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Creating Classes: Elementary school classroom assignments and their implications for student access to high-quality teaching

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We investigate the distribution of students across classrooms in North Carolina elementary schools. While tracking is ubiquitous and well-documented in secondary education, limited evidence exists regarding cross-classroom clustering in elementary schools and its consequences. Consistent with qualitative evidence suggesting that educators seek to create demographically balanced classrooms, we find that students are distributed quite evenly across their schools' classrooms based on race, ethnicity, and family economic background. However, we find that some elementary schools create classrooms in which students are clustered based on their prior achievement as well as their eligibility for gifted education or special education services. This clustering is most prominent in large schools, schools with highly experienced teachers, and schools in which parents have a high degree of influence. Skills-based classroom clustering is associated with inequalities in student access to high-quality teaching. These findings extend the study of classroom-level categorical inequalities to the elementary grades.

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Creating Classes: Elementary school classroom assignments and their implications for student access to high-quality teaching

Abstract: We investigate the distribution of students across classrooms in North Carolina elementary schools. While tracking is ubiquitous and well-documented in secondary education, limited evidence exists regarding cross-classroom clustering in elementary schools and its consequences. Consistent with qualitative evidence suggesting that educators seek to create demographically balanced classrooms, we find that students are distributed quite evenly across their schools' classrooms based on race, ethnicity, and family economic background. However, we find that some elementary schools create classrooms in which students are clustered based on their prior achievement as well as their eligibility for gifted education or special education services. This clustering is most prominent in large schools, schools with highly experienced teachers, and schools in which parents have a high degree of influence. Skills-based classroom clustering is associated with inequalities in student access to high-quality teaching. These findings extend the study of classroom-level categorical inequalities to the elementary grades.

Introduction

Every year, elementary principals and other school leaders sort students and teachers into classrooms for instruction. As they engage in this basic task of educational categorization (Domina et al. 2017, 2023), they wrestle with fundamental questions around the allocation of educational resources (Brighouse et al., 2018; Gutman, 1999; Jencks, 1988; Oakes & Guiton 1995): Should schools randomize students to classrooms and teachers, intentionally create balanced classroom assignments based on observed student characteristics, or group students who share key characteristics into the same classroom to strategically match students with teachers and other instructional resources? What student and teacher characteristics should be considered in the classroom assignment process, and what student-to-teacher pairings best align with local expectations and goals?

In this paper, we document classroom assignment patterns across mid-sized and large North Carolina elementary schools and their implications for student exposure to high-quality instruction. Bringing recent work on teacher effectiveness into conversation with scholarship exploring the processes that generate within-school inequalities, we develop and test a series of hypotheses regarding the composition of elementary school classrooms and their implications for inequality in student access to high-quality instruction. We use data from approximately 387,000 5th graders enrolled in moderate-to-large North Carolina public elementary schools in the 2011-12 to 2018-19 school years to develop novel school-by-year level measures of the degree of student sorting across classrooms. We pair this new measure with rich data on teacher experience, effectiveness, and school structure and culture to address the following research questions:

1. To what extent are 5th graders distributed unevenly across districts, schools, and classrooms in North Carolina public elementary schools based on their racial or ethnic identification, socioeconomic status, prior academic achievement, and/or identification for specialized academic services?
2. To what extent do schools vary in the degree to which their students are clustered across classrooms based on their racial or ethnic identification, socioeconomic status, prior academic achievement, and/or identification for specialized academic services?
3. What organizational characteristics are associated with cross-classroom clustering based on these observable student characteristics?
4. What is the association between teacher experience and effectiveness and the student composition of the classrooms to which they are assigned?

Consistent with prior research on school segregation (Reardon & Owens 2014), the elementary schools in our sample vary substantially in the racial and socioeconomic composition of the students they educate. Net of this cross-school student segregation, we find very little evidence of additional clustering on these student characteristics across classrooms within elementary schools. However, some schools appear to systematically sort students based on their prior achievement, special education status, and gifted status. We find that school size, the proportion of experienced teachers, and the degree of parental influence over school practices all associate positively with classroom-level clustering based on student prior achievement. We further find that more effective and experienced teachers tend to work in classes with higher levels of mean prior-year student achievement; a finding that links classroom-level clustering with inequalities in student opportunities to learn.

Our analyses extend the sociological literature on academic tracking in middle and high schools by demonstrating that skills-based classroom-level clustering occurs as early as the late elementary grades. This finding is notable, since explicit curricular differentiation is rare at the elementary school level and elementary grade teachers and school leaders often articulate a strong preference for heterogeneous classrooms. By documenting classroom-level clustering and its consequences for access to high-quality teaching, our work builds conceptual and empirical bridges between sociological work on within-school inequalities and recent work – lead, particularly by economists of education – around teacher quality. Our findings indicate that technical considerations such as school size and the distribution of student achievement, as well as political considerations such as teacher preference and parent influence, contribute to the classroom groupings that enable inequalities in student access to highly qualified, experienced, and effective teachers. Taken together, these findings suggest that strategic efforts to promote more equitable elementary school classroom assignment practices could disrupt persistent inequalities in access to high-achieving peers and highly effective teachers (Bailey & Michaels 2019; Cohen-Vogel, 2011; Goldhaber et al. 2018; Loeb et al., 2012; Rodriguez et al, 2023; Springer et al, 2022; Wolf et al. 2020).

Classroom assignment processes and their implications

While school leaders and classroom teachers arguably have little control over the student assignment policies, residential segregation patterns, and parental preferences that drive segregation across schools, they often have considerable discretion over the processes that create categorical inequalities within their schools (Domina et al. 2023; Oakes 2005). Contemporary public-school systems typically give principals and other school leaders primary responsibility for allocating students and teachers across classrooms (Burns & Mason 1998, 2002; Cohen-

Vogel & Osborne-Lampkin, 2007; Cohen-Vogel et al., 2013; Kraemer et al. 2011; Monk 1987; Osborne-Lampkin & Cohen-Vogel 2014).

The classroom is a central category in the day-to-day organization of contemporary elementary schools. Like other educational categories, classrooms have the potential to generate durable educational inequalities by shaping students' access to crucial educational resources. Classroom assignments determine the peers and teachers with whom students will learn with and from during much of their school days (Chingos & West, 2011; Cohen-Vogel, 2011; Cohen-Vogel et al., 2019). Prior research indicates that each of these has important implications. Classroom peers influence students' course-taking patterns (Crosnoe et al., 2008; Frank et al., 2008), educational aspirations (Raabe & Wolfer 2019), disciplinary outcomes (Hwang & Domina 2021), and academic achievement (Burke & Sass 2013). Likewise, teacher assignment to classrooms shape learning opportunity, with research using teacher value-added models indicates that teachers vary substantially in their contributions to a wide range of short- and long-term student outcomes (Chetty, et al., 2014a, 2014b; Hanushek & Rivkin, 2010; Jackson, 2018; Harris, 2011; Jackson et al., 2014; Jackson 2018; Koedel et al., 2015). The consequences of teacher assignments compound over students' academic careers, as repeated exposure to less effective teachers generates learning gaps (Hanushek et al., 2004).

Although last-minute enrollment and staffing changes often disrupt their carefully developed classroom assignment plans, U.S. school leaders, keenly aware of the implications of classroom assignment decisions, undertake highly strategic and deliberative rostering processes Many leaders articulate a desire to create "balanced" classrooms – particularly based on ascriptive characteristics such as race, ethnicity, family background, and gender (Burns & Mason 1998, 2002; Monk 1987; Kraemer et al. 2011; Osborne-Lampkin & Cohen-Vogel 2014).

It is important to note that “balanced” classrooms are not the same thing as “random” classrooms. Indeed, using data from Brazil, Leung-Gagne (2023) demonstrates that processes of random classroom assignment can generate notable racial imbalances across classrooms and school leaders report that they strategically use testing data, student records, and educators’ professional judgments during the assignment process. In most cases, leaders report they use these data in pursuit of classroom balance. However, some report clustering students with similar specialized academic needs – including students with individualized education plans, students with limited English proficiency, academically gifted students, etc. – into the same classroom when doing so helps to ensure they have access to appropriately credentialled teachers and other resources (Burns & Mason 2002; Osborne-Lampkin & Cohen-Vogel 2014).

Consistent with this qualitative evidence, recent research using large-scale educational administrative data suggests that students are distributed quite evenly within schools across classrooms based on ascriptive characteristics such as race, ethnicity, gender, and family economic background (Bosworth, 2014; Clotfelter et al., 2006, 2021; Conger 2005; Dalane & Marcotte, 2022; Kalogrides & Loeb 2013; Morgan & McPartland 1981; Spiegel et al. 2025). However, elementary grade students are sorted within schools across classrooms to a greater degree than one might expect in conditions of random assignment based on prior achievement (Aaronson, Barrow, & Sander 2007, Antonovics et al. 2023, Dieterle et al. 2015, Horvath 2015) and academic categories such as academically gifted and special education status (Clotfelter, Ladd, & Vigdor 2006; Dieterle et al. 2015).

Bringing together insights from prior qualitative and quantitative research, we propose two hypotheses related to our first research question:

> **Hypothesis 1:** Given educators' stated commitments to constructing "balanced" classrooms, we expect to observe less within-school clustering of students based on demographic characteristics than we observe across schools and across districts.

> **Hypothesis 2:** To the extent to which students are clustered across classrooms within schools, we expect that sorting to be predominately based on academic characteristics such as prior mathematics and reading achievement, language-learner status, special education status, and gifted education status; rather than ascriptive student characteristics such as race/ethnicity, gender, and family economic background.

In its application to education, categorical inequality theory draws attention to organizational decisions and processes that influence the distribution of educational opportunities and the nature of educational inequalities (Domina, et al. 2023). As such, this theory emphasizes the potential for meaningful cross-school variation in educational categories. This variation is quite well documented with regard to advanced course placement at the middle and high school level (Carbonaro et al., 2024; Domina et al. 2023, Hanselman, et al. 2019, Oakes 2005). By contrast, the existing evidence regarding variation across elementary schools in classroom assignments is limited, although Dieterle et al. (2015) and Horvath (2015) present evidence pointing to different levels of skills-based clustering at the elementary school level.

Based on this research, and in response to our second research question, we hypothesize that:

> **Hypothesis 3:** The degree of cross-classroom student sorting varies across schools. While rostering practices in many schools produce balanced classrooms on all measured student characteristics, students in some schools are clustered in classrooms based on academic characteristics.

Our third research question involves the sources of variation across elementary schools in classroom clustering.

Again, this is an area in which the existing research related to middle and high school advanced course placements is informative. Much of this work focuses on cross-school variation in the availability of math courses (see Carbonaro et al. 2024 for a recent review); a consideration that is not directly relevant to the elementary school level, where the assumption is that schoolmates at the same grade level are exposed to a common curriculum across classrooms. However, several studies point to a positive association between middle and/or high school size and the extent to which students are sorted into academically differentiated courses (Hanselman et al., 2022; Domina et al., 2019; Oakes, 2005; Kelly & Price 2011; Kelly & Carbonaro, 2012). Similarly, this literature suggests that academic tracking practices are common in racially diverse middle and high schools, as well as middle and high schools with a relatively high degree of variation in student achievement (Hanselman et al., 2019; Domina et al., 2019; Lewis & Diamond, 2015; Mickelson & Everett, 2022; Oakes, 2005). In the absence of parallel work documenting the correlates of clustering within elementary schools, we hypothesize that similar associations exist at the elementary school level.

We further draw on the rich literature documenting advantaged parents' efforts to ensure that their children have access to advanced, high-status, or otherwise privileged school learning environments (Crosnoe, 2001; Kelly, 2004; Lewis & Diamond, 2015; Oakes, 2005; Posey-Maddox et al. 2014). Scholarship conducted at the elementary school level indicates that advantaged parents directly lobby teachers and school leaders for desirable classroom assignments, coach their children to pursue desirable learning opportunities, and invest in academic enrichment to ensure that their children can thrive in academically rigorous settings (Calarco, 2018; Lareau, 2000; Murray et al., 2019). These interventions may have important implications for students' classroom and teacher assignments, and cross-school variation in the intensity of or receptiveness to parental pressure may help to explain variation in classroom clustering. For example, some school leaders describe rostering processes that solicit feedback from parents and attempt to accommodate parental requests, others sharply limit the role for parental input (Kraemer et al. 2011).

Several studies also highlight the role that educator preferences, biases, and conceptions of student intelligence play in the distribution of students to learning environments (Oakes & Guiton, 1995). This literature emphasizes that highly experienced teachers often prefer to teach relatively high-achieving students (Francis et al. 2019). While literature clearly suggests that school leaders lead the rostering process in elementary schools, it points to important differences across schools in the role that teachers play (Cohen-Vogel & Osborne-Lampkin, 2007; Finley, 1984; Kalogrides et al., 2011). We might expect, therefore, the degree of cross-classroom clustering to vary with the elementary school teachers' influence in classroom assignment processes.

In sum, we expect that school-level characteristics – including enrollment size, student diversity, the existence of mechanisms for parents to influence rostering practices, and the presence of highly experienced teachers – help account for variation in rostering practices across schools. We hypothesize that:

> **Hypothesis 4:** Cross-classroom student clustering associates with school size, racial diversity, skills heterogeneity, opportunities for parental input in school processes, and teacher experience.

Our fourth research question addresses the implications of clustered classroom assignments for student access to high-quality instruction. If, as Hypothesis 4 and the research upon which it is grounded suggests, advantaged parents use their power in schools to secure access to desirable learning environments, unbalanced classroom assignment processes will tend to match high achieving and otherwise socially advantaged students with highly experienced and otherwise desirable teachers. Such a finding would be consistent with research in middle and high school tracking, which demonstrates that students who gain access to high status classes receive more engaging instruction (Carbonaro & Gamoran, 2002; Gamoran & Nystrand, 1994; Kelly & Carbonaro 2012; Van Houtte, 2004).

> **Hypothesis 5:** Classrooms with relatively high concentrations of high achieving and otherwise high-status youth will tend to have access to more experienced, higher quality teachers.

Data and Sample

We test these five hypotheses using administrative data from the North Carolina Department of Public Instruction (NCDPI). As shown in Table 1, our primary analytic sample contains approximately 387,000 5th graders, taught by nearly 7,800 math teachers in 892 public elementary schools in the 2011-12 through 2018-19 academic years.[1] Our student-level data includes local educational agency and school identifiers; basic student-level demographic data, including data on students' participation in school programs such as special education, targeted instruction for students with limited English proficiency, and supplementary instruction for AIG students; and student test scores in math and reading, taken in the spring of 4th grade. We link these student-level data with administrative data describing the teachers assigned to students' 5th grade classrooms, including measures of their years of experience as classroom teachers; two different teacher value-added scores; and school leader ratings of teacher effectiveness based on the state's teacher observation protocol. In addition, we draw upon school-level aggregate data from North Carolina's bi-annual Teacher Working Conditions Survey describing the extent to which schools are receptive to parental input in crucial educational decisions.

[1] North Carolina administers end-of-grade tests each spring to nearly all students in math and reading beginning in the 3rd grade. These test scores are central to our analysis because they make it possible to investigate the distribution of students across classrooms based on their prior achievement. As such, we cannot describe the distribution of students across classrooms in the earlier elementary grades.

Our analyses focus on 5th grade mathematics course assignments, using a sample that includes only students with non-missing demographic, prior year test score, and classroom and teacher identifier data. We further restrict the sample to students who attend schools that have at least three 5th grade math classrooms with at least 15 students in each. Since this restriction eliminates many small elementary schools, our findings are only generalizable to mid-sized to large elementary schools, in which a substantial degree of cross-classroom clustering is theoretically possible. Approximately 50 percent of all North Carolina 5th-grade public school students met these subsample requirements. Table 1 enables a comparison of the analytic sample with the population of 5th grade students over the period between the 2011-12 and 2018-19 school years. Relative to all students statewide, our analytic sample has a slightly smaller proportion of students with a disability, a moderately smaller proportion of students that are economically disadvantaged, and a slightly higher concentration of LEP and AIG students. The racial composition of our analytic sample largely mirrors the statewide universe over this period, and our sample performs slightly higher on end of grade math test scores in 4th grade than students statewide.

Our analysis depends on our ability to accurately identify students' classrooms and teachers by subject (student-by-term-by-course level data structure). Over 80% of students in our analytic sample have only a single course record for their 5th grade math course; therefore, we flag that record as their primary math course. For the remaining 20 percent with multiple math course records in their 5th grade year, we use NCDPI's course code documentation to identify the primary math course.[2] We use the primary course record, teacher ID, school ID, course title,

[2] In some cases, these students attended multiple schools, took different courses in fall and spring, or had a teacher change partway through the year. In these instances, we kept the earliest entry available in the year (i.e., first teacher, first school attended, fall courses) to capture the rosters as constructed in the previous summer. In other

term, cycle, section, and period data to generate a unique classroom ID variable, which identifies the set of students taking a particular course together linked to the teacher of that course. This process yields a dataset with just one observation per 5th grader in each academic year in our sample.

Analytic methods

To answer our first research question, we estimate a series of unconditional multilevel models documenting the degree of student sorting based on observable characteristics across school districts, schools, and classrooms. These models, which build on previous studies on student classroom clustering (Clotfelter et al., 2006; Dieterle et al., 2012; Horvath, 2015)[3] as well as school and neighborhood segregation (Domina, 2006; Jargowsky, 1996; Reardon, 2016), take the following form:

$$(1)\ Y_{icsd} = \zeta_{csd}^{(2)} + \zeta_{sd}^{(3)} + \zeta_{d}^{(4)} + \epsilon_{icsd}.$$

The outcome in these models, Y_{icsd}, describe observed characteristics of student *i* enrolled in classroom *c*, in school *s* and school district (or LEA) *d*; including race/ethnicity (measured as a flag for Black, Hispanic, and American Indian students), economic disadvantaged (measured with an indicator flagging students who enrolled in free or reduced-price lunch), one-year-lagged student achievement on the end-of-grade standardized tests in math, identification for gifted education services, special education services (measured as an indicator for students with an individualized education plan associated with a physical, mental, or behavioral disability), and

cases, students were simultaneously enrolled in two or more math courses flagged as primary. In these cases, we keep the course with the modal course name in the given school-grade-subject to capture the most common 'primary' course assigned to students in that school. In the remaining cases, accounting for fewer than 1% the sample, we randomly select the focal select course, as there was no identifiable rationale for selection.

[3] This econometric literature, motivated by questions about the validity of value-added models of teacher effects on student achievement, focuses exclusively on sorting based on prior achievement. By contrast, we are focused on sorting on a range of student characteristics, including prior achievement as well as ascriptive characteristics, and membership in school-created instructional categories. As such, it is important for our analyses to generate estimates of sorting that are comparably scaled across continuously and dichotomously scaled student characteristics.

limited English proficiency services. By including random effects at the classroom ($\zeta_{csd}^{(2)}$), school ($\zeta_{sd}^{(3)}$), and district $\left(\zeta_{d}^{(4)}\right)$ level, the analysis decomposes the distribution of students based on characteristic Y_{icsd} across these three nested levels.

Model (1) allows us to calculate the proportion of total variance on the metric of interest explained by variation across classrooms, districts, and schools, a parameter that is referred to as the inter-class correlations (ICC) or ρ. The ICC for any given student characteristic is calculated as the within-group variance on the relevant student characteristic divided by the total variance and is equivalent to the square of the widely used Duncan segregation index (Jargowsky, 1996).

Model (1) also allows us to calculate school-specific measures of the degree of cross-classroom sorting on relevant student characteristics. We use these measures to answer our second research question. To calculate them, we estimate two parameters on each outcome variable for each school for which data are available: (1) $\widehat{\psi_{c,sd}}$, the variance of means across all classrooms *c* in school *s* located in district *d* , which is the square of the standard deviation of the difference between each of the classroom-level means on a student characteristic of interest and the school-level mean; and (2) $\widehat{\theta_{w,sd}}$, or the remaining variance on the student characteristic of interest within each of the classrooms *c* in school *s* in district *d*. Using these two parameters, we calculate school-specific ICCs measuring the degree of cross-classroom sorting in each school in our sample. This measure is defined as:

$$(2)\ ICC_{sd} = \frac{\widehat{\psi_{c,sd}}}{\widehat{\psi_{c,sd}}+\widehat{\theta w_{,sd}}}\,.$$

Scaled from a theoretical minimum of 0 to a theoretical maximum of 1 (representing a case of perfect sorting on the characteristic of interest), the school-specific ICC represents the proportion of the total within-school variance explained by variation across classrooms. To illustrate, imagine a school in which 12 of 60 5th graders qualify for AIG services. This hypothetical school would have a "0" ICC for AIG if it placed four AIG-eligible students in each of three 20-student 5th-grade math classes. Conversely, placing all 12 AIG-qualifying students in the same 5th grade classroom would yield an ICC of "1".

To answer our third research question, we examine the distribution of these school-specific ICCs and the school characteristics that correlate with higher levels of cross-classroom clustering. After reporting detailed descriptive data on clustering in 5th grade mathematics classrooms based on the full range of available ascriptive and academic measures, we undertake a more focused analysis of the school-level correlates of clustering in 5th grade mathematics classrooms based on their 4th grade mathematics achievement. This analytic decision is driven both by the previously cited qualitative evidence suggesting that school leaders are more likely to cluster students in classrooms based on academic characteristics than ascriptive characteristics as well as the results, reported below, indicating that there is little cross-school variation in clustering on ascriptive characteristics in these data to be explained. This analysis consists of a series of models of the following general form:

$$(3)\quad Y_{sy} = \beta_0 + \beta_1(Year) + \beta_2(School\ Size) + \beta_3(School\ Diversity) + \beta_4(Teacher\ Experience) + \beta_5(Parent\ Power) + \sigma_s + \varepsilon$$

In Model (3), Y_{sy} is the school-specific ICC for cross-classroom clustering based on prior-year test scores for school s in year y; Year is a series of dummy variables for each year included in the analysis; School Size is measured both via the number of students enrolled in 5th grade mathematics courses and the number of mathematics classrooms available in school s in year y; School Diversity is measured via the standard deviation of student scores on 4th mathematics end-of-grades administered in year y-1 and a Herfindahl-Hirschman index (HHI) of racial diversity among the school's 5th graders in year y; teacher experience is measured as the proportion of 5th grade mathematics teachers in the school who have three to five years of prior teaching experience and the proportion of 5th grade mathematics teachers who have six or more years of prior teaching experience in year y; Parent Power is measured as the mean of school-level aggregate responses to North Carolina Teacher Working Condition Survey questions asking teachers to assess the extent to which "Parents/guardians are influential decision makers in this school," "This school does a good job of encouraging parent/guardian involvement," and "Parents/guardians know what is going on in this school" in year y;[4] and σ_s is a random effect to account for repeated observations of schools across the analytic sample. All independent variables in this analysis are z-score standardized. Since the Teacher Working Conditions data upon which our measure of parent power is based are only available in 2012, 2014, 2016, and 2018, our model omits data from odd years.[5]

We first enter each of these predictors into the model one at a time, to estimate unconditional correlations. We then estimate the model as specified in Model (3) above. In addition to this basic model, we test the sensitivity of our findings by estimating additional models that add controls for schools' lagged mean 4th grade test scores, total school per pupil expenditures, the proportion of 5th graders in schools who are classified as Limited English Proficient, the proportion of 5th graders in schools who are classified as economically disadvantaged, and the proportion of 5th graders in schools who identify as Black or Hispanic as well as this proportion's quadratic term. Finally, we estimate a model in which we replace the

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[4] Responses are scored on a four-point Likert scale (1 = *Strongly Disagree*, 2 = *Disagree*, 3 = *Agree*, and 4 = *Strongly Agree*, with an option for *Don't Know*, which are treated as missing.)
[5] Analyses that exclude the TWC data and therefore include 2013, 2015, and 2017 data are included in Appendix D and have substantively similar results.

school-level random effective with a fixed effect term, exploiting within-school variation over time to control for time-invariant school characteristics

Finally, to address our fourth research question, we examine the implications of clustering for equitable access to effective or experienced teachers by measuring the relationship between teacher characteristics and classroom-level student characteristics. To do this, we run the following regressions:

$$(4)\ T_{csd} = \beta_0 + \beta_1 X_{csd} + \zeta_{sd}^{(2)} + \zeta_{d}^{(3)} + \epsilon_{csd}$$

$$(5)\ T_{csd} = \beta_0 + \beta_1 X_{csd} + \alpha_s + \alpha_d + \epsilon_{isd}.$$

The outcomes in these models, T_{csd}, consist of four variables describing the teacher assigned to classroom c in school s and school district (or LEA) d: (1) prior-year standardized value-added estimates of teacher effectiveness as calculated by the SAS Institute's Education Value-Added Assessment System (EVAAS); (2) prior-year researcher-generated value-added estimations that follow the leave-year out procedures outlined by Chetty et al. (2014a) that corrects for bias in value-added resulting from systematic non-random distributions of students to teachers over time;[6] (3) an indicator for whether a teacher has more than three years of teaching experience (hereafter referred to as experienced teachers); and (4) a 1-year lagged indicator for whether a teacher had a median composite rating of at least 4.5 out of 5 on North Carolina's teacher observation rubric standards (hereafter revered to as highly rated teachers).[7] X_{csd} is the standardized classroom-level mean of students' prior year math EOG scores. Model (3) investigates the unconditional correlation between classroom prior math score composition and

[6] The EVAAS, lagged EVAAS, and leave-year out estimates of teacher value-added are all z-score standardized by year and grade to facilitate comparison across models.
[7] While North Carolina has 5 observation standards, teachers with more than 3 years of employment may be evaluated on just standards 1 (Leadership) and 4 (facilitating student learning) in non-license renewal years.

teacher characteristics statewide, with random effects $\zeta_{sd}^{(2)}$ and $\zeta_{d}^{(3)}$ adjusting standard errors for clustering at the school- and district-level, respectively. Model (4) replaces these random effect terms with school- and district-level fixed effects, α_s and α_d, to isolate the relationship between classroom prior math score composition and teacher characteristics among 5th grade classrooms in the same school.

Findings

District-, school-, and classroom-level student clustering

To address our first research question and understand the extent to which students at the LEA, school, and classroom levels are clustered based on student achievement and demographic characteristics, we calculate ICCs for random effects representing the degree of LEA-level, school-level, and classroom level sorting and the total variance explained by these three levels for each student sorting characteristic. Table 2 reports the results of this analysis for the 2018-19 school year.

The results reported in Table 2's two first columns represent the degree to which 5th graders are clustered based on: (1) student race/ethnicity, operationalized as a dichotomous variable flagging students who identify as Black, Hispanic, or Native American and (2) student economic disadvantage. Consistent with prior research on between-school segregation (Dalane & Marcotte, 2022; Owens et al., 2016; Reardon, 2016; Reardon & Owens, 2014), these estimates reveal a substantial degree of racial and economic segregation across school districts and between elementary schools. For example, LEAs account for 7.5 percent of the total variation in 5th graders' racial/ethnic identification statewide, while schools account for an additional 18.9 percent.

However, we find very little evidence of additional sorting across classrooms within schools based on these ascriptive student characteristics. The ICCs reported in the first column of Table 2 indicates within-school cross-classroom sorting accounts for just 1.4 percent of the inequality observed in the concentration of Black, Hispanic, and Native American students across all classrooms in our sample; an increment that is not statistically significantly different from zero. Similarly, the ICCs reported in the second column of Table 2 indicate indicating that within-school cross-classroom sorting accounts for 2.5 percent of the inequality in the concentration of economically disadvantaged students across all classrooms in our sample. This increment is also not significantly different from zero at conventional levels. In sum, therefore, while the analyses reported in the first two columns of Table 2 point to a substantial degree of student sorting on race and economic status across North Carolina districts and schools, classroom rostering practices enacted in North Carolina elementary schools typically yield 5th grade math classrooms that largely reflect the racial, ethnic, and socio-economic make-up of all 5th graders in the school.

By contrast, the results reported in the third column of Table 2 suggest that students are clustered into 5th grade math classrooms based on their 4th grade math test scores. Further, this analysis indicates that there is *more* skills-based clustering across North Carolina classrooms than across districts and schools. Indeed, while inter-district clustering accounts for 2.6 percent of the total variation in 4th grade math test scores among 5th graders and cross-school clustering accounts for an additional 11.0 percent,[8] within-school sorting based on 5th grade math achievement accounts for 14.9 percent. T-tests indicate that within-school sorting here is

[8] We note that this school-level clustering on prior test scores likely reflects both the uneven sorting of students across schools and school-level variation in contributions to student test score growth. Our study is not designed to distinguish between these two phenomena.

statistically significantly different from zero. Importantly, since 5th grade classroom teachers do not directly contribute to 4th grade achievement, this variation solely reflects the sorting of students across classrooms (Bitler et al. 2021; Rothstein 2010). In sum, accounting for the LEA, school, and classroom in which a 5th grader is situated accounts for 28.5 percent of the total variation in prior-year test scores, and school-based classroom assignment decisions account for over half of this clustering.

The results reported in the fourth and fifth columns of Table 2 indicate that AIG and special education students are distributed relatively evenly across North Carolina districts and schools but cluster significantly at the classroom level. The degree of classroom clustering of AIG students is particularly notable, accounting for a statistically significant 21.5 percent of the total variance on this indicator. In contrast, we observe relatively little cross-classroom sorting for students identified as Limited English Proficient (LEP). Analyses of reading classrooms reported in Appendix Tables 1-3 show that this pattern holds for 4th grade math classes as well as 4th and 5th grade reading classes. Supplementary analyses reported in Appendix Figure 1 indicate that levels of within-school cross-classroom clustering on prior math achievement are stable across the 2011-12 to 2018-19 period. Supplementary analyses, available by request, indicate similar stability in within-school cross-classroom clustering levels on other student characteristics, with one notable exception: Levels of within-school cross-classroom clustering on AIG status rise from 0.22 in 2012 to a peak of 0.31 in 2015 before falling to 0.22 in 2019.

School-level heterogeneity in classroom-level clustering on prior achievement

While the ICCs reported in Table 2 provide a summary of the extent of student clustering in 5th-grade math classrooms in relatively large and mid-sized North Carolina public elementary schools, they conceal important cross-school variation in classroom-level clustering. In Figure 1, we present a series of histograms representing the distribution of school-specific classroom-level ICCs on demographic and academic variables for our sample across the 2011-12 to 2018-19 school years. Many of these histograms, which respond to our second research question, represent distributions in which nearly all schools are concentrated at 0, indicating that nearly all schools create highly balanced classrooms on these indicators. Figure 1a, for example, demonstrates that very few schools appreciably sort students based on race/ethnicity across classrooms. Figures 1b, 1e, and 1f illustrate a similar tendency toward creating balanced classrooms based on student economic background, special education status, and Limited English Proficient status.

However, Figures 1c and 1d indicate that schools vary considerably in the level of clustering by prior-year test scores and AIG status. For example, Figure 1c suggests that a substantial portion of schools have almost no cross-classroom clustering on prior-year math achievement, while others, at the rightward tail of the distribution, cluster at or near the theoretical maximum level of cross-classroom within-school clustering.[9] Figure 1d displays a similar pattern for cross-classroom clustering of students identified for AIG, with a substantial proportion of schools not sorting students by either educational category. But we observe a long right-hand tail, representing a small share of schools that extensively sort students across classrooms based on these educational categories.

[9] While ICCs are definitionally bounded between 0 and 1, constraints related to the number of students, the distribution of their test scores, and the number of classrooms in a school make it impossible to perfectly sort students across classrooms. To calculate maximum possible levels of clustering for each school we follow the following steps: (1) for each school in our sample, theoretical class rosters were constructed using the median class size for a given school, (2) in each school, students were assigned into these classes by the rank order of their prior-year math achievement (e.g., the 20 previously lowest performing students were assigned into a theoretical classroom A, the next 20 into theoretical classroom B, etc.), and (3) calculate school-specific cross-classroom ICC values using this theoretical set of maximally sorted classrooms. The mean ICC value for this maximal sorting across our sample is approximately 0.8. A version of Figure 1 that replaces the raw ICC in the x axis with the observed ICC as a proportion of the maximum possible is available upon request.

Figure 2 provides a visual illustration of the difference between schools with relatively balanced classrooms and schools that engage in a higher degree of cross-classroom clustering. Figure 3a, for example, displays the three classrooms in a grade in an actual school with almost no measured clustering (ICC=.003) by AIG, where a block represents a single student. In a school with relatively little sorting, we observe that, unsurprisingly, the AIG students are evenly spread across the three primary math classes. This stands in contrast to Figure 2b, a school with one of the highest amounts of within-school clustering on AIG in our data (ICC = .889), where one can see that one entire math class is comprised of AIG students, a clear and stark example of clustering by student characteristics in the class rostering process.

To summarize, our analyses of within-school clustering of students in the classroom assignments process reveal findings that largely align with Hypotheses 1-3 and prior literature on the topic. Consistent with our first two hypotheses, we observe a small degree of clustering of students into classrooms within-schools by demographic characteristics like race or income status, but a more substantial degree of clustering by academic characteristics, including prior-year achievement, AIG, and special education status. In addition, consistent with our third hypothesis, we find that the extent to which individual schools cluster by these academic characteristics varies substantially.

School-level correlates of cross-classroom clustering on prior achievement

Having found evidence that elementary schools, on average, cluster students in classrooms based on prior achievement and other academic characteristics and that the degree of this clustering varies substantially across schools, we seek to explore the school-level factors that correlate with cross-classroom clustering. In the analyses reported below, we focus on school-by-year-level measures of student clustering in 5th grade mathematics classrooms based on 4th grade mathematics achievement.

Table 3 reports the results of these analyses run on four biannual waves of elementary school data spanning 2011-12 to 2017-18. The model reported in column (1) reports unconditional relations between several school characteristics and the degree of cross-classroom clustering within a school in each of the study years. These models indicate that clustering levels tend to increase with school enrollment, the number of classrooms in a school, prior-year test score heterogeneity, the concentration of teachers with six or more years of experience in the field, and the degree of parent power in school operations (as reported by teachers in the biannual Teacher Working Conditions Survey.) Each of these findings is consistent with our fourth hypothesis. The models reported in columns (2) and (3) make it clear that these associations are robust to the addition of controls, with one exception: After controlling for the highly correlated number of classrooms in a school, we find no significant association between school enrollment and cross-classroom clustering.[10]

While these results are broadly consistent with our fourth hypothesis, we note that our models return no conditional association between racial diversity and within-school clustering. Similarly, the proportion of teachers with 3-5 years of teaching experience in the field does not associate with clustering, though the proportion of teachers with 6 or more years or experience in the field does. This finding may suggest that only the most senior teachers have the influence to meaningfully shape classroom assignment practices in their schools. We further note that adding

[10] In Appendix E we show that estimating the model using a Tobit regression indicated that these results are not artifacts of left-censoring on the dependent variable. Appendix E also reports the models in columns 1-3 using standardized terms to contextualize their magnitude. The conditional association between the standard deviation of student prior test scores and sorting is of a similar magnitude, while the conditional associations between school size and teacher experience are somewhat smaller.

controls for school fixed effects attenuates many key conditional associations and substantially increases confidence intervals. The one exception to this pattern, reported in Model 4 of Table 3, is the relationship between school achievement heterogeneity and clustering.

Implications of cross-classroom clustering on achievement for teacher-student matches

The presence of classroom-level clustering enables, but does not guarantee, the assignment of less advantaged students to less-effective teachers.

In the analyses reported in Figure 3, we investigate the relationship between classroom-level clustering on observable student characteristics and several teacher effectiveness and experience measures. These models are run on all available 5th grade math classrooms in our 2012-2019 sample of large and mid-sized elementary schools. Each of the coefficients plotted in these figures represents the correlation between 5^{th} grade classroom mean 4^{th} grade math test scores and a teacher effectiveness or experience measure. The first of these coefficients, represented by hollow diamonds, includes LEA- and school-level random effects to adjust standard errors for the non-independence of classrooms in the same LEA and school. The second coefficient, represented by black circles, includes a school-level fixed effect to control for the potentially confounding effects of unmeasured school-level characteristics. Since these two modelling approaches yield very similar results in all cases, we do not distinguish between the models in our discussion of findings.[11]

Each pair of plots in this figure represents a distinct teacher measure, each of which has an analytic virtue. We first explore the relationship between class composition and prior-year teacher value-added scores, as measured by the EVAAS. This value-added measure plays a central role in teacher assessment in North Carolina and is observable to school leaders when

[11] See Appendix Table 2 for full model outputs and coefficients. That table also reports correlations between other classroom characteristics and the four teacher characteristic variables.

classroom assignments are made. We then replace the lagged EVAAS estimate of teacher value-added with leave-year-out value-added estimates, as defined by Chetty and colleagues (2014a) to address potential confounds between classroom composition and value-added estimates. The next set of plots display the results of linear probability models estimating the relationship between classroom composition and the probability of assignment to teachers with three or more years of experience. The final set of plots report linear probability models estimating the relationship between classroom composition and the probability of assignment to teachers with high prior-year observation scores.

Consistent with the fifth hypothesis, each of these models indicate that classrooms with relatively high levels of student achievement tend to be assigned to relatively effective and experienced teachers. The magnitude of these relationships varies but is substantial. Students in a classroom with average prior math test performance, one standard deviation above the mean for all classrooms in the sample, have access to a teacher whose value-added scores are approximately 0.07 standard deviations higher than those of their peers in classrooms with average prior test scores. Further, they are nearly 3 percentage points more likely to have access to a teacher who ranks at the top in classroom observations, and more than 2 percentage points more likely to have access to a teacher with three or more years of classroom experience compared to peers in classrooms with average prior test scores.

Notably, across the four teacher quality and experience measures, the estimates from models including LEA and school fixed effects are largely consistent with the results of random effects models without fixed effects. The random effect models replicate research demonstrating the sorting of teachers across schools in ways that generate inequalities in access to highly effective or experienced teachers (Francis et al. 2019; Rodriguez et al. 2023). The fixed effect models, however, advance our understanding by showing that even within schools, more effective and more experienced teachers are assigned to classes with larger concentrations of higher-achieving students.

Discussion and conclusion

Each summer, as a new school year approaches, elementary school leaders and other educators sort students and teachers into classrooms for instruction. This classroom rostering process lays the foundational social structure for teaching and learning in elementary schools and has important parallels to well-examined academic tracking practices in middle and high schools. Despite its significance, elementary school classroom assignments have received comparatively little systematic study in the sociology of education.

Drawing upon categorical inequality theory, we conceptualize elementary classroom assignments as a set of decisions and processes that shape educational inequalities by allocating students and crucial educational resources within schools. Given that both this theoretical framework and existing research emphasize the pivotal role that principals and other educational leaders play in shaping the classroom assignment process, our analyses prioritize the school as the primary unit of analysis. Using data describing nearly 400,000 5th graders enrolled in nearly 900 elementary schools in North Carolina over eight years, we investigate: (1) the degree to which schools sort students into classrooms, (2) the characteristics of students who are sorted unevenly across classrooms, (3) the variation in sorting practices across schools, (4) the school-level characteristics that associate with the sorting behavior, and (5) the ways that cross-classroom sorting contributes to inequalities in students' opportunities to learn from experienced and effective teachers.

Consistent with our first hypothesis and the existing scholarship describing school-level classroom rostering processes (Monk, 1987; Burns & Mason, 1998; Cohen-Vogel et al., 2013), we find that students in North Carolina are distributed relatively evenly across elementary school mathematics classrooms based on race/ethnicity, economic disadvantage, and language status. However, consistent with our second hypothesis, we find a noteable degree of student sorting across classrooms based on prior achievement, AIG status, and, to a lesser extent, special education status.

Building on categorical inequality theory's emphasis on organizational decision-making and sorting processes, our third hypothesis proposes that cross-classroom clustering levels vary substantially across schools. While we observe minimal cross-classroom sorting on race/ethnicity, socioeconomic status, and student language status, there is considerable cross-school variation in skills-based classroom sorting. Elementary school students are sorted relatively evenly across classrooms based on their test scores in most of the schools in our sample. However, our analyses reveal pronounced skills-based classroom clustering in a select number of elementary schools.

Our fourth hypothesis draws on prior research on academic tracking at the middle and high school level, which indicates that both technical and political factors correlate with unequal school classroom assignment practices. Consistent with prior studies linking academic tracking practices with technical considerations related to teaching and learning, we find a tendency toward cross-classroom sorting based on prior achievement in large schools, schools with racially diverse student bodies, schools with a wide range of test scores, and schools employing a high proportion of experienced teachers. At the same time, consistent with scholarship that conceptualizes tracking as a mechanism for advantaged families to hoarding of educational opportunities, we find especially high levels of cross-classroom sorting in schools where parents have a strong voice.

Finally, our findings support the fifth hypothesis, which predicts that cross-classroom clustering practices contribute to long-standing inequalities in students' opportunities to learn. While there may be practical or normative reasons for clustering students by ability, our results suggest that such practices can create conditions that lead to within-school inequalities in access to effective teaching. Put differently, if schools created fully balanced classrooms on all relevant student characteristics, systematic inequities in access to highly effective teachers among observable students groups would likely be eliminated. Our analyses reveals that classrooms with a higher concentration of high achieving students are more likely to have access to teachers with higher value-added scores, stronger teacher evaluation scores, and greater experience. Conversely, we find that classes with larger proportions of non-AIG, English learning, or Black, Hispanic, or Native American students are more likely to be assigned less effective and less experienced teachers.

Previous research on the social organization of instruction has largely focused on academic tracking in middle and high school contexts. Our study extends this research agenda to the elementary school level. Since our analyses focus exclusively on sorting within elementary schools, a systemic comparison of sorting practices and the resulting student clustering across elementary, middle, and high school contexts liesbeyond the scope of this study. Nevertheless, given the extensive evidence of student sorting across middle and high school courses and classrooms (c.f. Carbonaro et al. 2024; Hanselman et al. 2022), we are struck by the degree of racial/ethnic, and socioeconomic balance that we observe in our sample of elementary schools. Future research should investigate educator attitudes and school assignment processes that drive classroom assignments, examine how these attitudes and processes differ across school levels and settings, and explore the attendant variation in cross-classroom clustering at the elementary, middle, and high school levels.

By extending research on academic tracking in middle and high school to the elementary level, our analysis highlights significant organizational variation in the use of test scores as a mechanism for producing categorical inequalities. While previous research documents differences among schools in the degree of test-based clustering within classrooms (Domina et al. 2019; Kelly & Price 2011), much of the scholarship on schools and inequality – particularly in the contemporary U.S. context – implicitly assumes that a meritocratic logic pervades organizational practice. This assumption can be theoretically generative. For example, Carbonaro, et al. (2024) explore how test score queuing shapes racial disparities in access to more advanced middle school math courses. However, this meritocratic logic may not apply in all educational contexts (Harvey 2023). In particular, our findings indicate that many elementary schools instead adopt a balancing logic in classroom assignments, prioritizing equitable distribution over strictly test-based meritocratic sorting.

In addition to documenting how and why educators in many elementary schools create balanced classrooms, future research should investigate the micropolitical, organizational, and practical forces driving cross-classroom sorting in the relatively few large, racially and academically diverse elementary schools where skills-based classroom clustering is more pronounced. Our findings suggest that investigating parents influence on classroom placement practices could provide valuable insights into the dynamics of classroom clustering. Further research into the negotiations among parents, teachers, and school leaders around classroom assignments holds promise for bridging family-focused research on the intergenerational reproduction of inequality with organizational scholarship on within-school inequality.

Future reesearch should also examine the role of individual school leaders, the key decisionmakers in the rostering process, in shaping how factors such as teacher experience and parental pressure influence uneven classroom assignments. Investigating the information school leaders consider and the criteria they prioritize when make these consequential decisions can provide valuable insights. Findings from this work could inform targeted interventions aimed at promoting more balanced classroom assignments and equitable distribution of effective teachers, ultimately helping schools offer fairer learning opportunities. Additionally, future studies should seek to identify examples of equitable student clustering practices, such as intentionally creating student-teacher race or sex congruences or strategically assigning the highest need or lowest performing students to the teachers best equipped to support their learning growth.

To conclude, it is critical to note that clustering students by academic characteristics into classrooms is not inherently inequitable. Such clustering practices may, for example, facilitate the distribution of supplemental educational opportunities tailored to students' specific needs or allow highly skilled teachers to concentrate their instructional efforts more effectively. However, there needs to be more deliberate research to better understand and document how the assignment of students and teachers to classrooms can be leveraged to promote greater equality of educational outcomes. Beyond advancing our understanding of the school as a social organization, this work can guide the development of innovative approaches and tools designed to improve classroom assignment processes and enhance the equitable distribution of educational opportunities within schools.

Table 1. Descriptive statistics for analytic sample and all North Carolina public school 5th Grade Math Classes, 2011-12 to 2018-19 School Years

	Analytic Sample					Statewide 5th Grade Population
	Percent/ Mean	SD	Min.	Max.	N =	Percent/ Mean
Student Characteristics						
Student with Disability Flag	12.3%	.	0	1	386,951	14.4%
Limited English Proficiency Flag	10.6%	.	0	1	386,951	8.9%
Academically or Int. Gifted Flag	18.3%	.	0	1	386,951	17.1%
Economically Disadvantaged Flag	43.0%	.	0	1	386,951	52.6%
Asian	3.8%	.	.	.	2.9%	3.1%
Black	23.4%	.	.	.	24.8%	25.3%
Hispanic	19.1%	.	.	.	17.2%	16.8%
Native American	0.54%	.	.	.	1.3%	1.2%
Multiple	4.12%	.	.	.	4.1%	4.1%
Pacific Islander	0.11%	.	.	.	.10%	.12%
White	48.9%	.	.	.	49.6%	49.3%
Lagged Math Score (std)	.08	.99	-3.73	2.6	386,951	.01
N(students)	386,602					808,604
N(teachers)	7,793					
N(Schools)	892					
N(Districts)	97					
Teacher Characteristics						
3+ Years Experience	81.99%		0	1	16,015	
Median Observation Score of 5 Out of 5 on All Available Standards	13.25%		0	1	11,697	
Lagged EVAAS (std)	.02	1	-4.02	4.47	10,856	
Lagged Leave-Year-Out VA (std)	.05	1.02	-3.74	4.46	8,439	

Note: Table summarizes the primary analytic sample in our analysis and includes all 5th grade students enrolled in North Carolina Public schools from the 2011-12 to 2018-19 school year with complete covariate records who attended a school with at least three 5th grade math courses with at least 15 students each, were enrolled in a course ranging from 5-34 students in size and had at least two students identified as AIG, ED, LEP, SWD, or Black, Hispanic, and Native American and class-level summary statistics for teacher characteristics for classes in schools that met the same criteria above. The columns on the right summarize information for all 5th grade students in North Carolina in the 2011-12 to 2018-19 school years with complete non-missing records of the listed variables.

Table 2. Aggregated Intraclass Correlations for 5th Grade Math Classrooms for all NC public schools in sample, 2018-19

	(1) Black, Hispanic, or Native Am.	(2) Economic Disad.	(3) Prior Math EOG	(4) AIG	(5) Special Education	(6) Limited English Proficiency
LEA	0.075***	0.044***	0.026**	0.005+	0.014***	0.016**
School	0.189***	0.117***	0.110***	0.034***	0.000	0.066***
Math classroom	0.014	0.025+	0.149***	0.215***	0.067***	0.030**
Total explained variance	0.277	0.185	0.285	0.254	0.080	0.113

Note: +, *, **, and *** indicate that a one-tailed Welch's t-test showed the estimated ICC is statistically different from 0 at the .10, .05, .01, or .001 level respectively. N(LEA) = 72, N(School) = 462, N(classroom) = 2,367, N(students) = 48,863. Sample includes all 2018-19 5th grade students enrolled in North Carolina Public schools with complete covariate records who attended a school with at least three 5th grade math courses with at least 15 students each, were enrolled in a course ranging from 5-34 students in size and had at least two students identified as AIG, ED, LEP, SWD, or Black, Hispanic, and Native American. These results are produced by Model (2) and represent the decomposed variance, ranging from 0-1, associated with each level of the model. Greater values indicate more clustering of students by a given characteristic in a given level.

Figure 1. School-by-year level histograms, within-school in 5th grade math classroom ICCs in mid-sized to large North Carolina public schools, 2011-12 to 2018-19 school year.

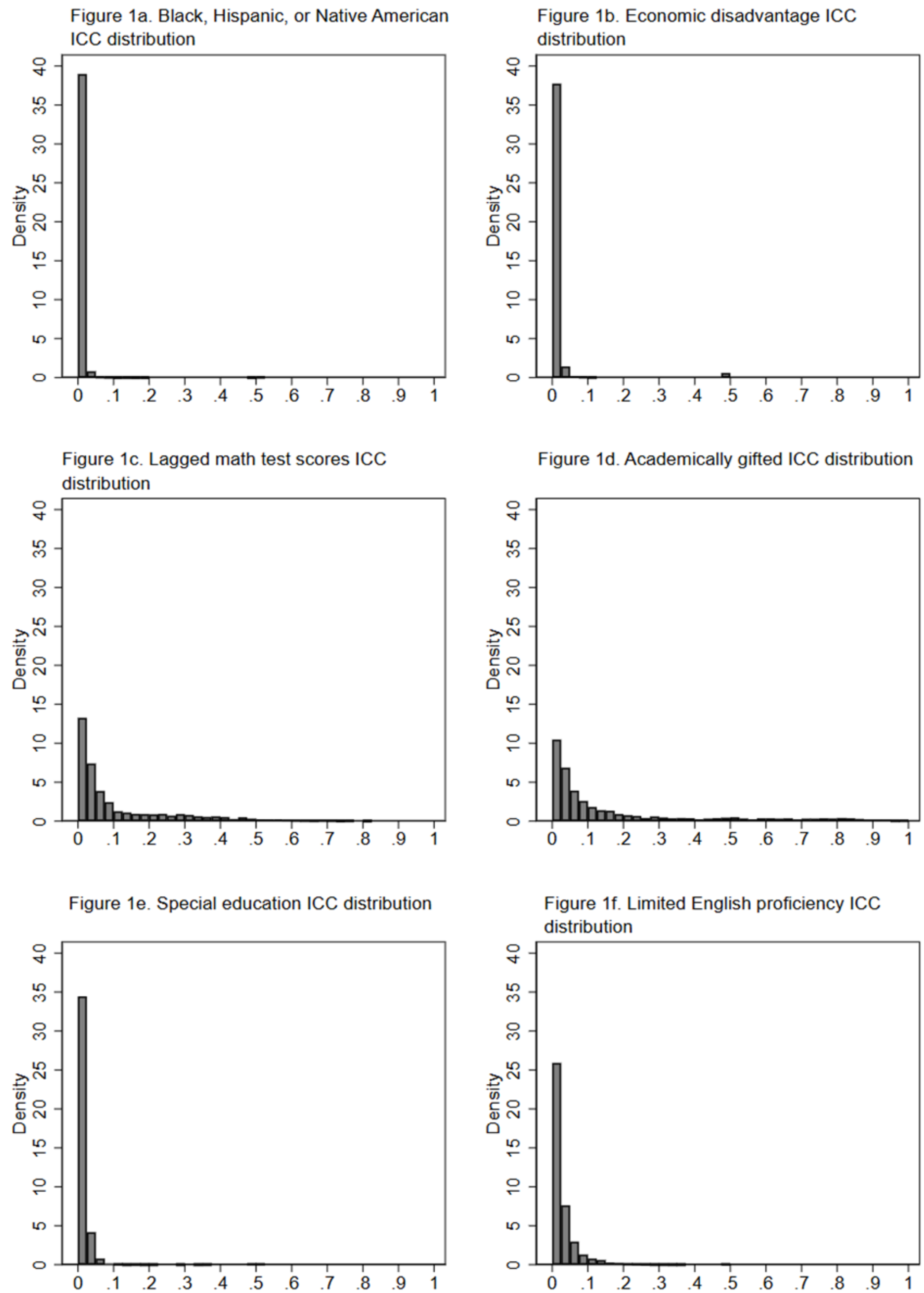
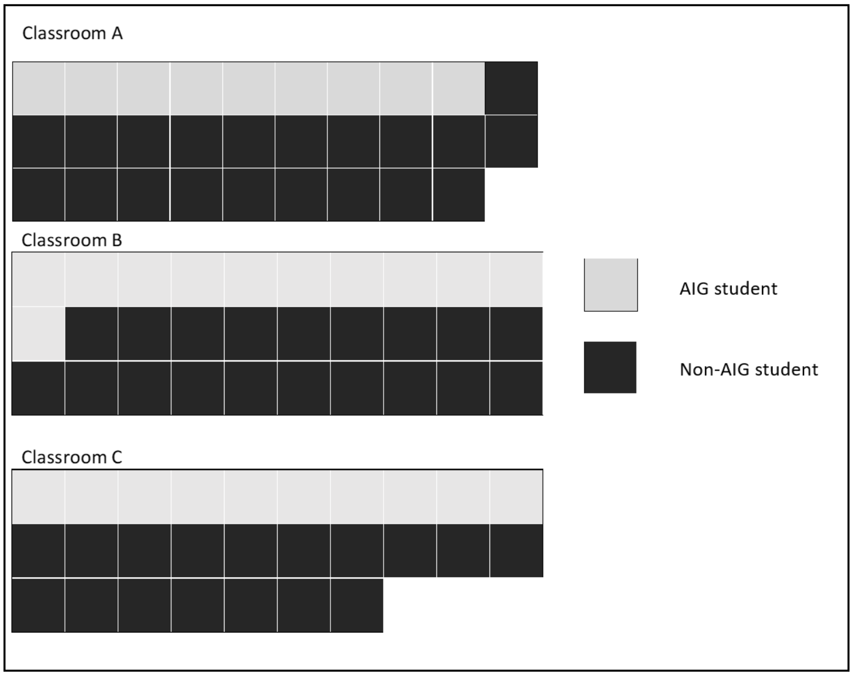


Figure 2. AIG student representation in 5th grade mathematics classrooms in NC two public elementary school

Highly balanced distribution of students identified for AIG (ICC_{sd} = 0.003)



Highly unbalanced distribution of students identified for AIG (ICC_{sd} = 0.889)

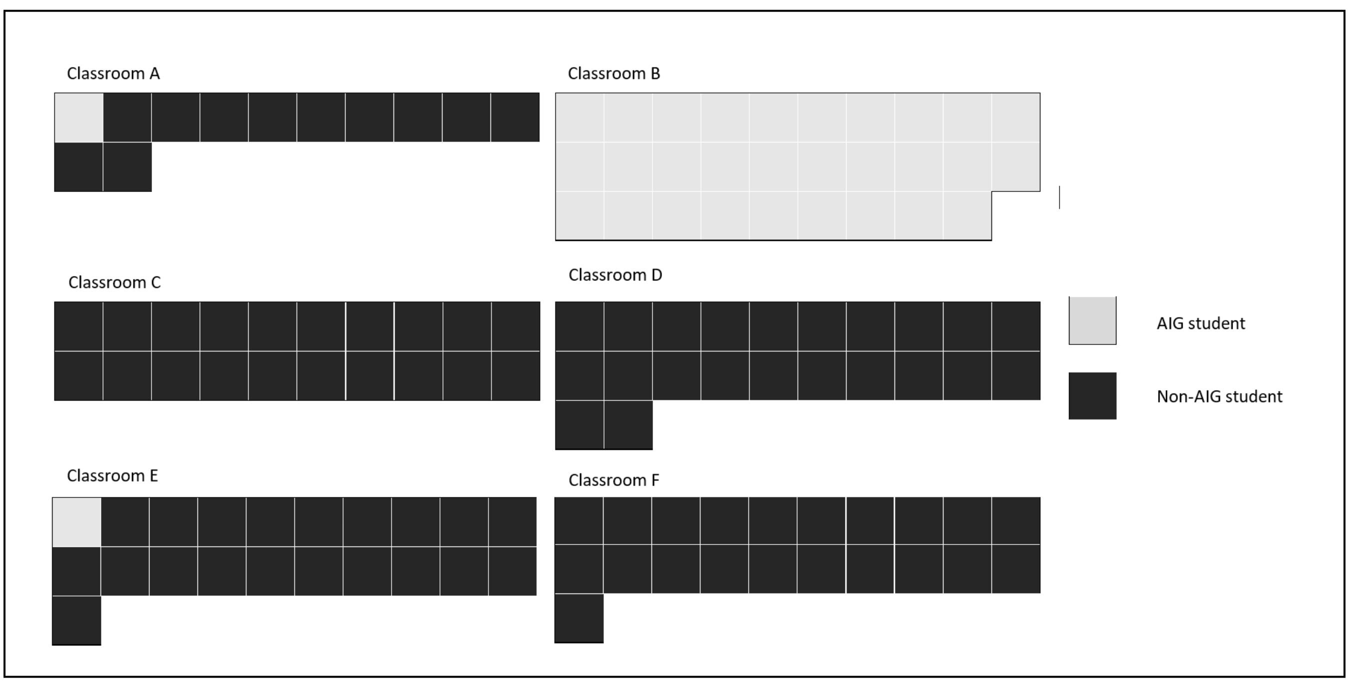
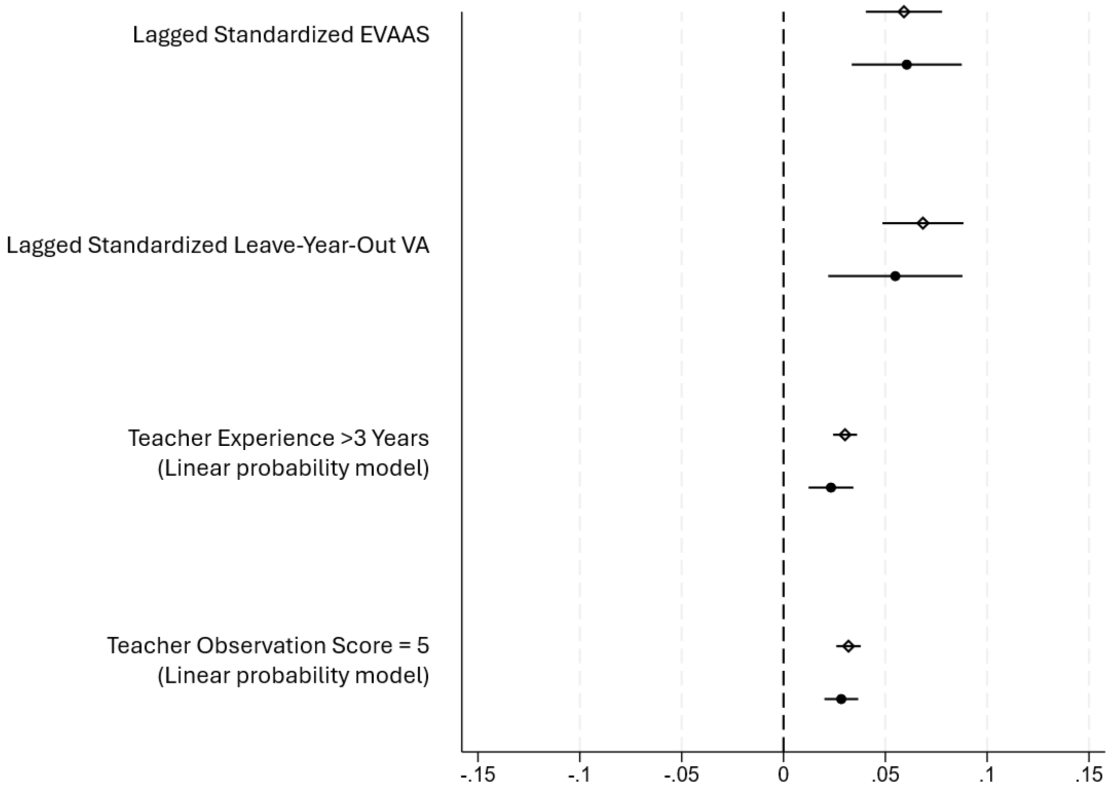


Table 3. Regression models predicting within-school math test score clustering in 5th grade math classrooms, SY 2011-12, 2013-14, 2015-16, and 2017-18

	(1) Unconditional Random Effects Coefficients Predicting Lagged Math Score ICC (std.)	(2) Conditional Random Effects Coefficients Predicting Lagged Math Score ICC (std.)	(3) Conditional Random Effects Coefficients Predicting Lagged Math Score ICC (std.)	(4) Conditional Fixed Effects Coefficients Predicting Lagged Math Score ICC (std.)
5th Grade Math Enrollment	0.116***	0.009	0.005	-0.002
	(0.029)	(0.006)	(0.006)	(0.011)
5th Grade Math Classes Count	0.053*	0.011*	0.011*	0.009
	(0.023)	(0.005)	(0.005)	(0.006)
5th Grade Racial Diversity (HHI; std.)	-0.013	-0.002	0	-0.007
	(0.027)	(0.004)	(0.008)	(0.014)
SD of Lagged Math Scores (std.)	0.094***	0.016***	0.017***	0.017***
	(0.021)	(0.003)	(0.003)	(0.004)
% teachers w/ 3-5 years of exp. (std.)	-0.005	0.004	0.004	0.005
	(0.018)	(0.004)	(0.004)	(0.004)
% teachers w/ 6+ years of exp. (std.)	0.056**	0.011**	0.011**	0.005
	(0.021)	(0.004)	(0.004)	(0.005)
Parent power (std.)	0.110***	0.017***	0.012*	0.008
	(0.025)	(0.004)	(0.005)	(0.007)
Lagged math test scores (std.)	.	.	0.003	-0.009
			(0.006)	(0.007)
School exp. per pupil (std.)	.	.	-0.008	0.001
			(0.006)	(0.01)
School % LEP (std.)	.	.	-0.006	-0.004
			(0.005)	(0.008)
% 5th grade Black, Hispanic, or Native Am. (std.)	.	.	0.004	0.066
			(0.035)	(0.059)
% 5th grade Black, Hispanic, or Native Am. (std.) ^{2}	.	.	-0.006	-0.086
			(0.032)	(0.055)
% 5th grade econ dis. (std.)	.	.	-0.001	0.001
			(0.006)	(0.008)
Constant	.	0.125***	0.119***	0.130***
		(0.007)	(0.01)	(0.013)
Year		X	X	X
School FE				X
N	1,968	1,968	1,968	1,968

Note: * p<0.05, ** p<0.01, *** p<0.001. Coefficients predict within-school clustering on student prior-year math achievement in sample of mid-sized to large North Carolina elementary schools using various school characteristics. The survey used to construct an estimate of parental power is administered every two years and therefore only four years of data are included in these estimates.

Figure 3. Associations between 5th grade classroom mean 4th grade math test scores and measures of teacher effectiveness and experience in North Carolina 5th grade classrooms, 2011-12 – 2018-19 academic years.



Note: Hollow diamonds represent models with random effects to account for school-level clustering; solid circles represent estimates from models with school-level fixed effects to control for school characteristics. Full model outputs and estimates for additional measures of classroom characteristics are available in Appendix Table 4.

Appendix Table 1. Statewide Aggregated Intraclass Correlations in 5th Grade Reading, 2018-19 (N=48,964)

	Black, Hispanic, or Native Am.	Econ Dis	Prior ELA EOG	AIG	Special Education	Limited English Proficiency
LEA	0.076	0.043	0.018	0.005	0.015	0.017
School	0.19	0.119	0.099	0.041	0	0.067
Reading classroom	0.011	0.022	0.12	0.192	0.075	0.029
Total explained variance	0.277	0.184	0.237	0.238	0.09	0.113

N(LEA) = 75, N(School) = 471, N(classroom) = 2,323, N(students) = 48,969

Appendix Table 2. Statewide Aggregated Intraclass Correlations in 4th Grade Math, 2018-19 (N=47,409)

	Black, Hispanic, or Native Am.	Econ Dis	Prior Math EOG	AIG	Special Education	Limited English Proficiency
LEA	0.085	0.043	0.025	0.012	0.012	0.018
School	0.184	0.119	0.094	0.055	0.002	0.064
Math classroom	0.011	0.022	0.132	0.193	0.034	0.028
Total explained variance	0.195	0.141	0.226	0.248	0.036	0.092

N(LEA) = 75, N(School) = 471, N(classroom) = 2,402, N(students) = 47,410

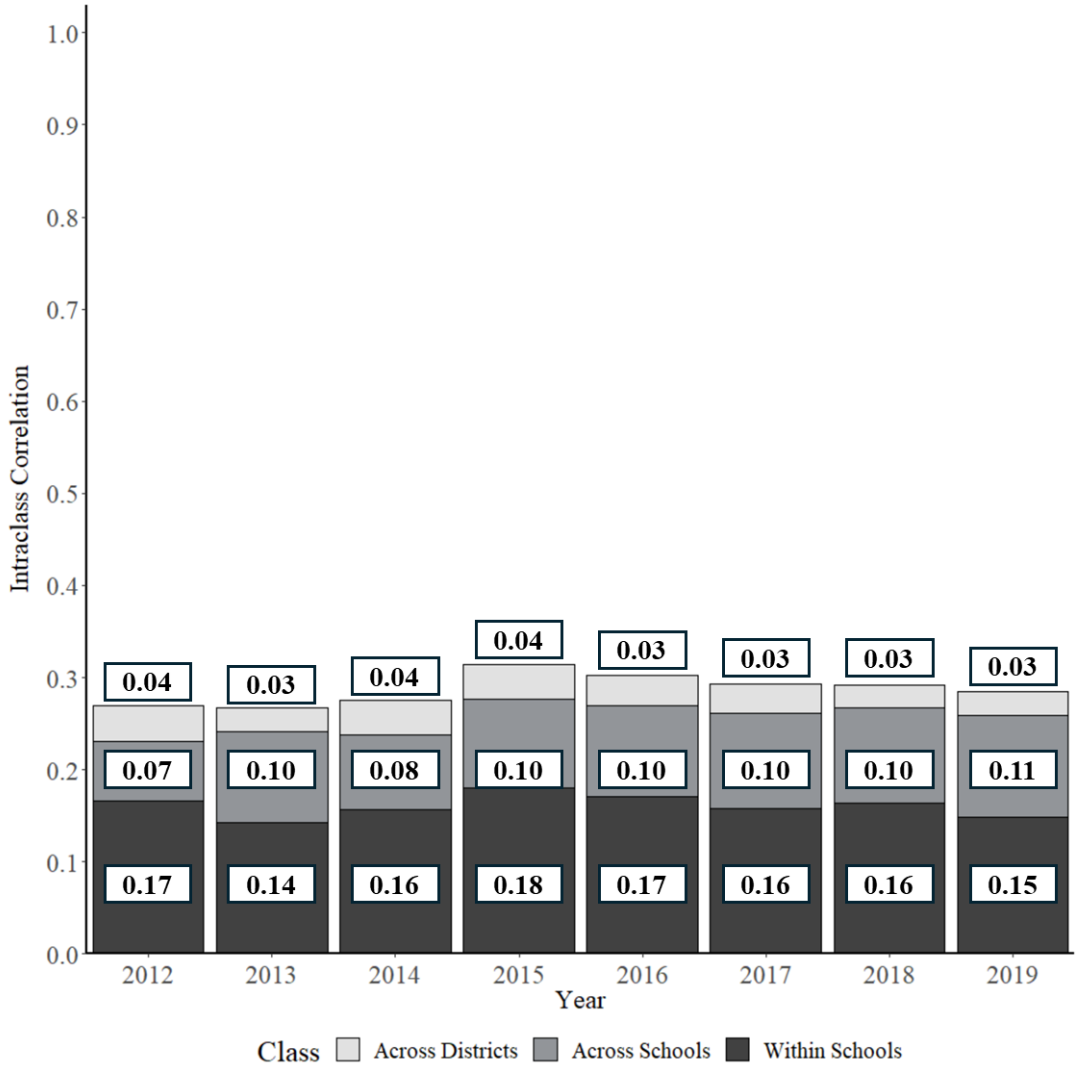
Appendix Table 3. Statewide Aggregated Intraclass Correlations in 4th Grade Reading, 2018-19 (N=47,253)

	Black, Hispanic, or Native Am.	Econ Dis	Prior ELA EOG	AIG	Special Education	Limited English Proficiency
LEA	0.086	0.043	0.018	0.011	0.014	0.018
School	0.184	0.119	0.079	0.052	0.002	0.064
Reading classroom	0.008	0.022	0.111	0.156	0.038	0.028
Total explained variance	0.278	0.184	0.208	0.218	0.054	0.11

N(LEA) = 72, N(School) = 462, N(classroom) = 2,353, N(students) = 47,253

Note: Sample includes all 2018-19 5th grade students enrolled in North Carolina Public schools with complete covariate records who attended a school with at least 3 5th grade math courses with at least 15 students each, were enrolled in a course ranging from 5-34 students in size and had at least 2 students identified as AIG, ED, LEP, SWD, or Black, Hispanic, and Native American. These results are produced by Model (2) and replicate those reported in Table 2, but using different samples of students and subject. Values are the decomposed variance, ranging from 0-1, with greater values indicating more clustering by a given student characteristic at that level of the model.

Appendix Figure 1. Statewide prior year test scores intraclass correlations trends in mid-size to large North Carolina 5th grade math classrooms, 2011-12 to 2018-19 school years.



Appendix Table 4 shows the full regression output for estimating association between class composition and teacher effectiveness. The following table is the full regression output for our class-level regression described in Model (4) and Model (5). Each teacher effectiveness or experience variable in the leftmost column was regressed on the class-aggregated characteristic presented in the top-level row as a bivariate regression. Therefore, each row-column pair represents a distinct regression coefficient for the horizontal independent variable and vertical dependent variable. As with Figures 3, each model was run once with fixed effects at the school and district level and once again with random intercepts at the school and district level.

Appendix Table 4. Regression Coefficients for the association between class composition and teacher effectiveness.

		Prior Math EOG	AIG	Economic Disadvantaged	Black, Hispanic, or Native Am.	Special Education	Limited English Proficiency	N=
EVAAS	RE	0.0592*** (0.00955)	0.0540*** (0.00793)	-0.0549*** (0.0115)	-0.0243 (0.0130)	0.00222 (0.00938)	0.000316 (0.00971)	14,637
	FE	0.0605*** (0.0136)	0.0537*** (0.0110)	-0.0677*** (0.0169)	-0.0331 (0.0175)	0.00263 (0.0147)	-0.00803 (0.0121)	
Leave-year-out VA	RE	0.0686*** (0.0101)	0.0515*** (0.00823)	-0.0437*** (0.0125)	-0.0267 (0.0147)	-0.00508 (0.00993)	-0.00390 (0.0103)	11,277
	FE	0.0550** (0.0167)	0.0488** (0.0172)	-0.0423* (0.0206)	-0.0280 (0.0198)	-0.000941 (0.0136)	-0.000843 (0.0145)	
Highly Rated	RE	0.0319*** (0.00306)	0.0294*** (0.00267)	-0.0361*** (0.00377)	-0.0375*** (0.00425)	-0.00184 (0.00259)	-0.0114*** (0.00314)	15,554
	FE	0.0284*** (0.00418)	0.0266*** (0.00481)	-0.0340*** (0.00557)	-0.0368*** (0.00719)	-0.00153 (0.00288)	-0.00937** (0.00289)	
3+ Years Exp	RE	0.0304*** (0.00300)	0.0340*** (0.00270)	-0.0427*** (0.00358)	-0.0418*** (0.00390)	0.00460 (0.00256)	-0.0149*** (0.00306)	20,985
	FE	0.0235*** (0.00550)	0.0313*** (0.00409)	-0.0371*** (0.00714)	-0.0248*** (0.00534)	0.00453 (0.00300)	-0.00820* (0.00386)	

Note: Standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Sample includes all 2018-19 5th grade students enrolled in North Carolina Public schools with complete covariate records who attended a school with at least three 5th grade math courses with at least 15 students each, were enrolled in a course ranging from 5-34 students in size and had at least two students identified as AIG, ED, LEP, SWD, or Black, Hispanic, and Native American. We ran Model (3) and Model (4) on these classroom-level data to estimate the relationship between course-level averages in student characteristics and measures of teacher effectiveness and experience. Coefficients represent the change in dependent variable associated with a one standard deviation increase in a classes composition by a given characteristic. Dependent variables EVAAS and leave-year-out VA are likewise standardized. 3+ Years Exp and Highly Rated are bivariate indicators for experienced teachers, or teachers rated highly by observations, and therefore these results are interpreted as the percentage point change in the likelihood of having such a teacher.

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