.062)\\ 0.469^{***}\\ (0.125)\\ -0.235^{***}\\ (0.057)\\ -0.120^{**} \end{array}$	$\begin{array}{c} -1.249^{***} \\ (0.054) \\ 0.033 \\ (0.078) \\ 0.024 \\ (0.046) \end{array}$	$-1.141^{***} \\ (0.061) \\ 0.153 \\ (0.088) \\ 0.083$	-0.710*** (0.069) 0.306** (0.103) 0.104
$\begin{array}{c} 0.201 \\ (0.132) \\ -0.065 \\ (0.064) \\ -0.012 \\ (0.051) \end{array}$	0.469*** (0.125) -0.235*** (0.057) -0.120**	$\begin{array}{c} 0.033 \\ (0.078) \\ 0.024 \\ (0.046) \end{array}$	$\begin{array}{c} 0.153 \\ (0.088) \\ 0.083 \end{array}$	0.306 ** (0.103) 0.104
$\begin{array}{c} (0.132) \\ -0.065 \\ (0.064) \\ -0.012 \\ (0.051) \end{array}$	(0.125) - 0.235 *** (0.057) - 0.120 **	(0.078) 0.024 (0.046)	$(0.088) \\ 0.083$	$(0.103) \\ 0.104$
(0.064) -0.012 (0.051)	(0.057) - 0.120 **	(0.046)		
(0.051)				(0.057)
-0.026	(0.040)	-0.025 (0.017)	-0.002 (0.019)	0.003 (0.021)
(0.032)	-0.071^{*} (0.029)	-0.174^{***} (0.030)	-0.174^{***} (0.033)	-0.156^{***} (0.038)
-0.036	-0.026	-0.182^{***}	-0.218^{***}	-0.186^{***}
(0.059) 0.004	(0.053) -0.032	(0.039) - 0.097 ***	(0.043) - 0.097 ***	(0.049) -0.109***
(0.021)	(0.019)	(0.021)	(0.024)	(0.027)
-0.006**	-0.004^{*}	-0.009**	-0.007^{*}	-0.006^{*}
(0.002) 0.014	(0.002) 0.005	(0.003) 0.005	(0.003) 0.003 (0.002)	(0.002) 0.003
(0.009)	(0.008)	(0.003)	(0.002)	(0.002)
2.400^{***}	2.524^{***}	2.235^{***}	2.295***	2.082^{***}
. ,	· /	. ,	()	(0.040)
				-15030.549 7540.274
				7540.274 7875
				658
				0.271
0.083	0.138	0.149	0.109	$0.102 \\ 0.018$
	(0.002) 0.014 (0.009)	$\begin{array}{cccc} (0.002) & (0.002) \\ 0.014 & 0.005 \\ (0.009) & (0.008) \end{array} \\ \\ \hline 2.400^{***} & 2.524^{***} \\ (0.052) & (0.046) \end{array} \\ \hline -12467.070 & -17039.813 \\ 6258.535 & 8544.907 \\ 7211 & 7208 \\ 959 & 958 \\ 0.272 & 0.211 \end{array}$	$\begin{array}{ccccc} (0.002) & (0.002) & (0.003) \\ 0.014 & 0.005 & 0.005 \\ (0.009) & (0.008) & (0.003) \\ \end{array} \\ \begin{array}{c} \mathbf{2.400^{***}} & \mathbf{2.524^{***}} & \mathbf{2.235^{***}} \\ (0.052) & (0.046) & (0.041) \\ \end{array} \\ \begin{array}{c} -12467.070 & -17039.813 & -16371.113 \\ 6258.535 & 8544.907 & 8210.557 \\ 7211 & 7208 & 7875 \\ 959 & 958 & 658 \\ 0.272 & 0.211 & 0.407 \\ \end{array}$	$\begin{array}{cccccccc} (0.002) & (0.002) & (0.003) & (0.003) \\ 0.014 & 0.005 & 0.005 & 0.003 \\ (0.009) & (0.008) & (0.003) & (0.002) \\ \end{array}$

Table 5: Racial Integration Models (No Outliers Removed)

 $^{***}p < 0.001; \ ^{**}p < 0.01; \ ^{*}p < 0.05$

		Texas			California	
	10mi	5mi	2mi	10mi	5mi	2mi
Charter Effects						
Charter	0.186 ** (0.069)	0.284^{***} (0.070)	0.410^{***} (0.074)	0.200 *** (0.044)	$\begin{array}{c} 0.254^{***} \\ (0.043) \end{array}$	0.304^{***} (0.046)
Charter:Academic_Performance	(0.005) -0.264^{***} (0.025)	-0.256^{***} (0.025)	(0.014) -0.230^{***} (0.026)	(0.044) -0.140^{***} (0.021)	(0.043) -0.143^{***} (0.022)	(0.040) -0.135^{***} (0.023)
Charter:Pop_Dens	(0.020) -0.032 (0.020)	(0.025) -0.050^{*} (0.020)	(0.020) -0.078^{***} (0.022)	(0.021) -0.028^{***} (0.009)	(0.022) -0.026^{**} (0.009)	(0.025) -0.015 (0.009)
Level 1 Controls	(0.020)	(0.020)	(0.022)	(0.000)	(0.000)	(0.000)
Academic_Performance	0.307 *** (0.017)	0.314^{***} (0.017)	0.288 *** (0.017)	0.501 *** (0.017)	0.502^{***} (0.017)	0.496^{***} (0.017)
Dual_Language	0.072 * (0.037)	(0.017) 0.058 (0.038)	(0.017) -0.001 (0.040)	(0.017) 0.154^{*} (0.068)	0.243***	0.219 ** (0.070)
Total_Enrollment	0.012***	0.010***	0.006***	0.004*	(0.068) 0.005^*	0.006**
Pop_Dens	(0.002) -0.002 (0.007)	(0.002) -0.006 (0.007)	(0.002) -0.004 (0.007)	(0.002) 0.029^{***} (0.005)	(0.002) 0.060^{***} (0.005)	(0.002) 0.065^{***}
White_pct	(0.007) 0.022^{***}	0.017***	(0.007) 0.015 ***	(0.005) 0.025^{***}	(0.005) 0.024^{***}	(0.005) 0.021^{***}
ELL	(0.001) -0.949***	(0.001) -0.804***	(0.001) -0.414***	(0.001) -1.635***	(0.001) -1.456***	(0.001) -0.841***
KIPP	(0.047) - 0.235 *	(0.048) -0.224*	(0.050) -0.096	(0.064) -0.467***	(0.064) -0.416***	(0.065) -0.379***
$School_TypeElementaryHighMiddle$	(0.098) -0.110*	(0.099) -0.078	(0.107) -0.186***	(0.094) -0.508***	(0.095) -0.480***	(0.098) -0.359***
School_TypeElementaryMiddle	(0.053) 0.165^{***}	(0.051) 0.152^{***}	(0.051) 0.110^{**}	(0.053) -0.168***	(0.054) -0.170***	(0.056) -0.174***
School_TypeHigh	(0.036) 0.108^{***}	(0.036) 0.136^{***}	(0.038) 0.220^{***}	(0.020) -1.022***	(0.020) -1.003***	(0.020) -0.920***
School_TypeHighMiddle	(0.023) 0.003	(0.023) 0.023	(0.024) 0.121**	(0.034) -0.739***	(0.034) -0.737***	(0.035) -0.724***
School_TypeMiddle	(0.043) 0.099^{***}	(0.044) 0.091^{***}	(0.046) 0.113^{***}	(0.045) -0.713***	(0.046) -0.701***	(0.047) -0.650***
Level 2 Controls	(0.015)	(0.015)	(0.016)	(0.024)	(0.024)	(0.024)
Num_TPS_in_District	0.010***	0.007^{***}	0.006^{***}	0.011^{***}	0.008^{**}	0.005
Num_Alt_Schools_in_District	(0.002) - 0.022 [*] (0.010)	(0.002) -0.014 (0.008)	(0.002) -0.011 (0.007)	(0.003) - 0.010 *** (0.003)	(0.003) - 0.008 ^{**} (0.003)	(0.003) - 0.005 * (0.002)
(Intercept)	-0.150^{**} (0.049)	$0.053 \\ (0.046)$	$\begin{array}{c} 0.124^{**} \\ (0.043) \end{array}$	$\begin{array}{c} 0.595^{***} \\ (0.055) \end{array}$	$\begin{array}{c} 0.581^{***} \\ (0.054) \end{array}$	$\begin{array}{c} 0.513^{***} \\ (0.052) \end{array}$
AIC Lee Libeliheed	-13532.654	-13366.211	-12675.308	-14793.655	-14572.374	-13929.196
Log Likelihood Num. obs.	$6791.327 \\7211$	$6708.106 \\ 7211$	$6362.654 \\7211$	$7421.827 \\7875$	$7311.187 \\ 7875$	$6989.598 \\7875$
Num. groups: District	959	959	959	658	658	658
Var: District (Intercept)	0.302	0.228	0.206	0.463	0.423	0.355
Var: District Charter	0.099	0.108	0.161	0.137	0.126	0.175
Var: District Academic_Performance	0.070	0.074	0.070	0.031	0.031	0.031

Table 6: SES Integration Models (No Outliers Removed)

 $^{***}p < 0.001; \ ^{**}p < 0.01; \ ^{*}p < 0.05$

		Texas			California	
	10mi	5mi	2mi	10mi	5mi	2mi
Charter Effects						
Charter	0.019	0.036	0.029	-0.167^{***}	-0.164^{***}	-0.103^{*}
	(0.079)	(0.081)	(0.073)	(0.034)	(0.036)	(0.038)
Charter:Academic_Performance	-0.094^{**}	-0.141^{***}	-0.152^{***}	0.038	0.021	-0.021
	(0.032)	(0.033)	(0.029)	(0.021)	(0.022)	(0.024)
Charter:Pop_Dens	-0.046^{*}	-0.049^{*}	-0.081^{***}	-0.003	-0.004	-0.015
	(0.023)	(0.024)	(0.021)	(0.006)	(0.006)	(0.006)
Controls						
Academic_Performance	0.178^{***}	0.173^{***}	0.196***	0.034^{*}	0.039^{*}	0.067^{***}
	(0.013)	(0.014)	(0.012)	(0.014)	(0.015)	(0.016)
Dual_Language	-0.135^{*}	-0.067	-0.121^{*}	0.031	0.019	-0.044
	(0.055)	(0.057)	(0.050)	(0.076)	(0.080)	(0.085)
Total_Enrollment	0.005^{*}	0.004	0.005^{*}	0.007^{***}	0.014^{***}	0.013^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Pop_Dens	-0.067^{***}	-0.077^{***}	-0.102^{***}	-0.079^{***}	-0.068^{***}	-0.051^{*}
	(0.007)	(0.007)	(0.007)	(0.003)	(0.003)	(0.004)
Econ_Dis	-0.001	-0.000	0.002^{***}	-0.003^{***}	-0.003^{***}	-0.001
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
ELL	-0.496^{***}	-0.444^{***}	-0.081	-1.547^{***}	-1.258^{***}	-0.759^{**}
	(0.062)	(0.064)	(0.058)	(0.050)	(0.053)	(0.057)
KIPP	-0.531^{***}	-0.384^{**}	-0.067	-0.188	-0.071	0.082
	(0.142)	(0.146)	(0.134)	(0.107)	(0.114)	(0.127)
$School_TypeElementaryHighMiddle$	0.035	-0.046	-0.181^{***}	0.150^{**}	0.188^{**}	0.146^*
	(0.060)	(0.061)	(0.054)	(0.056)	(0.059)	(0.063)
$School_TypeElementaryMiddle$	0.139^{*}	0.123^{*}	0.013	0.079^{***}	0.116^{***}	0.090***
	(0.054)	(0.055)	(0.049)	(0.017)	(0.018)	(0.019)
School_TypeHigh	-0.037	0.010	-0.007	-0.220^{***}	-0.235^{***}	-0.220^{**}
	(0.033)	(0.034)	(0.031)	(0.035)	(0.037)	(0.040)
School_TypeHighMiddle	0.051	0.032	0.060	-0.246^{***}	-0.259^{***}	-0.223^{**}
	(0.062)	(0.063)	(0.058)	(0.049)	(0.051)	(0.055)
School_TypeMiddle	0.053^{*}	0.066**	0.041	-0.105^{***}	-0.077^{**}	-0.091^{*}
	(0.024)	(0.024)	(0.022)	(0.026)	(0.028)	(0.030)
Num_TPS_in_District	-0.003^{***}	-0.004^{***}	-0.003^{***}	-0.001^{*}	-0.001	-0.002^{*}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Num_Alt_Schools_in_District	0.002	0.005***	0.006***	0.001**	0.001**	0.002***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
(Intercept)	1.550***	1.686***	1.901***	1.731***	1.706***	1.569***
	(0.038)	(0.039)	(0.036)	(0.024)	(0.026)	(0.027)
Pseudo \mathbb{R}^2	0.201	0.197	0.186	0.387	0.299	0.142
Log Likelihood	4836.871	5301.617	7573.832	6275.158	6396.476	6355.366
Num. obs.	7211	7211	7208	7875	7875	7875

Table 7: Racial Integration Models (No HLM)

	Texas			California		
	10mi	5mi	2mi	10mi	5mi	2mi
Charter Effects						
Charter	0.291^{***}	0.337^{***}	0.440***	0.204***	0.242^{***}	0.326***
	(0.062)	(0.062)	(0.065)	(0.038)	(0.038)	(0.039)
Charter:Academic_Performance	-0.264^{***}	-0.276^{***}	-0.254^{***}	-0.252^{***}	-0.250^{***}	-0.244^{**}
	(0.026)	(0.026)	(0.027)	(0.023)	(0.024)	(0.024)
Charter:Pop_Dens	-0.075^{***}	-0.075^{***}	-0.085^{***}	-0.031^{***}	-0.023^{***}	-0.024^{**}
	(0.019)	(0.019)	(0.020)	(0.006)	(0.006)	(0.006)
Controls						
Academic_Performance	0.488***	0.457^{***}	0.413***	0.734^{***}	0.695***	0.653^{**}
	(0.009)	(0.009)	(0.009)	(0.013)	(0.013)	(0.013)
Dual_Language	-0.055	-0.023	-0.033	0.134	0.236^{**}	0.181^{*}
	(0.046)	(0.045)	(0.047)	(0.084)	(0.086)	(0.086)
Total_Enrollment	0.025^{***}	0.020^{***}	0.016^{***}	0.012^{***}	0.011^{***}	0.011^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Pop_Dens	-0.000	0.002	0.013^{*}	-0.009^{**}	-0.005	-0.004
	(0.006)	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)
White_pct	0.010^{***}	0.009^{***}	0.009^{***}	0.013^{***}	0.013^{***}	0.012^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
ELL	-1.083^{***}	-0.865^{***}	-0.537^{***}	-1.309^{***}	-1.025^{***}	-0.497^{**}
	(0.046)	(0.046)	(0.048)	(0.058)	(0.058)	(0.059)
KIPP	-0.488^{***}	-0.442^{***}	-0.308^{**}	-0.790^{***}	-0.716^{***}	-0.657^{**}
	(0.116)	(0.113)	(0.120)	(0.119)	(0.119)	(0.120)
$School_TypeElementaryHighMiddle$	-0.166^{***}	-0.167^{***}	-0.326^{***}	-0.571^{***}	-0.549^{***}	-0.417^{*}
	(0.046)	(0.045)	(0.046)	(0.060)	(0.060)	(0.062)
${\it School_TypeElementaryMiddle}$	0.095^{*}	0.063	0.028	-0.217^{***}	-0.206^{***}	-0.226^{**}
	(0.042)	(0.042)	(0.044)	(0.018)	(0.018)	(0.018)
School_TypeHigh	-0.077^{**}	-0.015	0.064^{*}	-1.483^{***}	-1.378^{***}	-1.262^{*}
	(0.026)	(0.025)	(0.027)	(0.034)	(0.034)	(0.035)
School_TypeHighMiddle	-0.217^{***}	-0.186^{***}	-0.126^{*}	-1.064^{***}	-0.964^{***}	-0.919^{*}
	(0.048)	(0.047)	(0.049)	(0.052)	(0.053)	(0.053)
School_TypeMiddle	0.069***	0.075^{***}	0.104^{***}	-0.921^{***}	-0.860^{***}	-0.805^{**}
	(0.019)	(0.018)	(0.019)	(0.026)	(0.027)	(0.027)
Num_TPS_in_District	-0.000	-0.001	-0.001	-0.002^{***}	-0.001^{*}	-0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Num_Alt_Schools_in_District	-0.002	0.000	0.001	0.002***	0.001*	0.001
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
(Intercept)	0.560***	0.580***	0.525^{***}	1.152^{***}	1.058^{***}	0.931***
(····································	(0.027)	(0.026)	(0.027)	(0.036)	(0.036)	(0.036)
Pseudo R ²	0.559	0.527	0.466	0.609	0.583	0.537
Log Likelihood	5656.700	5711.882	5380.754	6025.946	5960.686	5745.011
Num. obs.	7211	7211	7211	7875	7875	7875

Table 8:	SES	Integration	Models ((No HLM)
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