Is Within-Group Segregation a Substitute for Between-Group Segregation? Evidence from North Carolina Elementary Schools

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December 8, 2023

Abstract

Do people segregate within a group in response to increased group diversity? I study the impact of increased exposure to low-income students on gifted program assignment in North Carolina elementary schools. Using cohort-to-cohort variation within a school, I find that a 10 percentage point increase in the low-income share of a student's peers increases high-income students' reading gifted status by 4.8% the following year, with no impacts for low-income students. Both high- and low-income students also experience gains in teacher evaluations from more low-income peers, consistent with a relative-rank theory of grading, but low-income students face greater negative impacts on test scores. These results indicate that increased economic diversity in schools worsens inequality in gifted program enrollment.

Keywords: Peer Effects, Segregation, Inequality

*I am extremely grateful to Raj Chetty, David Deming, John Friedman, Matthew Staiger, and the participants of the Harvard Pre-Doctoral Research Seminar for their invaluable feedback and comments. All opinions expressed are my own.

1 Introduction

Social networks play a large role in determining outcomes across a variety of settings, including education, health, and employment (Cattan et al., 2022; Klärner et al., 2022; Eilers et al., 2022; Jackson, 2021). Consequently, a lack of social connectedness between high- and low-income people is a major contributor to economic inequality (Jackson, 2021; Chetty et al., 2022). Economists highlight the key role of homophily– the tendency for people to seek out those like themselves– in driving divisions in social networks, and decompose homophiliy into two parts: exposure, and choices conditional on exposure (Currarini et al. 2009). Chetty et al. (2022) document that increased exposure to people of different socioeconomic backgrounds leads to greater levels of "friending bias"– homophily in the choices that determine social networks. One potential explanation is that exposure to a more diverse set of peers leads people to sort into groups with people more like themselves, potentially diminishing the benefits of integration (Carrell et al., 2013).

This paper provides new evidence quantifying the extent that within-group segregation substitutes for between-group segregation by studying assignment to gifted programs in North Carolina elementary schools. Between school segregation has received much political and academic attention in the United States, and school integration has large positive impacts across a variety of outcomes (Johnson, 2011). However, recent work suggests that school integration may also lead to greater within-school tracking, decreasing experienced exposure to diversity (Clotfelter et al., 2021; Bergman, 2018). I contribute to this literature, finding that an increase in the low-income share of students in a school increases gifted enrollment for high-income students but not for low-income students, worsening between classroom segregation in more economically integrated schools. To my knowledge, this is the first work to identify peer effects on classroom assignments in Elementary schools. By studying test score and teacher evaluation responses, I highlight potential mechanisms driving within-group sorting early in students' educational experiences.

Gifted programs offer differentiated and advanced coursework to elementary school students, often in separate classrooms from their peers. There is significant economic inequality in gifted program enrollment across the United States (Oakes, 1985; Card and Giuliano, 2015; Grissom and Redding, 2016). For example, in North Carolina, low-income students are 18% less likely in Reading and 15% less likely in Math to be enrolled in Academically and Intellectually Gifted (AIG) programs than high income students with the same test scores (Figure 1). Thus gifted programs serve to sort students within schools by economic status, limiting students exposure to economically diverse peers, even in settings with diverse school populations.[1]

Assignment to gifted programs is determined using multiple criteria, including standardized test scores, teacher evaluations, and parent and student decisions. Grissom and Redding (2016) highlight the role of teacher discretion in determining gifted status, documenting that racially-concordant teachers boost gifted enrollment for Black students. Card and Giuliano (2015) identify informal referral processes as a barrier for low-income students in gaining gifted status. This paper extends these findings by documenting the role of exposure to low-income peers on students' gifted assignments, revealing that having more low-income peers increases gifted enrollment for high-income students.

I employ longitudinal data from North Carolina to estimate peer effects on gifted assignment, using variation in the share of low-income students across cohorts within a school under a consistent school-assignment policy. I define student cohorts as the set of first-time third graders within a school in a given school year. I find that a 10 percentage point increase in the number of low-income peers in one's cohort increases a high-incomes student's probability of being considered gifted in reading by 4.8%; there are no impacts on low-income students' gifted status. Consequently, increased economic diversity in a school exacerbates inequality in access to gifted programs and increases within-school sorting. Both high- and low-income students see gains in teacher evaluations,[2] but low-income students experience larger negative effects on test scores, potentially cancelling out the positive gains in evaluations. The impacts of low-income peers are greater for outcomes in reading than math.

The key challenge in identifying the role of economic diversity on gifted assignment is that the choice of schools, and thus one's peers, is endogenous to student ability. This paper follows an established literature which uses cohort-to-cohort variation within a school to isolate peer effects. (See Hoxby 2000; Lavy and Schlosser 2007; Diette and Uwaifo Oyelere 2012; Cattan et al. 2022). The intuition behind this approach is, while families may be able to choose their schools, they

[1] Chetty et al. (2022) find that schools with higher shares of students in gifted programs exhibit greater levels of friending bias.

[2] These effects are consistent with teachers grading students based on their relative-rank within a cohort rather than by objective standards (Hill et al., 2023).

are unable to perfectly predict the economic composition of a student's specific cohort due to idiosyncratic variation such as the timing of births of low- and high-income students in a community. By controlling for school and cohort fixed effects, this empirical strategy seeks to isolate unexpected variation.

One threat to identification is that families sort around certain expected changes to a school's low-income share in ways correlated with students' unobserved ability. To combat this threat, I identify the years in which schools experience large shocks to their low-income share in multiple grades and drop these years from my analysis, defining the school before and after the shock as separate "assignment regimes" and controlling for assignment regime fixed effect in my analysis.

I employ several robustness checks on the validity of my empirical design. Following Hoxby (2000), I account for families ability to sort on trends in the change in school composition in two ways: first by adding linear time trends for each assignment regime and second by operationalizing Hoxby's "Drop if more than Random" test to eliminate assignment regimes that exhibit non-linear time trends. My results are robust to the inclusion of these additional controls. Additionally, I find that the variation in the low-income share of students in an assignment regime across years closely resembles simulated random variation and is balanced on observable characteristics of students. Importantly, I find that peer effects are driven entirely by the low-income share of a student's own cohort within a school, rather than the low-income share in any of the three prior or following cohorts.

My data covers all elementary school students in North Carolina between 2000 and 2016. I focus my analysis on students in the third grade, the first year I am able to observe students, in school districts that primarily assign gifted status beginning in fourth grade. My primary outcome of interest is students' gifted status in the fourth grade.

This work relates to the large economic literature that studies the effects of the racial and socioeconomic peer composition on academic outcomes in schools.[3] Hoxby (2000) uses gender and race variation to find higher achieving peers raise test scores. Angrist and Lang (2004) find modest negative impacts in the short-run from a school desegregation program, but little impact in the long-run. Billings et al. (2013) use the end of bussing in North Carolina to show that a 10% increase in the share of racial minorities in a school leads to a 0.02SD decrease in reading test

[3]For a more comprehensive overview, see Sacerdote (2014).

scores, with a similar but smaller effect on math scores. Interestingly, they find negative impacts of increased minority share on AP and honors course taking for high school students, but no impact for middle school students. Also in North Carolina, Hill et al. (2023) use periodic school reassignments in Wake County and likewise find increases in math and reading test scores coming from higher achieving peers, but also find lower grades in English and Language Arts (ELA) courses, consistent with a theory of relative-rank grading. There's also evidence that higher class ranks can offset the negative consequences of low-achieving peers, perhaps by boosting student confidence (Murphy and Weinhardt 2020). Denning et al. (2023) find long-run positive impacts of increased classroom ranks in elementary school, including positive effects on enrollment in AP classes. This research builds on the existing literature by studying peer effects on enrollment in gifted programs in elementary schools, when academic tracking begins, and investigating teacher evaluations of student ability.

The remainder of this paper proceeds as follows. Section 2 discusses the context of gifted programs in North Carolina. Section 3 details the data and presents summary statistics. Section 4 covers my empirical strategy and addresses threats to identification. Section 5 discusses my results and section 6 concludes.

2 AIG Programs in North Carolina

Public schools in North Carolina are run by 117 separate school districts known as Local Education Agencies (LEAs). By state law, each LEA must maintain a program to identify Academically and Intellectually Gifted (AIG) students in reading and mathematics. Identified students receive differentiated education and instruction, taking the form of classroom pull-outs, additional enrichment activities, or separate classrooms with accelerated curricula.

The state of North Carolina defines Academically and Intellectually Gifted students as those who "perform or show the potential to perform at substantially high levels of accomplishment when compared with others of their age, experience, or environment." The definition adds that "outstanding abilities are present in students from all cultural groups, across all economic strata, and in all areas of human endeavor." (Article 9B N.C.G.S. § 115C-150.5).

Giftedness, by definition, is a relative measure of student ability. However, it is nominally global, compared to all students of a shared background, rather than local, compared to the students in one's cohort. Additionally, the North Carolina's AIG policy makes explicit mention of students' economic background, emphasizing the importance of placing students in their personal context when evaluating their gifted potential.

Identification procedures vary across that state, but typically involve both standardized testing and teacher referrals/evaluations. Figure A.1 shows published graphics from three LEAs in North Carolina to illustrate the variation in AIG identification processes. In both Mount Airy City Schools and Rutherford County Schools, AIG identification begins with standardized testing. In Mount Airy City Schools, testing is followed by teacher evaluations and AIG committee decisions. In Rutherford County Schools, students can place into AIG programs directly from their test scores, or undergo a more holistic review process if they do not meet the score threshold. In Nash Rocky Mount Schools, in contrast, the AIG identification process begins with teacher referrals. In each district, there is no single criteria that determines a student's gifted status. Many LEAs use multiple screening criteria with the explicit goal of helping all qualified students achieve gifted status.[4] If students don't qualify for AIG services in a given year, they can be considered again in the next year through teacher, parent, or self-referral.

Depending on the school district, students are typically identified in either the third or fourth grade using the prior year's achievement. In 58% of LEAs, the majority of students are recognized as gifted for the first time in the fourth grade.[5] Because third grade is the earliest year I observe, I restrict analyses to this subset of school districts. This subset of school districts are highly representative of the state as a whole (Appendix Table 1).

Every three years, LEAs must review and revise their AIG identification policies. Between 2000 and 2017, AIG enrollment has remained relatively stable, with roughly 17% of high-income students and 4% of low-income students in the state classified as AIG in Reading in the fourth grade (Figure A.2).

[4]While some advocates champion multiple screening criteria as being able to better capture the diversity of ways students can be gifted, holistic and informal processes can serve as barriers for low-income students seeking elite education by increasing the extent to which admissions procedures can be gamed (Chetty et al. 2023, Card and Giuliano 2015).

[5]I do not directly measure if a school district assigns gifted status primarily in the third or fourth grade. Instead, I look at the ratio of third to fourth graders assigned AIG in each school district. The distribution of ratios is highly bimodal, with clusters at 0 and 1. I define a LEA as primarily first assigning AIG in the fourth grade if the ratio of third to fourth grade AIG students is less than 0.4 across all years.

3 Data

This paper uses data from the North Carolina Education Data Research Center (NCEDRC) covering all public school students in 3rd-5th grade from 1997-2017. For my primary analysis, I focus on the 2000-2016 cohorts of third grade students, for whom I observe their gifted status in the fourth grade.

3.1 Data Construction

I take advantage of two sets of data provided by the NCEDRC: End of Grade Testing data, which covers years 2000-2012, and the Masterbuild files, which cover 2006-2017. There is a high degree of overlap in the information recorded in the two sets of files for the years they both cover; when the files disagree, I defer to the Masterbuild files. I drop the year 2013 from my analysis due to data limitations in measuring AIG status. I drop students observed in multiple schools in a single year from my analysis, representing 1% of students. I further narrow my focus to traditional public schools in school districts that first assign AIG status in the fourth grade, dropping charter and magnet schools from my analysis and any school-grade-years with less than 10 students. I am left with a sample of 679,836 first-time 3rd graders.

3.2 Data Definitions

For each student, I observed their school and cohort, detailed demographic information including the student's gender, ethnicity, free and reduced price lunch status, and birth date. I also observe academic achievement, including AIG status, end of course test scores, and teacher evaluations. This paper uses the following data definitions.

AIG Status. The NCERDC data contains indicators for AIG status in reading and math. I additionally consider IG (Intellectually Gifted) and AG (Academically Gifted) students as AIG.

Test Scores. Every year, students in North Carolina take state-wide tests in Math and Reading and receive a numeric score. Over the period of this study, North Carolina had several testing regimes in which the scale for numeric scores changed. To account for these regime changes and variation in the difficulty of the exam each year, I drop scores that fall outside of the defined test score range in a given year and normalize scores in each grade-year to be mean 0 standard deviation

1, using data from the whole state rather than my subset of school districts. Students scores are also placed into achievement buckets 1-4, representing their mastery of the state standards for their grade level. I define students as receiving “high test scores” if they meet achievement level 4, defined as “comprehensive understanding”. 37.1% of third grade students have high reading achievement, among whom 30% have gifted reading status in the fourth grade.

Teacher Judgements. For a subset of years (2006-2012), I also observe teacher evaluations of student ability on the same 1-4 proficiency scale as the end of grade tests. I analogously define high teacher evaluations as meeting achievement level 4. 25.8% of third grade students have high reading achievement according to their teachers. Teacher evaluations in reading (math) correlate 65.2% (63.7%) with observed achievement on end of grade tests.

Gender. Over this period, NCERDC categorized all students as male or female.

Ethnicity. NCERDC classifies students as belonging to one of five racial categories: White, Black, Asian/ Pacific Islander, American Indian/ Alaskan Native, or Missing/Unknown.

Low-Income. Following the existing literature, I define students as low-income if they are eligible for free or reduced price lunches. I use low-income and low socioeconomic status (SES) interchangeably in this paper.

Learning Disability and Limited English Proficiency. NCERDC contains indicators for if a student has a learning disability or is on a limited English proficiency learning plan. I define these charcteristics using a student’s status in the third grade.

Above Median Age for Grade. Within each year and grade, I calculate the median birth date. I then define a student as old for their grade if they were born prior to the median birth date.

Assignment Regime. My unit of analysis is “Assignment Regimes”, schools under a consistent policy that determine who attends the school. For details on how I construct assignment regimes, see Section 4.1.

3.3 Summary Statistics

Table 1 presents summary statistics. Column 1 presents statistics for all first time third graders in my sample from 2000-2016. Columns 2 and 3 present statistics for high- and low-income students separately.

Over this period half of North Carolinian Elementary School students are eligible for free and reduced price lunch. Low-income students are more likely to be Black or Hispanic, have a learning disability, and have limited proficiency in English. 3.7% of low-income students are considered gifted in the fourth-grade, compared to 16.7% of high-income students.

The median third-grade cohort has 97 students. Despite the large observable differences between high- and low-income students, schools are relatively integrated by income. On average, 40% of a high-income student's peers are low-income, for low-income students, the share is 60%.

4 Empirical Strategy

What is the relationship between the low-income share of a student's cohort and their own gifted status? Figure 2 plots the share of students considered AIG in Reading in the fourth grade against the share of their third grade cohort that are low-income in ventile bins by income status, controlling for third-grade math and reading test scores. For both high- and low-income students, the relationship is positive and linear. Students are more likely to be considered gifted in reading when they have more low-income peers, conditional on having the same test score in the third grade. The relationship is much stronger for high-income students (Figure 2a); a 10% increase in a high-income student's third grade cohort increases the likelihood of gifted gifted reading status by 0.3pp. For low-income students, the coefficient is 0.1pp. Consequently, at schools with few low-income students, high- and low-income students with the same test scores are considered gifted at similar rates, but at schools with more low-income students, the AIG enrollment gap is larger. These results imply that schools with more low-income students suffer more within-school sorting, conditional on test scores.

However, this observational comparison suffers from two sources of bias. First the relationship between AIG share and low-income share may be downward biased due to students sorting between schools. Students at schools with fewer low-income students likely have higher unobservable academic ability, conditional on test score, that would make them more likely to be considered gifted. Second, test scores are a "bad" control, as they are an outcome of the share of low-income peers (Billings et al., 2013; Hill et al., 2023). More low-income peers decrease standardized test scores, and therefore students with more low-income peers may have higher underlying academic aptitude than their test scores suggest, biasing the effect of low-income share conditional on test scores upward.

To address both of these biases, I employ an empirical strategy first developed by Hoxby (2000) that uses cohort and school fixed effects to isolate peer effects from idiosyncratic variation in the share of low-income students in a specific cohort within a school.

The intuition underlying this design is that, while families can choose the schools they want to attend based on the student-body composition, they cannot perfectly predict the composition of a school in a given year due to idiosyncratic variation in the low-income share within a school between years. For example, this variation cam arise from idiosyncrasies in the timing of births by families of different incomes within a neighborhood. The primary identifying assumption is that students' unobservable determinants of AIG enrollment are uncorrelated with the variation in the share of low-income peers in a students' cohort relative to other cohorts in the same assignment regime.

I define students' cohorts as the first year they enter the third grade. To identify the effect of low-income peers on student outcomes, I estimate the following equation for student i in school s and cohort c

$$Y_{isc} = \beta_1 P_{-i,sc} + \beta_2 P_{is\{c-3,c+3\}} + \beta_3 X_{itc} + \gamma_c + \alpha_s + \delta_{LEA,c} + \eta_{ics} \tag{1}$$

Where $P_{-i,sc}$ is the share of students in assignment regimes s's third grade cohort c that are low-income, leaving out student i. Under the identifying assumption described above, β_1 estimates the causal effect of an increase in the share of low-income peers on student outcomes Y_{isc}. $P_{is\{c-3,c+3\}}$ is the share of low-income third-grade students in the same school in the three cohorts preceding and following cohort t, respectively. X_{ics} is a vector of controls for students' gender, ethnicity, and limited English proficiency status. γ_c are cohort fixed effects, α_s are assignment regime fixed effects, and $\delta_{LEA,c}$ are school district by cohort fixed effects, capturing time-varying school district policies, such as changes to curricula or AIG identification procedures. η_{ics} is an idiosyncratic error term.

If the variation in low-income share of peers is truly random, and there are no spillovers in peer effects between cohorts,[6] the coefficient on β_2 should equal 0 for all prior and following cohorts.

[6] Lavy and Schlosser (2007) find this assumption to be true in an Israeli context.

Encouragingly, in most specifications, I am unable to reject the null hypothesis that $\beta_2 = 0$ for AIG status, test scores, and teacher evaluations.

Even if families cannot sort into schools based on a specific cohort's low-income share, they may take into account the long term trend of a school. For example, higher ability students may choose to attend schools that are growing richer over time. To account for selection on trends in the share of low-income students in a school, I add linear controls in time by school to my preferred specification.

$$Y_{isc} = \beta_1 P_{-i,sc} + \beta_2 P_{is\{c-3,c+3\}} + \beta_3 X_{itc} + \gamma_c + \alpha_s + c \times D_{is} + \delta_{LEA,c} + \eta_{ics} \quad (2)$$

Where $c \times D_{is}$ is a cohort by assignment regime linear trend.

One limitation of this design is that it may be under-powered to detect effects on gifted classification, as gifted assignment is a rare outcome and within-school variation of the low-income share of students is small. However, my analysis spans a large number of years and I find statistically significant peer effects across a range of outcomes, including AIG status, test scores, and teacher evaluations.

4.1 Expected Shocks and School Reassignments

A threat to the identifying assumption of equation 1 is that families may be able to expect and sort around certain shocks to a school's share of low-income students, re-introducing selection bias. An example of this threat is school reassignment plans– changes in the rules that govern which students attend which schools. Reassignments happen periodically in districts around the state in response to school openings/closings, to alleviate overcrowding in schools, and occasionally with the explicit purpose of diversifying schools racially and economically (see Hill et al. (2023) for examples in Wake County). Reassignments produce large, non-random shocks in the share of low-income students in a school, and thus families may be able to anticipate them and change the schools they attend accordingly. Evidence from two separate reassignments in North Carolina find 50-60% compliance with new school assignments (Hill et al., 2023; Billings et al., 2013).[7] Consequently, the students attending a school after a reassignment policy are not comparable to the students prior

[7]Unlike previous studies, I do not have access to detailed address information for students that would allow me to instrument for peer effects using these reassignment plans.

to the change.

Figure 3a illustrates the non-random nature of shocks to low-income shares in North Carolina elementary schools. I begin by residualizing the share of low-income students in each cohort for each school on year and LEA by year fixed effects and linear time trends for each school. I am left with the identifying (and theoretically idiosyncratic) variation within each school. For each school, I then calculate the standard deviation in the residual variation across years; Figure 3a plots the density of school's standard deviation in residualized low-income share. Following Lavy and Schlosser (2007), I then simulate the expected variation in low-income shares based on the average share of low-income students in each school. To do this, I randomly generate the low-income status of each student using a binomial distribution function where p is the average low-income share of students in each school across years. I recalculate the standard deviation of low-income share within a school across cohorts using randomized low-income status. In gray, Figure 3a plots the results of 100 such simulated distributions. The figure clearly shows that schools exhibit greater variation in their low-income shares than would be expected by random year-to-year fluctuations, after accounting for linear time trends. This non-randomness threatens identification because of students' ability to choose schools if changes are expected.

To address expected non-random shocks, I identify schools with large, correlated changes in student composition across multiple grades in a single year. I then drop the year with the large shock, as well as the three following years to allow families to re-sort according to the new assignment plan. I identify the periods pre- and post- shock as separate "Assignment Regimes". In all of my analysis, I control for assignment regime rather than schools. In practice, this is equivalent to treating schools under different regimes as separate schools.

My procedure for identifying expected shocks is as follows: I start by calculating the percent change in low-income share in grades 3, 4, and 5 in each school year-to-year from 1997-2017. I identify years in which the percent change is more than a standard deviation away from the mean percent change in the school for that grade. If in any year, 2 or more grades are both above or both below a standard deviation from the mean, I flag the school as having large shocks across grades that year in the same year. In addition, I flag a year if the school has no enrollment in the prior year (but did have enrollment in *a* prior year).

This procedure identifies large correlated shocks in the low-income share that occurs in multiple grades in a single school in a year. These shocks may be changes to school reassignment plans, but this procedure also captures other large expected shocks to the low-income share in a school, such as a new housing development assigned to a school that represents a large permanent change in the low-income share.

From my initial sample of 1,408 schools, I generate 3,576 assignment regimes. 13.1% of first-time third graders attend school $\times$ years that I flag as having large, correlated shocks. Reassuringly, I identify shocks at known school reassignment plans– I flag 42.7% of schools in Charlottte-Mecklenburg Schools in the 2003 school year, the year it ended it's bussing program (Billings et al., 2013), but less than 16% in adjacent years.

Figure 3b replicates Figure 3a using assignment regimes instead of schools. In contrast to Figure 3a, the variation within assignment regimes closely resembles random variation across cohorts.[8] This is not a mechanical result– my procedure for identifying assignment regimes does not eliminate all large shocks in the low-income share of students in a school, only shocks that effect multiple grades in the same year. Random variation provides evidence supporting the assumption that student propensity for AIG status is uncorrelated with the low-income share in their cohort within an assignment regime.

4.2 Balance Tests

However, random variation does not eliminate the potential of families to sort based on unobservables into schools with higher or lower low-income share in a specific cohort. To test for selection, I perform a series of balance tests, swapping in fixed student characteristics for the outcome variable in Equation 2. Figure 4 illustrates the result. Conditional on assignment regime fixed effects, both high- and low-income students in cohorts with more low-income students are no more likely to be female, Black, speak a language other than English at home, have a disability, or be above the median age for their grade. These balance tests provide supporting evidence that families are not selecting into schools based on the low-income share in their third grade cohort.

[8]Using 1,000 simulations, I obtain empirical 90 percent confidence intervals for the standard deviation of low-income share for each school. 82% of assignment regimes fall within the 90 percent confidence intervals of random standard deviation.

4.3 Drop if More Than Random

Linear time controls may not be sufficient if families sort on time trends not captured by a linear model. To test for this possibility, I use Hoxby's "Drop if More Than Random" test. I begin by residualizing the 3rd grade low-income share in each school by year with year by LEA fixed effects and school specific linear trends. For each school, I fit a cubic in year to the residualized low-income shares and record the R^2 from the regression. I then re-shuffle the years randomly five times, ensuring that the random order is not the same as the true order, and refit the cubic. If the R^2 from the true ordering is 5% larger than the minimum R^2 from the random orderings, I flag the school as exhibiting a time trend.

This is a strict procedure. 69% of 3rd-grade students in my sample attend assignment regimes that exhibit "more than random" non-linear time trends. Reassuringly, however, my point estimates are robust to dropping these assignment regimes, although I lose much of my statistical power, indicating that selection on non-linear time trends are not driving the peer effects I document. Consequently, I choose to primarily display results that include schools that exhibit non-linear time trends in the share of low-income students.

5 Results

5.1 AIG Status

Figure 5 presents the effects of a 10 percentage point increase in the share of low-income students in a student's own cohort and adjacent cohorts on reading test scores, AIG status, and teacher evaluations. Figure 5a shows a 10 percentage point increase in the share of low-income peers raises reading gifted status for high-income students by 0.8 percentage points, a large effect on a baseline of 16.7%. I find no peer effects on reading gifted status for low-income students (Figure 5b).

Importantly, the effects are driven entirely by the low-income share in a student's own third-grade cohort, rather than any of the three cohorts preceding or following them. Thus it is unlikely for these results to be driven by selection on trends within a school, but rather by the peers in one's own cohort.

Table 2 presents the robustness of these results to various models: not including school's linear time trends and implementing Hoxby's "drop if more than random" test (see section 4.3). Across various models, I find the effect of increased low-income share on AIG status for high-income students to be between 0.51–0.80 percentage points and I find no effect for low-income students. When implementing Hoxby's "drop if more than random" test, I drop a large number of observations and lose precision, but my point estimates remain relatively stable across a variety of outcomes. Again, these effects are driven entirely by one's own cohort, rather than adjacent cohorts.

Table 3 replicates table 2 with outcomes in math. Consistent with prior work, I find larger peer impacts on reading outcomes than math (Burke and Sass, 2013; Hill et al., 2023; Denning et al., 2023).[9]

5.2 Mechanisms

Why do high-income students see large increases in gifted assignment from an increase in low-income peers but low-income students do not? One potential explanation is that low-income peers effect academic achievement differently for high- and low-income students, as academic achievement is an input to gifted assignment. Figures 5c and 5d show the impact of an increase in low-income peers on third grade reading test scores for high- and low-income students respectively. Low-income students see large negative impacts on their reading test scores, -0.021 – -0.024 SD across various specifications (table 2), whereas high-income students see much smaller impacts (-0.005 – -0.016 SD). The magnitudes of these effects are consistent with other estimations of peer effects on test scores; Billings et al. (2013) find a 10% increase in the share of minority students decreases high-school test scores by 0.02 SD.

Heterogeneous treatment effects by income make it clear that a linear-in-means model of peer effects is insufficient to explain changes in AIG Status. Larger negative impacts for low-income students are consistent with a subculture theory of peer effects, as developed by Hoxby and Weingarth (2006), in which disadvantaged students face negative impacts when the size of their group reaches a critical mass. Peer effects may also be stronger among students belonging to the same group. For example, low-income students may be more likely to change their classroom behavior in the presence of more low-income peers, worsening academic achievement (Bursztyn et al., 2017).

[9] Hill et al. (2023) speculate this is due to specific instructional challenges of teaching mixed ability reading classes as opposed to math.

Another set of explanations focuses on the relative rank of students and impacts on teacher evaluation of student ability. If teacher's engage in relative comparisons between students, an increase in the low-income share of students may raise teacher assessments for all students (Murphy and Weinhardt, 2020; Hill et al., 2023; Denning et al., 2023). Because high-income students are more likely to be in the upper tail of the achievement distribution, an increase in teacher assessment from increased exposure to low-income peers will propel more high-income students to be gifted.

Indeed, I see evidence that teachers engage in relative-rank comparisons when evaluating student achievement. For years 2006-2012, I observe teacher "judgments" of student achievement levels on a scale of 1-4 for math and reading, corresponding to the achievement levels on end of grade tests. I find a 10% increase in low-income peers results in a 1.9pp increase in a teacher considering a high-income student highly proficient in reading (Figure 5e) despite a 1.0pp *decrease* in the share of high-income students actually achieving high proficiency in reading according to standardized testing. Low-income students also see large gains in their teacher judgements from an increase in low-income peers (Figure 5f). Relative-rank may also impact other inputs to the gifted assignment, such as increasing student confidence (Murphy and Weinhardt, 2020).

A third set of explanations centers the role of student and parent decisions in determining AIG status. In many LEAs, parents and students can determine AIG identification, such as by opting out of identification processes, appealing to teachers, or hiring private IQ tests for identification (Joseph Neff and Raynor, 2018). If parents and students have increased preferences for homophilly in diverse settings (Carrell et al., 2013), high-income families may take increased action to place their students in gifted programs, and low-income families may be more likely to opt out.

6 Conclusion

This paper provides novel evidence on the impact of economic diversity on gifted program assignment and within-school segregation. Using cohort-to-cohort variation in North Carolina elementary schools, I find that increased exposure to low-income peers widens inequality in access to gifted programs by boosting gifted assignment for high-income students but having no effect on low-income students.

I explore several potential mechanisms driving these heterogeneous peer effects. Both high-and low-income students see improvements in teacher evaluations of their reading achievement, consistent with teachers engaging in relative comparisons when evaluating students. However, low-income students experience larger negative impacts on reading test scores from more low-income peers, potentially cancelling out gains from positive impacts on teacher evaluations.

Future work should aim to better understand the role of student and parent preferences in determining gifted status. Obtaining data on gifted program identification processes across school districts could shed light on how parents and students change their behavior in response to increased diversity. Linking students to administrative records can also allow for long run analysis of AIG programs and quantify the impacts of within school segregation on long-run educational and labor market outcomes.

This paper adds to a growing body of evidence that within-group sorting increases in response to increased diversity, potentially worsening inequality in integrated settings. This evidence highlights the importance of institutional design in reaping the benefits from integration.

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Table 1: Summary Statistics

	All 3rd Grade Students	High-Income 3rd Grade Students	Low-Income 3rd Grade Students
A: Demographics	(1)	(2)	(3)
% Low Income	48.3%	0.0%	100.0%
% Female	49.4%	49.1%	49.9%
% White	50.4%	65.8%	33.6%
% Black	21.1%	9.6%	33.4%
% Hispanic	11.6%	3.7%	20.2%
% Learning Disability	8.6%	6.3%	11.0%
% Limited English Proficiency	9.8%	2.8%	16.8%
B: Achievement and AIG			
High Math Achievement	34.6%	47.0%	20.3%
High Reading Achievement	37.6%	50.4%	22.8%
High Math Teacher Eval	25.0%	34.8%	14.6%
High Reading Teacher Eval	25.0%	34.7%	14.2%
AIG Math in 4th Grade	11.7%	18.5%	4.5%
AIG Reading in 4th Grade	10.4%	16.7%	3.7%
C: School			
Median # of Days Member of School	167	167	167
Median Cohort Size	97	102	92
Average Share Low-Income in Cohort	49.4%	39.4%	60.2%
Standard Deviation Share Low-Income in Cohort	22.7%	20.2%	20.2%
D: Counts			
Number of Students	674,675	346,192	323,322
Number of School Districts	68	68	68
Number of Schools	633	630	630
Number of Assignment Regimes	1,589	1,575	1,585

Notes: The table presents summary statistics for the samples defined in Section 3.2. Column 1 presents statistics for all first time third-graders in traditional North Carolina public schools in Local Education Agencies that primarily first assign AIG status in the fourth grade from 2000-2017, excluding 2013. Columns 2 and 3 subset to High- and Low-Income Students Respectively.

Table 2: Effect of Low-Income Peers on Reading Outcomes

	High-Income			Low-Income		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: AIG Status						
Low-Income Share						
Own Cohort	0.6032***	0.7993***	0.5116	-0.0195	-0.0887	0.3288
	(0.1895)	(0.2534)	(0.4471)	(0.0957)	(0.1162)	(0.2511)
Previous Cohort	0.0900	0.2109	-0.3470	0.1034	0.1204	0.1651
	(0.1704)	(0.2370)	(0.5077)	(0.0923)	(0.1166)	(0.2822)
Next Cohort	-0.1552	-0.0213	0.2726	0.0361	-0.0346	0.2557
	(0.1513)	(0.1920)	(0.4208)	(0.0786)	(0.0975)	(0.2114)
# Observations	177,846	177,846	52,204	180,449	180,449	53,026
R^2	0.0699	0.0750	0.0775	0.0360	0.0406	0.0412
Panel B: Test Score						
Low-Income Share						
Own Cohort	-0.0095*	-0.0050	-0.0160	-0.0226***	-0.0207***	-0.0244*
	(0.0049)	(0.0057)	(0.0109)	(0.0054)	(0.0065)	(0.0129)
Previous Cohort	-0.0075	0.0002	0.0012	-0.0014	-0.0023	-0.0158
	(0.0047)	(0.0057)	(0.0114)	(0.0051)	(0.0061)	(0.0118)
Next Cohort	-0.0025	-0.0017	-0.0105	0.0016	0.0007	0.0125
	(0.0036)	(0.0046)	(0.0118)	(0.0038)	(0.0051)	(0.0104)
# Observations	175,007	175,007	51,367	173,036	173,036	50,847
R^2	0.1043	0.1105	0.1087	0.0995	0.1055	0.1060
Panel B: High Teacher Judgements						
Low-Income Share						
Own Cohort	1.0258**	1.8909***	1.2004	0.7646***	1.3883***	2.4566***
	(0.4106)	(0.5015)	(0.9004)	(0.2650)	(0.3551)	(0.8272)
Previous Cohort	0.3118	0.5896	-0.6794	-0.0155	0.5219	1.9347***
	(0.4510)	(0.5185)	(0.9995)	(0.2471)	(0.3544)	(0.7378)
Next Cohort	-0.4541	0.1534	-1.4634	-0.2494	0.4292	0.9780
	(0.3449)	(0.4483)	(0.9246)	(0.2215)	(0.3100)	(0.6347)
# Observations	109,920	109,920	33,018	107,942	107,942	32,582
R^2	0.0678	0.0761	0.0777	0.0508	0.0581	0.0658
Assignment Regime Fixed Effect	X	X	X	X	X	X
Assignment Regime Linear Trend		X	X		X	X
Drop if More Than Random			X			X

Notes: This table reports coefficients and standard errors from running the regression in equation 1 for high-income (columns 1-3) and low-income (columns 4-6) students seperately. The effects reported are the coefficient on a 10 percentage point increase in low-income share in one's own cohort, the previous cohort, and the next cohort in a school. Panel A reports the percentage point effect on reading AIG status. Panel B reports the standard deviation effect on third grade reading test scores. Panel C reports the percentage point effect on being considered "Proficient" in reading by one's third grade teacher. All regressions control for a students' own low-income status, race, gender, and English proficiency status, with year and LEA by year fixed effects. Columns 1 and 4 include assignment regime fixed effects. Columns 3 and 5 additionally add linear by year assignment regime trends. Columns 4 and 6 additionally implement the "Drop if More Than Random" (Hoxby 2000) test to eliminate schools with non-linear time trends. 3rd grade reading test scores are normalized to be mean 0 standard deviation 1 in each school year. Data covers all third grade students in North Carolina from 2000-2016 in LEAs that first assign AIG status in the fourth grade. All standard errors are clustered by assignment regime.

Table 3: Effect of Low-Income Peers on Math Outcomes

	High-Income			Low-Income		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: AIG Status						
Low-Income Share						
Own Cohort	0.3219	0.4622*	0.3907	0.0246	-0.1507	0.1061
	(0.2013)	(0.2378)	(0.4898)	(0.1008)	(0.1169)	(0.2588)
Previous Cohort	0.1660	0.3665	-0.3294	0.2395**	0.1173	0.1472
	(0.1879)	(0.2392)	(0.5234)	(0.1003)	(0.1163)	(0.3099)
Next Cohort	-0.2210	-0.1783	-0.2205	0.0783	-0.0356	0.4162
	(0.1521)	(0.1936)	(0.4524)	(0.0853)	(0.1079)	(0.2691)
# Observations	177,846	177,846	52,204	180,449	180,449	53,026
R^2	0.0829	0.0883	0.0887	0.0343	0.0392	0.0468
Panel B: Test Score						
Low-Income Share						
Own Cohort	-0.0159**	-0.0084	-0.0326**	-0.0123**	-0.0164**	-0.0019
	(0.0064)	(0.0069)	(0.0127)	(0.0062)	(0.0074)	(0.0159)
Previous Cohort	-0.0064	0.0034	-0.0176	-0.0002	-0.0017	-0.0079
	(0.0056)	(0.0062)	(0.0127)	(0.0060)	(0.0066)	(0.0184)
Next Cohort	0.0010	0.0037	-0.0073	0.0067	0.0034	0.0297**
	(0.0044)	(0.0053)	(0.0123)	(0.0047)	(0.0063)	(0.0135)
# Observations	175,483	175,483	51,510	174,185	174,185	51,200
R^2	0.1304	0.1401	0.1405	0.1152	0.1250	0.1327
Panel B: High Teacher Judgements						
Low-Income Share						
Own Cohort	0.8638*	1.2167*	2.5436	0.4653	0.6740	2.9851***
	(0.4692)	(0.6734)	(1.6147)	(0.3260)	(0.5232)	(1.1058)
Previous Cohort	0.6094	0.5404	1.1078	-0.2342	-0.2715	1.7797*
	(0.4839)	(0.6803)	(1.4428)	(0.2870)	(0.4636)	(1.0397)
Next Cohort	-0.3053	-0.3547	-0.3857	-0.4683*	-0.1595	1.9125*
	(0.4682)	(0.6611)	(1.5524)	(0.2535)	(0.4674)	(1.0213)
# Observations	81,843	81,843	24,761	84,206	84,206	25,617
R^2	0.0600	0.0695	0.0770	0.0479	0.0558	0.0614
Assignment Regime Fixed Effect	X	X	X	X	X	X
Assignment Regime Linear Trend		X	X		X	X
Drop if More Than Random			X			X

Notes: This table replicates table 2 with outcomes in Math.

Figures

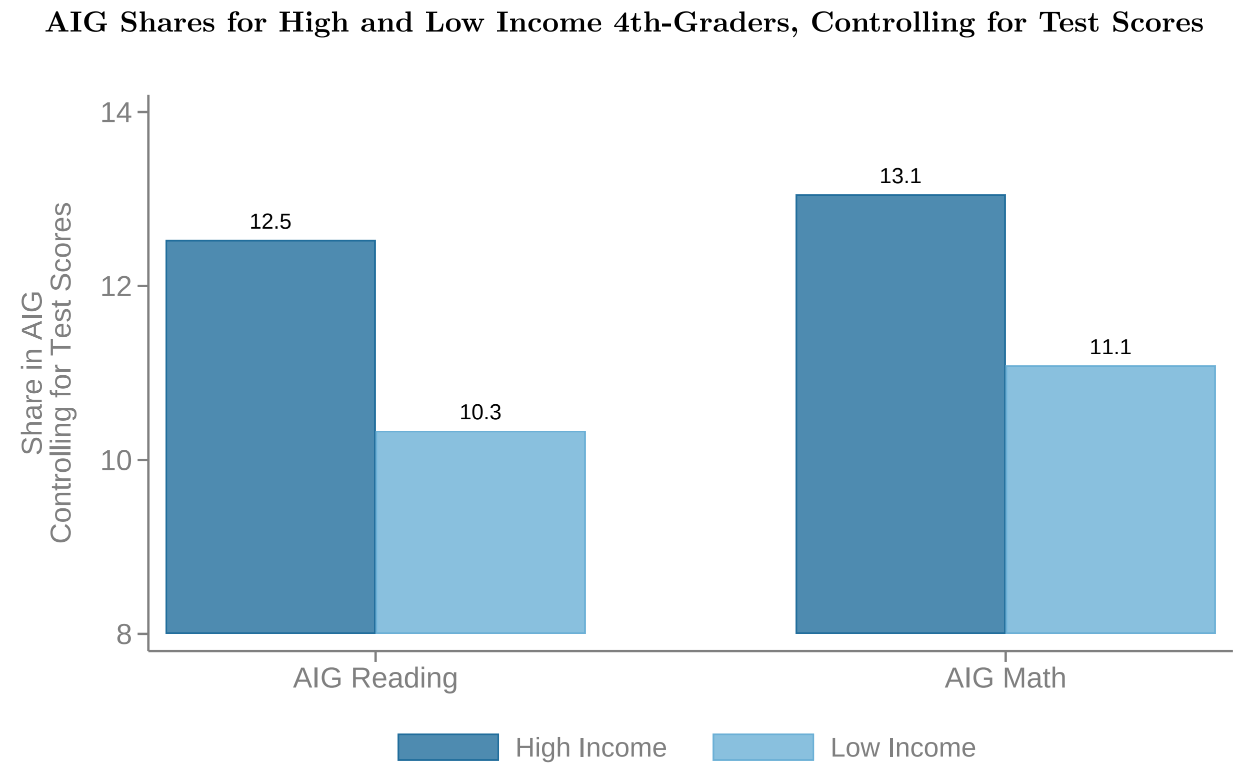
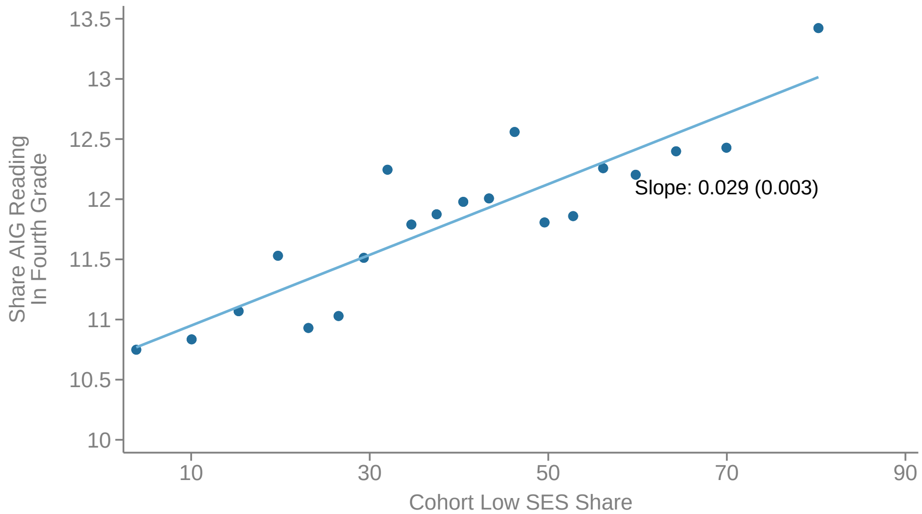


Figure 1: This figure plots the share of high- and low-income 4th grade students in Academically and Intellectually Gifted (AIG) reading and math programs respectively. AIG shares are residualized on cubics in reading and math third grade test scores and year and school district fixed effects. High- and low-income status are defined using free and reduced price lunch eligibility. Data covers North Carolina fourth grade students from 2000-2016 in school districts that first assign AIG in 4th Grade. See Section 3 for more details.

AIG Reading vs. Share of Peers Low-Income, Controlling for Test Scores

(a) High SES



(b) Low SES

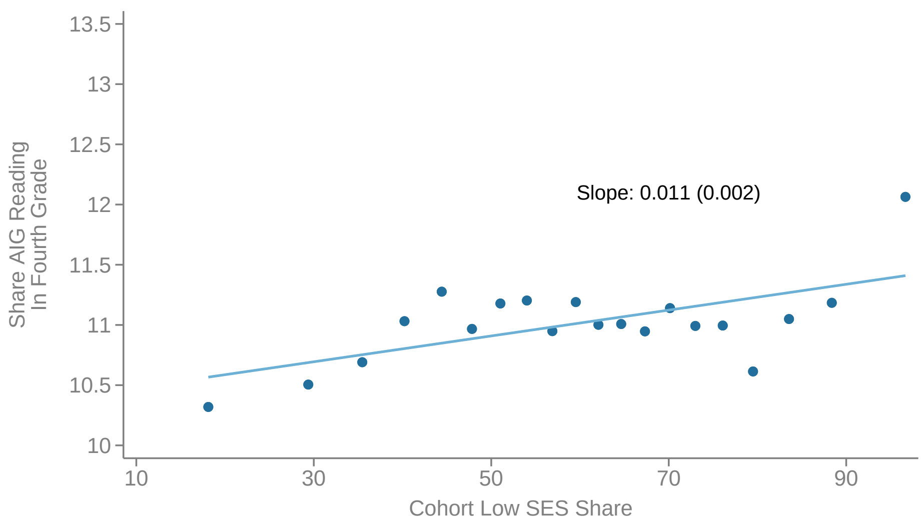
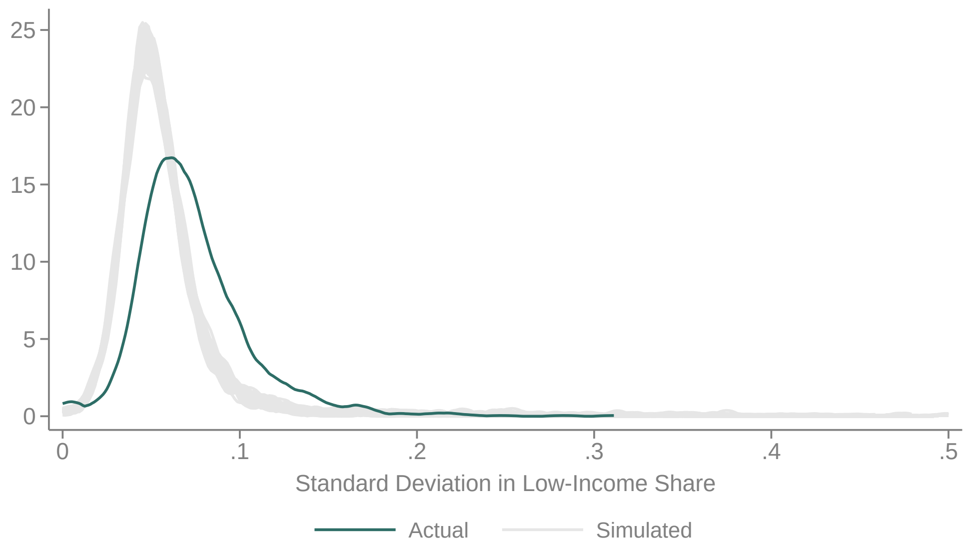


Figure 2: This figure plots binscatters of the share of North Carolina students considered gifted in reading in the fourth grade against the low-income share of their school cohort in the third grade. Figures 2a and 2b plot the relationship for high-income students and low-income students respectively. Cohort low SES share is calculated as the leave-out mean of low-income students in the same school, year, and grade as a student. AIG reading share is residualized on cubics of math and reading end of course grades as well as Local Education Agency (LEA) and year fixed effects. The binscatter additionally controls for a student's race, gender, and English proficiency status. This figure restricts to LEAs that first assign AIG status in the fourth grade.

Standard Deviation in Low-Income Share, Actual and Simulated

(a) Schools



(b) Assignment Regimes

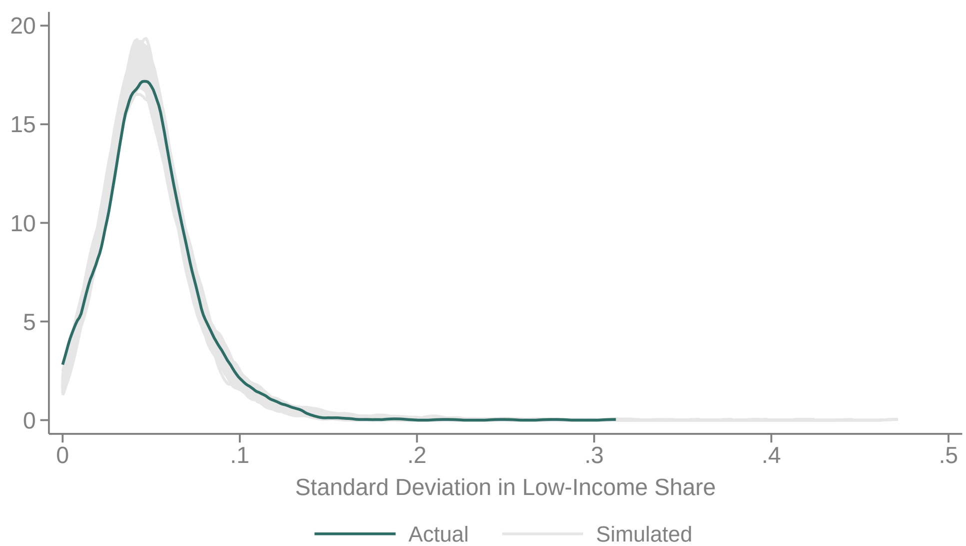


Figure 3: This figure plots the density of standard deviations of low-income share within each school and assignment regime. The blue line plots the true density of standard deviations, residualized on year and Local Education Agency by year fixed effects and linear time trends for each school/ assignment regime. The gray lines plot the results of 100 simulations, where each student's low-income status is generated randomly from a binomial distribution where p is the average share of low-income students in the school/ assignment regime. For more details on the Monte Carlo simulations, see Section 4.1.

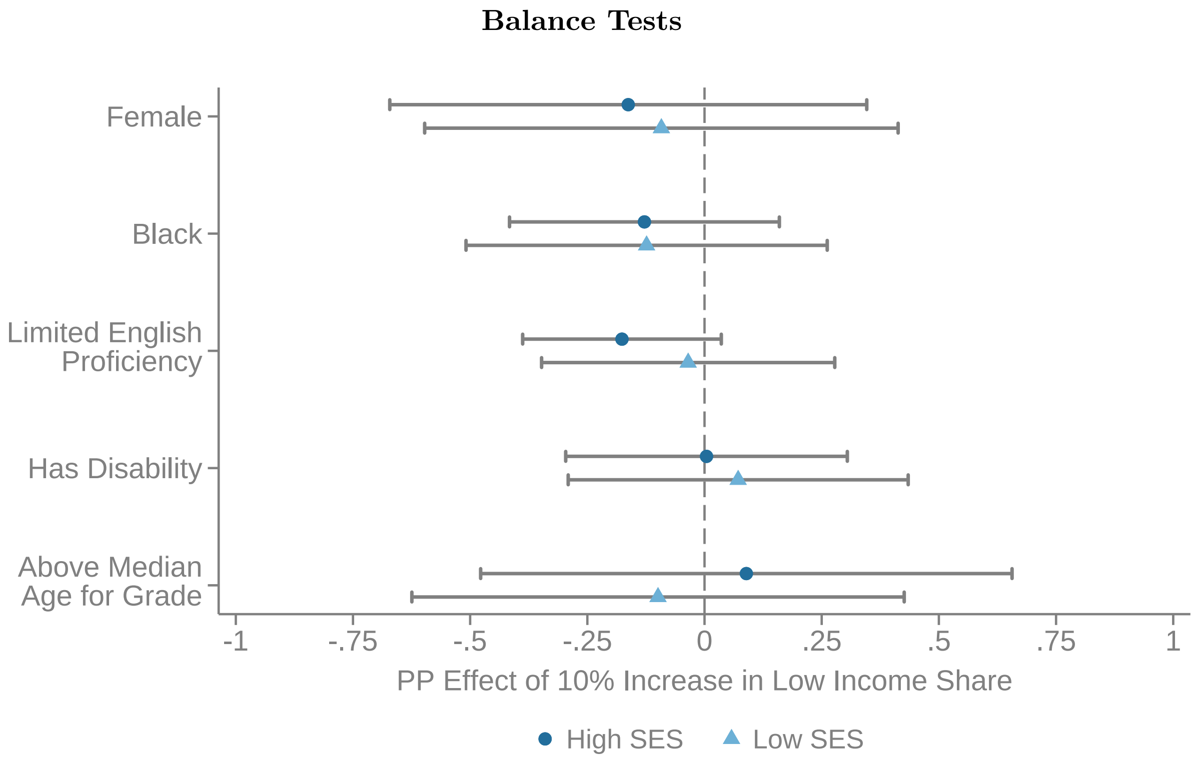
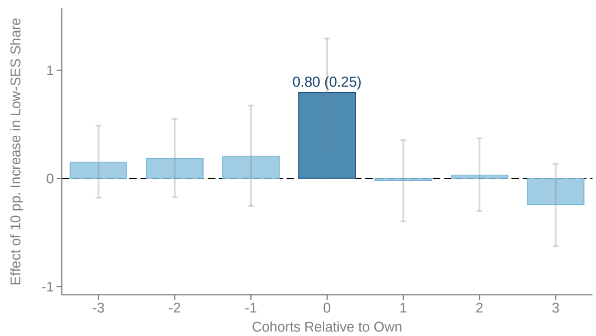


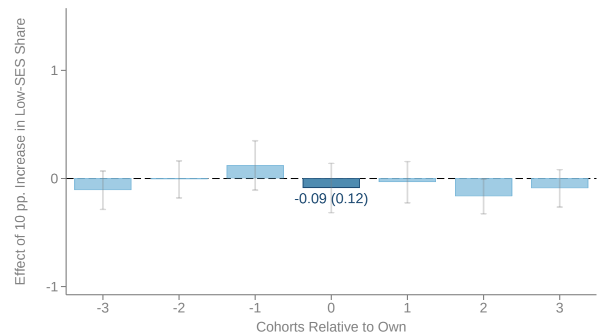
Figure 4: This figure plots the treatment effect of a 10 percentage point increase in low income share in a student's third grade cohort on fixed student characteristics for high- and low-income students. For data definitions of student characteristics, see section 3. Estimates plotted control for the low-income share in the three preceding and following cohorts, cohort, assignment regime, and Local Education Agency by cohort fixed effects, and assignment regime linear trends. Estimates control for race, gender, and limited English proficiency (dropping the control for specifications where the variable is the outcome). Error bars report 95% confidence intervals. All standard errors are clustered by assignment regime.

Effect of Increase in Low-Income Share of Students by Cohort

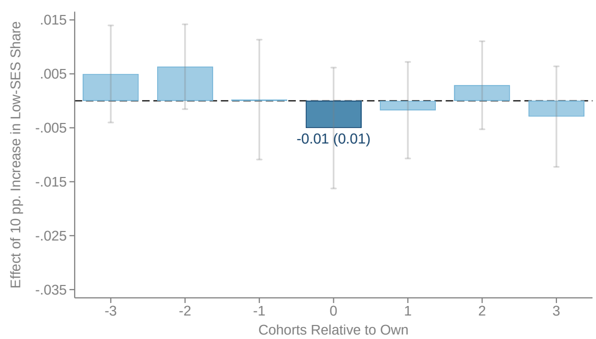
(a) High SES 4th Grade AIG Reading



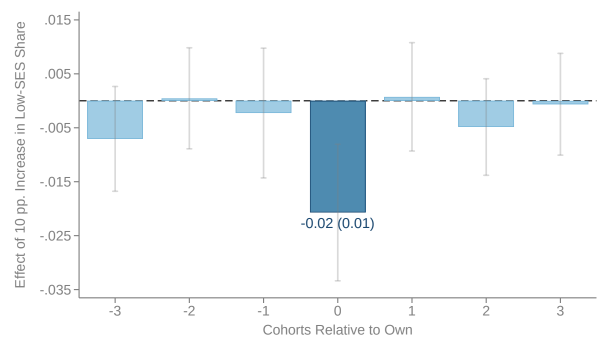
(b) Low SES 4th Grade AIG Reading



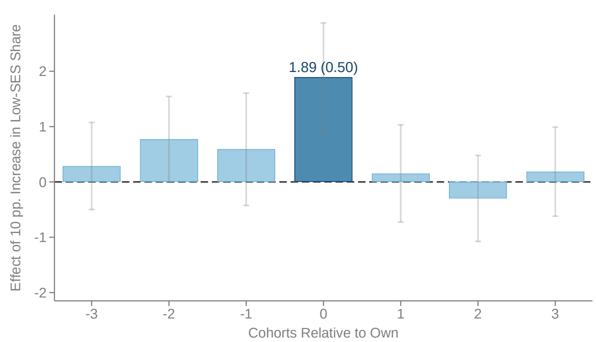
(c) High SES 3rd Grade Reading Test Score



(d) Low SES 3rd Grade Reading Test Score



(e) High SES 3rd Grade High Teacher Eval.



(f) Low SES 3rd Grade High Teacher Eval.

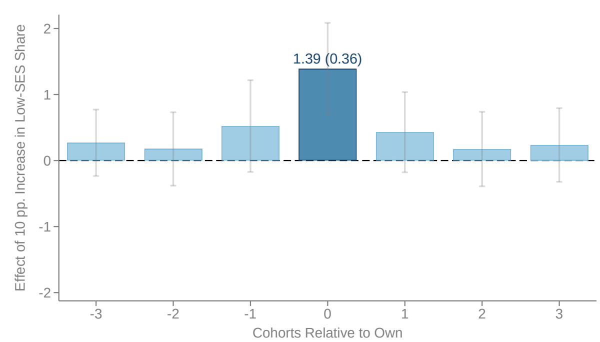


Figure 5: This figure reports the effects of a 10 percentage point increase in low-income share in one's own cohort and the three preceding and following cohorts in each assignment regime. Each figure plots the estimates of a single regression which controls for cohort, assignment regime, and LEA by cohort fixed effects, assignment regime linear trends, race, gender, and English proficiency. Figures 5a, 5c, and 5e plot estimates for high-income students, Figures 5b, 5d, and 5f for low-income students. Outcomes are defined in Section 3. Error bars report 95% confidence intervals. All standard errors are clustered by assignment regime.

Appendix Table 1: Comparing All Districts to Districts with AIG first Assigned in 4th Grade

	All North Carolina School Districts	Districts that First Assign AIG in 4th Grade
A: Demographics	(1)	(2)
% Low Income	50.3%	48.3%
% Female	49.4%	49.4%
% White	47.1%	50.4%
% Black	24.7%	21.1%
% Hispanic	11.7%	11.6%
% Learning Disability	8.7%	8.6%
% Limited English Proficiency	10.0%	9.8%
B: Achievement and AIG		
High Math Achievement	33.6%	34.6%
High Reading Achievement	37.0%	37.6%
High Math Teacher Eval	25.3%	25.0%
High Reading Teacher Eval	25.8%	25.0%
AIG Math in 4th Grade	12.0%	11.7%
AIG Reading in 4th Grade	11.4%	10.4%
C: School		
Median # of Days Member of School	167	167
Median Cohort Size	99	97
Average Share Low-Income in Cohort	51.3%	49.4%
Standard Deviation Share Low-Income in Cohort	23.2%	22.7%
D: Counts		
Number of Students	1,522,989	674,675
Number of School Districts	117	68
Number of Schools	1,408	633
Number of Assignment Regimes	3,576	1,589

Notes: The table presents summary statistics for all traditional public school third-grade students in North Carolina (Column 1) and third-graders in Local Education Agencies that primarily first assign AIG status in the fourth grade (Column 2). Data covers 2000-2017, excluding 2013.

AIG Identification Procedures

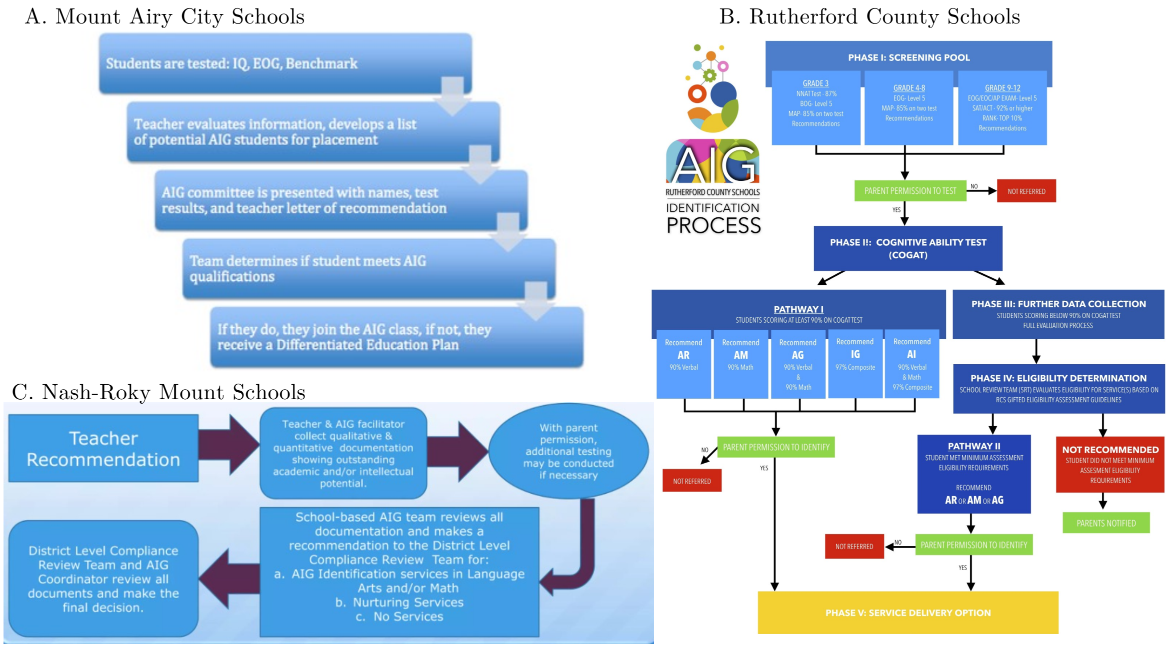


Figure A.1: This figure shows published graphics from three Local Education Agencies on their AIG identification procedures. Graphic A. comes from Mount Airy City Schools, graphic B. from Rutherford County Schools, and graphic C. from Nash Rocky Mount Schools.

AIG Reading Shares for 4th-Graders in North Carolina, 2000-2016

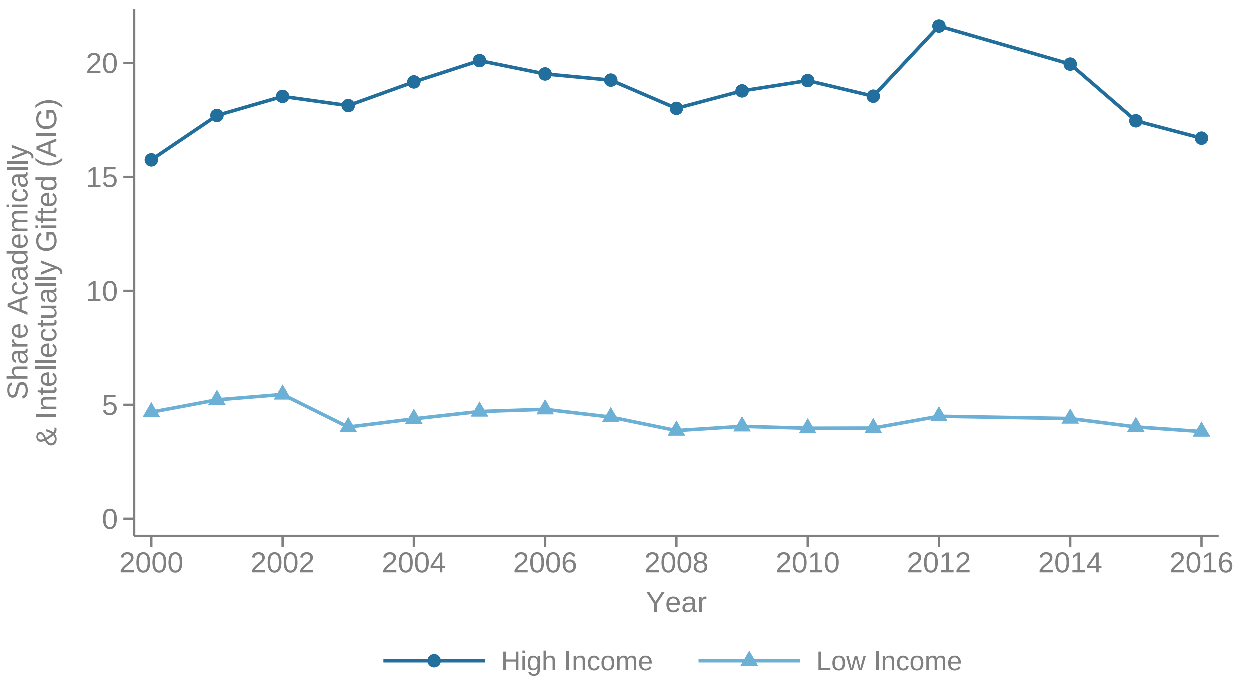


Figure A.2: This figure plots the share of 4th grade students in Academically and Intellectually Gifted (AIG) reading programs in North Carolina from 2000-2016 for high- and low-income students respectively. This figure restricts to Local Education Agencies that first assign AIG status in the fourth grade. See Section 3 for sample definitions.