School Competition, Classroom Formation, and Academic Quality

Angela Crema*

November 2026

Abstract

This paper studies how public schools compete when families value academic and nonacademic attributes. Exploiting a North Carolina school choice reform, I show that schools respond to competition by increasing their value added to test scores and changing how they assign students to classrooms. As a result, within-school segregation by demographics and achievement rises. By forming classrooms, each school shapes the peers different students are exposed to and, therefore, its attractiveness to different families. I ask whether competition along this margin weakens incentives to provide academic quality and whether regulating it can harness more of school choice's potential learning gains. I estimate an equilibrium model of school choice and competition that incorporates classroom formation into parental demand and school supply. The estimates reveal substantial heterogeneity in parental preferences for academic quality and classroom peers. Requiring integrated classrooms raises aggregate quality, with gains concentrated among nonwhite students, and reduces between-school segregation.

Keywords: school competition; classroom formation; academic quality; segregation
JEL classification: H75, I21, I24, I28

*Department of Economics, University of Rochester (email: acrema@ur.rochester.edu). I am deeply grateful to Dan Waldinger, Mike Gilraine, Chris Conlon, and Elena Manresa for their constant guidance and invaluable support. Special thanks to Alberto Bisin, Pierre Bodéré, Raquel Fernández, Martin Rotemberg, John Singleton, and Quang Vuong for numerous conversations that greatly improved this project. For their comments, I thank Robert Ainsworth, Joe Altonji, Michele Baggio, Nano Barahona, Sandy Black, Giulia Brancaccio, Chris Campos, Carolina Concha-Arriagada, Michael Dinerstein, Steven Durlauf, David Figlio, Ian Fillmore, Chris Flinn, Guillaume Fréchette, Jane Cooley Fruehwirth, Chloe Gibbs, Charles Hodgson, Lisa Kahn, Adam Kapor, Rob McMillan, Chris Neilson, Matt Notowidigdo, Ronni Pavan, Ellie Prager, Paulo Somaini, Sharon Traiberman, Seth Zimmerman, and audiences at Aarhus University, ASU, Boston College, CEMFI, Chicago Harris, EIEF, Kelley Business School, Minneapolis Fed, NYU, Penn State, Texas A&M, UConn, University of Geneva, UNC-Chapel Hill, University of Oslo, University of Rochester, University of Toronto, UW-Madison, Yale University, NBER Economics of Education, Cowles, SITE, ASSA, IIOC, NLS-E, the Dynamic Structural Econometrics conference, the Structural Microeconomics Conference at SEA, BSE Summer Forum, and the TSE Economics of Education workshop. I thank Lyn Ong for excellent research assistance and the North Carolina Education Research Data Center (especially Clara Mushkin and Kara Bonneau) for providing the data. This research was supported by a grant from the Department of Economics at the University of Rochester. All remaining errors are my own.

1 Introduction

Almost forty years have passed since the school choice "revolution" began reshaping U.S. public education (Bush, 1991; Clinton, 1999). Its bipartisan appeal was based on a simple premise: greater parental choice would induce schools to improve their academics to attract students (Friedman, 1962). Yet empirical evidence suggests that competitive pressure has often yielded only modest learning gains (Cohodes and Parham, 2021; Figlio, Hart, and Karbownik, 2023). The expansion of parental choice continues to be central to education reforms in the U.S.,[1] making it all the more important to understand what limits these competitive effects.

One possible explanation for these modest gains is that parental preferences are multidimensional: parents may care about both the academic and the nonacademic attributes of a school, including the peer group their children are exposed to.[2] Recognizing this, schools competing for students may do so along nonacademic dimensions in addition to, or rather than, academic ones. Policy and media discussions suggest this may be the case,[3] but systematic empirical evidence that schools compete in this way is scarce. Moreover, and crucially, little is known about whether competition on non-academics displaces investments in academic quality.

This paper studies how public schools respond to competition along both academic and nonacademic dimensions, and what these responses imply for the learning gains that competition generates. To do so, I exploit a shock to local competition that was announced two school years before implementation. This gap allows me to examine how schools respond to the anticipated increase in competition *before* students re-sort across schools (Figlio and Hart, 2014). I provide causal evidence that public schools respond to choice by both raising their academic quality—measured as school value added to student learning, net of classroom peer characteristics[4]—and changing how they assign students to classrooms. Within-school segregation by demographics and achievement rises as a result. I interpret

[1] Participation in private school choice programs, including vouchers, nearly doubled over the past five years, from about 540,000 students in 2019 to over one million in 2024. Nearly 22 million students, about 40% of the student population, now have access to a private school choice program in their state (EdChoice, 2024).

[2] On parental preferences for peers and school composition, see Rothstein (2006); Burgess et al. (2015); Barseghyan et al. (2019); Abdulkadiroğlu et al. (2020); Ainsworth et al. (2023); on non-test-score outcomes, see Beuermann et al. (2023). Campos (2025) studies how parents perceive and value school and peer quality as distinct attributes in an experimental setting.

[3] See Hill et al. (2003), Harris (2017), and Ura and Swaby (2018).

[4] See Chetty, Friedman, and Rockoff (2014a); Angrist, Hull, Pathak, and Walters (2024).

this pattern as suggesting that schools respond to parental preferences over peers through classroom formation. This is a margin schools choose directly: holding their student body fixed, they can shape the peer composition each demographic group experiences.

Given this evidence, I ask whether regulating classroom formation could improve academic quality when paired with school choice, and how much more of competition's potential learning gains this policy combination could harness. These questions add a dimension to the design of school choice markets—how regulation shapes schools' responses to competition—complementing work on how families learn about schools and how students are assigned to them (e.g., Kapor, Neilson, and Zimmerman, 2020).[5] To answer my questions, I develop an equilibrium model of school choice and competition whose novelty is to embed classroom formation in parental demand, through expected classmate characteristics, and in school supply, as a margin chosen alongside quality. A key feature of the model is that a change in a school's classroom segregation can make its enrollment more or less responsive to quality, by changing which students are near the margin of indifference between the school and its alternatives (Spence, 1975; Bau, 2022). This contributes to making the market-wide effect of regulating classroom formation on academic quality an empirical question. I estimate household preferences and school cost parameters, using the competitive shock to identify the former. I find substantial heterogeneity in parental preferences for academic quality and classroom peer characteristics. A mandate requiring schools to maximize classroom integration changes their incentives to provide academic quality, and different schools respond in different directions. In equilibrium, aggregate quality rises, with gains concentrated among nonwhite students, and cross-school segregation falls.

I study Charlotte-Mecklenburg Schools (CMS), a large public system in North Carolina. In 2002, CMS replaced a residence-based assignment system overlaid with desegregation busing with a choice plan that allowed families to apply to schools outside their neighborhoods. I use this reform to identify schools' competitive responses, interpreting its open enrollment nature as weakening residential constraints and making families' enrollment choices more responsive to other school characteristics (Campos and Kearns, 2024).[6,7] My event study

[5] See also Arteaga et al. (2022); Agte et al. (2026).

[6] Studying the Zones of Choice, an intradistrict school choice program in Los Angeles, Campos and Kearns (2024) document competitive responses in value added and attribute them to principals' aversion to enrollment declines, and the staff cuts these imply, as well as to their career concerns.

[7] The reform has been studied extensively, including the role of information in school choice, racial re-sorting across schools, and the short- and long-run consequences of segregation (Hastings and Weinstein, 2008; Billings, Deming, and Rockoff, 2014; Deming, Hastings, Kane, and Staiger, 2014; Bibler and Billings, 2020). This paper instead studies schools' competitive responses to it.

design compares CMS schools to schools in unaffected large urban districts in North Carolina around the CMS policy change. Identification requires that, absent the policy, outcomes in CMS schools would have continued to evolve in parallel with those in comparison schools.

Identifying competitive effects is often complicated because, as school choice is introduced in a local education system, students sort across schools. This sorting may mechanically affect academic quality and classroom segregation in ways correlated with schools' exposure to competition. I address this challenge by exploiting the two school years between the announcement and implementation of the CMS choice plan, setting the event time at the announcement and investigating changes to school value added and within-school segregation during this window to identify competitive responses before reform-induced sorting begins (Figlio and Hart, 2014; Gilraine, Petronijevic, and Singleton, 2021). I restrict the analysis to elementary schools, where differentiation by curriculum and extracurricular activities is more limited than in secondary grades, narrowing the set of potential competitive margins.

I find that both value added and classroom segregation by race[8] rise in CMS after the policy announcement. Both effects are statistically and economically significant: in the year following the announcement, value added rises by 0.05 student-level standard deviations of math achievement, and classroom segregation by 10% of its pre-announcement mean. In addition to race, segregation within schools rises by socioeconomic status and achievement. Value added increases more in areas with more college graduates, consistent with stronger demand for academic quality among more educated families (Hastings, Kane, and Staiger, 2009; Abdulkadiroğlu, Pathak, Schellenberg, and Walters, 2020). Where the 2000 Republican presidential vote share is higher, classroom segregation rises more and value added less, conditional on local educational attainment. In my context, this vote share proxies for support for race-neutral, neighborhood-based assignment (Lassiter, 2004; Smith, 2004). Across schools, the average increase in value added reflects a rightward shift of the whole quality distribution, whereas the increase in segregation reflects a widening of its distribution.

The data patterns are consistent with a story in which horizontal and vertical differentiation across schools interact: families generally like greater academic quality but differ in whether they prefer more or less classroom segregation. When school choice makes parental decisions less tied to neighborhood assignments and more responsive to other school attributes, classroom formation may differentiate schools, attracting specific groups of

[8]The measure is the white–nonwhite dissimilarity index across classrooms within each school-grade, averaged across grades (Duncan and Duncan, 1955).

students and making enrollment less responsive to quality differences across schools. This may soften schools' incentives to compete on academic quality (D'Aspremont, Gabszewicz, and Thisse, 1979). Determining whether this mechanism operates, and how policy could enhance quality investment under competition, requires knowing how families trade off school attributes and schools' relative costs of providing the two attributes. The competitive responses documented above cannot, on their own, separate these forces: they are equilibrium outcomes, jointly shaped by families' preferences and schools' costs.

I therefore develop an empirical model of school choice and competition. On the demand side, parents choose a school to maximize their indirect utility from academic quality, expected classmate characteristics, and other school attributes determined outside the model. Expected classmate characteristics depend on both classroom segregation and school composition. Classroom segregation measures a school's position between the least and most segregated classroom configurations feasible for its student body; school composition is determined endogenously by families' enrollment choices. On the supply side, schools choose academic quality and classroom segregation to maximize the payoff from enrollment net of total costs. The equilibrium concept is static complete-information Nash, with families holding rational expectations about school composition. The school choice reform enters directly through demand, reducing the weight families place on their neighborhood assignment and making their enrollment choices relatively more responsive to other school attributes. Methodologically, the model builds on a growing literature estimating demand for schools (e.g., Hastings, Kane, and Staiger, 2009; Walters, 2018; Ferreyra and Kosenok, 2018; Corradini, 2024) and equilibrium models of school choice and competition for policy evaluation (e.g., Neilson, 2026; Dinerstein and Smith, 2021; Singleton, 2019; Gilraine et al., 2025).[9]

In the model, both classroom segregation and school composition are defined by race. Selecting one of the correlated dimensions along which classroom segregation rises (race, socioeconomic status, and achievement) is necessary for identification and tractability and fits the model's purpose: studying the equilibrium effects of turning off classroom formation as a strategic variable, rather than distinguishing among its margins. The choice still matters for interpreting the counterfactuals. I select race because it is measured most reliably in

[9]More broadly, the model connects to equilibrium models of competition with endogenous product characteristics (Seim, 2006; Ho, 2009; Fan, 2013; Sweeting, 2013; Crawford, Shcherbakov, and Shum, 2019; Barahona, Otero, and Otero, 2023) and of individual choice with social interactions (Brock and Durlauf, 2005; Bayer and Timmins, 2007), including residential sorting models in which segregation arises in equilibrium from households' preferences over schools and neighbors (e.g., Bayer, Ferreira, and McMillan, 2007).

the data and best accounts for the immediate change in classroom assignments around the reform. It need not matter to parents in itself: it can proxy for classmates' social class, academic potential, or behavior, or for friendships that tend to form within race and through proximity.[10] The framework can accommodate other dimensions that may be more relevant in other settings.

Given the model, whether regulating classroom formation raises academic quality in equilibrium is an empirical question. Consider requiring a single school to form the most integrated classrooms its student body permits, holding other schools' choices fixed while students re-sort across schools. Under preference heterogeneity over classroom segregation, the mandate changes how close students are to indifference between that school and the alternatives. Students who become more marginal may value quality more or less than those previously most marginal, so the school's incentive to provide quality can rise or fall. The direction also depends on how families value school composition, itself shaped by heterogeneous preferences and the sorting they induce, and on the school's cost of adjusting quality relative to segregation. As the policy is applied market-wide, these forces interact as schools best respond to one another and students re-sort, shaping learning outcomes via both quality changes and peer reallocation. Which forces dominate depends on parental preferences and schools' cost structures.

I recover parental preferences over quality and peers in two parts: benchmark components common to all students, and deviations from them, consisting of systematic differences across demographic groups and unobserved heterogeneity within groups. Identifying the benchmark components poses two challenges. Schools' value added, classroom segregation, and composition may correlate with dimensions of attractiveness that families observe but I do not. They also tend to move together, as they would, for instance, if some demographic groups were more responsive than others to all school characteristics. Separately identifying preferences over them therefore requires variation that shifts them in different directions. I address both challenges using the school choice reform. Motivated by the data patterns, I use the local shares of college graduates and Republican voters, which predict different competitive responses, as instruments for school-level *changes* in academic quality and classroom segregation, under the exclusion restriction that within-school innovations in unobserved attractiveness are orthogonal to the baseline composition of the surrounding

[10] Parents may use race as a proxy for characteristics that are harder to observe, such as behavior (Castillo and Petrie, 2010); friendships tend to form within race and through proximity (Moody, 2001; Marmaros and Sacerdote, 2006; Echenique and Fryer, 2007).

area. The benchmark preference for school composition is identified from the reform-induced redrawing of catchment areas. Heterogeneity requires no instruments: unobserved attractiveness is assumed to be valued equally by all students (Berry, Levinsohn, and Pakes, 2004), so differences in choices of schools with higher value added, classroom segregation, or white share across demographic groups identify the group deviations, while differences among students within groups identify the distribution of unobserved heterogeneity.

The estimates reveal substantial heterogeneity in parental preferences. Families of higher socioeconomic status are willing to travel farther for academic quality; families prefer more classroom segregation at predominantly nonwhite schools and less at predominantly white ones, with white parents of high socioeconomic status favoring it over the widest range of compositions; sorting on school composition is strong. At most schools, segregation keeps students away from the margin of indifference between the school and its alternatives, so integrating classrooms makes enrollment more responsive to quality. I simulate a policy that removes classroom formation as a strategic variable by requiring every school to form the most integrated classrooms feasible, so that each classroom's racial composition mirrors the school's as closely as class sizes allow. The mandate raises quality at around 60% of schools, where integrating classrooms makes demand more responsive to quality. Declines in quality, mostly at relatively white schools, mainly reflect a lower per-student payoff under the ban. In aggregate, enrollment-weighted quality rises nearly as much as under universal free transportation. The gain for nonwhite students is roughly half as large as that from making them as responsive to quality as white families of high socioeconomic status and about a quarter of the effect of one-standard-deviation better math teachers over the same years of exposure (Chetty, Friedman, and Rockoff, 2014b); white students, by contrast, experience lower quality. The policy also reduces between-school segregation. The model-implied learning impacts exclude peer effects; if lower segregation benefits nonwhite students through peers,[11] their total learning gains would be even larger.

This work is grounded in the theoretical literature on how competition shapes public schools' educational offerings, either through changes in peer composition (Epple and Romano, 1998; Nechyba, 2000) or through productivity adjustments by schools or districts that compete for students (Hoxby, 2003; MacLeod and Urquiola, 2013, 2015). In McMillan's (2004) theoretical framework, public schools may optimally respond to private school vouchers by reducing productivity, as cost savings outweigh enrollment losses. Here, the key channel

[11] See, e.g., Guryan (2004); Hanushek et al. (2009); Billings et al. (2014).

instead operates through endogenous differentiation along multiple dimensions of perceived educational quality: parents value both academic and nonacademic attributes, and schools control both. My framework lets these margins interact in equilibrium and, similar to Bau (2022), views horizontally differentiated schools as arising in competitive markets where households differ in both their preferred offering and the intensity of their preferences.

In MacLeod and Urquiola's (2015) model, it is the fact that students prefer colleges with good reputations—as a signal of skills to the labor market—that creates incentives for schools. (In that case, the incentive is to be selective and small; colleges' quality choices are not modeled.) The same idea extends to K-12 education, where parents have been found to be quite responsive to the characteristics of schools' student bodies (Rothstein, 2006; Abdulkadiroğlu et al., 2020). In Allende (2021), school-level peer composition shapes how parents sort across schools, along with the prices and quality that schools set. Schools internalize the implications of these social interactions: a school with a natural advantage in attracting peers perceived as desirable (because of its location, for example) may therefore enjoy a "compositional rent" that allows it to charge higher prices and provide lower quality in equilibrium. This paper builds on the observation that schools can also shape the structure of social interactions—who interacts with whom—directly, through classroom formation. As a result, schools with the same student body can offer students from a given demographic group very different peer environments. The finding that classroom formation responds to competition shows that it is a competitive margin, adding a dimension to the role of peers in demand. This distinction matters for policy: unlike location, classroom formation is directly chosen by schools, creating scope for policies that target school discretion rather than relying solely on busing or gerrymandering to reallocate students across campuses.

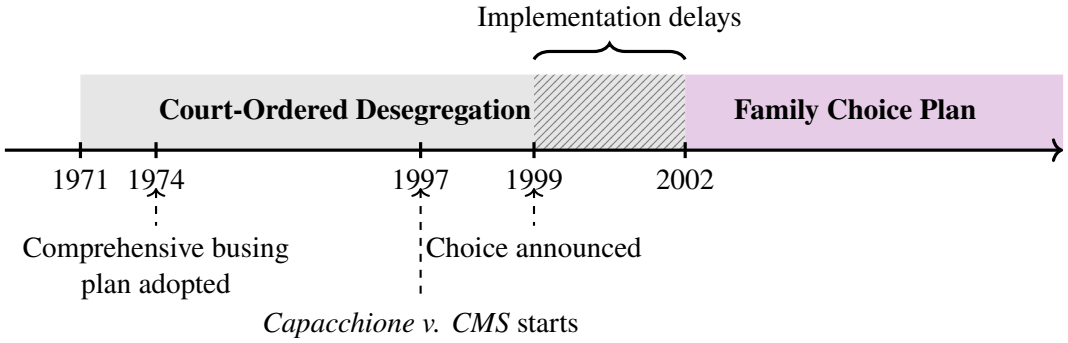
2 Institutional Background

This section describes the institutional context. Section 2.1 presents the CMS school choice reform. Section 2.2 illustrates the classroom formation process and discusses mechanisms through which schools can, in practice, use classroom formation to attract families.

2.1 The Introduction of School Choice in CMS

In 2000–2001, CMS enrolled 103,336 students, ranking 25th for size among U.S. public school districts; 53.4% of the students were classified as minority (Young, 2002). Before the reform, CMS assigned students to schools through a residence-based system overlaid with a race-based desegregation plan. In November 1999, the superintendent announced a move

Figure 1: Timeline of events leading to school choice in CMS



toward school choice, which was first implemented for the 2002–2003 school year as the "Family Choice Plan" (Hastings et al., 2009; Mickelson et al., 2009; Billings et al., 2014). Figure 1 orders the main phases on a timeline.

1971–1999: Court-ordered desegregation. In *Swann v. Charlotte-Mecklenburg Board of Education*, the U.S. Supreme Court held in 1971 that CMS had not dismantled its state-imposed segregated system and authorized busing across catchment areas. Under the comprehensive plan adopted in 1974, each school's share of black students had to remain within 15 percentage points of the district average (Billings et al., 2014). CMS periodically redrew catchment areas to maintain compliance, most notably by busing students from inner-city, majority-black "satellite" zones to suburban schools, though sometimes in reverse (Kane et al., 2003). Appendix Figure D.1 illustrates one such zone.[12] Beginning in the 1990s, CMS also reserved magnet-school seats for students of color (Pierpoint, 2018).

1999–2002: Transition to choice. A 1997 lawsuit by William Capacchione, alleging that CMS had denied his daughter a magnet school seat on racial grounds, brought together parents opposed to mandated racial integration (Pierpoint, 2018). Following a September 1999 ruling against race-based assignment (Capacchione v. Charlotte-Mecklenburg Schools, 1999), Superintendent Eric Smith announced a choice-based plan that November. After public hearings, delays, and litigation, the U.S. Supreme Court declined to revisit the consolidated *Swann/Capacchione* case in April 2002, allowing CMS to implement the plan that fall and end race-based busing.[13]

The prospective choice regime was publicly discussed and preparations were underway

[12] In 1999–2000, students from the urban area shown in blue were assigned to suburban Long Creek Elementary. The school was then 57% white, compared with 76% five years after busing ended and choice was introduced. Consistent with the empirical analysis below, I classify Asian students as white.

[13] For a more detailed chronology, see the CMS website (last accessed September 19, 2026).

during the "announcement window" (2000–2001 and 2001–2002): in November 2000, CMS publicized a district-wide school showcase and dozens of school open houses, tours, and choice presentations; a year later, coverage described CMS as "amid preparations for choice."[14] Parents and schools were therefore plausibly aware of the coming change, creating incentives for schools to be forward-looking and respond before choice took effect.

Since 2002: Choice-based assignment. The new plan guaranteed students access to their neighborhood schools, redrew catchment areas, and eliminated satellite zones (Hastings et al., 2009). Families could also apply to any other district school, subject to capacity, by ranking up to three choices. CMS divided the district into four geographic Choice Zones, providing free transportation within a student's zone but not to schools outside it. Following an extensive information campaign, more than 95% of families submitted choice forms in spring 2002 (Hastings et al., 2009; Hastings and Weinstein, 2008; Deming et al., 2014). A centralized lottery allocated oversubscribed seats, while CMS expanded capacity where high demand was anticipated (Hastings et al., 2009; Deming et al., 2014).[15]

In my sample (Appendix Table E.4), the probability that a student attends an assigned or default school falls sharply around the reform, indicating substantial take-up of open enrollment. The distribution of home-school distance becomes more dispersed, reflecting both expanded choice and the end of desegregation busing. School racial composition becomes more polarized, with greater mass at both ends of the distribution (Appendix Figure D.2).

2.2 Classroom Formation

Unlike school assignments, classroom formation is largely governed within schools, with little to no district or state guidelines. Henderson (2011) finds that elementary schools in North Carolina mix automation and discretion; discretion can turn classroom formation into "a deliberate process that dedicates days or months, creating just the right 'mix' of students

[14] See *Educate!*, Nov. 12, 2000, pp. 3–5, and Nov. 18, 2001, pp. 1, 4–6.

[15] Section 5 estimates families' preferences over schools from where their children enroll, using 2004–2005 as the post-reform year. Under the Family Choice Plan, enrollment may also reflect lottery outcomes: a student who lost the lottery at her preferred school would appear to have chosen a different one. CMS was no longer accepting requests for lottery data as of 2023, so I cannot observe such rejections, but the resulting bias is likely limited. At most 13.8% of the grade 4–8 applicants studied by Hastings et al. (2009) did not receive their first choice, and constraints were probably weaker in my elementary school sample, which had more local options and is observed in 2004–2005, after families had additional opportunities to apply. Moreover, oversubscribed schools were disproportionately magnet schools (Deming et al., 2014), so any remaining bias should mainly affect how much families value magnet status, rather than how they trade off academic quality against classroom segregation, the focus of the analysis.

for each first- through fifth-grade class" (Henderson, 2011, p.10). Hopkins (1999) and Burns and Mason (2002) document similar practices in other states. Importantly, in the U.S., a given cohort is generally reshuffled across classrooms from one grade to the next.

Parental requests often enter the classroom formation process. St. John (2014) reports that principals tend to take them into consideration, and principals observe that families' intervention can make classroom formation burdensome.[16] In her ethnographic work, Lareau (2000, 2011) documents that upper-middle-class parents are relatively more likely to actively engage with the classroom formation process by requesting specific assignments. A rich body of literature in sociology and education has documented that classroom assignments within schools tend to be non-random in a way that creates within-school segregation by demographics (Conger, 2005; Bosworth and Li, 2013; Kalogrides and Loeb, 2013; Dieterle et al., 2015; Horváth, 2015; Clotfelter et al., 2021, 2003) and in access to educational resources (Kalogrides and Loeb, 2013; Mickelson, 2015; Grissom and Redding, 2016).

Classroom formation practices need not be formally advertised to be salient to parents. Families gather substantial soft information about schools through visits and conversations with principals and staff, through other parents and social networks, and through their own or others' prior experience with the school (Altenhofen et al., 2016; Fong, 2019). Repeated classroom assignment practices can therefore become predictable to families, allowing schools to communicate a classroom formation approach even in the absence of formal tracking or curricular differentiation.

3 Data and Key Patterns

3.1 Data Source and Variable Construction

I use administrative student- and classroom-level records from the North Carolina Education Research Data Center (North Carolina Education Research Data Center, 1995–2017) for the school years 1997–1998 to 2004–2005. For every student enrolled in a traditional public school in a given year, I observe demographics, Census block group of residence,[17] school and grade of enrollment, and standardized test scores. At the classroom level, I observe the number of students enrolled and their racial breakdown. I focus on elementary schools,

[16] See, for instance, the discussion posted on the website "We Are Teachers" at https://www.weareteachers.com/buried-in-parent-requests/ (last access: October 29, 2022).

[17] CMS students' residential information in the study years is limited; Appendix B.2 addresses this.

grades one to four.[18] Standardized end-of-grade tests start in grade three; third graders also take a pretest at the beginning of the year, which serves as their baseline score.

Classroom segregation: I use classroom records to measure within-school segregation using the standard Duncan index of dissimilarity (Duncan and Duncan, 1955). For any binary student characteristic (e.g., white-nonwhite), the index is defined between 0 and 1, with larger values indicating greater segregation. For example, an index of 0.2 in a given school-grade cell means that 20% of nonwhite students in that cell would need to be reassigned across classrooms for their distribution across sections to match that of white students. Formally, the index for school s in year t is the average across grades g of

$$D^A_{stg} = \frac{1}{2} \sum_c \left| \frac{w_{cstg}}{\overline{w}_{stg}} - \frac{b_{cstg}}{\overline{b}_{stg}} \right| \tag{1}$$

where w_{cstg} (b_{cstg}) denotes the number of white (nonwhite) students enrolled in classroom c and $\overline{w}_{stg}$ ($\overline{b}_{stg}$) stands for the total number of white (nonwhite) students. White and Asian students are pooled together, following Card and Giuliano (2014). I use classroom records for self-contained classes, in which one teacher teaches all subjects, and for math classes, excluding school-grade-year combinations with either no racial diversity, or one classroom only, or any classroom with fewer than 5 or more than 40 students.[19]

The equilibrium model in Section 4 represents classroom formation as a margin chosen by schools: each school chooses a position between the least and most segregated classroom allocations feasible given the students who ultimately enroll. The empirical counterpart of this choice is therefore best measured by the school's position within its feasible range, rather than by the absolute level of the standard dissimilarity index, whose attainable values depend mechanically on student body composition and the number and sizes of classrooms.[20] I therefore construct a complementary segregation measure that rescales the observed index

[18] Results are qualitatively the same if I include grade five. I exclude it because statewide standards tying promotion from fifth to sixth grade to test performance took effect in 2000–2001, the first post-announcement school year. Since nearly all sample schools serve the same grade span, year fixed effects absorb the policy's common effects across CMS and comparison districts. Excluding grade five further ensures the estimates isolate competitive pressure rather than differential responses to the new accountability incentives. See North Carolina Department of Public Instruction, *Student Accountability Standards: Implementation Guide* (2000).

[19] The main finding is robust to relaxing the classroom size restriction. Conditional on the preferred restriction, about 10% of school-grade-year combinations are excluded because neither the self-contained nor the math classroom records yield at least two classrooms with racial diversity.

[20] For example, with 17 white students, three nonwhite students, and two classrooms of ten students each, the minimum feasible value of D^A is 0.196 and the maximum is 0.588.

by its feasible range. For each school-grade-year cell,

$$D_{stg} = \frac{D^{A}_{stg} - D^{A,\min}_{stg}}{D^{A,\max}_{stg} - D^{A,\min}_{stg}}. \tag{2}$$

Here, $D^{A,\min}_{stg}$ and $D^{A,\max}_{stg}$ are computed from the least and most segregated feasible classroom assignments given the observed student composition and class sizes.[21] I then average D_{stg} across grades to obtain D_{st}, the measure used in the structural model. The measure equals zero when the school attains the least segregated feasible allocation, and one when it attains the most segregated feasible allocation in every grade.

Academic quality: I estimate academic quality through a standard value-added model, following the structural education literature (Neilson, 2026; Allende, 2021; Bau, 2022; Gilraine et al., 2025). The model expresses the achievement of student i in year t as:

$$Y_{isgct} = X'_{isgct}\beta + \overline{X}'_{sgt}\gamma + \overline{X}'_{scgt}\delta + \omega_{gt} + q_{st} + \epsilon_{isgct} \tag{3}$$

where s, g, and c are the school, grade, and classroom of enrollment; Y denotes the end-of-grade standardized math test score; X is a vector of individual characteristics including a cubic in baseline math and reading scores interacted with grade dummies, ethnicity, a binary indicator for economic disadvantage, parental education, along with English learner, disability, and gifted status. I also flexibly control for the average of these characteristics at the grade and classroom level. ω_{gt} are grade-by-year dummies; q_{st} are school-by-year fixed effects; and ϵ_{isgct} is an idiosyncratic achievement shock. The main parameter of interest is q_{st}: under the conditional exogeneity assumption that baseline test scores and other observables capture selection into schools and classrooms, it identifies the treatment effect of the school on student learning in a given year (Chetty, Friedman, and Rockoff, 2014a; Angrist, Hull, Pathak, and Walters, 2024).

I use estimated school value added as the measure of academic quality. Since the specification conditions on classroom composition, classroom peer effects associated with that composition are not mechanically folded into measured quality. This separation matches the structural model, which treats academic quality and classroom formation as distinct school choices.

[21] I treat the observed distribution of classroom sizes as fixed because I find no evidence that it changes after the reform, making it unlikely that schools adjust class sizes to achieve a particular demographic mix. In fewer than 0.3% of school-grade-year cells in the event-study sample, $D^{A,\min}_{stg} = D^{A,\max}_{stg}$. In every such case, the school-grade-year cell contains only one white student or only one nonwhite student. The standardized measure is undefined in these cells, which are therefore excluded.

Appendix B.1 details value-added estimation. Appendix Table E.1 reports summary statistics for the competitive-response sample (Section 3.2).

3.2 Competitive Responses

3.2.1 Classroom segregation varies across schools. Figure 2 plots classroom segregation across CMS schools in 2004–2005. Schools are ordered by their observed cross-classroom segregation, D^A_{st} (equation (1)), shown by the navy dots. The gray bars show the feasible range of segregation at each school, $D^{A,\max}_{st} - D^{A,\min}_{st}$, which also varies substantially across schools. The maroon crosses report the standardized measure D_{st} (equation (2)), indicating where each school's observed allocation falls within its own feasible range; this measure is likewise widely dispersed. Appendix Figure D.3 shows that both the raw and standardized measures are strongly right-skewed, with most schools far from the maximum feasible level of racial separation.

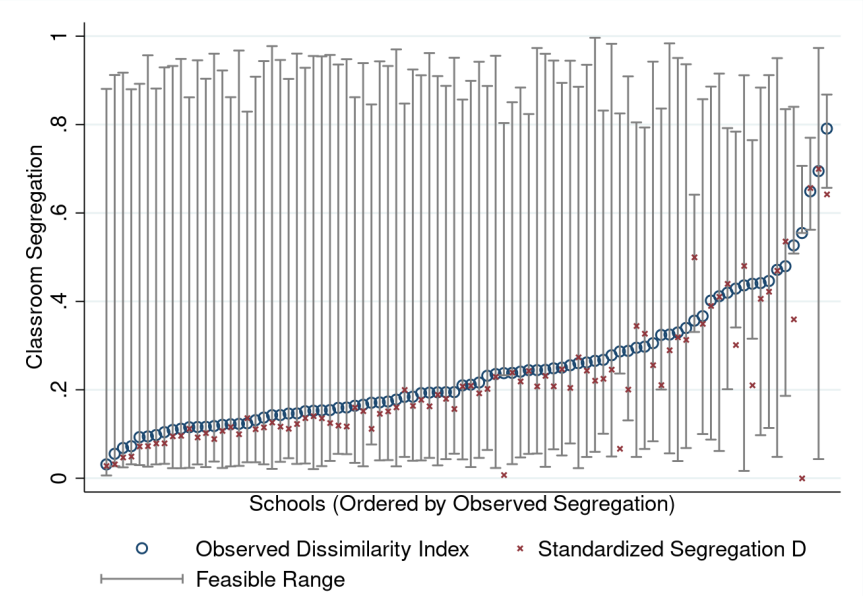
Appendix Figure D.4 also reveals that the levels of classroom segregation observed in the data (navy dots) generally deviate, either above or below, from the average values simulated under random allocations of students to classrooms (maroon densities), holding each school's student composition and class sizes fixed at observed values. This finding is consistent with previous literature (Kalogrides and Loeb, 2013; Horváth, 2015) and the idea that classroom formation is the outcome of a decision-making process internal to schools.

3.2.2 Both classroom segregation and value added respond to the reform. I now document competitive responses to the school choice reform. Identification is difficult because sorting can mechanically change average performance and classroom composition. I address this challenge by exploiting the announcement window (Section 2.1) to observe schools' responses before students could re-sort (Figlio and Hart, 2014; Gilraine et al., 2021). Concretely, I estimate

$$y_{st} = \alpha + \sum_{k=1997}^{1998} \beta_k \Big(\mathbb{1}[t = k] \times CMS_s \Big) + \sum_{k=2000}^{2004} \gamma_k \Big(\mathbb{1}[t = k] \times CMS_s \Big) + \delta X_{st} + \phi_s + \phi_t + \epsilon_{st} \quad (4)$$

where s denotes the school, t is the fall year in the academic year, y is the dependent variable (classroom segregation or academic quality), X is a vector of covariates, ϕ_s and ϕ_t are school and year fixed effects, and ϵ is the error term. The parameters β_k and γ_k measure the average difference in the dependent variable y across schools in CMS (treated)

Figure 2: Classroom segregation varies across schools



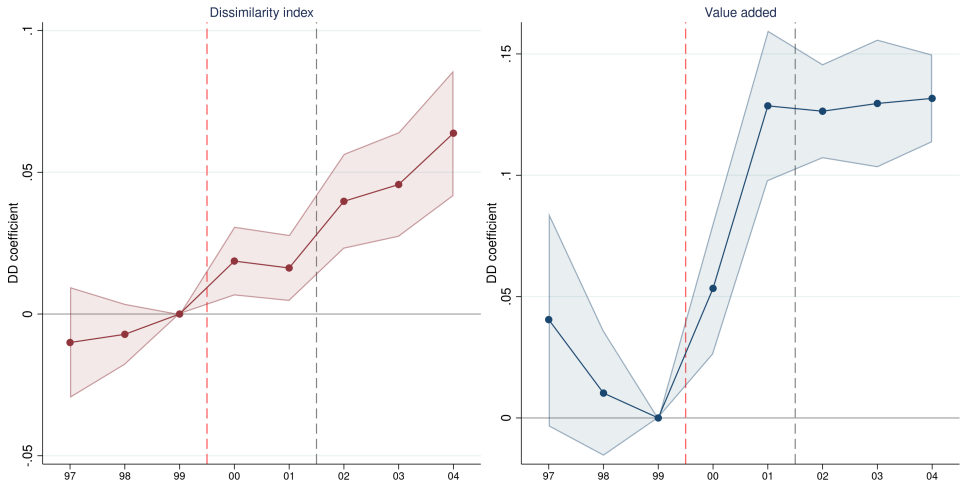
Notes: The figure uses the CMS sample for the 2004–2005 academic year. Each bar corresponds to a school in the sample. The lower and upper whiskers indicate the minimum and maximum feasible levels of classroom segregation given the school's student-body composition and class-size distribution. Navy dots show the standard index of dissimilarity computed from the data using equation (1). Maroon crosses show the standardized measure of classroom segregation, or the fraction of the feasible range attained by each school, as defined in equation (2). Segregation measures are averaged across grades 1–4.

versus other large districts not affected by the school choice reform (control),[22] before and after the announcement in fall 1999. The main coefficients of interest are γ_{2000} and γ_{2001}, which capture the average difference between treated and control schools relative to the pre-announcement period, before reform-induced across-school sorting begins.[23]

[22] I restrict the analysis to districts that, like CMS, have a pre-reform total enrollment above the 90th percentile of the state distribution, i.e., Buncombe County, Cumberland County, Durham Public, Forsyth County, Gaston County, Guilford County, Johnston County, Robeson County, Union County Public, and Wake County Schools. The results are nearly identical when I instead select comparison districts based on the number of schools. Under that definition, Johnston County drops out of the comparison group, while Alamance-Burlington, New Hanover County, and Pitt County enter it.

[23] Outcome construction further limits the extent to which sorting-induced mechanical changes may confound the interpretation of estimated changes as competitive responses. Value added conditions flexibly on baseline achievement and student characteristics (Chetty et al., 2014a; Deming, 2014; Angrist et al., 2017, 2024). The standard dissimilarity index is invariant to school-level racial group shares when each group's proportional distribution across classrooms remains unchanged. In finite school-grade cells, however, integer student counts and fixed classroom sizes make the index's attainable minimum and maximum depend on the cell's racial composition. Thus, even if a school maintains the same position within its feasible set, sorting-induced changes in composition can change the raw index by shifting the endpoints of that set. Appendix Figure D.5 shows that the results are qualitatively similar when using the standardized index (equation (2)).

Figure 3: Classroom segregation and value added respond to competition



Notes: Event-study estimates from specification (4). The control group includes elementary schools in districts with pre-reform total enrollment above the 90th percentile of the state distribution. The dependent variable is the standard Duncan index of dissimilarity (equation (1)) in the left panel and math value added in the right panel. Shaded areas are 90% confidence intervals. Standard errors are clustered at the district level.

Figure 3 plots the coefficients by school year. Dashed lines mark the announcement and implementation of school choice, dividing the sample period into three phases: before announcement, between announcement and implementation, and after implementation, when families could enroll in any district school subject to capacity.

Both classroom segregation and value added rise in CMS immediately after the reform is announced. Relative to non-CMS schools, the pre-announcement estimates do not reveal a differential trend that anticipates the subsequent increases. Both outcomes respond before students can re-sort under the new open-enrollment system, pointing to competitive responses rather than mechanical changes in school composition.

Value added jumps by 0.05 student-level standard deviations of math achievement in the year after the announcement.[24] For comparison, Campos and Kearns (2024) find that the first cohort fully exposed to Los Angeles's Zones of Choice scored 0.09 standard deviations higher in reading. The increase in value added is nearly identical across white and nonwhite students (Appendix Table E.2), consistent with academic quality being common to all of the school's students. It is also reflected in a significant rise in the average math score (Appendix Figure D.5).

[24] In 1997–1998 and 1998–1999, CMS value added draws on few or no third graders, whose baseline scores can rarely be linked (Appendix B.1). The post-announcement increase and the overall pattern are robust to alternative grade spans, such as grade 4 only or grades 4–5.

Classroom segregation rises immediately by 0.019 on a 0–1 scale, or 10% of its pre-announcement mean.[25] The increase does not coincide with a break in student body composition or in the classroom size distribution, consistent with the choice plan not yet having been implemented.[26] The pattern is also qualitatively similar when the standardized index in equation (2) is used as the dependent variable. The increase in within-school grouping is not limited to race: it also appears along correlated student characteristics, including parental education and lagged achievement (Appendix Table E.3). Appendix Figure D.6 examines whether these classroom reassignments coincide with changes in white students' relative exposure to low baseline value-added or early-career teachers. I find no systematic changes, nor evidence that schools increasingly assign students to teachers with stronger baseline value added for their own racial group.

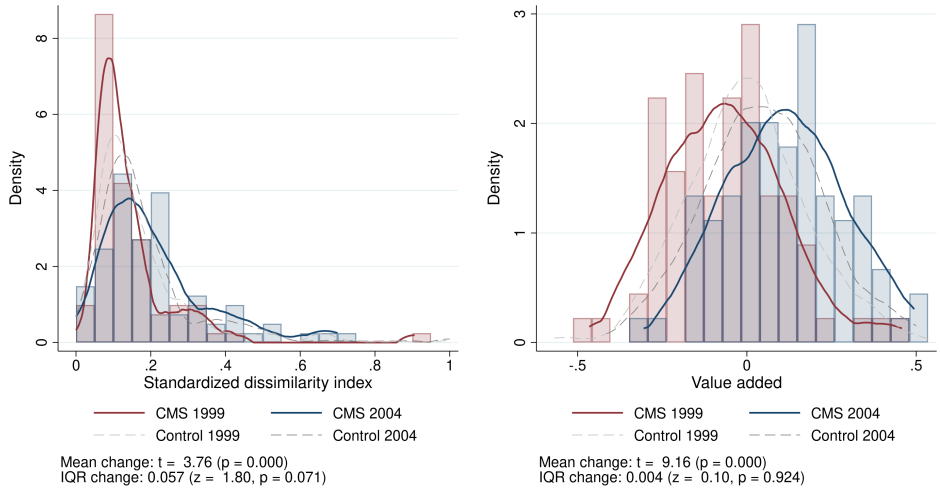
3.2.3 Segregation disperses; value added shifts right. Figure 4 plots the cross-school distributions of classroom segregation and value added in CMS and control districts, before and after the school choice reform. In CMS, the post-reform distribution of standardized classroom segregation (navy) is more dispersed than the pre-reform one (maroon): the rise in average segregation documented in Figure 3 comes with growing differences across schools. By contrast, the value-added distribution shifts right: its mean rises, but its dispersion does not. The gray dashed densities show no comparable change in control districts.

These patterns suggest that schools may use classroom formation and academic quality differently in response to competition. Value added behaves more like a vertical dimension that is broadly valued by families: the full CMS distribution shifts right after the reform, consistent with generally stronger incentives to raise academic quality. (Since the figure compares distributions rather than school-level changes, this shift need not mean that every school raises value added.) The widening in the classroom segregation distribution, on the other hand, is consistent with greater variation across schools in the incentive to adjust classroom formation. That incentive depends on the families a school competes for, whose

[25] Crema (2026) documents a similar response to the announcement of a charter school opening.

[26] On enrollment and classroom size: CMS enrollment in grades 1–4 rises by less than 5% relative to comparison districts, consistent with the announcement retaining or attracting students from other educational options. However, I find no evidence of differential changes in the school-level mean, minimum, or maximum classroom size. Controlling for grade 1–4 enrollment leaves the main estimate qualitatively similar. On composition: CMS was already losing white students faster than comparison districts, but this differential trend is linear through the announcement window, and the main estimate is qualitatively similar when controlling for white share or allowing year effects to vary flexibly with baseline enrollment and white share. Finally, the main estimate is unchanged when dropping school-years whose classroom records substantially undercount CCD enrollment, the main source of the imperfect enrollment correlation in Appendix Table E.1.

Figure 4: Dispersion of classroom segregation rises; value added shifts right



Notes: The control group includes elementary schools in districts with pre-reform total enrollment above the 90th percentile of the state distribution. The sample is restricted to schools observed in both 1999 and 2004 with nonmissing standardized classroom segregation and value added, so the pre- and post-reform distributions are plotted for a fixed set of schools. The left panel reports the standardized dissimilarity index (equation (2)); the right panel reports school value added estimated from math achievement. Below each panel, "Mean change" reports a paired t-test of the 1999–2004 change across CMS schools, and "IQR change" reports the change in the CMS interquartile range, with a z-statistic based on 999 bootstrap replications over schools.

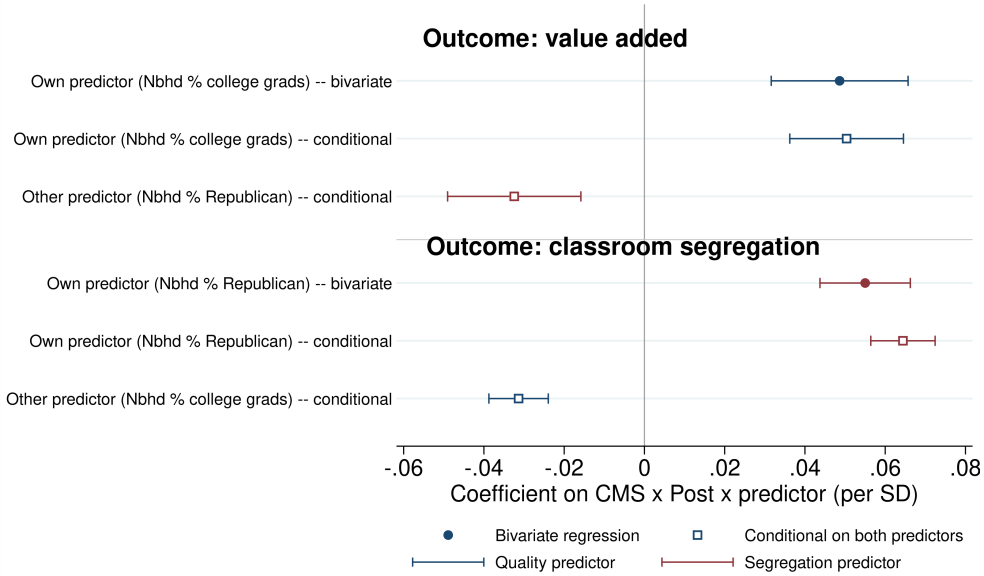
responses to segregation can differ in sign and size, and on its adjustment costs.

3.2.4 Each margin responds to its own demand predictor. If families differ in the school attributes they value, the composition of demand a school faces should predict the dimensions along which it responds to an increase in competition. I examine this implication by interacting a pooled version of the difference-in-differences in specification (4) with separate predictors of local demand for value added and classroom segregation. For value added, I use the 2000 Census share of college graduates near the school, following evidence that households with higher socioeconomic status are more responsive to academic quality (Abdulkadiroğlu et al., 2020). For classroom segregation, I use the nearby share of Republican votes in the 2000 presidential election as a predetermined proxy for local support for race-neutral, neighborhood-based assignment, given the political salience of busing and desegregation in CMS.[27]

Figure 5 shows that each competitive margin responds more where local families are predicted to value it more. Relative to control districts, CMS value added increases more in

[27]The proxy is imperfect because positions on racial assignment in CMS were not purely partisan; Appendix C provides the relevant historical context.

Figure 5: Different local demographics predict responses on different margins



Notes: Each marker reports the coefficient on CMS × Post × predictor from a school-year triple-difference regression with school and year fixed effects and all lower-order interactions, estimated over fall years 1998–2004; Post equals one from fall 2000. The outcome is school value added in the top panel and standardized classroom segregation (equation (2)) in the bottom panel. The quality demand predictor (navy) is the neighborhood share of college graduates in the 2000 Census; the segregation demand predictor (maroon) is the neighborhood Republican vote share in the 2000 presidential election. Both are standardized, so coefficients are per one standard deviation. Filled circles report regressions with only the outcome's own predictor; open squares report regressions with both predictors, estimated on the same sample. The control group includes elementary schools in districts with pre-reform total enrollment above the 90th percentile of the state distribution. Regressions control for distance to nearest charter school and an indicator for missing distance. Whiskers report 90% confidence intervals. Standard errors are clustered at the district level.

areas with a higher concentration of college graduates (filled navy circle), while classroom segregation rises more where the Republican vote share, my proxy for support for race-neutral, neighborhood-based assignment, is higher (filled maroon circle).

3.2.5 Larger predicted returns to segregation correlate with smaller quality gains. Figure 5 also reveals that the same local characteristics predict how schools combine the two margins. When both predictors enter the value-added regression, schools in areas with higher Republican vote shares show smaller value-added gains (top panel, maroon open square), even conditional on the share of college graduates around the school (navy open square). One interpretation is "incentive dilution": where classroom formation matters more for local demand, it can lock in part of that demand, making enrollment less responsive to quality differences with other schools and weakening those schools' incentives to compete on it. A second interpretation does not require dilution: conditional on educational attainment,

the Republican vote share may proxy for families who place less weight on academic quality and more on classroom segregation, so schools there simply shift their response toward the margin those families value. While the two stories have different counterfactual implications, the data alone cannot distinguish them. This motivates the equilibrium model, in which the effects of restricting classroom segregation depend on whether the families marginal to academic quality are also marginal to classroom segregation, and on school costs.

3.3 From data patterns to the empirical model

The patterns in Section 3.2 indicate that schools compete on both value added and classroom formation, with different local environments predicting different bundles of responses. Within-school segregation rises not only by race but also by socioeconomic status and achievement (Appendix Table E.3), unsurprisingly: in CMS, white students are 45.8 percentage points more likely than nonwhite students to have highly educated parents and score 0.96 standard deviations higher on average. Race may therefore serve parents as an easily observable proxy for classmates' social class, academic potential, or behavior.

For identification and tractability (see Sections 4 and 5), my model captures classroom formation along a single dimension. This suits the model's purpose, which is to study the equilibrium effects of turning off classroom formation as a strategic variable, rather than to distinguish among its margins. I choose this dimension to be race: parents value the expected racial composition of their classrooms, and schools assign students to classrooms by race. This choice still matters for quantifying the effects of policies such as a ban on racial segregation within schools. If schools instead grouped students by achievement, such a ban would still let them do so within race, and the model would misstate schools' quality responses. The rest of this section justifies modeling classroom formation along the racial dimension, before Section 4 presents the model.

3.3.1 Racial classroom composition is measured most reliably. The classroom-level records used to construct segregation contain aggregate student counts by classroom for all grades, but only for race, gender, and disability or impairment status. Measuring segregation by socioeconomic status or lagged achievement instead requires student-level records, which start in grade 3 and define pseudo-classrooms by end-of-grade test proctor. As discussed in Appendix B.1, these pseudo-classrooms need not coincide with actual classrooms because fewer than half of students before 2006 can be credibly assigned to their instructor. Racial segregation can therefore be measured most reliably.

3.3.2 Race best explains changes in classroom assignment around the reform. Despite their lower data quality, pseudo-classrooms built from student-level records detect rising classroom segregation by race, socioeconomic status, and achievement in CMS under choice (Appendix Table E.3). Since these characteristics are correlated, I use the student-level data to run a horse race among them as potential margins along which classrooms were reorganized, to inform how the structural model specifies classroom formation.

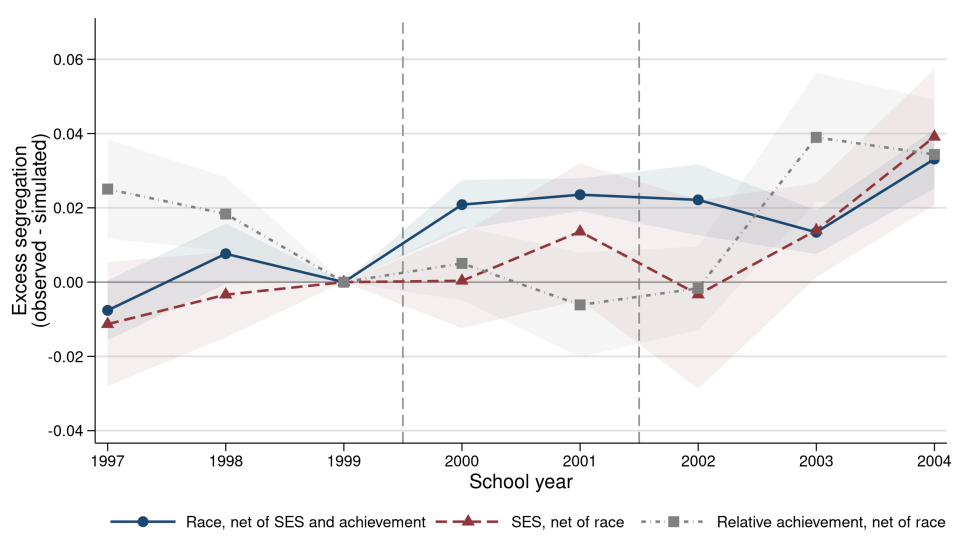
I do so by comparing observed segregation by each characteristic with a simulated benchmark. Within each school-grade-year cell, I randomly reassign students across classrooms within groups, holding each classroom's composition by those groups fixed. For socioeconomic and achievement segregation, the groups are racial, so the benchmark captures the segregation that grouping by race alone would produce. For racial segregation, the groups are defined jointly by socioeconomic status and achievement, so the benchmark captures the racial segregation that grouping by those two characteristics would produce. Excess segregation is the gap between observed segregation and its benchmark. An increase in this gap suggests that the characteristic was itself a margin along which classrooms were reorganized. The test is stacked against race: racial segregation must exceed what both alternatives jointly produce, whereas each need only exceed what race alone produces.[28]

Figure 6 shows the results. Focusing on the announcement window, I find that excess racial segregation rises by about 0.02 in both 2000 and 2001 relative to 1999. This rise cannot be fully explained by the observed changes in classroom composition by socioeconomic status and achievement, even jointly. Excess socioeconomic and relative achievement segregation, by contrast, are statistically indistinguishable from zero in the announcement window, giving no clear evidence of additional grouping by these characteristics beyond what random assignment within racial groups would produce. The pattern suggests that race best explains the immediate change in classroom formation.

3.3.3 Classroom formation: interpretation. The student-level evidence on reassignment patterns, together with the higher quality of the classroom records, makes race the best-supported dimension of classroom segregation for the empirical model in Section 4. Race need not matter to parents in itself. It can serve as an easily observable proxy for dimensions that are harder to observe ex ante, such as achievement, social class, or behavior (Castillo

[28]The comparison is asymmetric. If schools grouped students only by race, random reassignment within racial groups would reproduce the resulting socioeconomic segregation on average, leaving no excess. Random reassignment within socioeconomic groups, however, would generally reduce racial segregation, since those groups can contain both white and nonwhite students.

Figure 6: Race best explains the immediate change in classroom formation



Notes: Event-study estimates from specification (4), for grades 3–4. The control group includes elementary schools in districts with pre-reform total enrollment above the 90th percentile of the state distribution. Each outcome is observed segregation minus its conditional-randomization benchmark. Segregation is measured by Duncan dissimilarity indices (equation (1)) computed across end-of-grade pseudo-classrooms within school-grade-year cells and averaged to the school-year level (Appendix B.1). Socioeconomic status indicates whether at least one parent has a four-year college degree. Relative achievement indicates whether the average of statewide-standardized lagged math and reading scores is at or above the school-grade-year median. For the racial benchmark, students are randomly reassigned across classrooms within joint socioeconomic-status and relative-achievement groups within each school-grade-year, holding each classroom's composition by these groups fixed. For the socioeconomic-status and achievement benchmarks, students are randomly reassigned within racial groups, holding classroom racial composition fixed. Benchmarks average 100 randomizations. All coefficients are relative to 1999. Shaded bands are pointwise 90% confidence intervals from regressions of the observed-minus-simulated outcomes; standard errors are clustered by district. Dashed vertical lines mark the reform announcement and the first school year under school choice.

and Petrie, 2010), or it may capture friendships, which tend to form within race and through proximity (Moody, 2001; Marmaros and Sacerdote, 2006; Echenique and Fryer, 2007). Either way, racially segregated classrooms can arise without racial animus on either side. Following a "disparate impact" approach (Gastwirth, 1992), I treat classroom segregation by race as a policy-relevant equilibrium outcome, whatever its motive; the model's preferences over classroom composition summarize these motives. The framework could easily nest dimensions that may be more relevant in other applications.

4 Empirical Model

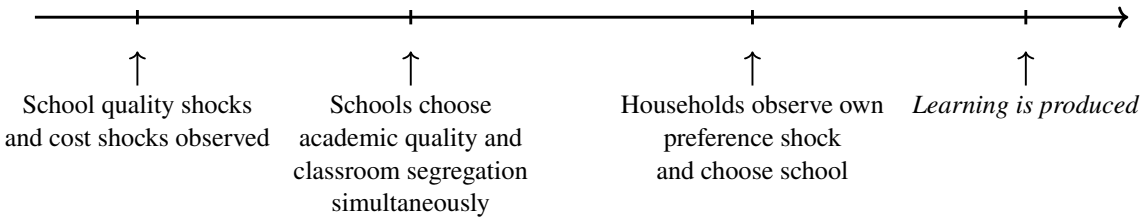
This section develops an empirical model of public school demand and supply that incorporates classroom formation on both sides. Families choose schools based on academic

quality, the classroom peers they expect their children to encounter, distance from home, and other attributes. Together with schools' costs, how families trade off different characteristics determines which attributes schools choose in equilibrium. Two modeling challenges are central. First, the policy counterfactuals depend on which families respond to different school attributes, so demand must allow rich preference heterogeneity and flexible substitution patterns without making the model intractable. Second, the classroom peer environment that families value is jointly determined by how a school assigns students to classrooms and who attends the school in the first place. The former is chosen directly by each school; the latter results from families' choices over all schools' equilibrium bundles of characteristics. Separating these two components while allowing them to jointly shape expected classroom peers is essential for mapping demand into the school's problem and keeping equilibrium simulation manageable. As discussed in Section 3.3.2, peer characteristics are captured along a single demographic dimension, race.

4.1 Market Definition and Timing

A market comprises all CMS elementary public schools and district families in a given year. Figure 7 shows the timing.

Figure 7: Timing of the model



Before detailing demand and supply, three features of this framework are worth emphasizing. First, schools choose academic quality and classroom segregation before families select schools. This timing implies that classroom segregation enters the model as a classroom formation "policy" rather than an absolute segregation level: schools choose a position between the least and most segregated allocations feasible given the students who ultimately enroll. Each school's choice therefore lies between 0 and 1 regardless of composition. Section 3 describes how the segregation variable is constructed (equation (2)).[29]

[29] In the structural model, I prefer this index to alternatives such as the deviation from random allocation (Appendix Figure D.4) because its bounds stay fixed at 0 and 1 as school composition changes in counterfactuals, whereas the random benchmark and attainable range shift with composition and class sizes. Treating schools' choice over classroom segregation as continuous is a reasonable approximation in the data: in simulated grade-level allocations, each school's attainable values are generally dense over its feasible range.

Second, schools play a complete information game in expected payoffs. Before choosing their characteristics, they observe all school-year-specific demand and cost shocks relevant to their decisions, including idiosyncratic factors that make them more or less attractive to families (for reasons other than the modeled attributes) or that affect their cost structure.

Third, learning is produced after families choose schools and depends jointly on academic quality and the classroom peers students experience. For any policy environment, the model determines both; for the counterfactual analysis, the learning effects of peers are benchmarked against the literature rather than estimated within the model.

4.2 Demand

In any year t, each student i chooses the school s that maximizes their indirect utility:

$$\begin{aligned} U_{ist} = \beta_i^q q_{st} + \overbrace{\beta_i^D D_{st} + \beta_i^W \overline{W}_{st} + \beta_i^{DW} D_{st}\overline{W}_{st}}^{\text{Expected classroom composition}} + \beta_i^M Magnet_{st} + \xi_{st} \\ -\gamma_i Distance_{ist} + \gamma_i^M Distance_{ist} \times Magnet_{st} + \gamma_i^T Distance_{ist} \times Post_t \times Transportation_{st} \\ + \eta_i Default_{ist} + \eta_i^P Default_{ist} \times Post_t + \tilde{\nu}_{ist} \end{aligned} \tag{5}$$

The first line of equation (5) contains the school attributes that are constant across students. q_{st} denotes academic quality. D_{st} is the fraction of feasible within-school across-classroom segregation that the school attains (feasible given its student body composition); in the empirical application, it will capture racial segregation. $\overline{W}_{st}$ is the share of white students at the school level that parents expect, given school attributes. q, D, and W are the only attributes in demand that are endogenous to the model. $Magnet_{st}$ captures whether the school is a magnet. ξ_{st} is a demand shock.

The D and $\overline{W}$ overbraced terms provide a reduced-form representation of the expected classmate composition. Intuitively, for a white student, if the school distributes white and nonwhite students across classrooms as evenly as possible, so that $D = 0$, the expected share of white classmates is approximately the school's expected white share, $\overline{W}$. As classroom segregation D increases, so does the expected share of white classmates. Given school composition, the expected classroom composition for white students mechanically pins down that for nonwhite students. Since, as discussed below, preferences over classroom segregation and school composition are allowed to differ by race, white and nonwhite students may prefer different values of D within the same school.

The rest of the utility function includes exogenous attributes that vary across schools and students. $Distance_{ist}$ is log home-school distance, while $Default_{ist}$ is an indicator for the

residence-assigned school. I allow the preference for the default school to vary with the school choice regime $Post_t$, which is a post-reform indicator. This captures the fact that open enrollment significantly reduces the administrative and psychic cost that households face to enroll their children outside their catchment area. Preferences for proximity to home are allowed to vary across regular and magnet schools and depend on whether free transportation is offered under open enrollment (see Section 2 for institutional details). Lastly, $\tilde{v}_{ist}$ is an idiosyncratic match value observed only to parents at the time of the enrollment decision.

Preferences for the endogenous school attributes are allowed to vary across households:

$$\begin{pmatrix} \beta_i^q \\ \beta_i^D \\ \beta_i^W \end{pmatrix} = \begin{pmatrix} \bar{\beta}^q \\ \bar{\beta}^D \\ \bar{\beta}^W \end{pmatrix} + \begin{pmatrix} \beta_z^q \\ \beta_z^D \\ \beta_z^W \end{pmatrix} Z_i + \begin{pmatrix} \nu_i^q \\ \nu_i^D \\ \nu_i^W \end{pmatrix} \tag{6}$$

where $\bar{\beta}^q, \bar{\beta}^D, \bar{\beta}^W$ are linear preference parameters identifying the preferences of a reference demographic group; $\beta_z^q, \beta_z^D, \beta_z^W$ are non-linear preference parameters that identify deviations in the preference parameters of demographic group z; ν^q, ν^D, ν^W are random coefficients that capture the residual, unobservable heterogeneity in preferences. Other preference parameters only vary across demographic groups.

I parameterize ν^q as lognormal (Train, 2009; Allende, 2021) with unknown mean and variance, and (ν^D, ν^W) as zero-mean correlated normals with unknown covariance matrix:

$$\nu_i^q \sim \ln \mathcal{N}(\mu^q, \sigma^q), \qquad \begin{pmatrix} \nu_i^D \\ \nu_i^W \end{pmatrix} \sim \mathcal{N}(0, \Sigma^{DW}) \tag{7}$$

The idiosyncratic preference shock $\tilde{v}$ is assumed to follow a Type-I Extreme Value distribution.

The Type-I Extreme Value assumption implies closed-form choice probabilities:

$$p_{ist} = \frac{\exp(V_{ist})}{\sum_{j \in \Omega_{it}} \exp(V_{ijt})} \tag{8}$$

with $V_{ist} = U_{ist} - \tilde{v}_{ist}$ and Ω_{it} denoting household i's choice set in year t . I assume that $\Omega_{it} = \Omega_t \quad \forall i$ where Ω_t includes all public schools in the market. It will prove useful to re-express choice probabilities as

$$p_{ist} = \frac{\exp(\delta_{st} + u_{ist})}{\sum_{j \in \Omega_t} \exp(\delta_{jt} + u_{ijt})} \tag{9}$$

where the mean utility term δ_{st} is defined as

$$\delta_{st} = \bar{\beta}^q q_{st} + \bar{\beta}^D D_{st} + \bar{\beta}^W \overline{W}_{st} + \bar{\beta}^{DW} D_{st} \times \overline{W}_{st} + \bar{\beta}^M Magnet_{st} + \xi_{st} \tag{10}$$

while u_{ist} captures systematic heterogeneity in preferences

$$\begin{aligned} u_{ist} = {} & (\beta_z^q Z_i + \nu_i^q) q_{st} + (\beta_z^D Z_i + \nu_i^D) D_{st} + (\beta_z^W Z_i + \nu_i^W) \overline{W}_{st} + \beta_z^{DW} Z_i (D_{st} \times \overline{W}_{st}) \\ & - \gamma_i Distance_{ist} + \gamma_i^M Distance_{ist} \times Magnet_{st} + \gamma_i^T Distance_{ist} \times Post_t \times Transportation_{st} \\ & + \eta_i Default_{ist} + \eta_i^P Default_{ist} \times Post_t + \tilde{\nu}_{ist} \end{aligned} \tag{11}$$

4.3 Supply

Given parental preferences and its realized quality shock, school s at time t chooses academic quality q_{st} and classroom segregation D_{st} to maximize:

$$\Big(\psi - MC_{st}(q_{st}, D_{st})\Big) \times E_{st}(q_{st}, D_{st}; q_{-st}, D_{-st}) \tag{12}$$

subject to the natural fraction bounds $D_{st} \in [0, 1]$. E_{st} denotes total school enrollment. The parameter ψ measures the benefit accruing to the school from enrolling an additional student. The per-student cost is

$$MC_{st}(q_{st}, D_{st}) = \underbrace{\left(\omega_{st}^q + \mu e^{q_{st}}\right)}_{\text{academic quality}} + \underbrace{\left(\omega_{st}^D D_{st} + \frac{\alpha}{2} D_{st}^2\right)}_{\text{classroom segregation}}. \tag{13}$$

The quality component of marginal cost represents productive effort and grows exponentially with q_{st}, with a scale parameter μ common across schools and a school-year-specific intercept observed by the school. Thus a marginal increase in q_{st} is costlier from a higher baseline. I decompose ω_{st}^q into a time-invariant school component $\overline{\omega}_s^q$, capturing permanent features that make quality particularly easy or costly to deliver, and a transitory component $\widetilde{\omega}_{st}^q$. (This decomposition is relevant for identification in Section 5.)

The segregation component of marginal cost is interpretable as reputational. The quadratic specification allows the model to rationalize the asymmetric distribution of classroom segregation observed in the data (Figure D.3) via a convex cost. ω_{st}^D can also be thought of as capturing any school-specific aversion (or lack thereof) to classroom segregation, alongside transitory factors.

4.4 Equilibrium

An equilibrium is a four-tuple $(\mathbf{q}, \mathbf{D}, \mathbf{W}, \mathbf{E})$ in which families maximize indirect utility under composition expectations that equal realized values, and schools choose quality and segregation to maximize expected payoffs. The equilibrium concept is static complete-information Nash with rational expectations.[30] The key conditions are, for demand,

$$\overline{W}_{st} = \frac{\sum_i \left(p_{ist}(q_t, D_t) \mathbb{1}(White_i) \right)}{E_{st}(q_t, D_t)} \tag{14}$$

and for supply,

$$\mu e^{q_{st}} = (\psi - MC_{st})\eta^q_{st}, \tag{15}$$

$$\omega^D_{st} + \alpha D_{st} = (\psi - MC_{st})\eta^D_{st} \tag{16}$$

for every s in market t. η^q_{st} denotes the total semi-elasticity of enrollment to academic quality

$$\eta^q_{st} = \frac{1}{E_{st}} \frac{dE_{st}(\mathbf{q}, \mathbf{D}, \mathbf{W})}{dq_{st}} = \frac{1}{E_{st}} \left(\underbrace{\frac{\partial E_{st}(\mathbf{q}, \mathbf{D}, \mathbf{W})}{\partial q_{st}}}_{\text{Partial effect}} + \underbrace{\sum_j \frac{\partial E_{st}(\mathbf{q}, \mathbf{D}, \mathbf{W})}{\partial W_{jt}} \frac{dW_{jt}}{dq_{st}}}_{\text{Indirect effect}} \right) \tag{17}$$

where j indexes schools in the market. The first term is the partial or direct effect of academic quality q_{st} on enrollment E_{st}, holding school composition fixed. It captures the demand return to increasing academic quality itself. The second term captures the indirect effect that goes through the change in schools' composition: by changing quality, school s can change how white and nonwhite students sort across schools in the market, thereby changing their composition. Since school composition enters utility, this channel can amplify or dampen school s's enrollment gain from higher quality, depending on how preferences for quality and composition vary across demographics. η^D_{st} is the total semi-elasticity of enrollment to classroom segregation and follows the same structure:

$$\eta^D_{st} = \frac{1}{E_{st}} \frac{dE_{st}(\mathbf{q}, \mathbf{D}, \mathbf{W})}{dD_{st}} = \frac{1}{E_{st}} \left(\frac{\partial E_{st}(\mathbf{q}, \mathbf{D}, \mathbf{W})}{\partial D_{st}} + \sum_j \frac{\partial E_{st}(\mathbf{q}, \mathbf{D}, \mathbf{W})}{\partial W_{jt}} \frac{dW_{jt}}{dD_{st}} \right). \tag{18}$$

[30] The model therefore does not explicitly capture schools' forward-looking adjustment during the announcement window, which does not enter estimation (Section 5.2). It does capture how classroom formation affects demand and schools' returns to investing in quality, the forces through which regulating classroom formation can change equilibrium academic quality.

To illustrate how the differentiation margins interact in a school's best response, I consider a "partial ban": a restriction requiring a school s to lower D_{st}, possibly to zero, while other schools' choices remain fixed. School s reoptimizes q_{st}, while families are free to re-sort, so enrollment and school composition adjust. The quality first-order condition in equation (15) reveals three channels through which the restriction affects the school's quality choice.

First, the per-student payoff $(\psi - MC_{st})$ changes with D. The direction depends on the sign of ω^D, with a larger cost shock raising the payoff under the partial ban, and, more generally, on the relative size of the linear and quadratic segregation costs (equation (13)).

Second, the partial effect in equation (17) mediates the quality response by capturing school s's enrollment responsiveness to own quality, holding school composition fixed. Denote it by $\eta^{q,0}_{st}$. Then

$$\frac{\partial \eta^{q,0}_{st}}{\partial D_{st}} = \frac{1}{E_{st}} \sum_i \left(\beta^D_i + \beta^{DW}_i \overline{W}_{st}\right) P_{ist}(1 - P_{ist}) \left(\beta^q_i (1 - 2P_{ist}) - \eta^{q,0}_{st}\right). \tag{19}$$

This term can be positive or negative depending on the correlation between tastes for quality and segregation among families whose choices are responsive to changes in school s's characteristics, and on whether banning D moves their probability of choosing s toward or away from intermediate values, at which responsiveness to the quality of school s is greatest. While this model admits, as a possible outcome, the reduced substitutability across schools that horizontal differentiation generates in Hotelling-type models (D'Aspremont et al., 1979), it does not build it in.[31] That is because, unlike in those models, where the horizontal attribute enters utility through a convex loss from a bliss point, here classroom segregation enters linearly, conditional on school composition. Thus, here, differently from what a Hotelling-type framework would imply, the quality change required to compensate a student for a marginal change in classroom segregation does not depend on D; it is constant for that student, conditional on school composition, and can be positive or negative. The trade-off varies across students with their relative preferences for quality and segregation. This is at the heart of the ambiguity in the sign of equation (19) and highlights the role of heterogeneous

[31] Schools choose classroom segregation and quality simultaneously, so the model also does not feature an incentive to differentiate on classroom segregation in order to soften rivals' subsequent competition on quality. Such an incentive, which arises when classroom formation is chosen first, would add a channel through which competition on classroom formation could weaken schools' incentives to provide quality, and through which restricting it could strengthen them.

preferences in this model. It will prove useful below to re-express equation (19) as

$$\frac{\partial \eta^{q,0}_{st}}{\partial D_{st}} = \underbrace{(1 - C_{st})\,\mathrm{Cov}_{m,st}\left(\beta^q_i, \widetilde{\beta}^D_{ist}\right)}_{\text{Preference alignment}} + \underbrace{(1 - C_{st})\left[C_{st}\mathbb{E}_{m,st}\left[\beta^q_i\right]\mathbb{E}_{m,st}\left[\widetilde{\beta}^D_{ist}\right] - 2\mathbb{E}_{m,st}\left[P_{ist}\beta^q_i\widetilde{\beta}^D_{ist}\right]\right]}_{\text{Choice-probability reweighting}}, \tag{20}$$

where

$$\widetilde{\beta}^D_{ist} \equiv \beta^D_i + \beta^{DW}_i \overline{W}_{st}, \qquad C_{st} \equiv \frac{\sum_i P^2_{ist}}{E_{st}},$$

and $\mathbb{E}_{m,st}[\cdot]$ and $\mathrm{Cov}_{m,st}(\cdot,\cdot)$ denote expectations and covariances under weights proportional to $P_{ist}(1 - P_{ist})$.

Third, the quality response is shaped by the indirect effect in equation (17), which captures how a change in school s's own quality affects its enrollment through the resulting change in racial sorting across schools. The partial ban changes both components of this indirect effect. As families re-sort, choice probabilities and school compositions change throughout the market, potentially altering both $\frac{\partial E_{st}}{\partial W_{jt}}$ and $\frac{dW_{jt}}{dq_{st}}$ for every school j. For $j = s$, lowering D_{st} additionally changes families' utility responsiveness to school composition, given by $\beta^W_i + \beta^{DW}_i D_{st}$. The directions are ambiguous and may vary across students, so the sign of the composition channel is also determined in equilibrium.[32]

The relationship between classroom segregation and schools' incentives to provide quality is therefore determined in equilibrium by the distribution of parental preferences and school costs. The next section discusses their identification and estimation.

5 Identification and Estimation

I denote by θ_1 the linear preference parameters, those that discipline the responsiveness of the reference demographic group to the school attributes that do not vary across households (equation (10)); by θ_2 the non-linear preference parameters, governing preference heterogeneity and demand for exogenous attributes that are school and student specific, such as home-school distance (equation (11)); by θ_3 the parameters that enter schools' cost function and regulate the trade-off between academic quality and classroom segregation

[32] Appendix A provides the derivations of the enrollment semi-elasticities and of the quality–segregation decomposition used in this section.

implied by the cost structure (equation (13)).

5.1 Identification

Identification is challenging for two reasons. The first is endogeneity: the utility shocks ξ (equation (10)) and cost shocks (ω^q, ω^D) (equation (12)) are observed by the model agents and affect their choices, but are not observed to the econometrician. A high-ξ school might, because of its "unobservably" good principal, have both a large treatment effect on its students (or high value added), and many students who are attracted to the school by its principal. Ignoring the potential for endogeneity might lead to erroneously loading the attractiveness of a good principal onto taste for academic quality. The second challenge is limited independent variation: academic quality, classroom segregation, and school composition are, along with the interaction between the last two, the endogenous attributes that enter demand. These characteristics are correlated, as one expects if some demographic groups sort more strongly than others. Empirically, this means not only that one needs exogenous variation to deal with endogeneity, but also that different exogenous shifters must move different school attributes differentially. This is amplified by academic quality and classroom segregation attracting parameters in both the household and the school problem.

The parameters in θ_1 are identified from the school mean utilities (equation (10)) using the school choice reform. The variation in quality and segregation used to identify $\overline{\beta}^q$ and $\overline{\beta}^D$ comes from heterogeneity in schools' responses to the increase in competitive pressure. As shown in Section 3, larger quality responses are predicted by a higher local share of college graduates, while larger segregation responses are predicted by lower local support for race-based school integration policies. Since each local characteristic shifts academic quality and classroom segregation in different proportions, the two jointly instrument for the changes in quality and segregation around the reform. Identification requires that the two instruments move the bundle of responses in non-proportional directions, which Figure 5 supports: conditional on each other, the share of college graduates shifts responses toward quality and the Republican vote share toward segregation. The identifying assumption is that innovations in schools' unobserved attractiveness, ξ, are orthogonal to the baseline characteristics of the areas in which schools are located. This approach allows local characteristics to be correlated with the time-invariant component of unobserved school attractiveness.

The variation in school-level racial composition used to identify $\overline{\beta}^W$ comes from the redrawing of catchment areas following the elimination of busing. I instrument for changes in school composition with the component predicted by changes in school boundaries,

assumed to be orthogonal to within-school innovations in ξ. I complement this variation with the change in school composition predicted by the model when demand and cost shocks are set to zero, in the spirit of Chamberlain (1987). Finally, $\overline{\beta}^{DW}$ is identified using interactions between the segregation and composition instruments. The complete set of instruments—including predictors constructed from NCDOT traffic counts (North Carolina Department of Transportation, n.d.) and state daycare star ratings (North Carolina Division of Child Development and Early Education, 2006)—is listed in Appendix Section B.2. Identification of θ_1, which enters mean utilities, requires a location normalization, as mean utilities are identified only up to a market-specific location normalization; given the lack of an outside option, I set one mean utility to zero in each market as in Neilson (2026).

The parameters in θ_2 enter choice probabilities (equation (8)) and are identified from student-level variation in demographics and school of enrollment by revealed preference. How a demographic group sorts across schools with different attributes, relative to how the reference group sorts, identifies that group's relative preferences for those attributes. Variation in choices within demographic groups identifies unobserved heterogeneity under distributional assumptions on the random coefficients: log-normal with unrestricted mean and variance for academic quality, and mean-zero correlated normals with unrestricted covariance for segregation and composition. Identification of θ_2 also relies on the Type-I Extreme Value assumption on the idiosyncratic shocks, which provides a scale normalization.

The cost parameters in θ_3, governing the marginal cost of quality (μ) and segregation (α), are identified up to their ratio absent a scale normalization. I impose no such normalization, as the relative cost parameter is sufficient for the counterfactuals. The relative cost parameter $r = \frac{\alpha}{\mu}$ is then identified from the schools' first-order conditions (equations (15) and (16)) holding demand fixed. As for demand, the identification argument is in changes, and the exclusion restriction is that the instrument—a measure of baseline market differentiation in classroom segregation, in the spirit of Gandhi and Houde (2019)—is orthogonal to within-school innovations over time in the unobserved cost shocks. The location normalization is $\psi = 1$, with ψ the school's marginal benefit from enrolling a student.

5.2 Estimation

Estimation relies on two school years of data, one before open enrollment (1999–2000) and one after (2004–2005), described in Appendix Table E.4.

First, θ_2—the vector of parameters governing preference heterogeneity—is estimated via Simulated Maximum Likelihood, using the predicted choice probabilities from the model

and data on individual enrollment choices. Estimation consists of an outer and an inner loop. Given a candidate parameter vector θ_2^r, the inner loop recovers the vector of mean utilities $\widehat{\delta}_t^r$ that matches predicted and observed market shares via a fixed point algorithm (Berry et al., 1995). The outer loop uses $\widehat{\delta}_t^r$ to compute the simulated enrollment probabilities and evaluate the log-likelihood function. Probabilities are computed as

$$\widehat{p}_{ist}^r = \int \frac{\exp\left(\widehat{\delta}_{st}^r + u_{ist\iota}(\theta_2^r)\right)}{\sum_j \exp\left(\widehat{\delta}_{jt}^r + u_{ijt\iota}(\theta_2^r)\right)} dF(\iota)d\iota$$

Here, ι denotes the three-dimensional vector of unobserved heterogeneity in preferences. I approximate the integral over the random coefficients using 500 quasi-Monte Carlo draws. The log-likelihood at θ_2^r is

$$\mathcal{L}(\theta_2 = \theta_2^r) = -\sum_i y_{ist} ln\big(\widehat{p}_{ist}^r(\theta_2^r)\big) \tag{21}$$

where $y_{ist} = 1$ if student i at time t enrolls in school s, and 0 otherwise; θ_2^* minimizes $\mathcal{L}$.

Second, I estimate θ_1—the set of linear preference parameters—by linear instrumental variables using a two-step GMM estimator and the mean utilities backed out from the first step at θ_2^*. The moments are built off of the exclusion restriction

$$\mathbb{E}\big[\Delta\xi \mid \mathbf{Z}^\xi\big] = 0 \tag{22}$$

where $\mathbf{Z}$ stands for instruments and

$$\Delta\xi = \Delta\widehat{\delta}(\theta_2^*) - \overline{\beta}^q \Delta q - \overline{\beta}^D \Delta D - \overline{\beta}^W \Delta W - \overline{\beta}^{DW} \Delta DW - \overline{\beta}^M \Delta Magnet \tag{23}$$

Third, given (θ_1^*, θ_2^*), I use the same approach to estimate the cost parameters θ_3. The restriction is

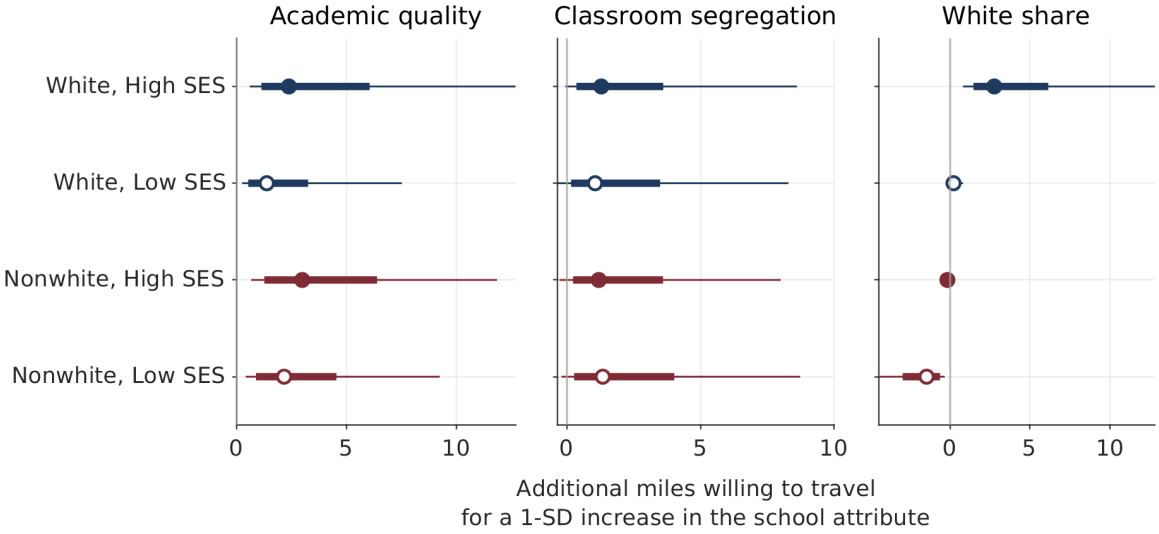
$$\Big(\mathbb{E}[\Delta\omega^q \mid \mathbf{Z}^q]\,,\ \mathbb{E}\big[\Delta\omega^D \mid \mathbf{Z}^D\big]\Big)' = \mathbf{0} \tag{24}$$

6 Results

6.1 Estimates

Appendix Table E.5 reports the parameter estimates, grouped into nonlinear demand parameters, linear demand parameters, and supply parameters. Figure 8 expresses the

Figure 8: Willingness to travel varies across and within demographic groups



Notes: The figure reports the additional distance, in miles, that students are willing to travel for a one-standard-deviation increase in academic quality, classroom segregation, or the school's white share, as implied by the estimated demand parameters. Calculations use the post-reform market and each student's observed home-to-attended-school distance as the baseline; for students with missing residential locations, the baseline distance is computed using the residential location associated with each simulation draw. The post-reform distance coefficient incorporates free transportation when the attended school is in the student's Choice Zone. For classroom segregation, willingness to travel is evaluated at the median school white share; for school white share, it is evaluated at the median level of classroom segregation. Rows distinguish students by race and socioeconomic status. Circles report medians across student-draw observations within each group; thick and thin horizontal segments report the 25th–75th and 10th–90th percentiles. Negative values indicate that the attribute increase must be compensated by a reduction in travel distance.

estimated preferences for academic quality, classroom segregation, and the school's white share in terms of willingness to travel: the additional distance, in miles, that a family would travel for a one-standard-deviation increase in each school attribute. High-socioeconomic-status (high-SES) families are generally willing to travel farther for academic quality, with median values between two and three miles. Holding the school's white share fixed at its sample median, preferences for classroom segregation are predominantly positive, and their distribution is more similar across demographic groups than the distribution of preferences for quality. By contrast, holding classroom segregation at its median, groups differ widely in how they value a whiter school: white high-SES families value it positively, whereas nonwhite low-SES families value it negatively.

Since classroom segregation and the school's white share enter the demand model both directly and through an interaction term (equation (5)), the marginal valuation of either attribute depends on the level of the other, so interpreting it requires holding the other fixed at a reference level. This interdependence matters quantitatively. Figure 9 shows that,

within demographic groups, preferences for classroom segregation vary in both sign and intensity with the school's racial composition. This pattern indicates that families do not value classroom segregation as a characteristic in its own right, but for what it implies about their child's classroom: the same degree of segregation produces very different classmates depending on the school's racial mix, and hence on who is separated from whom.

These preferences imply that enrollment responds positively to a school's own academic quality (Figure 10), whereas its semi-elasticity with respect to own classroom segregation takes both signs across schools. Under school choice, the utility of attending the assigned school declines (Appendix Table E.5), consistent with easier movement across catchment boundaries. Demand consequently becomes more responsive to other school attributes. Figure 10 shows a rightward shift in quality semi-elasticities after the reform and wider dispersion in segregation semi-elasticities. Appendix Figure D.8 shows that cross-school responses concentrate among schools with similar composition: cells far from the diagonal are mostly near zero, while competition among schools with higher white shares operates mainly through quality and among schools with lower white shares through segregation.

Appendix Figure D.9 applies the decomposition in equation (20) to each school in the post-reform market, holding school racial composition fixed. At most schools, greater classroom segregation lowers the responsiveness of enrollment to quality. The effect is highly uneven across schools: a few experience reductions several times larger than the rest. The two components also contribute differently across schools. The preference alignment component is negative at most schools but comparatively small, whereas the choice-probability reweighting component accounts for most of the reduction, especially where the effect is largest. These estimates are consistent with segregation keeping families away from the margin of indifference between the school and its alternatives. Since families disagree about segregation, raising it does not make a school uniformly more or less attractive: it draws in families who value segregation and pushes away those who do not. Such re-sorting can concentrate the school's demand among students who are strongly attached to it, leaving fewer students on the margin where quality could change their choice.

6.2 Model Fit

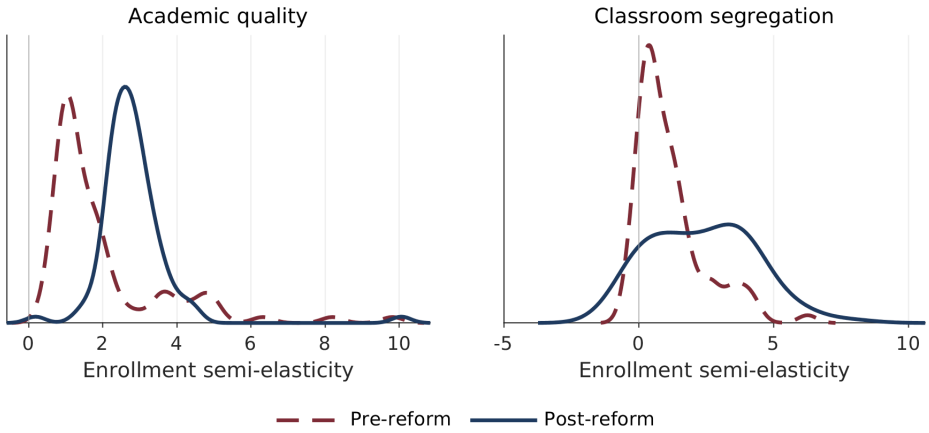
I assess model fit by solving for the equilibrium implied by the estimated parameters and recovered shocks: an outer loop updates schools' academic quality and classroom segregation using their first-order conditions, and an inner loop solves for schools' racial composition. Appendix Section B.3 describes the algorithm and the possibility of multiple equilibria.

Figure 9: Segregation preferences vary across households and with school composition



Notes: The figure reports the estimated marginal utility of classroom segregation for each race-by-socioeconomic-status student type at different school white shares. The calculations combine the estimated mean preference parameters for the reference group with the corresponding demographic interactions and set the unobserved random coefficient on classroom segregation to its mean of zero. Columns indicate the school's white share; rows indicate student type. Cell entries report the resulting preference parameters. Blue cells denote positive values and red cells denote negative values, with color intensity increasing in absolute magnitude. Positive values indicate that, holding other school characteristics fixed, the student type prefers greater classroom segregation; negative values indicate a preference for less classroom segregation.

Figure 10: School choice amplifies enrollment responsiveness to school attributes

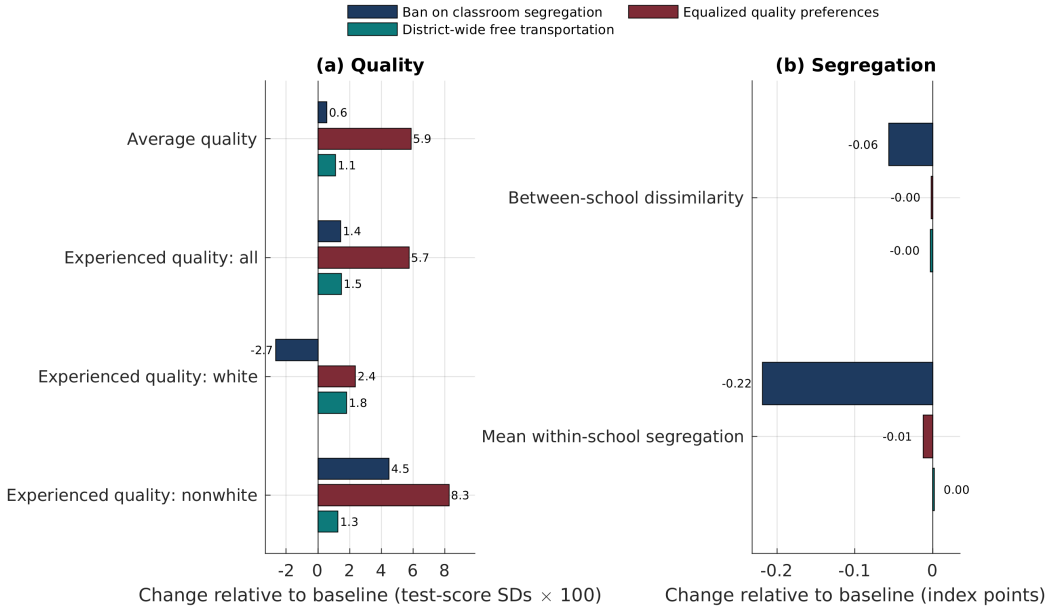


Notes: The figure plots the distribution in the estimation sample of the model-implied total semi-elasticities of enrollment with respect to a school's own academic quality and classroom segregation. Each semi-elasticity is the derivative of log enrollment with respect to the indicated attribute, evaluated at the observed market state and estimated demand parameters. Total semi-elasticities incorporate both the direct enrollment response, holding school racial composition fixed, and the indirect response operating through equilibrium changes in racial composition across schools, as defined in equations (17) and (18). Dashed maroon lines report the pre-reform (1999–2000) and solid navy lines the post-reform (2004–2005) market. Vertical lines mark zero.

The simulated equilibrium closely reproduces academic quality, classroom segregation, white share, and enrollment at the school level (Appendix Figure D.10), as well as students' exposure to these outcomes by demographic group (Appendix Figure D.11). It also reproduces larger quality responses and smaller segregation responses in highly educated areas (Appendix Figure D.12), consistent with Section 3.2.

7 Counterfactuals

Figure 11: Ban raises nonwhite exposure to quality and integrates schools



Notes: The figure reports changes relative to the post-reform baseline equilibrium under three counterfactuals. The segregation ban sets classroom segregation to zero at every school. The equal-preferences counterfactual sets the group-specific deviations in preferences for academic quality to zero, so that every group values quality as white high-socioeconomic-status families do. The transportation counterfactual extends the estimated post-reform free-transport distance adjustment to every student–school pair. Panel A reports changes in average school quality and in the quality experienced by all, white, and nonwhite students, in hundredths of a student achievement standard deviation. Average school quality weights schools equally; experienced quality weights schools by total, white, or nonwhite enrollment in each equilibrium. Panel B reports changes in the between-school dissimilarity index and the enrollment-weighted mean of classroom segregation across schools, both measured on a 0–1 scale.

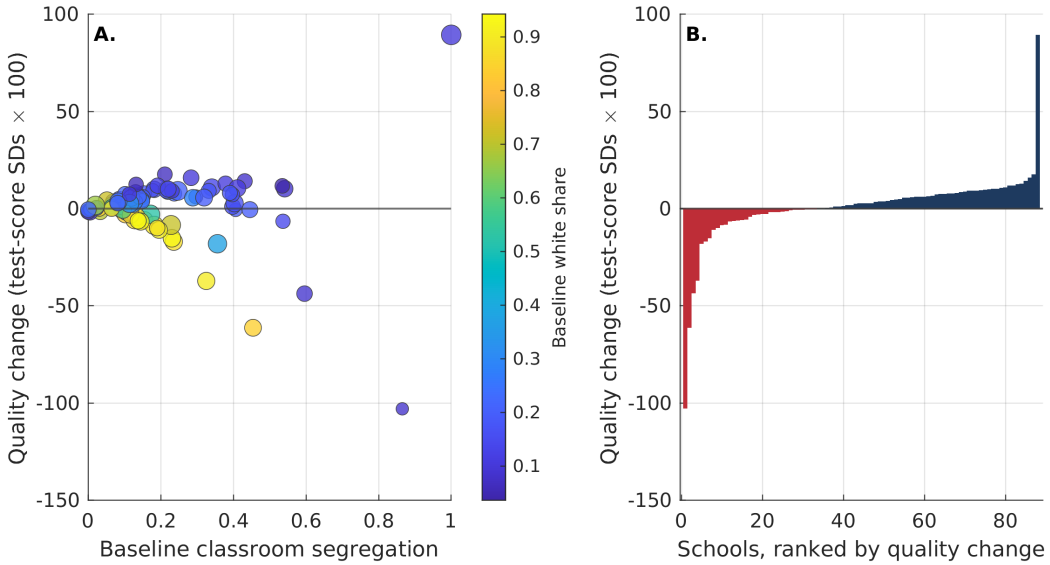
Discretion over classroom formation may soften schools' incentives to improve academically. At most schools, segregation keeps families away from the margin of indifference between the school and its alternatives, so integrating classrooms makes enrollment more responsive to quality (Section 6). Multidimensional competition may thus join limited parental responsiveness to quality and spatial differentiation among the mechanisms that insulate schools from pressure to increase their effectiveness. Figure 11 reports the equilibrium

consequences of a market-wide ban on classroom segregation, under which every school must offer the most integrated classroom configuration feasible given its student composition. It compares the ban with two alternative policies: eliminating observed demographic differences in preferences for academic quality and providing free transportation for every student to every school. If these differences partly reflect information frictions, this counterfactual provides a stylized benchmark for an information policy that increases disadvantaged families' responsiveness to value added. The ban produces the smallest increase in unweighted average school quality—approximately half the effect of free transportation and one-tenth that of equalized quality preferences. Weighted by the students experiencing it in each equilibrium, however, the gain under the ban is nearly as large as under free transportation. The distributional consequences differ sharply: free transportation raises experienced quality by similar amounts for white and nonwhite students, whereas the ban lowers the quality experienced by the average white student and substantially raises that experienced by the average nonwhite student, by about 54% as much as equalized quality preferences, the policy generating the largest overall quality improvements. Relative to baseline, the ban changes experienced math value added by 0.0143 achievement standard deviations overall, 0.0447 for nonwhite students, and −0.0265 for white students, closing about 75% of the baseline racial gap in experienced quality. Using the estimates in Chetty et al. (2014a,b), accumulated over five years of elementary school, these changes correspond to changes in the present value of lifetime earnings of approximately $3,100, $9,600, and −$5,700 per student, respectively, in 2010 dollars. The first two amounts are approximately 9% and 27% of the earnings effect of having math teachers whose value added is one standard deviation higher in each of those years; for white students, the loss is approximately 16% of that benchmark.[33] Finally, the ban is the only policy that meaningfully reduces segregation across schools: the between-school dissimilarity index falls by 0.056, or approximately 9.8% of its simulated baseline value, in addition to the policy's mechanical elimination of within-school segregation. The model-implied learning effects exclude classroom peer effects, which the

[33]The calculation maps 0.163 achievement standard deviations to one standard deviation of elementary-school math teacher value added (Chetty et al., 2014a). Chetty et al. (2014b) estimate that a one-standard-deviation increase in teacher value added in a single grade raises earnings at age 28 by 1.34%; assuming this percentage gain persists over the life cycle, it implies a present value of about $7,000 per student at age 12. Their estimate pools math and English in grades 4–8, so the mapping is approximate. The calculation adopts their earnings and discounting assumptions and further assumes that the change in school value added applies in each of the five years, that its earnings effects add up across years, and that it has the same long-run return per achievement standard deviation as teacher value added, with returns homogeneous across racial groups. Appendix Figure D.6 shows no reform-induced change in the racial gap in exposure to effective teachers, which supports a common shift in academic exposure but does not establish equal earnings returns.

value-added estimates net out by conditioning on classroom composition (Section 3.1). If integration also narrows achievement gaps through peers,[34] the resulting reduction in the racial achievement gap would exceed that implied by changes in academic quality alone.[35]

Figure 12: Ban raises quality at most segregated nonwhite schools



Notes: The figure compares the post-reform baseline equilibrium with a counterfactual equilibrium in which classroom segregation is set to zero at every school. Panel A plots each school's change in academic quality, in hundredths of a student achievement standard deviation, against its baseline classroom segregation. Marker color indicates the school's baseline white enrollment share, and marker size increases with baseline enrollment. Panel B ranks all 88 schools by their quality response; blue bars indicate increases and red bars indicate decreases. The largest increase occurs at the one school whose enrollment is at the 550-student capacity in the baseline equilibrium (Appendix Section B.3); under the ban, its enrollment falls below capacity.

Figure 12 shows substantial heterogeneity: quality rises at about 60% of schools and falls at the remainder. Responses tend to be larger in magnitude at higher baseline classroom segregation, with gains concentrated at predominantly nonwhite schools and declines at predominantly white schools. Among schools that raise quality, a Shapley decomposition attributes a bit more than half of the average increase to changes in demand, including how responsive enrollment is to quality, and the remainder to changes in schools' payoff per enrolled student—the two forces discussed in Section 4.4. Among schools that reduce quality, the payoff channel accounts for the great majority of the average decline, consistent with the loss of a school-side benefit from segregation.[36]

[34] E.g., Guryan, 2004; Angrist and Lang, 2004; Hanushek et al., 2009; Johnson, 2011; Billings et al., 2014; on grouping by ability, see Antonovics et al., 2022.

[35] Most of this evidence concerns the racial composition of schools rather than of classrooms.

[36] Following Dinerstein and Smith (2021), who decompose schools' supply responses to policy into

8 Conclusion

This paper develops an empirical framework to study how public schools compete when families care about more than academic quality. Exploiting a school choice reform in North Carolina, I show that schools respond to competition along two margins: academic quality and classroom formation. The model indicates that disagreement over classroom formation can allow schools to differentiate and keep families away from the margin of indifference between schools, thereby weakening their incentives to improve academically in response to competition; schools' own payoff from classroom formation further shapes the heterogeneous responses to restrictions on this margin. Coupling school choice with a ban on classroom segregation shifts competitive pressure toward academic quality, generating average gains concentrated among nonwhite students, whose gain in experienced value added is more than half as large as under equalized quality preferences. Overall, the analysis highlights the limits of relying on school choice alone to translate parental preferences into learning gains and suggests that policies engaging with how schools compete and how differentiation arises may yield larger gains, especially for academically disadvantaged students.

References

Abdulkadiroğlu, Atila, Parag A. Pathak, Jonathan Schellenberg, and Christopher R. Walters (2020), "Do parents value school effectiveness?" *American Economic Review*, 110, 1502–1539.

Agte, Patrick, Claudia Allende, Adam Kapor, Christopher Neilson, and Fernando Ochoa (2026), "Search and biased beliefs in education markets." *NBER Working Paper No. 32670*.

Ainsworth, Robert, Rajeev Dehejia, Cristian Pop-Eleches, and Miguel Urquiola (2023), "Why do households leave school value added on the table? The roles of information and preferences." *American Economic Review*, 113, 1049–1082.

Allende, Claudia (2021), "Competition under social interactions and the design of education policies." *Stanford Graduate School of Business Working Paper*.

Altenhofen, Sarah, Mark Berends, and Thomas G. White (2016), "School choice decision making among suburban, high-income parents." *AERA Open*, 2, 1–14.

Angrist, Joshua, Peter Hull, Parag A. Pathak, and Christopher Walters (2024), "Credible

mechanisms, I compare equilibria relative to a common fitted baseline to separate the ban's effect on demand from its effect on schools' payoffs. Each channel's Shapley contribution averages its incremental quality effect when introduced first and second. Group averages use baseline enrollment weights.

school value-added with undersubscribed school lotteries." *The Review of Economics and Statistics*, 106, 1–19.

Angrist, Joshua D., Peter D. Hull, Parag A. Pathak, and Christopher R. Walters (2017), "Leveraging lotteries for school value-added: Testing and estimation." *The Quarterly Journal of Economics*, 132, 871–919.

Angrist, Joshua D. and Kevin Lang (2004), "Does school integration generate peer effects? Evidence from Boston's Metco Program." *American Economic Review*, 94, 1613–1634.

Antonovics, Kate, Sandra E. Black, Julie Berry Cullen, and Akiva Yonah Meiselman (2022), "Patterns, determinants, and consequences of ability tracking: Evidence from Texas public schools." *NBER Working Paper No. 30370*.

Arteaga, Felipe, Adam J. Kapor, Christopher A. Neilson, and Seth D. Zimmerman (2022), "Smart matching platforms and heterogeneous beliefs in centralized school choice." *The Quarterly Journal of Economics*, 137, 1791–1848.

Barahona, Nano, Cristóbal Otero, and Sebastián Otero (2023), "Equilibrium effects of food labeling policies." *Econometrica*, 91, 839–868.

Barseghyan, Levon, Damon Clark, and Stephen Coate (2019), "Peer preferences, school competition, and the effects of public school choice." *American Economic Journal: Economic Policy*, 11, 124–158.

Bau, Natalie (2022), "Estimating an equilibrium model of horizontal competition in education." *Journal of Political Economy*, 130, 1717–1764.

Bayer, Patrick, Fernando Ferreira, and Robert McMillan (2007), "A unified framework for measuring preferences for schools and neighborhoods." *Journal of Political Economy*, 115, 588–638.

Bayer, Patrick and Christopher Timmins (2007), "Estimating equilibrium models of sorting across locations." *The Economic Journal*, 117, 353–374.

Berry, Steven, James Levinsohn, and Ariel Pakes (1995), "Automobile prices in market equilibrium." *Econometrica*, 63, 841–890.

Berry, Steven, James Levinsohn, and Ariel Pakes (2004), "Differentiated products demand systems from a combination of micro and macro data: The new car market." *Journal of Political Economy*, 112, 68–105.

Beuermann, Diether W., C. Kirabo Jackson, Laia Navarro-Sola, and Francisco Pardo (2023), "What is a good school, and can parents tell? Evidence on the multidimensionality of school output." *The Review of Economic Studies*, 90, 65–101.

Bibler, Andrew and Stephen B. Billings (2020), "Win or lose: Residential sorting after a school choice lottery." *Review of Economics and Statistics*, 102, 457–472.

Billings, Stephen B., David J. Deming, and Jonah Rockoff (2014), "School segregation, educational attainment, and crime: Evidence from the end of busing in Charlotte-Mecklenburg." *The Quarterly Journal of Economics*, 129, 435–476.

Bosworth, Ryan and Hao Li (2013), "Patterns in student assignment to elementary school classrooms." *Education Policy Analysis Archives/Archivos Analíticos de Políticas Educativas*, 21, 1–23.

Brock, William A. and Steven Durlauf (2005), "Multinomial choice with social interactions." In *The Economy as an Evolving Complex System III: Current Perspectives and Future Directions* (Lawrence E. Blume and Steven N. Durlauf, eds.), 175–206, Oxford University Press.

Burgess, Simon, Ellen Greaves, Anna Vignoles, and Deborah Wilson (2015), "What parents want: School preferences and school choice." *The Economic Journal*, 125, 1262–1289.

Burns, Robert B. and DeWayne A. Mason (2002), "Class composition and student achievement in elementary schools." *American Educational Research Journal*, 39, 207–233.

Bush, George H. W. (1991), "Remarks to the Ohio Education Community." The American Presidency Project, November 25, 1991.

Campos, Christopher (2025), "Social interactions, information, and preferences for schools: Experimental evidence from Los Angeles." Working paper, November 2025.

Campos, Christopher and Caitlin Kearns (2024), "The impact of public school choice: Evidence from Los Angeles's Zones of Choice." *The Quarterly Journal of Economics*, 139, 1051–1093.

Capacchione v. Charlotte-Mecklenburg Schools (1999), "57 F. Supp. 2d 228." United States District Court for the Western District of North Carolina.

Card, David and Laura Giuliano (2014), "Does gifted education work? For which students?" *NBER Working Paper No. 20453*.

Castillo, Marco and Ragan Petrie (2010), "Discrimination in the lab: Does information trump appearance?" *Games and Economic Behavior*, 68, 50–59.

Chamberlain, Gary (1987), "Asymptotic efficiency in estimation with conditional moment restrictions." *Journal of Econometrics*, 34, 305–334.

Chetty, Raj, John N. Friedman, and Jonah E. Rockoff (2014a), "Measuring the impacts of teachers I: Evaluating bias in teacher value-added estimates." *American Economic Review*, 104, 2593–2632.

Chetty, Raj, John N. Friedman, and Jonah E. Rockoff (2014b), "Measuring the impacts of teachers II: Teacher value-added and student outcomes in adulthood." *American Economic Review*, 104, 2633–2679.

Clinton, William J. (1999), "The President's Radio Address." The American Presidency Project, August 28, 1999.

Clotfelter, Charles T., Helen F. Ladd, Calen R. Clifton, and Mavzuna R. Turaeva (2021), "School segregation at the classroom level in a southern 'new destination' state." *Race and Social Problems*, 13, 131–160.

Clotfelter, Charles T., Helen F. Ladd, and Jacob L. Vigdor (2003), "Segregation and resegregation in North Carolina's public school classrooms." *North Carolina Law Review*, 81, 1463–1511.

Cohodes, Sarah R. and Katharine S. Parham (2021), "Charter schools' effectiveness, mechanisms, and competitive influence." In *Oxford Research Encyclopedia of Economics and Finance*, Oxford University Press.

Conger, Dylan (2005), "Within-school segregation in an urban school district." *Educational Evaluation and Policy Analysis*, 27, 225–244.

Corradini, Viola (2024), "Information and access in school choice systems: Evidence from New York City." Working paper.

Crawford, Gregory S., Oleksandr Shcherbakov, and Matthew Shum (2019), "Quality overprovision in cable television markets." *American Economic Review*, 109, 956–995.

Crema, Angela (2026), "The segregative effects of charter schools." *American Economic Journal: Economic Policy*, 18, 242–274, URL https://doi.org/10.1257/pol.20230539.

D'Aspremont, Claude, J. Jaskold Gabszewicz, and J.-F. Thisse (1979), "On Hotelling's 'Stability in Competition'." *Econometrica*, 47, 1145–1150.

Deming, David J. (2014), "Using school choice lotteries to test measures of school effectiveness." *American Economic Review*, 104, 406–411.

Deming, David J., Justine S. Hastings, Thomas J. Kane, and Douglas O. Staiger (2014), "School choice, school quality, and postsecondary attainment." *American Economic Review*, 104, 991–1013.

Dieterle, Steven, Cassandra M. Guarino, Mark D. Reckase, and Jeffrey M. Wooldridge (2015), "How do principals assign students to teachers? Finding evidence in administrative data and the implications for value added." *Journal of Policy Analysis and Management*, 34, 32–58.

Dinerstein, Michael and Troy D. Smith (2021), "Quantifying the supply response of private schools to public policies." *American Economic Review*, 111, 3376–3417.
Duncan, Otis Dudley and Beverly Duncan (1955), "A methodological analysis of segregation indexes." *American Sociological Review*, 20, 210–217.
Echenique, Federico and Roland G. Fryer, Jr. (2007), "A measure of segregation based on social interactions." *The Quarterly Journal of Economics*, 122, 441–485.
EdChoice (2024), "One Million Students in School Choice Programs, By the Numbers." EdChoice Blog, post by Alli Aldis, June 18, 2024.
Epple, Dennis and Richard E. Romano (1998), "Competition between private and public schools, vouchers, and peer-group effects." *American Economic Review*, 88, 33–62.
Fan, Ying (2013), "Ownership consolidation and product characteristics: A study of the U.S. daily newspaper market." *American Economic Review*, 103, 1598–1628.
Ferreyra, Maria Marta and Grigory Kosenok (2018), "Charter school entry and school choice: The case of Washington, DC." *Journal of Public Economics*, 159, 160–182.
Figlio, David and Cassandra Hart (2014), "Competitive effects of means-tested school vouchers." *American Economic Journal: Applied Economics*, 6, 133–156.
Figlio, David N., Cassandra M. D. Hart, and Krzysztof Karbownik (2023), "Effects of maturing private school choice programs on public school students." *American Economic Journal: Economic Policy*, 15, 255–294.
Fong, Kelley (2019), "Subject to evaluation: How parents assess and mobilize information from social networks in school choice." *Sociological Forum*, 34, 158–180.
Friedman, Milton (1962), *Capitalism and Freedom*. University of Chicago Press.
Gandhi, Amit and Jean-François Houde (2019), "Measuring substitution patterns in differentiated-products industries." *NBER Working Paper No. 26375*.
Gastwirth, Joseph L. (1992), "Employment discrimination: A statistician's look at analysis of disparate impact claims." *Law & Inequality*, 11, 151.
Gilraine, Michael, Uros Petronijevic, and John D. Singleton (2021), "Horizontal differentiation and the policy effect of charter schools." *American Economic Journal: Economic Policy*, 13, 239–276.
Gilraine, Michael, Uros Petronijevic, and John D. Singleton (2025), "School choice, competition, and aggregate school quality." *NBER Working Paper No. 31328*.
Grissom, Jason A. and Christopher Redding (2016), "Discretion and disproportionality: Explaining the underrepresentation of high-achieving students of color in gifted programs." *AERA Open*, 2, 1–25.

Guryan, Jonathan (2004), "Desegregation and black dropout rates." *American Economic Review*, 94, 919–943.

Hanushek, Eric A., John F. Kain, and Steven G. Rivkin (2009), "New evidence about Brown v. Board of Education: The complex effects of school racial composition on achievement." *Journal of Labor Economics*, 27, 349–383.

Harris, Douglas N. (2017), "Why Managed Competition Is Better than a Free Market for Schooling." The Brookings Institution.

Hastings, Justine, Thomas J. Kane, and Douglas O. Staiger (2009), "Heterogeneous preferences and the efficacy of public school choice." Working paper, May 2009.

Hastings, Justine S. and Jeffrey M. Weinstein (2008), "Information, school choice, and academic achievement: Evidence from two experiments." *The Quarterly Journal of Economics*, 123, 1373–1414.

Henderson, John Michael (2011), "Strategic class roster creation in elementary schools: Indicative of student reading growth or a waste of time?" *Doctoral Dissertation; ERIC Online Submission*.

Hill, Paul T., Julian R. Betts, David Ferrero, Brian P. Gill, Dan Goldhaber, Laura Hamilton, Jeffrey R. Henig, Frederick M. Hess, Tom Loveless, Stephen Macedo, Lawrence Rosenstock, Charles Venegoni, Janet Weiss, and Patrick J. Wolf (2003), "School Choice: Doing It the Right Way Makes a Difference." Technical report, The Brookings Institution, Washington, DC. Report from the National Working Commission on Choice in K–12 Education.

Ho, Katherine (2009), "Insurer-provider networks in the medical care market." *American Economic Review*, 99, 393–430.

Hopkins, Gary (1999), "From the principal files: Making class lists needn't be a nightmare!" *Education World*. Originally published 06/21/1999. Last updated 05/08/2009.

Horváth, Hedvig (2015), "Classroom assignment policies and implications for teacher value-added estimation." Working paper, January 2015.

Hoxby, Caroline M. (2003), "School choice and school productivity: Could school choice be a tide that lifts all boats?" In *The Economics of School Choice* (Caroline M. Hoxby, ed.), 287–342, University of Chicago Press.

Johnson, Rucker C. (2011), "Long-run impacts of school desegregation & school quality on adult attainments." *NBER Working Paper No. 16664*.

Kalogrides, Demetra and Susanna Loeb (2013), "Different teachers, different peers: The magnitude of student sorting within schools." *Educational Researcher*, 42, 304–316.

Kane, Thomas J., Douglas O. Staiger, Gavin Samms, Edward W. Hill, and David L. Weimer

(2003), "School accountability ratings and housing values [with comments]." *Brookings-Wharton Papers on Urban Affairs*, 83–137.

Kapor, Adam J., Christopher A. Neilson, and Seth D. Zimmerman (2020), "Heterogeneous beliefs and school choice mechanisms." *American Economic Review*, 110, 1274–1315.

Lareau, Annette (2000), *Home Advantage: Social Class and Parental Intervention in Elementary Education*. Rowman & Littlefield Publishers, 2nd ed.

Lareau, Annette (2011), *Unequal Childhoods: Class, Race, and Family Life, With an Update a Decade Later*. University of California Press, 2nd ed.

Lassiter, Matthew D. (2004), "The suburban origins of 'color-blind' conservatism: Middle-class consciousness in the Charlotte busing crisis." *Journal of Urban History*, 30, 549–582.

MacLeod, W. Bentley and Miguel Urquiola (2013), "Competition and educational productivity: Incentives writ large." In *Education Policy in Developing Countries* (Paul Glewwe, ed.), 243–284, University of Chicago Press.

MacLeod, W. Bentley and Miguel Urquiola (2015), "Reputation and school competition." *American Economic Review*, 105, 3471–3488.

Marmaros, David and Bruce Sacerdote (2006), "How do friendships form?" *The Quarterly Journal of Economics*, 121, 79–119.

McMillan, Robert (2004), "Competition, incentives, and public school productivity." *Journal of Public Economics*, 88, 1871–1892.

Mickelson, Roslyn A., Stephen S. Smith, and Stephanie Southworth (2009), "Resegregation, achievement, and the chimera of choice in post-unitary Charlotte-Mecklenburg schools." In *From the Courtroom to the Classroom: The Shifting Landscape of School Desegregation* (Claire E. Smrekar and Ellen B. Goldring, eds.), 129–156, Harvard Education Press, Cambridge, MA.

Mickelson, Roslyn Arlin (2015), "The cumulative disadvantages of first- and second-generation segregation for middle school achievement." *American Educational Research Journal*, 52, 657–692.

Moody, James (2001), "Race, school integration, and friendship segregation in America." *American Journal of Sociology*, 107, 679–716.

Nechyba, Thomas J. (2000), "Mobility, targeting, and private-school vouchers." *American Economic Review*, 90, 130–146.

Neilson, Christopher A. (2026), "Targeted vouchers, competition among schools and the academic achievement of poor students." *Econometrica*. Forthcoming.

North Carolina Department of Transportation (n.d.), "Historical Annual Average Daily Traffic Counts [dataset]." Transportation Planning Division, Traffic Survey Group.

North Carolina Division of Child Development and Early Education (2006), "List of Child Care Facilities with Star-Rated Licenses [dataset]."

North Carolina Education Research Data Center (1995–2017), "Student, class, and personnel files."

Pierpoint, James Andrew (2018), "Charlotte's integration era: The life and death of court-mandated busing, 1971–1999." *Honors Thesis, Duke University*.

Rothstein, Jesse (2006), "Good principals or good peers? Parental valuation of school characteristics, Tiebout equilibrium, and the incentive effects of competition among jurisdictions." *American Economic Review*, 96, 1333–1350.

Seim, Katja (2006), "An empirical model of firm entry with endogenous product-type choices." *The RAND Journal of Economics*, 37, 619–640.

Singleton, John D. (2019), "Incentives and the supply of effective charter schools." *American Economic Review*, 109, 2568–2612.

Smith, Stephen Samuel (2004), *Boom for Whom? Education, Desegregation, and Development in Charlotte*. State University of New York Press, Albany.

Spence, A. Michael (1975), "Monopoly, quality, and regulation." *The Bell Journal of Economics*, 6, 417–429.

St. John, E. M. (2014), *Understanding the factors that influence the grouping and assignment of students to elementary classrooms*. Ph.D. thesis, University of Washington.

Sweeting, Andrew (2013), "Dynamic product positioning in differentiated product markets: The effect of fees for musical performance rights on the commercial radio industry." *Econometrica*, 81, 1763–1803.

Train, Kenneth E. (2009), *Discrete Choice Methods with Simulation*, second edition. Cambridge University Press.

Ura, Alexa and Aliyya Swaby (2018), "San Antonio ISD Is Innovating to Integrate Its Schools. Is It Leaving Some Behind in the Process?" The Texas Tribune.

Walters, Christopher R. (2018), "The demand for effective charter schools." *Journal of Political Economy*, 126, 2179–2223.

Young, Beth Aronstamm (2002), "Characteristics of the 100 Largest Public Elementary and Secondary School Districts in the United States: 2000–01." Technical Report NCES 2002-351, U.S. Department of Education, National Center for Education Statistics, Washington, DC.

Online Appendix

A Derivation of the Semi-Elasticities of Enrollment

This section derives analytically all the terms in equations (17) and (18). As for the semi-elasticities of total enrollment over q_{st}, D_{st}, $\overline{W}_{st}$, and $\overline{W}_{lt} \quad \forall l \neq s$,

$$E_{st} = \sum_{i \in \mathcal{I}_t} p_{ist}$$

where $\mathcal{I}_t$ is the set of households in year t and

$$\frac{\partial p_{ist}}{\partial q_{st}} = \beta_i^q p_{ist}(1 - p_{ist})$$

$$\frac{\partial p_{ilt}}{\partial q_{st}} = -\beta_i^q p_{ist} p_{ilt} \quad \forall l \neq s$$

$$\frac{\partial p_{ist}}{\partial D_{st}} = (\beta_i^D + \beta_i^{DW} \overline{W}_{st}) p_{ist}(1 - p_{ist})$$

$$\frac{\partial p_{ilt}}{\partial D_{st}} = -(\beta_i^D + \beta_i^{DW} \overline{W}_{st}) p_{ist} p_{ilt} \quad \forall l \neq s$$

The partial semi-elasticity of school s's enrollment with respect to own academic quality, holding school composition fixed, is

$$\eta_{st}^{q,0} = \frac{1}{E_{st}} \sum_i \beta_i^q p_{ist}(1 - p_{ist}).$$

Differentiating this object with respect to D_{st}, still holding school composition fixed, gives equation (19):

$$\frac{\partial \eta_{st}^{q,0}}{\partial D_{st}} = \frac{1}{E_{st}} \sum_i \left(\beta_i^D + \beta_i^{DW} \overline{W}_{st}\right) p_{ist}(1 - p_{ist}) \left(\beta_i^q (1 - 2p_{ist}) - \eta_{st}^{q,0}\right).$$

To obtain the decomposition reported in equation (20), define the effective preference for classroom segregation at school s as

$$\widetilde{\beta}_{ist}^D \equiv \beta_i^D + \beta_i^{DW} \overline{W}_{st},$$

and let

$$m_{ist} \equiv P_{ist}(1 - P_{ist})$$

denote the extent to which household i is marginal with respect to school s. For any household-level object x_{ist}, define its marginal-household expectation as

$$\mathbb{E}_{m,st}[x_{ist}] \equiv \frac{\sum_i m_{ist} x_{ist}}{\sum_i m_{ist}}.$$

The associated covariance is

$$\begin{aligned}\text{Cov}_{m,st}(x_{ist}, y_{ist}) \equiv \mathbb{E}_{m,st}[x_{ist} y_{ist}] \\ - \mathbb{E}_{m,st}[x_{ist}]\, \mathbb{E}_{m,st}[y_{ist}]\,.\end{aligned}$$

Define the enrollment-weighted mean choice probability of school s as

$$C_{st} \equiv \frac{\sum_i P_{ist}^2}{E_{st}}.$$

Since $E_{st} = \sum_i P_{ist}$,

$$\begin{aligned}\sum_i m_{ist} &= \sum_i P_{ist}(1 - P_{ist}) \\ &= E_{st} - \sum_i P_{ist}^2 \\ &= E_{st}(1 - C_{st}).\end{aligned}$$

It follows that the partial semi-elasticity of enrollment with respect to academic quality can be written as

$$\begin{aligned}\eta_{st}^{q,0} &= \frac{1}{E_{st}} \sum_i \beta_i^q m_{ist} \\ &= (1 - C_{st}) \mathbb{E}_{m,st}\left[\beta_i^q\right].\end{aligned}$$

Using this notation, equation (19) becomes

$$\begin{aligned}\frac{\partial \eta_{st}^{q,0}}{\partial D_{st}} &= \frac{1}{E_{st}} \sum_i \widetilde{\beta}_{ist}^D m_{ist} \left[\beta_i^q (1 - 2P_{ist}) - \eta_{st}^{q,0}\right] \\ &= (1 - C_{st}) \Bigg\{ \mathbb{E}_{m,st}\left[\beta_i^q \widetilde{\beta}_{ist}^D\right] - 2\mathbb{E}_{m,st}\left[P_{ist} \beta_i^q \widetilde{\beta}_{ist}^D\right]\end{aligned}$$

$$
\begin{aligned}
&\qquad\qquad - \eta_{st}^{q,0}\mathbb{E}_{m,st}\left[\widetilde{\beta}_{ist}^{D}\right]\Bigg\} \\
&= (1-C_{st})\Bigg\{\mathbb{E}_{m,st}\left[\beta_i^q\widetilde{\beta}_{ist}^{D}\right] - 2\mathbb{E}_{m,st}\left[P_{ist}\beta_i^q\widetilde{\beta}_{ist}^{D}\right] \\
&\qquad\qquad - (1-C_{st})\mathbb{E}_{m,st}\left[\beta_i^q\right]\mathbb{E}_{m,st}\left[\widetilde{\beta}_{ist}^{D}\right]\Bigg\}.
\end{aligned}
$$

Adding and subtracting $\mathbb{E}_{m,st}[\beta_i^q]\mathbb{E}_{m,st}[\widetilde{\beta}_{ist}^{D}]$ inside the braces yields

$$
\begin{aligned}
\frac{\partial \eta_{st}^{q,0}}{\partial D_{st}} = &\underbrace{(1-C_{st})\,\mathrm{Cov}_{m,st}\left(\beta_i^q, \widetilde{\beta}_{ist}^{D}\right)}_{\text{Preference alignment}} \\
&+ \underbrace{(1-C_{st})\left[C_{st}\mathbb{E}_{m,st}\left[\beta_i^q\right]\mathbb{E}_{m,st}\left[\widetilde{\beta}_{ist}^{D}\right] - 2\mathbb{E}_{m,st}\left[P_{ist}\beta_i^q\widetilde{\beta}_{ist}^{D}\right]\right]}_{\text{Choice-probability reweighting}},
\end{aligned}
$$

which is equation (20).

Having established the decomposition of the composition-fixed channel, I now turn to the remaining derivatives required to obtain the total semi-elasticities. The choice-probability derivatives with respect to school composition are

$$
\frac{\partial p_{ist}}{\partial \overline{W}_{st}} = (\beta_i^W + \beta_i^{DW} D_{st})\, p_{ist}(1-p_{ist})
$$

$$
\frac{\partial p_{ilt}}{\partial \overline{W}_{st}} = -(\beta_i^W + \beta_i^{DW} D_{st})\, p_{ist} p_{ilt} \quad \forall l \neq s
$$

As for the total derivative of $\overline{W}_{st}$ over q_{st} or D_{st}, it proves useful to rewrite $\overline{W}_{st}$ as

$$
\overline{W}_{st} = \frac{E_{st}^{WH} + E_{st}^{WL}}{E_{st}^{WH} + E_{st}^{WL} + E_{st}^{BH} + E_{st}^{BL}}
$$

where $\{WH, WL, BH, BL\}$ denote the four observable types for which heterogeneous preferences are estimated (W and B denote white and nonwhite, respectively, while L and H stand for economically disadvantaged and not economically disadvantaged). Then,

$$
\frac{d\overline{W}_{st}}{dq_{st}} = \sum_{z\in\{WH,WL,BH,BL\}} \frac{\partial \overline{W}_{st}}{\partial E_{st}^{z}} \frac{dE_{st}^{z}}{dq_{st}} = \sum_{z\in\{WH,WL,BH,BL\}} \kappa_{st}^{z} \frac{dE_{st}^{z}}{dq_{st}}
$$

and

$$\frac{d\overline{W}_{st}}{dD_{st}} = \sum_{z\in\{WH,WL,BH,BL\}} \frac{\partial \overline{W}_{st}}{\partial E^z_{st}} \frac{dE^z_{st}}{dD_{st}} = \sum_{z\in\{WH,WL,BH,BL\}} \kappa^z_{st} \frac{dE^z_{st}}{dD_{st}}$$

where

$$\kappa^{WH}_{st} = \kappa^{WL}_{st} = \frac{E^{BH}_{st} + E^{BL}_{st}}{E^2_{st}}$$

and

$$\kappa^{BH}_{st} = \kappa^{BL}_{st} = -\frac{E^{WH}_{st} + E^{WL}_{st}}{E^2_{st}}$$

A.1 Solving for the Total Derivatives of Enrollment with respect to q_{st} and D_{st}

In this subsection I derive the total derivative of enrollment with respect to academic quality. The formulae for classroom segregation are analogous.

For each school s in year t, equation (17) implies the following system of four equations

$$\frac{\partial E^{WH}_{st}}{\partial q_{st}} = \frac{dE^{WH}_{st}}{dq_{st}}\left(1 - \frac{\partial E^{WH}_{st}}{\partial \overline{W}_{st}}\kappa^{WH}_{st}\right) - \sum_{l\neq s}\left(\frac{\partial E^{WH}_{st}}{\partial \overline{W}_{lt}}\kappa^{WH}_{lt}\right)\frac{dE^{WH}_{lt}}{dq_{st}} - \sum_j \left(\frac{\partial E^{WH}_{st}}{\partial \overline{W}_{jt}}\kappa^{WL}_{jt}\right)\frac{dE^{WL}_{jt}}{dq_{st}} - \sum_j \left(\frac{\partial E^{WH}_{st}}{\partial \overline{W}_{jt}}\kappa^{BH}_{jt}\right)\frac{dE^{BH}_{jt}}{dq_{st}} - \sum_j \left(\frac{\partial E^{WH}_{st}}{\partial \overline{W}_{jt}}\kappa^{BL}_{jt}\right)\frac{dE^{BL}_{jt}}{dq_{st}}$$

$$\frac{\partial E^{WL}_{st}}{\partial q_{st}} = -\sum_j \left(\frac{\partial E^{WL}_{st}}{\partial \overline{W}_{jt}}\kappa^{WH}_{jt}\right)\frac{dE^{WH}_{jt}}{dq_{st}} + \frac{dE^{WL}_{st}}{dq_{st}}\left(1 - \frac{\partial E^{WL}_{st}}{\partial \overline{W}_{st}}\kappa^{WL}_{st}\right) - \sum_{l\neq s}\left(\frac{\partial E^{WL}_{st}}{\partial \overline{W}_{lt}}\kappa^{WL}_{lt}\right)\frac{dE^{WL}_{lt}}{dq_{st}} - \sum_j \left(\frac{\partial E^{WL}_{st}}{\partial \overline{W}_{jt}}\kappa^{BH}_{jt}\right)\frac{dE^{BH}_{jt}}{dq_{st}} - \sum_j \left(\frac{\partial E^{WL}_{st}}{\partial \overline{W}_{jt}}\kappa^{BL}_{jt}\right)\frac{dE^{BL}_{jt}}{dq_{st}}$$

$$\frac{\partial E^{BH}_{st}}{\partial q_{st}} = -\sum_j \left(\frac{\partial E^{BH}_{st}}{\partial \overline{W}_{jt}}\kappa^{WH}_{jt}\right)\frac{dE^{WH}_{jt}}{dq_{st}} - \sum_j \left(\frac{\partial E^{BH}_{st}}{\partial \overline{W}_{jt}}\kappa^{WL}_{jt}\right)\frac{dE^{WL}_{jt}}{dq_{st}} + \frac{dE^{BH}_{st}}{dq_{st}}\left(1 - \frac{\partial E^{BH}_{st}}{\partial \overline{W}_{st}}\kappa^{BH}_{st}\right) - \sum_{l\neq s}\left(\frac{\partial E^{BH}_{st}}{\partial \overline{W}_{lt}}\kappa^{BH}_{lt}\right)\frac{dE^{BH}_{lt}}{dq_{st}} - \sum_j \left(\frac{\partial E^{BH}_{st}}{\partial \overline{W}_{jt}}\kappa^{BL}_{jt}\right)\frac{dE^{BL}_{jt}}{dq_{st}}$$

$$\frac{\partial E_{st}^{BL}}{\partial q_{st}} = -\sum_j \left(\frac{\partial E_{st}^{BL}}{\partial \overline{W}_{jt}} \kappa_{jt}^{WH}\right) \frac{dE_{jt}^{WH}}{dq_{st}} - \sum_j \left(\frac{\partial E_{st}^{BL}}{\partial \overline{W}_{jt}} \kappa_{jt}^{WL}\right) \frac{dE_{jt}^{WL}}{dq_{st}} - \sum_j \left(\frac{\partial E_{st}^{BL}}{\partial \overline{W}_{jt}} \kappa_{jt}^{BH}\right) \frac{dE_{jt}^{BH}}{dq_{st}}$$
$$+ \frac{dE_{st}^{BL}}{dq_{st}} \left(1 - \frac{\partial E_{st}^{BL}}{\partial \overline{W}_{st}} \kappa_{st}^{BL}\right) - \sum_{l \neq s} \left(\frac{\partial E_{st}^{BL}}{\partial \overline{W}_{lt}} \kappa_{lt}^{BL}\right) \frac{dE_{lt}^{BL}}{dq_{st}}$$

For every school s in year t, this system of equations can be rewritten in matrix form as

$$P_{st} = C_t T_{st}$$

where

$$P_{st}^{'} = \left[\tilde{P}_{1st}^{'}, \tilde{P}_{2st}^{'}, ..., \tilde{P}_{S-1,st}^{'}, \tilde{P}_{Sst}^{'}\right]$$

and

$$\tilde{P}_{lst}^{'} = \left[\frac{\partial E_{lt}^{WH}}{\partial q_{st}}, \frac{\partial E_{lt}^{WL}}{\partial q_{st}}, \frac{\partial E_{lt}^{BH}}{\partial q_{st}}, \frac{\partial E_{lt}^{BL}}{\partial q_{st}}\right]$$

$$T_{st}^{'} = \left[\tilde{T}_{1st}^{'}, \tilde{T}_{2st}^{'}, ..., \tilde{T}_{S-1,st}^{'}, \tilde{T}_{Sst}^{'}\right]$$

and

$$\tilde{T}_{lst}^{'} = \left[\frac{dE_{lt}^{WH}}{dq_{st}}, \frac{dE_{lt}^{WL}}{dq_{st}}, \frac{dE_{lt}^{BH}}{dq_{st}}, \frac{dE_{lt}^{BL}}{dq_{st}}\right]$$

$$C_t = \begin{bmatrix} C_t^{11} & \cdots & C_t^{1s} & \cdots & C_t^{1S} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ C_t^{s1} & \cdots & C_t^{ss} & \cdots & C_t^{sS} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ C_t^{S1} & \cdots & C_t^{Ss} & \cdots & C_t^{SS} \end{bmatrix}$$

where for any school s

$$C_t^{ss} = \begin{bmatrix} \left(1 - \frac{\partial E_{st}^{WH}}{\partial \overline{W}_{st}} \kappa_{st}^{WH}\right) & -\frac{\partial E_{st}^{WH}}{\partial \overline{W}_{st}} \kappa_{st}^{WL} & -\frac{\partial E_{st}^{WH}}{\partial \overline{W}_{st}} \kappa_{st}^{BH} & -\frac{\partial E_{st}^{WH}}{\partial \overline{W}_{st}} \kappa_{st}^{BL} \\ -\frac{\partial E_{st}^{WL}}{\partial \overline{W}_{st}} \kappa_{st}^{WH} & \left(1 - \frac{\partial E_{st}^{WL}}{\partial \overline{W}_{st}} \kappa_{st}^{WL}\right) & -\frac{\partial E_{st}^{WL}}{\partial \overline{W}_{st}} \kappa_{st}^{BH} & -\frac{\partial E_{st}^{WL}}{\partial \overline{W}_{st}} \kappa_{st}^{BL} \\ -\frac{\partial E_{st}^{BH}}{\partial \overline{W}_{st}} \kappa_{st}^{WH} & -\frac{\partial E_{st}^{BH}}{\partial \overline{W}_{st}} \kappa_{st}^{WL} & \left(1 - \frac{\partial E_{st}^{BH}}{\partial \overline{W}_{st}} \kappa_{st}^{BH}\right) & -\frac{\partial E_{st}^{BH}}{\partial \overline{W}_{st}} \kappa_{st}^{BL} \\ -\frac{\partial E_{st}^{BL}}{\partial \overline{W}_{st}} \kappa_{st}^{WH} & -\frac{\partial E_{st}^{BL}}{\partial \overline{W}_{st}} \kappa_{st}^{WL} & -\frac{\partial E_{st}^{BL}}{\partial \overline{W}_{st}} \kappa_{st}^{BH} & \left(1 - \frac{\partial E_{st}^{BL}}{\partial \overline{W}_{st}} \kappa_{st}^{BL}\right) \end{bmatrix}$$

and for any pair of schools (s, l)

$$C_t^{sl} = \begin{bmatrix} -\frac{\partial E_{st}^{WH}}{\partial \overline{W}_{lt}} \kappa_{lt}^{WH} & -\frac{\partial E_{st}^{WH}}{\partial \overline{W}_{lt}} \kappa_{lt}^{WL} & -\frac{\partial E_{st}^{WH}}{\partial \overline{W}_{lt}} \kappa_{lt}^{BH} & -\frac{\partial E_{st}^{WH}}{\partial \overline{W}_{lt}} \kappa_{lt}^{BL} \\ -\frac{\partial E_{st}^{WL}}{\partial \overline{W}_{lt}} \kappa_{lt}^{WH} & -\frac{\partial E_{st}^{WL}}{\partial \overline{W}_{lt}} \kappa_{lt}^{WL} & -\frac{\partial E_{st}^{WL}}{\partial \overline{W}_{lt}} \kappa_{lt}^{BH} & -\frac{\partial E_{st}^{WL}}{\partial \overline{W}_{lt}} \kappa_{lt}^{BL} \\ -\frac{\partial E_{st}^{BH}}{\partial \overline{W}_{lt}} \kappa_{lt}^{WH} & -\frac{\partial E_{st}^{BH}}{\partial \overline{W}_{lt}} \kappa_{lt}^{WL} & -\frac{\partial E_{st}^{BH}}{\partial \overline{W}_{lt}} \kappa_{lt}^{BH} & -\frac{\partial E_{st}^{BH}}{\partial \overline{W}_{lt}} \kappa_{lt}^{BL} \\ -\frac{\partial E_{st}^{BL}}{\partial \overline{W}_{lt}} \kappa_{lt}^{WH} & -\frac{\partial E_{st}^{BL}}{\partial \overline{W}_{lt}} \kappa_{lt}^{WL} & -\frac{\partial E_{st}^{BL}}{\partial \overline{W}_{lt}} \kappa_{lt}^{BH} & -\frac{\partial E_{st}^{BL}}{\partial \overline{W}_{lt}} \kappa_{lt}^{BL} \end{bmatrix}$$

The vector of total derivatives T_{st} can then be solved for as

$$T_{st} = C_t^{-1} P_{st}$$

B Estimation Details

B.1 Value-Added Estimation

Sample and baseline achievement: The estimation sample contains students in grades three and four with valid current and baseline math and reading scores, a single school of enrollment, an unambiguous current grade, and a valid teacher link. For third graders, baseline achievement is measured using the beginning-of-third-grade assessments. For fourth graders, it is measured using the end-of-grade assessments from the preceding calendar year; the student records are explicitly required to be consecutive across those years. For CMS, third graders' pretest scores can rarely be linked to their end-of-grade records in 1997–1998 and 1998–1999: the file providing the pretests contains no CMS records for the first year and uses a different student identifier format for CMS third graders in the second. CMS value added in these two years therefore draws on few or no third graders.

Controls and missing values: In addition to the controls summarized in the main text, the specification includes school-grade and classroom size, indicators for missing individual characteristics, and interactions between each individual characteristic and the corresponding measure of classroom composition. Parental education and ethnicity enter categorically, with missing values retained as separate categories. Missing values of the remaining characteristics are set to zero and accompanied by missing-value indicators. For the race-specific value-added estimates and descriptive statistics, students with missing ethnicity are included in the nonwhite category.

Purging out student sorting and the productive returns to homogeneous classrooms: Following the literature, the specification flexibly controls for own, school, and classroom-average lagged achievement so as to minimize potential bias from student sorting across schools and classrooms (Chetty et al., 2014; Deming, 2014; Angrist et al., 2017, 2024). Classroom controls are also intended to purge out classroom peer effects implied by the level of classroom segregation chosen by the school.

Purging out classroom peer effects and, more generally, the productive returns to homogeneous classrooms is important because the structural model treats classroom segregation and academic quality as distinct dimensions that are not mechanically linked through the education production function. Beyond peer effects, two additional channels could make classroom segregation and academic quality technologically related: a "teaching to the level" effect (Duflo et al., 2011), and the assignment of teachers to classrooms.

As for the former, because race and achievement are correlated, segregated classrooms may generate learning gains by increasing homogeneity in the optimal pace of instruction (Duflo et al., 2011). To purge this component from estimated value added, the classroom-level controls are interacted with individual characteristics, including race. These controls have a negligible impact on estimated school value added.

The value added estimated from equation (3) could still be technologically related to classroom composition if schools assign teachers to classrooms based on teachers' comparative advantage in teaching either racial group (Ahn et al., 2025; Aucejo et al., 2022; Lim and Meer, 2017, 2020). Appendix Figure D.6, however, shows no evidence that schools respond to competition by increasingly assigning teachers to classrooms based on relative effectiveness. This makes such teacher-classroom sorting unlikely to account for the learning effects associated with schools' competitive responses.

Classroom controls: For the years of interest, fewer than half of students can be matched with confidence to actual classroom rosters. I therefore compute classroom controls using

pseudo-classrooms, defined as groups of students who take the end-of-grade standardized test under the supervision of the same listed proctor (North Carolina Education Research Data Center, 2012, 2025; Hanselman, 2018). This information is available for nearly all students, and the distribution of *pseudo*-classroom sizes is similar to the class size distribution observed in the classroom-level data. Because students enrolled in different sections may share the same exam proctor, however, these groups may measure classrooms with error. Reassuringly, excluding classroom controls yields value-added estimates that correlate almost perfectly with those obtained using *pseudo*-classroom controls; a similar conclusion is reached when validated proctor links are used to partially reconstruct classroom groups.

Shrinkage: Following the literature (Kane and Staiger, 2008; Gilraine et al., 2025), I shrink the value added estimated from equation (3) toward zero to minimize mean squared prediction error (Morris, 1983). Formally, the value-added estimator is

$$q_{st} = \tilde{q}_{st} \frac{\sigma_q^2}{\sigma_q^2 + \left(\frac{\sigma_\epsilon^2}{N_{st}}\right)},$$

where $\tilde{q}_{st}$ is the school-by-year fixed effect in equation (3), N_{st} is the number of students in school s and year t, σ_ϵ^2 is the student-level noise variance, and σ_q^2 is the variance of true school-year value added. The two variance components are recovered from the variance of the residualized student-level outcomes and the variance of their school-year means, and then plugged into the expression above.

B.2 Structural Estimation Details

Non-linear demand parameters (SML) This section provides implementation details for the simulated maximum likelihood estimation of θ_2, the vector of parameters that govern preference heterogeneity on the demand side. For each candidate θ_2, I first recover the mean utilities that rationalize schools' market shares in the data and then evaluate the simulated likelihood of individual enrollment choices. The estimator chooses θ_2 to maximize this likelihood.

I recover mean utilities using the standard BLP contraction mapping (Berry et al., 1995). Since mean utilities are identified only up to a market-specific additive constant, I normalize the mean utility of one school in each year to zero (Neilson, 2026; Allende, 2021). I invert mean utilities separately and sequentially across the two markets, warm-starting each contraction from its previous solution and using SQUAREM acceleration. The contraction is considered converged when the maximum difference between observed and predicted

market shares falls below 10^{-12} (Conlon and Gortmaker, 2020).

I compute the simulated probabilities by jointly integrating over random coefficients and unobserved residential locations. I use 500 equally weighted simulation draws. For each draw, the three random coefficients on school quality, classroom segregation, and school composition are generated from a three-dimensional scrambled Halton sequence. When a student's location is unobserved, the same simulation draw also selects a Census block group from the relevant residential distribution.

The NCERDC does not report residential addresses for CMS students before the 2006–2007 school year because Mecklenburg County is not represented in the Transportation Information Management System data before 2007 (North Carolina Education Research Data Center, 2019). Addresses are available from 2006–2007 onward, but I use only those first observed by 2008–2009 to limit the period over which I assume that students do not move. I therefore impute residential locations as follows. For 2004–2005, 84.1% of in-sample students have a CMS address first observed by 2008–2009: 82.5% of the sample are first observed in 2006–2007, 0.9% in 2007–2008, and 0.7% in 2008–2009. I assign these students to their earliest observed Census block group, assuming that they did not move in the intervening period. For the remaining 15.9%, I draw locations from demographic type-specific block-group distributions constructed using the 2000 Census. The four student types are race-by-socioeconomic-status and match those used to model observed preference heterogeneity; the corresponding Census distributions are based on race and poverty status. Using pre-reform residential densities limits the influence of residential resorting following the introduction of open enrollment. For 1999–2000, I proceed in three steps. First, for the 76.4% of students attending a non-magnet school represented in the 2000 boundary maps, I draw uniformly across the Census block groups that intersect the school's catchment area. Each intersecting block group receives equal probability, regardless of its population or the share of its area inside the catchment. This procedure follows directly from the pre-reform assignment regime: outside the magnet program, CMS assigned students to schools according to residential catchment areas, with out-of-catchment attendance allowed only in special circumstances. Magnet schools are excluded because attendance could instead arise through application and therefore was not a reliable signal of residence: CMS describes magnet admission as operating through an application lottery (Charlotte-Mecklenburg Schools, n.d.), while the Fourth Circuit's account explains that the magnet program relied on voluntarism and was intended in part to "attract more white youngsters into the inner city schools" (Belk v. Charlotte-Mecklenburg Board of Education,

2001, p. 44). Second, for students outside this group who have a CMS address first observed between 2006–2007 and 2008–2009, representing 15.2% of the sample, I assign the earliest observed block group, again assuming no residential move. Finally, for the remaining 8.4%, I use the same demographic type-specific 2000 Census distributions used for 2004–2005. Table E.4 reports the implied summary statistics.

I do not impose the rational expectations condition for school-level racial shares (equation (14)) in estimation. The parameter estimates minimize the average negative simulated log-likelihood based only on individual enrollment choices. Under this approach, observed racial shares need not coincide with those generated by the estimated model at equilibrium. A mechanical match would require either race-specific school-level demand unobservables or imposing the rational expectations condition as an additional hard constraint, beyond rationalizing individual choices and matching market shares perfectly. My preferred approach treats racial shares as an equilibrium object implied by the demographic-specific preferences identified from individual choices. I then compare observed racial shares with those generated when I compute the equilibrium at the estimated parameters. Model fit is shown in Section 6.2. As a robustness check, augmenting the estimation criterion with a penalty for violations of the rational expectations condition produces qualitatively similar results. The penalized estimates imply greater unobserved heterogeneity in preferences for classroom segregation, but yield similar model fit and equilibrium outcomes when evaluated holding the linear demand and supply parameters fixed.

I minimize the resulting criterion using a quasi-Newton algorithm with analytical gradients and a first-order optimality tolerance of 10^{-6}.

Linear demand and supply parameters (GMM) The demand specification includes a constant and the change in magnet status as included instruments. The excluded instruments for changes in academic quality build on the neighborhood share of college graduates, which enters a leave-one-school-out prediction of the change in quality together with correlated baseline demographic characteristics (the Black share, household size, median income, and housing prices) and pre-reform traffic exposure. Household size and housing prices also enter separately. A second source of variation in quality is the Equity Plus eligibility discontinuity, which shifts the resources schools have for producing quality: the Equity Plus program provided extra resources to schools in which more than 66% of students were low-income (Appendix Figure D.7).[37] Average daycare quality near the school provides

[37] In April 2001, the CMS Board of Education resolved to "support the Superintendent's implementation of the *Achieving the CMS Vision: Equity and Student Success* framework (the 'Equity Plan', adopted by the

an additional supply-side shifter, which can affect the cost of adjusting academic quality through local teacher supply. The instruments for classroom segregation instead build on the baseline Republican vote share, which enters directly as a predictor of schools' segregation responses, and on a model-predicted change in classroom segregation obtained with the structural shocks set to zero, in the spirit of Chamberlain (1987). To separate preferences for classroom segregation, school racial composition, and their interaction, these segregation shifters are combined with changes in racial composition generated by the redrawing of attendance boundaries or predicted by the model with structural shocks set to zero. The selected instruments include interactions of the Republican vote share and daycare quality with these composition shifters, the squared model-predicted change in racial composition, and a rival-based differentiation instrument, in the spirit of Gandhi and Houde (2019), that combines cross-school differences in baseline classroom segregation with differences in racial composition. Together, these direct, interaction, and nonlinear sources of variation separately identify the preference parameters governing preferences over classroom peers.

The supply instrument is likewise a rival-based measure of baseline market differentiation in classroom segregation, in the spirit of Gandhi and Houde (2019); the exclusion restriction is that this predetermined measure is orthogonal to within-school innovations over time in unobserved cost shocks.

B.3 Computing The Model Equilibrium

Algorithm 1 illustrates how I solve for an equilibrium of the model in a given period. The input is a guess for each school's academic quality, classroom segregation, and share of white students at the school level. The algorithm comprises an outer fixed point and an inner fixed point. In each iteration of the outer fixed point, I simultaneously update the vectors of academic quality and classroom segregation using the first-order conditions derived from the school problem (equations (15) and (16)), projecting classroom segregation directly onto the interval between 0 and 1. In all simulations, I also cap each school's enrollment at 550 students, approximately the enrollment of the largest observed school in the post-reform

Board in March 1999) (...) to attain the goal of raising the academic achievement of all students." The Equity Plan provided high-poverty schools, designated as Equity Plus schools, with extra resources such as additional teachers, teacher bonuses, and bond funds for renovation. Specifically, the Board mandated a template that would systematically specify and record "what teacher qualifications, differentiated staffing, curriculum, and instruction, support staff (e.g. parent/family advocates, social workers, psychologists, nurses, speech pathologists, mentor teachers), material and supplies will be assigned and/or available to those [i.e., Equity Plus] schools" (Board Resolution 2002–2003, retrieved from the CMS website via the Wayback Machine; last accessed November 30, 2022).

period. This constraint is consequential for one school that, in the baseline equilibrium, offers a particularly attractive combination of characteristics to nonwhite students and would otherwise grow to an implausibly large size. When the constraint binds, the algorithm incorporates the corresponding multiplier and complementary slackness conditions into the school's first-order conditions. Within each iteration of the outer loop, the inner loop solves for the vector of school racial shares consistent with the current vectors of academic quality and classroom segregation. These shares are computed using the fixed-point equation (14). The inner loop is necessary because households' choices depend on schools' expected racial composition, which in turn depends on households' choices. The algorithm terminates when the updates to academic quality and classroom segregation, the corresponding first-order and KKT conditions, and the fixed-point condition for racial composition satisfy their respective convergence criteria.

Initial guess: $\{q_t^0, D_t^0, W_t^{0,0}\}$
for $r = 0, 1, ..., R$
while $||q_t^{r+1} - q_t^r||_\infty > \epsilon^q$ *or* $||D_t^{r+1} - D_t^r||_\infty > \epsilon^D$ **do**
  for $\psi = 0, 1, ..., \Psi_r$
  while $||W_t^{r,\psi+1} - W_t^{r,\psi}||_\infty > \epsilon^W$ **do**
    Compute matrix of individual enrollment probabilities $p_t^{r,\psi+1}$ as function of $(q_t^r, D_t^r, W_t^{r,\psi})$
    Compute $W_t^{r,\psi+1}$ using equation (14)
  end
  Compute q_t^{r+1} as function of $(q_t^r, D_t^r, W_t^{r,\Psi_r})$ using equation (15)
  Compute D_t^{r+1} as function of $(q_t^r, D_t^r, W_t^{r,\Psi_r})$ using equation (16)
  W_t^{r,Ψ_r} becomes $W_t^{r+1,0}$
end
Result: $\{q_t^R, D_t^R, W_t^{R,\Psi_R}\}$ (simulated data)

Algorithm 1: Solving for time-t equilibrium

Multiple equilibria are theoretically possible in this model through both demand and supply. On the demand side, social interactions can generate multiple self-consistent patterns of household sorting (Brock and Durlauf, 2005). On the supply side, schools simultaneously choose academic quality and classroom segregation in a nonlinear game, and the model does not impose restrictions on own- and cross-school payoff derivatives sufficient to guarantee a unique equilibrium (Rosen, 1965). I assess the practical relevance of multiplicity by solving the model from several initial conditions and find no evidence of multiple equilibria.

C Data Sources

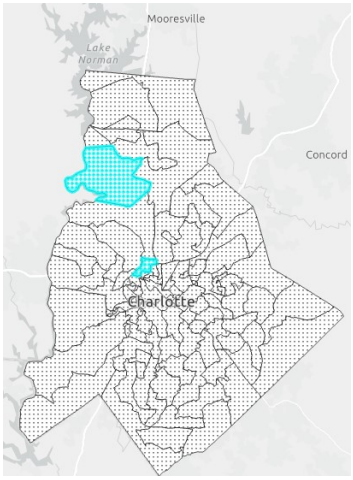
The student, classroom, school, and personnel records used throughout the analysis come from the North Carolina Education Research Data Center (North Carolina Education Research Data Center, 1995–2017). School attendance boundaries, magnet status, and Equity Plus eligibility come from contemporaneous CMS maps and administrative records. The residential distributions used to impute missing student locations draw on poverty-by-race counts from the 2000 Census obtained through IPUMS NHGIS (Schroeder et al., 2026).

The neighborhood measures used to construct the instruments combine several external sources. Race, educational attainment, household size, and median income come from the 2000 Census Summary Files 1 and 3 (U.S. Census Bureau, 2001, 2002). Precinct-level returns for the 2000 election come from the North Carolina files distributed by the Harvard Election Data Archive (Ansolabehere and Rodden, 2012). Baseline housing values use the Zillow Home Value Index (Zillow Research, n.d.); traffic exposure uses historical annual average daily traffic counts from the North Carolina Department of Transportation (North Carolina Department of Transportation, n.d.); and daycare quality uses the North Carolina Division of Child Development and Early Education's list of facilities with star-rated licenses (North Carolina Division of Child Development and Early Education, 2006). These inputs are aggregated over the neighborhoods surrounding each school as described in the instrument construction.

Historical basis for the political proxy. Republican vote share is an imperfect proxy because positions on racial assignment in CMS were not purely partisan. Lassiter (2004, p. 580) argues that the city's "color-blind" suburban politics overlapped with Republican conservatism but extended beyond its right-wing base. Nevertheless, desegregation was highly salient in the 1999 school-board election, when advocates of neighborhood schools challenged race-based assignment. Republican candidates ran with explicit party support, and support during the 2001 assignment-plan conflict varied with precinct partisan composition (Smith, 2004, pp. 179, 181–182, 202). Although this evidence concerns assignment across schools, within-school grouping could provide a related margin: even when busing produced substantial racial balance between schools, CMS retained considerable racially correlated tracking within schools (Smith, 2004, pp. 4, 81–83).

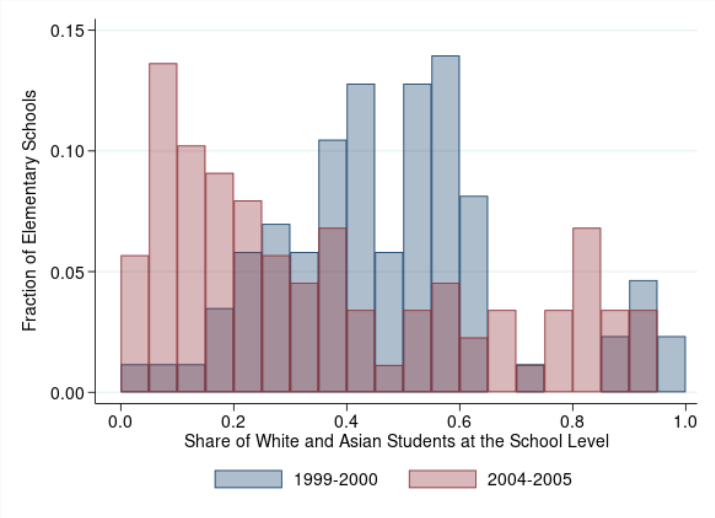
D Additional Figures

Figure D.1: Example of a satellite zone under mandatory busing



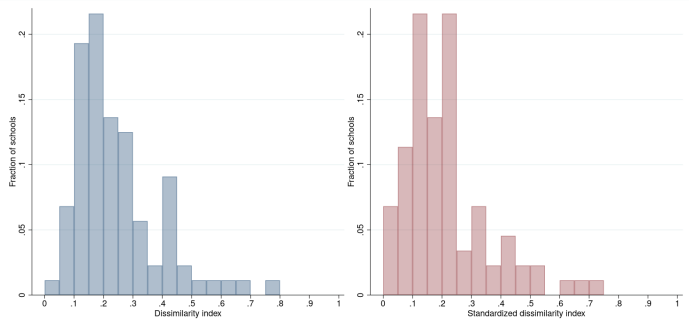
Notes: The map shows CMS elementary-school catchment areas in 1999–2000. Light blue marks the Long Creek Elementary zone; students in the small urban "satellite" zone were bused to this northern suburb. After busing ended and choice began in fall 2002, Long Creek's white enrollment share rose from 57% to 76%.

Figure D.2: Distribution of white student shares at the school level before and after the reform



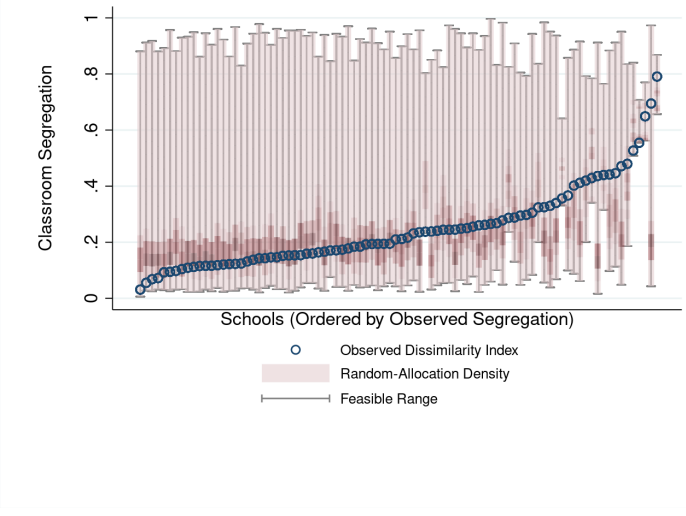
Notes: The figure plots white or Asian enrollment shares across CMS elementary schools in the structural sample in 1999–2000 and 2004–2005, using school-level CCD membership counts. Bins are five percentage points wide; heights report the fraction of schools in each bin.

Figure D.3: Distribution of raw and standardized dissimilarity



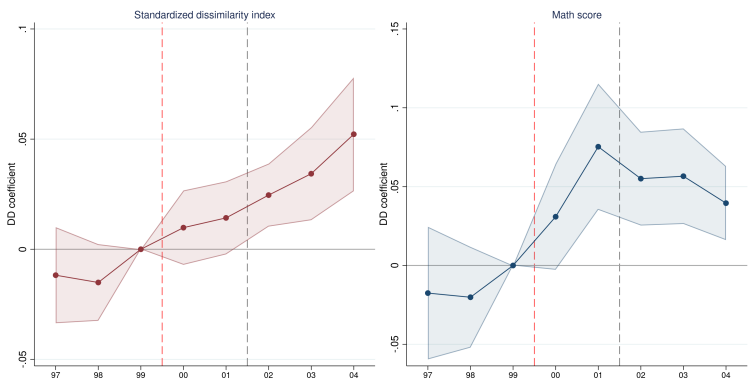
Notes: The figure uses the CMS sample for the 2004–2005 academic year. It shows the distributions of classroom segregation across schools in the sample. The left panel reports the standard index of dissimilarity computed from the data using equation (1). The right panel reports the standardized measure of classroom segregation, defined as the fraction of the feasible range attained by each school according to equation (2). Segregation measures are averaged across grades 1–4.

Figure D.4: Observed classroom segregation relative to random-allocation density across schools



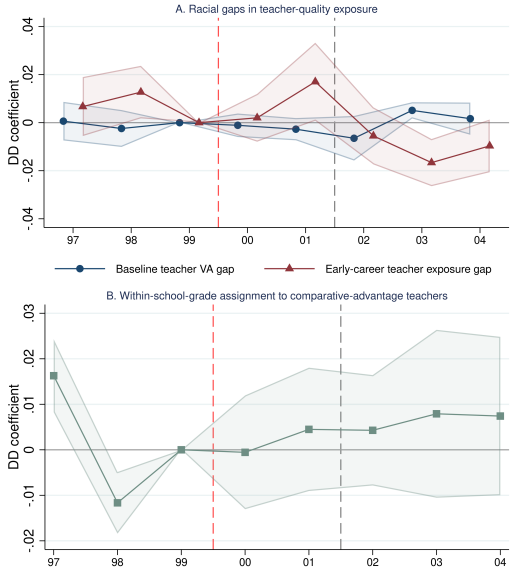
Notes: The figure uses the CMS sample for the 2004–2005 academic year. Each bar corresponds to a school in the sample. The lower and upper whiskers indicate the minimum and maximum feasible levels of classroom segregation given the school's student-body composition and class-size distribution. Navy dots show the standard index of dissimilarity computed from the data using equation (1). The maroon-shaded densities show the distribution of dissimilarity indices obtained from 1000 simulated random allocations of students across classrooms within each school, holding student-body composition and class sizes fixed. Segregation measures are averaged across grades 1–4.

Figure D.5: Competitive responses on alternative measures of within-school segregation and academic quality



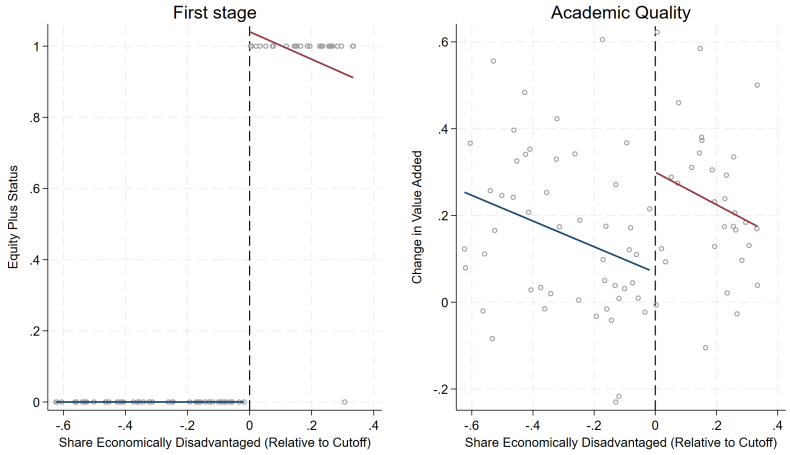
Notes: Estimates of specification (4). The control group includes elementary schools in districts with pre-reform total enrollment above the 90th percentile of the state distribution. The dependent variable is the standardized Duncan index of dissimilarity (2) in the left panel and average math scores in the right panel. Shaded areas are 90% confidence intervals; standard errors are clustered at the district level.

Figure D.6: No differential change in teacher quality or match quality around the reform



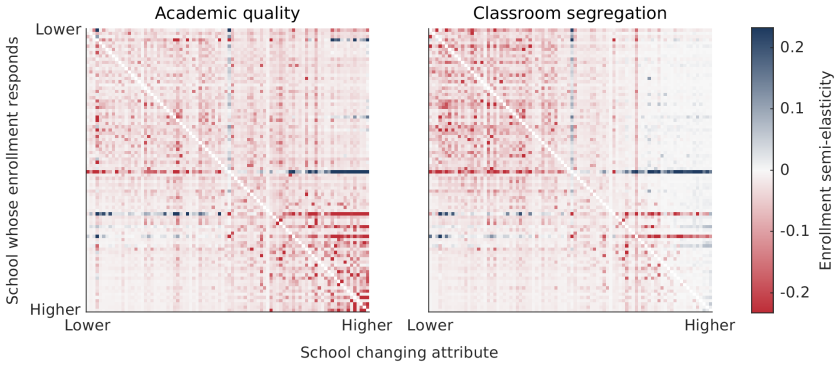
Notes: Panel A reports school-year event-study estimates analogous to specification (4) for white-minus-nonwhite gaps in exposure to teachers' pre-reform value added and to early-career teachers (those within five calendar years of first public-school employment). Panel B reports student-level event-study estimates, with school-by-grade-by-year fixed effects, for assignment to teachers whose pre-reform race-specific value added implies above-median comparative advantage for white students; the result is qualitatively similar using the continuous measure after dropping teachers with fewer than ten baseline white or nonwhite students, or after additionally winsorizing it at the first and ninety-ninth percentiles. Teacher links use the EOG teacher identifier (Appendix Section B.1). School-year outcomes use the main event-study sample. Shaded areas are 90% confidence intervals; standard errors are clustered at the district level.

Figure D.7: Value-added gains at the Equity Plus eligibility threshold



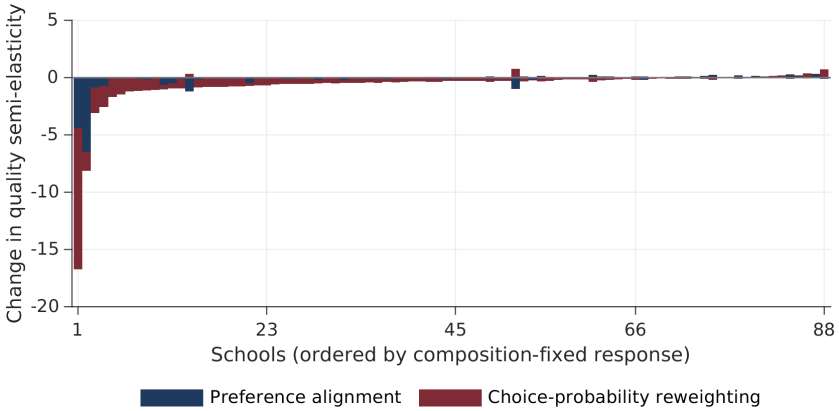
Notes: Equity Plus provided additional resources to CMS schools in which more than 66% of students were economically disadvantaged (Appendix Section B.2). The running variable is the school-level share of economically disadvantaged students in 2003, centered at the Equity Plus eligibility cutoff. The left panel shows the first-stage relationship between the running variable and Equity Plus designation. The right panel shows the relationship between the running variable and the change in school value added between 1999–2000 and 2004–2005. The vertical dashed line marks the eligibility cutoff, and the solid lines are separate linear fits on either side of the cutoff.

Figure D.8: Schools compete most strongly with schools of similar racial composition



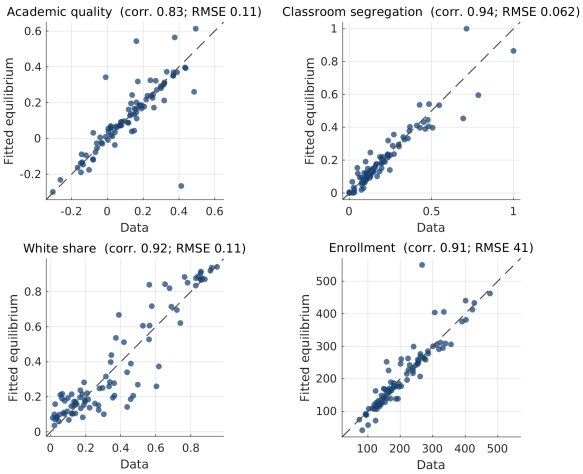
Notes: The figure reports model-implied cross-school enrollment responses in the post-reform market (2004–2005). Each cell gives the total semi-elasticity of enrollment at the school indexed by the row with respect to the indicated attribute at the school indexed by the column: academic quality in the left panel and classroom segregation in the right panel. Total responses incorporate both the direct demand response and the indirect response operating through endogenous changes in racial composition across schools. Schools are ordered from lower to higher observed white share along both axes. Red cells indicate that increasing the attribute at the column school reduces enrollment at the row school; blue cells indicate that it increases enrollment there. Own-school responses are omitted, producing the blank diagonal. Both panels use a common color scale, capped at the pooled 99th percentile of the absolute cross-school responses to limit the influence of extreme values.

Figure D.9: Segregation reduces responsiveness to quality



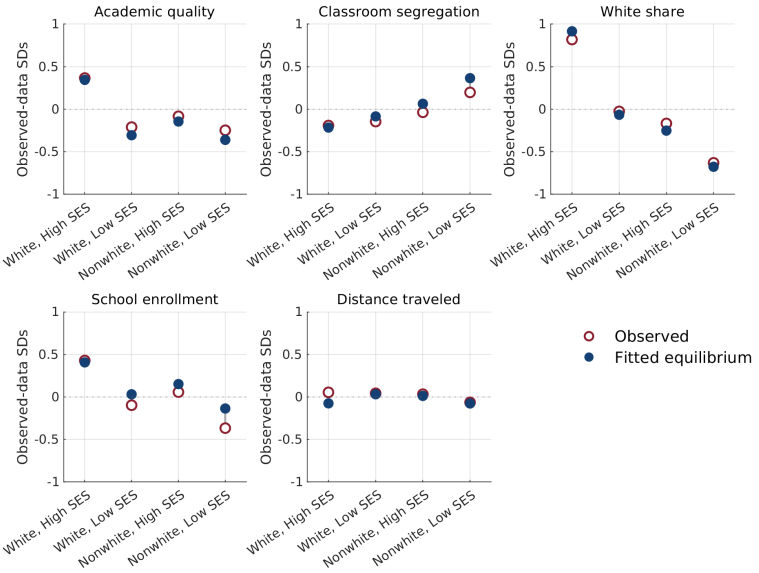
Notes: The figure decomposes the model-implied derivative of each school's composition-fixed enrollment semi-elasticity with respect to academic quality, $\eta_s^{q,0}$, with respect to its own classroom segregation, D_s, as defined in equation (19). Each bar represents a school in the post-reform market (2004–2005) and is the sum of two components. The preference alignment component captures how the response depends on the association between students' preferences for academic quality and classroom segregation among students marginal to the school. The choice-probability reweighting component captures how classroom segregation changes the degree to which the school's enrollment is contested, through students' baseline choice probabilities. Schools are ordered by the sum of the two components. School racial composition is held fixed; the figure therefore excludes responses operating through endogenous changes in racial composition across schools.

Figure D.10: Model fit: post-reform levels



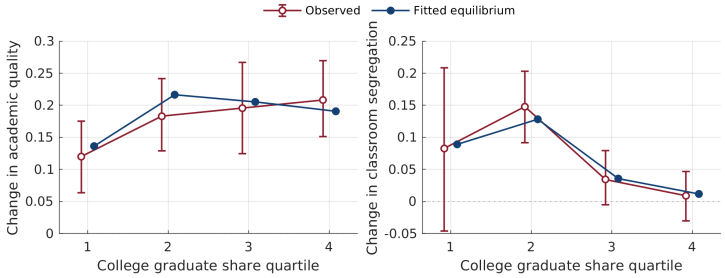
Notes: The figure compares school outcomes in the data with those generated by the model in the post-reform equilibrium. Each point represents one school. The horizontal axis reports the observed value, and the vertical axis reports the corresponding value in the model. The dashed 45-degree line denotes exact fit. Panel headings report the unweighted correlation and root mean squared error across schools.

Figure D.11: Model fit: post-reform outcomes by demographic group



Notes: The figure compares observed post-reform outcomes with those generated by the model in equilibrium for four student groups defined by race and socioeconomic status. Open circles report the data, and filled circles report the model. Lines connect the observed and model-generated values for each group. Academic quality, classroom segregation, white share, and school enrollment are averages across the schools attended by students in each group, weighted by group-specific enrollment. School enrollment is the average total enrollment of the schools attended by the indicated group. Distance traveled is the average distance between students' residences and the schools they attend, measured in miles before standardization. Each outcome is centered at its overall post-reform mean in the data and divided by its post-reform standard deviation in the data. The distance between the observed and model-generated markers measures the model's discrepancy for that group and outcome in observed-data standard deviations.

Figure D.12: Model fit: changes around the reform



Notes: The figure compares observed changes in schools' academic quality and classroom segregation with the changes predicted by the model between the pre- and post-reform equilibria. Schools are divided into equal-sized quartiles based on the college graduate share of the local area. Open maroon circles report the unweighted mean observed change among schools in each quartile; filled navy circles report the corresponding mean change predicted by the model. Vertical bars show 90 percent bootstrap confidence intervals for the observed means.

E Additional Tables

Table E.1: Summary statistics for the event-study estimation sample

	1997–1999		2000–2004		
Variable	CMS	Other	CMS	Other	Corr.
Value added	-0.090 (0.208)	-0.033 (0.184)	0.091 (0.184)	0.044 (0.184)	–
Dissimilarity index	0.153 (0.109)	0.201 (0.145)	0.207 (0.136)	0.210 (0.141)	–
White share (CCD)	0.491 (0.195)	0.563 (0.276)	0.404 (0.254)	0.516 (0.283)	0.964
Enrollment, gr. 1–4 (CCD)	396.9 (128.1)	393.5 (135.8)	412.5 (156.5)	374.0 (135.1)	0.928
Average class size	22.06 (2.05)	21.72 (2.48)	21.34 (2.56)	20.78 (2.68)	–
Observations (school-year)	253	871	415	1,516	

Notes: Means are reported with standard deviations in parentheses; "Other" denotes the comparison districts. The observation count is the common school-year sample used for the dissimilarity and value-added event studies. Enrollment is CCD membership in grades 1–4; the white share is measured from CCD school membership. The final column reports the correlation with the analogous classroom-record measure. For the white share, the correlation is computed on the full common event-study sample. For enrollment, it is computed only for school-years in which all four grades survive the classroom-segregation cleaning. Average class size is measured from the classroom records used to construct dissimilarity and excludes school-years outside the pooled 1st–99th percentile range. Value added is estimated from grades 3–4.

Table E.2: Difference-in-differences estimates for CMS relative to comparison districts

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Dissimilarity	Dissimilarity standardized	Value added	Math score	VA white students	VA nonwhite students
Treated × Post	0.042***	0.035***	0.097***	0.064***	0.092***	0.102***
	(0.010)	(0.007)	(0.010)	(0.017)	(0.011)	(0.014)
R-squared	0.764	0.555	0.659	0.858	0.644	0.590
N obs.	3055	3055	3055	3055	3030	3054
Baseline average	0.190	0.164	-0.0463	-0.0148	-0.0305	-0.0409

Notes: Each column reports the coefficient on CMS × Post from a difference-in-differences regression with school and year fixed effects. The control group includes elementary schools in districts with pre-reform total enrollment above the 90th percentile of the state distribution. Regressions control for distance to nearest charter school and an indicator for missing distance. Standard errors, clustered at the district level, are reported in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent levels.

Table E.3: Difference-in-differences estimates: Other dimensions of classroom grouping (student records; pseudo-classrooms)

	EOG-based segregation measures						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Race	Parent education	Test score median	Test score p25	Test score p75	Test score p10	Test score p90
Treated × Post	0.049***	0.047***	0.018**	0.011**	0.034**	0.007	0.019
	(0.010)	(0.010)	(0.008)	(0.004)	(0.012)	(0.009)	(0.013)
Observations	2,847	2,854	2,907	2,900	2,902	2,882	2,750
R-squared	0.696	0.592	0.560	0.539	0.588	0.571	0.630

Notes: Each column reports the coefficient on CMS × Post from the specification in Table E.2, with alternative Duncan dissimilarity indices computed across *pseudo*-classrooms within school-grade-year cells and averaged to the school-year level (see Appendix Section B.1). Unlike the main analysis, which uses complete classroom records, these indices rely on student-level records. *, **, and *** denote significance at the 10, 5, and 1 percent levels.

Table E.4: Summary statistics for estimation sample

	1999–2000	2004–2005
Students		
% White high-SES	43.35	35.91
% White low-SES	7.35	6.78
% Nonwhite high-SES	14.33	14.84
% Nonwhite low-SES	34.97	42.47
% Attending assigned school	77.51	50.19
Distance to school attended: Q1	1.33	1.26
Distance to school attended: Median	2.55	2.68
Distance to school attended: Q3	5.13	6.02
Number of students	16,902	18,628
Schools		
Estimated value added	-0.071 (0.177)	0.120 (0.175)
Classroom segregation	0.169 (0.135)	0.245 (0.159)
Fraction of feasible classroom segregation attained	0.154 (0.145)	0.217 (0.185)
Share of white students at the school level	0.471 (0.210)	0.367 (0.284)
Market share	0.012 (0.004)	0.011 (0.005)
Number of schools	86	88

Notes: Summary statistics for the structural estimation sample, by year. *Students panel*: computed on the full estimation sample. The attended school counts as consistent with a residential draw when its assignment share for that draw is positive. This indicator is averaged across residential draws using the student-specific weights from demand estimation; home–school distance percentiles (in miles) are computed using the same weights (Appendix Section B.2). *Schools panel*: means, with standard deviations in parentheses, for the schools in each market.

Table E.5: Demand and supply estimates

	Estimate	S.E.		Estimate	S.E.
A. Household preferences (Simulated maximum likelihood)					
White, Low SES: academic quality	-1.808	(0.208)	Log distance	-1.350	(0.018)
White, Low SES: segregation	-0.179	(0.403)	Log distance x Low SES	0.119	(0.017)
White, Low SES: white share	-2.382	(0.234)	Log distance x magnet	0.298	(0.019)
White, Low SES: segregation × white share	-1.321	(0.906)	Log distance x post x transportation	0.273	(0.012)
Nonwhite, High SES: academic quality	-0.200	(0.164)	Assigned school, pre-reform	6.676	(0.077)
Nonwhite, High SES: segregation	0.561	(0.308)	Assigned school, post-reform	2.406	(0.037)
Nonwhite, High SES: white share	-2.600	(0.182)	Random quality coefficient: mean	1.882	(0.284)
Nonwhite, High SES: segregation × white share	-2.899	(0.716)	Random quality coefficient: SD	3.708	(0.388)
Nonwhite, Low SES: academic quality	-1.065	(0.145)	Segregation coefficient: SD	2.295	(0.248)
Nonwhite, Low SES: segregation	0.924	(0.263)	White-share coefficient: SD	0.030	(0.088)
Nonwhite, Low SES: white share	-4.594	(0.162)	Correlation: segregation and white share	0.992	(0.047)
Nonwhite, Low SES: segregation × white share	-3.509	(0.619)			
B. School mean utility (GMM)					
Post-reform intercept	-1.957	(0.426)	White share	3.729	(2.000)
Academic quality	2.765	(1.557)	Segregation × white share	-6.162	(5.191)
Classroom segregation	4.924	(2.981)	Magnet school	1.001	(0.353)
C. School costs (GMM)					
Relative segregation cost, α/μ	7.271	(3.321)			
D. Recovered shocks					
Pre-reform	Mean	SD	*Post-reform*	Mean	SD
Demand shock, ξ	-0.175	1.376	Demand shock, ξ	-0.180	1.578
Quality-cost shifter, ω^q/μ	-0.576	0.447	Quality-cost shifter, ω^q/μ	-0.566	0.247
Segregation-cost shifter, ω^D/μ	-0.630	1.030	Segregation-cost shifter, ω^D/μ	-0.746	1.691

Notes: Standard errors are in parentheses. Panel A reports simulated maximum-likelihood estimates using 500 integration draws. Race-by-SES coefficients are deviations from white high-SES households. Random-coefficient moments describe unobserved components; mean quality preferences also include the linear quality coefficient and demographic deviations. SML standard errors use the Hessian–OPG sandwich formula with delta-method transformations. Panels B and C report GMM estimates; their standard errors condition on earlier-stage estimates without propagating their uncertainty. The supply standard error is HC1. Distance coefficients retain their estimated signs; transportation indicates free-transport eligibility. The relative cost parameter is $r = \alpha/\mu$, where α governs segregation cost curvature and μ scales quality costs. Panel D reports unweighted pre- and post-reform means and standard deviations across schools of ξ, ω^q/μ, and ω^D/μ, under $\psi/\mu = 1$.

References

Ahn, Tom, Esteban M. Aucejo, and Jonathan James (2025), "The importance of student-teacher matching: A multidimensional value-added approach." *Review of Economics and Statistics*. Forthcoming.

Allende, Claudia (2021), "Competition under social interactions and the design of education policies." *Stanford Graduate School of Business Working Paper*.

Angrist, Joshua, Peter Hull, Parag A. Pathak, and Christopher Walters (2024), "Credible school value-added with undersubscribed school lotteries." *The Review of Economics and Statistics*, 106, 1–19.

Angrist, Joshua D., Peter D. Hull, Parag A. Pathak, and Christopher R. Walters (2017), "Leveraging lotteries for school value-added: Testing and estimation." *The Quarterly Journal of Economics*, 132, 871–919.

Ansolabehere, Stephen and Jonathan Rodden (2012), "Harvard Election Data Archive."

Aucejo, Esteban, Patrick Coate, Jane Cooley Fruehwirth, Sean Kelly, and Zachary Mozenter (2022), "Teacher effectiveness and classroom composition: Understanding match effects in the classroom." *The Economic Journal*, 132, 3047–3064.

Belk v. Charlotte-Mecklenburg Board of Education (2001), "269 F.3d 305." United States Court of Appeals for the Fourth Circuit.

Berry, Steven, James Levinsohn, and Ariel Pakes (1995), "Automobile prices in market equilibrium." *Econometrica*, 63, 841–890.

Brock, William A. and Steven Durlauf (2005), "Multinomial choice with social interactions." In *The Economy as an Evolving Complex System III: Current Perspectives and Future Directions* (Lawrence E. Blume and Steven N. Durlauf, eds.), 175–206, Oxford University Press.

Chamberlain, Gary (1987), "Asymptotic efficiency in estimation with conditional moment restrictions." *Journal of Econometrics*, 34, 305–334.

Charlotte-Mecklenburg Schools (n.d.), "History of Charlotte-Mecklenburg Schools." Accessed September 19, 2026.

Chetty, Raj, John N. Friedman, and Jonah E. Rockoff (2014), "Measuring the impacts of teachers I: Evaluating bias in teacher value-added estimates." *American Economic Review*, 104, 2593–2632.

Conlon, Christopher and Jeff Gortmaker (2020), "Best practices for differentiated products demand estimation with PyBLP." *The RAND Journal of Economics*, 51, 1108–1161.

Deming, David J. (2014), "Using school choice lotteries to test measures of school effectiveness." *American Economic Review*, 104, 406–411.

Duflo, Esther, Pascaline Dupas, and Michael Kremer (2011), "Peer effects, teacher incentives, and the impact of tracking: Evidence from a randomized evaluation in Kenya." *American Economic Review*, 101, 1739–1774.

Gandhi, Amit and Jean-François Houde (2019), "Measuring substitution patterns in differentiated-products industries." *NBER Working Paper No. 26375*.

Gilraine, Michael, Uros Petronijevic, and John D. Singleton (2025), "School choice, competition, and aggregate school quality." *NBER Working Paper No. 31328*.

Hanselman, Paul (2018), "Do school learning opportunities compound or compensate for background inequalities? Evidence from the case of assignment to effective teachers." *Sociology of Education*, 91, 132–158.

Kane, Thomas J. and Douglas O. Staiger (2008), "Estimating teacher impacts on student achievement: An experimental evaluation." *NBER Working Paper No. 14607*.

Lassiter, Matthew D. (2004), "The suburban origins of 'color-blind' conservatism: Middle-class consciousness in the Charlotte busing crisis." *Journal of Urban History*, 30, 549–582.

Lim, Jaegeum and Jonathan Meer (2017), "The impact of teacher–student gender matches: Random assignment evidence from South Korea." *Journal of Human Resources*, 52, 979–997.

Lim, Jaegeum and Jonathan Meer (2020), "Persistent effects of teacher–student gender matches." *Journal of Human Resources*, 55, 809–835.

Morris, Carl N. (1983), "Parametric empirical Bayes inference: Theory and applications." *Journal of the American Statistical Association*, 78, 47–55.

Neilson, Christopher A. (2026), "Targeted vouchers, competition among schools and the academic achievement of poor students." *Econometrica*. Forthcoming.

North Carolina Department of Transportation (n.d.), "Historical Annual Average Daily Traffic Counts [dataset]." Transportation Planning Division, Traffic Survey Group.

North Carolina Division of Child Development and Early Education (2006), "List of Child Care Facilities with Star-Rated Licenses [dataset]."

North Carolina Education Research Data Center (1995–2017), "Student, class, and personnel files."

North Carolina Education Research Data Center (2012), "Technical Report #1: Linking Teachers in the ABC Data to Teachers in the School Activity Report." Technical report, North Carolina Education Research Data Center, Duke University.

North Carolina Education Research Data Center (2019), "Geocoding Addresses and Assigning MASTIDs." Technical Report 5, Duke University, Center for Child and Family Policy.

North Carolina Education Research Data Center (2025), "Summary of Data Files Available." Duke Center for Child and Family Policy.

Rosen, J. B. (1965), "Existence and uniqueness of equilibrium points for concave n-person games." *Econometrica*, 33, 520–534.

Schroeder, Jonathan, David Van Riper, Steven Manson, Grace Cooper, Zachary Krause, Tracy Kugler, Tsu Zhu, and Steven Ruggles (2026), "IPUMS National Historical Geographic Information System: Version 21.0 [dataset]." Minneapolis, MN: IPUMS.

Smith, Stephen Samuel (2004), *Boom for Whom? Education, Desegregation, and Development in Charlotte*. State University of New York Press, Albany.

U.S. Census Bureau (2001), "Census 2000 summary file 1." *Washington, DC: U.S. Census Bureau*.

U.S. Census Bureau (2002), "Census 2000 summary file 3." *Washington, DC: U.S. Census Bureau*.

Zillow Research (n.d.), "Zillow Home Value Index [dataset]."