School Racial Segregation and Access to High Growth Schools

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Racial and economic segregation have potentially large implications for individuals' life chances and for the intergenerational transmission of social inequalities. Persistent segregation exposes children from different social backgrounds to quite different environmental contexts, which have implications for developmental and adult outcomes (Harding 2003, Sharkey and Faber 2014). One prominent hypothesized mechanism through which segregation generates social inequalities is through differential access to school quality. In the United States, residential segregation drives continued school segregation, which may redound to the benefit of students in more advantaged communities, given local control (including funding) of schooling and local attendance patterns (Vigdor and Ludwig 2008). Indeed, persistent school segregation can be viewed as a form of opportunity hoarding by advantaged social actors (Fiel 2013).

There is clear evidence linking school segregation to school characteristics, but the link between segregation and school quality or opportunities to learn is less clear. For instance, segregation is tied to disparities in a variety of measured school-based resources, but these resources are not consistently strong predictors of student achievement (Coleman et al. 1966, Hanushek 1997). Furthermore, although school attendance patterns lead disadvantaged students to attend substantially lower-achieving schools (Logan, Minca and Adar 2012), average achievement scores are poor indicators of schools' contribution to student learning, as they mix differences in the quality of schooling with differences in non-school factors that affect student achievement (Downey, von Hippel and Hughes 2008). Therefore, it is unclear to what extent segregation drives disparities in the opportunities to learn that schools provide.

It is even less clear how we might address such disparities. The political will for widespread desegregation has faded, and even where it persists the local autonomy of the American educational system relegates such efforts to the district level. This is problematic given that segregation is increasingly a between-district phenomenon (Clotfelter 2004, Fiel 2013, Reardon, Yun and Eitle 2000). An alternative is to eliminate disparities in opportunities that are linked to segregation. But given the difficulties in measuring school quality, we know little about the extent of these disparities, let alone where they are located in our school system.

This paper elaborates the "geography of inequality" (Logan, Minca and Adar 2012) by addressing these shortcomings. We use data from California public elementary schools to measure school quality using cohort achievement growth profiles rather than average achievement levels. We then assess the degree of inequality in these growth profiles across schools, both between and within social groups, and decompose these disparities across organizational (i.e., school districts) and geographic (metropolitan areas, counties) space. This better describes how economic and racial-ethnic segregation shape exposure to school-based opportunities to learn, and it better informs efforts to address these disparities.

We find that exposure to high-growth schools represents a unique dimension of the consequences of school attendance, above and beyond the documented disparities in access to high-achieving schools. In contrast to levels of achievement, disparities in exposure to school growth largely occur within rather between school districts.

Background

The question motivating this paper is: to what extent does school segregation consign poor and minority students to lower quality schools? While there is large body of literature linking racial attendance patterns to inequality in student outcomes (Berends, Lucas and Peñaloza 2008, Hanushek, Kain and Rivkin 2009, Mickelson, Bottia and Lambert 2013), explanations for this link are elusive. The most obvious culprit is inequality in opportunities to learn. Several studies link school racial composition to school resources (Clotfelter, Ladd and Vigdor 2005, Condron and Roscigno 2003, Jackson 2009, Lankford, Loeb and Wyckoff 2002), but this explanation is complicated by the fact that observable differences in school resources explain very little of the development of racial achievement gaps (Condron 2009).

An alternative is to capture opportunities to learn indirectly using measures of student learning as a proxy. For instance, a recent paper documents the drastic differences between average test scores in schools attended by white and non-white students (Logan, Minca and Adar 2012). However, absolute levels of achievement are poor measures of school quality in terms of contribution to student learning; many schools ostensibly failing (or succeeding) according to average achievement levels vary widely in both the amount of material students learn throughout the year and when school is in session, which are more plausible measures of schools' contributions to student learning (Downey, von Hippel and Hughes 2008).

How might a growth-based measure of school quality be related to segregation? We identify two theoretical possibilities. First, school segregation may be a mechanism by which groups compete over true opportunities to learn (e.g., the best learning environments and the best teachers), in which case we would expect whites and non-poor students to be overrepresented and minorities and poor to be underrepresented in high-growth schools. Under this opportunity hoarding scenario, inequality in exposure to school effectiveness may be as great or greater than inequality in exposure to high-achieving schools or school resources.

Alternatively, school segregation may not be related to school growth at all. For instance, advantaged actors may simply value maintaining social distance from out-groups rather than monopolizing resources that actually promote learning—in other words, segregation could be more about hoarding status than learning opportunities. Even if segregation is about hoarding learning opportunities, parents may only have access to information about weak indicators of school quality. If so, advantaged groups' efforts to hoard better schools may lead to sorting with respect to proxies like resources or school composition that are poor predictors of schools' contribution to learning. Under this scenario, racial inequality in exposure to school quality may be much smaller than inequality in exposure to high-achieving schools or school resources.

Another issue that has been prominent in segregation research is the importance of geographic and organizational boundaries. For one, it is useful to disentangle large-scale dispersion of groups that stem from demographic processes from the smaller-scale, local imbalances that stem from the sorting processes that we think of when we consider segregation (Fiel 2013, Logan 2004). Desegregation across states or different metropolitan areas, for example, seems misguided and impractical. For another, understanding the scale and location of segregation is critical to addressing it through policy (Reardon et al. 2008). The most salient finding with respect to racial segregation has been the drastic shift away from within-district segregation to between-district segregation that arose amid mandatory desegregation (Clotfelter 2004). There is a similar story for large-scale economic segregation amid suburbanization and growing income inequality in recent decades (Reardon and Bischoff 2011). These shifts effectively moved segregation to a larger scale and presented legal barriers to further progress given the local autonomy and power of school districts. Other boundaries such as the private-public sector divide or the distinction of charter from traditional public schools create similar avenues of segregation and barriers to desegregation.

It is equally important to attend to these geographic and organizational boundaries when considering the consequences of segregation for learning opportunities or disparities in school quality more generally. Although large-scale geographic imbalances in racial composition may not constitute segregation or be amenable to desegregation policy, corresponding disparities in school quality could still contribute to inequality in opportunities to learn and be addressed through state or federal policies. Recent state-level school finance reforms are one such example (Card and Payne 2002). Similarly, organizational disparities in school quality constitute an important aspect of any explanation of the consequences of segregation and efforts to mitigate these consequences. We are particularly attuned to district-level disparities given the well-documented disparities in economic resources and racial segregation at this level (Walters 2001).

Data/Methods

To characterize achievement levels and growth for a large and diverse population of schools, we collect achievement and demographic data for public elementary schools in California. We focus on elementary schools, where between-school segregation is likely to be greatest; there are a greater number of smaller elementary schools than middle or high schools, and attendance at this level is most closely related to residential location. We focus on the years 1998-2002, when students were tested in consecutive grades and years on a vertically equated test, and when we can link school information to geographic information from the 2000 Census. We also merge school-level information from the National Center for Education Statistics' Common Core of Data.

Sample

We use data from approximately 53,000 yearly aggregate mathematics scores for over 15,000 cohort groups in 4435 public elementary schools in California in grades 2-5 between 1997 and 2002. Schools were included in the sample if they met the following criteria based on information in the Common Core of Data: public schools (excluding home school and home bound educational entities), enrolled students in grades including 2-5, operated in each year between 1997-08 to 2001-02, and enrolled at least 10 students in a focal cohort. Within these schools, cohort-year observations contribute to school learning estimates, as described below, if they include at least 10 valid test scores, and therefore mean cohort achievement is publically reported. Sample descriptives for the measures reported below, are presented in Table 1.

Measures

Cohort achievement is measured as the mean mathematics scale score in each grade and year on the Stanford Achievement Test, Version 9, Form T (SAT9).[1] The SAT9 is a multiple choice, nationally normed assessment, administered in the spring of each school year between 1997-98 and 2001-02 to students in grades 2-11. Scale scores are vertically equated across grades and years, facilitating measures of average achievement growth over time. Additional information about the testing procedures and is available at the California Department of Education Standardized Testing and Reporting website (http://star.cde.ca.gov/).

Estimates of School Achievement Growth

We construct a measures of school-level initial achievement and growth, based on the following 3-level cohort growth model of observed mean achievement for cohort *c* in school *s* for year *i*:

Level 1 (cohort-year):

$$y_{sci} = \pi_0 + \pi_1(grade_{sci}) + \pi_2(year_{sci}) + \varepsilon_{sci}$$

Level 2 (cohort):

$$\pi_0 = \beta_{00} + u_{0c}$$

$$\pi_1 = \beta_{10}$$

Level 3 (school):

$$\beta_{00} = \gamma_{000} + u_{00s}$$

[1] Students also took SAT9 tests in English language arts areas. We focus on mathematics outcomes because mathematics skills may be more sensitive to schooling inputs than language development, which may be relatively more influenced by home factors.

$$\beta_{10} = \gamma_{100} + u_{10s}$$

Variance components:

$$\varepsilon_{sci} \sim N(0.\sigma)$$

$$u_{0c} \sim N(0, \sigma_{0c})$$

$$\binom{u_{0s}}{u_{1s}} \sim N\left(0, \begin{matrix} \sigma_{00s} & \rho_{01} \\ \rho_{01} & \sigma_{10s} \end{matrix}\right)$$

In this model, observed achievement at any point in time is a function of initial achievement, growth from grade to grade, and a secular trend over time (reflecting increasing achievement over time). Average initial achievement at the end of grade 2 is represented by the parameter γ_{000}, and initial achievement is allowed to vary randomly by the cohort (u_{0c}) and school level (u_{00s}). Annual achievement growth over time is paramenterized as linear, with average growth of γ_{100} and random variation in growth at the school-level (u_{10s}). Supplementary analyses provided no evidence of either non-linear average trajectories or random variation in achievement trajectories between cohorts within schools. All variance terms are assumed to be normally distributed with mean zero and uncorrelated with one another, except the intercept and slope random effects at the school level, which are allowed to covary with one another.

Our substantive interest is on the school-level parameters representing average initial achievement and average yearly growth. We calculate the best linear unbiased predictors of both values for each school: (1) average initial (2nd grade) achievement ($\hat{\gamma}_{000} + \hat{u}_{00s}$) and (2) average yearly achievement growth from 2nd to 5th grade ($\hat{\gamma}_{100} + \hat{u}_{10s}$).

Levels and growth capture potentially distinct aspects of school qualities. Achievement levels in grade 2 are largely influenced by students' prior preparation for school, and is likely a poor proxy for school quality (although it may reflect school influences on students in the early elementary grades). Yearly achievement growth is a more direct measure of the learning that occurs while students are in school.[2] These two achievement measures are not independent of one another, however. Figure 1 represents the systematic negative correlation between these two measures, such that schools with initially lower-scoring students tend to see larger achievement gains over time.

Analyses

In our first set of analyses, we model estimated school average initial levels of achievement and achievement growth as a function of school demographic characteristics. Based on previous research, we expect to find greater proportions of minority and poor students to predict lower levels of absolute achievement. However, there are two competing hypotheses about the association between growth and student demographics. The opportunity hoarding hypothesis implies a similar social gradient for growth as for levels. However, the neutral hypothesis predicts no disparities in growth, or less pronounced disparities than for levels.

In a second set of analyses, we decompose school quality measures across levels of educational organization and student groups. We use the Theil Index (Theil 1972) to

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[2] Two notable limitations of these achievement growth measures are: that social background differences (rather than school effects) may also contribute to students' learning over time, perhaps especially so in the summer learning, and that we cannot separate out the influence of changes in the student population at a school due to mobility.

measure inequality in achievement levels, growth, and residual growth that accounts for differences in starting points. This index has the desirable properties shared by many inequality measures, but it is particularly useful because it is additively decomposable (Allison 1978).[3] We first calculate overall between-school inequality in each indicator of quality using the following equation, where n_i and q_i indicate school *i*'s enrollment and measured quality, respectively, N indicates total enrollment, and $\bar{q}$ indicates average school quality in the sample (weighted by enrollment).

$$T = \sum_{i=1}^{N} \frac{n_i}{N} \frac{q_i}{\bar{q}} \ln \frac{q_i}{\bar{q}}$$

We then decompose overall inequality geographically as follows, with the first quantity capturing disparities in quality between metropolitan areas (or non-metropolitan counties) m, and the second capturing the sum of between-school disparities within these areas. Next we decompose the within-area component into between- and within-district components in the same manner.

$$T = \underbrace{\sum_{m=1}^{M} \frac{N_m}{N} \frac{\bar{q}_m}{\bar{q}} \ln\left(\frac{\bar{q}_m}{\bar{q}}\right)}_{\text{between-msa}} + \underbrace{\sum_{m=1}^{M} \sum_{i=1}^{N} \frac{n_{im}}{N} \frac{q_{im}}{\bar{q}} \ln\left(\frac{q_{im}}{\bar{q}_m}\right)}_{\text{within-msa}}$$

[3] A weakness of this measure is that it assumes the variable has a theoretically meaningful zero point and is on a ratio scale. When this assumption is violated, the measure may be sensitive to arbitrary changes in the scale. Although our achievement level and growth measures are unlikely to satisfy this assumption, our results are robust to a variety of transformations.

To assess racial inequality, we use a similar decomposition that partitions overall inequality into that between racial/ethnic groups and within those groups. We distinguish the five groups delineated in the data: American Indian, Asian, black, Hispanic, and white. The decomposition is shown below, with groups indexed by *r*. The first component captures between-group inequality and the second captures within-group inequalities.

$$T = \underbrace{\sum_{r=1}^{R} \frac{N_r}{N} \frac{\bar{q}_r}{\bar{q}} \ln\left(\frac{\bar{q}_r}{\bar{q}}\right)}_{\text{between-race}} + \underbrace{\sum_{r=1}^{R} \sum_{i=1}^{N} \frac{n_{ir}}{N} \frac{q_{ir}}{\bar{q}} \ln\left(\frac{q_{ir}}{\bar{q}_r}\right)}_{\text{within-race}}$$

Each of these components can be decomposed geographically and organizationally. Decomposing the within-group component follows the same logic as above, yielding the following.

$$T = \underbrace{\sum_{r=1}^{R} \sum_{m=1}^{M} \frac{N_{rm}}{N} \frac{\bar{q}_{rm}}{\bar{q}} \ln\left(\frac{\bar{q}_{rm}}{\bar{q}_r}\right)}_{\text{within-race, between-msa}} + \underbrace{\sum_{r=1}^{R} \sum_{m=1}^{M} \sum_{i=1}^{N} \frac{n_{irm}}{N} \frac{q_{irm}}{\bar{q}} \ln\left(\frac{q_{irm}}{\bar{q}_{rm}}\right)}_{\text{within-race, within-msa}}$$

Decomposing the between-group decomposition is a bit more complicated. Shown below, the first two components capture between-race, between-area inequality (total between-area inequality minus within-race between-area inequality). The third captures between-race, within-area inequality. The latter is further decomposed into between-and within-district inequality in a similar manner.

$$T = \underbrace{\sum_{r=1}^{R} \sum_{m=1}^{M} \frac{N_{rm}}{N} \frac{\bar{q}_{rm}}{\bar{q}} \ln\left(\frac{\bar{q}_m}{\bar{q}}\right)}_{\text{between-msa}} - \underbrace{\sum_{r=1}^{R} \sum_{m=1}^{M} \frac{N_{rm}}{N} \frac{\bar{q}_{rm}}{\bar{q}} \ln\left(\frac{\bar{q}_{rm}}{\bar{q}_r}\right)}_{\text{between-msa, within-race}} + \underbrace{\sum_{r=1}^{R} \sum_{m=1}^{M} \frac{N_{rm}}{N} \frac{\bar{q}_{rm}}{\bar{q}} \ln\left(\frac{\bar{q}_{rm}}{\bar{q}_m}\right)}_{\text{within-msa, between race}}$$

Comparing the results of these calculations and decompositions for the school achievement level and growth measures not only speaks to the opportunity hoarding hypothesis, but also identifies the levels at which disparities in opportunities to learn are concentrated.

Results

Student Composition and School Achievement Levels and Growth

Estimates from models of school achievement levels by demographic characteristics are presented in Table 2. Disparities are present in grade 2, when students were first tested, for schools with more American Indian, African American, and Hispanic students. Unconditional differences (Model 1) are quite large. A standard deviation increase in the proportion of African American students in a school predicts initial achievement of 7.1 (=0.124*-57.6) fewer scale score points, corresponding to about a third of a standard deviation in achievement levels among schools. These racial disparities are about half as large net of school poverty, but remain statistically significant and substantively important (Model 2). The predictive effects of school poverty (as indicated by eligibility for free or reduced lunch), controlling for racial demographics, are also quite large. Finally, the disadvantages associated with minority and poor student populations seem to be additive; there is little evidence of interactions between these effects in predicting achievement.

In short, these results replicate previous research that demonstrates that schools serving higher proportions of poor and many racial minority groups are lower achieving. These differences are apparent at the first standardized test administration in elementary schools, which highlights that they may not be due to school influences so much as systematic differences in academic preparedness between schools. A natural question is whether there are similar demographic disparities in access to high-growth schools.

Results from models predicting growth are presented in Table 3. Model 1 suggests only small differences in average growth by racial composition; only the estimated association for African American students is significant, and it is substantively small, amounting to at most a single scale score point in yearly growth. However, Model 2 reveals that initial achievement is a suppressor variable in this context. After controlling for where school achievement starts out, there are large gaps in learning at schools serving Native American, African American, and Hispanic students. Paralleling results above, these effects are smaller but still important net of school poverty, which is an especially strong predictor of lower growth, even net of racial composition (Model 3). Finally, there is only mixed evidence of interactions between school racial composition and poverty. Interaction estimates (Model 4) imply less negative predictive effects for Native Americans and Hispanic student shares at schools with high poverty. By contrast, negative associations for African American and poor students are additive, implying double disadvantage at poor, black schools.

The magnitude of all of these differences can be interpreted relative to average yearly growth in mathematics knowledge in the cohort growth model, which is 22.5 scale score points. A standard deviation increase in the share of African American students is associated with a different starting point of a third of year less mathematics knowledge (0.317=[0.124*-57.6)/22.5]). However, the comparable gap in overall growth is less than one percent of average yearly learning (0.006=[0.124*-1.03)/22.5]); the disparity net of initial achievement amounts to 4% of a years' worth of learning (0.040=[0.124*-7.21)/22.5]). Assuming a 40 week school year, this implies a difference in learning opportunities that translate to a week and half of typical learning.

In short, this set of results reveals disparities in exposure to achievement growth that are weaker but in the same direction as those for achievement levels, at least controlling for initial achievement. To the extent that attendance at a high growth school represents particular educational opportunities, this suggests that racial and economic segregation contribute to disparities in this resource independent of sorting related only to achievement levels. We now turn to decomposing differences in school achievement growth by social group and level of educational organization.

Decomposing School Achievement Levels and Growth

Table 4 summarizes results for the decompositions of inequality in achievement levels.[4] The decomposition of overall inequality shows that 90 percent of inequality lies within metropolitan areas or counties, with only 10 percent between these areas. Of the within-area inequality, about half lies between districts and half lies within districts. A significant portion of overall inequality—22 percent—is between racial/ethnic groups. Of between-race inequality, over 96 percent is within metro areas/counties, and about two-thirds of this lies between districts. In comparison, within-race inequality is less concentrated within metropolitan areas and counties, and the majority of within-area

[4] For all decomposition analyses, we present only results by racial group. Results for decompositions by free/reduced price lunch status are very similar.

inequality lies within school districts. These results are consistent with the notion that segregation at local levels, and most prominently between districts, creates disparities in opportunities to learn.

The decomposition of inequality in achievement growth, however, suggests a different story (Table 5). The overall degree of inequality is similar to that measured for achievement levels, but more of this inequality is concentrated within metropolitan areas/counties and school districts. That is, it is more of a small-scale phenomenon. More importantly, it is almost entirely a within-race phenomenon. Less than one percent of disparities in school growth lie between racial/ethnic groups. And what little between-race inequality exists lies within school districts rather than between them.

These results accord with those from the multilevel models, but those models also suggested racial disparities in growth rates after accounting for schools' initial achievement levels.[5] We find interesting patterns in the decompositions of inequality in these residual growth rates, which are summarized in Table 6. The overall degree of inequality in residual growth and its concentration within metropolitan areas/counties and school districts resembles that of the overall growth measure. Similarly, most inequality in residual growth is within racial/ethnic groups, and most of this is concentrated within school districts. However, the 6 percent of inequality in residual growth that lies between groups is notably higher than for overall growth, and almost two-thirds of this lies between school districts.

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[5] We calculate residual growth as the residual from a regression of observed achievement growth on initial achievement level.

Discussion

Despite a vast literature linking segregation to educational inequality (Vigdor and Ludwig 2008), we know little about the mechanisms behind this link. We often assume that segregation creates or accompanies disparities in opportunities to learn—disadvantaged groups attend less effective schools and thus learn less than their more advantaged peers. Because observable school-based resources tend to be poor predictors of achievement, we use measures of achievement growth,—which ostensibly capture schools' contributions to learning—as proxies for school-based opportunities to learn. Racial inequality in these opportunities can only exist as a result of racial school segregation. We analyze the magnitude of these disparities among California elementary schools as well as their distribution across geographic and organizational space.

The stark differences across our measures of school quality indicate that the implications of segregation for opportunities to learn depend on how school quality is assessed. Although segregation, particularly between districts, is linked to disparities in schools' average achievement levels, it is not linked to disparities in schools' average achievement trajectories. But when we compare schools with similar starting points, segregation—again mainly between districts—is related to disparities in achievement growth.

The large racial disparities in achievement levels are likely driven by a combination of two factors that are not directly caused by school segregation. First, a variety of family background factors likely affect children's learning as well as their residential locations and school attendance. Second, residential segregation may have effects on children's developmental and academic outcomes that operate independently of school experiences.

The lack of disparities in overall growth indicate that children of different racial/ethnic groups attend schools that contribute to similar academic progress over time. Yet schools that start with lower baseline levels tend to have faster achievement growth—it may be easier for schools to improve achievement test scores when students have more room to improve. The emergence of racial disparities in growth after accounting for baseline achievement levels suggests that school segregation does promote inequality in learning opportunities, albeit to a lesser extent than average achievement levels would indicate. Reducing these inequalities will require large-scale policies to improve struggling schools and school districts.

Nonetheless, most inequality in all of these school quality measures lies within racial/ethnic groups and within school districts—this is particularly true for growth-based measures. Therefore, our results suggest the continued importance of within-district policies focusing on struggling schools to reduce disparities in opportunities to learn experienced by all students.

Citations

Allison, Paul D. 1978. "Measures of Inequality." *American Sociological Review* 43(6):865-80. doi: Doi 10.2307/2094626.

Berends, Mark, Samuel R. Lucas and Roberto V. Peñaloza. 2008. "How Changes in Families and Schools Are Related to Trends in Black-White Test Scores." *Sociology of Education* 81(4):313-44.

Card, David and A. Abigail Payne. 2002. "School Finance Reform, the Distribution of School Spending, and the Distribution of Student Test Scores." *Journal of Public Economics* 83(1):49-82. doi: Doi 10.1016/S0047-2727(00)00177-8.

Clotfelter, C. T., H. F. Ladd and J. Vigdor. 2005. "Who Teaches Whom? Race and the Distribution of Novice Teachers." *Economics of Education Review* 24(4):377-92. doi: 10.1016/j.econedurev.2004.06.008.

Clotfelter, Charles T. 2004. *After Brown: The Rise and Retreat of School Desegregation*. Princeton, NJ: Princeton University Press.

Coleman, James S., Ernest Q. Campbell, Carol J. Hobson, James M. McPartland, Alexander M. Mood, Frederic D. Weinfeld and Robert L. York. 1966. "Equality of Educational Opportunity." Vol. Washington, DC: U.S. Dept. of Health, Education, and Welfare, Office of Education.

Condron, D. J. 2009. "Social Class, School and Non-School Environments, and Black/White Inequalities in Children's Learning." *American Sociological Review* 74(5):683-708.

Condron, Dennis J. and Vincent J. Roscigno. 2003. "Disparities Within: Unequal Spending and Achievement in an Urban School District." *Sociology of Education* 76(1):18-36.

Downey, Douglas B., Paul T. von Hippel and Melanie Hughes. 2008. "Are 'Failing' Schools Really Failing? Using Seasonal Comparison to Evaluate School Effectiveness." *Sociology of Education* 81:242-70.

Fiel, Jeremy E. 2013. "Decomposing School Resegregation: Social Closure, Racial Imbalance, and Racial Isolation." *American Sociological Review* 78(5):828-48. doi: 10.1177/0003122413496252.

Hanushek, Eric A. 1997. "Assessing the Effects of School Resources on Student Performance: An Update." *Educational Evaluation and Policy Analysis* 19(2):141-64. doi: 10.3102/01623737019002141.

Hanushek, Eric A., John F. Kain and Steven G. Rivkin. 2009. "New Evidence About Brown V. Board of Education: The Complex Effects of School Racial Composition on Achievement." *Journal of Labor Economics* 27(3):349-83.

Harding, D. J. 2003. "Counterfactual Models of Neighborhood Effects: The Effect of Neighborhood Poverty on Dropping out and Teenage Pregnancy." *American Journal of Sociology* 109(3):676-719.

Jackson, C. Kirabo. 2009. "Student Demographics, Teacher Sorting, and Teacher Quality: Evidence from the End of School Desegregation." *Journal of Labor Economics* 27(2):213-56.

Lankford, H., S. Loeb and J. Wyckoff. 2002. "Teacher Sorting and the Plight of Urban Schools: A Descriptive Analysis." *Educational Evaluation and Policy Analysis* 24(1):37-62.
Logan, John R. 2004. "Resegregation in American Public Schools? Not in the 1990s." Vol. Albany, NY: Lewis Mumford Center for Comparative Urban and Regional Research, University at Albany.
Logan, John R., Elisabeta Minca and Sinem Adar. 2012. "The Geography of Inequality: Why Separate Means Unequal in American Public Schools." *Sociology of Education* 85(3):287-301. doi: 10.1177/0038040711431588.
Mickelson, Roslyn Arlin, Martha Cecilia Bottia and Richard Lambert. 2013. "Effects of School Racial Composition on K-12 Mathematics Outcomes: A Metaregression Analysis." *Review of Educational Research* 83(1):121-58. doi: 10.3102/0034654312475322.
Reardon, Sean F., John T. Yun and Tamela Mcnulty Eitle. 2000. "The Changing Structure of School Segregation: Measurement and Evidence of Multiracial Metropolitan-Area School Segregation, 1989-1995." *Demography* 37(3):351-64.
Reardon, Sean F., Stephen A. Matthews, David O'Sullivan, Barrett A. Lee, Glenn Firebaugh, Chad R. Farrell and Kendra Bischoff. 2008. "The Geographic Scale of Metropolitan Racial Segregation." *Demography* 45(3):489-514.
Reardon, Sean F. and Kendra Bischoff. 2011. "Income Inequality and Income Segregation." *American Journal of Sociology* 116(4):1092-153.
Sharkey, Patrick and Jacob W. Faber. 2014. "Where, When, Why, and for Whom Do Residential Contexts Matter? Moving Away from the Dichotomous Understanding of Neighborhood Effects." *Annual Review of Sociology, Vol 40* 40:559-79. doi: 10.1146/annurev-soc-071913-043350.
Theil, Henri. 1972. *Statistical Decomposition Analysis: With Applications in the Social and Administrative Sciences*. Amsterdam: North-Holland
Vigdor, Jacob and Jens Ludwig. 2008. "Segregation and the Test Score Gap." Pp. 181-211 in *Steady Gains and Stalled Progress: Inequality and the Black-White Test Score Gap*, edited by K. A. Magnuson and J. Waldfogel. New York: Russell Sage Foundation.
Walters, Pamela Barnhouse. 2001. "Educational Access and the State: Historical Continuities and Discontinuities in Racial Inequality in American Education." *Sociology of Education* 74:35-49. doi: 10.2307/2673252.

Tables and Figures

Table 1. Characteristics of the Analytic Sample (N = 4381 schools)

	Mean	SD	Min	Max
% Free Lunch	0.526	0.298	0.000	0.978
% American Indian	0.011	0.036	0.000	0.918
% Asian	0.110	0.137	0.000	0.899
% African American	0.084	0.124	0.000	0.960
% Hispanic	0.397	0.287	0.003	1.000
% White	0.394	0.292	0.000	0.981
Total Enrollment	620.6	270.7	27.4	2588.2
Initial Achievement	524.1	20.9	450.1	589.0
Yearly Growth	22.5	2.3	11.4	32.6

Table 2. Estimates from Multilevel Models Predicting Initial Achievement

	Model 1	Model 2	Model 3
Intercept	549.46	551.51	553.49
	(0.74)*	(0.63)*	(0.93)*
% American Indian	-85.17	-37.11	-71.11
	(6.88)*	(6.27)*	(21.15)*
* % FRL			47.06
			-27.2
% Asian	0.56	14.2	15.85
	-2.06	(1.92)*	(3.01)*
* % FRL			-3.72
			-5.36
% African American	-57.63	-24.35	-20.65
	(2.00)*	(2.17)*	(5.57)*
* % FRL			-3.51
			-7.23
% Hispanic	-59.67	-19.13	-29.97
	(1.03)*	(1.66)*	(3.00)*
* % FRL			13.86
			(3.46)*
% FRL		-39.48	-42.2
		(1.40)*	(2.17)*
Variance Estimates			
District	158.62	83.16	80.82
	(12.48)*	(7.32)*	(7.21)*
School	115.64	105.11	104.85
	(2.75)*	(2.48)*	(2.48)*
Log likelihod	-17219.7	-16874.4	-16863
Parameters	7	8	12
AIC	34453.31	33764.79	33750.07
BIC	34498.01	33815.87	33826.69

* $p < 0.05$

Table 3. Estimates from Multilevel Models Predicting Average Yearly Achievement Growth

	Model 1	Model 2	Model 3	Model 4
Intercept	22.6	29.61	31.08	31.24
	(0.10)*	(0.15)*	(0.15)*	(0.17)*
% American Indian	1.42	-8.89	-3.1	-11.01
	-1.04	(0.85)*	(0.77)*	(2.69)*
* % FRL				10.64
				(3.50)*
% Asian	0.71	1.12	2.65	3.15
	-0.34	(0.27)*	(0.24)*	(0.39)*
* % FRL				-1.19
				-0.7
% African American	-1.03	-7.21	-3.95	-3.34
	(0.35)*	(0.29)*	(0.28)*	(0.74)*
* % FRL				-0.82
				-0.98
% Hispanic	0.16	-6.41	-2.16	-3.32
	-0.16	(0.17)*	(0.21)*	(0.40)*
* % FRL				1.38
				(0.48)*
% FRL			-5.69	-5.86
			(0.19)*	(0.30)*
Variance Estimates				
District	1.09	1.27	0.75	0.73
	-0.14	-0.13	(0.08)*	(0.08)*
School	4.26	2.21	1.92	1.91
	(0.10)*	(0.05)*	(0.04)*	(0.04)*
Control for Initial Achievement Level?	No	Yes	Yes	Yes
Log likelihod	-9635.01	-8345.8	-7958.29	-7946.36
Parameters	7	16	17	21
AIC	19284.02	16723.6	15950.58	15934.71
BIC	19328.71	16825.76	16059.12	16068.8

* p < 0.05

Table 4. Decomposition of Inequality in Achievement Levels

	Total	Between MSA	Within MSA	Between District	Within District
Overall	0.0115	0.0012	0.0104	0.0051	0.0053
Share of overall		10.23	89.77	43.92	45.85
Share of within-MSA				48.93	51.07
Between Race	0.0025	0.0001	0.0024	0.0016	0.0008
Share of overall	21.78	0.81	20.97	14.10	6.87
Share of between-race		3.72	96.28	64.73	31.55
Share of between-race within-MSA				67.23	32.77
Share of column		7.92	23.36	32.10	14.99
Within Race	0.0090	0.0011	0.0079	0.0034	0.0045
Share of overall	78.22	9.42	68.80	29.83	38.98
Share of within-race		12.04	87.96	38.13	49.83
Share of within-race within-MSA				43.35	56.65
Share of column		92.08	76.64	67.90	85.01

Table 5. Decomposition of Inequality in Achievement Growth

	Total	Between MSA	Within MSA	Between District	Within District
Overall	0.0104	0.0004	0.0100	0.0025	0.0075
Share of overall		4.18	95.82	24.13	71.69
Share of within-MSA				25.18	74.82
Between Race	0.0000	-0.0001	0.0001	0.0000	0.0001
Share of overall	0.22	-0.95	1.17	0.02	1.14
Share of between-race		-437.61	537.61	9.69	527.88
Share of between-race within-MSA				1.80	98.19
Share of column		-22.69	1.22	0.09	1.60
Within Race	0.0104	0.0005	0.0099	0.0025	0.0074
Share of overall	99.78	5.13	94.66	24.11	70.55
Share of within-race		5.14	94.86	24.16	70.70
Share of within-race within-MSA				25.47	74.53
Share of column		122.69	98.78	99.92	98.40

Table 6. Decomposition of Inequality in Residual Achievement Growth

	Total	Between MSA	Within MSA	Between District	Within District
Overall	0.0107	0.0007	0.0100	0.0031	0.0070
Share of overall		6.43	93.57	28.47	65.11
Share of within-MSA				30.42	69.58
Between Race	0.0006	0.0000	0.0006	0.0004	0.0002
Share of overall	6.04	0.33	5.71	3.64	2.07
Share of between-race		5.45	94.55	60.34	34.22
Share of between-race within-MSA				63.81	36.19
Share of column		5.12	6.10	12.80	3.17
Within Race	0.0101	0.0007	0.0094	0.0027	0.0068
Share of overall	93.96	6.10	87.86	24.82	63.04
Share of within-race		6.49	93.51	26.42	67.09
Share of within-race within-MSA				28.25	71.75
Share of column		94.88	93.90	87.20	96.83

Figure 1. Estimated School Average Yearly Growth and Initial Achievement