School Opportunity Hoarding? Racial Segregation and Access to High Growth Schools

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Abstract

Persistent school segregation may allow advantaged groups to hoard educational opportunities and consign minority students to lower quality educational experiences. Although minority students are concentrated in low-achieving schools, relatively little previous research directly links segregation to measures of school quality based on student achievement growth, which more plausibly reflect learning opportunities. Using a dataset of public elementary schools in California, this study provides the first analysis detailing the distribution of a growth-based measure of school quality using standard inequality indices, allowing disparities to be decomposed across geographic and organizational scales. We find mixed support for the school opportunity hoarding hypothesis. We find small White and Asian advantages in access to high-growth schools, but most of the inequality in exposure to school growth is within racial groups. Growth-based disparities both between and within groups tend to be on a more local scale than disparities in absolute achievement levels, focusing attention on within-district policies to mitigate school-based inequalities in opportunities to learn.

Keywords: segregation, race/ethnicity, school quality, achievement growth, opportunity hoarding

There is little doubt that segregation has hindered the life chances of racial/ethnic minorities and poor children and contributed to the intergenerational transmission of social inequality. Spatial processes generate disparate exposure to formative social environments for children, with important if complex consequences for educational attainment, health, and adult economic outcomes (Harding 2003; Sampson 2008; Sharkey 2013). Yet the specific mechanisms for these deleterious effects—and avenues to reduce them—remain a pressing area of research (Sharkey and Faber 2014).

As a formative and traditionally local institution, schools figure prominently in explanations of these spatial stratification processes, but the potential mechanisms of school segregation effects—compositional effects, resource disparities, etc.—are also poorly understood (Reardon and Owens 2014). A common perspective is that segregation consigns minority and poor students to schools with relatively few educational opportunities (e.g., Bankston and Caldas 1996; Roscigno 1998; Condron et al. 2013; Mickelson 2015). On this view, school segregation is a means for advantaged groups to hoard school-based educational opportunities (Tilly 1998), and the distribution of access to high quality schools is therefore a crucial mechanism of educational inequality. For instance, based on analyses of predictors of early Black-White educational inequalities, Fryer and Levitt (2004:461) speculate that Black students lose ground "because they attend lower quality schools" and Condron (2009:699) posits that racial segregation is the "leading culprit" for school influences on achievement inequality.

Despite the prominence of the opportunity hoarding perspective, surprisingly little evidence directly links segregation—the distribution of students across schools—to inequality in the quality of school-based opportunities. Doing so requires separating "school quality," how schools promote learning, from "student quality," the student characteristics (high achievement, high status background, etc.) valued by our society (see Wells and Crain 1992). Yet to the extent that segregation research has addressed school quality, it has tended to focus on indicators that are more related to student characteristics (race, SES, achievement levels) or schools' material resources (per pupil expenditures) than the quality of learning opportunities at school. Conversely, school effects research identifies important differences in learning opportunities across schools but has not detailed how these opportunities are distributed within and between social groups.

It is also important to consider the scale at which segregation is linked to school quality disparities. School desegregation efforts and many other education policies have typically been implemented within fairly autonomous local school districts, but segregation is increasingly located between districts (Clotfelter 2004; Reardon, Yun, and Eitle 2000). If larger-scale segregation contributes to inequality, then broader approaches to equalizing opportunity are required (e.g., Card and Payne 2002).

In this paper, we provide a new direct test of the *school opportunity hoarding hypothesis*, the notion that segregation consigns minority students to lower quality school experiences. We provide the first application of standard inequality indices to measures of school quality based on student achievement growth. We characterize the magnitude of between- and within-race disparities in this measure of school quality; decompose these disparities across organizational (district) and geographic (metropolitan area or county) scales; and contrast these results with those using a naïve achievement level-based indicator of school quality. These analyses have important theoretical and practical implications for understanding and rectifying spatial inequalities in our society amid a shifting landscape of school segregation and education policy.

School Segregation, Educational Opportunities, and Stratification

Segregation remains a troubling feature of the American educational system. Decades of declining school segregation gave way to stagnation in the 1990s amid a rollback of desegregation policy (Clotfelter 2004; Logan, Oakley, and Stowell 2008; Reardon and Owens 2014). Racial achievement gaps have followed similar patterns (Berends, Lucas, and Peñaloza 2008; Lee 2002), leading to speculation about segregation's role in achievement inequality. Student-level studies support a link between minority racial isolation and achievement inequality (Billings, Deming, and Rockoff 2014; Hanushek, Kain, and Rivkin 2009; Mickelson 2015; Mickelson, Bottia, and Lambert 2013; Vigdor and Ludwig 2008), a link commonly attributed to segregation consigning students from disadvantaged backgrounds to low-quality schools.

Drawing on Tilly's (1998) framework, we refer to the view that advantaged social groups maintain educational advantages through segregation as the *school opportunity hoarding hypothesis*. An implication is that the racial and economic disparities stemming from residential segregation could be ameliorated by equalizing the distribution of school quality, despite the rollback of desegregation efforts. An alternate explanation for the association between school composition and student achievement is that the sources of these disparities operate independently of school quality. Many sources of racial and economic segregation—such as economic disparities, discrimination, and housing preferences—may affect children in ways that are not be mediated by schools at all. These factors make it difficult to isolate the consequences of school segregation (Reardon and Owens 2014), and they likely lead typical proxies for school quality—such as those based on average achievement levels—to overstate disparities related to school composition (Downey, von Hippel, and Hughes 2008).

Therefore, although we can clearly map many racial educational inequalities across schools, the extent to which schools themselves create or exacerbate these inequalities is unclear. In the following subsections, we elaborate the theoretical basis for the school opportunity hoarding hypothesis, review practical challenges in assessing this hypothesis, and identify outstanding questions about the scale at which opportunity hoarding occurs.

School Segregation, Exclusion, and Opportunities

Recent scholarship on the determinants of school segregation casts it as a mechanism of social closure that allows privileged groups to monopolize access to status and resources associated with schools (Fiel 2015). Although school quality is an obvious candidate for hoarding or monopolization, competition may also be oriented around factors less pertinent to academic achievement such as symbolic status.

In the terminology of Charles Tilly's account of categorical inequality, the key theoretical question is to what extent school segregation constitutes *the hoarding of learning opportunities*. Tilly (1998:91) identifies opportunity hoarding as a mechanism through which groups use bounded networks to monopolize access to valuable and renewable resources. Examples include access to occupational niches within migrant networks and citizenship benefits within the nation-state. As in a migrant network or nation-state, a school provides clear boundaries for access to potentially valuable resources; school segregation entails the *exclusion* of some groups from the formal educational experiences of other groups. The specific exclusionary mechanisms are rooted in processes of residential sorting, local school assignment policies, and school choice. They are manifested in attendance at organizationally distinct educational institutions (schools and districts). Such exclusion is a necessary condition for opportunity hoarding, but it is not sufficient. Segregation supports the hoarding of educational learning opportunities to the extent that exclusive schools provide greater educational opportunities.

Empirical evidence pertaining to this hypothesis is mixed. The school opportunity hoarding hypothesis implies that parents from advantaged social groups especially value, recognize, or seek out high-quality schools, or that they are able to monopolize school-level educational resources. Research highlights advantaged parents' attention to schools when choosing residences (Goyette and Lareau 2014). Opportunity hoarding may explain systematic differences between schools in financing (Condron and Roscigno 2003), staffing (Clotfelter, Ladd, and Vigdor 2005; Lankford, Loeb, and Wyckoff 2002), and achievement (Logan, Minca, and Adar 2012), as well as the disadvantages faced by students in predominantly minority schools that are not explained by measured school characteristics (Condron 2009).

However, the exclusion inherent in contemporary school segregation need not align closely, or at all, with differences in school quality per se. Previous research points to three ways that school sorting can exclude less advantaged groups without leading to opportunity hoarding: preferences, information, and competing influences. First, residential and school choices may be influenced by preferences related to factors other than school quality—at least with respect to promoting academic development. Segregation may reflect efforts to preserve social status by maintaining distance from lower-status groups (Holme 2002) or "pure race" effects related to racial attitudes (Billingham and Hunt 2016). In other words, it may be more about boundary maintenance than opportunity hoarding (Tilly 1998).

Second, parents may not have access to reliable information about school quality. Qualitative research describes parents' acting on reputational information that may not map closely onto relevant differences between schools (Holme 2002). Moreover, available school quality information typically reflects academic performance rather than schools' success in promoting academic learning. Since performance is sensitive to out-of-school influences and weakly related to achievement growth, documented parental preferences for high-achieving schools (e.g., Billingham and Hunt 2016) and responses to official performance information based on achievement (e.g., Rich and Jennings 2015) may concentrate students in schools with similar students rather than better schools.

Third, opportunity hoarding may be counteracted by competing social forces, most notably educators' efforts to promote institutional equity. For instance, as court-mandated desegregation has receded, targeted compensatory resources for schools serving minority and poor students may counteract some school disparities (e.g., Billings et al. 2014; Gamoran and An 2016). If some combination of these possibilities holds, persistent racial and economic school segregation may reflect exclusion that is symptomatic of rather than a determinant of achievement inequality.

It is important to note that school segregation likely plays a role in perpetuating social inequality regardless of whether it entails the hoarding of opportunities related to school quality. Even if learning opportunities are not systematically different between groups, segregation may reinforce stratification processes through other means, such as disparate peer networks that influence later outcomes independent of learning (e.g., Wells and Crain 1994). But there is an important substantive and practical distinction: if segregation reflects the hoarding of learning opportunities in school, then the deleterious consequences could be ameliorated by addressing aspects of school quality without addressing segregation. If segregation promotes inequality through other means, then addressing these mechanisms, or segregation itself, is paramount. This distinction highlights the critical importance of operationalizing what we mean by school quality.

Segregation and School Quality

School quality refers to how successfully a school supports the development of its students. This concept is difficult to operationalize, and different measures may lead to different conclusions about the distribution of quality (Downey et al. 2008; Jennings et al. 2015). While the segregation literature has not focused on these differences, a long-standing body of research on school effects on student development provides background for gauging various approaches.

A fundamental distinction among school quality measures is the domain of student development. Because the mission of schooling is to provide varied and multidimensional educational opportunities, a single comprehensive measure of school quality is implausible. For instance, conceptually valid measures could focus on opportunities that promote academic attainment, motivation, or social and emotional development (e.g., Rumberger and Palardy 2005; Jennings et al. 2015). While recognizing this diversity, we follow the majority of previous research by focusing on the domain of academic development as measured via standardized assessments. Promoting learning is a central goal of education, and this is a key domain for school quality given the benefits of learning for long-term outcomes (e.g., Chetty et al. 2011).

Within the domain of academic learning, school quality measures vary widely in how effectively they reflect the learning opportunities that schools provide. School effects research highlights pitfalls for two common strategies. One approach uses easily observable school resources—such as funding and staff characteristics—as proxies for educational quality. The problem is that these resources are relatively weakly related to student outcomes, even in studies concluding that resources matter (Coleman 1968; Greenwald, Hedges, and Laine 1996; Hanushek 1997). Moreover, given the complexity of instruction and schooling, the effect of any resource is also likely contingent on many others. Observable resources are thus poor proxies for understanding the distribution of learning opportunities in school.

A second common approach to school quality focuses on measures of student achievement outcomes, such as the number of students who met a proficiency threshold on state testing. However, achievement levels are substantially influenced by out-of-school factors—large disparities are present before students begin school (Zill and West 2001), and these disparities grow during the summer (Heyns 1978; Alexander, Entwisle, and Olson 2001; Downey, von Hippel, and Broh 2004). Therefore, achievement levels do not isolate school influences on learning. This is illustrated by evidence that school quality measures based on achievement growth over time or that account for out-of-school learning are only weakly correlated with measures based on absolute achievement (Downey et al. 2008).

Imperfect measures can be valuable for answering some questions. However, traditional proxies for school quality—resources and achievement levels—are especially problematic for questions of segregation and inequality because they may systematically misstate disparities across groups. This is because measurement error in such school quality measures is likely correlated with social background. Because social background is associated with student achievement at the individual level, schools serving more advantaged groups will necessarily appear better by absolute achievement. Moreover, family choices are directly responsive to these proxies for school quality. Advantaged families have greater resources to realize preferences for schools with newer buildings and higher achievement (Billingham and Hunt 2016). As a result, segregation may be more directly aligned with such observable proxies than differences in school quality. In either case, disparities in traditional school quality measures conflate the causes of school segregation with its potential consequences for inequality.

As a result of these challenges, existing research linking segregation to disparities in school resources or achievement levels does not adequately assess opportunity hoarding. To take one example, Logan et al. (2012) provide one of the most comprehensive recent descriptions of the distribution of students across schools in the United States, highlighting a “geography of inequality” in access to high-achieving schools. These results likely reflect more about systematic sorting in the kind of students that attend different schools than the quality of those schools themselves. While the results nicely highlight widespread exclusion from schools attended by advantaged (and high-achieving) students, they do not reveal the relative quality of these disparate schools nor do they provide a compelling test of the school opportunity hoarding hypothesis.

Assessing the distribution of school quality requires separating the aspects of achievement related to school opportunities from non-school determinants (e.g., Jennings et al. 2015). School quality research suggests that one key to isolating school effects is repeated observations of student achievement, which allow separating initial achievement from the rate of learning over time. Since initial achievement is a powerful summary of the advantages that students bring to school, controlling for it yields growth-based measures of school quality that correspond with school effects estimated based on random assignment (Deming 2014). School achievement growth measures therefore provide a valuable opportunity to clarify our understanding of the link between segregation and school quality and to assess the opportunity hoarding hypothesis.

The Scale of School Segregation Disparities

If school segregation enables educational opportunity hoarding, a key question is how or where opportunities are separated. Research highlights segregation at multiple geographic scales, reflecting different underlying spatial processes (Lee et al. 2008). Similarly, school segregation occurs across several geographic and organizational levels, most notably between and within school district boundaries (Clotfelter 2004; Fiel 2013; Lee 2002). In contrast to the recent attention to decomposing school segregation between and within districts (e.g., Reardon et al. 2000), there is relatively little research focusing on the scale of disparities in measures of school quality. This is partly a function of the limitation of data based on probability samples, which do not provide the density of schools per district to separate between- and within-district differences (e.g., Downey et al. 2008). A notable exception is research on the distribution of teachers that draws on administrative records. Both Clotfelter et al. (2005) in North Carolina and Goldhaber et al. (2015) in Washington describe social background disparities in access to higher quality teachers—based on experience, certification, or measures of effectiveness—and find non-trivial disparities both between and within school districts.

Segregation patterns suggest specific versions of the school opportunity hoarding hypothesis at three levels: within-district, between-district, and between-metropolitan area or county. At the smallest scale, the *local school opportunity hoarding* hypothesis implies disparities among schools within individual school districts. Local differentiation may reflect local neighborhood segregation, coupled with the strong influence of place of residence on school attendance. Local political and economic influence may also provide advantaged schools disproportionate ability to secure resources and attract high quality school experiences including more experienced and qualified staff (Condron and Roscigno 2003; Lankford et al. 2002).

However, there may also be social forces counteracting inequality, especially through formal institutional policies. Although school district administrators have little control over where students live, they can influence the assignment of students and the distribution of resources across schools to promote equity. An obvious example is court-mandated desegregation attendance policies. Even as districts have abandoned these policies, they may put into place policies to focus resources on schools serving disadvantaged social groups (Reardon et al. 2012). Nashville, for instance, targeted “enhanced options”—including reduced class size, an extended school year, and additional tutoring—to schools serving disproportionate numbers of poor and Black students. Gamoran and An (2016) present evidence that these efforts mitigated unequal consequences of resegregation. Such policies may offset local school opportunity hoarding via segregation.

Another (not mutually exclusive) possibility is *between-district opportunity hoarding*, in which advantaged students attend school districts with relatively high-quality schools. This hypothesis implies that segregation between districts corresponds to systematic differences in educational opportunities. Underlying processes mirror those for local inequality: advantaged families pursue putatively better districts (e.g., Goyette and Lareau 2014), and educational resources—especially experienced teachers—flow disproportionately to districts serving advantaged families (e.g., Hanushek, Kain, and Rivkin 2004). Local funding sources related to property taxes—which comprise one third of educational revenues on average (Kena et al. 2015)—also contribute to potential inequalities between districts.

The district level may be a particularly effective scale for advantaged families to hoard educational opportunities because in contrast to within-district disparities, district autonomy and decentralized governance present fewer formal mechanisms to counteract between-district disparities. Consistent with opportunity hoarding efforts between districts, segregation is higher in areas where greater numbers of districts and greater resource disparities between districts create greater opportunities for resource monopolization (Fiel 2015). These trends may reflect efforts by advantaged families to hoard educational opportunities in more exclusive districts.

A final possibility is *area-level opportunity hoarding*, that quality differences are related to sorting between larger geographic units such as metropolitan areas and nonmetropolitan counties. Although segregation and inequality at these levels is rarely considered, recent work has begun to pay more attention to “macro-level” segregation patterns (Lichter, Parisi, and Taquino 2015), which are critical to understanding spatial stratification and targeting efforts to reduce inequality. These large-scale racial imbalances may also be construed as consequences of demographic forces rather than the social processes typically understood to promote segregation. Disparities at this scale may be related to average differences in educational quality or economic development between different places or between rural and urban areas.

Research Questions

Building on previous research on school segregation and inequality, our motivating research question concerns disparities in access to school quality. Does between-school segregation consign minority and poor students to inferior schools, which would likely contribute to disparities in achievement, as suggested by the opportunity hoarding hypothesis?

In addition to this primary research question, we also address two related questions. First, how do conclusions about the link between segregation and school quality compare when measuring quality based on average achievement as opposed to achievement growth? This question echoes Downey et al. (2008), who compare multiple measures of school quality, but we extend those results by measuring inequalities directly, and by doing so in a more comprehensive sample for a single state. This allows much more statistical precision in our quality measures and in our description of inequality.

Second, how much of the disparities in school quality occurs within school districts, how much occurs between districts, and how much occurs between geographic areas? This question builds on research on the multiple levels of school segregation (e.g., Reardon et al. 2000) and disparities in school resources across distinct levels (e.g., Clotfelter et al. 2005). Our study is unique, however, in that it uses a standard inequality index to decompose the distribution of school quality between and within groups and across organizational and geographic levels.

Methodology

Data

Assessing the school opportunity hoarding hypotheses with an achievement growth measure of school quality requires unique data: repeated achievement measures for a large number of students in each school; assessments that are designed to measure growth and are comparable across years and grades; and a large number of diverse schools within and between districts. Previous research has been limited by the trade-off between breadth and depth of achievement measures. The state-of-the-art measures collected by the National Center for Education Statistics' surveys are suited to estimate growth-based measures of school quality, but they cover a limited number of students, time points, and schools, causing imprecision and precluding investigations of scale (e.g., Downey et al. 2008). More rudimentary measures based on state accountability tests in single year are available for entire populations of public school students (e.g., Logan et al. 2012), but they do not necessarily support learning-based measures of school quality and make it difficult to compare results over time and across states. Our approach is to focus on all schools in a single large state—California—during a period when accountability assessments were reported on a scale designed for comparability across grades and over time. These data allow us to estimate learning-based quality measures for all California public schools.

To put California in national perspective, we compare its levels of school segregation within metropolitan areas and nonmetropolitan counties, as well as between and within school districts, to national averages in 1999-2000. Our calculations using the Common Core of Data show that California ranks higher than the national average at each of these levels across racial/ethnic comparisons. Using the entropy-based Theil Index (H), a measure of racial imbalance or unevenness, within-metro/county school segregation between Whites and Nonwhites was .259 in CA and .155 in the U.S. Almost two-thirds of this was between school districts, both in CA and nationally. California also ranked among the lowest states in terms of Black-White and Hispanic-White intergroup exposure in schools during this time period (Orfield and Lee 2007).

We collect aggregate achievement and demographic data for all public elementary schools in California. We focus on elementary schools for several reasons. First, early educational experiences are a formative period for the development of educational achievement gaps. Because related previous studies consider elementary grades (e.g., Downey et al. 2008), focusing on this level allows the closest comparison. Second, we expect opportunity hoarding to be most apparent at this level given the organization of elementary schooling. Schools are smallest and attendance is most local at this level, creating greater and finer-grained opportunities of organizational exclusion, and segregation is highest in the elementary grades (Sohoni and Saporito 2009). Finally, curricular differentiation in later grades would complicate the interpretation of growth trajectories based on aggregate scores employed here.

We consider the 1997-1998 to 2001-2002 school years for three reasons. First, this is a period when all students in California were tested in consecutive grades and years on a nationally normed and vertically equated general achievement assessment. This assessment, the Stanford Achievement Test, is more appropriate for assessing learning over time than later instruments that focus on proficiency with respect to grade-specific content standards. Second, this period predates most of the expansion of schools of choice.[1] Third, focusing on this time period allows the clearest comparison to related previous research (e.g., Downey et al. 2008).

We collect school and community characteristics from the National Center for Education Statistics' Common Core of Data and district-level geographic information from the 2000 Census, which we merge with the cohort-level achievement data from the California Department of Education.

Sample

We use data from approximately 53,000 yearly school-level aggregate mathematics scores in California public elementary schools in grades 2-5 between 1997 and 2002 (e.g., the average 4th grade score at a school in 1999). These data provide information on the average achievement trajectories of over 15,000 student cohorts (e.g., the 2nd grade class of 1997 in a school, observed in 2nd to 5th grade), which we use to calculate growth-based measures of school quality.

Schools are included in the sample if they meet the following criteria based on information in the Common Core of Data: public schools (excluding home school and home bound educational entities) that enrolled students in grades including 2-5, operated in each year between 1997-98 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 publicly reported. Table 1 presents characteristics of the analytic sample of 4,381 schools.

Demographic and Achievement Measures

Demographic measures of the proportion of the student body in each of five racial/ethnic groups (American Indian, Asian, Black, Hispanic, and White) and total school enrollment were reported to the National Center for Education Statistics in each year. We calculate mean values of these measures across all years to characterize school racial attendance during the study period. Cohort yearly achievement is measured as the mean mathematics scale score in each grade and year on the Stanford Achievement Test, Version 9, Form T (SAT9).[2] 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.[3]

School Quality Measures

To measure school quality with respect to student learning, we model achievement trajectories over time and calculate Empirical Bayes estimates of each school's mean typical 2nd grade achievement level and yearly growth (for details, see Supplementary Materials). Figure 1 illustrates the intuition for the underlying multi-level model of achievement growth. Gray points plot observed achievement values. When grouped by cohort, these observations reveal specific achievement trajectories (represented by grey lines) and the aggregate achievement trajectory at each school (represented by a black line). Figure 1 also illustrates the importance of distinguishing between achievement levels and growth. School A is higher achieving, especially when students are first tested, but students tend to learn more over time in School B.

We derive three alternate measures of school quality from estimated school achievement trajectories. First, we calculate model-based estimates of *initial achievement level*, the typical achievement score at the start of testing in grade 2 (represented by the height of the solid black lines at grade 2 in Figure 1). This measure corresponds with previous research employing achievement levels to characterize school quality, but it is likely primarily influenced by students' academic preparation when they arrive at school, and therefore a poor measure for testing the school opportunity hoarding hypothesis. Second, we estimate yearly *achievement growth*, reflecting the typical learning of students in grades 2-5 (represented by the slope of the black lines in Figure 1). Achievement growth is a better indicator of the school learning opportunities that students experience.

Our third measure of school quality, *residual achievement growth*, is defined as growth relative to other schools in the same decile of initial achievement (the growth values for schools A and B in Figure 1 are therefore adjusted relative to different comparison groups). This addresses the concern that it may be inappropriate to compare slopes across schools with different initial achievement. In our data, initially high-achieving schools exhibit lower subsequent growth (correlation = -.21), which may reflect idiosyncratic properties of the achievement instrument in this setting.[4] Residual growth is an imperfect measure of quality because it ignores true variation between deciles, but it provides a robustness check for our main growth measure.

The key advantage of our growth-based measures of school quality is that they focus on school-age learning, removing differences present when students arrive at school. It is still possible, however, that aggregate annual growth misrepresents schools' true contributions to learning. While we cannot rule out this possibility definitively, we address two specific potential threats to validity—summer learning and student churning—and conclude that each is unlikely to be problematic for our analyses (see Supplementary Materials).

Analyses

Our analyses use estimated initial achievement level, achievement growth, and growth net of initial achievement (residual growth) as alternate measures of school quality. The school opportunity hoarding hypothesis implies that quality is substantially higher at schools serving advantaged student populations, and different versions of this hypothesis locate advantages at the level of schools, districts, and geographic areas.

To test these hypotheses, we conduct two types of analyses. In the first, we describe the distribution of these measures experienced by students from different racial groups. These distributions provide a picture of disparities in access to school quality on an intuitive metric, but they do not address the organizational/geographic scale of inequalities.

In our second set of analyses, we calculate the total degree of between-school inequality in each quality measure, then decompose it into the portions that lie between and within racial groups as well as between and within large geographic areas and school districts. Decomposing access to school quality between racial groups provides a precise accounting of the magnitude of the within- and between-group disparities portrayed in our first analyses. The opportunity hoarding hypothesis predicts that a substantial portion of the overall variation in school quality is between racial groups. Further decompositions by organizational and geographic units are more relevant to the link between segregation and inequality; they allow us to assess to what extent these differences are driven by the distribution of students and opportunities among schools, districts, and larger geographic areas.

Our decompositions are based on the Theil Index (Theil 1972), a common measure of inequality in access to social goods. This index has the desirable properties shared by many inequality measures, but it is particularly useful because it is additively decomposable (Allison 1978).[5] We first calculate overall between-school inequality in each indicator of quality using Equation 1, where n_i and q_i represent 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* is essentially an aggregation of schools' deviations from average quality.

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

(1)

To assess racial inequality, we decompose overall inequality into the portions that lie between and within racial/ethnic groups. Our data distinguish five groups: American Indian, Asian, Black, Hispanic, and White. Our index accommodates all of these groups to decompose "multigroup" inequality. The decomposition is shown below in Equation 2, with groups indexed by *r*. The first component captures between-group inequality by aggregating the deviation of each group's mean quality from the population mean; the second captures within-group inequality by calculating between-school inequality (as in Equation 1) for each group and aggregating across groups. The school opportunity hoarding hypothesis predicts that between-group inequality is large relative to within-group inequality.

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

(2)

We then decompose both the between- and within-race components geographically and organizationally to assess the school opportunity hoarding hypotheses at specific scales. Decomposing the within-race component yields the between-area, between-district, and within-district decomposition shown in equation 3. Between-area inequality is based on each area's deviation from average quality, measured separately for each group and aggregated across groups. Between-district inequality is based on each district's deviation from average quality in the area in which it is located, measured separately for each area and group, and aggregated across areas and groups. Similarly, within-district inequality begins with race-specific school deviations from district quality, and aggregates them across districts, areas, and groups.

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

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

$$+ \underbrace{\sum_{r=1}^{R}\sum_{m=1}^{M}\sum_{d=1}^{D}\sum_{i=1}\frac{n_{irmd}}{N}\frac{q_{irmd}}{\bar{q}}\ln\left(\frac{q_{irmd}}{\bar{q}_{rmd}}\right)}_{\text{within-race, within-district}}$$

(3)

Decomposing between-race inequality geographically and organizationally is more complicated, as shown in Equation 4. The first two components in brackets capture between-race, between-area inequality by subtracting within-race, between-area inequality from total between-area inequality. Similarly, the next two terms in brackets capture between-race, between-district inequality by subtracting within-race, between-district inequality from total between-district inequality. The fifth and final term captures between-race within-district inequality using each racial group's deviation from overall mean district-level quality, and aggregating across districts and groups.

$$\underbrace{\sum_{r=1}^{R}\frac{N_r}{N}\frac{\bar{q}_r}{\bar{q}}\ln\left(\frac{\bar{q}_r}{\bar{q}}\right)}_{\text{between-race}}$$

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

$$+\left[\underbrace{\sum_{r=1}^{R}\sum_{m=1}^{M}\sum_{d=1}^{D}\frac{N_{rmd}}{N}\frac{\bar{q}_{rmd}}{\bar{q}}\ln\left(\frac{\bar{q}_{md}}{\bar{q}_m}\right)}_{\text{between-district}}-\underbrace{\sum_{r=1}^{R}\sum_{m=1}^{M}\sum_{d=1}^{D}\frac{N_{rmd}}{N}\frac{\bar{q}_{rmd}}{\bar{q}}\ln\left(\frac{\bar{q}_{rmd}}{\bar{q}_{rm}}\right)}_{\text{within-race, between-district}}\right]$$

$$+\underbrace{\sum_{r=1}^{R}\sum_{m=1}^{M}\sum_{d=1}^{D}\frac{N_{rmd}}{N}\frac{\bar{q}_{rmd}}{\bar{q}}\ln\left(\frac{\bar{q}_{rmd}}{\bar{q}_{md}}\right)}_{\text{between-race, within-district}}$$

(4)

In addition to these multigroup decompositions that incorporate all racial/ethnic groups, we execute similar decompositions to explore inequality between particular groups. For instance, we examine inequality between each group and all others (e.g., White-Nonwhite, Black-Nonblack, etc.), and inequality between all two-group combinations (White-Black, White-Hispanic, Black-Hispanic, etc.). The two-group analyses ignore other groups and treat the two focal groups as the total population.

Results

Student Composition and School Achievement Levels and Growth

We begin by describing the distribution of school achievement characteristics across students from different racial backgrounds. Figure 2 presents kernel density estimates of the distribution of each school achievement characteristic for each racial group, while Table 2 summarizes several features of each distribution. For interpretability, each outcome is presented in units of average growth compared to the mean value observed in the school population.[6] For example, the value of 0.426 for White students in Panel A signifies that the typical White student attends a school with an initial achievement measure over 40 percent of year of typical learning higher than the average school.

Consistent with prior research, we find large raw differences between the schools attended by different student groups when quality is assessed in terms of achievement level (Panel A).[7] The initial scores at the mean school attended by a Black student are over three-quarters of a year lower than the mean school attended by White students (0.807 = 0.423 – (-0.384)). This difference corresponds to almost a standard deviation in the quality experienced by all students (0.873). White-Hispanic differences are even larger, while White-Asian differences are smaller, and all of these patterns are similar throughout the distribution.

Group differences are much less pronounced when school quality is measured by typical learning growth (Panel B). Black students attend the lowest growth schools on average, but the mean White-Black difference corresponds to only 0.015 (-0.001 – (-0.016)) years of average learning, or 16% of the overall standard deviation (0.015/0.096). Differences among other groups are even smaller, and the overall distributions (Figure 2, Panel B) highlight that the vast majority of variation in exposure to achievement growth occurs within rather than between racial groups.

When considering achievement growth relative to other schools with similar initial achievement (Panel C of Table 2), racial differences are larger. The White-Black mean difference, for instance, is 0.035 (0.010 – (-0.025)) years of average learning. This difference is non-trivial, especially as students experience school over many years; it also corresponds to a third of a standard deviation in the outcome measure (37.2% = 0.035/0.094).

This residual growth result implies that access to high-growth school environments is a meaningful dimension of racial educational inequality, independent of the well-documented differences in school achievement levels. However, the size of school growth gaps pales in comparison to the size of initial achievement gaps, suggesting that between-race disparities in school quality are much smaller than implied by achievement levels. Instead, the distributions of school growth measures imply that much of the important variation in access to learning opportunities at school occurs within racial groups. Our decomposition analyses quantify the relative magnitudes of between- and within-group inequality and assess the concentration of these disparities at different geographic and organizational levels.

Decomposing School Achievement Levels and Growth

Table 3 presents results for the decompositions of multigroup inequality in each school quality measure. Figure 3 illustrates these decompositions graphically alongside similar decompositions for selected two-group comparisons discussed later. A considerable portion of overall inequality in achievement levels—25 percent—lies between the five racial/ethnic groups. Only 6 percent of this between-race inequality lies between metropolitan areas and nonmetropolitan counties; over 94 percent lies within these areas. Furthermore, most racial inequality lies between (64 percent) rather than within (30 percent) school districts. This means that racial inequality in school achievement levels corresponds fairly closely to segregation within schooling markets (areas), and it is largely linked to between-district segregation.

Inequality in achievement levels within racial/ethnic groups is also mainly within metropolitan areas and nonmetropolitan counties (87 percent). Compared to between-group inequality, within-group inequality is more concentrated within (46 percent) than between (41 percent) school districts. This means that there is substantial inequality in achievement levels within racial/ethnic groups, it is largely located within schooling markets, and driven by differences both within and between districts.

The decomposition of inequality in schools' achievement growth suggests a different story. Here inequality is almost entirely a within-race phenomenon. Less than one percent of disparities in school-level achievement growth lies between racial/ethnic groups, almost all of which lies within school districts. In short, in contrast the school opportunity hoarding hypothesis, segregation does not contribute much to race disparities in exposure to high-growth schools. Within-race inequality in achievement growth is also concentrated within areas (95 percent), and it lies primarily within (71 percent) rather than between (24 percent) districts.

The analyses of residual achievement growth (net of initial achievement level) are similar to those for achievement growth, but with slightly more racial inequality. Only two percent of inequality lies between racial/ethnic groups and it remains a within-area phenomenon, but split more evenly between (55 percent) and within (61 percent) school districts.[8] Of the 98 percent of inequality within racial/ethnic groups, most is concentrated within areas (95 percent), especially within school districts (70 percent). Hence, based on residual growth rates, segregation both within and between districts contributes to race disparities in opportunities to learn, but much less than suggested by achievement levels.

Figure 3 illustrates these decomposition results along with those for four selected two-group comparisons—Black-White, Hispanic-White, Asian-Black, and Asian-Hispanic—as well as a comparison of students who do and do not qualify for free or reduced-price lunch. These are the only cases for which any between-group disparities emerged; there is practically no inequality in any measure of school quality between Whites and Asians or American Indians, or between any other Nonwhite groups. As expected from our prior analyses, between-race inequality is largest for school achievement levels: 15 percent of total inequality in the Black-White analysis, 29 percent in the Hispanic-White analysis, 12 percent in the Asian-Black analysis, and 14 percent in the Asian-Hispanic analysis. In each case, the vast majority of racial inequality is within metro areas/counties, mostly between school districts (60-71 percent). Again, however, there is no appreciable between-group inequality in growth-based quality measures. Only 2-3 percent of inequality in residual growth is between groups, most of this is within metro areas/counties, and both between- and within-district inequalities contribute. Thus, while there is little evidence of any form of opportunity hoarding, the small between-race differences that exist are consistent with both the local and district-level opportunity hoarding hypotheses.

To summarize, Whites and Asians are advantaged relative to Blacks and Hispanics in terms of the quality of their schools, most racial inequality is linked to segregation within local schooling markets, and an important share is linked to segregation both between and within districts. These racial disparities, however, are much smaller when school quality measures are based on achievement growth than initial achievement levels. The vast majority of inequality in exposure to schools with high achievement growth is within racial/ethnic groups and within school districts.

Decompositions using free/reduced-price lunch status as a proxy for poverty yield results similar to those for multigroup racial inequality. About 25 percent of inequality in achievement levels is between the free/reduced-lunch group and others, but there is negligible between-group inequality in the growth-based measures.

Discussion

The relationship between school segregation and educational opportunities is complex, but understanding these processes is critical to identifying and responding to core social inequalities. We have focused on the possible link between school segregation and the hoarding of educational opportunities. By comparing different aspects of school-level academic achievement (levels and growth), we have come closer to distinguishing racial achievement disparities that arise outside of school from those that are more plausibly due to differences in school quality. And by decomposing disparities in school quality across organizational and geographic levels, we have illustrated the landscape of inequality in school-based learning opportunities.

Our analyses provide mixed support for the school opportunity hoarding hypothesis. We find that Black and Hispanic students not only attend lower-achieving schools than Whites and Asians, but also attend schools with lower rates of learning. These results suggest some hoarding by advantaged groups of school learning opportunities, as measured by achievement growth. However, these disparities in learning opportunities are much less pronounced than disparities in students' initial advantages. Racial differences in growth-based school quality are much smaller than differences in achievement levels, both because there is less between-school variation in achievement growth, and because almost all variation in school growth is within rather than between racial groups. Our results imply that pre-existing learning differences weigh much more heavily than school opportunity hoarding in spatial between-race educational inequality.

In this respect, our census school-level results complement findings from rich micro-level data on student learning. Most notably, our findings align with insights from individual-level seasonal learning comparisons (Heyns 1978; Alexander et al. 2001; Downey et al. 2004), even though our annual growth measures do not isolate learning during the school year. Both approaches suggest that *between-race* disparities in school-based learning experiences pale in comparison to racial disparities in learning opportunities outside of school. We also find less *within-race* variability in school growth measures than achievement measures, which is broadly consistent with smaller "residual" disparities in achievement growth when school is in session (Downey, von Hippel and Broh 2004). In short, learning more directly linked to schooling experiences is less variable than overall learning.[9]

A unique contribution of our decomposition analyses is a picture of the organizational and geographic scale of these inequalities. Like the magnitude of disparities themselves, the scale of inequality depends on the measure of school quality. In contrast to differences in mean achievement levels, which are present within and between school districts, variation in growth-based measures of school quality is primarily located within districts. This is true of both the small disparities between racial groups and the larger disparities within groups, and it suggests that differences in school-based learning opportunities are more local than recent trends toward between-district economic and racial segregation suggest (Owens 2016).

Before considering the implications of our research, it is important to note that our analyses do not directly test the causal effects of segregation. Doing so would require a broader framework for defining and isolating specific counterfactual comparisons of different levels of school segregation (Reardon and Owens 2014). Rather, our results clarify one important, and commonly hypothesized, link between segregation and educational opportunity. If school racial segregation contributes to the racial achievement gap through opportunity hoarding, we would expect to find minority students concentrated in schools where children learn less. This is not the case, suggesting that a consequential effect of segregation via differential school quality is implausible. But our results do not reveal how school learning opportunities became relatively equal between racial groups or how changing segregation would change the relative distribution of school quality. We also remind readers that our analyses do not speak to inequality in experiences and resources important to outcomes other than early academic achievement.

With these caveats in mind, our findings offer two lessons for social and educational policy. One is that, given that racial disparities in school quality do not accompany school segregation, addressing school segregation may not have the substantial impact on racial achievement inequalities typically imagined. Moreover, an undue focus on schools may distract from more important sources of stratification in learning opportunities. School desegregation may have other benefits, and schools can perhaps do more to overcome racial achievement gaps, but efforts to address racial achievement inequality should highlight home- and neighborhood-based factors that affect learning outside of school (Downey and Condron 2016; Sharkey and Elwert 2011).

Our results also highlight disparities in school quality for which race does not figure prominently. Substantial differences in achievement growth imply that school attendance patterns expose some students to richer learning opportunities than others, but these differences are primarily experienced within racial groups, and they lie primarily within school districts. This means that local district-level policies are a key to addressing school-based achievement inequality in the population. Specifically, districts should aim to identify their struggling schools and help them catch up to their more successful schools. Promising efforts to direct supplemental resources to specific schools provide some optimism for addressing these local disparities (e.g., Gamoran and An 2016). The autonomy and power of school districts in the American educational system makes these strategies plausible, but the decentralization underlying this autonomy also means it will be difficult to produce systemic change.

These practical implications ultimately depend on the specific social processes that give rise to these patterns, which brings us to some theoretical implications of our findings. Staying with Tilly's (1998) framework, the admittedly small racial differences in exposure to high-growth schools imply that some degree of school segregation can be construed as opportunity hoarding. Yet the weak link between segregation and school quality suggests that segregation is more important for social distancing and boundary maintenance than opportunity hoarding. Segregation may also be more about hoarding symbolic status than effectiveness in promoting learning (Holme 2002). With respect to the substantial within-race disparities in school quality, perhaps opportunity hoarding occurs among groups not differentiated in our data.

An alternate explanation for relatively small student background differences in achievement growth-based measures of school quality is that advantaged families may act with the intentions of hoarding learning opportunities but lack accurate information on school quality. Limited school information plays a role in parents' reliance on indirect proxies of quality such as general reputation, indicators such as average achievement, or demographic composition (Lareau 2014). However, if poor information has muted opportunity hoarding in educational learning environments, then recent efforts to publicize richer measures of school quality, including some based on achievement growth, may exacerbate the modest disparities seen in the context considered here. Alternatively, better information could also reduce segregation by reducing parents' reliance on school composition as a proxy for school quality.

We must also highlight limitations of our analyses. For one, our results reflect the case of elementary schools in California. Future work is needed to assess whether these results generalize to later grades and to other states. In addition, school opportunity hoarding may have increased or decreased since the period covered by these data. One the one hand, several trends in education may have increased inequality, such as the proliferation of schools of choice, greater economic inequalities in our society, and the wider availability of school quality measures related to achievement growth. On the other hand, accountability and targeted assistance policies may have equalized learning opportunities across schools, reducing the potential for school-based hoarding. In addition, the scale of school quality disparities may have shifted toward between-district differences, mirroring changes in children's contexts (Owens 2016). Our results provide a baseline for future work to assess whether and how inequalities have changed in the last two decades.

Our data also do not allow us to explore other potential dimensions of educational inequality. School-level measures of quality overlook "second-generation segregation," or within-school disparities that could contribute to racial inequality (Mickelson 2015; Oakes 1985; Tyson 2011). We expect this to be less problematic in our elementary school context than it would be in middle schools or high schools, where tracking is more pervasive. Nonetheless, it will be important for future analyses to consider disparities in learning opportunities within schools or even within classrooms. We also lack information on private schools, which provide another potential avenue of segregation and opportunity hoarding. Finally, schools provide opportunities other than learning the material covered on these standardized tests, and we are unable to assess disparities in these opportunities.

Nonetheless, our findings demonstrate that absolute achievement measures of school quality provide a potentially misleading diagnosis of the magnitude and scale of educational disparities linked to school segregation as well as the extent to which advantaged racial and economic actors hoard educational opportunities provided by schools. Much of the apparent racial inequality in school quality is due to achievement disparities when students are first assessed and not reflected in growth rates that are more plausibly attributable to schools. This suggests a need to focus policy priority on the spatial and racial sources of inequality that lie outside of (and predate) school.

Endnotes

[1] Just 1.8% of all public school enrollment in 1999-2000 was in charter schools; 7.6% in 2012-2013. See: https://nces.ed.gov/programs/digest/d14/tables/dt14_216.90.asp.
[2] Students also took SAT9 tests in English Language Arts. We focus on mathematics outcomes because mathematics skills may be more sensitive to schooling inputs than language development, which are more likely to be influenced by home factors. However, Language Arts results are substantively similar.
[3] 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/).
[4] Note that the assessments were designed to have an interval scale and we find no signs of floor or ceiling effects. However, it still may have been easier for low-achieving students to demonstrate learning, such as if curricular mandates focus on basic proficiency.
[5] A weakness of this measure is that it assumes the variable has a meaningful zero point (a ratio scale). When this assumption is violated, results may be sensitive to arbitrary shifts in the scale. The metric of units of typical achievement growth may not satisfy this assumption, but our results are robust to alternate shifts to values. For all decompositions presented here, we have standardized each variable to have a mean of 100 and standard deviation of 15.
[6] The rescaled and demeaned values (X*) are calculated from the raw values (X) as: $X^* = ((X - E(X))/22.5)$. Note that 22.5 is the estimated average yearly growth in the data.
[7] American Indians, who make up a very small share of the overall population, are omitted from the figure to reduce overplotting.
[8] Note that portions sum to more than 100% because the between-area inequality decomposition component is negative.
[9] This is not to say that schools do not contribute to within-race inequality. We do find some evidence of this in the form of meaningful within-race differences in growth-based measures of school quality, especially within districts. These disparities are simply small in comparison to differences in the average initial achievement.

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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
Achievement Growth (per year)	22.5	2.3	11.4	32.6

Table 2. Distribution of School Achievement Characteristics by Racial Group

	Students	Mean	SD	25th Percentile	50th Percentile	75th Percentile
A. Initial Achievement Level						
All	2687817	-0.089	0.873	-0.779	-0.192	0.518
White	940637	0.426	0.783	-0.142	0.406	1.031
Asian	294268	0.250	0.901	-0.466	0.206	0.941
Black	234409	-0.384	0.759	-0.936	-0.482	0.085
Hispanic	1218503	-0.511	0.688	-1.007	-0.640	-0.116
B. Achievement Growth						
All	2687817	-0.003	0.096	-0.061	-0.001	0.058
White	940637	-0.001	0.098	-0.062	0.000	0.062
Asian	294268	0.004	0.098	-0.060	0.009	0.068
Black	234409	-0.016	0.100	-0.076	-0.013	0.048
Hispanic	1218503	-0.004	0.092	-0.059	-0.002	0.055
C. Residual Achievement Growth						
All	2687817	-0.005	0.094	-0.066	-0.006	0.055
White	940637	0.010	0.095	-0.051	0.011	0.070
Asian	294268	0.009	0.097	-0.056	0.010	0.074
Black	234409	-0.025	0.097	-0.087	-0.024	0.037
Hispanic	1218503	-0.017	0.088	-0.073	-0.017	0.039

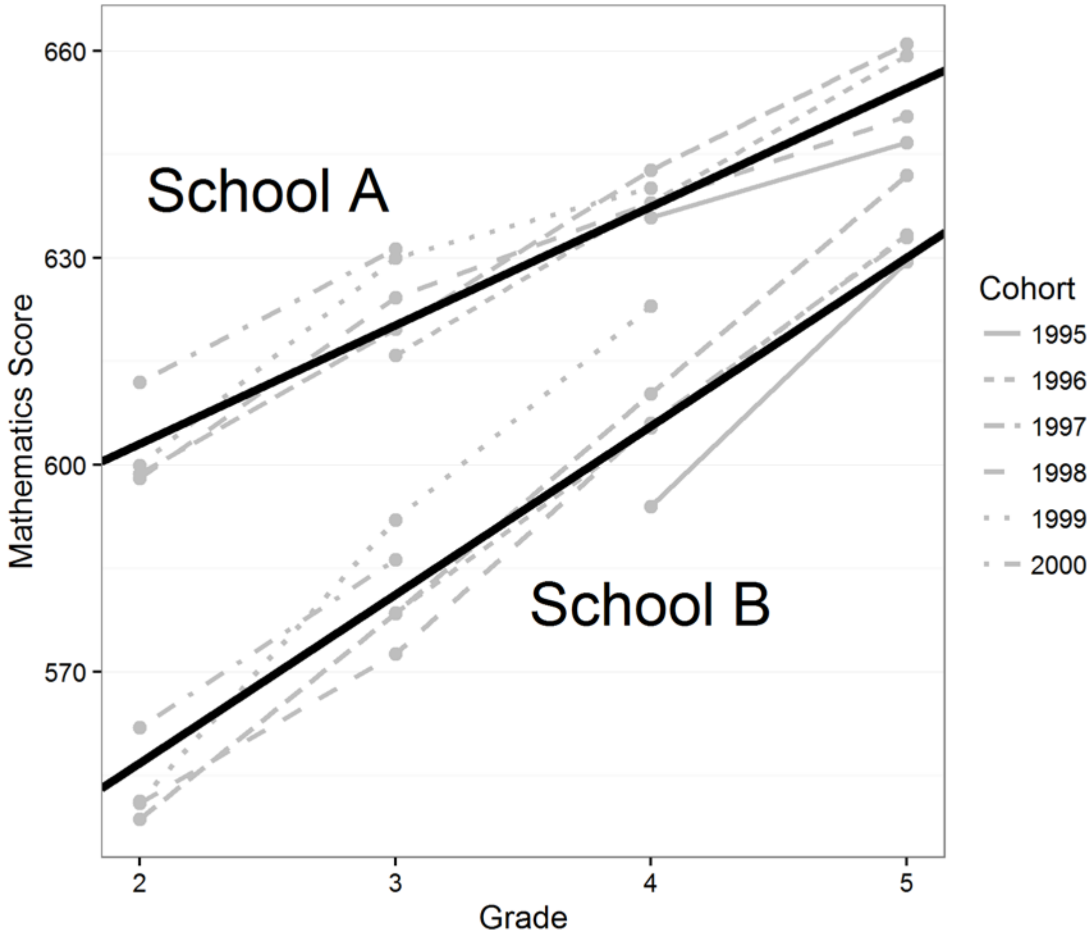
Note: All outcome variable rescaled to units of average yearly growth, centered at the overall mean across all schools.

Table 3. Decomposition of Multigroup Inequality

	Total	Between Area	Between District	Within District
A. Initial Achievement Level				
Overall	0.0118	0.0013	0.0055	0.0049
Share of overall (%)		11.4	46.6	41.9
Between Race	0.0030	0.0002	0.0019	0.0009
Share of overall (%)	25.4	1.5	16.3	7.6
Share of between-race (%)		5.8	64.3	29.9
Within Race	0.0088	0.0012	0.0036	0.0040
Share of overall (%)	74.6	9.9	30.3	34.4
Share of within-race (%)		13.3	40.6	46.0
B. Achievement Growth				
Overall	0.0104	0.0004	0.0025	0.0075
Share of overall (%)		4.2	24.1	71.7
Between Race	0.0000	-0.0001	0.0000	0.0001
Share of overall (%)	0.2	-0.9	0.0	1.1
Share of between-race (%)		-437.6	9.7	527.9
Within Race	0.0104	0.0005	0.0025	0.0074
Share of overall (%)	99.8	5.1	24.1	70.5
Share of within-race (%)		5.1	24.2	70.7
C. Residual Achievement Growth				
Overall	0.0105	0.0005	0.0027	0.0073
Share of overall (%)		5.0	25.2	69.7
Between Race	0.0002	0.0000	0.0001	0.0001
Share of overall (%)	2.2	-0.3	1.2	1.3
Share of between-race (%)		-16.0	54.7	61.3
Within Race	0.0103	0.0006	0.0025	0.0072
Share of overall (%)	97.8	5.4	24.0	68.4
Share of within-race (%)		5.5	24.6	69.9

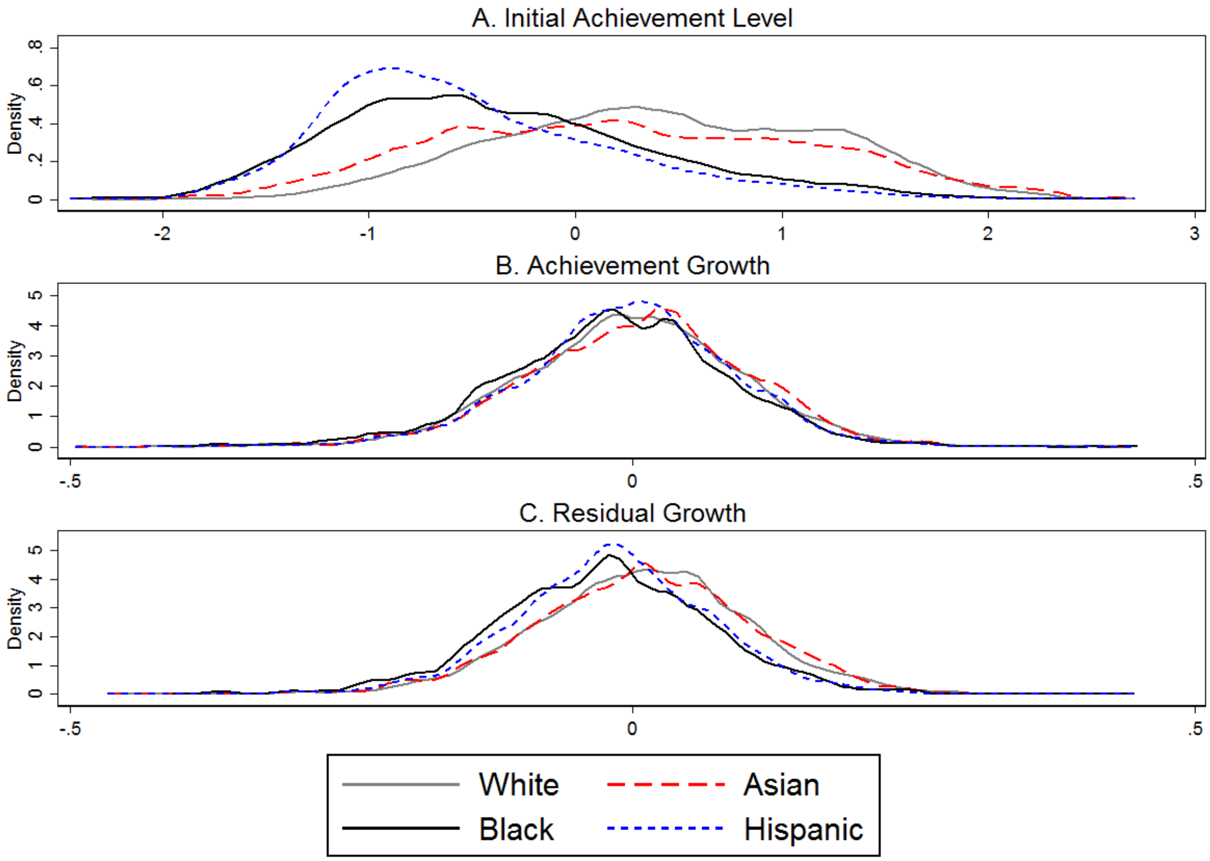
Notes: Inequality measured with the Theil Index. Area refers to metropolitan area or non-metropolitan county. Racial ethnic groups include American Indian, Asian, Black, Hispanic, and White.

Figure 1. Observed Scores and Estimated Aggregate Growth Trajectory for Two Schools



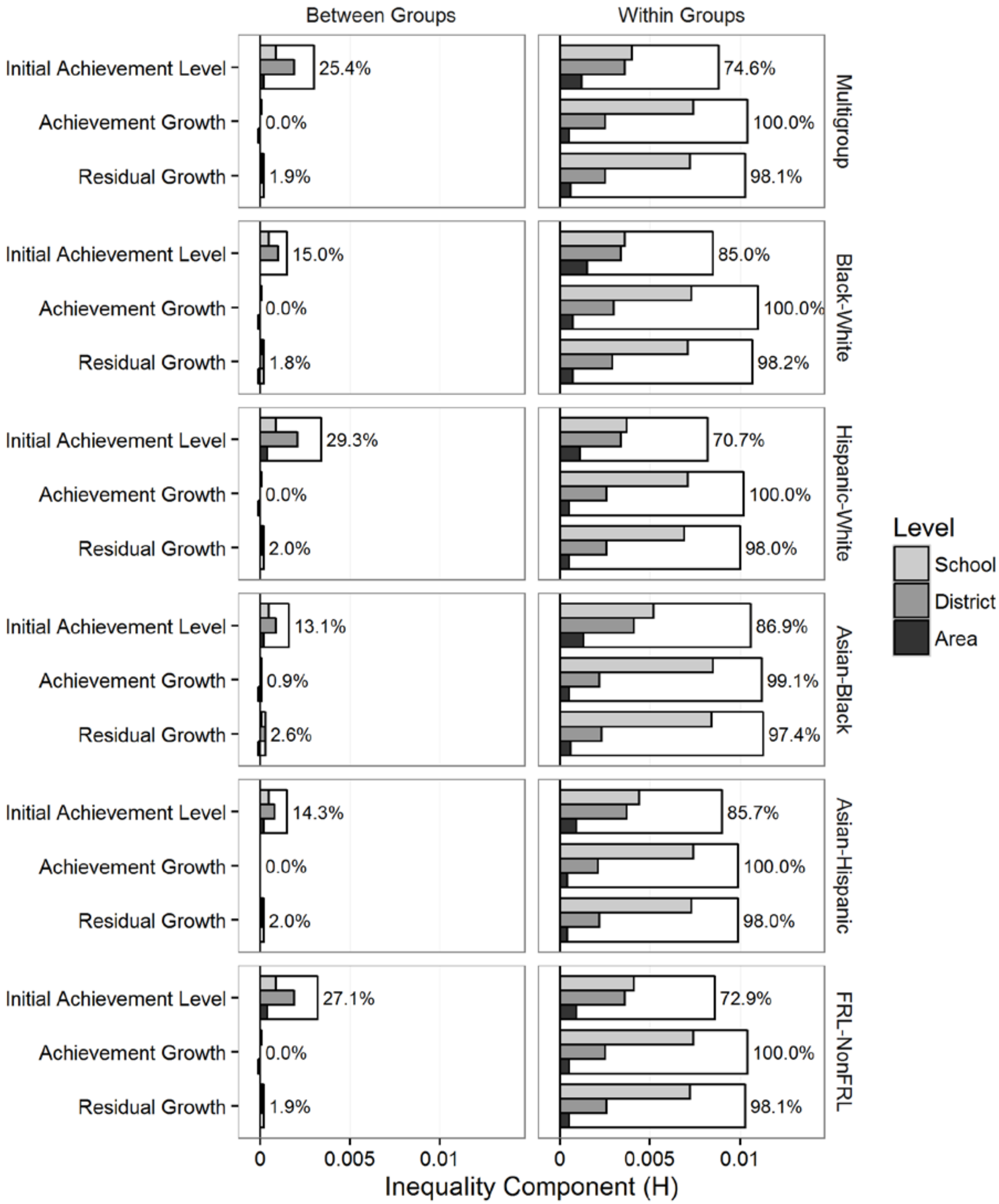
Notes: Points represent observed achievement scores. Grey lines connect multiple achievement scores for each cohort; cohorts are labeled by their second grade year. Black lines represent the school average growth trajectory, estimated as detailed in the Supplementary Materials.

Figure 2. Distribution of Achievement Characteristics of Schools Attended by Different Racial Groups



Note: Each variable is rescaled to units of average yearly growth and to have a mean value of zero.

Figure 3. Summary of Decompositions of School Quality Within and Between Groups



FRL = Eligibility for Free or Reduced Price Lunch
Notes: White bars and listed percentages reflect the total share of inequality between (left panels) and within (right panels) groups. The level inequalities (filled bars) sum to this overall value. The top panels summarize the Multigroup decompositions reported in Table 3.

Supplement A. Achievement Growth Model and School Quality Estimates

Data Structure

Growth models are based on achievement trajectory information for student cohorts within schools. The achievement data by year provide multiple observations for six cohorts of students, represented in Table A1: the second grade classes of 1995 to 2000. We conduct growth analyses of all schools with sufficient achievement information. These data include approximately 53,000 school-year-grade aggregate mathematics scores for over 15,000 student cohorts in 4,435 schools (this number is larger than our analytic sample because not all schools are represented in other sources, but we use all available data to construct school quality measures). On average, growth models are based on 5.9 cohorts per school and 3.0 observations per cohort.

Main Growth Model Specification

The measures of school quality we report are based on the 3-level (cohort-year, cohort, and school) random effects growth model represented in Figure A1. In this model, observed grade-level achievement at any point in time is modeled as a function of initial achievement (the intercept term, π_0), linear growth from grade to grade (the slope term, π_1), and a flexible secular trend over time (the vector of year coefficients, π_2), which accounts for increasing achievement overall during this period. The achievement intercept, representing initial achievement in grade 2, varies randomly by cohort within schools (u_{0c}) and by school (u_{00s}). The achievement slope, representing yearly growth, also varies randomly at the school-level (u_{10s}). All variance terms are parameterized as mean zero normally distributed random variables, and we allow the school-level random intercepts and slopes to be correlated with one another to allow for a systematic relationship between starting points and growth trajectories.

Based on the estimated parameters of this model, we calculate two school characteristics: (1) *average initial achievement* in 2nd grade ($\hat{\gamma}_{000} + \hat{u}_{00s}$) and (2) *average yearly achievement growth* from 2nd to 5th grade ($\hat{\gamma}_{100} + \hat{u}_{10s}$). For the random components ($\hat{u}_{00s}$ and $\hat{u}_{10s}$), we calculate the Empirical Bayes or best linear unbiased predictions of the school-specific values, which we add to the estimates of the non-varying parameters ($\hat{\gamma}_{000}$ and $\hat{\gamma}_{100}$).
Figure A2 presents the distribution of predicted school initial achievement and growth in the sample. The modestly negative association between the two motivates our final measure of school quality, *residual achievement growth*, which compares school growth only relative to schools with comparable initial achievement. To construct residual achievement growth, we calculate the average growth for each decile of the initial achievement measure, and subtract this value from the observed growth for each school.

Growth Model Specifications

As represented in Figure A1, our preferred estimates of school average achievement trajectories are based on a parsimonious linear growth model. Table A2 presents the estimates from this model (in Model 3) as well as those from a sequence of alternate specifications.

Models 1 and 2 partition the overall variance in all cohort achievement scores occurring between schools, within schools between cohorts, and within cohorts over time. Approximately 29% (332.4 / (332.4 + 0 + 828.8)) of the unconditional variance in mean yearly achievement scores (Model 1) is between schools, while 71% (828.8 / (332.4 + 0 + 828.8)) is within cohorts, and there is little systematic variation between different cohorts within schools. Model 2, which adds indicator variables for each year (relative to the omitted category of 1997), demonstrates that scores increased substantially over time; this likely reflects both rising achievement and test familiarity effects. It is important to take this secular trend into account when characterizing student achievement. Net of the time trend, between-cohort variation is particularly pronounced, which is an artifact of the unbalanced cohort panel: early cohorts are observed only in later (higher-achieving) grades, while later cohorts are observed in earlier (lower-achieving) grades.

Model 3 presents estimates of the preferred growth curve model, which is linear with respect to grade level, with the grade variable coded so that the intercept reflects grade 2. The average cohort in an average school has a mean mathematics score of 568.9 in second grade (this estimate applies to the omitted year 1997) and achievement grows by 22.5 points on average in each subsequent grade. Not surprisingly, the inclusion of the grade-level growth trend explains virtually all of the within-school between-cohort variation in mean achievement scores in Model 2 (99% = (1709.2 – 10.3)/1709.2). Notably, most of the residual variation in observed test scores occurs between schools (83% = (370.2 / (370.2 + 10.3 + 67.9))), which indicates the importance of between-school variation in these data. Recall that observations are grade-year mean scores, so the undoubtedly larger variation in individual achievement that exists within a cohort at any point in time are omitted from these models. However, the large between-school variation in achievement levels relative to between-cohort differences within schools implies that school differences are robust over time.

The remaining models in Table A1 present estimates for two more complex growth model specifications: estimates from the quadratic specification (Model 4) imply a slight deceleration of growth over time, but those from the non-parametric specification (Model 5) imply more idiosyncratic variation in grade-specific growth, with largest gains from grade 2 to 3 and smallest in grades 3 to 4. On the whole, however, neither alternate specification deviates substantially from linear growth on average, as reflected by the mean predicted values presented in Figure A3. Given the similarity among specifications, we select the linear version as the most parsimonious. It is substantively and practically simplest to describe growth trajectories in terms of two key parameters: intercept (initial achievement) and slope (yearly growth).

School-level Variation in Growth

Having selected the parsimonious linear growth model, we next assess variation in growth trajectories between schools and/or cohorts within schools. Table A3 presents the estimates from several varying slope specifications of average mathematics achievement growth. Model 1 presents a random intercept model (replicating Model 3 from Table A2). Model 2 allows the grade slope to vary across schools. The estimated variance in yearly growth between schools is 7.4; this variation is statistically significant and substantively meaningful. The difference in expected yearly learning between a school one standard deviation below the mean and another one standard deviation above the mean is 5.5 (sqrt(7.434) * 2), compared to average yearly growth of 22.5 points. The estimates from Model 2 show a negative correlation between school initial achievement level and yearly growth (correlation = -0.24), suggesting that measured growth tends to be higher for the lowest achieving schools but that the two growth parameters vary largely independently.

In contrast, we find little evidence of variation in achievement growth between cohorts within schools. Slope variation between cohorts overall (Model 3), which includes variation between schools since there is no separate school parameter, is estimated to be about as large as between school variation alone (7.7 vs. 7.4). Moreover, cohort-level variation in growth is highly negatively correlated with initial achievement (correlation = -0.87), implying little distinguishable slope variation separate from starting scores. This interpretation is supported by the results of a model that allows for varying achievement growth at the school and cohort level simultaneously (Model 4). These results show that almost all of the variation in growth slopes occurs at the school level; after accounting for this variation, cohort-level slope variation is substantively negligible (0.5 points) and indistinguishable from variation in initial achievement levels (perfectly negatively correlated).

The main conclusion from the progression of models presented in Table A3 is that there is meaningful variation in achievement growth between schools, but not between cohorts within schools. Stated differently, between-school differences in achievement growth are meaningful and consistent for different cohorts of students over time. Combined with the variation in achievement levels discussed above, these results support the use of school-level achievement trajectories as measures of substantive differences in school experiences. As a result, we base our estimates of school-level initial achievement and growth on the model reported in Model 2 of Table A2.

Assessing Potential Threats to Validity: Summer Learning and Student Churning

The main limitation of this growth-based measure of school quality is that it may still reflect non-school influences on learning. Such influences are highlighted in the literature on summer learning, which distorts conclusions about school quality based on full-year learning (Downey et al. 2008; von Hippel 2009). However, such distortions are not overly problematic for our assessment of the relative distribution of school quality. For one, biases in the growth quality measure due to summer learning—or any other confounder—are problematic only to the extent that they are systematically different for schools serving different student populations. Our analyses operate under the assumption that the achievement growth measure is comparable across schools with different student compositions. Stated differently, we assert that differential bias related to composition is negligible.

Although we cannot assess this assumption with our data, research on seasonal learning measures suggests that differential biases may be small. Downey et al. (2008, see Table 6) report the associations between school composition characteristics—free lunch eligibility and minority share—and different measures of average learning, including: *12-month growth* and an improved *impact* measure, which adjusts for out-of-school learning. The associations between social background and impact are similar to those for the conventional growth measure, and confidence intervals include the point estimates of the 12-month measure. This suggests that differential biases due to out of school learning related to student characteristics may not be large enough to change our conclusions about inequality. While this result partly reflects the lower statistical precision of the impact measure, it is consistent with overall evidence that both learning measures are clearly superior to absolute achievement despite trade-offs in precision (von Hippel 2009). We also mitigate biases due to out-of-school learning by adjusting for initial achievement level in our residual growth measure specification. Initial achievement is a proxy for non-school influences on achievement. By comparing schools within initial achievement categories, residual growth controls for the out-of-school differences that contribute to second grade achievement. In addition, to the extent that out-of-school bias remains, we expect it to work in the favor of the school opportunity hoarding hypothesis—lower summer learning rates among poor and minority students would make their schools appear worse than they actually are. Given our findings, such biases would not alter our main conclusions.

A related limitation of our growth-based measures is that aggregate gains may be influenced by student “churning.” Churning entails students changing schools, entering or leaving public schools, or changing cohorts (via retention). This would distort a school’s growth measure to the extent that the achievement of entering students is different than that of exiting students; these distortions will bias inferences about inequality if they are systematically related to school composition.

We cannot directly assess this bias without student-level data, but there are several reasons that it is likely a minor concern in our analyses. First, few students move schools in any given year, mathematically limiting potential impacts on aggregate measures. For instance, exits from elementary schools in Los Angeles just after the sample period were less than 10% per year (Dauter and Fuller 2016). Second, retention is most common in first grade, before students enter our cohorts, and it is much lower in subsequent grades (Warren, Hoffman, and Andrew 2014). Third, the net influences of churning on apparent growth are limited by the similarity of movers and stayers. We find that churning does very little to alter our cohorts’ total enrollments or racial compositions across grades, and that these changes are weakly related to our growth-based measures of school quality. In any cohort, the cross-grade correlations of each racial/ethnic group’s size and proportion of enrollment (across schools) are above .90 for all groups except American Indians, and most are above .95. The correlations between changes in any cohort’s racial composition and school quality are never above .06 for growth and never above .10 for residual growth.

To the extent that churning does distort our growth-based measures, we expect our analyses to overestimate racial inequality in favor of the opportunity hoarding hypothesis. Theory predicts that advantaged groups with higher-achieving students will sort into higher-quality schools, which would amplify racial disparities. In our data, the only significant correlations between changes in cohort composition and growth indicate that Hispanic enrollment shares declined in high-growth schools (r = -.04), whereas Asian enrollment increased in high-growth schools (.06). Since some of the learning observed in advantaged schools may be related to influxes of higher-achieving students, our analyses may overstate advantaged groups’ (e.g., Asians) access to school growth. Nonetheless, we expect this to be a minor problem given the weak correlations.

Citations

Dauter, Luke and Bruce Fuller. 2016. “Student Movement in Social Context The Influence of Time, Peers, and Place.” *American Educational Research Journal* 53(1):33–70.

Downey, Douglas B., Paul T. von Hippel, and Melanie Hughes. 2008. “Are ‘Failing’ Schools Really Failing? Using Seasonal Comparison to Evaluate School Effectiveness.”

von Hippel, Paul. 2009. “Achievement, Learning, and Seasonal Impact as Measures of School Effectiveness: It’s Better to Be Valid than Reliable.” *School Effectiveness and School Improvement* 20(2):187–213.

Warren, John Robert, Emily Hoffman, and Megan Andrew. 2014. “Patterns and Trends in Grade Retention Rates in the United States, 1995–2010.” *Educational Researcher* 43(9):433–43.

Tables

Table A1. Cohorts represented in the aggregate achievement data

Year	Grade 2	Grade 3	Grade 4	Grade 5
1997	Cohort 3 [1997]	Cohort 2 [1996]	Cohort 1 [1995]	
1998	Cohort 4 [1998]	Cohort 3 [1997]	Cohort 2 [1996]	Cohort 1 [1995]
1999	Cohort 5 [1999]	Cohort 4 [1998]	Cohort 3 [1997]	Cohort 2 [1996]
2000	Cohort 6 [2000]	Cohort 5 [1999]	Cohort 4 [1998]	Cohort 3 [1997]
2001		Cohort 6 [2000]	Cohort 5 [1999]	Cohort 4 [1998]

Note: Year in brackets is 2nd grade year.

Table A2. Estimates from Multilevel Models of Mean Mathematics Achievement

Model	(1)	(2)	(3)	(4)	(5)
Grade(a)			22.52*	26.67*	
			(0.0308)	(0.0931)	
Grade Squared(a)				-1.383*	
				(0.0293)	
Grade Categories (2 omitted)					
3					27.15*
					(0.0834)
4					47.13*
					(0.0860)
5					68.75*
					(0.0966)
Year (1997 omitted)					
1998		29.14*	6.985*	7.430*	7.227*
		(0.0976)	(0.0974)	(0.0960)	(0.0950)
1999		58.02*	14.07*	14.56*	14.35*
		(0.107)	(0.100)	(0.0990)	(0.0982)
2000		83.21*	17.63*	18.07*	17.85*
		(0.119)	(0.103)	(0.102)	(0.101)
2001		109.4*	21.78*	21.77*	21.34*
		(0.134)	(0.116)	(0.115)	(0.115)
Intercept	615.1*	559.1*	568.9*	567.1*	566.7*
	(0.290)	(0.300)	(0.297)	(0.299)	(0.299)
Variance Components					
School	332.4*	85.55*	370.2*	370.1*	370.1*
	(8.014)	(8.424)	(7.902)	(7.900)	(7.901)
Cohort	0.000*	1709.2*	10.26*	11.36*	12.21*
	(0.000)	(16.78)	(0.362)	(0.363)	(0.364)
Residual	828.8*	67.42*	67.92*	65.09*	63.36*
	(4.280)	(0.419)	(0.422)	(0.404)	(0.394)
Observations	79537	79537	79537	79537	79537
Cohorts	26857	26857	26857	26857	26857
Schools	4540	4540	4540	4540	4540
Log Likelihood	-384803.9	-338494.8	-294996.7	-293908.4	-293278.2
Parameters	4	9	10	11	13
AIC	769615.7	677005.7	590011.4	587836.8	586578.3
BIC	769652.9	677080.0	590095.0	587929.7	586680.5

* p<.05
(a) Grade variable rescaled relative to grade 2 (0 = grade 2, 1 = grade 3, etc.)
Standard errors in parentheses

Table A3. Estimates from Multilevel Models of Mean Mathematics Achievement with Varying Slopes

Model	(1)	(2)	(3)	(4)
Grade(a)	22.52*	22.54*	22.50*	22.52*
	(0.0308)	(0.0502)	(0.0339)	(0.0500)
Intercept	523.9*	523.9*	524.0*	524.0*
	(0.308)	(0.341)	(0.314)	(0.340)
School Level				
Intercept	370.2*	391.6*	371.3*	390.5*
	(7.902)	(8.510)	(7.923)	(8.521)
Grade		7.434*		7.304*
		(0.226)		(0.226)
Correlation(Intercept, Grade)		-0.236*		-0.226*
		(0.0170)		(0.0172)
Cohort Level				
Intercept	10.26*	12.75*	41.11*	21.16*
	(0.362)	(0.362)	(1.101)	(0.746)
Grade			7.738*	0.452*
			(0.258)	(0.0581)
Correlation(Intercept, Grade)			-0.871*	-1.000
			(0.006)	(0.000)
Residual				
Intercept	67.92*	57.34*	57.74*	56.82*
	(0.422)	(0.376)	(0.438)	(0.371)
Observations	79537	79537	79537	79537
Cohorts	26857	26857	26857	26857
Schools	4540	4540	4540	4540
Log Likelihood	-294996.7	-292847.7	-294257.2	-292727.5
Parameters	10	12	12	14
AIC	590011.4	585717.4	588536.5	585481.1
BIC	590095.0	585819.5	588638.6	585601.8

* $p<.05$
(a) Grade variable rescaled relative to grade 2 (0 = grade 2, 1 = grade 3, etc.)
Standard errors in parentheses. All models include indicator variables for each year (1997 omitted).

Figures

Figure A1. Multi-level Achievement Growth Model

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):

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

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

Variance Components:

$$\varepsilon_{sci} \sim N(0, \sigma_{sci})$$

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

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

Note: s indexes schools, c indexes cohorts, and i indexes cohort-year observations

Figure A2. Distributions of and Associations between Estimates of School Achievement Characteristics

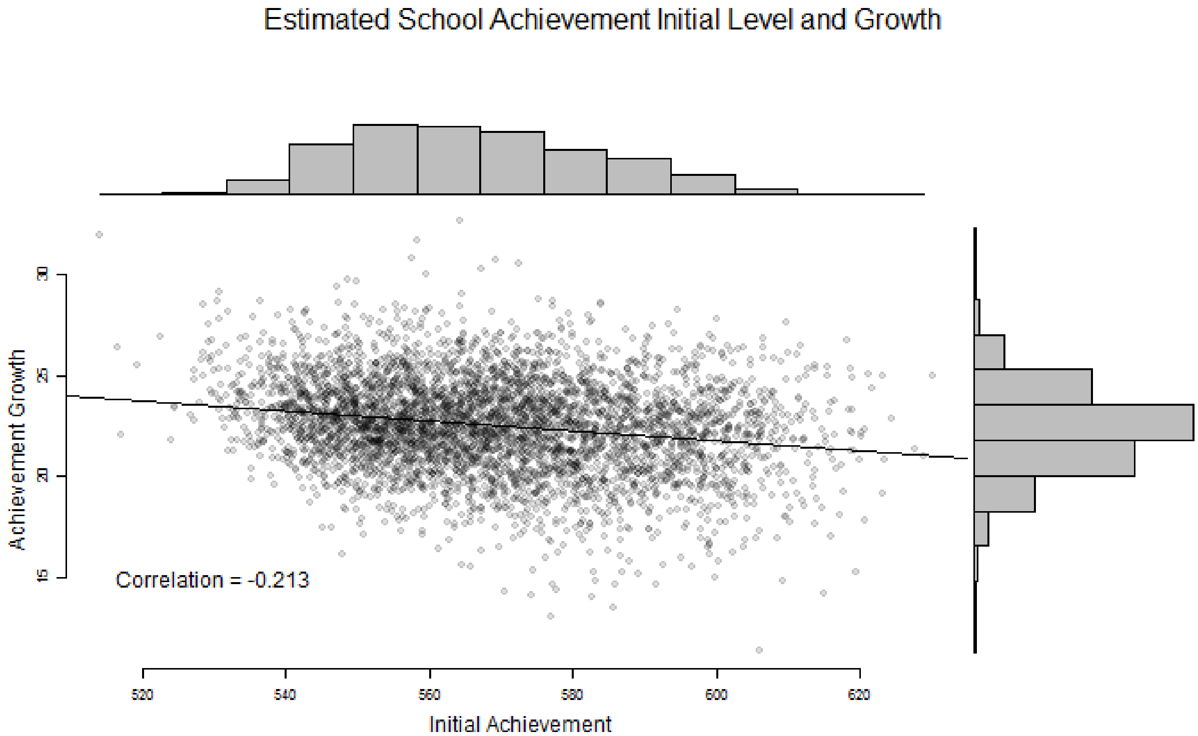
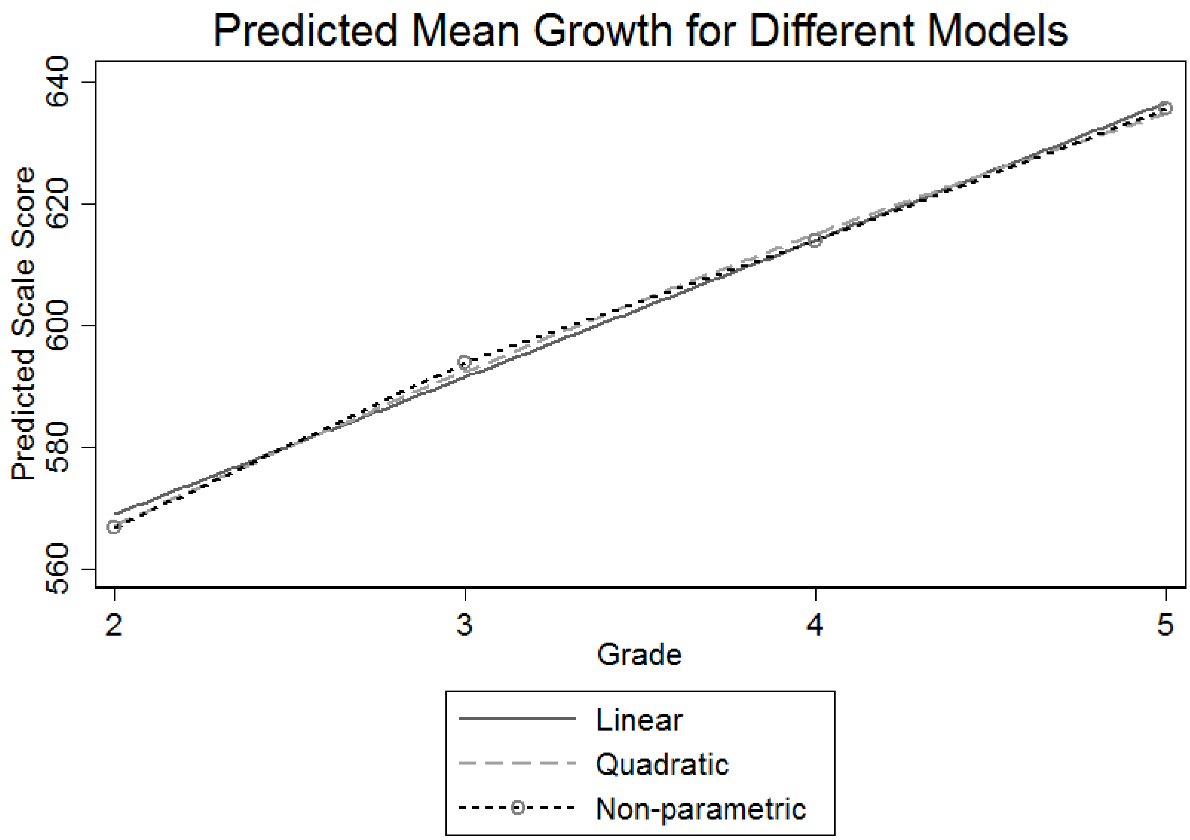


Figure A3. Predicted Average Growth Curves from Three Model Specifications



Note: Predicted values are based on Models 3-5 reported in Table A2.

Supplement B. Multiple Regression Models

This supplement presents the results from multilevel regressions of school achievement characteristics (initial level and yearly growth) on school characteristics. The unconditional and conditional associations between school demographic characteristics and achievement measures provide a complement to the raw distributional differences presented in the main text. The general form for these multi-level models is:

$$Y_{ij} = \boldsymbol{\beta X_i} + \eta_j + \varepsilon_i \qquad \text{(B1)}$$

where Y_{ij} is the outcome for school i in district j, $\boldsymbol{X_i}$ represents a vector of school characteristics, including racial composition, η_j is a district-specific random intercept, and ε_i is an individual school residual.

Table B1 presents the estimates from models of school initial achievement levels. Model 1 presents the unconditional relationships between the percentage of different groups in the student body and average achievement in second grade. Consistent with the raw distributional results, higher Black and Hispanic student concentrations (relative to the White omitted group) predict substantially lower achievement. Disparities are actually largest for American Indian students (omitted from the main text due to their small number). After controlling for student racial composition, nearly two thirds of the variation in average achievement levels is between districts (65.6% = 131.6 / 131.6 + 69.0).

Model 2 in Table B1 adds a series of control variables to the model collected from the Common Core of Data collected by the National Center for Education Statistics: the proportion of students eligible for free or reduced price lunch, the size of the student body, proportion of migrant students, geographic locale (7 category), student to staff ratio, and indicators for whether the school is designated for school-wide Title I assistance, a charter school, and a magnet school.

Racial differences are smaller net of these covariates, as schools with larger shares of poor students and larger schools tend to have lower achievement scores. However, disparities are still apparent for American Indian, Black, and Hispanic students. Some but not all of the association between race and school achievement is attributable to related demographic factors. Interestingly, a larger Asian population is associated with significantly higher achievement, net of controls. Control variables also explain much more of the previous between-district variance in outcomes than within; as a result, only about half of residual score variance is between districts (50.9% = 58.3 / (58.3+56.3)).

Given the simultaneous association between achievement levels and both racial indicators and economic characteristics, Model 3 in Table B1 adds interactions between these variables. The results suggest that the disadvantages for Hispanic student populations and for poor student populations are not additive. The significant negative sign of this interaction implies that the detriments associated with either characteristic alone is less pronounced when the other is greater. The same is true for American Indian students. However, we find no interaction between the share of the student body that is Black and the share that is eligible for free or reduced price lunch. This implies that the combination of these two factors is associated with a double disadvantage in school achievement levels.

Table B2 presents the results of analogous models for the achievement growth measure of school quality. Unconditional associations (Model 1) show that only the proportion of Black students at the school is significantly related with average achievement growth. Consistent with the models of achievement levels, this association is negative. In contrast to achievement levels, however, there is not detectable systematic variation in achievement growth between districts in this or any of the model specifications represented in Table B2.

One important confounder of the relationship between school racial composition and achievement growth is initial achievement levels. Because achievement is lower in high-minority schools and because achievement levels are somewhat negatively correlated with growth overall, school initial achievement acts as a suppressor of racial disparities in achievement growth. Model 2 demonstrates this by adding estimated initial achievement level as a control variable. As in the "residual growth" measure presented in the main text, initial achievement is treated flexibly, with a dummy indicator for each decile of the distribution (omitting the lowest group). After controlling for differences in starting places, there are statistically significant achievement growth disparities mirroring those for achievement levels: gaps for American Indian, Black, and Hispanic students (relative to Whites) and advantages for Asians. The magnitudes of these differences are small but non-trivial. For instance, the predicted difference between a school with all Black students and all White students is 5.8 points, or roughly a quarter of average yearly growth per year.

Model 3 adds the set of school control variables. These variables again explain White advantages, reducing the conditional disparities associated with disadvantaged racial groups and increasing the size of Asian advantage. This is largely because student poverty is a strong predictor of lower achievement growth. In contrast to the levels results, however, we find no evidence of interactive predictive effects between the racial and economic variables.

In summary, this multivariate approach highlights several points from the main manuscript. Namely that there are large racial disparities in access to high achieving schools and that school achievement growth is an independent dimension (controlling for initial achievement) of racial inequality, although the differences in growth are much smaller in magnitude than differences in initial achievement. The multivariate models additionally suggest that some but not all of both sets of disparities are related to correlated school characteristics that also are associated with achievement trajectories, especially poverty, as measured by the share of students eligible for free or reduced price lunch.

Tables

Table B1. Estimates from Multivariate Multilevel Models of School Mean Initial Achievement Level

Model	(1)	(2)	(3)
Intercept	594.84	597.85	600.11
	(0.62)*	(1.13)*	(1.24)*
Proportion American Indian	-80.70	-34.21	-73.19
	(5.59)*	(4.85)*	(16.05)*
x Prop. FRL			52.78
			(20.47)*
Proportion Asian	0.72	15.81	19.70
	(1.62)	(1.51)*	(2.26)*
x Prop. FRL			-7.73
			(3.99)
Proportion Black	-60.10	-27.83	-24.97
	(1.56)*	(1.69)*	(4.13)*
x Prop. FRL			-2.39
			(5.34)
Proportion Hispanic	-59.82	-18.68	-30.48
	(0.81)*	(1.41)*	(2.29)*
x Prop. FRL			15.46
			(2.63)*
Proportion Free/reduced Lunch (FRL)		-38.30	-41.43
		(1.26)*	(1.85)*
1000s of Students		-3.72	-4.35
		(0.60)*	(0.61)*
Proportion Migrant Students		0.49	-1.60
		(2.10)	(2.11)
Locale (Large Central City omitted)		0.00	0.00
		(.)	(.)
Mid-size Central City		-0.46	-0.31
		(0.91)	(0.90)
Urban Fringe of a Large City		1.02	0.97
		(0.59)	(0.59)
Urban Fringe of a Mid-size City		-2.33	-2.17
		(1.08)	(1.08)
Large Town		4.51	4.91
		(3.16)	(3.13)
Small Town		-1.19	-0.75
		(1.52)	(1.51)
Rural		-2.41	-2.39
		(1.14)	(1.14)

School-wide Title I		-0.12	0.25
		(0.39)	(0.39)
Charter School		-1.81	-1.92
		(4.83)	(4.80)
Magnet School		1.98	2.24
		(0.62)*	(0.62)*
Student-Teacher Ratio		0.02	0.02
		(0.04)	(0.04)
Variance Components			
District	129.27	57.90	56.43
	(9.36)*	(4.64)*	(4.57)*
Residual	68.93	56.24	55.63
	(1.63)*	(1.32)*	(1.31)*
Schools	4381	4381	4381
Districts	709	709	709
Log Likelihood	-16171.96	-15567.37	-15539.64
Parameters	7.00	20.00	24.00
AIC	32357.92	31174.74	31127.28
BIC	32402.61	31302.44	31280.53

Standard errors in parentheses
* p<.05

Table B2. Estimates from Multivariate Multilevel Models of School Mean Yearly Achievement Growth

Model	(1)	(2)	(3)	(4)
Intercept	22.60	27.71	30.22	30.41
	(0.10)*	(0.20)*	(0.32)*	(0.34)*
Proportion American Indian	1.44	-6.32	-2.55	-8.65
	(1.04)	(0.99)*	(0.98)*	(3.44)
x Prop. FRL				8.31
				(4.49)
Proportion Asian	0.71	1.15	2.60	2.93
	(0.34)	(0.31)*	(0.32)*	(0.49)*
x Prop. FRL				-0.67
				(0.89)
Proportion Black	-1.03	-5.81	-3.86	-3.09
	(0.35)*	(0.36)*	(0.37)*	(0.96)*
x Prop. FRL				-0.94
				(1.27)
Proportion Hispanic	0.16	-4.71	-1.55	-2.64
	(0.16)	(0.22)*	(0.29)*	(0.52)*
x Prop. FRL				1.45
				(0.66)
Proportion Free/reduced Lunch (FRL)			-5.11	-5.45
			(0.29)*	(0.44)*
1000s of Students			-0.60	-0.63
			(0.14)*	(0.14)*
Proportion Migrant Students			-0.43	-0.55
			(0.43)	(0.43)
Locale (Large Central City omitted)				
Mid-size Central City			0.03	0.03
			(0.17)	(0.17)
Urban Fringe of a Large City			0.02	0.01
			(0.12)	(0.12)
Urban Fringe of a Mid-size City			0.00	0.00
			(0.20)	(0.20)
Large Town			-0.40	-0.38
			(0.54)	(0.54)
Small Town			0.16	0.19
			(0.28)	(0.28)
Rural			0.06	0.06
			(0.22)	(0.23)
School-wide Title I			-0.04	-0.01
			(0.09)	(0.09)

Charter School			0.56	0.55
			(1.10)	(1.10)
Magnet School			0.55	0.57
			(0.14)*	(0.14)*
Student-Teacher Ratio			-0.01	-0.01
			(0.01)	(0.01)
Variance Components				
District	1.09	0.99	0.77	0.76
	(0.14)	(0.12)	(0.10)	(0.10)
Residual	4.26	3.50	3.23	3.22
	(0.10)*	(0.08)*	(0.07)*	(0.07)*
Controls for Initial Achievement	No	Yes	Yes	Yes
Schools	4381	4381	4381	4381
Districts	709	709	709	709
Log Likelihood	-9635.08	-9219.18	-9018.27	-9013.21
Parameters	7	16	29	33
AIC	19284.16	18470.35	18094.54	18092.41
BIC	19328.86	18572.51	18279.71	18303.12

Standard errors in parentheses
* p<.05

Supplement C. Selected Two-group Decompositions of Achievement Characteristics

Table C1. Decomposition of Black-White Inequality

	Total	Between Area	Between District	Within District
Achievement Levels				
Overall	0.0100	0.0015	0.0044	0.0041
Share of overall (%)		14.96	43.83	41.20
Between Race	0.0015	0.0000	0.0010	0.0005
Share of overall (%)	14.93	0.07	9.74	5.13
Share of between-race (%)		0.44	65.22	34.35
Within Race	0.0085	0.0015	0.0034	0.0036
Share of overall (%)	85.07	14.90	34.10	36.08
Share of within-race (%)		17.51	40.08	42.41
Achievement Growth				
Overall	0.0111	0.0007	0.0031	0.0074
Share of overall (%)		5.99	27.52	66.49
Between Race	0.0000	-0.0001	0.0000	0.0001
Share of overall (%)	0.34	-0.55	0.39	0.50
Share of between-race (%)		-162.21	114.56	147.64
Within Race	0.0111	0.0007	0.0030	0.0073
Share of overall (%)	99.66	6.55	27.13	65.98
Share of within-race (%)		6.57	27.22	66.21
Residual Achievement Growth				
Overall	0.0110	0.0007	0.0031	0.0072
Share of overall (%)		6.26	28.48	65.26
Between Race	0.0002	-0.0001	0.0002	0.0001
Share of overall (%)	2.05	-0.55	1.76	0.84
Share of between-race (%)		-26.65	85.71	40.93
Within Race	0.0108	0.0007	0.0029	0.0071
Share of overall (%)	97.95	6.80	26.73	64.42
Share of within-race (%)		6.94	27.29	65.77

Area refers to metropolitan area or non-metropolitan county. Inequality measured with Theil Index. Other racial/ethnic groups are ignored.

Table C2. Decomposition of Hispanic-White Inequality

	Total	Between Area	Between District	Within District
		Achievement Levels		
Overall	0.0117	0.0015	0.0055	0.0046
Share of overall (%)		12.89	47.55	39.55
Between Race	0.0034	0.0004	0.0021	0.0009
Share of overall (%)	28.83	3.31	18.13	7.39
Share of between-race (%)		11.48	62.87	25.65
Within Race	0.0083	0.0011	0.0034	0.0037
Share of overall (%)	71.17	9.58	29.43	32.16
Share of within-race (%)		13.47	41.35	45.19
		Achievement Growth		
Overall	0.0102	0.0004	0.0026	0.0072
Share of overall (%)		4.33	25.42	70.24
Between Race	0.0000	-0.0001	0.0000	0.0001
Share of overall (%)	0.02	-0.78	-0.07	0.87
Share of between-race (%)		-3712.21	-312.26	4124.47
Within Race	0.0102	0.0005	0.0026	0.0071
Share of overall (%)	99.98	5.11	25.49	69.38
Share of within-race (%)		5.11	25.49	69.39
		Residual Achievement Growth		
Overall	0.0102	0.0006	0.0027	0.0070
Share of overall (%)		5.41	25.99	68.61
Between Race	0.0002	0.0000	0.0001	0.0001
Share of overall (%)	1.97	0.11	0.87	0.99
Share of between-race (%)		5.38	44.46	50.17
Within Race	0.0100	0.0005	0.0026	0.0069
Share of overall (%)	98.03	5.30	25.11	67.62
Share of within-race (%)		5.41	25.62	68.98

Area refers to metropolitan area or non-metropolitan county. Inequality measured with Theil Index. Other racial/ethnic groups are ignored.

Table C3. Decomposition of Asian-Black Inequality

	Total	Between Area	Between District	Within District
		Achievement Levels		
Overall	0.0122	0.0015	0.0050	0.0057
Share of overall (%)		12.29	40.88	46.83
Between Race	0.0015	0.0002	0.0009	0.0005
Share of overall (%)	12.46	1.35	7.12	3.98
Share of between-race (%)		10.83	57.18	31.99
Within Race	0.0107	0.0013	0.0041	0.0052
Share of overall (%)	87.54	10.94	33.76	42.84
Share of within-race (%)		12.50	38.56	48.94
		Achievement Growth		
Overall	0.0113	0.0004	0.0023	0.0086
Share of overall (%)		3.85	20.31	75.83
Between Race	0.0001	-0.0001	0.0001	0.0001
Share of overall (%)	0.89	-0.57	0.92	0.54
Share of between-race (%)		-64.09	103.28	60.82
Within Race	0.0112	0.0005	0.0022	0.0085
Share of overall (%)	99.11	4.43	19.39	75.29
Share of within-race (%)		4.47	19.56	75.97
		Residual Achievement Growth		
Overall	0.0116	0.0005	0.0026	0.0085
Share of overall (%)		4.53	22.62	72.85
Between Race	0.0003	-0.0001	0.0003	0.0001
Share of overall (%)	2.97	-0.65	2.58	1.04
Share of between-race (%)		-21.96	86.93	35.04
Within Race	0.0113	0.0006	0.0023	0.0084
Share of overall (%)	97.03	5.18	20.04	71.81
Share of within-race (%)		5.34	20.65	74.01

Area refers to metropolitan area or non-metropolitan county. Inequality measured with Theil Index. Other racial/ethnic groups are ignored.

Table C4. Decomposition of Asian-Hispanic Inequality

	Total	Between Area	Between District	Within District
		Achievement Levels		
Overall	0.0105	0.0011	0.0045	0.0050
Share of overall (%)		10.00	42.88	47.13
Between Race	0.0015	0.0002	0.0008	0.0005
Share of overall (%)	14.41	1.66	7.65	5.10
Share of between-race (%)		11.50	53.12	35.39
Within Race	0.0090	0.0009	0.0037	0.0044
Share of overall (%)	85.59	8.34	35.22	42.03
Share of within-race (%)		9.75	41.15	49.10
		Achievement Growth		
Overall	0.0099	0.0003	0.0021	0.0074
Share of overall (%)		3.39	21.44	75.17
Between Race	0.0000	0.0000	0.0000	0.0000
Share of overall (%)	0.10	-0.19	-0.17	0.46
Share of between-race (%)		-202.30	-176.67	478.96
Within Race	0.0099	0.0004	0.0021	0.0074
Share of overall (%)	99.90	3.59	21.61	74.70
Share of within-race (%)		3.59	21.63	74.78
		Residual Achievement Growth		
Overall	0.0100	0.0004	0.0023	0.0074
Share of overall (%)		3.91	22.58	73.51
Between Race	0.0001	0.0000	0.0001	0.0001
Share of overall (%)	1.26	-0.10	0.68	0.67
Share of between-race (%)		-7.58	54.13	53.45
Within Race	0.0099	0.0004	0.0022	0.0073
Share of overall (%)	98.74	4.01	21.90	72.83
Share of within-race (%)		4.06	22.18	73.76

Area refers to metropolitan area or non-metropolitan county. Inequality measured with Theil Index. Other racial/ethnic groups are ignored.