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School Density and Inequality in Student Achievement

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June 2024

School Density and Inequality in Student Achievement

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Abstract: In the US, test score gaps by socioeconomic status and race increase with city size. This paper examines to what extent residential sorting on school quality can explain this fact. We combine 15 years of data on public elementary school students in North Carolina with geocoded school locations and proxy city size with a measure of school density in a local labor market. Assortative matching between student advantage and school quality markedly increases with city size, accounting for 10% of the city-size gradient in test score inequality. Assortativeness is strongest in the high-income neighborhoods of large cities.

Key words: assortative matching, inequality, residential sorting

JEL classification: I24, J15, J24, R12

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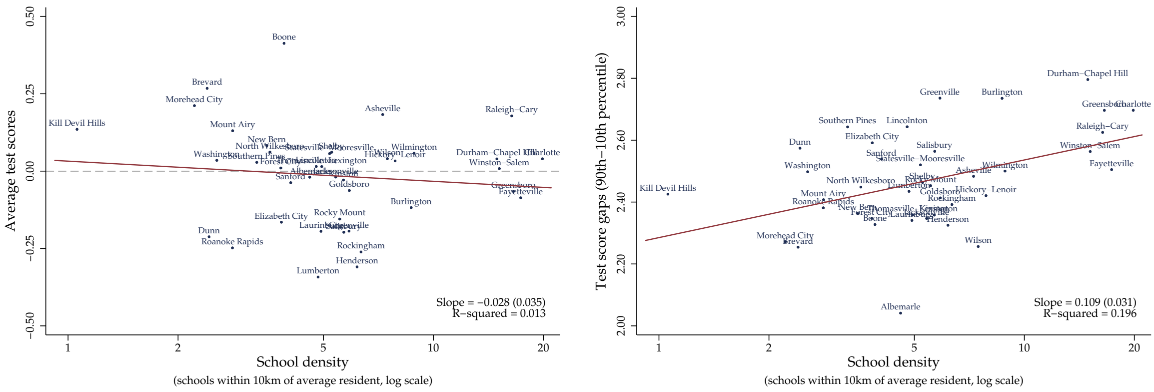
1. Introduction

In many countries, educational achievement differs strongly by socioeconomic status and race, resulting in low economic and social mobility for disadvantaged groups (Blanden, Doepke, and Stuhler, 2023). Disparities are often most salient in the largest cities, where the quality of local amenities and services, including schools, varies between low- and high-poverty neighborhoods.

Figure 1 shows that educational inequality increases with city size, using data from North Carolina—a state with low overall upward mobility (Chetty, Hendren, Kline, and Saez, 2014*b*). While elementary school students' average test scores do not vary along city size (panel a), the test scores are significantly more dispersed in large cities than in smaller ones (panel b).[1] For instance, in Charlotte, North Carolina's largest city, performance gaps between students at the 90^{th} and 10^{th} percentile of the test score distribution are 20% higher than in Brevard, a small city just 120 miles west of Charlotte. Performance gaps by race and socioeconomic status display similar patterns (see online appendix figure A.1).



Panel (a)
Average test scores

Panel (b)
Test score gaps

Figure 1: Test score averages and gaps by city size

Notes: The data come from the North Carolina Education Data Research Center (1997–2011). Each dot represents one city (Core-Based Statistical Area or local labor market) in North Carolina. Panel (a) plots city-level averages of elementary school test scores (grades 3–5) against city size, proxied by school density (number of schools available to a representative resident in a 10 km radius). Panel (b) plots city-level test score gaps against city size. The fitted lines are regression estimates based on 40 observations. Test scores are standardized by grade and year (mean zero and standard deviation one).

Potential explanations for the city-size gradient in educational inequality include greater academic diversity among students in large cities and a wider dispersion of school

[1]We use Core Based Statistical Areas (CBSAs) to delineate cities, i.e., local labor markets that contain one or many interconnected counties. We provide details in section 4.

quality. Another contributing factor is "assortativeness," the tendency of advantaged (disadvantaged) students to systematically enroll in high (low) performing schools. Such assortativeness may be more pronounced in large cities, where households can choose from a broader set of neighborhoods within commuting distance of productive jobs. Household neighborhood sorting (Tiebout, 1956) exacerbates inequality if disadvantaged families have fewer opportunities to move closer to good schools than wealthier families.

This study examines the role of assortative matching between school quality and student advantage in explaining the city-size gradient in educational inequality. We start by investigating whether student-to-school assortativeness increases with city size. We then examine to what extent assortativeness explains the relationship between city size and test score inequality, as well as between city size and racial and socioeconomic test score gaps.

The analysis uses detailed administrative data on the universe of public elementary school students (grades 3–5) in North Carolina, where most students attend their neighborhood school. We construct a matched student-school panel spanning 15 years (1997–2011) and 1.2 million students. The data contain student-level, standardized measures of academic performance throughout elementary school, baseline performance at school entry, and detailed information on student background alongside geocoded school locations. We construct a measure of city size that takes advantage of granular school locations: we compute the number of schools within a 10 km radius for a representative resident of a city in a given year. This measure captures a dimension of cities relevant to our application because higher school density allows parents to choose from a broader set of schools while remaining within commuting distance of their workplace.

Our measure of assortativeness is the correlation between student advantage and school quality in each city and year. We focus on within- instead of across-city assortativeness because the across-city variation in test scores is negligible in the data. To measure school quality, we estimate school value-added following Jackson, Porter, Easton, Blanchard, and Kiguel (2020). Value-added captures a school's contribution to students' year-to-year test score growth; it serves as a summary measure for the quality of school-level inputs. We show that our value-added estimates strongly correlate with school resources, such as teacher turnover rates and expenditures per student.[2] To measure student advantage, we use an index of baseline test scores and demographic characteristics, resulting in a summary measure of various student and parental inputs that impact academic performance.

[2]Extant work has convincingly proxied school quality using a school choice lottery in Charlotte-Mecklenburg schools (e.g., Deming, 2011). Such an approach is not applicable in our setting, as we cover more years and a larger geographical area. To mitigate measurement error concerns in school value-added, we use a large set of student-level controls and shrinkage methods in the spirit of Kane, Rockoff, and Staiger (2008) and Chetty, Friedman, and Rockoff (2014*a*).

Our findings show a strong and statistically significant association between city size and student-to-school assortativeness. A doubling of city size corresponds to an increase in the correlation between student advantage and school value-added of 0.037, a marked increase relative to the average sample correlation of 0.087. This association is substantial considering our sample's range of school density. For instance, in Charlotte, students are exposed to 20 schools within a radius of 10 km; here, the correlation between student advantage and school value-added amounts to 0.22. In Brevard, by contrast, students are exposed on average to only two schools within a 10 km radius; here, the correlation amounts to 0.04 and is thus only a fifth of the correlation found in Charlotte. The association between school density and assortativeness is robust to controlling for population density, suggesting that school density is relevant for educational inequality over and above other features of large agglomerations.

We simulate test score gaps in the hypothetical absence of assortativeness to interpret our results. Student-to-school assortativeness explains about 2.0–2.4% of the racial and socioeconomic test score gaps in large cities but none of the gaps in small cities. About 10% of the city-size gradient in inequality can be attributed to student-to-school assortativeness. In supplementary analyses, we show that affluent neighborhoods mainly drive the higher assortativeness levels observed in large cities.

We contribute to several strands of the education and urban economics literature. Prior work has linked differences in educational attainment and performance across regions to urban density and school choice. Notably, Hoxby (2000, 2003) finds that school choice and, thus, the possibility of Tiebout sorting positively impact student achievement through increased competition among schools in the US. Similarly, Gibbons and Silva (2008) document that urban density positively affects student performance in the UK. Moreover, van Maarseveen (2021) shows that children who grow up in urban environments are more likely to attend university in the Netherlands, even when controlling for cognitive ability and family background. These studies focus on average educational gaps across regions; by contrast, our study centers on inequality within cities in a context where average achievement does not vary along city size.

A second strand of the literature investigates how access to school-level inputs impacts student achievement and educational inequalities. Prior work has documented that school-level inputs—such as class sizes, teacher quality, and school funding—matter for students' achievement and later-life outcomes (e.g., Rivkin, Hanushek, and Kain, 2005; Chetty, Friedman, Hilger, Saez, Schanzenbach, and Yagan, 2011; Lafortune, Rothstein, and Whitmore Schanzenbach, 2018). Students of lower socioeconomic status are more exposed to lower-quality inputs, which exacerbates disadvantages among places and socioeconomic groups (Card and Rothstein, 2007; Sass, Hannaway, Xu, Figlio, and Feng, 2012; Owens, 2018; Reardon, Kalogrides, and Shores, 2019). Our work demonstrates that unequal exposure to school-level inputs—summarized by school value-added—is a source of inequality, primarily in areas with high school density. Moreover, despite the robust assortativeness between student advantage and school quality, assortativeness explains only a modest proportion of the inequality within cities.

Finally, several studies in urban economics investigate how cities act as places of agglomeration and opportunities and generate inequality in labor market and post-secondary educational outcomes. Studies have mainly examined the positive causal effect of city size on wage inequality (De la Roca and Puga, 2017; Baum-Snow, Freedman, and Pavan, 2018), while others have looked at how skill-intensive occupations and college attainment rates increase with city size (Bacolod, Blum, and Strange, 2009; Davis and Dingel, 2020). Most closely related to our study, Dauth, Findeisen, Moretti, and Suedekum (2022) investigate the relationship between worker-to-firm assortativeness and city size, finding associations of similar magnitudes compared to ours. We document one channel, elementary schooling, through which inequality emerges in large cities well before labor market entry.

2. Background: School choice in North Carolina

The vast majority of students in North Carolina attend elementary schools based on their residential address. North Carolina has 113 public school districts as of 2010, typically overlapping county delineations. These school districts are divided into attendance zones, which determine enrollment in 'traditional' public schools; open enrollment is generally not permitted, barring students from applying to traditional public schools outside their attendance zone. Since 87% of all students are enrolled in traditional public schools,[3] most students attend an elementary school close to their residence.[4]

The students who opt out of traditional public schools can attend 'non-traditional' public schools—charter or magnet schools—outside their attendance zone. Charter schools are publicly funded but administered with private oversight. Magnet schools are public schools with a special curricular focus (e.g., STEM or the arts). Enrollment in non-traditional public schools was less than 10% during our observational period (1997–2011). Parents can also send their children to private schools that charge tuition fees or can opt for home-schooling.

Some school districts deviated from the residential school choice paradigm during our analysis period. Such exceptions aimed to achieve a more balanced student composition

[3] See https://www.publicschoolsfirstnc.org/resources/fact-sheets/nc-public-ed-at-a-glance/, based on 2008 school year data.

[4] See https://reports.ecs.org/comparisons/view-by-state/590/NC.

in terms of student achievement and offered parents some freedom to choose schools.[5] Race-based assignment and busing policies existed in several school districts (Wake County, Mecklenburg County, Cumberland County, and Guilford County) until the early 2000s. However, they were abolished following a court order (Supreme Court, Tuttle v. Arlington County School Board, 1999).

Notably, the Charlotte-Mecklenburg school district had a race-based busing policy until 2001 and switched to a neighborhood-based school choice plan in 2002 (Jackson, 2009; Deming, Hastings, Kane, and Staiger, 2014). Moreover, in 2000, Wake County introduced an assignment policy based on socioeconomic criteria to avoid a concentration of disadvantaged students in certain schools. Aside from these specific cases, most schools in North Carolina follow a system based on attendance zones (McMillian *et al.*, 2018).

Since these exemptions from the residential school-choice paradigm were meant to counteract segregation by race and socioeconomic status, they likely attenuate the assortativeness in the data. Our analysis tackles these exemptions in two ways. First, in robustness analysis, we exclude years prior to 2002 when race-based assignment and busing policies were still active in a handful of school districts. Second, we control for the share of students enrolled in charter and magnet schools in the metropolitan area to account for parental outside options. Third, in some specifications, we drop the metro area encompassing the Charlotte-Mecklenburg school district. Our results are robust to these sample restrictions and the inclusion of controls.

3. Empirical approach

3.1 Assortative matching and city size

The primary goal of the analysis is to investigate the relationship between student-to-school assortativeness and city size. The empirical approach follows Dauth *et al.* (2022), who study the association between worker-to-firm assortativeness and city size in Germany. We adjust their framework to capture the features of the education context. Our main equation is,

$$\hat{\rho}_{ct} = \tau \, \textit{city size}_{ct} + \delta_t + \epsilon_{ct}, \tag{1}$$

where $\hat{\rho}_{ct}$ is a measure of assortativeness between student advantage and school quality in city c at time t. We proxy $\textit{city size}_{ct}$ using school density in city c at time t to capture a feature of large cities central to our application. As our preferred measure, we use the number of schools available to a typical resident within a 10-kilometer radius (see section 4

[5]McMillian, Fuller, Hill, Duch, and Darity (2018) summarize the school choice policies in the five largest school districts from 1995 to 2005.

for details). The parameter δ_t captures time fixed effects, and ϵ_{ct} is an idiosyncratic error term. Our coefficient of interest, τ, denotes the relationship between city size and assortativeness.

The main empirical challenge is to construct the dependent variable $\hat{\rho}_{ct}$, i.e., student-to-school assortativeness. If student advantage and school quality were readily observed, one could compute the correlation between the two measures in each city c and time t to assess within-city assortativeness. However, school quality is generally difficult to capture using observable school characteristics, and student advantage can be proxied in various ways.

Our solution to this challenge is to use school value-added following Jackson *et al.* (2020) as a measure of school quality and to approximate student advantage using an index of characteristics that predict student performance, including prior test scores. We then correlate the two measures in each city and year. We will explain the procedure in detail next.

3.2 *Measures of student advantage, school value-added, and assortativeness*

Student advantage

We use the term "student advantage" as shorthand for an index of student characteristics that predict student performance in elementary school (grades 3–5). We compute it as a weighted average of background characteristics and baseline performance. We obtain the vector of weights by estimating the following education production model:

$$y_{isctg} = X'_{isct}\beta + y'_{isc,t-1}\gamma + \alpha_{sct} + \delta_g + \epsilon_{isctg}, \tag{2}$$

where y_{isct} is student i's test score outcome (average of math and reading) in grade g, year t, and school s in city c, $y_{isc,t-1}$ is a vector of prior-year test scores in math and reading, and X_{isct} is a vector of student-level covariates measured in the baseline year. This vector includes proxies for academic ability (i.e., whether the student is an English language learner, a gifted student, or a disadvantaged learner in math, reading, or writing), socioeconomic status (proxied by parental education and free/reduced-price lunch receipt), and demographic characteristics (age, gender, and race). The variables α_{sct} and δ_g are school-by-year and grade fixed effects, respectively, and ϵ_{isct} is an idiosyncratic error term.[6]

Using the parameters of the education production function in equation (2), we construct an index of student advantage,

$$X'_{it}\hat{\beta} + y'_{i,t-1}\hat{\gamma}. \tag{3}$$

[6]See online appendix table A.1 for the full regression specification.

Notice that the weights, $\hat{\beta}$ and $\hat{\gamma}$, are computed net of school-by-year level influences, as we control for school-by-year fixed effects. We use a leave-own-cohort-out estimate of $\hat{\beta}$ and $\hat{\gamma}$; that is, we estimate these coefficients using OLS but based on the sample of students that does not contain student i's cohort. This approach ensures that $\hat{\beta}$ is not a function of a student's test score outcome. In practice, however, there is little difference between the leave-own-cohort-out measures of $\hat{\beta}$ and those based on the entire sample.

The index is more informative than one that uses prior-year test scores only, and the share of the variation these observed variables jointly capture is large: student-level observables, including prior-year test scores, account for 63% of the variation in the test score outcome, whereas prior-year test scores alone explain 60% (see online appendix table A.1).[7]

School value-added

We define school value-added as the contribution of school s at time t to students' year-to-year test score growth. It is a relative measure that indicates how much better or worse a school is than a base school with zero value-added. We capture school value-added through the term α_{sct} in equation (2), which varies by school and year.

Initially, one can obtain estimates of school value-added ($\hat{\alpha}_{sct}$) as fixed effects by estimating equation (2) via OLS. Under the assumption that covariates capture all the factors that jointly determine student performance and school value-added, $\hat{\alpha}_{sct}$ is an unbiased estimator of school value-added. Equation (2) comprises a rich set of student-level controls typically used in value-added estimations, including prior-year test scores, to mitigate concerns that student characteristics confound value-added. The complete list of control variables is displayed in table A.1.

In practice, however, $\hat{\alpha}_{sct}$ is not always well-suited for prediction purposes. Whereas value-added estimates for large schools are obtained from many students' test scores, estimates for smaller schools are noisier since they result from relatively few scores. Such noisy measurement inflates the variance of school value-added and could, therefore, affect measures of assortativeness (see Chetty *et al.*, 2014*a*; Jackson *et al.*, 2020, for discussions).

Our preferred measure of school value-added follows Jackson *et al.* (2020) and shrinks noisier value-added estimates towards zero. Considering that the unconditional mean of school value-added is zero, from a Bayesian perspective, the value zero is a suitable prior for school value-added in the absence of any information (for instance, if a school

[7]One limitation is that the index does not account for student-level unobservables, such as household wealth or student motivation. While prior-year test scores and other controls may broadly absorb them, we cannot discard that they may partly impact performance. We could mitigate this concern by looking at students who switch schools. However, only 14% of students in the sample ever switched schools, and switchers belong to highly disadvantaged groups.

has no data). In practice, we predict the (unshrunken) school-by-year fixed effects in a given year, $\hat{\alpha}_{sct}$, using their (unshrunken) lags and leads; the predicted value then serves as a shrunken measure of value-added. The prediction places more weight on adjacent years, indicating that school quality in more distant years is less informative about current school quality (see online appendix A.2 for details). Our main results sre robust to using a non-shrunken value-added measure instead.

Assortativeness

As the dependent variable in equation (1), we compute the within-city correlation between school value-added and student advantage for each year t and city c as,

$$\hat{\rho}_{ct} = Corr\left[\left(X'_{isct}\hat{\beta} + y'_{isct}\hat{\gamma}\right), \hat{\mu}_{sct}\right], \tag{4}$$

where $\hat{\mu}_{sct}$ is the estimated value-added of school s in city c at time t, and $X'_{isct}\hat{\beta} + y'_{isct}\hat{\gamma}$ is the index of student advantage.

3.3 *Interpretation and validity checks*

The coefficient τ in equation (1) measures the association between city size and student-to-school assortativeness. We do not wish to interpret this association as a causal effect because higher city assortativeness may attract residents, leading to a reverse causality concern, or because unobserved confounders could have influenced city size and assortativeness. Although the setup is not ideal for causal analysis, we undertake concerns about confounders and reverse causality in several ways.

To mitigate confounders, we add relevant control variables in robustness analyses, specifically, the average school size in the city and the fractions of charter, magnet, and private schools. We are primarily concerned with the latter confounders because such school types may affect sorting and are more prevalent in large cities. In addition, we estimate specifications with CBSA fixed effects, where the identifying variation stems entirely from school openings and closings. As such, we alleviate concerns about time-invariant unobserved confounders, such as higher historical racial or income segregation levels in some cities or city-level geographic traits that may facilitate segregation.

In supplementary analyses, we address concerns about reverse causality by instrumenting contemporaneous school density with historical city size from the 1900 US census. Large cities in North Carolina in 1900 are likely to remain large today and thus exhibit higher levels of school density (Ciccone and Hall, 1996). Historical city size is unlikely to directly affect student-to-school assortativeness today and can be considered a valid instrument.

4. Data and descriptive statistics

4.1 Student data

We use annual administrative records for children in North Carolina's public elementary schools (grades 3–5) for 1997–2011, provided under a restricted use agreement with the North Carolina Education Data Center (NCERDC). The data contain rich information on standardized measures of student performance, student background, and geocoded school locations.[8] Our panel construction closely follows Jackson (2013) and Rothstein (2017).

Our outcome is the average score of students' end-of-grade tests in math and reading. These tests are the same across all schools and school districts in North Carolina in a given grade and year. We standardize the test scores to have a mean of zero and a standard deviation of one at the year-by-grade level. We also carry out additional analyses disaggregated by subject (math and reading).

The data set includes student background characteristics from administrative records. The variables capture students' demographic characteristics (gender, age, and race/ethnicity), socioeconomic background (highest parental educational attainment, eligibility for free/reduced-price lunch), and student preparedness (indicators for whether the student is gifted, learning disadvantaged, disadvantaged in reading, math, or writing, or an English-language learner). To measure performance at the baseline in each year, we extract prior-year test scores from end-of-grade test files or, where missing, from the "master-build" files. These files also contain pretest scores collected for grade-3 students before they enter elementary school.

The data allow us to identify the precise location of every school. Schools' latitudes and longitudes are available from 2001 onwards, whereas addresses are available before 2001. We use this information to compute measures of school density at the city level. The data also contain information on students' residential location at the census block group level, which we use to approximate travel distances between students and schools.

4.2 City size

We use Core Based Statistical Areas (CBSAs), as defined by the Office of Management Budget in 2008, to delineate cities in North Carolina. A CBSA is a collection of one or more counties, consisting of a core and a commuting shed, that encompasses an integrated labor market. There were 41 CBSAs with a population range from 33,087 (Brevard) to 1,758,038 (Charlotte-Concord-Gastonia) in 2010, comprising 71 of the 100 counties in North Carolina. Since county and school district boundaries largely coincide, districts lie entirely within a CBSA. However, CBSAs can stretch across state borders, such as Charlotte-Concord-Gastonia

[8] The data do not include information on private school students.

("Charlotte") in North and South Carolina and Virginia Beach-Norfolk-Newport News in North Carolina and Virginia. We exclude the latter from the analysis since most of its territory lies in Virginia.

We use school density in a CBSA as a proxy of city size. To construct this measure, we overlap maps of CBSAs, census tracts (i.e., neighborhood delineations within a CBSA that contain, on average, 4,000 residents), and the coordinates of all public schools. For every census tract centroid, we calculate the distances to all schools in the CBSA and count the number of schools available within a 10 km radius. This radius is appropriate because 90% of the students live within a 10 km radius of their school, though we also test the robustness of our result to a 5 km radius.[9] Since census tracts vary in population, we compute a weighted average across all census tracts in a CBSA, using the share of people in the CBSA that live in each census tract as weights. Consequently, the school density measure reflects how many elementary schools lie within a radius of ten kilometers for a typical resident in a CBSA.

The school density measure varies annually as schools open or close during the analysis period. The distance calculations include traditional elementary public schools, charter, and magnet schools. In the sample, approximately 92%, 3%, and 5% of students attend traditional public schools, charter, and magnet schools. School density varies widely across CBSAs and years, from 1.06 schools in Kill Devil Hills in 1998 to 22.81 schools in Charlotte in 2011, with a median of 5.43 schools in Kinston in 1999.

4.3 Sample selection and descriptive statistics

The final sample contains over 2.3 million student-year observations across 40 CBSAs from 1998 to 2011. We exclude observations in 1997—the first data year—because our computations of school value-added and student advantage rely on prior-year test scores. We also drop charter school students because the data do not contain unique school identifiers for these students. Lastly, we drop school-by-year cells with less than five observations. The sample includes 2,384,452 student-year observations, 1,198,237 students, 13,747 school-year observations, 1,198 schools, and 533 CBSA-by-year observations.

Table 1 presents descriptive statistics of selected student- and CBSA-level variables for the entire student sample (column 1) and by levels of school density (columns 2–5), divided into four categories: low school density (less than four schools available within a 10 km radius), moderate (4–6 schools), high (6–15 schools), and very high (15 or more schools). Students in our sample are 10.4 years old on average and live in households

[9]We approximate the distances of students to schools using the centroids of students' block groups of residence: 90% of students live within 10 km of their school. The typical (median) student lives 3.48 km away from their school. This distance declines with city size from 4.49 km in cities with low school density to 3.03 km in cities with very high school density.

with relatively low socioeconomic status: 42% are eligible for free/reduced-price lunch, and 27% have at least one college-educated parent. Most students in the sample are white (60%) or Black (27%).

Test score gaps by race and socioeconomic status are substantial (see the middle panel of table 1). On average, white students score at the 62$^{\text{nd}}$ percentile of the test score distribution (0.302), while Black students score at the 30$^{\text{th}}$ percentile (-0.521), a gap of 0.823 test score standard deviations. Similarly, test score gaps by parental education and economic disadvantage (i.e., eligibility for free/reduced-price lunch) are sizable at 0.816 and 0.781 standard deviations, respectively.

Test score gaps increase monotonically and markedly with city size. The gap between students at the 90^{th} and 10^{th} percentile of the test score distribution rises by 8% in cities with low to very high school density. Test score gaps by race and socioeconomic status also increase with city size. For example, the white-Black test score gap grows from 0.701 in cities with low school density to 0.891 in cities with very high school density, a 27% increase.

4.4 Student advantage and school value-added estimates

The bottom panel of table 1 presents our estimates of student advantage and school value-added. The estimated index of student advantage has a standard deviation of 0.804, implying that a one-standard-deviation increase in student advantage raises test scores by 0.804 standard deviations. The magnitude is close to the test score gap by race, as shown in the middle panel. Student advantage is slightly higher and more dispersed in cities with high school density.

School value-added has a standard deviation of 0.065, meaning that a one-standard-deviation increase in school value-added raises test scores by 0.065 standard deviations. Jackson *et al.* (2020) report a similar magnitude of 0.061, using 9$^{\text{th}}$-grade test scores from Chicago. The mean and variance of school value-added are stable across city sizes.

Schools with higher value-added are characterized by better school-level resources, suggesting that our value-added measure meaningfully captures school quality (see appendix table A.2). Low teacher turnover, teaching experience and qualifications, and expenses per student are statistically significant predictors of higher school value-added.

Differences in school value-added by race and socioeconomic status augment with city size (lower panel of table 1). For example, Black and white students attend schools of similar value-added in small cities, but the value-added gap amounts to 0.018 standard deviations in large cities (column 5). Such within-city differences in school quality are minor compared to within-city achievement gaps across racial and socioeconomic groups:

Table 1: Summary statistics by school density

	Full sample	School density: Low (< 4)	Moderate (4–6)	High (6–15)	Very high (15+)
	(1)	(2)	(3)	(4)	(5)
Student characteristics					
Age (years)	10.4	10.4	10.4	10.3	10.4
Female (%)	49.7	49.6	49.5	49.8	49.7
Free/reduced-price lunch (%)	41.5	46.6	44.8	38.4	41.0
White (%)	59.8	66.8	60.8	67.6	53.7
Black (%)	27.1	24.3	26.3	21.7	30.9
Hispanic (%)	7.0	5.2	5.4	5.7	8.7
Other race or ethnicity (%)	6.1	3.8	7.5	5.0	6.6
College-educated parent (%)	27.4	25.1	23.9	29.7	28.0
Test score gap 90^{th}-10^{th} percentile	2.575	2.452	2.461	2.547	2.659
90^{th} pctile	1.275	1.201	1.154	1.276	1.337
10^{th} pctile	-1.299	-1.251	-1.307	-1.270	-1.321
Test score gap white-Black	0.823	0.701	0.708	0.827	0.891
White	0.302	0.206	0.185	0.268	0.385
Black	-0.521	-0.495	-0.523	-0.559	-0.505
Test score gap parental education	0.816	0.702	0.726	0.811	0.886
College-educated parent	0.517	0.472	0.442	0.550	0.543
No college-educated parent	-0.298	-0.231	-0.284	-0.261	-0.343
Test score gap FRL-no FRL	0.781	0.652	0.661	0.750	0.867
No free/reduced-price lunch	0.355	0.332	0.263	0.349	0.397
Free/reduced-price lunch	-0.426	-0.320	-0.397	-0.400	-0.470
Student advantage					
mean	0.004	-0.020	-0.055	0.036	0.014
standard deviation	0.804	0.764	0.763	0.807	0.825
School value-added (VA)					
mean	0.003	0.014	-0.002	0.000	0.003
standard deviation	0.065	0.069	0.063	0.060	0.068
VA gap white–Black	0.010	-0.005	-0.001	0.008	0.018
VA gap parental education	0.011	0.002	0.004	0.004	0.021
VA gap FRL–no FRL	0.012	0.003	0.005	0.004	0.021
Average schools within 10k	12.1	3.0	5.2	9.5	18.1
Student-by-year observations	2,384,452	228,893	432,324	604,153	1,119,082
CBSA-by-year observations	533	155	181	127	70

Notes: Test score levels and gaps and value-added gaps are computed within each CBSA and weighted by the number of students in the CBSA. "College-educated parent" indicates at least one parent has a college degree.

they account for 2.0% (0.018/0.891) of racial test score gaps and 2.4% (0.021/0.867) of test score gaps by economic disadvantage (free/reduced-price lunch eligibility).

Finally, to justify our focus on test score differences within- rather than across cities, we perform a variance decomposition and document that the within-city variation is quantitatively more relevant (table A.3): 91%, 98%, and 99% of the total variation in school value-added, student advantage, and test scores outcomes are due to within-city variation, respectively.

5. Results

5.1 Assortativeness and city size

Table 2 displays the main results based on a regression of student-to-school assortativeness on city size (equation 1). In column (1), we estimate a coefficient of 0.052 ($p < 0.01$), meaning that doubling school density corresponds to an increase in the correlation between student advantage and school value-added of 0.037 (i.e., $2^{0.052} - 1$). This effect implies that the correlation increases by 0.098 when moving from a low-density to a very-high-density city, a marked increase. The findings align closely with those of Dauth *et al.* (2022), who analyze the correlation between worker and firm value-added across 204 German cities for two sample periods. They report coefficients of 0.038 (1985–1991) and 0.061 (2008–2014).

Figure 2 illustrates the regression results of column (1) in a scatter plot. Each dot corresponds to the average CBSA-year correlation (533 observations) for the 40 CBSAs in the sample. Cities with only 2.2 to 2.45 schools within 10 km of the typical resident, such as Morehead City, Brevard, and Dunn, have correlation values between 0.016 and 0.057. Conversely, the three largest cities, Charlotte, Fayetteville, and Greensboro, with 16.5 to 20 schools around the typical resident, show correlations between 0.152 and 0.217.

The baseline results in column (1) of table 2 are robust to several specifications. The estimated coefficient is similar when we approximate city size with the number of schools within a 5 km radius instead of a 10 km one (column 2) or when we use population density instead of school density (column 3). Notably, the baseline results persist when we add the log of population density as a control variable (coefficient of 0.045 in column 4, $p < 0.05$); this suggests that student-to-school assortativeness is driven by school density rather than population density or other amenities that concentrate people in a location. In column (5), we control for the average school size and the fraction of charter and magnet schools in the CBSA. We obtain a coefficient of 0.047 ($p < 0.01$), only slightly lower than the preferred specification in column (1). Finally, we disaggregate the analysis by subject and find a lower coefficient for math than reading.

Table 2: Assortative matching and city size

	Dep.var.: Correlation (student advantage, school VA)						
	Math and reading combined					Math	Reading
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log schools within 10k	0.052***			0.045**	0.047***	0.034***	0.057***
	(0.013)			(0.020)	(0.013)	(0.011)	(0.015)
Log schools within 5k		0.048***					
		(0.014)					
Log population density			0.049**	0.009			
			(0.018)	(0.027)			
Average school size					0.302	0.073	0.431*
					(0.186)	(0.150)	(0.226)
Fraction charter schools					0.554*	0.467*	0.515
					(0.319)	(0.255)	(0.386)
Fraction magnet schools					-0.012	0.021	-0.030
					(0.064)	(0.056)	(0.066)
Year indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dep. variable	0.087	0.087	0.087	0.087	0.087	0.084	0.082
Observations	533	533	533	533	533	533	533
R^2	0.141	0.125	0.113	0.142	0.171	0.120	0.202

Notes: Results of OLS regressions of student-to-school assortativeness on city size. Coefficients are reported with standard errors in parenthesis and clustered at the CBSA level (40 clusters). Average school size is the number of students per school divided by 1,000 for readability. ***, **, and * indicate significance at the 1, 5, and 10% levels.

We report the results of additional robustness checks in appendix table A.4. We first examine the sensitivity of the results to using a non-shrunken school value-added measure (columns 1 and 2). The correlation between school value-added and student achievement drops when using the non-shrunken measure (0.059 vs. 0.087), with the highest absolute decrease in the largest cities. As a result, the estimated coefficient drops from 0.052 to 0.037 but remains statistically significant ($p < 0.01$). The results are also robust when excluding Charlotte, the largest city, a potential outlier given its busing and school choice plan policies (columns 3 and 4). We then focus on the years post-2001 because several school districts used busing to mitigate sorting until 2001 (columns 5 and 6). The coefficients increase slightly, consistent with previous findings that busing reduced student-to-school assortativeness (Jackson, 2009). Lastly, we control for the fraction of private schools in each CBSA because they may allow wealthier families to exit the public school system. Our data includes information on private schools only for a subset of years (1998–2004). Controlling for the fraction of private schools does not affect the results (column 7).

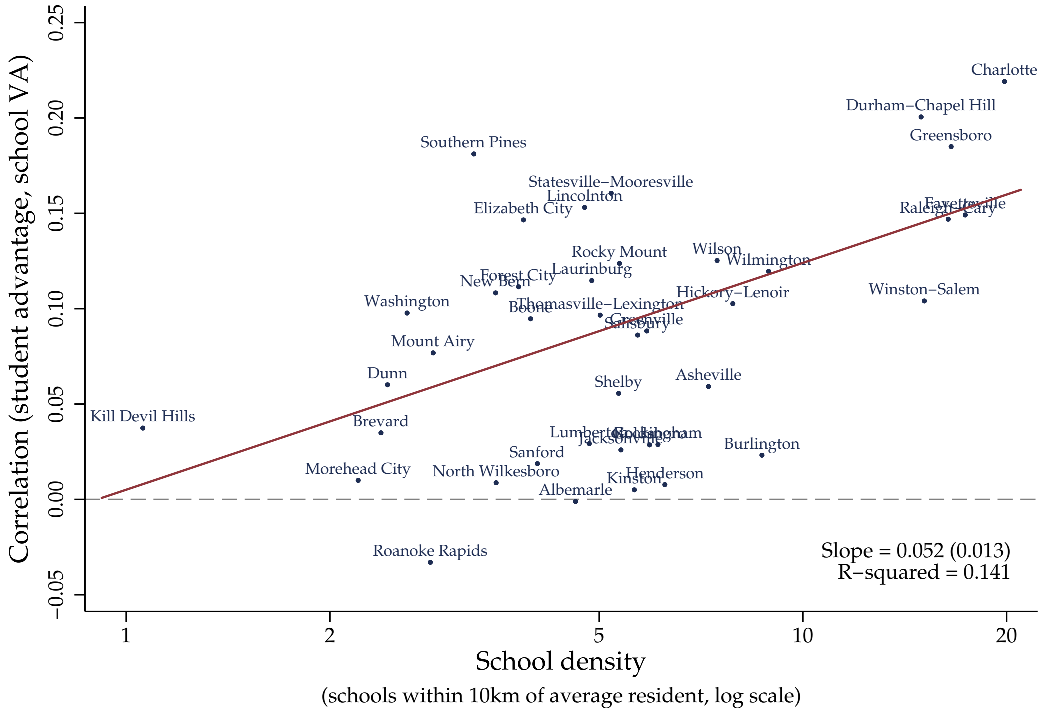


Figure 2: Assortativeness and city size

Notes: The plotted line follows from the regression in column (1) of table 2. The dots represent CBSA-level averages across all years.

We present two supplementary checks in tables A.5 and A.6. First, to address reverse causality concerns, we instrument contemporaneous school density with historical city size in 1900, averaging the data across years. The IV estimates are slightly larger than OLS ones, albeit not statistically different from each other (table A.5, columns 2 and 4). We are cautious about these results since they rely on 39 observations. In a different robustness check, we include CBSA fixed-effects, using solely school openings and closings for identification (see online appendix table A.6). Our results remain similar in magnitude; however, the standard errors increase, rendering our results insignificant at conventional levels (columns 2 and 4). This outcome is unsurprising as school closings and openings are infrequent events: the annual rates of school closings and openings are 1% and 2% in our sample, respectively.

5.2 *Simulations of student-to-school assignment*

We quantify the impact of assortativeness on racial and socioeconomic test score gaps using simulations. The simulation design mimics a no-sorting scenario. We randomly match students to a school within each CBSA, year, and grade level, fixing the number of

Table 3: Simulations

	Full sample	School density: Low (< 4)	Moderate (4–6)	High (6–15)	Very high (15+)
	(1)	(2)	(3)	(4)	(5)
90^{th}–10^{th} percentile gap					
status quo	2.575	2.452	2.461	2.547	2.659
counterfactual	2.556	2.444	2.451	2.535	2.631
% explained by assortativeness	0.7%	0.3%	0.4%	0.5%	1.0%
Racial gap (white–Black)					
status quo	0.823	0.701	0.708	0.827	0.891
counterfactual	0.814	0.704	0.708	0.823	0.873
% explained by assortativeness	1.1%	-0.4%	0.1%	0.4%	2.0%
Parental education high vs. low					
status quo	0.816	0.702	0.726	0.811	0.886
counterfactual	0.805	0.701	0.721	0.807	0.866
% explained by assortativeness	1.3%	0.2%	0.6%	0.5%	2.3%
No free lunch vs. free/reduced-price					
status quo	0.781	0.652	0.661	0.750	0.867
counterfactual	0.769	0.650	0.656	0.744	0.847
% explained by assortativeness	1.6%	0.4%	0.7%	0.7%	2.3%

Notes: All numbers denote fractions of a test score standard deviation. The test score gaps are computed within each CBSA and weighted by the number of students in the CBSA. Parental education is "high" if at least one parent has a college degree and "low" otherwise. The percent explained by assortativeness is the difference between the status quo and the counterfactual outcomes, divided by the status quo outcome.

students enrolled in a school at a given grade level. We compute a counterfactual test score for each student by subtracting the student's actual (status-quo) school value-added from observed test scores and adding the randomly assigned school value-added. We then compare overall, racial, and socioeconomic test score gaps under the no-sorting scenario with the status-quo gaps. We repeat this procedure 100 times and average the counterfactuals across all 100 draws to ensure the stability of our results across different random draws.

Table 3 presents the simulation results. On average, student-to-school assortativeness accounts for 0.7% of test score gaps between the students at the 90^{th} and 10^{th} percentile of the test score distribution and for 1.1%–1.6% of the test score gaps by race and economic disadvantage. Assortativeness is highest in the largest cities, accounting for 1.0–2.3% of test score gaps. By contrast, it explains less than 0.7% of these gaps in smaller-sized cities. Consequently, the contribution of sorting to overall test score gaps appears modest, even in the largest cities.

Using back-of-the-envelope calculations, we determine the contribution of sorting to the city-size gradient in inequality. Overall, sorting explains about 8% to 11% of the city-size gradient in inequality. For instance, the racial gap differs by 0.190 test score standard deviations between very-high-density cities (0.891) and low-density cities (0.701). Our simulation results attribute 11.1% of such gradient to student-to-school assortativeness.[10]

6. Discussion: The role of affluence

Lastly, we descriptively examine within-city patterns of assortativeness to explore whether the city-size gradient in inequality is driven by high-, low-, or middle-income neighborhoods. We divide cities into smaller, homogeneous areas along measures of affluence. Specifically, for each CBSA, we group census tracts (i.e., neighborhoods) into quartiles of the within-CBSA distribution of tract-level income. This grouping results in four similarly sized areas in the CBSA with different income levels. We then compute the student-to-school assortativeness within these four areas. Thus, we can analyze whether the correlations vary across low-, lower-middle-, upper-middle-, and high-income areas in a CBSA (see appendix table A.7).

Sorting is stronger in higher-income compared to lower-income areas and most pronounced in the highest-income areas of large cities (panel A of appendix table A.7). On average, the correlation between school value-added and student advantage amounts to 0.08 in low-income areas, increases to 0.10 in middle-income and to 0.15 in high-income areas (column 1). This pattern is driven by large cities, where student-to-school assortativeness rises from 0.11 in low-income areas to 0.20 in high-income areas (column 4). We obtain consistent results using alternative proxies of affluence (share of poor households and share of college-educated residents, see panels B and C).

The results suggest that households in affluent areas of large cities can better sort on school quality. The sorting is less pronounced but still present in the low-opportunity areas of large cities. Assortative behavior appears less feasible for households in medium-sized cities, even in well-off neighborhoods.

7. Concluding remarks

This study documents a positive relationship between student-to-school assortativeness and city size in North Carolina. In large cities, advantaged students are more likely to attend better schools, and assortativeness explains around 2% of the test score gaps

[10]The actual racial gap between the largest and smallest cities stands at 0.190 (0.891-0.701), as indicated in the first row of table 3. The counterfactual racial gap is lower at 0.169 (0.873-0.704), as shown in row 2. The contribution of assortativeness to the city-size gradient follows from $(0.169 - 0.190)/0.190 \approx -0.111$.

across racial and socioeconomic groups. Student-to-school assortativeness accounts for around 10% of the city-size gradient in test score gaps, with affluent neighborhoods primarily driving the effect.

To better contextualize the results, it is fundamental to consider that inequality accumulates over time. The examined outcome captures year-to-year changes in standardized test scores, yet assortativeness might have more pronounced impacts on test score gaps over an entire schooling trajectory. Moreover, student-to-school assortativeness might affect outcomes other than test scores. Studying these relationships remains a task for further research.

Finally, student-to-school assortativeness might be more pronounced in large metropolitan areas. The size of North Carolina's largest metro area, Charlotte, is modest (1.8 million) compared with the nation's largest CBSAs—New York (18.9 million inhabitants as of 2010), Los Angeles (12.8 million), and Chicago (9.5 million). Future research may assess whether sorting amplifies in larger agglomerations outside North Carolina.

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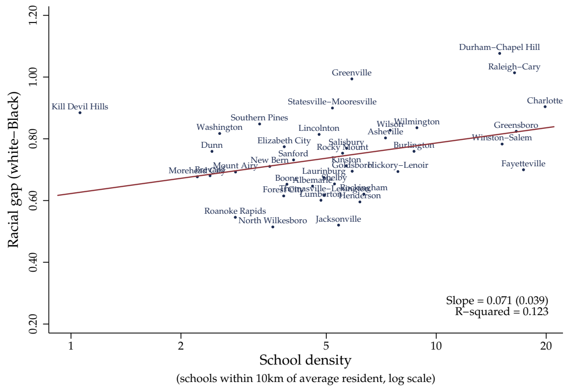
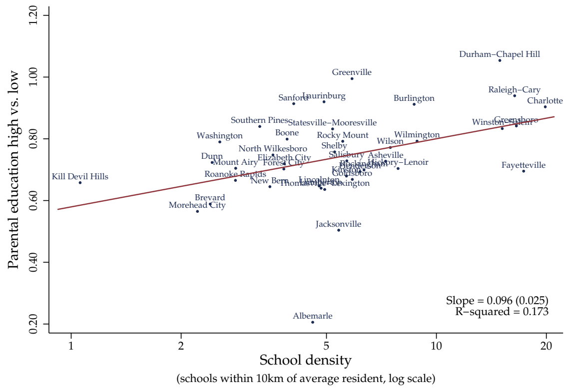
Online appendix (not for publication)

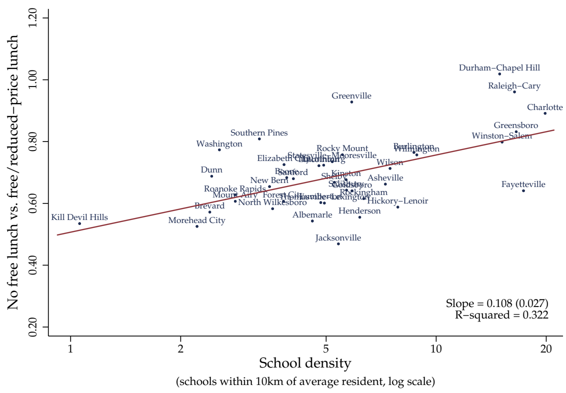
A.1. Tables and figures



Panel (a)
Racial gap (white-Black)



Panel (b)
Gap by parental education



Panel (c)
Gap by FRL eligibility

Figure A.1: Test score gaps and city size by race and socioeconomic status

Notes: The data come from the North Carolina Education Data Research Center (1997–2011). Each dot represents one city (Core-Based Statistical Area or local labor market) in North Carolina. All panels plot city-level test score gaps against city size, proxied by school density (number of schools available to a representative resident in a 10 km radius). The fitted lines are regression estimates based on 40 observations. Test scores are standardized by grade and year (mean zero and standard deviation one). Parental education is high if at least one parent has a college degree and low otherwise. FRL denotes free/reduced-price lunch.

Table A.1: Regressions of test scores on prior-year test scores and student background

	Dep.var.: Test score (avg. of math and reading)	
Prior-year test score math	0.472*** (0.001)	0.401*** (0.001)
Prior-year test score reading	0.418*** (0.001)	0.339*** (0.001)
Female		0.009*** (0.001)
Age		-0.080*** (0.001)
Race/ethicity: Black		-0.189*** (0.001)
Race/ethicity: Hispanic		-0.008*** (0.002)
Race/ethicity: other		-0.003* (0.002)
Parental education: high school		0.091*** (0.001)
Parental education: vocational degree		0.154*** (0.002)
Parental education: community college		0.162*** (0.002)
Parental education: four-year college		0.232*** (0.002)
Parental education: graduate school		0.294*** (0.002)
Free/reduced-price lunch eligible		-0.099*** (0.001)
English language-learner		-0.210*** (0.002)
Gifted		0.315*** (0.001)
Disadvantaged learner		-0.128*** (0.003)
Disadvantaged learner math		-0.090*** (0.003)
Disadvantaged learner reading		-0.184*** (0.003)
Disadvantaged learner writing		-0.007** (0.003)
Mean of dependent variable	0.013	0.013
Observations	2,384,452	2,384,452
R^2	0.659	0.685
Within-R^2	0.603	0.633

Notes: The table shows OLS regression results. The reference categories are "white/non-Hispanic" for race/ethnicity and "no high-school degree" for parental education. Parental education denotes the highest education of any parent. Both specifications include school-by-year and grade fixed effects, and indicators for missing values on prior-year test scores, parental education, free/reduced-price lunch eligibility, English language learner status, gifted status, and learning disadvantage status categories. The within-R^2 denotes the share of the variation explained by all variables, except for the school-by-year fixed effects. ***, **, and * indicate significance at the 1, 5, and 10% levels.

Table A.2: School value-added and school resources

	Dep.var.: School value-added						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1-year teacher turnover rate	-0.091***						-0.046***
	(0.012)						(0.012)
Frac. teachers $\leqslant$ 3 yrs exper.		-0.100***					-0.047***
		(0.012)					(0.015)
Frac. teachers 11+ yrs exper.			0.072***				0.027*
			(0.011)				(0.014)
Frac. licensed teachers				0.128***			0.056**
				(0.023)			(0.023)
Frac. teachers advanced degree					0.079***		0.037**
					(0.015)		(0.016)
District expenditure per student						0.006*	0.006***
						(0.004)	(0.002)
Year indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dependent variable	0.002	0.002	0.002	0.002	0.002	0.002	0.002
Observations	9,868	9,903	9,918	9,920	9,920	13,747	9,832
R^2	0.013	0.024	0.019	0.009	0.013	0.006	0.041

Notes: The table presents correlates of school value-added resulting from OLS regressions on measures of school resources. Coefficients are reported with standard errors in parenthesis and clustered at the school-district level in column (6) and at the school level in all other columns. The teacher information comes from school report cards and is recorded by schools every year from 2002 onwards. The information on expenditure per student (in 1,000 USD per year) comes from district-level finance data and is available for all years (1998–2011). ***, **, and * indicate significance at the 1, 5, and 10% levels.

Table A.3: Within- vs. across-city variation in test scores

	total	across	within
Variance of test scores	0.996	0.014	0.981
	100%	1.4%	98.6%
Variance of student advantage	0.647	0.010	0.637
	100%	1.6%	98.4%
Variance of school value-added	0.004	0.000	0.004
	100%	8.6%	91.4%
$2 \times$ Cov (student advantage, school VA)	0.015	0.002	0.013
	100%	10.3%	89.7%

Notes: The table displays a variance decomposition of test score outcomes, school value-added, and student advantage into a within- and an across-city component. We decompose the variance in school value-added, $\hat{\mu}_i$, using the following formula:

$$\text{Var}(\hat{\mu}_i) = \underbrace{\text{Var}[\mathbb{E}_m(\hat{\mu}_i)]}_{\text{between}} + \underbrace{\mathbb{E}[\text{Var}_m(\hat{\mu}_i)]}_{\text{within}},$$

where m denotes the CBSA, and $\mathbb{E}_m$ and Var_m are the CBSA respective moments (see Dauth *et al.* (2022), page 1490). The bottom row presents a decomposition of the covariance between student advantage and school value-added based on the following formula:

$$\text{Cov}((X_i'\hat{\beta} + y_{i,t-1}'\hat{\gamma}), \hat{\mu}_i) = \underbrace{\text{Cov}\left(\mathbb{E}_m[(X_i'\hat{\beta} + y_{i,t-1}'\hat{\gamma})], \mathbb{E}_m[\hat{\mu}_i]\right)}_{\text{between}} + \underbrace{\mathbb{E}\left[\text{Cov}_m\left((X_i'\hat{\beta} + y_{i,t-1}'\hat{\gamma}), \hat{\mu}_i\right)\right]}_{\text{within}},$$

where $\mathbb{E}_m$ and Cov_m are the CBSA respective moments.

Table A.4: Robustness checks

	Dep.var.: Correlation (student advantage, school VA)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log schools within 10k	0.037***	0.036***	0.044***	0.041***	0.057***	0.064***	0.038**
	(0.009)	(0.013)	(0.013)	(0.014)	(0.015)	(0.022)	(0.017)
Average school size		0.237*		0.269		0.416*	0.232
		(0.139)		(0.184)		(0.230)	(0.227)
Fraction charter schools		0.302		0.555*		0.667*	0.349
		(0.275)		(0.324)		(0.341)	(0.436)
Fraction magnet schools		-0.154***		-0.016		-0.098	-0.020
		(0.056)		(0.058)		(0.086)	(0.057)
Fraction private schools							0.054
							(0.393)
Year indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School VA without shrinkage	Yes	Yes					
Without Charlotte			Yes	Yes			
End of busing (post-2001)					Yes	Yes	
Pre-2005							Yes
Mean of dependent variable	0.059	0.059	0.084	0.084	0.094	0.094	0.074
Observations	533	533	519	519	377	377	267
R^2	0.160	0.181	0.111	0.139	0.147	0.194	0.140

Notes: The table shows the results of several robustness checks from OLS regressions. Coefficients are reported with standard errors in parenthesis and clustered at the CBSA level (40 clusters). In columns (1) and (2), we use an unshrunken measure of value-added to compute the correlation between student advantage and school value-added (see the main text for details). We exclude the largest CBSA, Charlotte, from the sample in columns (3) and (4). We only consider the years after the end of busing in North Carolina, 2002–2011, in columns (5) and (6). Based on a private school survey for 1998–2004, we include the fraction of private schools in a CBSA in column (7). Average school size is the number of students per school divided by 1,000 for readability. ***, **, and * indicate significance at the 1, 5, and 10% levels.

Table A.5: IV estimation of assortative matching on city size

	Dep.var.: Correlation (student advantage, school VA)			
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Log schools within 10k	0.049***	0.065***	0.043***	0.072***
	(0.012)	(0.016)	(0.013)	(0.025)
Average school size			0.400*	0.391*
			(0.205)	(0.201)
Fraction charter schools			0.537	0.545
			(0.431)	(0.407)
Fraction magnet schools			-0.004	-0.220
			(0.159)	(0.186)
Mean of dependent variable	0.086	0.086	0.086	0.086
Observations	39	39	39	39
R^2	0.252	0.225	0.345	0.290
First-stage F-statistics		52.38		12.00

Notes: The table shows the OLS and IV regression results of student-to-school assortativeness on city size. All specifications include a constant term. Coefficients are reported with robust standard errors in parenthesis. We pool the data across years and each observation represents a CBSA. We use the 1900 log population (from US census county-level headcounts) in a CBSA to instrument for school density. Average school size is the number of students per school divided by 1,000 for readability. ***, **, and * indicate significance at the 1, 5, and 10% levels.

Table A.6: Estimation with CBSA indicators

	Dep.var.: Correlation (student advantage, school VA)			
	(1)	(2)	(3)	(4)
Log schools within 10k	0.047***	0.034	0.055***	0.075
	(0.013)	(0.063)	(0.015)	(0.110)
Average school size	0.302	0.106	0.359*	0.327
	(0.186)	(0.381)	(0.196)	(0.509)
Fraction charter schools	0.554*	0.451	0.677**	0.385
	(0.319)	(0.417)	(0.332)	(0.448)
Fraction magnet schools	-0.012	-0.024	-0.095	-0.167***
	(0.064)	(0.043)	(0.089)	(0.057)
Year indicators	Yes	Yes	Yes	Yes
CBSA indicators		Yes		Yes
Post-2001			Yes	Yes
Mean of dependent variable	0.087	0.087	0.094	0.094
Observations	533	533	377	377
R^2	0.171	0.448	0.193	0.510

Notes: Results of OLS regressions of student-to-school assortativeness on city size. Coefficients are reported with standard errors in parenthesis and clustered at the CBSA level (40 clusters). We only consider the years after the end of busing in North Carolina, 2002-2011, in columns (3) and (4). Average school size is the number of students per school divided by 1,000 for readability. ***, **, and * indicate significance at the 1, 5, and 10% levels.

Table A.7: Sorting by neighborhood affluence

		School density		
	Full sample	Moderate (4–6)	High (6–15)	Very high (15+)
	(1)	(2)	(3)	(4)
Panel A. Sorting in high- vs. low-income neighborhoods				
Mean income (tract-level)	Correlation (student advantage, school VA)			
Low	0.08	0.02	0.01	0.11
Lower middle	0.10	0.04	0.08	0.11
Upper middle	0.10	0.06	0.06	0.12
High	0.15	0.05	0.06	0.20
Panel B. Sorting in high- vs. low-poverty neighborhoods				
Percent above poverty line (tract-level)	Correlation (student advantage, school VA)			
Low	0.11	0.06	0.09	0.13
Lower middle	0.08	0.05	0.06	0.09
Upper middle	0.14	0.06	0.12	0.16
High	0.17	0.08	0.08	0.21
Panel C. Sorting in neighborhoods with high vs. low education				
Percent with college degree (tract-level)	Correlation (student advantage, school VA)			
Low	0.10	0.07	0.06	0.12
Lower middle	0.08	0.04	0.05	0.10
Upper middle	0.10	0.00	0.09	0.12
High	0.18	0.08	0.08	0.23
Average schools within 10k	14.6	5.4	7.7	18.6
Student-by-year observations	714,136	92,159	151,402	470,575
CBSA observations	25	9	10	6
Census-tract observations	897	151	245	501

Notes: The table displays correlations between student advantage and school value-added in different areas within a CBSA. In panel A, each CBSA is split into quartiles of mean neighborhood income. This grouping results in four similarly sized areas within each CBSA with varying income levels. In panel B, each CBSA is split into neighborhood poverty quartiles based on the fraction of individuals above the poverty line in a census tract. In panel C, each CBSA is split into college attainment quartiles based on the fraction of individuals with a bachelor's degree in a census tract. We compute the student-to-school assortativeness for each area in a CBSA. Tract-level characteristics come from the 2011 5-year ACS files. The sample includes student and school data for 2007–2011. We only include CBSAs with 12 or more census tracts to avoid small-sample issues and exclude CBSAs with low school density values (i.e., less than four schools within a 10 km radius).

A.2. Estimation of school value-added

The estimation of school value-added follows Jackson *et al.* (2020) and proceeds in two steps.

We first compute the residual of a modified version of equation (2), which does not contain school-by-year fixed effects. For ease of exposition, we drop the subscript c since schools do not switch cities:

$$y_{istg} = X'_{ist}\beta + y'_{i,t-1}\gamma + \delta_t + \delta_g + \nu_{istg}, \tag{5}$$

where y_{istg} is student i's average test score outcome (average of math and reading) in school s, year t, and grade g, X_{ist} is a vector of student-level covariates measured in the baseline year, $y_{i,t-1}$ is a vector of prior-year test scores in math and reading, δ_t and δ_g are school and grade fixed-effects, respectively, and ν_{istg} is the student-level residual.

We define u_{istg} as the empirical student-level residual obtained from equation (5). Averaging over the number of students in a school in a given year, we calculate the standard estimate of school value-added,

$$\hat{\theta}^{VA}_{st} = \sum_{i \in st} \left(\frac{u_{istg}}{N_{st}} \right), \tag{6}$$

where $\hat{\theta}^{VA}_{st}$ denotes a school's value-added in year t, and N_{st} is the number of students in school s at time t (notice that school value-added is not grade-specific in our model).

Next, we create a shrunken or contracted measure of value-added. Again, we construct leave-own-out predictions of value-added to avoid using contemporaneous school value-added measures to predict current student outcomes. Specifically, we use four leads and four lags of school value-added to predict school value-added in t, as

$$\hat{\mu}_{st} = \sum_{m \in \{t-4,\dots,t+4\}, m \neq t} \hat{\phi}_m \hat{\theta}^{VA}_{sm}. \tag{7}$$

The weights, $\hat{\phi}_m$, are computed by OLS and minimize the mean squared prediction error for school value-added in t (Chetty *et al.*, 2014*a*; Jackson *et al.*, 2020). The empirical weights place more weight on years adjacent to t than on years further away, indicating that school quality in more distant years is less informative about current school quality. The analysis is robust to using fewer than four leads or lags.

In equation (5), we include a rich set of student-level controls that could confound our measure of school value-added. In contrast to Jackson *et al.* (2020), however, we do not control for school-level means of these controls. The reason is that controlling for school composition when computing school value-added would mechanically lead to zero student-to-school sorting measures. Namely, school-composition controls would remove the portion of school value-added related to student sorting into schools; yet, this is precisely the object of our interest. Therefore, in our framework, school value-added encompasses peer quality and school-level inputs (such as teachers' skills, school facilities, and school management).