School Competition, Classroom Formation, and Academic Quality *

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Abstract

Racial segregation is an enduring feature of U.S. K-12 education. Up to half of it originates within schools due to how classrooms are formed. This paper develops an empirical framework to understand the implications of discretionary classroom formation in competitive education markets. I leverage a school competition reform to document via an event-study that in anticipation of a competitive shock, public schools both raise their academic quality and change students' assignments to classrooms such that classroom segregation increases. I then estimate an empirical model of school choice and competition to understand whether schools choose their level of classroom segregation so as to differentiate horizontally, thereby relaxing vertical competition on costly academic quality. The model's novelty is that it embeds classroom segregation both on the demand side, as a dimension that parents have preferences over, and on the supply side, as a margin of differentiation that schools choose directly alongside academic quality. I estimate preferences for classroom segregation so as to rationalize the reduced-form effects of competition identified through the event-study. I use the model to evaluate a policy that requires schools to form racially integrated classrooms, given the composition of the student body at the school. I find that the policy raises aggregate academic quality and the average test score in equilibrium. Magnitude-wise, present value lifetime earnings rise by up to $1,620 per student. Since the schools that increase academic quality the most are located in non-white areas, learning gains accrue mostly to non-white students, decreasing the racial test score gap by 2%.

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1 Introduction

Racial segregation is a pervasive and enduring feature of American society. Schools are no exception: As of May 2021, 45% of white K-12 students attend a school where they account for 75% or more of the student body (United States Government of Accountability Office, 2022). The detrimental consequences of childhood segregation on educational and occupational attainment, crime, and intergenerational mobility (Guryan, 2004; Johnson, 2011; Billings et al., 2014a; Chetty and Hendren, 2018a,b) have motivated massive scholarly efforts at unveiling and quantifying the determinants of racial isolation in schools. Residential segregation and unequal access to school choice (Billings et al., 2014a; Zheng, 2022; Monarrez et al., 2022; Monarrez, 2023) have been the targets of countless policy interventions since *Brown v. Board of Education*, including desegregation busing, the expansion of the charter sector, and the introduction of open enrollment. Segregation, however, originates also within schools, with classroom formation accounting for up to half of the racial segregation that students experience within a given grade in North Carolina (Clotfelter et al., 2021).

This paper develops an empirical framework to understand the implications of schools' discretion over classroom formation in competitive education markets. When school choice is available, (i) Do schools use classroom assignments to attract and retain students, leveraging parental preferences for peer characteristics? (ii) If schools differentiate horizontally in terms of how much classroom segregation they create, does this reduce their incentive to compete vertically through costly academic quality? (iii) What are the net implications for student segregation (both within and across schools) and learning? Using a quasi-experimental design, I show that public schools both raise their academic quality and alter students' classroom assignments along the racial dimension in *anticipation* of a competitive shock. The changed classroom assignments cause average classroom segregation to rise: White students get exposed to an increasingly large share of white classmates, relative to comparable non-white students in the same school and grade. The increase in average classroom segregation is driven by the right tail of the distribution. Also, the more schools increase classroom segregation, the less they raise academic quality. I then estimate an empirical model of school choice and competition that rationalizes the reduced-form estimates and quantifies how schools trade-off classroom segregation for academic quality under competition. The model's novelty is that it embeds classroom segregation both on the demand side, as a dimension that parents value, and on the supply side, as a margin of differentiation that schools choose directly along with academic quality.

My empirical setting is the introduction of school choice in the Charlotte-Mecklenburg Schools district (CMS henceforth), the sixteenth largest district in the country, in the Fall of 2002. The school reform led to a dramatic change in the competitive landscape (Mickelson et al., 2009; Hastings and Weinstein, 2008; Hastings et al., 2009; Billings et al., 2014a): Open enrollment was introduced for all levels of instruction, which granted families the ability to apply for a seat at any school in the district. Prior to open enrollment, school assignment was strictly residence-based. As school choice is introduced, schools' incentives to retain students strengthen as enrollment is tied to funding and to the probability of avoiding closure (Epple et al., 2018).

The timing of the reform allows me to cleanly identify schools' competitive responses: Since the introduction of school choice was announced in November 1999, more than two school years before its implementation, I can observe whether schools modify students' assignments to classrooms before the size and racial composition of their enrollment are affected by reform-induced student sorting across schools. Using student- and classroom-level data provided by the North Carolina Education Research Data Center, I estimate the effect of competition on classroom segregation using an event-study design where the event is the announcement of the introduction of school choice. The event-study compares changes in classroom segregation at schools with different exposures to the competitive pressure around the announcement. Exposure depends on school locations, which are fixed and determined before the advent of open enrollment. I focus on elementary schools, where students learn all subjects and spend the majority of their time in the same classroom.[1]

I show that the announcement of the introduction of school choice leads to an immediate rise in classroom segregation (as measured by the index of dissimilarity; Duncan and Duncan, 1955): On average, classroom segregation within CMS schools increases by 0.019 (on a scale from 0 to 1), relative to comparable non-CMS schools that are not subject to the reform. The estimated effect is significant both statistically and economically: 9.7% of the pre-announcement average. Upon the announcement, white students get exposed to an increasingly large fraction of white classmates, relative to non-white students in the same school and grade with the same prior achievement and socio-economic status.[2] Within CMS, classroom segregation increases more at schools whose location is closer to the nearest competitor. The rise in average classroom segregation is driven by the right tail of the distribution. The increase in classroom segregation is accompanied by an analogously timed and statistically significant rise in academic quality (as measured by school value-added) among CMS schools, relative to comparable non-CMS schools. The effect is large: approximately a fourth of the value-added standard deviation in the year following the announcement. In addition, school responses are suggestive that classroom segregation and academic quality might be substitutes as schools that respond to the reform by raising classroom segregation relatively more increase academic quality relatively less, and vice versa.

Motivated by this evidence, I develop and estimate an empirical model of school choice and competition whose novelty is to embed classroom segregation both on the demand side as a characteristic that parents value, and on the supply side as a dimension of differentiation that schools choose directly, along with academic quality. The purpose is to understand the equilibrium implications of schools exercising discretion over classroom formation for the supply of academic quality, racial segregation across schools, and the distribution of learning. If for a given racial mix at the school level, preferences for classroom segregation are

[1] In the elementary public school context that I study, there is limited scope for margins of differentiation other than classroom formation (e.g., admission criteria, curriculum, schedule, transportation, sports clubs). This indicates that the range of strategies that elementary traditional public schools can adopt to differentiate themselves is limited, relative to private or higher education institutions (MacLeod and Urquiola, 2013, 2015; MacLeod et al., 2017) and even charter schools (Gilraine et al., 2021; Singleton, 2019; Clotfelter et al., 2021).

[2] High-achieving students, on the other hand, do not experience any increase in the average achievement of their classmates, relative to low-achieving students of the same race and socio-economic status: see Section 3.2 for further details.

heterogeneous across households, then schools may differentiate horizontally by choosing different segregation levels. This might reduce schools' incentive to compete vertically on costly academic quality, for the same reason why the scope for product differentiation tends to relax price competition among firms (see Irmen, 1998 for a discussion of the literature).

On the demand side of the model, parents value a school based on its contribution to their children's achievement *growth* (i.e., academic quality) as well as the perceived quality *level* of the peers (Abdulkadiroğlu et al., 2020; Allende, 2019; Campos, 2023). My novelty is to allow parents to place different weights on the expected racial composition of the classroom, where children spend most of their instructional time, and the expected racial composition of the school. More formally, households choose the school within the district that maximizes their indirect utility, which depends on academic quality (Neilson, 2021; Bau, 2022; Singleton, 2019), the racial mix at the school level (Allende, 2019), and the degree of classroom segregation. Parents also care about distance from home and whether transportation is offered. (Residential choices are taken as given.) Parental preferences for school attributes are allowed to vary across observable types as defined by race and socioeconomic status (SES henceforth). I also allow preferences for academic quality, the racial composition of the student body, and classroom segregation to vary unobservably within race-by-SES types. Preferences for classroom segregation may also depend on the racial mix at the school level: For example, the same household may value segregation positively at majority-nonwhite schools but negatively at majority-white schools.

On the supply side, schools choose academic quality and classroom segregation[3] to maximize enrollment net of costs (i.e., the portion of the "full" objective function that responds to competitive incentives; McMillan, 2004; Gilraine et al., 2022). Both academic quality and classroom segregation are allowed to be costly for the school: I interpret the cost of academic quality as effort and the cost of classroom segregation as reputational. The cost structure is flexible enough to match some key data patterns. For example, I allow the cost of classroom segregation to be convex so as to match the right-skewness in the distribution of classroom segregation that I observe in the data (see Figure 4 in the paper). I also allow the cost of providing a given level of academic quality to vary with the demographic composition of the school's student body: This is consistent with the evidence that providing a given level of academic quality might be more costly for schools with larger shares of "hard-to-teach" students, where experienced teachers (who typically have transfer priorities) are reluctant to stay (Jackson, 2009; Singleton, 2019; Muriel and Smith, 2011).

The model interprets race as the dimension by which parents evaluate their children's peers because students' race (and not, for instance, lagged achievement) appears to drive the competition-induced change in classroom assignments observed in the data (see Section 3.2 for details). The model remains agnostic as to why parents value the racial composition of their children's peers, nor does it assume that any racial

[3] Academic quality and classroom segregation are "technologically independent" in the model in that classroom segregation is not an input for academic quality. In the empirics, I ensure that this holds by carefully purging any productive returns to homogeneous classrooms when estimating academic quality (see Section 3.1 and appendix Section B.1). Moreover, the empirical literature on U.S. elementary schools tends to rule out significant productive returns to homogeneous classrooms by prior achievement (Bui et al., 2014; Card and Giuliano, 2014; Antonovics et al., 2022).

intent drives schools. It is consistent with stories of interactions between parents and principals that lead to an equilibrium with racially segregated classrooms even in the absence of racial animosity on either side. For example, parents may use race as an easily observable proxy for dimensions that are harder to observe *ex ante* such as achievement, family resources and stability, social class and involvement in the educational process,[4] and behavior (Castillo and Petrie, 2010; Castillo et al., 2011; see Billingham, 2016 for a review of the literature). Alternatively, parents may ask for their children to be matched with their friends and neighbors, in which case classroom segregation would be tied to residential segregation.[5] This paper takes a "disparate impact" approach (Gastwirth, 1992) to the study of discretionary classroom formation: Classroom segregation by race is a policy-relevant equilibrium outcome, the determinants of which are worth understanding and addressing, regardless of whether or not any racially discriminatory intent exists on any part.

The equilibrium of the model is determined by the first-order conditions for academic quality and classroom segregation derived from the school problem along with a rational expectation condition imposed on the demand side: The racial composition of the schools that parents expect and include in their utility comparisons is correct at equilibrium. From the point of view of a single rent-maximizing school (McMillan, 2004), whether classroom segregation and academic quality are substitutes or complements in equilibrium depends on two types of factors: I label one as *direct* and the other one as *compositional.* To exemplify, suppose that all students value academic quality positively and that there is no reason for the school to care about the composition of its enrollment. If both white and non-white students value classroom segregation positively (negatively), then academic quality and classroom segregation are unambiguously substitutes (complements) in that the school can offset the enrollment loss from lowering the former by raising (lowering) the latter. If white and non-white students disagree, then the relation between the two attributes is determined by what type is more responsive and hence worth competing for (i.e., is "more marginal"; Spence, 1975; Bau, 2022). This is the *direct* channel. To see the second channel, suppose that the school faces an incentive to enroll a larger share of white students, as that enters all students' utility positively or implies a cost advantage (Singleton, 2019). All students value academic quality positively, while only white students value classroom segregation positively. The school might have an incentive to substitute classroom segregation for academic quality so as to attract white students, even if non-white students are more responsive. This is the *compositional* channel. Whether classroom segregation and academic quality are substitutes or complements for a given school depends on how preferences vary across households as well as on how the direct and the

[4] Lareau (2000, 2011) documents pronounced social class differences in "cultural capital" (Bourdieu, 1986) (e.g., family communication practices, critical thinking within the household, parental involvement in the classroom dynamics) that correlate with large cross-child differences in the acquisition of skills highly valued by schools and other institutions (e.g., the ability to negotiate, use proper language, and organize time), as well as in long-term educational, labor market, and health outcomes.

[5] Sociologists have documented that social networks are racially homophilous, meaning that friendships tend to be created among people of the same race (McPherson et al., 2001). More broadly, the literature offers several examples of how racial segregation can arise in equilibrium without racial preferences. In labor markets, low non-white hiring rates may arise among referral-based employers whose employees are mostly white (Mouw 2002; Waldinger and Lichter 2003; see also Small and Pager 2020). Within cities, segregated neighborhoods may be explained by heterogeneous preferences over public goods (Fernandez and Rogerson, 1996; Ross and Ross, 2003; Banzhaf and Walsh, 2013). In healthcare, physicians may have difficulties communicating with minority patients (Balsa and McGuire, 2001), resulting in disparities in health outcomes and services.

compositional channels combine and is, therefore, an empirical question.

I estimate the model in two steps. In the first step, I estimate the parameters that discipline preference heterogeneity across households (henceforth: non-linear preference parameters). Identification relies on the availability of student-level data (Berry and Haile, 2022). Concretely, my demand model generates a closed-form expression for the enrollment probabilities that can be mapped to individual enrollment choices via Simulated Maximum Likelihood. At the estimated non-linear preference parameters, I back out the portion of household utility derived from each school that contains the preference parameters that do *not* vary across households (henceforth: linear preference parameters): I retrieve these "mean utilities" by matching the school market shares predicted by the model to those observed in the data (Berry et al., 1995).

The second step uses the first-order conditions derived from the school problem along with the expressions for the "mean utilities" to estimate the linear preference and cost parameters via a Generalized Method of Moments estimator. An identification challenge arises in that schools' academic quality, classroom segregation, and racial composition are likely correlated with the quality and cost components that vary across schools and are unobserved to the econometrician. I rely mainly on two policy instruments to deal with endogeneity. First, my reduced-form measure of competitive pressure (i.e., distance to the closest competitor) helps identify the linear preference parameter for classroom segregation. It does so by providing variation in how the responsiveness of enrollment to classroom segregation changes within schools around the reform. In the first-order conditions derived from the school problem, the semi-elasticity of enrollment links school choices to competitive incentives. Since I derive estimating equations from the first-order conditions, the linear preference parameter for classroom segregation identified through my instrument is the one that best rationalizes the competitive response observed in the event-study. The identifying assumption is that exposure to competition only affects the within-school change in classroom segregation directly through the within-school change in the semi-elasticity of enrollment and not through within-school innovations to unobserved cost factors (Gilraine et al., 2022). My second instrument helps identify the linear preference parameter for academic quality and consists of the eligibility to receive extra teachers, support staff, and other instructional resources that CMS granted to schools with more than two-thirds of economically disadvantaged students. The instrument can be considered an exogenous cost-shifter: Eligibility shifts the effort cost of providing academic quality and can be treated as random conditional on the composition of the student body, which enters the first-order condition for academic quality linearly as a cost component. Estimation of the cost parameters relies on "differentiation IVs" measured at baseline (Gandhi and Houde, 2019). The linear preference parameter on the share of white students at the school level is estimated by projecting the "mean utilities" recovered in the first step onto baseline demographics, which is a standard approach in the structural education literature.

The estimates indicate that there is substantial heterogeneity in household preferences for classroom segregation, both across and within race-by-SES types. Preferences for classroom segregation also vary with the racial composition of the student body at the school level. On average, white high-SES households value classroom segregation positively at schools with a share of white students up to 88%, while the threshold for non-white students is lower, around 36%. Both white and non-white students tend to be "more marginal" (i.e., more responsive to a marginal change in classroom segregation) when they are the minority group in the school. From a competitive standpoint, preference heterogeneity is consistent with horizontal differentiation along the classroom segregation dimension. In particular, setting aside any schools' direct incentives over the racial composition of the enrollment, the fact that different schools face different marginal types, who in turn have different preferences for classroom segregation is consistent with an equilibrium where both high and low classroom segregation are offered, and vertical competition on academic quality is relaxed as a result (Spence, 1975; D'Aspremont et al., 1979). Moreover, all households attach a positive weight to academic quality, with white high-SES students being the most responsive. Almost all schools' total enrollment responds positively to an increase in (own) academic quality. Because the (expected) share of white students at the school level enters parental demand, the semi-elasticities of enrollment capture both households' direct preference for academic quality and preferences for the racial composition of the student body, which in turn depends on academic quality. On the supply side, schools face incentives to enroll a larger share of white students. Such incentives are both demand-driven, as most households value a higher concentration of white students at the school level positively, and cost-driven, as a larger share of white students reduces the effort cost of providing any given level of academic quality. These incentives rationalize the increase in classroom segregation observed in the data (and predicted by my model) on aggregate terms. Also, I estimate that the cost of increasing academic quality (classroom segregation) at the margin is convex in the level of academic quality (classroom segregation).

I use the model estimates to simulate the equilibrium values of academic quality, classroom segregation, and implied shares of white students at the school level under alternative policy environments and cost structures. In particular, I evaluate a policy that requires schools to form racially integrated classrooms (given the racial composition of the enrollment), thus prohibiting competition along the classroom segregation margin. I find that the policy raises aggregate academic quality and the average test score in equilibrium by 0.012σ and 0.004σ, respectively, where σ denotes a test score standard deviation. (The increase in the average test score is smaller in part because it is enrollment-weighted, and large schools display weaker responses, in part because of how students sort across schools.) Magnitude-wise, present value lifetime earnings increase by up to $1,620 per student, which is large given that the policy could be implemented at limited administrative or budgetary costs. The direction and size of the quality adjustment vary across schools, which reflects the heterogeneity in the student pools that schools cater to and in the cost incentives that they face. Since the schools that increase academic quality the most under the ban on classroom segregation are located in non-white areas, the learning gains accrue mostly to non-white students, and the racial test score gap decreases by 2%.

Policy Implications The policy implications of this paper are twofold. First, this work shows that even traditional public schools – which cannot set prices, introduce admission thresholds, or differentiate their curriculum like private or charter schools (Hsieh and Urquiola, 2006; MacLeod and Urquiola, 2015; Allende, 2019; Gilraine et al., 2021; Bau, 2022) – respond to competition in a way that increases racial stratification by segregating students across classrooms. This finding highlights a new channel whereby increasing school competition can have undesirable equilibrium implications (McMillan, 2004; MacLeod and Urquiola, 2013, 2015; Bau, 2022). This perspective is at odds with the line of reasoning that has made the expansion of school choice a bipartisan priority since at least the Nineties (Strauss, 2018): To retain enrollment, schools become more productive (Friedman, 1962; Hoxby, 2000). This paper shows that schools' incentive to increase academic quality in response to a competitive shock can be diluted when (i) parents have preferences for peers (Abdulkadiroğlu et al., 2020), and (ii) schools have direct control over the composition of the social interactions that they offer to their students (in other terms, who is exposed to whom).

Second, my framework is the first in the literature that allows for an equilibrium evaluation of classroom formation policies under competition. In recent years, some of the largest districts in the country, as well as entire states have tabled initiatives to impede "ability tracking", i.e., the practice of grouping students into classrooms by past achievement. These policies share an explicit intent to reduce racial segregation within schools (as white students tend to outperform non-white students) and have ignited protests among the families of high-achieving students along with threats of leaving the public system for the private one. Examples are the de-tracking of middle or high school math classes in San Francisco (Loveless, 2022), the State of California (Nierenberg, 2021), Ithaca (Yoden, 2020) and Nassau County, New York (Burris and Levin, 2006), and the phasing out or dilution of Gifted and Talented programs in New York City (Shapiro, 2021), Seattle (Calvan, 2021), Boston (Woolhouse, 2021), Charlottesville, Virginia (Hess, 2021), and Anchorage, Alaska (Aina, 2020). This paper adds a new perspective to the conversation: In competitive education markets, prohibiting schools from exercising discretion over classroom formation spurs competition which can lead to gains in academic quality that improve learning for both white and non-white students.

Related Literature This paper contributes to the literature on the distorting effects of competition in education markets (McMillan, 2004), specifically those that arise because of parental preferences for peers (Rothstein, 2006; MacLeod and Urquiola, 2013, 2015; Allende, 2019). To the best of my knowledge, the empirical contributions to this literature study price-setting private schools or higher education institutions deciding admission rules. I show novel, quasi-experimental evidence that, in response to increased competitive pressure, traditional public schools change students' assignments to classrooms, thereby increasing racial segregation within schools. I then embed classroom segregation in an empirical model of school choice and competition among public schools to understand how parents and schools trade off classroom segregation for academic quality. My results suggest that schools substitute classroom segregation for directly productive investments, thereby reducing the learning benefits from competition. This response increases student segregation in the absence of prices and explicit admission criteria.

Moreover, this paper contributes to the literature that takes a quantitative approach to the analysis of horizontal differentiation in education markets (Bau, 2022; Gilraine et al., 2021, 2022). Bau (2022) endogenizes the school curriculum choice as a dimension of horizontal differentiation in a model of school choice and competition. In this paper, the margin of differentiation is classroom segregation and hence (given enrollment) the expected composition of the classroom peers (Rothstein, 2006; Abdulkadiroğlu et al., 2020). My results indicate that classroom segregation is a dimension of horizontal differentiation, especially at racially diverse schools. On aggregate, these schools increase classroom segregation and cater to white parents not only because white parents are on average more responsive to school characteristics (which is the mechanism at play in Bau, 2022), but also because schools face direct (demand and cost) incentives to attract white students over non-white students.

This paper also belongs to a growing structural education literature that estimates empirical models of school choice and competition to conduct policy evaluation (Hastings et al., 2009; Walters, 2018; Ferreyra and Kosenok, 2018; Singleton, 2019; Abdulkadiroğlu et al., 2020; Neilson, 2021; Dinerstein and Smith, 2021; Allende, 2019; Bau, 2022; Gilraine et al., 2022; Dinerstein et al., 2023). More broadly, this paper relies on the line of work that models firms choosing more than one characteristic (Ho, 2009; Fan, 2013; Wollmann, 2018; Crawford et al., 2019; Barahona et al., 2023) and is related to prior research that studies equilibrium models of individual choice under social interactions (Brock and Durlauf, 2005; Bayer and Timmins, 2018). I make an empirical contribution to the structural education literature by embedding classroom segregation both on the demand side as a characteristic that parents value, and on the supply side as a dimension of differentiation that schools choose directly. To the best of my knowledge, this is also the first paper that allows traditional public schools to compete along dimensions other than academic quality.

Lastly, this paper contributes to studies of the consequences of the end of the desegregation plan and introduction of open enrollment in CMS (see e.g. Hastings and Weinstein, 2008; Billings et al., 2014a; Hastings et al., 2009; Deming et al., 2014; Bibler and Billings, 2020). I contribute to this literature by showing that the *announcement* that open enrollment would be introduced was perceived by schools as a salient competitive shock that had long-lasting consequences on both school effectiveness and racial segregation within schools. These aspects seem relevant from the perspective of a global evaluation of that policy.

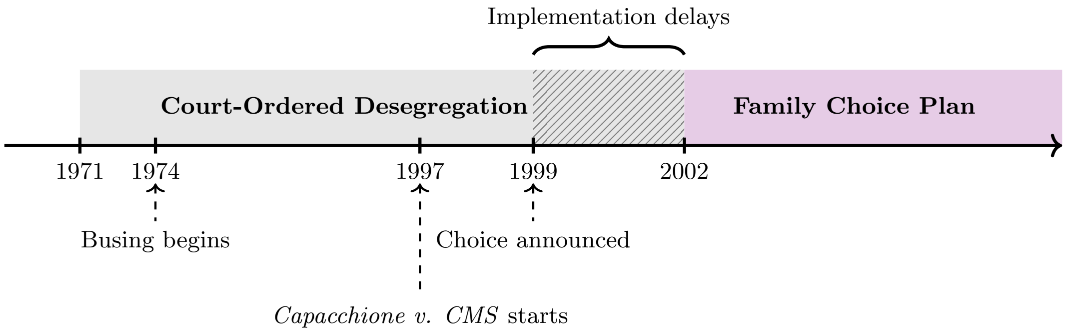
2 Institutional Background

This section describes the institutional context in which I study schools' competitive responses. Section 2.1 illustrates the school choice reform that dramatically altered the CMS competitive landscape. Section 2.2 reviews existing qualitative and survey evidence on the classroom formation process in public schools.

2.1 The Introduction Of School Choice In CMS

In November 1999, CMS Superintendent Eric Smith announces the advent of school choice. School choice is first implemented for the school year 2002-2003 in the form of open enrollment: CMS families are granted the possibility to apply for a seat at any traditional public school in the district while being guaranteed a

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



seat at the school in their catchment area of residence. The so-called "Family Choice Plan" (Mickelson et al., 2009; Billings et al., 2014b) is particularly tormented and controversial, given the district's recent history of actively limiting racial segregation across schools. The timeline in Figure 1 identifies the main phases of CMS history around the reform, while the following paragraphs provide further details on the key events.

1971-2002: Court-ordered desegregation. From 1971 to 2002, CMS is subject to a district-wide desegregation plan that mandates keeping the share of black students at every school within 15 percentage points of the district average (Billings et al., 2014b). The mandate results from the 1971 U.S. Supreme Court case *Swann v. Charlotte-Mecklenburg Board of Education* (402 U.S. 1), where the Supreme Court maintains that CMS schools are *de facto* segregated and authorizes the use of busing across catchment areas to break the vicious cycle between residential and school segregation. Under the plan, CMS redraws its catchment areas periodically to ensure compliance. Racial balance across schools is preserved using an assignment scheme based on "satellite" zones: Every day, students living in satellite inner-city zones with a high concentration of minority households are bused to schools located in suburban, highly white neighborhoods, while occasionally students residing in white, advantaged neighborhoods would be bused to non-white, disadvantaged schools (Kane et al., 2003). An example of a satellite zone activated for the school year 1999-2000 is shown in Appendix Figure C.1. Colored in light blue is the catchment area of Long Creek Elementary School. Students residing in the satellite zone located in the urban heart of Charlotte are bused to a northern suburb. In the school year 1999-2000, 57% of the students enrolled at Long Creek Elementary are white. Five years later, following the elimination of mandatory busing and the introduction of choice, the share is up to 74%. Since the Nineties, the use of satellite zones to preserve integrated schools is accompanied by setting aside a certain number of slots at magnet schools for students of color, in spite of their relatively low demand for magnet education (Pierpoint, 2018).

Late Nineties: Transition to choice. In 1997, William Capacchione sues CMS for denying his white daughter a seat at a magnet school, allegedly on racial grounds. This episode brings together parents drained by the consequences of busing, eager to regain control of their children's educational opportunities, and fundamentally hostile to racially diverse classrooms as a goal (Pierpoint, 2018).

Spurred by these events, in November 1999 the CMS Superintendent Eric Smith announces the advent of a new student assignment plan that would introduce school choice. After the announcement, the plan goes through a series of delays, public hearings, and legal challenges.[6] It is implemented only in the Fall of 2002, when *Capacchione v. CMS* ends with the official phasing out of racial busing.

Since 2002: Choice-based assignment plan. Under the new plan, students maintain guaranteed access to their neighborhood schools. Catchment areas are redrawn and substantially modified, and satellite zones eliminated (Hastings et al., 2009). Moreover, families can now apply for a seat at any other traditional public school within CMS, up to capacity constraints. In the spring of 2002, CMS first asks parents to submit choice forms listing up to three choices, listed in order of preference, for the upcoming school year. CMS encourages participation by conducting an extensive information campaign, which includes the distribution of a comprehensive booklet and website with information on each school and the opening of a Family Application Center (Hastings and Weinstein, 2008), and over 95% of the families participate. Over-subscription at popular schools is handled via a centralized lottery (Deming et al., 2014) and anticipated by the district, which expands capacity at schools where high demand is expected. Among elementary school students, approximately 8% do not get a seat at their first-choice school and are re-assigned to their neighborhood school (Hastings et al., 2009).[7]

Table 1: CMS students before and after the open enrollment reform

Students		**1999-2000**	**2004-2005**
% White high-SES		41.97	35.91
% White low-SES		7.32	6.78
% Non-white high-SES		14.44	14.84
% Non-white low-SES		36.27	42.47
% Attending default school		81.97	57.03
	White	82.11	68.73
	Non-white	81.83	48.32
Distance to school of attendance (in miles)			
	Q1	1.68	1.28
	Median	2.89	2.77
	Q3	4.20	7.17
Number of students		16,452	18,626

Notes: This Table reports summary statistics for the full sample of CMS students enrolled in elementary school in the school years 1999-2000 and 2004-2005, grades 3 and 4. Residential addresses are imputed for part of the sample: see Appendix Section B.2 for details. The data source is presented in Section 3.1.

Table 1 reports summary statistics for CMS students before and after the introduction of open enrollment.

[6] See the CMS website for details (last access: August 10, 2023).

[7] CMS adopts a "first-choice-maximizer" lottery mechanism (Hastings et al., 2009), under which the probability of being assigned to either the second or third preferred school is very limited. At the time of writing, CMS denies access to the lottery data to new researchers.

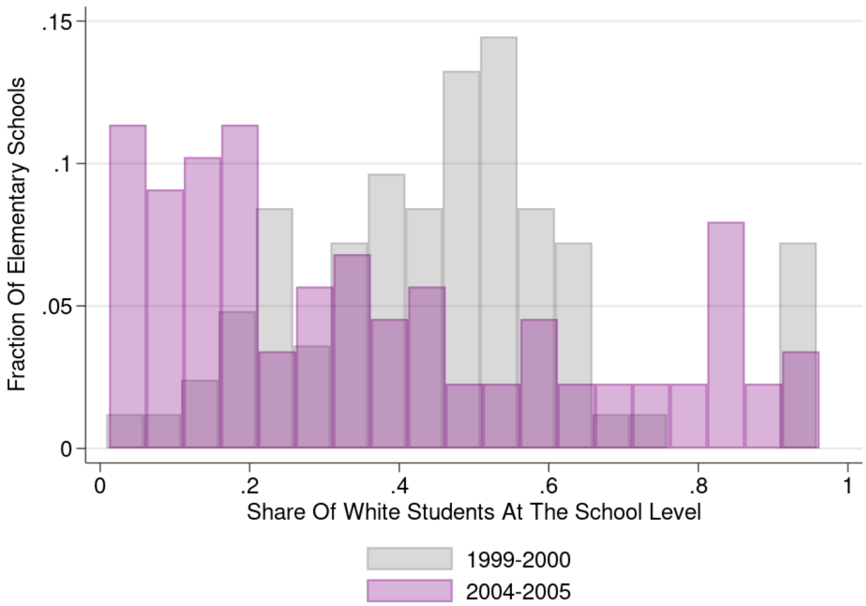


Figure 2: Distribution of the share of white students at the school level before and after the reform

Notes: Calculations based on the estimation sample described in Section 5.3.

The data source, described in detail in Section 3.1, is the North Carolina Education Research Data Center. Approximately half of the student population is white, and almost 80% of the students are either white and high-SES or non-white and low-SES. Around the reform, the fraction of students attending the default school (i.e., the school assigned based on the residential address) drops from above 80% to less than 60%, indicating that families take advantage of open enrollment. The reduction is relatively larger among non-white students, which is consistent with white students having access to "better" schools via residential sorting. The distribution of home-school distance becomes more spread out after the reform, reflecting both the introduction of school choice and the elimination of desegregation busing. These two factors also result in a dramatic increase in racial segregation across schools after the reform. Figure 2 shows the distribution of the share of white students at the school level across CMS elementary schools for the school years 1999-2000 and 2004-2005. (Students enrolled for the school year 1999-2000 before school choice was even announced in November 1999.) The distribution becomes significantly more "polarized" after the reform, with a smaller incidence of racially integrated schools (i.e., schools whose share of white students lies between 40% and 60%) and a larger fraction of racially homogeneous schools (i.e., schools with a share of white students under 20% or above 80%). This shift implies that the share of non-white students that should change schools within CMS for schools to be fully integrated rises from 33% to 54% (Duncan and Duncan, 1955).

The "Equity Plan". The district expects choice and the elimination of busing to damage schools located in underprivileged areas. In April 2001, the CMS Board of Education decides to "support the Superintendent's implementation of the *Achieving the CMS Vision: Equity and Student Success* framework (the 'Equity Plan',

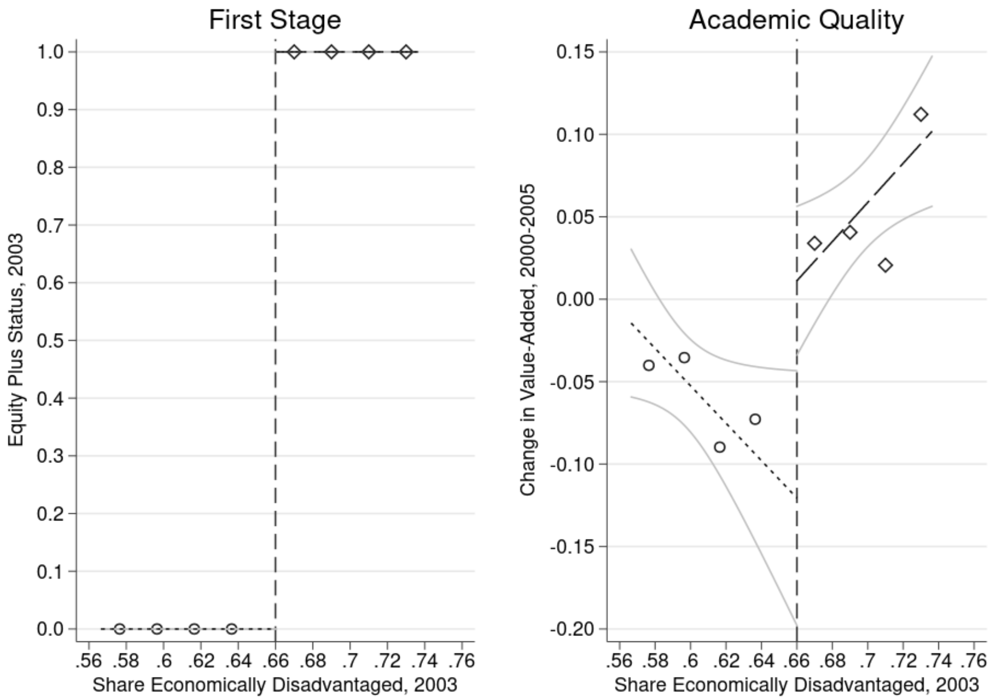


Figure 3: Effect of eligibility for Equity Plus resources on within-school change in academic quality

Notes: The left panel plots the fraction of schools designated as Equity Plus against the share of economically disadvantaged students at the school level. Both variables refer to the school year 2002-2003. The right panel plots the average change in value-added attained by schools between 2000 and 2005 against the share of economically disadvantaged students at the school level in 2002-2003. In both panels, the vertical dashed line indicates the 2002-2003 eligibility cutoff for the Equity Plus status. Each dot represents a within-bin average, and the width of each bin spans a 2 percentage point difference in the share of economically disadvantaged students at the school level. The averages in the right panel are conditional on baseline value-added. N = 45. Observations are school-by-grade, grades 3 to 5.

adopted by the Board in March 1999) (...) to attain the goal of raising the academic achievement of all students."[8] The Equity Plan provides high-poverty schools with extra resources, such as additional teachers, teacher bonuses, and bond funds for renovation. Concretely, the Board mandates the creation of 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."[9] Equity Plus schools are determined on a yearly basis, based on a strict cutoff rule: For the school year 2002-2003, a school is designated Equity Plus if more than 66% of its students are economically disadvantaged (see Figure 3, left panel).[10] The right panel of Figure 3 shows that, within a subset of schools with a relatively large share of economically disadvantaged enrollment, those eligible for Equity Plus

[8] Extract from the Board Resolution 2002-2003 retrieved from the CMS website via Wayback Machine (last access: November 30, 2022).

[9] Extract from the Board Resolution 2002-2003 retrieved from the CMS website via Wayback Machine (last access: November 30, 2022).

[10] The cutoff rule varies slightly across years and levels of instruction. It consistently relies on the shares of economically disadvantaged and underperforming students at the school level.

resources in the school year 2002-2003 achieve a larger average increase in academic quality (as measured by school value-added: see Section 3.1) around the reform, relative to ineligible schools. In this paper, I use the eligibility for Equity Plus resources as a (conditionally exogenous) cost-shifter to identify preferences for academic quality: see Section 5.2 for details.

2.2 Classroom Formation

Studying the effect of competition on classroom segregation in public schools requires that schools have discretion over classroom formation. Henderson (2011) documents the process in North Carolina. He observes that most elementary school principals mix automation and discretion when forming classrooms. In Union County Public Schools, Monroe, the focus of Henderson (2011)'s analysis, principals have autonomy in determining how the formation of class rosters occurs, and no specific state or school district guidelines discipline the process. The degree to which principals use this discretion varies substantially. On the one hand, some principals are highly involved throughout the class roster development and adopt "a deliberate process that dedicates days or months, creating just the right 'mix' of students for each first- through fifth-grade class" (Henderson, 2011, p.10). On the other hand, some other principals delegate or fully rely on computer programs. Hopkins (1999) and Burns and Mason (2002) document similar class formation practices in other states.

Principals can also decide whether or not to take parental requests into account. There is ample anecdotal evidence that parents get involved in the classroom formation process: St. John (2014) reports that PTA parents tend to be particularly active in this regard, which reflects the broader observation that parents who face no language, socio-economic status, and social network barriers tend to get relatively more involved in school issues (Kim, 2009). In her ethnographic work, Lareau (2000, 2011) documents profound and persistent social class differences in the degree of parental intervention in the classroom: Upper middle class families would see education as a responsibility shared with the teachers and the principal, build relationships around interconnectedness and scrutiny, and be more prone to demand specific classroom assignments and "pressure teachers into placing their children into the gifted program although they did not formally qualify" (Lareau, 2000, p. 33). Working class parents on the other hand would see education as a school responsibility and hardly ever intervene in the educational process.

Principals report that the classroom formation process can become overwhelming because of the interactions with parents,[11] and St. John (2014) documents that parental preferences are a factor that principals tend to take into consideration. Districts vary in their guidelines on the extent to which parents should be involved in the classroom formation process: While some instruct their schools to openly invite written requests from parents, others discourage such requests or even explicitly forbid demands for specific teachers. In either case, principals remain in charge of assigning enrolled students to classrooms.

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

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 separates students along several observable dimensions, including race (Conger, 2005; Bosworth and Li, 2013; Kalogrides and Loeb, 2013; Dieterle et al., 2015; Horvath, 2015). In North Carolina, up to half of the racial segregation that students experience can be attributed to how white and non-white students enrolled in the same school and grade are assigned to classrooms (Clotfelter et al., 2021; see also Clotfelter et al., 2002; Conger, 2005; Kalogrides and Loeb, 2013). Classroom segregation is closely related to racial inequality insofar as it implies different peer environments as well as differential access to instructional resources: White, economically advantaged students are more likely to be assigned to experienced teachers (Kalogrides and Loeb, 2013) and enrolled in advanced or gifted classes, even conditional on achievement (Mickelson, 2015; Grissom and Redding, 2015).

3 Data Description And Key Data Patterns

This section illustrates how CMS schools respond to the introduction of open enrollment. Section 3.1 describes the data and the measures of classroom segregation and academic quality that I use to study schools' competitive responses empirically, while Section 3.2 presents the key data patterns.

3.1 Data And Measures

I use administrative records from the North Carolina Education Research Data Center for the school years 1997-1998 through 2004-2005. The data are either at the individual or at the classroom level. At the individual level, for every student enrolled at any traditional public school in a given year, I observe demographics, residential address (at the Census block group level),[12] school and grade of enrollment, and standardized test scores.[13] At the classroom level, I observe the number of students enrolled and the racial breakdown. I focus on elementary schools, grades one to four.[14] Standardized test scores are only available for grades two to.[15]

Measure of classroom segregation: I rely on the classroom-level data to measure racial segregation across classrooms using the index of dissimilarity (Duncan and Duncan, 1955), which is the most popular in applied work (Allen et al., 2015). The index is defined between 0 and 1, and larger values stand for more segregation. In my setting, the value of the index for a given school and grade is equal to the share of non-white students in that school and grade that must change classrooms for non-white students to be distributed across classrooms with the same proportions as white students. Formally, the index for school s

[12]For CMS, the availability of information on students' exact addresses for the years of interest is limited: See Section B.2 for details on how I handle this limitation.

[13]Classroom assignments at the individual level are only available for approximately 40% of the sample.

[14]I exclude grade 5 throughout the analysis of competitive responses as schools may have little or no incentive to respond within terminal grades. As a matter of fact, I observe no response for grade five in the data.

[15]Students take their first standardized test at the beginning of third grade. After that, they are tested at the end of each school year.

at year t is defined as the average across grades g[16] (one to four) of

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

where w_{cstg} (b_{cstg}) denotes the number of white[17] (non-white) students enrolled in classroom c and $\overline{w}_{stg}$ ($\overline{b}_{stg}$) stands for the total number of white (non-white) students. I use data on Math and self-contained classes, excluding school-grade-year combinations with either no racial diversity, one classroom only, or any odd-sized classroom with less than 5 or more than 40 students.[18]

The index of dissimilarity in equation (1) is easy to interpret but has the drawback of changing mechanically with the size of the classrooms (Elbers, 2021).[19] For example, within the same school and grade, the index of dissimilarity might change across subsequent years just because the distribution of class size changes, even absent any decision of the school to separate white and non-white students across classrooms to a greater extent.[20] To isolate the segregation component that most closely captures the school's decision, I construct a measure of feasible segregation that takes value 0 (1) if the school segregates as little (much) as possible, given the class sizes observed in the data. Concretely, I measure the *fraction of feasible segregation* that school s implements at time t given the class sizes, which is defined as:

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

where $D^{A,min}_{st}$ and $D^{A,max}_{st}$ are computed off the (simulated) least and most segregated classroom configurations that are feasible under the class sizes observed in the data, applying the same data restrictions and averaging across grades as for D^A_{st} (equation (1)).

Figure 4a shows the distribution of classroom segregation across the schools in my sample for the school year 2004-2005. The left panel shows that schools vary significantly both in their index of dissimilarity D^A_{st}, shown by the violet dots, and in the range of classroom segregation levels that are feasible under the class sizes observed in the data $D^{A,max}_{st} - D^{A,min}_{st}$, given by the gray bars. There is significant variation also in the fraction of feasible segregation that schools attain, D_{st}, which for each school is captured by the relative distance between the purple dot and the lower whisker of the bar. The fraction of feasible classroom segregation attained by a given school is therefore given by the relative distance between the purple dot and the lower whisker of the bar. Figure 4b shows this distribution of feasible classroom segregation attained. The distribution is heavily skewed to the right, suggesting that schools rarely get close to fully separating

[16] I take the simple average. The main result is near-identical if I take the average weighted by grade enrollment. Results are available upon request.

[17] I follow Card and Giuliano (2014) and classify Asian students (4% of the total) among White students. The non-white category includes African American, Hispanic, American Indian, Pacific Islander, and multi-racial students.

[18] School-grade combinations with either no racial diversity or one classroom only within CMS are 2% of the yearly total on average. The main finding is robust if I relax the class size criterion. Results are available upon request.

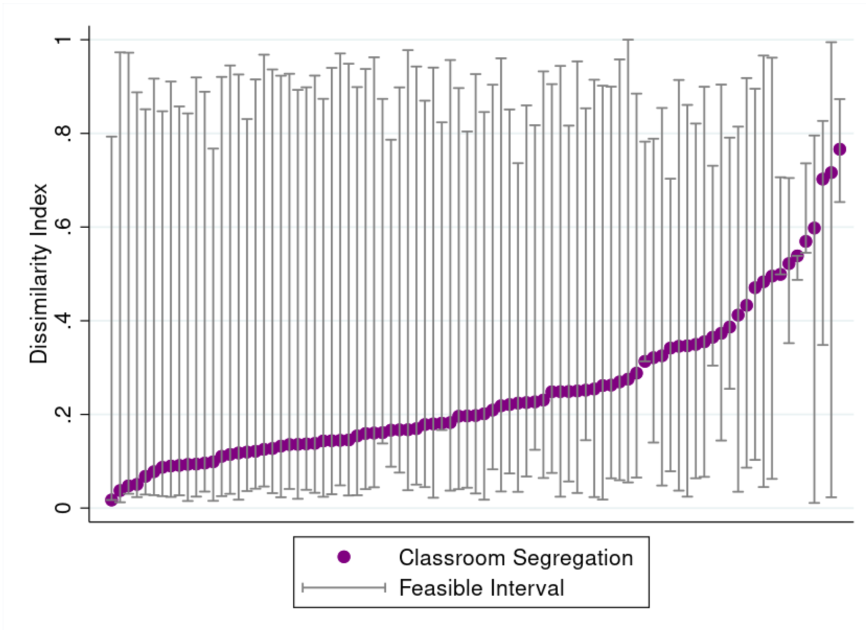
[19] The dissimilarity index is instead theoretically robust to changes in the racial composition of the population of interest (Elbers, 2021).

[20] In the reduced form, I show that the distribution of class size within school-grade does not change significantly in response to competition: see Appendix Figure C.5 for details.

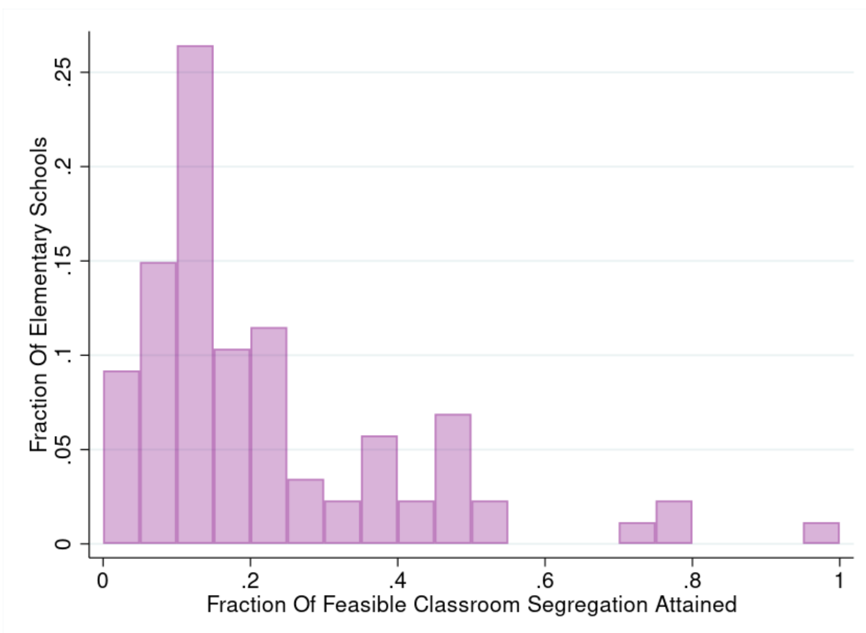
students by race. This fact is consistent with high levels of classroom segregation being very costly (e.g., reputationally).

Figure 4: Classroom segregation at CMS elementary schools in 2004-2005

(a) Dissimilarity index: values and feasible ranges



(b) Distribution of the fraction of feasible segregation attained by schools



Notes: In Figure 4a, each bar corresponds to a school in my sample. The lower (upper) whisker corresponds to the smallest (largest) feasible level of segregation that the school can attain, given the class sizes observed in the data. On each bar, the purple dot indicates the degree of classroom segregation actually in place at the school, computed according to the formula in equation (1). Figure 4b plots the distribution of the fraction of feasible segregation attained by the schools in my sample, computed according to equation (2).

Academic quality: Following the structural education literature (Neilson, 2021; Allende, 2019; Bau, 2022; Gilraine et al., 2022), I estimate academic quality through a value-added model. The model expresses the achievement of student i enrolled at school s in year t as:

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

where g is the grade of enrollment (three and four), and c is the classroom. Y is the end-of-grade standardized math test score: I focus on math as it tends to respond to educational inputs more than reading. X denotes a vector of individual characteristics: I include a cubic in prior math and reading test scores interacted with grade dummies, ethnicity, socio-economic status (i.e., parental education and economic disadvantage), English learner status, disability status, and gifted status. I also control for the average of these characteristics at the grade and classroom level. ω_{gt} are grade-by-year fixed effects, q_{st} are school-by-year fixed effects, and ϵ_{ist} is the error term which is assumed to be i.i.d. and to follow a normal distribution. The main parameter of interest is q_{st} which captures school s' value-added in year t, i.e., the "treatment effect" of the school on its students' achievement growth, net of individual and peer observable characteristics. The estimated value of q_{st} is my measure of academic quality for school s at year t.

Appendix Section B.1 provides more details on how I estimate value-added. An important aspect discussed therein is how the productive returns to homogeneous classrooms are purged out of my measure of academic quality. This is important as in the model I want to think about classroom segregation and academic quality as "technologically independent", in the sense that classroom segregation is not an input of value-added. Section 7 discusses how the productive returns to homogeneous classrooms can be taken into account within the policy evaluations that my model allows for. (Empirically, the learning effects of homogeneous classrooms by lagged achievement in U.S. elementary schools appear negligible: see e.g. Bui et al., 2014; Card and Giuliano, 2014; Antonovics et al., 2022). Appendix Figure C.2 plots the distribution of estimated value-added. Appendix Table D.2 describes the statewide student-level sample used to estimate equation 3.

Table 2 reports summary statistics for the sample of schools that I use in Section 3.2 to analyze competitive responses. On average, both value-added and the within-school dissimilarity index increase in CMS around the reform. The distribution of my measure of classroom segregation within the district becomes more spread out as well, as captured by the standard deviation. This change is driven by the right tail of the distribution (see Appendix Figure C.3.)

3.2 Quasi-Experimental Evidence On School Competitive Responses

I now document CMS schools' response to the introduction of open enrollment along the dimensions of classroom segregation and academic quality. Identifying the effect of competition on classroom segregation presents an empirical challenge: The introduction of choice allows students to re-sort across schools. If

Table 2: Summary statistics for event-study estimation sample

	1998 to 2000		2001 to 2005	
VARIABLE	**CMS Y**	**CMS N**	**CMS Y**	**CMS N**
Value-added	-0.096	-0.029	0.094	0.047
	(0.219)	(0.192)	(0.185)	(0.190)
Dissimilarity index	0.153	0.193	0.209	0.207
	(0.109)	(0.142)	(0.138)	(0.140)
Share of white students	0.488	0.565	0.407	0.504
	(0.196)	(0.270)	(0.255)	(0.283)
Number of students	388.684	292.147	385.876	285.665
	(130.070)	(146.360)	(160.330)	(142.235)
Class size	22.151	21.727	21.373	20.725
	(2.130)	(2.825)	(2.580)	(3.022)
N. obs. (school-year)	253	1,005	418	1,779

Notes: This Table reports summary statistics for the event-study estimation sample separately before the reform (1998-2000) and after the reform (2001-2005). The sample includes schools in CMS ("CMS Y" columns) along with schools located in other large urban districts in North Carolina ("CMS N" columns). Grades 1 to 4 are included. Value-added is estimated from equation 3 using statewide student-level data for third and fourth graders. The dissimilarity index is computed as in equation (1).

re-sorting changes a school's enrollment size and racial composition, then classroom segregation therein may increase mechanically, even in the absence of a competitive response on the part of the school.[21] I address this identification threat by exploiting the timing of the CMS reform (see Figure 1): The competitive response can be isolated by looking at how classroom segregation changes upon the *announcement* of open enrollment in the school year 1999-2000 before students can actually re-sort in the school year 2002-2003. I exploit this intuition to compare schools exposed to different intensities of competitive pressure, before and after the announcement (Figlio and Hart, 2014; Gilraine et al., 2021). Concretely, I estimate

$$y_{st} = \alpha + \sum_{k=1998}^{1999} \beta_k \Big(\mathbb{1}[t=k] \times treated_s \Big) + \sum_{k=2001}^{2005} \gamma_k \Big(\mathbb{1}[t=k] \times treated_s \Big) + \delta X_{st} + \phi_s + \phi_t + \epsilon_{st} \tag{4}$$

where s denotes the school, t is the school year, y is the dependent variable (classroom segregation or academic quality), X is a vector of covariates (namely enrollment size, share of white students at the school level, and distance to the closest charter), 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 *treated* and *control* schools, before and after the announcement of the introduction of open enrollment in the school year 1999-2000. The main coefficient of interest is γ_{2001} as it captures the difference between treated and control schools in the school year immediately following the competitive announcement (i.e., the school year 2000-2001), relative to the school year before which the announcement is made (i.e., the school year 1999-2000). I estimate two specifications of equation (4) which differ in their definition of *treated* and the sample used for

[21] Academic quality on the other hand is measured net of sorting: see Section B.1. Also, in this application the dissimilarity index is theoretically robust to changes in the school racial composition, although not to changes in the distribution of class size within the school (Elbers, 2021).

estimation. In one specification (specification A), $treated_s = 1$ if school s is located in CMS, 0 if it is located in another large urban district in North Carolina.[22] In the other specification (specification B), $treated_s$ is a continuous variable that captures the intensity of competition faced by school s: I use the distance to the closest competitor.[23] In this case, the sample is restricted to CMS schools.

The first novel fact that I document is that classroom segregation responds to competitive incentives. I find that racial segregation within CMS schools increases right upon the announcement of the introduction of open enrollment, relative to schools located in other large urban districts in North Carolina. This result is shown in Figure 5a, which reports estimates for specification (A), where the control group comprises other large urban districts in North Carolina. The horizontal axis indicates the school years, while the vertical axis reports the estimated coefficients. The two vertical dashed lines divide the time window into three periods: During the first period (to the left of the first dashed vertical line), CMS offers no school choice within its traditional public system; In the second period (between the two dashed vertical lines), there is still no school choice, but the advent of open enrollment has been announced and is, therefore, public knowledge; In the third period (to the right of the second dashed vertical line), school choice is in place, and families can enroll their children at any school in the district, up to capacity constraints. The left panel of Figure 5 shows that classroom segregation at CMS v. non-CMS schools does not evolve along differential trends before the announcement. However, classroom segregation at CMS schools jumps as soon as the introduction of open enrollment becomes public knowledge. The increase is economically significant: On average, classroom segregation rises by .019 on a scale from 0 to 1, which is equivalent to 9.7% of the pre-announcement mean. Crucially, the fact that classroom segregation jumps right upon the announcement, but before students can re-sort across schools demonstrates that the effect is a competitive response and not a mechanical by-product of compositional changes.[24] As students begin to re-sort across schools through the new choice system in the Fall of 2002, classroom segregation within CMS schools increases even further: The size of the effect quadruples.

The second relevant fact is that academic quality also rises in CMS upon the competitive announcement. This is shown in the right panel of Figure 5: The specification is the same as in the left panel but for the dependent variable, which in this case is the estimated school value-added. The timing of the response is analog to that discussed above for classroom segregation. Magnitude-wise, the immediate increase is .06, approximately a fourth of a value-added standard deviation, which is almost three times as large as that obtained system-wide upon firing the 5% least effective teachers in Chetty et al. (2014b) and Gilraine et al. (2020). The estimated effect aligns with prior research studying schools' competitive responses: Using North Carolina data, Gilraine et al. (2022) estimate an increase in value-added at traditional public schools in

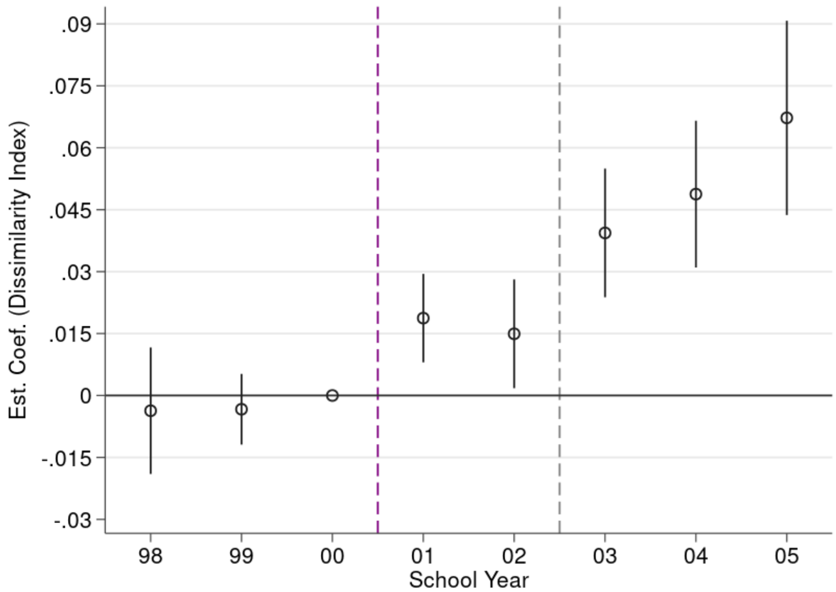
[22] I restrict the analysis to districts that, like CMS, have a number of schools above the 90th percentile of the state distribution, i.e., Alamance-Burlignton, Buncombe County, Cumberland County, Durham Public, Forsyth County, Gaston County, Guilford County, New Hanover County, Pitt County, Robeson County, Union County Public, and Wake County Schools.

[23] The result is robust to alternative measures of spatial competition intensity. Results are available upon request.

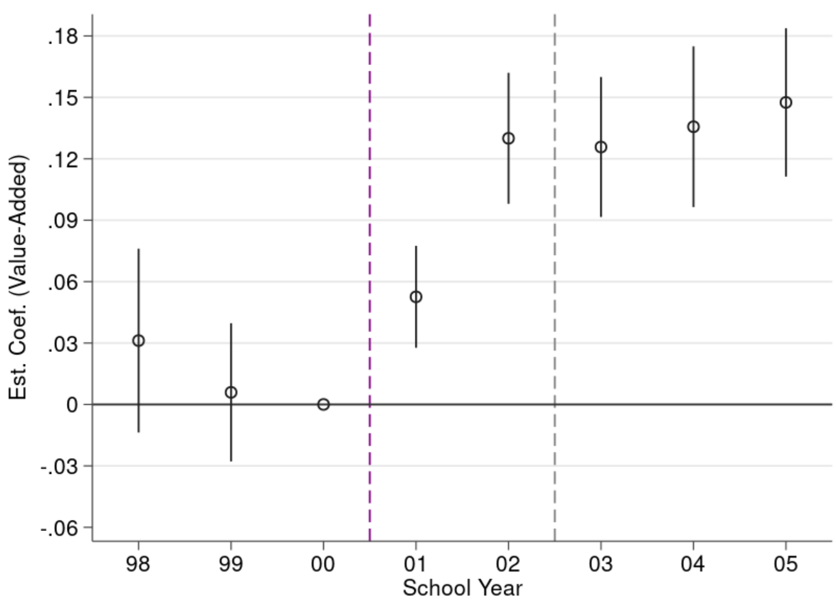
[24] Appendix Figures C.4 and C.5 show no evidence of re-sorting across schools or change in class size within CMS upon the competitive announcement.

Figure 5: Classroom segregation and academic quality in CMS jump upon the competitive announcement

(a) Classroom segregation



(b) Academic quality



Notes: Estimates obtained from estimating specification 4 (A). The control group includes elementary schools located in districts with a total number of schools above the 90th percentile. Figure 5a: the dependent variable is defined as in equation (1), and standard errors are clustered at the district level. Figure 5b: the dependent variable is value-added estimated off specification 3, and standard errors are bootstrapped (1,000 repetitions) to account for the fact that the dependent variable is estimated with error. Both regressions control for school size and racial composition as well as distance to the closest charter. N = 3,455.

response to a charter opening nearby[25] that is not significantly different from what I find.

[25]More precisely, the nearby opening of a charter school that offers a standard, non-differentiated curriculum.

The third fact is that the magnitude of the classroom segregation response varies across schools in CMS depending on the intensity of the (spatial) competitive pressure that schools face. This finding is reported in Figure 6: The estimated specification is (B), where the treatment variable measures school proximity to the closest competitor, and the sample is restricted to CMS schools. The pattern is robust to how I define classroom segregation, whether through the standard index of dissimilarity (Figure 6a; equation (1)) or as a fraction of the feasible segregation that schools attain (Figure 6b; equation (2)). Magnitude-wise, the estimated effect on classroom segregation of being one-mile closer to the nearest competitor is 0.015, 9% of the CMS pre-treatment average. This implies that holding other factors fixed, moving from the least to the most competitive location within CMS implies an average treatment effect of 0.054, 33% of the pre-treatment mean.

Race vs. "Ability" Segregation: That classroom segregation by race rises within CMS does not necessarily imply that schools are increasingly relying on race to form classrooms. Schools for example may intensify "ability tracking", i.e., the extent to which students are grouped together based on their prior achievement. In this case, since white students outperform non-white students on average, racial segregation will rise even if schools do not consider race directly. I investigate the drivers of classroom assignments in CMS around the school reform by estimating:

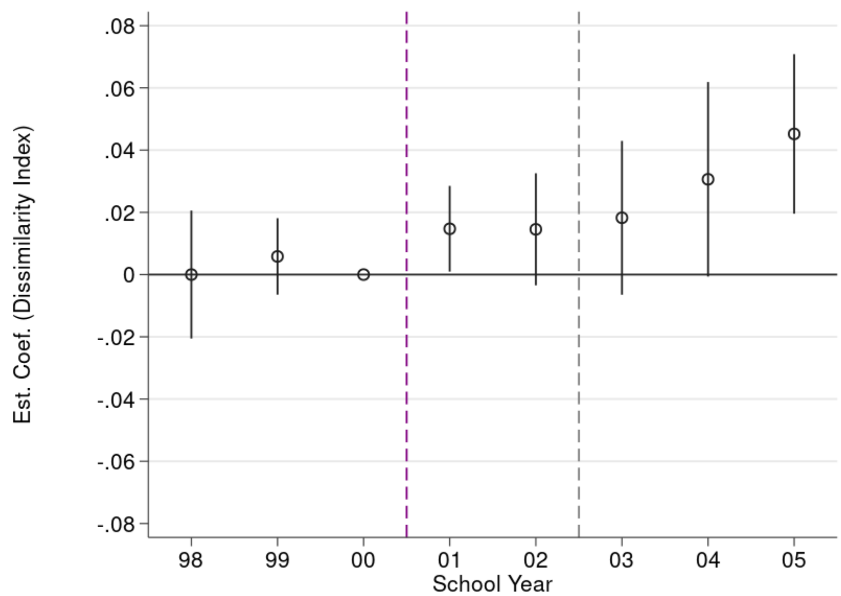
$$\overline{W}_{icgst}^{-i} = \alpha + \beta \times W_{icgst} + \tilde{\beta} \times W_{icgst} \times \mathbb{1}(t = Post) + \gamma \times X_{icgst} + \tilde{\gamma} \times X_{icgst} \times \mathbb{1}(t = Post) + \phi_{gst} + \epsilon_{icgst} \quad (5)$$

where i denotes the student, c the classroom, g the grade, s the school, t the school year, and ϕ is a vector of grade-school-year fixed effects. On the left-hand side, $\overline{W}_{icgst}^{-i}$ can be either student i's share of white classmates (i.e., the leave-one-out share of white students in student i's classroom) or student i's average class achievement (i.e., the leave-one-out average lagged test scores of student i's classmates). On the right-hand side, W_{icgst} is a dummy that takes value one if student i is white, X_{icgst} is a vector of individual observable characteristics other than race (i.e., lagged math test score, socioeconomic status, and disability status), and *Post* denotes the school years following the announcement of the introduction of open enrollment.

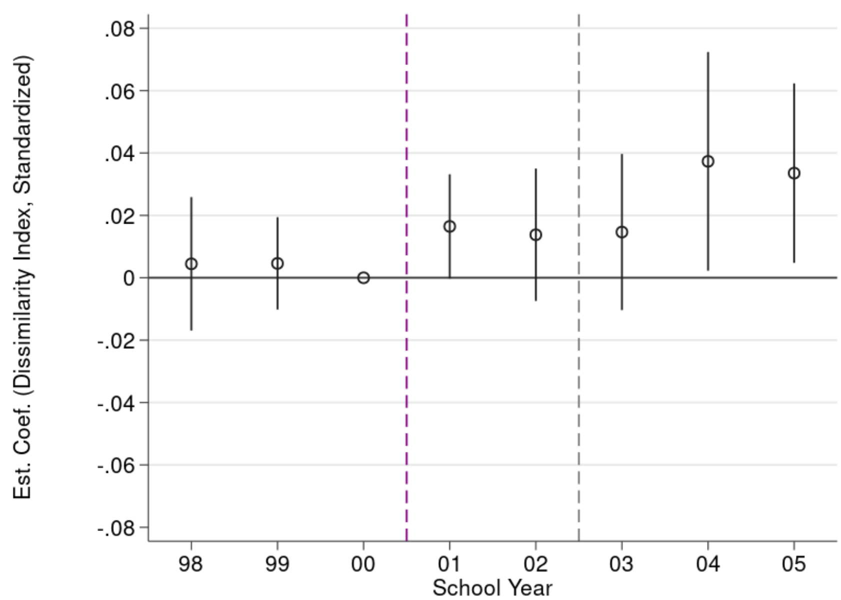
The coefficients of interest are $\tilde{\beta}$ and the vector $\tilde{\gamma}$. If schools are increasingly relying on race to form classrooms following the competitive shock, then I expect the partial correlation between own race and classmates' race ($\tilde{\beta}$) to be positive and statistically significant. In other terms, consider two students in the same school and grade with the same lagged achievement and socioeconomic status, although one is white and the other one is not: If race is driving the change in classroom assignments, then I expect the white student to be more likely exposed to a whiter classroom after the reform, relative to his or her non-white comparable grade-mate. If, instead, schools respond by placing a larger weight on attributes that only correlate with race (e.g., lagged test scores), I expect the partial correlations between those characteristics and classmates' lagged achievement ($\tilde{\gamma}$) to become stronger after the change in the competitive landscape.

Figure 6: Classroom segregation increases more at schools that face stronger competition

(a) In levels



(b) As a fraction of feasible segregation attained



Notes: Estimates obtained from estimating specification 4 (B). The sample is restricted to CMS schools. Figure 6a: the dependent variable is the absolute level of classroom segregation as defined in equation (1). Figure 6b: the dependent variable is the fraction of feasible segregation attained as defined in equation (2). Both regressions control for school size and racial composition. Standard errors are clustered at the school level. N = 758.

Specifically, consider two students in the same school and grade with the same race and socioeconomic status, although different lagged test scores: If achievement explains the change in classroom formation, then on average the high-achieving student will be exposed to a higher-achieving classroom after the reform, relative to his or her lower-achieving grade-mate.

Table 3 reports selected results from estimating equation (5) using data on CMS schools for the school years 1997-1998 to 2001-2002 (i.e., two pre- and post-treatment periods). I find that around the school choice announcement, white students experience a significant increase in the share of white classmates, relative to non-white students with the same prior test score (and socio-economic and disability status). The same is not true for high-achieving students, relative to low-achieving students of the same race (and socio-economic and disability status). These findings support the hypothesis that schools increasingly rely on race to form classrooms after the reform, relative to before. These results support how parental preferences are specified in the empirical framework introduced in Section 4.

Table 3: Predictors of classmate attributes before and after the competitive announcement

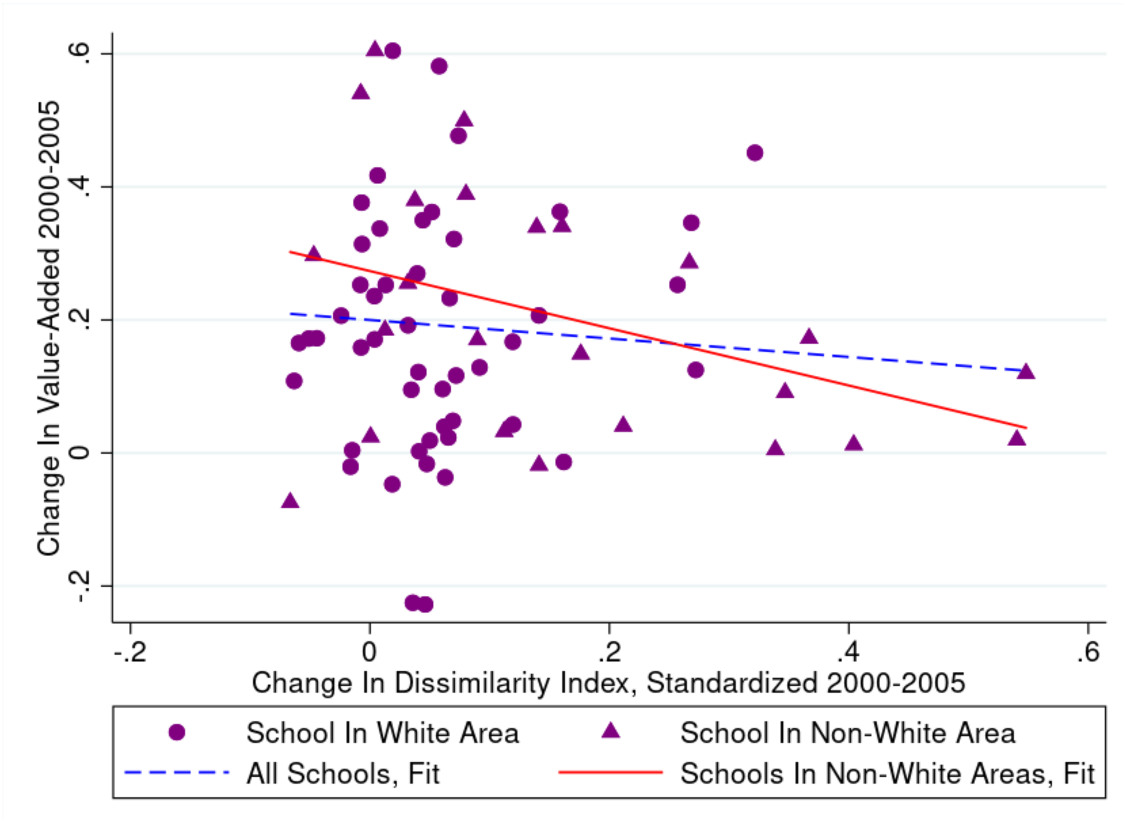
DEPENDENT VARIABLE	**White (Own) × Post ($\tilde{\beta}$)**	**Lagged Math Test Score (Own) × Post ($\tilde{\gamma}^{TS}$)**
Share of white classmates	0.007***	0.002
	(0.002)	(0.001)
Classmates' average lagged test score	0.012*	0.005
	(0.006)	(0.003)

Notes: This table reports estimates from equation 5 using as a dependent variable either the leave-one-out share of white students in the classroom or the leave-one-out classroom average lagged standardized math test score. I also control for class size. The estimating sample includes CMS schools for the years 1997-1998 to 2001-2002, grades 3 and 4. The results are robust to clustering standard errors at the grade-school-year level. N = 42,142.

Substitution between Quality and Segregation: Competition in education markets is oftentimes thought of as a "tide that lifts all boats" (Hoxby, 2003) as schools compete for students by increasing their productivity. Figure 5 suggests that this virtuous dynamic is fully at play in the CMS context. However, Figure 5 indicates that this is not the only consequence of increased competition: Students' assignments to classrooms change too, and in a way that raises racial segregation within schools. This constitutes indirect evidence that parents care about not only academic quality but also the expected racial composition of their children's peers when choosing a school (Rothstein, 2006; Abdulkadiroğlu et al., 2020; Campos, 2023), along with school distance from home. As schools control directly both academic quality and students' assignments to classrooms, classroom segregation might substitute for costly, directly productive investments in competitive education markets.

This pattern clearly emerges in Figure 7, where I plot schools' competitive responses along the academic quality and classroom segregation dimensions. On the vertical axis is the within-school change in value-added around the reform. On the horizontal axis is the within-school change in classroom segregation. Circles represent schools located in majority-white neighborhoods, while triangles indicate schools in majority-nonwhite neighborhoods. I document that schools that respond to the reform by raising classroom segregation relatively more increase academic quality relatively less, and vice versa, as indicated by the downward-sloping lines of fit. The negative correlation is stronger among schools located in majority-non-white neighborhoods

Figure 7: Negative correlation between within-school change in academic quality and classroom segregation



Notes: The horizontal axis displays within-school changes in the fraction of feasible segregation attained as defined in equation (2). The vertical axis reports within-school changes in value-added. Circles represent schools located in majority-white neighborhoods, while triangles indicate schools in majority-nonwhite neighborhoods. The dashed line linearly fits the relation between the two variables using all schools, while the solid line restricts the sample to schools in majority-nonwhite neighborhoods. Correlation coefficient: -0.14 for all schools; -0.43** for schools in non-white areas. N=73. The 10% of schools with the largest reductions in classroom segregation are excluded.

(i.e., the solid line).[26] This analysis indicates that on average, as competitive incentives are triggered, the schools that rely *less* on increasing academic quality are those that adjust (mostly raise) classroom segregation *more*. While suggestive, this analysis is limited as reduced-form comparative statics are insufficient to study the nature of the "strategic" relation between classroom segregation and academic quality as dimensions that schools use to compete. Multiple factors, including what type of students the school is catering to, how heterogeneous preferences for classroom segregation are across households, and what the cost is of marginal changes in either classroom segregation or academic quality for different starting levels, may be relevant. Therefore one cannot quantify the degree of substitutability between classroom segregation and academic quality without imposing some structure.

[26] I exclude from the figure the 10% of schools in the sample with the largest *reductions* in classroom segregation. Among the excluded schools, the relation between academic quality and classroom segregation is reversed: Larger negative responses (reductions) in classroom segregation correspond to smaller increases in academic quality, and vice versa.

4 Empirical Model

In this section I develop an empirical model of public school demand and supply. The novelty of this model is that it embeds classroom segregation both on the demand side as a characteristic that parents value, and on the supply side as a dimension of differentiation that schools choose directly. The goal of the model is to shed light on how households and schools trade off academic quality and classroom segregation.

On the demand side, households choose the school within the district that maximizes their indirect utility. Some of the school characteristics that enter utility are common across households, while others are household-specific. The former category includes the school's academic quality, the racial composition of the student body, classroom segregation (as a fraction of the feasible segregation that the school attains; see equation (2)), and an unobservable school-specific quality component. Given the racial composition of the student body, as classroom segregation increases, so does the extent to which white and non-white students are separated within the school. The school characteristics that vary across households are the distance from home, whether free transportation is offered from the neighborhood of residence to the school, and an idiosyncratic match value. (Residential choices are taken as given.)

On the supply side, schools choose academic quality and classroom segregation so as to maximize enrollment net of costs, given parental preferences and school locations. I model public schools as enrollment-maximizing (or "rent-seeking": McMillan, 2004) to focus on how schools respond to competitive incentives. For public schools, enrollment is closely related to funding, and so is the probability of avoiding closure, which is a major concern for principals in depopulating urban areas (Epple et al., 2018). Enrollment retention is systematically among the top priorities that school leaders report to the National School Boards Association.

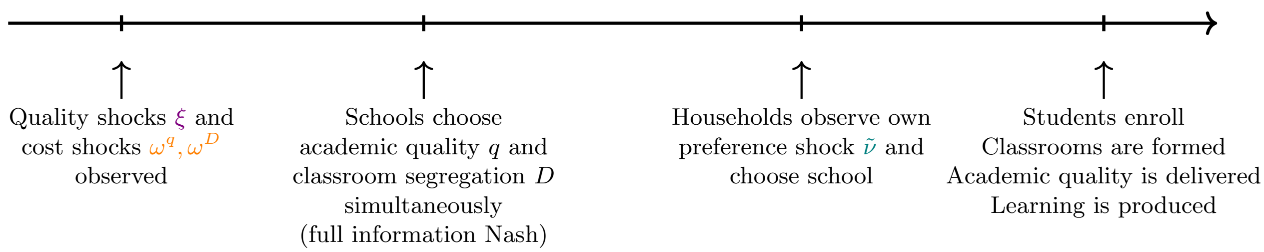
In the model, parents value (and schools choose) the level of *racial* segregation across classrooms. This modeling assumption is consistent with the quasi-experimental evidence described in Section 3.2 and with race becoming more important in explaining classroom assignments in CMS after the reform, relative to before, conditional on other individual characteristics such as lagged achievement. The exact specification of parental preferences for peer attributes affects the quantitative implications of the model. Conceptually, however, the scope of the model is more general and extends to contexts where parents value peer characteristics other than race. For example, parents may demand (and schools adjust) "ability tracking", i.e., the assignment of students to classrooms based on their lagged achievement. The purpose of the model is to quantify to what extent discretion over classroom formation is diluting schools' incentive to increase academic quality. For instance, if preferences are heterogeneous across households, schools may differentiate horizontally by choosing different levels of classroom segregation so as to cater to different market segments. Vertical competition on academic quality may be thereby diluted (Irmen, 1998).

The model is disciplined by the household preference parameters and the cost parameters faced by the schools. Household preferences for academic quality, the racial composition of the student body, and classroom segregation are allowed to vary both across and within racial groups. Preferences for classroom segregation are allowed to depend also on the racial mix at the school level. The remaining preference parameters vary across demographic types. The supply parameters govern the cost function that schools face for providing academic quality and classroom segregation: I think of the cost of providing academic quality as effort and of cost of segregating classrooms as reputational. I estimate both the preference and the cost parameters, following the estimation strategy described in Section 5.

4.1 Market Definition and Timing

A market is defined as all the elementary public schools located in CMS and the households with at least one elementary school-aged child living therein in a given year.

Figure 8: Timing of the model



The timing is summarized in Figure 8 and is articulated as follows:

1. Schools simultaneously choose academic quality and classroom segregation to maximize enrollment net of costs. They do so by playing a full information Nash game: At the moment of the choice, each school observes its own quality shock and cost shocks, as well as its competitors' realizations. (The cost shocks are unobserved to the econometrician.)

2. Households choose the school in the market that maximizes their indirect utility based on academic quality, classroom segregation, the racial composition of the student body that they expect as a result of all households' enrollment choices, and a school-specific quality shock that is constant across households. Households also care about home-school distance and whether the school offers free transportation in their neighborhood. Each household also faces a preference shock for each school, which captures the idiosyncratic household-school match value. (Both the quality shocks and the idiosyncratic match values are unobserved to the econometrician.)

3. Schools produce academic quality and form classrooms consistently with their choices. Learning is produced and observed in the form of test scores. (I present my empirical model of student achievement in Section 3.1.)

4.2 Demand for Schools

The indirect utility to student i from attending school s in year t is given by:

$$U_{ist} = \beta_i^q q_{st} + \beta_i^D D_{st} + \beta_i^W \overline{W}_{st}(q_t, D_t) + \beta_i^{DW}\Big(D_{st} \times \overline{W}_{st}(q_t, D_t)\Big) + \beta_i^M Magnet_{st} + \xi_{st}$$
$$-\gamma_i Distance_{ist} + \gamma_i^M Distance_{ist} \times Magnet_{st} + \gamma_i^M Distance_{ist} \times Post_t \times Transportation_{st} \quad (6)$$
$$+ \eta_i Default_{ist} + \eta_i^P Default_{ist} \times Post_t + \tilde{v}_{ist}$$

q_{st} denotes academic quality as measured by school value-added (see Section 3.1). D_{st} is classroom segregation measured as the fraction of feasible segregation that the school attains (see equation (2)). $\overline{W}_{st}$ is the share of white students at the school level according to parental expectations: It is a function of all schools' levels of academic quality and classroom segregation and, therefore, determined at equilibrium. The interaction between classroom segregation and the expected share of white students at the school level allows preferences for classroom segregation to vary with the racial composition of the student body. Utility also depends on the magnet status of the school $Magnet_{st}$ and on ξ_{st}, a school-by-year quality component that is common across households and unobserved to the econometrician.

The specification of the portion of utility that depends on classroom segregation and the racial composition of the student body at the school level, which I choose for tractability, can be thought of as a way to measure parental preferences for the expected racial composition of their child's classroom. Intuitively, from the point of view of a white student, if the school allocates white and non-white students across classrooms as evenly as possible (i.e., $D_{st} = 0$), then the expected share of white classmates is well approximated by the expected share of white schoolmates, $\overline{W}_{st}$. As classroom segregation D_{st} grows, so does the expected share of white classmates. Conditional on the racial composition of enrollment at the school level, the expected share of white classmates *for white students* mechanically implies the expected share of white classmates *for non-white students*. Because I allow the preference parameters on classroom segregation and on the expected share of white students at the school level to vary across racial groups (see below for details), this specification allows for disagreement between white and non-white students on what classroom configuration is the most desirable within a given school.[27]

$Distance_{ist}$ and $Default_{ist}$ are characteristics that vary at the school-by-student level: $Distance_{ist}$ is the home-school distance in logs,[28] while $Default_{ist}$ is a dummy that takes value 1 if school s at time t is assigned to student i based on his or her residential address. I allow the preference for the default school to vary with the school choice regime ($Post_t$): This captures the fact that open enrollment significantly reduces the (time, administrative, effort) cost that households face to enroll their children at a public school

[27] Appendix Figure C.6 shows that in the data, the function $f(D_{st}, W_{st}) = 0.03 + 0.10 \times D_{st} + 0.92 \times W_{st} + 0.19 \times D_{st} \times W_{st}$ (where W_{st} is the actual share of white students at the school level) closely fits the weighted average share of white classmates for white students. (The R-squared is 98%.) I allow parents to have preferences for each term in $f(D_{st}, \widehat{W}_{st})$, rather than on $f(D_{st}, \widehat{W}_{st})$ as I want to separately quantify the utility weights that parents place on the racial composition of the school v. of the classroom, where students spend most of their time. Households on the other hand might value the racial composition of the student body at the school level for reasons other than the classroom composition, such as teacher quality or donations. My specification is a parsimonious way to allow for all these forces.

[28] I take households' residential locations as given, in line with the literature (Neilson, 2021; Allende, 2019; Gilraine et al., 2022). The implicit assumption is that preferences for academic quality and classroom segregation are not correlated with residential location.

different from the default one. 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.[29] Lastly, $\tilde{v}_{ist}$ is an idiosyncratic match value observed only to parents at the time of the enrollment decision.

Preferences are allowed to vary across households along observed and unobserved dimensions. Specifically, for q_{st}, D_{st}, and $\overline{W}_{st}$

$$\begin{pmatrix} \beta_i^q \\ \beta_i^D \\ \beta_i^W \end{pmatrix} = \begin{pmatrix} \bar{\beta}^q \\ \bar{\beta}^D \\ \bar{\beta}^W \end{pmatrix} + \begin{pmatrix} \beta_z^q \\ \beta_z^D \\ \beta_z^W \end{pmatrix} Z_i + \begin{pmatrix} \nu_i^q \\ \nu_i^D \\ \nu_i^W \end{pmatrix} \tag{7}$$

where $\bar{\beta}^q, \bar{\beta}^D, \bar{\beta}^W$ are linear preference parameters that are common across households; $\beta_z^q, \beta_z^D, \beta_z^W$ are non-linear preference parameters that vary across race-by-SES observable types $Z = \{WH, WL, NH, NL\}$, where W (N) stands for white (non-white) and H (L) stands for high-SES (low-SES); ν^q, ν^D, ν^W are random coefficients that capture the residual, unobservable heterogeneity in preferences. Other preference parameters vary along the observable dimensions.[30]

Parametrization: As for the unobservable heterogeneity in preferences, I assume that

$$\nu_i^q \sim ln\mathcal{N}(\mu^q, \sigma^q) \tag{8}$$

$$\begin{pmatrix} \nu_i^D \\ \nu_i^W \end{pmatrix} \sim \mathcal{N}(0, \Sigma^{DW}) \tag{9}$$

with the variance-covariance matrix defined as

$$\Sigma^{DW} = \begin{pmatrix} {\sigma^D}^2 & \rho^{DW}\sigma^D\sigma^W \\ \rho^{DW}\sigma^D\sigma^W & {\sigma^W}^2 \end{pmatrix}$$

where σ denotes a standard deviation and ρ a correlation coefficient.

The log-normal assumption for the distribution of the random coefficient on academic quality captures the economic intuition that all agents should prefer an effective school to an ineffective one, holding other characteristics fixed (Train, 2009; for an application, see Allende, 2019). The random coefficients on the attributes related to peer quality, i.e., classroom segregation and the share of white students at the school level are modeled as correlated normals.

The idiosyncratic preference shock $\tilde{v}$ is assumed to follow a Type-1 Extreme Value distribution.

[29] After the reform, CMS students were offered free busing from home to non-default schools within Choice Zones, i.e., geographical quadrants in which the district was divided for transportation purposes.

[30] I interpret the preference parameters as perfect information parameters, i.e., households' utility weights under perfect information on school characteristics. The perfect information assumption is consistent with the intense informational campaign in which CMS engaged upon the reform, including the website set up by the district where detailed information on test scores, student body composition, attendance and suspension rates, etc. was reported at the school level (Hastings and Weinstein, 2008). Such information however may not have been fully understood by parents, especially those constrained by lack of time, language barriers, or thin social networks (Kim, 2009; Bergman et al., 2020). While the interpretation of the demand parameters is affected by uncertainty Allende, 2019, all my counterfactuals hold the informational environment fixed.

4.2.1 Enrollment Probabilities

Let $V_{ist} = U_{ist} - \tilde{v}_{ist}$ with U_{ist} defined in equation (6). Then, the Type-1 Extreme Value distributional assumption on $\tilde{v}_{ist}$ implies the following closed-form choice probabilities:

$$p_{ist} = \frac{exp(V_{ist})}{\sum_{j \in \Omega_{it}} exp(V_{ijt})} \tag{10}$$

where j denotes a school in the market and Ω_{it} is 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.[31] [32]

Choice probabilities can be re-expressed as

$$p_{ist} = \frac{exp(\delta_{st} + u_{ist})}{\sum_{j \in \Omega_t} exp(\delta_{jt} + u_{ijt})} \tag{11}$$

where

$$\delta_{st} = \bar{\beta}^q q_{st} + \bar{\beta}^D D_{st} + \bar{\beta}^W \overline{W}_{st} + \bar{\beta}^{DW} D_{st} \times \overline{W}_{st} + \bar{\beta}^M Magnet_{st} + \xi_{st} \tag{12}$$

is the "mean" utility, i.e., the component of utility that is common across households, and

$$\begin{aligned} u_{ist} = {} & (\beta_z^q Z_i + \nu_i^q) q_{st} + (\beta_z^D Z_i + \nu_i^D) D_{st} + (\beta_z^W Z_i + \nu_i^W) \overline{W}_{st} + \beta_z^{DW} Z_i (D_{st} \times \overline{W}_{st}) \\ & - \gamma_i Distance_{ist} + \gamma_i^M Distance_{ist} \times Magnet_{st} + \gamma_i^M Distance_{ist} \times Post_t \times Transportation_{st} \\ & + \eta_i Default_{ist} + \eta_i^P Default_{ist} \times Post_t + \tilde{v}_{ist} \end{aligned} \tag{13}$$

is the portion of utility that captures systematic heterogeneity in preferences. I refer to equations 12 and 13 in Section 5 where I discuss the estimation strategy.

4.3 Supply of Academic Quality and Classroom Segregation

On the supply side of the model, school s at time t chooses academic quality q_{st} and classroom segregation D_{st} so as to solve the following maximization problem:

$$\arg \max_{\{q_{st}, D_{st}\}} \left[\psi E_{st}(q_{st}, D_{st}; q_{-st}, D_{-st}) - C_{st}\Big(q_{st}, D_{st}, E_{st}(q_{st}, D_{st}; q_{-st}, D_{-st}), W_{st}(q_{st}, D_{st}; q_{-st}, D_{-st})\Big) \right] \tag{14}$$

[31] I do not restrict households' consideration sets based on distance from home.

[32] I abstract away from capacity constraints. If capacity constraints bind, then the revealed preference argument underlying my demand model breaks. Capacity constraints could be embedded if the choice forms submitted by parents were available. Unfortunately, CMS is denying all new applications for lottery data at this time. Reassuringly, based on the lottery data statistics reported in Hastings et al. (2009), at most 9% of the students in my estimation sample are not enrolled in their first-choice school. Also, most oversubscribed schools are magnet schools (Deming et al., 2014), and I allow parents to have preferences for the magnet status of the school. Abstracting away from capacity constraints is therefore unlikely to affect my analysis of the trade-off between academic quality and classroom segregation.

subject to the constraint

$$0 \leq D_{st} \leq 1 \tag{15}$$

$E_{st}(\cdot)$ denotes school s's total enrollment at time t. This is an equilibrium outcome of schools' and students' choices. $C_{st}(\cdot)$ is the cost function that school s faces at time t and is illustrated in Section 4.3.1. The choice of D_{st} (defined in equation (2)) faces a feasibility constraint: The fraction of feasible segregation that school s attains cannot be smaller than zero or larger than one.[33]

Henceforth (including in estimation) I normalize the utility parameter on enrollment, ψ, to one.

4.3.1 Cost Function

The cost function faced by school s in year t is specified as follows:

$$C_{st}\Big(q_{st}, D_{st}, E_{st}, W_{st}\Big) = \underbrace{\overbrace{\Big(w_{st} + \mu q_{st} + \omega^q_{st}\Big)}^{\text{Marginal Cost}} E_{st} - \overbrace{\zeta W_{st}}^{\substack{\text{Compositional}\\ \text{Premium}}} + \overbrace{\kappa_1 q_{st} + \frac{\kappa_2}{2} q^2_{st}}^{\text{Fixed Cost}}}_{\substack{\text{Cost of}\\ \text{Academic Quality}}} + \underbrace{\omega^D_{st} \cdot D_{st} + \frac{\alpha}{2} D^2_{st}}_{\substack{\text{Cost of}\\ \text{Classroom Segregation}}} \tag{16}$$

The cost of vertical quality comprises a marginal cost (i.e., a component that is multiplied by enrollment) and a quadratic fixed cost. The marginal cost is the sum of an exogenous cost shifter, w_{st}, a linear component in academic quality, μq_{st}, and an unobserved school-by-year-specific cost shock, ω^q_{st}. The compositional premium ζW_{st} allows for a cost reduction that is proportional to the share of white students enrolled at the school (Jackson, 2009; Singleton, 2019). The fixed cost of vertical quality captures the component of productive effort that does not vary with the enrollment size and composition. The quadratic specification in q_{st} allows for marginal improvements in academic quality to be more costly, the higher the school's baseline effectiveness.

The cost of classroom segregation, which can be interpreted as a reputational cost,[34] is specified as quadratic in D_{st} and invariant to changes in enrollment size and composition. The quadratic assumption reflects the positive skewness in the distribution of D_{st} observed in the data (Figure 4). Lastly, ω^D_{st} can be thought of as a multiplicative cost shock that captures the school-specific degree of aversion to classroom segregation, alongside transitory factors.

[33] The approximation to a continuous choice problem (necessary to keep the model tractable in estimation) is justified by the fact that schools have some margin of discretion over class sizes, which generally makes the set of classroom segregation levels that they can choose from quite dense (given enrollment). Table 2 reports that the within-school-grade standard deviation of the distribution of class size ranges between 2 and 2.5 in CMS for the time period of interest. At the time of writing, the State of North Carolina requires an average K-3 class size of at most 18 at the district level, with no section larger than 21 as per House Bill 90.

[34] "In virtually all school districts, principals (...) must create classes balanced in size, academic performance, race, gender, and certain behavior problems. These organizational needs preclude principals from meeting parents' requests in several areas" (Lareau, 2000, p.163).

4.4 Equilibrium

The equilibrium concept is that of full information Nash equilibrium with rational expectations on the demand side. The equilibrium of the model is determined by the first-order conditions for academic quality q_{st} and classroom segregation D_{st} derived from the school's problem alongside a rationality condition on households' expectation of the share of white students at the school level, $\overline{W}_{st}$.[35]

4.4.1 Rational Expectation Condition

At the time-t equilibrium, households form a correct expectation of the share of white students that enroll at each school s, i.e.:

$$\overline{W}_{st} = \frac{\sum_{i \in \mathcal{W}_t} p_{ist}(q_t, D_t)}{E_{st}(q_t, D_t)} \tag{17}$$

$\mathcal{W}_t$ denotes the set of white students in the market, and the enrollment probability p_{ist} is defined in equation (10).

4.4.2 First Order Conditions

At the time-t equilibrium, each school s offers the level of academic quality q_{st} and classroom segregation D_{st} that maximize the school's enrollment net of costs, given its competitors' choices q_{-st} and D_{-st}. The equations for q_{st} and D_{st} are derived from the school problem as first-order conditions: For $\kappa_2 = 0$,[36]

$$q_{st} = -\frac{1}{\epsilon^q_{st}(q_t, D_t)} \left(1 + \frac{\kappa_1}{\mu} \frac{1}{E_{st}(q_t, D_t)} - \frac{\zeta}{\mu} \frac{dW_{st}(q_t, D_t)}{dq_{st}} \frac{1}{E_{st}(q_t, D_t)} \right) + \frac{1 - w_{st}}{\mu} - \frac{\omega^q_{st}}{\mu} \tag{18}$$

$$D_{st} = \frac{1}{\alpha} \frac{\epsilon^D_{st}(q_t, D_t)}{\epsilon^q_{st}(q_t, D_t)} \left(\mu E_{st}(q_t, D_t) + \kappa_1 - \zeta \frac{dW_{st}(q_t, D_t)}{dq_{st}} \right) + \frac{\zeta}{\alpha} \frac{dW_{st}(q_t, D_t)}{dD_{st}} - \frac{\omega^D_{st}}{\alpha} \tag{19}$$

where ϵ^q_{st} and ϵ^D_{st} are the semi-elasticities of enrollment to own academic quality and classroom segregation, respectively.

The optimality conditions above show how competitive incentives operate in this model. As school choice is introduced, students' choices become more responsive to school characteristics. Assuming that all students value academic quality positively, competition implies an increase in academic quality via a larger (positive) semi-elasticity of enrollment to own academic quality (equation (18)), holding fixed other factors. Competition on the other hand may or may not imply higher classroom segregation: For example, for a school that faces a positive semi-elasticity of enrollment to classroom segregation, classroom segregation increases (decreases) if enrollment responds more (less) to classroom segregation than to academic quality (i.e., the semi-elasticity ratio is larger than one), holding other terms constant.

[35] While multiple equilibria are theoretically possible in the presence of parental preferences for the composition of the student body, which is an equilibrium object, I did not find evidence of multiplicity (or non-existence).

[36] I write the first-order conditions at $\kappa_2 = 0$ to make interpretation more intuitive. Also, I omit the dependence of q_{st} and D_{st} on (q_{-st}, D_{-st}) for the sake of brevity.

From the point of view of a single rent-seeking school (McMillan, 2004), whether classroom segregation and academic quality are substitutes or complements in equilibrium depends on two types of factors: I label one as *direct* and the other one as *compositional*. To exemplify, suppose that all students value academic quality positively, and there is no reason for the school to care about the composition of its enrollment. If both white and non-white students value classroom segregation positively (negatively), then academic quality and classroom segregation are unambiguously substitutes (complements) in that the school can offset the enrollment loss from lowering the former by raising (lowering) the latter. If white and non-white students disagree, then the relation between the two attributes is determined by what type is more responsive and hence worth competing for (i.e., is "more marginal"). This is the *direct* channel. To see the second channel, suppose that the school faces an incentive to enroll a larger share of white students, as that enters all students' utility positively or implies a cost advantage. All students value academic quality positively, while only white students value classroom segregation positively. The school might have an incentive to substitute classroom segregation for academic quality so as to attract white students, even if non-white students are more responsive. This is the *compositional* channel. Whether classroom segregation and academic quality are substitutes or complements depends on how the two channels combine and is therefore an empirical question.

Decomposing the semi-elasticities of enrollment: The fact that the share of white students at the school level W_{st}, which is an equilibrium object, enters parental utility (equation (6)) directly affects the expression for the semi-elasticities of enrollment. For academic quality, the semi-elasticity of enrollment ϵ^q_{st} is defined as

$$\epsilon^q_{st} = \frac{1}{E_{st}} \frac{dE_{st}}{dq_{st}} \tag{20}$$

where the total derivative of enrollment over academic quality can be decomposed as

$$\frac{dE_{st}(\mathbf{q},\mathbf{D},W)}{dq_{st}} = \underbrace{\frac{\partial E_{st}(\mathbf{q},\mathbf{D},W)}{\partial q_{st}}}_{\text{Partial effect}} + \underbrace{\sum_j \frac{\partial E_{st}(\mathbf{q},\mathbf{D},W)}{\partial W_{jt}} \frac{dW_{jt}}{dq_{st}}}_{\text{Indirect effect}} \tag{21}$$

where j indexes schools in the market. The first term is the partial or direct effect of academic quality q_{st} on total enrollment E_{st} and captures schools' differentiation via academic quality. In this model, the effect of changing school s's academic quality on the extent of differentiation is mediated by the fact that parents value also the racial composition of the student body at the school level W_{st}. If both academic quality and a large concentration of white schoolmates are desirable school characteristics, then school s becomes more attractive by marginally increasing q_{st} via both its higher effectiveness and more desirable student body composition.

The second term captures the indirect effect of changing q_{st} on E_{st}, i.e., the effect that goes through the change in W_{st}. It is the product of the responsiveness of total enrollment to the school composition, $\frac{\partial E_{st}(\mathbf{q},\mathbf{D},W)}{\partial W_{jt}}$, and the sensitivity of the school composition to quality, $\frac{dW_{jt}}{dq_{st}}$. This term highlights the potential "white-skimming" incentive stemming from the demand side that might schools face, and how this motif is factored into schools' quality decisions (Allende, 2019).

The same considerations hold for the semi-elasticity of total enrollment to classroom segregation:

$$\epsilon_{st}^{D} = \frac{1}{E_{st}} \frac{dE_{st}}{dD_{st}} \tag{22}$$

where

$$\frac{dE_{st}(\mathbf{q},\mathbf{D},W)}{dD_{st}} = \underbrace{\frac{\partial E_{st}(\mathbf{q},\mathbf{D},W)}{\partial D_{st}}}_{\text{Partial effect}} + \underbrace{\sum_{j} \frac{\partial E_{st}(\mathbf{q},\mathbf{D},W)}{\partial W_{jt}} \frac{dW_{jt}}{dD_{st}}}_{\text{Indirect effect}} \tag{23}$$

All terms in equations 21 and 23 are derived in Appendix A.

5 Estimation Strategy

Estimation of the model proceeds in two steps. In the first step, I estimate the parameters that govern the heterogeneity in household preferences and retrieve the mean utilities (equation (12)). In the second step, I estimate the linear preference parameters alongside the supply (cost) parameters. In what follows, the linear preference parameters are denoted as θ_1; the non-linear preference parameters as θ_2; the cost parameters as θ_3. Sections 5.1 and 5.2 illustrate the estimation strategy in greater detail.

Section 5.3 describes the estimation sample. I use CMS data for two school years: one before the introduction of open enrollment (1999-2000) and one after (2004-2005). This is crucial as my estimation approach heavily relies on within-school changes in classroom segregation and academic quality around the reform.

5.1 Step 1: Estimating the Non-Linear Preference Parameters θ_2

Identification of how preferences for school attributes vary in the population of households relies on the availability of student-level data (Berry and Haile, 2022; Grieco et al., 2023). Intuitively, as long as the student population varies sufficiently along the observable dimensions of race and SES, such observables create within-market variation in families' choice problems that can be used to identify household preferences: Variation *across* observable types helps identify observable preference heterogeneity, while variation *within* observable types helps identify unobserved preference heterogeneity.

The parameters that discipline heterogeneity in household preferences can therefore be estimated by mapping the enrollment choices observed in the data to the enrollment probabilities implied by the model (equation (11)) via Simulated Maximum Likelihood. 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 (i.e., BLP inversion; Berry et al., 1995). The outer loop uses $\widehat{\delta}_t^r$ to compute the simulated enrollment probabilities and log-likelihood function. The simulated enrollment probabilities are computed as

$$\widehat{p}^r_{ist} = \int \frac{exp\Big(\widehat{\delta}^r_{st} + u_{ist\iota}(\theta^r_2)\Big)}{\sum_j exp\Big(\widehat{\delta}^r_{jt} + u_{ijt\iota}(\theta^r_2)\Big)} dF(\iota)d\iota$$

where ι denotes the (three-dimensional) unobserved heterogeneity in preferences. I use Gaussian quadrature to integrate out the random coefficients on academic quality, classroom segregation, and the share of white students at the school level (see equation (7)). The value of the log-likelihood function at θ^r_2 can then be expressed as

$$\mathcal{L}(\theta_2 = \theta^r_2) = -\sum_i y_{ist} ln\big(\widehat{p}^r_{ist}(\theta^r_2)\big) \tag{24}$$

where $y_{ist} = 1$ if student i at time t enrolls in school s, 0 otherwise. The estimation procedure stops when $\mathcal{L}(\theta_2)$ is minimized, i.e., at the R-th iteration of the outer loop such that $\mathcal{L}(\theta^R_2) = \arg\min_{\theta_2} \mathcal{L}(\theta_2)$. More details on the estimation of θ_2 are reported in appendix B.2.

5.2 Step 2: Estimating the Linear Preference and Cost Parameters (θ_1, θ_3)

I estimate θ_1 and θ_3 by exploiting the expressions for the mean utilities backed out in step one (equation (12)) along with the first-order conditions for academic quality and classroom segregation derived from the school problem (equations 18 and 19).

Identification: An econometric challenge arises in estimating the linear preference and cost parameters on academic quality q_{st}, classroom segregation D_{st}, and the share of white students at the school level W_{st}. The problem is that these endogenous variables may be correlated with the unobserved quality shock ξ_{st} and cost shocks $(\omega^q_{st}, \omega^D_{st})$, which enter the estimated mean utilities $\widehat{\delta}_{st}$ and the optimality conditions for academic quality and classroom segregation. The endogeneity threat is threefold. First, the unobservable quality shock may be correlated with academic quality and classroom segregation: For example, a school that experiences a particularly favorable realization of the shock may be able to attract the same market share as a school with an unfavorable realization by offering lower academic quality or classroom segregation. If this is the case, then identifying preferences naively off enrollment levels becomes problematic. Second, the quality and cost shocks might be correlated among themselves: For example, the principals who spend the most time meeting with parents and taking care of students' problems might be the same who spend the most time meeting with teachers and giving them feedback to improve. This would imply that schools with high unobserved quality are also those with an unobserved (effort) cost advantage, which prohibits identifying the cost parameters directly off the schools' choices of academic quality and classroom segregation. The unobserved cost shocks for academic quality and classroom segregation might be correlated, too. Third, if white and non-white households differ in the relative importance that they attribute to the observable school attributes (relative to the unobserved quality shock), then the share of white students at the school level may be correlated with the unobserved quality shock. If so, then more structure is needed to learn about parental preferences from the racial composition of the student body across schools.

I solve the identification problem using instruments for the endogenous variables. I rely on three sets of instruments: instruments for classroom segregation, Z^D; instruments for academic quality, Z^q; instruments for the share of white students at the school level, Z^W. The main instrument in Z^D is the competitive pressure that schools face upon the introduction of open enrollment, i.e., the treatment variable in the event-study shown in Figure 6. The main instrument in Z^q is eligibility for Equity Plus resources, i.e., the treatment variable in the regression discontinuity specification estimated in Figure 3. The main instruments in Z^W are lagged characteristics of the school's teacher body interacted with baseline neighborhood demographics. The following paragraphs discuss the instruments' validity and relevance.

I use Z^D to write moment conditions based on the following exclusion restriction:

$$E\left[\Delta\omega^D \middle| Z^D\right] = 0 \tag{25}$$

where Δ denotes the first-difference operator applied to time periods $\tau^{'}$ (post-reform) and τ (pre-reform) and for any school s and time t, ω^D_{st} is backed out of the first-order conditions for classroom segregation (equation (19)):

$$\begin{aligned}\Delta\omega^D_s = \omega^D_{s\tau'} - \omega^D_{s\tau} = -\alpha\Delta D_s + &\left(\frac{dE_{s\tau'}(\theta_1)}{dD_{s\tau'}}\Big(1 - w_{s\tau'} - \mu q_{s\tau'}(\theta_1,\theta_3) - \omega^q_{s\tau'}\Big) + \zeta\frac{dW_{s\tau'}(\theta_1)}{dD_{s\tau'}}\right)\\ &- \left(\frac{dE_{s\tau}(\theta_1)}{dD_{s\tau}}\Big(1 - w_{s\tau} - \mu q_{s\tau}(\theta_1,\theta_3) - \omega^q_{s\tau}\Big) + \zeta\frac{dW_{s\tau}(\theta_1)}{dD_{s\tau}}\right)\end{aligned}$$

The restriction in 25 implies that school-level competitive pressure is a valid instrument in Z^D insofar as it is orthogonal to the *within-school* innovations to the cost shock ω^D_s. This restriction seems credible: The first difference $\Delta\omega^D_s$ is purged out of any school-specific cost factors that do not vary over time (e.g., a principal who is particularly averse to segregation) and might be correlated with the (pre-determined and fixed) school location (e.g., segregation-averse principals sort into schools located in diverse, high-density urban areas, which are those that face the strongest competitive pressure). On the other hand, any omitted time-varying factors that affect a school's cost of segregation and whose evolution over time is correlated with competitive pressure are a threat to identification. For example, the introduction of choice might lead principals to re-sort across schools in response to the reform, or to changes in the set of "schools at risk" that are under the district's scrutiny and thus face a larger reputational cost of classroom segregation. The fact that the cost structure directly accounts for the demographic composition of the school's student body (equation (16)) reduces the scope of the concern as long as principals and district's scrutiny re-allocate toward schools that are *observably* easier or harder to teach (Jackson, 2009; Singleton, 2019).

The relevance of competitive pressure in explaining changes in classroom segregation around the reform is documented in the event-study in Figure 6. In the (first-differenced) first-order condition for classroom segregation for any school s, competitive pressure affects the optimal level of classroom segregation at school s by making the size and composition of enrollment more responsive to the school characteristics. In other terms, the semi-elasticity of enrollment to own classroom segregation is the model object that links the competitive incentives to the within-school response in classroom segregation via the first-order conditions of the school.

Using the reduced-form measure of competitive pressure as an instrument for identification of the preferences for classroom segregation implies that the estimated linear preference parameter rationalizes the reduced-form effect of competition on classroom segregation identified in the event-study (given the utility estimates obtained in the first step) (Gilraine et al., 2022). I complement the reduced-form instrument with other instruments that measure the pre-reform degree of market differentiation in classroom segregation (Newey, 1990; Gandhi and Houde, 2019; Bodéré, 2023). The identification argument is the same as that discussed for the reduced-form instrument, while relevance is verified through a linear first-stage regression (see Section B.3).

In a similar vein, for academic quality I use the vector of instruments Z^q to write moment conditions based on

$$E\Big[\Delta\omega^q\Big|Z^q\Big] = 0 \tag{26}$$

where

$$\begin{aligned}\Delta\omega^q_s = &\left\{-q_{s\tau'}\left[\mu+\kappa_2\left(\frac{dE_{s\tau'}(\theta_1)}{dq_{s\tau'}}\right)^{-1}\right]+1-w_{s\tau'}-\frac{\mu}{\epsilon^q_{s\tau'}}+\left(\zeta\frac{dW_{s\tau'}(\theta_1)}{dq_{s\tau'}}-\kappa_1\right)\left(\frac{dE_{s\tau'}(\theta_1)}{dq_{s\tau'}}\right)^{-1}\right\}\\ &-\left\{-q_{s\tau}\left[\mu+\kappa_2\left(\frac{dE_{s\tau}(\theta_1)}{dq_{s\tau}}\right)^{-1}\right]+1-w_{s\tau}-\frac{\mu}{\epsilon^q_{s\tau}}+\left(\zeta\frac{dW_{s\tau}(\theta_1)}{dq_{s\tau}}-\kappa_1\right)\left(\frac{dE_{s\tau}(\theta_1)}{dq_{s\tau}}\right)^{-1}\right\}\end{aligned}$$

The vector of instruments Z^q includes eligibility for Equity Plus resources upon the introduction of school choice (see Section 2). The exclusion restriction requires that the cost of providing academic quality does not evolve differentially across schools with and without Equity Plus status through innovations to the unobservable cost shock. A factor that might threaten validity is student sorting across schools that receive Equity Plus resources v. do not. Sorting could go either way: Parents might be attracted to better-equipped schools or perceive the Equity Plus status as a red flag. Allowing the cost of academic quality to depend directly on the demographics of the student body reduces the scope of the concern.[37]

Relevance is documented in Figure 3, where I report results from a regression discontinuity design where within-school changes in academic quality around the reform are compared across schools nearby the eligibility cutoff with different Equity Plus statuses. In the model, Equity Plus resources are captured by

[37] In estimation, I impose that the exclusion restriction in equation (26) holds globally (rather than locally around the cutoff) because of the small number of schools observed both before and after the reform (78 in total). Reassuringly, the RD results in Figure 3 are not particularly sensitive to the degree of extrapolation away from the cutoff. Also importantly, the RD "running variable" (school demographics) enters my cost function directly.

the (conditionally) exogenous cost-shifter w_{st}, which enters the optimality condition for academic quality.[38] Intuitively then, my estimation approach matches the difference in academic quality changes across schools with different Equity Plus statuses *predicted* by the model to that *observed* in the data. As for classroom segregation, I complement the policy instrument with other variables that measure the pre-reform degree of market differentiation in academic quality (Gandhi and Houde, 2019). The identification argument is analog, and relevance is verified through a linear first-stage regression (see Section B.3).

Lastly, following previous work that estimates demand models with unobserved heterogeneity and endogenous prices (Berry et al., 1995, 2004; Nevo, 2001; Petrin, 2002; Neilson, 2021), I project the estimated mean utilities ξ_{st} (equation (12)) onto local demographics Z_{st}^{W}. Mean utilities estimated for the pre- and post-reform are stacked into a single vector, and the instruments vary at the school-by-year level. Such instruments comprise lagged characteristics of the teacher body interacted with demographic characteristics of the neighborhood before the reform (see Section B.3). The orthogonality condition is

$$E\Big[\xi|Z^{W}\Big] = 0 \tag{27}$$

and relies on (lagged) characteristics of the teachers and households in the neighborhood not responding to (contemporaneous) unobserved quality shocks.

Estimation: I use the orthogonality conditions in 25, 26, and 27 to write moment conditions and construct a Generalized Method of Moments estimator for the linear preference parameters θ_1 and cost parameters θ_3:

$$\widehat{\theta}_{1,3} = \arg\min_{\theta_{1,3}} \Bigg(g_S(\theta_{1,3})' W g_S(\theta_{1,3}) \Bigg)$$

where S is the number of schools, g_s is a vector of moment conditions

$$g_S(\theta_{1,3}) = \frac{1}{S} \begin{bmatrix} \mathcal{Z}^D & 0 & 0 \\ 0 & \mathcal{Z}^q & 0 \\ 0 & 0 & \mathcal{Z}^W \end{bmatrix} \begin{bmatrix} \Delta\omega^D \\ \Delta\omega^q \\ \xi \end{bmatrix}$$

and W is a $K \times K$ weighting matrix, with K denoting the number of moment conditions. Section B.3 provides further estimation details.

5.3 Estimation Sample

Appendix table D.3 shows summary statistics for the estimation sample by school year: 1999-2000 (pre-reform) and 2004-2005 (post-reform). The top panel reports students' characteristics, while the bottom

[38] In estimation, w_{st} is the teacher-to-pupil ratio, which I see increase more for Equity Plus schools (relative to non-Equity Plus schools) in the RD.

panel describes the relevant features of the schools.

The student sample includes third- and fourth-graders attending a traditional public school in CMS and living therein. Student data is on demographics, residential locations, and enrollment choices. At least half of each year's sample is non-white, which is consistent with the highly diverse population residing in the city of Charlotte (non-white for the 45%, according to 2000 Census data). Between 40% and 50% of the students are economically disadvantaged. Underprivileged children are overwhelmingly non-white, with students who are either white and high-SES *or* non-white and low-SES making up approximately 80% of the total. Regarding enrollment decisions, the probability of choosing the default school (i.e., the school assigned by the district based on home address) changes significantly across years: from more than 80% in 2000 to slightly less than 60% in 2005. This drop reflects the introduction of open enrollment.[39] The probability of attending a non-default school is higher among non-white students,[40] which is consistent with white students having access to default schools perceived as "higher-quality" on average. The median home-school distance is between 2.7 and 2.9 miles and is similar across years.[41] Notably, under open enrollment a quarter of the students travel at least 7 miles to reach their school of choice: This is a relatively long distance, given that the closest school is located only 1.1 miles away for the median student in 2005. Importantly, the variables described in the *Students* panel of Table D.3 are quite balanced across the full sample (columns 1 and 3) and the 10% random sub-sample used for estimation (columns 2 and 4).

The *Schools* panel of Table D.3 reports summary statistics for the schools included in my analysis. The 2000 and 2005 sets of schools do not fully overlap mainly due to school openings and closures that happened in between.[42] Average value-added and classroom segregation increase between 2000 and 2005: Section 3.2 discusses how this increase mirrors schools' competitive responses to the introduction of open enrollment. The full distributions of the share of white students at the school level for both years are plotted in Figure 2.

6 Estimation Results

6.1 Non-Linear Preference Parameters

Table 4 reports estimates for the vector of parameters that govern the heterogeneity in household preferences, or θ_2 (equation (13)). Although these parameters cannot be fully interpreted in isolation, the estimates are indicative of several worth highlighting features of school demand.

First, there is substantial heterogeneity in the weight that parents attribute to academic quality and

[39]Before the reform, enrolling at a school other than the default one is possible either if that school is an open-enrollment magnet, or under some special circumstances (e.g., proximity to parents' working locations, currently enrolled siblings, etc.) and upon approval.

[40]This pattern is confirmed by the lottery data statistics reported in Hastings et al. (2009).

[41]Gilraine et al. (2022) report an average home-school distance for K-2 North Carolina students of approximately 2.3 miles between 2012 and 2016.

[42]Three schools that remained active throughout the period are excluded from the 2000 school set because of missing coordinates, which prohibits me from determining their 2000 locations reliably.

classroom segregation. Relative to white high-SES students (the reference group), on average low-SES students appear less responsive to an increase in academic quality. This pattern is relatively stronger for the non-white low-SES group and is in line with prior literature (Bau, 2022; Neilson, 2021; Allende, 2019; Gilraine et al., 2022). Moreover, non-white students value classroom segregation less positively (or more negatively), compared to white high-SES students. For non-white students, classroom segregation appears particularly undesirable at schools where non-white students themselves are the minority. Preferences are significantly heterogeneous not only across race-by-SES observable types, but also within. This is particularly true for classroom segregation.

Second, households face a disutility from traveling longer distances to school, which is consistent with spatial competition (Agostinelli et al., 2023). Preferences for proximity to home do not vary significantly by SES: This is consistent with CMS offering free busing within Choice Zones, i.e., geographical quadrants into which the district was divided for transportation purposes. Free transportation appears salient in this context: As Choice Zones are enacted after the introduction of open enrollment, the within-quadrant average distaste for distance is reduced by almost a quarter. Holding other factors fixed, students are willing to travel longer distances to magnet schools.

Third, the utility premium attributed to the default (zoned) school drops by more than half upon the introduction of open enrollment. This is consistent with the interpretation of the reform in Section 2: Open enrollment makes it much easier for parents to enroll their children at a non-default school. Parents then become relatively more responsive to school attributes other than the default status, which in turn triggers schools' competitive responses.

6.2 Linear Preference and Cost Parameters

Table 5 reports estimates for the linear preference parameters θ_1 (associated white high-SES households; equation (12)) and the cost parameters θ_3 (equation (16)).

On the demand side, white high-SES households tend to prefer schools that offer higher academic quality and higher classroom segregation and that enroll a larger share of white students. Classroom segregation is however undesirable at schools where white students account for the overwhelming majority (i.e., more than 88%) of the student body.

On the supply side, the cost parameters are to be interpreted in enrollment units (as I normalize the parameter on enrollment in the school problem to one). For a hypothetical school of 100 students that offers a level of academic quality of 0.2 (i.e., approximately one standard deviation above the mean), enrolling one extra student increases the cost of providing academic quality by .02, 2% of the utility gain. Conditional on the size of enrollment, schools face a cost incentive to attract a larger share of white students: For our hypothetical school, switching from having no white students to having all white students allows to increase academic quality from 0.2 to 0.24 (i.e., by a fifth of a standard deviation) holding costs fixed. This calculation includes the fixed costs of providing academic quality, i.e., the costs that do not vary with the enrollment

Table 4: Estimates of the non-linear preference parameters

Parameter		Point Estimate	Standard Error
Endogenous Characteristics			
Observable Heterogeneity			
q x White x Low SES	β^q_{WL}	-1.3494	0.6643
q x Non-White x High SES	β^q_{NH}	-0.6041	0.4402
q x Non-White x Low SES	β^q_{NL}	-2.2873	0.3644
D x White x Low SES	β^D_{WL}	-0.9833	0.7425
D x Non-White x High SES	β^D_{NH}	-0.3919	0.4150
D x Non-White x Low SES	β^D_{NL}	-1.1513	0.3498
W x White x Low SES	β^W_{WL}	-3.3682	0.4554
W x Non-White x High SES	β^W_{NH}	-0.0643	0.3010
W x Non-White x Low SES	β^W_{NL}	-1.3007	0.2810
D x W x White x Low SES	β^{DW}_{WL}	0.3711	1.6207
D x W x Non-White x High SES	β^{DW}_{NH}	-4.5862	0.9115
D x W x Non-White x Low SES	β^{DW}_{NL}	-2.3239	0.8241
Unobservable Heterogeneity			
q (Log-Normal), Mean	μ^q	0.1696	0.1796
q (Log-Normal), Standard Deviation	σ^q	1.1664	0.0812
D (Normal), Standard Deviation	σ^D	2.2856	0.5968
W (Normal), Standard Deviation	σ^W	0.4328	0.6570
W (Normal), Correlation With D	ρ^{DW}	0.9999	0.1434
Exogenous Characteristics			
Log Distance	γ_i	-1.1812	0.0249
Log Distance x Low SES		0.0712	0.0336
Log Distance x Magnet		0.1834	0.0479
Log Distance x Post-Reform x Choice Zone		0.2611	0.0368
Assigned (Zoned) School	η_i	8.3358	0.0671
Assigned School x Post-Reform		-5.7035	0.0700

Notes: Table 4 reports point estimates and standard errors for the parameters that govern the heterogeneity in household preferences. The estimate of the interaction between an indicator for missing D (equal to 1 for only one school with evident reporting errors) and the Non-White dummy is not reported. Standard errors are computed using the BHHH outer-product of gradients estimator (Berndt et al., 1974; Train, 2009). The standard errors for the unobserved heterogeneity parameters are retrieved using the delta method. See Section 5 and Appendix Section B.2 for further estimation details. Number of observations: 30,786. Number of students: 3,507.

level. Such fixed costs are only slightly convex in the level of academic quality. The convexity in the cost of classroom segregation on the other hand is economically significant: On average, a marginal increase in segregation in the post-reform CMS (where the average dissimilarity index is approximately .22) increases school costs by 33% more than in the pre-reform CMS (where the average dissimilarity index is around .16).

Appendix Figure C.7 plots the distribution of the unobserved quality shocks implied by my estimates of the mean utilities (step one) and linear preference parameters (step two). Appendix Figure C.8 shows the

Table 5: Estimates of the linear preference parameters and cost parameters

Parameter		**Point Estimate**	**Standard Error**
Preference parameters (White x High SES)			
Academic quality	$\bar{\beta}^q$	5.3989	0.4518
Classroom segregation	$\bar{\beta}^D$	3.3940	0.4437
Share of white students at the school level	$\bar{\beta}^W$	3.1848	0.1724
Segregation × Share white	$\bar{\beta}^{DW}$	-3.8475	0.2951
Cost parameters			
Marginal cost of q, linear (in q)	μ	0.1064	0.1662
Share of non-white students at the school level	ζ	0.5012	0.4484
Fixed cost of q, linear term	κ_1	2.0581	2.0930
Fixed cost of q, quadratic term	κ_2	1.8940	3.0219
Cost of D, quadratic term	α	99.9701	2.7442

Notes: Table 4 reports point estimates and standard errors for the linear preference parameters and cost parameters on the endogenous variables. Not reported are the estimates for the parameters on the (conditionally) exogenous variables, i.e., the exogenous cost shifter, a dummy for the magnet status, a dummy for missing classroom segregation (equal to 1 for only one school with evident reporting errors), and the year fixed effects. Number of schools: 78 for the moments based on cost shock innovations (equations 25 and 26); 171 for the moments based on quality shocks (or mean utilities; equation (27)). See Section 5 and Appendix Section B.3 for further estimation details.

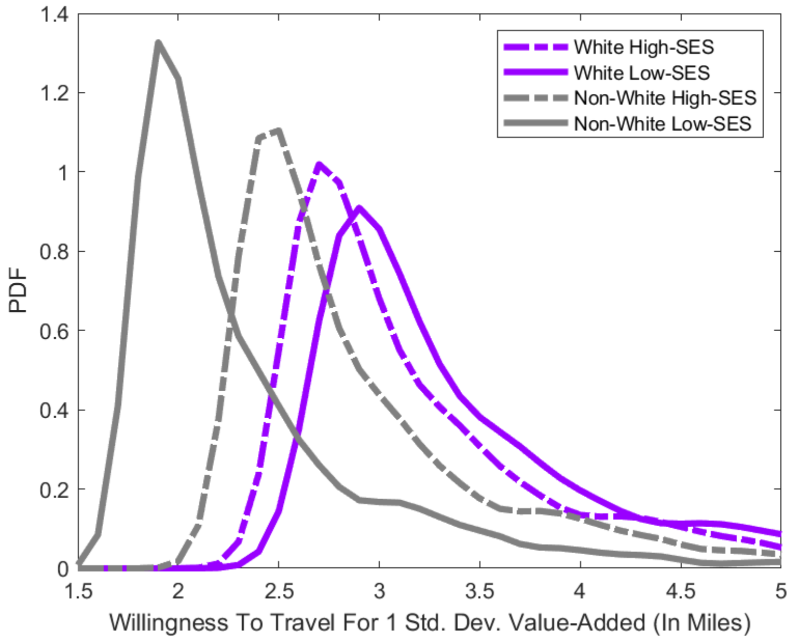
distribution of the estimated cost shocks to academic quality and classroom segregation.

6.3 Interpretation Of The Demand Estimates

The results indicate that all households value academic quality positively. The average white high-SES student is willing to increase home-school distance from 1 to 3.9 miles for a one-standard-deviation increase in academic quality. Non-white high-SES and white low-SES students follow: They are willing to increase home-school distance from 1 to 3.6 and 3.5 miles, respectively. Non-white low-SES students appear to be the least responsive to academic quality, with an average increase in their willingness to travel from 1 to 3.1 miles. Figure 9 illustrates this race-by-SES gradient, along with the significant amount of preference heterogeneity that I estimate within observable types.

Preferences for classroom segregation vary greatly across households. The extent of heterogeneity is represented in Figure 10. The values in the cells correspond to preference parameters implied by the point estimates in Tables 4 and 5. The columns correspond to different shares of white students at the school level (as I allow preferences for classroom segregation to vary with the school racial mix). Different rows are for different household types: The blocks of rows correspond to observable race-by-SES types, while the rows within a block correspond to unobservable types or values of the random coefficient for classroom segregation. Blue (red) cells indicate a positive (negative) evaluation of classroom segregation, while the color intensity increases with the magnitude of the preference parameter. Figure 10 indicates that classroom segregation tends to become undesirable as the share of white students at the school level grows. Above which concentration of white students classroom segregation turns undesirable, however, and how undesirable

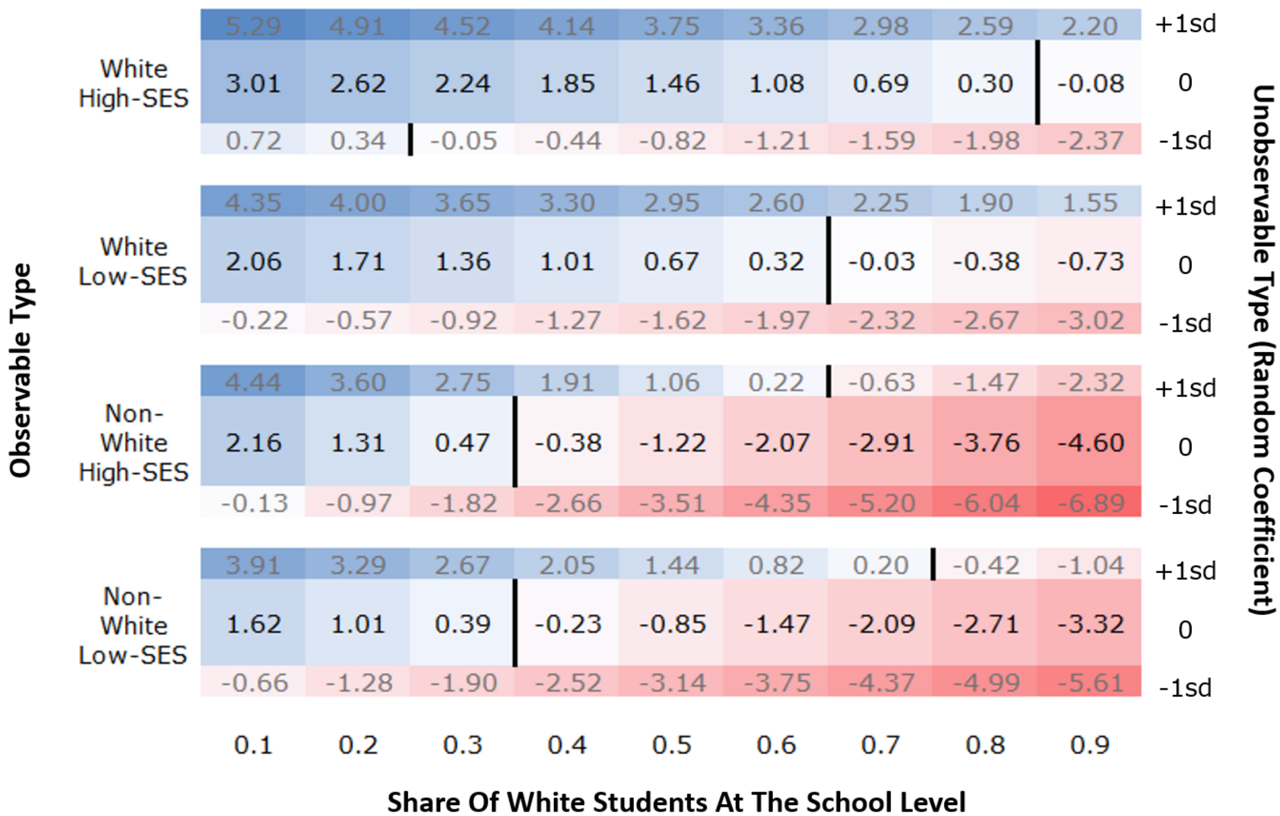
Figure 9: Marginal willingness to travel for academic quality (in miles)



Notes: This figure plots the distribution of the marginal willingness to travel (in miles) for a one-standard-deviation increase in academic quality implied by the estimates in Tables 4 and 5. The baseline distance is 1 mile. Each curve describes the distribution of the willingness to travel for the average student of a given race-by-SES student type, where average refers to the unobserved preference (random coefficient) for academic quality.

classroom segregation is for a given student body composition varies significantly across households. The average white high-SES student (i.e., a white high-SES student with a random coefficient of zero) values classroom segregation positively at schools with less than 88% of white students. The threshold is lower for the average white low-SES student (69%) and lowest for the average non-white student of either SES (36%). These averages for the observable types mask substantial unobserved heterogeneity. For white students, moving one standard deviation to the right (left) of the average random coefficient implies a positive (negative) evaluation of classroom segregation across the board, i.e., regardless of the racial mix at the school level. For non-white students, moving one standard deviation to the right of the average unobserved taste for classroom segregation is not enough to obtain an indiscriminately positive evaluation: For a non-white high-SES student with a random coefficient one standard deviation above the mean, classroom segregation remains undesirable at schools whose student body is more than 62% white. In terms of preference intensity, white high-SES students tend to be the most responsive to changes in classroom segregation at minority-white schools, while on average non-white high-SES students are the most marginal at majority-white schools. From a perspective of competitive incentives, preference heterogeneity is consistent with horizontal differentiation along the dimension of classroom segregation. Specifically, let aside any schools' direct incentives over the racial composition of the enrollment, the fact that different schools face different marginal types with different preferences for classroom segregation is consistent with an equilibrium where both high and low classroom

Figure 10: Preference parameters for classroom segregation

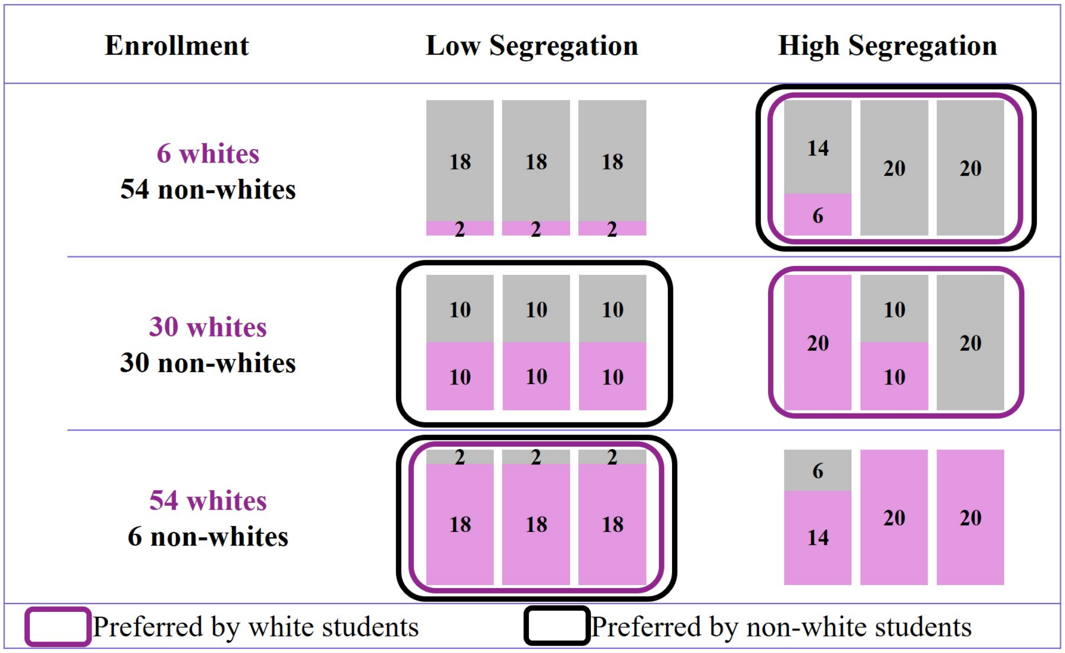


Notes: Preference parameters for classroom segregation implied by the estimates reported in Tables 4 and 5. The values in the cells are the estimated preference parameters. The columns correspond to different shares of white students at the school level. The blocks of rows correspond to different observable race-by-SES types. The rows within a block correspond to different values of the random coefficient.

segregation are offered, and vertical competition on academic quality is relaxed (Spence, 1975; D'Aspremont et al., 1979).

Figure 11 shows an example of what these estimates imply for the preferred classroom configuration at a toy school with one grade, 60 students, and three equally sized classrooms. The three rows correspond to three different shares of white students at the school level: 10% (top row), 50% (middle row), and 90% (bottom row). The two columns compare classrooms under no segregation (left column) v. full segregation (right column). Within each row, the classroom configuration in the violet circle (black rectangle) is the one preferred by white (non-white) students. At minority-white schools, both white and non-white students prefer *segregated* classrooms. From the perspective of non-white students, this result is consistent with the benefits from integration (e.g., perceived learning gains) being smaller than the costs (e.g., disruption of instructional pace and grading standards) when the school is mostly non-white. Conversely, both white and non-white students prefer *integrated* classrooms at majority-white schools. From the perspective of white students, this pattern points to segregation being perceived as undesirable when it harms a minority. Disagreement emerges at racially integrated schools, where white students prefer segregated classrooms and

Figure 11: Example of preferences over classroom configurations



Notes: Examples of classroom configurations for a school with 60 students, one grade, and three equally-sized classrooms. The share of white students at the school level varies across rows. The middle column depicts fully integrated classrooms, while the right column describes racially segregated classrooms: The gray (pink) bars are proportional to the share of non-white (white) students per section. A black rectangle identifies the classroom configuration most preferred by non-white students, given the racial composition of the school. A violet rectangle indicates the same for white students.

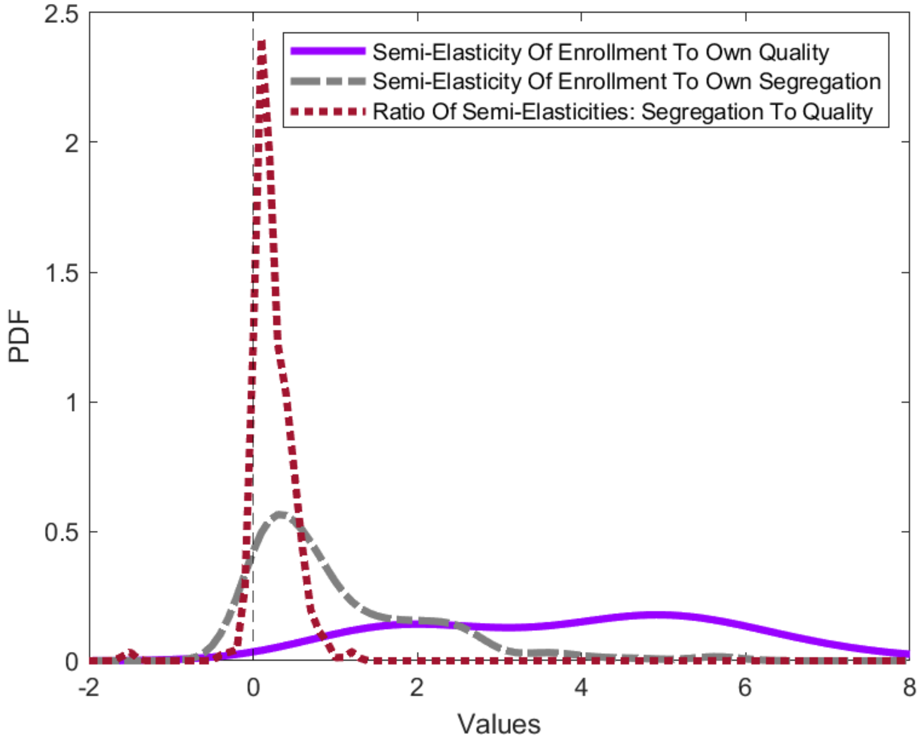
non-white students favor integrated classrooms instead. This result is sensible as racially integrated schools are those where switching from no to full segregation implies the largest increase (decrease) in the average share of white classmates for white (non-white) students at the school.

Figure 12 plots the distributions of the semi-elasticities of enrollment to own academic quality (violet smooth line) and classroom segregation (gray dash line) implied by my estimates. Almost all schools' total enrollment responds positively to a rise in academic quality, while a relatively larger share of schools faces negative semi-elasticities to own classroom segregation. These semi-elasticities capture not only households' "direct" preferences for academic quality or classroom segregation, but also their predominantly positive evaluation of a larger share of white students at the school level (see Appendix Figure C.9),[43] which is determined in equilibrium as a result of schools' choices (see Section 4.4). The ratio between semi-elasticities (classroom segregation to academic quality; red dotted line) takes both positive and negative values, although most of the mass of its distribution lies to the right of the zero vertical line. The sign of this ratio is important as it drives the direction in which classroom segregation responds to competitive incentives (see Section 4.4).

Figure 13 plots the semi-elasticities separately by market: before the introduction of open enrollment

[43] As reported in Figure C.9, I estimate that on average, white high-SES students value positively a higher concentration of white students at the school level for any level of classroom segregation up to approximately 0.80. The same holds for non-white students (regardless of their SES) at levels of classroom segregation up to 0.35-0.40. White low-SES students are an exception, with a negative average preference parameter for a larger share of white students at the school level at any value of classroom segregation.

Figure 12: Semi-elasticities of enrollment to own academic quality and classroom segregation



Notes: Semi-elasticities computed according to formulae 21 and 23 at estimated parameters and data values of academic quality and classroom segregation.

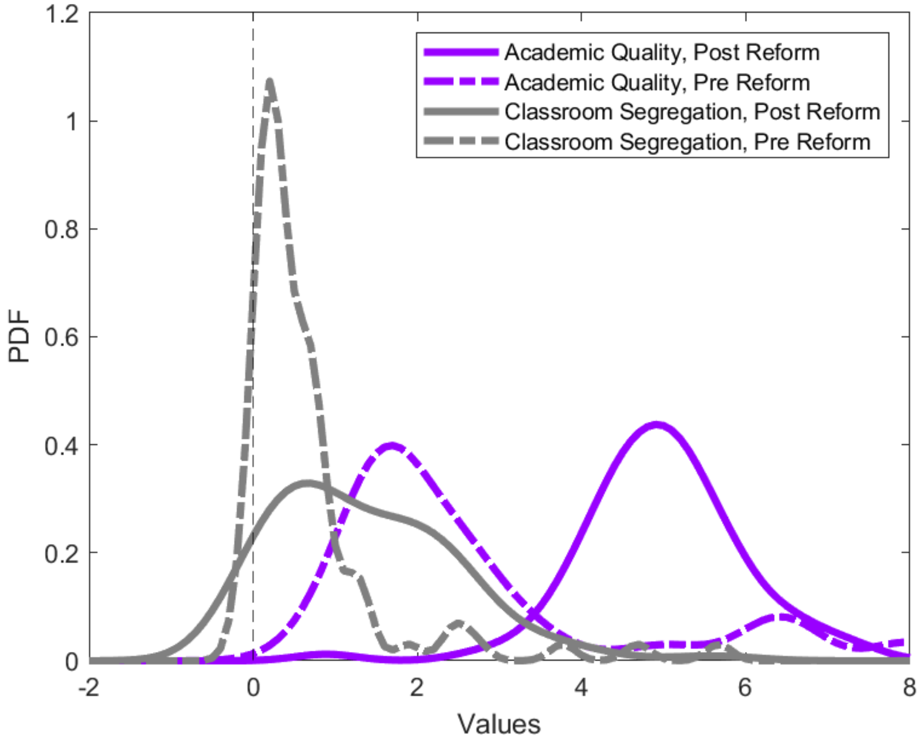
(smooth lines) vs. after (dashed lines). As school choice is introduced, enrollment becomes more responsive to academic quality. As a result, the distribution of semi-elasticities (in violet) shifts to the right. Similarly, enrollment becomes more responsive to classroom segregation. The distribution of semi-elasticities (in gray) becomes more spread out: Positive semi-elasticities tend to become "more positive", while negative semi-elasticities tend to become more negative. These results are expected and in line with the intuition that schools adjust academic quality and classroom segregation upon the competitive shock to retain students.

6.4 Model Fit

Appendix Figure C.10 compares the values of academic quality and classroom segregation predicted by my model at the estimated parameter values to those observed in the real data. (Appendix Section B.4 illustrates the algorithm that I use to compute the model equilibrium). The model predicts values of academic quality very close to those observed in the data. Moreover, the model accurately fits the ranking of schools from the most to the least segregated, although the predicted levels of classroom segregation tend to be smaller than the ones in the real data. This is particularly true for highly segregated schools.

Figure 14 visualizes the model predictions for classroom segregation. Both panels show a map of CMS subdivided into its 2004-2005 catchment areas. (Schools that do not enroll based on residence, such as magnet

Figure 13: Semi-elasticities of enrollment before and after the introduction of school choice

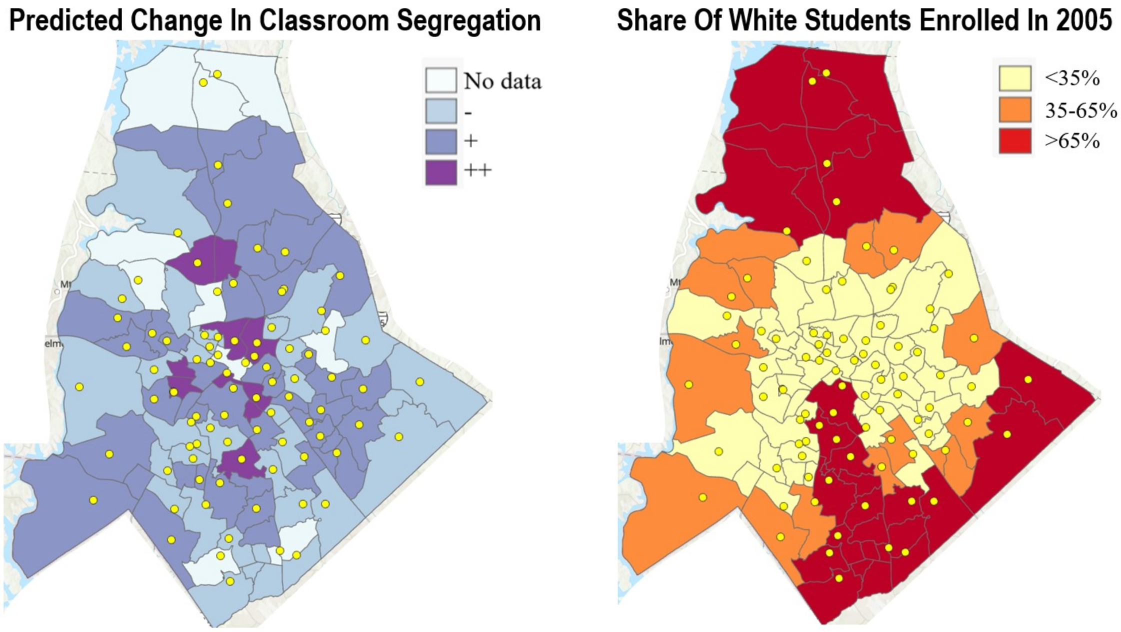


Notes: Semi-elasticities computed according to formulae 21 and 23 at estimated parameters and data values of academic quality and classroom segregation.

schools, are not included.) The yellow dots locate schools operating in the school year 2004-2005. The left panel represents school-level changes in classroom segregation around the reform: Schools that decrease classroom segregation are in periwinkle, those that increase it by at most 0.14 (the standard deviation of the distribution of simulated changes) are in violet, and those that raise by more than 0.14 are in grape. The right panel reports the share of white students enrolled at each school for the year 2004-2005. Schools with less than 35% white students are in yellow, those with a share of white students between 35% and 65% are in orange, while those with more than 65% white students are in red. The results suggest that the schools that increase classroom segregation the most face the strongest competitive pressure as they are located in areas with a high spatial concentration of schools. These schools also happen to be majority non-white: The estimates illustrated in Figure 10 indicate that classroom segregation at majority non-white schools tends to be valued positively by both white and non-white students. Classroom segregation is predicted to increase also at schools located on the west and north-east sides of the district, which face weaker local competition and attract intermediate shares of white students. At these student body compositions, classroom segregation is valued positively mostly by white students (see Figure 10). This response can therefore by rationalized by the finding that schools face demand- and cost-side incentives to enroll a larger share of white students.

In line with the real data (Appendix Figure C.3), the simulated distribution of classroom segregation in

Figure 14: Simulated Increase In Classroom Segregation Around The School Reform



Notes: Maps of CMS subdivided into its 2004-2005 catchment areas. The yellow dots locate schools operating in the school year 2004-2005. The left panel reports data simulated by my model. It indicates (i) which schools are predicted to decrease classroom segregation around the reform (periwinkle), (ii) which schools increase classroom segregation by no more than 0.14, the standard deviation of the distribution of simulated changes (violet), and (iii) which schools increased classroom segregation by more than 0.14 (grape). Schools in white are only included in the sample for one of the two years, which prohibits me from computing the simulated change in classroom segregation around the reform. The right panel is informative of the share of white students enrolled at the school level for the school year 2004-2005. It distinguishes between schools with a share of white students enrolled below 35% (yellow), between 35% and 65% (orange), or above 65% (red).

the post-reform market is more spread out, relative to the pre-reform market (see Appendix Figure C.11).

7 Counterfactual Analysis

In this section, I use the model and the estimates to conduct policy evaluation. Section 7.1 explains how I solve for the model equilibrium. Section 7.2 quantifies to what extent the cost structure affects schools' choices of classroom segregation and academic quality. Lastly, Section 7.3 evaluates a policy that requires all schools to form racially integrated classrooms, given enrollment.

7.1 Computing The Model Equilibrium

Computing the equilibrium of the model presents two main challenges. The first is that classroom segregation can only take values between zero and one, as the variable that I use to measure it is not defined out of the zero-one interval (equation (2)). The second is that the expected shares of white students at the school level enter parental demand. Under rational expectations, these expected shares are correct at equilibrium. This implies that at equilibrium, my model must satisfy a fixed point condition (equation (17)) where the market vector of expected shares appears on both sides: on the left-hand side, as the object being equated to true shares, as well as on the right-hand side, where true shares are computed as integrals of enrollment probabilities which in turn depend on expected shares (equation (6)). I simulate the model through two nested fixed point algorithms. In the inner loop, for given values of academic quality and classroom segregation, I compute the shares of white students at the school level that satisfy the fixed point condition in equation (17). In the outer loop, given the shares calculated in the inner loop, I update the values of academic quality and classroom segregation using the first-order conditions derived from the school problem (equations 19 and 18). I shift the negative values of classroom segregation to zero, and those larger than one to one. The inner loop iterates until convergence at every iteration of the outer loop, and the equilibrium is reached when the outer loop converges (provided that sufficient conditions for optimality under inequality constraints on classroom segregation are met by all schools). The algorithm is illustrated in detail in Appendix Section B.4.

Theoretically, neither the existence nor uniqueness of equilibrium is guaranteed for this model (at least not for any values of the fundamentals). D'Aspremont et al. (1979) show that in a Hotelling-like model with strategic differentiation, the existence of a pure strategy equilibrium is guaranteed only under quadratic transportation costs (i.e., transportation costs that are quadratic in distance). Since I estimate a convex cost function in classroom segregation (which is a dimension of horizontal differentiation in my model, like distance in Hotelling's and D'Aspremont et al., 1979's models), existence may be *de facto* implied in my specific case. This is consistent with what I observe in simulation. Multiplicity on the other hand is theoretically possible as the equilibrium shares of white students at the school level enter parental utility. In simulation, however, I do not find evidence of multiplicity.

7.2 Decomposition Of Segregation Incentives

Table 6: Counterfactuals under alternative values of policy-malleable cost parameters

Scenario	**Parameters**	**Academic Quality (Average)**	**Classroom Segregation (Average)**
Full model	Estimates	0.1043	0.1168
Cost of segregation doubles	$\alpha = \widehat{\alpha} \times 2$	0.0449 (-57%)	0.0313 (-73%)
Cost of academic quality homogeneous across students	$\zeta = 0$	0.0274 (-73%)	0.0397 (-66%)

Notes: In each simulation, the parameters not listed in the second column are fixed at the parameter estimates. Each equilibrium is simulated by applying Algorithm 1. I simulate using the 10% random sample of students used in estimation.

This section explores to what extent the cost structure affects schools' choices of classroom segregation and academic quality. Compared to household preferences,[44] the cost parameters seem more malleable to policy interventions. For example, if classroom segregation entails a reputational cost for schools, then

[44] In this paper I think of households as perfectly informed. In other terms, I interpret the demand parameters as reflecting true preferences for school attributes and not imperfect information on such attributes.

accountability measures could make this cost more salient, thus deterring the use of classroom segregation as a competitive leverage. Similarly, if schools face a cost incentive to enroll larger shares of white students, then supporting minority schools with extra resources could reduce classroom segregation wherever it is used as a "white-skimming" tool.

Table 6 reports the results of counterfactual analyses conducted in this spirit. The first column briefly describes the scenario; The second column indicates what parameters are varied and how; The third and fourth columns report the average values of simulated academic quality and classroom segregation, respectively. The benchmark is the equilibrium simulated using the full set of estimated parameters (top row). I simulate the model using the algorithm described in Section 7.1.

The first scenario that I examine is one where all parameters are set equal to the estimated values except for the one on the square of classroom segregation, α (see equation (16)), which is doubled. This exercise makes it disproportionately more costly to offer high levels of classroom segregation and maps to policies that raise the salience of the reputational cost of classroom segregation. As α doubles in magnitude, average classroom segregation in equilibrium drops substantially, by more than 70%. Appendix Figure C.12 shows that almost all schools decrease classroom segregation. Average academic quality decreases too, by almost 60%. Schools tend to reduce academic quality across the board, even though as revealed by the scatter plot in Appendix Figure C.12, the magnitude of the drop in average quality is so large because of a few outliers. These findings are suggestive that classroom segregation and academic quality are not necessarily substitutes, nor is there any assumption in the model that makes them substitutes mechanically. In Section 7.3, I discuss what forces in my model rationalize classroom segregation and academic quality being complements. An implication is that not any policy that succeeds at decreasing classroom segregation in equilibrium would imply gains in academic quality.

In the second scenario, the cost advantage from enrolling a larger share of white students, ζ (see equation (16)) is set equal to zero. This means that teaching white students becomes as costly effort-wise as teaching non-white students. Classroom segregation decreases by 66%, which is consistent with the use of classroom segregation as a "white-skimming" tool: As the cost advantage from enrolling white students is reduced, holding other factors fixed, schools face a reduced incentive to use classroom segregation as a leverage to attract white students. Average academic quality, however, plummets: The reduction is almost 73% relative to the benchmark. Once again, the magnitude of the drop is inflated by a few outliers, as shown in Figure C.13. From a policy perspective, this implies that a policy that operates in the opposite direction by making non-white students as costly to teach as white students (for example, by providing extra teachers, bonuses, and instructional resources to schools with a large share of non-white enrollment) could lead to substantial gains in academic quality and a reduction in classroom segregation.

7.3 Evaluation Of A Ban On Classroom Segregation

I evaluate a policy that bans classroom segregation: This means that all schools are mandated to form classrooms as racially integrated as possible, given the size and composition of their enrollment and the number of classrooms that they can form.[45] Concretely, I simulate the model imposing that the fraction of feasible classroom segregation attained (equation (2)) is zero at all schools, and the only decision that schools make optimally is on academic quality. This counterfactual closely resembles policies that have been implemented to limit racial segregation across schools. For example, by implying that the racial composition of the classrooms within a given grade resembles the racial composition of the school, my policy has a similar flavor to the CMS desegregation plan that ended in 2002: The percentage of black students at any school could not deviate from the district average by more than 15 percentage points (see Section 2 for details). Also, more importantly, the qualitative implications of this policy are analog to any policy that makes schools *ex ante* identical as far as classroom segregation is concerned (e.g., random assignments to classrooms).

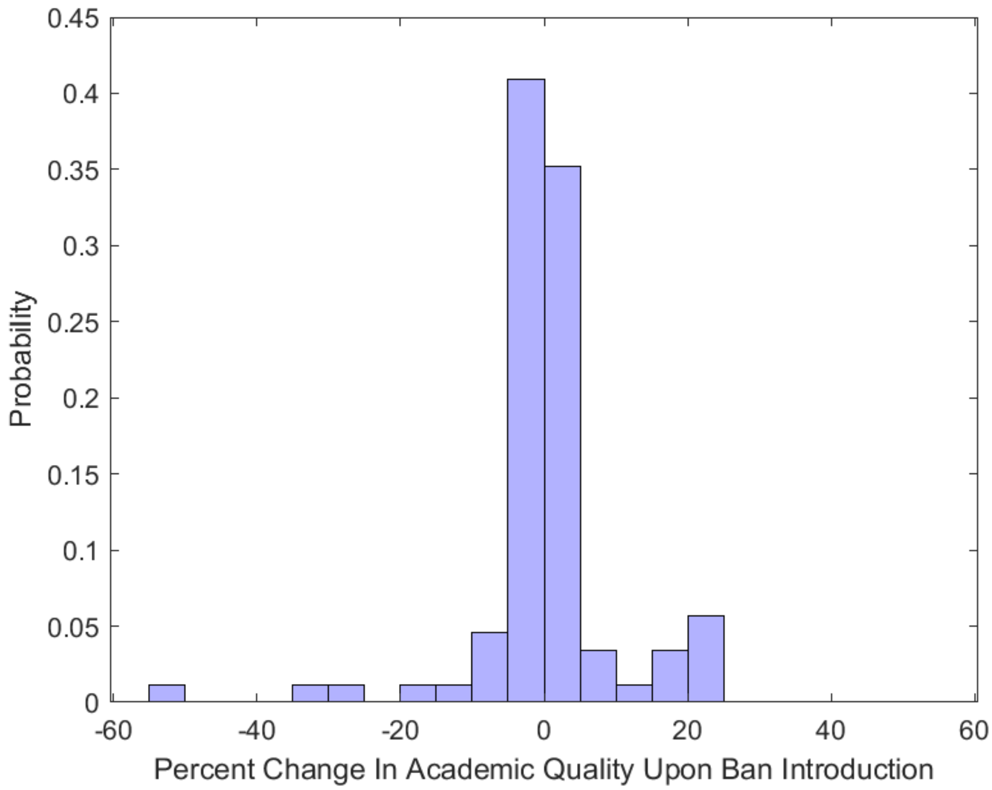
Whether banning classroom segregation along the lines hereby described increases academic quality in equilibrium is an empirical question. On the one hand, as schools lose a margin of horizontal differentiation, vertical competition on academic quality may intensify (Irmen, 1998). If on the other hand under the baseline policy environment, all schools adjust classroom segregation and academic quality to cater to white students (Bau, 2022), because of demand- or cost-side incentives to do so (see Section 6), then the quality gains from banning classroom segregation may be more limited. Under the ban, some schools may even reduce academic quality whenever the enrollment loss that this causes is more than offset by the (effort) cost reduction (McMillan, 2004). This interpretation is particularly sensible under a convex cost function.

I find that under the ban, average academic quality (as measured by value-added) increases by 0.012, more than 6% of a value-added standard deviation. Based on my simulations, had open enrollment in CMS been introduced under a ban on classroom segregation, the jump in academic quality shown in the event-study Figure 5 would have been 7% larger. On an aggregate level, the finding that academic quality increases under the ban is consistent with substitutability between academic quality and classroom segregation: When schools are allowed to differentiate horizontally via classroom segregation, their incentive to compete vertically on academic quality is reduced. This interpretation is further corroborated by the fact that, on average, schools with a relatively high value of classroom segregation under the baseline policy environment increase academic quality more in response to the ban. Not all schools however respond to the policy by increasing academic quality: As shown in Figure 15, approximately half decrease it. This finding confirms the intuition that the optimal response to the policy varies across schools, as different schools face different cost incentives depending on factors such as their baseline levels of academic quality and classroom segregation and the composition of the student pool that they are naturally good at attracting, given their location.[46]

[45] This means that the teacher allotment rule is implicitly held fixed.

[46] The cost function is convex in both academic quality and classroom segregation, and the cost of providing a given level of academic quality changes with the demographic composition of the school (see equation (16) and table 5). Another reason why some schools may decrease academic quality in response to the ban is that they face a negative cost shock to classroom formation (see Figure C.8), which can be thought of as a principal's "taste" for classroom segregation. Under the baseline

Figure 15: Change In Academic Quality Upon Banning Classroom Segregation



Notes: This figure plots the distribution of the percent change in academic quality under a ban on classroom segregation, relative to the baseline policy environment. Under the baseline policy environment, schools choose both academic quality and classroom segregation optimally. Under the ban, the fraction of feasible classroom segregation attained by each school is set to zero in simulation, and the only choice that schools make optimally is that of academic quality. To account for negative values of academic quality, I compute the percent change between q and $q^{'}$ using the formula $\frac{q^{'}-q}{|q|}$. In both counterfactuals, the simulated values of academic quality that deviate by more than 2.5 standard deviations from the mean are fixed to the real data (Gilraine et al., 2022). In the Figure, the percent changes larger than the 95th percentile are set equal to the 95th percentile. The equilibria are simulated using Algorithm 1. I simulate using the 10% random sample of students used for estimation.

Table 7: Equilibrium effects of mandating racially integrated classrooms

Effect of mandating integrated classrooms on average	**Change w.r.t. baseline**
Academic quality	$+0.012\sigma$
Racial segregation across schools (dissimilarity)	+0.1 p.p.
Test scores	$+0.004\sigma$
Racial test score gap	-2%

Notes: This table reports average changes in academic quality, cross-school segregation, and learning outcomes simulated under the ban on classroom segregation, relative to the baseline policy environment. Under the baseline policy environment, schools choose both academic quality and classroom segregation optimally. Under the ban, the fraction of feasible classroom segregation attained by each school is set to zero in simulation, and the only choice that schools make optimally is that of academic quality. σ denotes a test score standard deviation. Changes in test scores are computed assuming no learning effect of the classroom composition. The change in the racial test score gap is computed relative to 0.7σ, the racial test score gap in the real data. In both counterfactuals, the simulated values of academic quality that deviate by more than 2.5 standard deviations from the mean are fixed to the real data (Gilraine et al., 2022). The equilibria are simulated using Algorithm 1. I use the 10% random sample of students used for estimation.

Table 7 describes the equilibrium implications of the policy for student segregation, aggregate learning, and the racial test score gap. The average test score increases by 0.004σ[47] (where σ denotes a test score standard deviation), assuming momentarily that desegregating classrooms has no immediate effect on test scores. I benchmark the effect on aggregate learning in three ways to assess its economic significance. First, the effect is 80% as large as the impact of the 2012 cap lift on the maximum number of charters allowed in North Carolina as estimated by Gilraine et al. (2022). Second, the impact of banning classroom segregation translates into approximately 18% of a standard deviation change in teacher quality for one year, which increases lifetime earnings by 1.34% according to the estimates reported in Chetty et al. (2014b). Under this standard, banning classroom segregation in grades 1 to 5 increases present value lifetime earnings by \$1076.[48] Second, the impact of banning classroom segregation is equivalent to 18% of the test score impact of replacing the 5% least effective teachers in North Carolina as estimated by Gilraine et al. (2020). Based on Chetty and Hendren (2018b)'s benchmark,[49] my policy increases present value lifetime earnings by \$1,620. This effect is large given that the policy could be implemented at reduced administrative or budgetary costs.

Under the ban, the racial test score gap decreases by 1.6% (where the benchmark is the pre-reform gap observed in the real data). This happens because the schools that raise academic quality the most under the ban are located in non-white areas: These are schools that under the baseline policy environment rely substantially on classroom composition to attract white students, in spite of their locations. Even though white students are more responsive to changes in academic quality relative to non-white students (figure 9),

policy environment, schools that face "direct" utility gains from segregating classrooms might do so at the cost of losing some enrollment. As such schools are mandated to set classroom segregation to zero, they may be able to maintain their market share by decreasing academic quality.

[47]This is smaller than the change in average academic quality in part because the change in the average test score is enrollment-weighted, and large schools display weaker responses, in part because of student sorting across schools.

[48]I follow Gilraine et al. (2022) and estimate that banning classroom segregation increases present value lifetime earnings by $\frac{0.004\times5}{0.13} \times 0.0134 \times 522,000 = 1076$ U.S. dollars, where 0.004 is the simulated increase in the average test score under the ban, 5 is the number of years over which I assume that students experience the ban (grades 1-5), 0.13 is the standard deviation of teacher quality (in test score standard deviations) estimated by Chetty and Hendren (2018b), 1.34% is the one-year impact of Chetty and Hendren (2018b)'s policy on lifetime earnings, and \$522,000 is present value lifetime earnings.

[49]Chetty and Hendren (2018b) estimate that the earnings impact of the 5% teacher replacement policy is approximately \$9,000 per student.

non-white students gain from being located near schools that compete strongly to attract white students.[50]

As classroom segregation is banned, racial segregation across schools (as measured by the district-wide dissimilarity index) increases by only a tenth of a percentage point due to student sorting. This means that the fraction of non-white students that should change schools to attain racially integrated campuses increases from 54.3 to 54.4%. The small increase in cross-school segregation is consistent with schools substituting classroom segregation with academic quality once the former is banned to maintain their enrollment, leading to limited student sorting across schools.

So far, the evaluation of the policy has abstracted away from any learning effects of the classroom composition. The empirical evidence on whether such effects exist in the U.S. elementary school context is mixed. On the one hand, according to the estimates of grade-level racial peer effects in Hanushek et al. (2009), the racial test score gap under the ban may decrease even further as non-white students benefit from racially integrated classrooms, whereas there is no peer effect on white students. Therefore, my results could potentially be a lower bound of the effect of the policy on the racial test score gap. On the other hand, most of the empirical literature that evaluates "ability tracking" in the U.S. elementary school context (where white students outperform non-white students on average) finds no evidence of productive returns to homogeneous classrooms (Bui et al., 2014; Card and Giuliano, 2014).[51]

Lastly, while I do not directly observe outcomes other than standardized test scores, the fact that desegregation appears beneficial to educational and occupational attainment (Guryan, 2004; Johnson, 2011), criminal behavior (Billings et al., 2014b), health (Wang et al., 2022), and intergenerational mobility (Chetty and Hendren, 2018a) is worth considering in a global evaluation of a policy that bans racial segregation across classrooms.

8 Concluding Remarks

Up to half of the racial segregation that North Carolina students experience in public schools can be attributed to how white and non-white students are assigned to classrooms with the same school and grade. Classroom formation falls under school managers' authority and discretion and attracts significant attention from parents, whose satisfaction is salient to schools operating in competitive education markets. Understanding how schools use their discretion over classroom formation, and what this discretion implies is important to understand how schools compete and whether distortions could be corrected that reduce the learning benefits from competition.

This paper develops an empirical framework to understand the implications of schools exercising discretion over classroom formation in competitive education markets. My results indicate that classroom segregation substitutes for directly productive investments, as horizontal differentiation relaxes schools' incentive to

[50] According to my estimates, schools face both demand-side and cost-side incentives to enroll a larger share of white students.

[51] Fruehwirth (2013, 2014) identifies methodological challenges in the estimation of peer effects (namely, peer effects arising from unobservables and the imperfect overlap between race and achievement) that contribute to rationalizing the conflicting results in the literature.

compete vertically on academic quality. On net terms, this reduces the benefits from competition. More broadly, my framework lends itself to evaluating policies that over the last few years have targeted other dimensions of classroom formation in an attempt to reduce racial segregation within schools. Most proposals have suggested the de-tracking of math classrooms or the phasing out of gifted and talented programs, as white students tend to be over-represented in accelerated tracks. These initiatives have been perceived as detrimental to learning and hence fiercely opposed by vocal groups of parents who have threatened to leave the public school system for the private one. These reactions have raised concern about whether a fundamental trade-off exists between segregation within schools and across schools: If classroom segregation were the only way for public schools to retain enrollment, then a reduction in classroom segregation would be likely offset by higher segregation across schools as a result of enrollment choices. My equilibrium model is the first in the literature that allows us to evaluate whether this concern is empirically grounded in a context where classroom formation is delegated to individual schools. In my setting, making schools *ex ante* identical along the classroom formation dimension does not lead to higher segregation across schools as schools respond to the ban by re-optimizing their level of academic quality.

The model allows to evaluate different policies making schools *ex ante* identical along the classroom segregation margin (e.g., random assignments), which may have different implications in terms of human capital formation beyond schools' academic quality responses (e.g., via parental effort responses; Cunha et al., 2010; Fu and Mehta, 2018). Future work will also extend the model to evaluate policies that directly change schools' incentives to supply academic quality (e.g., pay-for-performance schemes). Another avenue for future research is allowing for endogenous school entry: The goal is to study how competitive incentives among traditional public schools are affected by the coexistence with the charter sector, within which the scope for horizontal differentiation (e.g., via curriculum, schedule, transportation, etc.) is much wider and whose expansion has been relentless.

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A Derivation of the Semi-Elasticities of Enrollment

This section derives analytically all the terms in equations 21 and 23. As for the semi-elasticities of total enrollment over q_{st}, D_{st}, W_{st}, and $W_{lt} \quad \forall l \neq s$,

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

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

$$\begin{aligned}
\frac{\partial p_{ist}}{\partial q_{st}} &= \beta_i^q p_{ist}(1 - p_{ist}) \\
\frac{\partial p_{ist}}{\partial D_{st}} &= (\beta_i^D + \beta_i^{DW} W_{st}) p_{ist}(1 - p_{ist}) \\
\frac{\partial p_{ist}}{\partial W_{st}} &= (\beta_i^W + \beta_i^{DW} D_{st}) p_{ist}(1 - p_{ist}) \\
\frac{\partial p_{ist}}{\partial W_{lt}} &= -(\beta_i^W + \beta_i^{DW} D_{st}) p_{ist} p_{ilt} \quad \forall l \neq s
\end{aligned}$$

As for the total derivative of W_{st} over q_{st} or D_{st}, it proves useful to rewrite W_{st} as

$$W_{st} = \frac{E_{st}^{WH} + E_{st}^{WL}}{E_{st}^{WH} + E_{st}^{WL} + E_{st}^{BH} + E_{st}^{BL}}$$

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

$$\frac{dW_{st}}{dq_{st}} = \sum_{z \in \{WH,WL,BH,BL\}} \frac{\partial W_{st}}{\partial E_{st}^z} \frac{dE_{st}^z}{dq_{st}} = \sum_{z \in \{WH,WL,BH,BL\}} \pi_{st}^z \frac{dE_{st}^z}{dq_{st}}$$

and

$$\frac{dW_{st}}{dD_{st}} = \sum_{z \in \{WH,WL,BH,BL\}} \frac{\partial W_{st}}{\partial E_{st}^z} \frac{dE_{st}^z}{dD_{st}} = \sum_{z \in \{WH,WL,BH,BL\}} \pi_{st}^z \frac{dE_{st}^z}{dD_{st}}$$

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 all in all analog.

For each school s in year t, equation (21) implies the following system of four equations

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

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

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

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

For every school s in year t, this system of equations can be re-written in matricial 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

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

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

where for any school s

$$C_t^{ss} = \begin{bmatrix} \left(1 - \frac{\partial E^{WH}_{st}}{\partial W_{st}} \kappa^{WH}_{st}\right) & -\frac{\partial E^{WH}_{st}}{\partial W_{st}} \kappa^{WL}_{st} & -\frac{\partial E^{WH}_{st}}{\partial W_{st}} \kappa^{BH}_{st} & -\frac{\partial E^{WH}_{st}}{\partial W_{st}} \kappa^{BL}_{st} \\ -\frac{\partial E^{WL}_{st}}{\partial W_{st}} \kappa^{WH}_{st} & \left(1 - \frac{\partial E^{WL}_{st}}{\partial W_{st}} \kappa^{WL}_{st}\right) & -\frac{\partial E^{WL}_{st}}{\partial W_{st}} \kappa^{BH}_{st} & -\frac{\partial E^{WL}_{st}}{\partial W_{st}} \kappa^{BL}_{st} \\ -\frac{\partial E^{BH}_{st}}{\partial W_{st}} \kappa^{WH}_{st} & -\frac{\partial E^{BH}_{st}}{\partial W_{st}} \kappa^{WL}_{st} & \left(1 - \frac{\partial E^{BH}_{st}}{\partial W_{st}} \kappa^{BH}_{st}\right) & -\frac{\partial E^{BH}_{st}}{\partial W_{st}} \kappa^{BL}_{st} \\ -\frac{\partial E^{BL}_{st}}{\partial W_{st}} \kappa^{WH}_{st} & -\frac{\partial E^{BL}_{st}}{\partial W_{st}} \kappa^{WL}_{st} & -\frac{\partial E^{BL}_{st}}{\partial W_{st}} \kappa^{BH}_{st} & \left(1 - \frac{\partial E^{BL}_{st}}{\partial W_{st}} \kappa^{BL}_{st}\right) \end{bmatrix}$$

and for any pair of schools (s, l)

$$C_t^{sl} = \begin{bmatrix} -\frac{\partial E^{WH}_{st}}{\partial W_{lt}} \kappa^{WH}_{lt} & -\frac{\partial E^{WH}_{st}}{\partial W_{lt}} \kappa^{WL}_{lt} & -\frac{\partial E^{WH}_{st}}{\partial W_{lt}} \kappa^{BH}_{lt} & -\frac{\partial E^{WH}_{st}}{\partial W_{lt}} \kappa^{BL}_{lt} \\ -\frac{\partial E^{WL}_{st}}{\partial W_{lt}} \kappa^{WH}_{lt} & -\frac{\partial E^{WL}_{st}}{\partial W_{lt}} \kappa^{WL}_{lt} & -\frac{\partial E^{WL}_{st}}{\partial W_{lt}} \kappa^{BH}_{lt} & -\frac{\partial E^{WL}_{st}}{\partial W_{lt}} \kappa^{BL}_{lt} \\ -\frac{\partial E^{BH}_{st}}{\partial W_{lt}} \kappa^{WH}_{lt} & -\frac{\partial E^{BH}_{st}}{\partial W_{lt}} \kappa^{WL}_{lt} & -\frac{\partial E^{BH}_{st}}{\partial W_{lt}} \kappa^{BH}_{lt} & -\frac{\partial E^{BH}_{st}}{\partial W_{lt}} \kappa^{BL}_{lt} \\ -\frac{\partial E^{BL}_{st}}{\partial W_{lt}} \kappa^{WH}_{lt} & -\frac{\partial E^{BL}_{st}}{\partial W_{lt}} \kappa^{WL}_{lt} & -\frac{\partial E^{BL}_{st}}{\partial W_{lt}} \kappa^{BH}_{lt} & \frac{\partial E^{BL}_{st}}{\partial W_{lt}} \kappa^{BL}_{lt} \end{bmatrix}$$

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

Purging out student sorting and the productive returns to homogeneous classrooms: I follow the literature and flexibly control for own, school, and classroom average lagged achievement so as to minimize the potential bias introduced by student sorting across schools and classrooms (Chetty et al., 2014a; Deming, 2014; Angrist et al., 2017). Classroom controls specifically are meant to purge out classroom peer effects, which are implied by the level of classroom segregation that the school chooses.

Purging out classroom peer effects and more generally the productive returns to (racially) homogeneous classrooms is important as in the structural model I want to think about classroom segregation and academic quality as two dimensions that are not related via the education production function. On top of peer effects, two more potential channels make classroom segregation and academic quality technologically related: one is the "teaching to the level effect" (Duflo et al., 2011), while the other has to do with teachers' assignments to classrooms.

As for the former, since race and achievement are correlated, segregated classrooms might lead to learning gains in that they are more homogeneous in terms of the optimal pace of instruction (Duflo et al., 2011). To purge this component out of the estimated value-added, I interact the classroom-level controls with individual characteristics, including race. Yet, the empirical literature shows that these returns tend to be negligible in U.S. elementary schools (Bui et al., 2014; Card and Giuliano, 2014; Antonovics et al., 2022).

The value-added that I estimate with these controls off equation (3) might still be technologically related to the classroom composition if schools assign teachers to classrooms based on teachers' comparative advantage at teaching either racial group (Ahn et al., 2020; Aucejo et al., 2022; Lim and Meer, 2017, 2020). Appendix Table D.1 shows however that schools do not respond to competition by increasingly assigning teachers to classrooms based on teachers' relative effectiveness. This suggests that I can rule out this mechanism as I study the learning implications of schools' competitive responses.

Classroom controls: For the years of interest, only approximately 40% of the students can be matched to their classrooms. Therefore, I compute the classroom controls for *pseudo*-classrooms, i.e., groups of students that take the end-of-grade standardized test under the supervision of the same proctor. This piece of information is available for all students, and the distribution of the size of the *pseudo*-classrooms is similar to the class size distribution observed in the classroom-level data. Since it is technically possible, however, that students enrolled in different sections share the same exam proctor, classrooms might be inferred incorrectly. Reassuringly, estimated value-added responds very little to the classroom controls: As I exclude them, the value-added that I obtain correlates almost perfectly (i.e., by more than 99%) with the value-added estimated with *pseudo*-classroom controls. I reach a similar conclusion when I use information on the 40% of students that can be matched to their teachers to partially reconstruct real classrooms. Overall, this suggests that measurement error is likely a second-order problem in this setting.

Shrinkage: Following the literature (Kane and Staiger, 2008; Gilraine et al., 2022), I shrink the value-added estimated off equation (3) via empirical Bayes to minimize mean squared error (Morris, 1983). Formally, my value-added estimator is defined as follows

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

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 variance of ϵ_{ist} in equation (3) and σ_s^2 is the variance of $\tilde{q}_{st}$. I estimate both variances via maximum likelihood and plug-in.

B.2 Simulated Maximum Likelihood

This section provides details on the estimation of the non-linear preference parameters θ_2 via simulated maximum likelihood.

Estimation of the mean utilities: I recover the mean utilities via a standard BLP contraction mapping (Berry et al., 1995). Identification of the mean utilities requires a location normalization: I normalize the mean utility of one school per year to zero (Neilson, 2021; Allende, 2019). (Choosing one school versus another implies no loss of generality.) Convergence is reached when the maximum difference between observed and predicted market shares is smaller than e^{-12}. I choose this threshold based on Conlon and Gortmaker (2020)'s recommendation aimed at minimizing numerical error within the inversion of the mean utilities, which would propagate to the rest of the estimation routine.

An alternative, more standard location normalization would imply including an outside option and normalizing its mean utility to zero. In my context, the outside option would be charter schools. I do not include charter schools and implement this type of normalization as the market share of charter schools in the years of interest is extremely small.[52] This is problematic because a smaller outside good share implies that the inversion of the mean utilities requires increasingly more iterations to converge (Dubé et al., 2012). As a matter of fact, with the outside option normalization, I fail at reaching a threshold smaller than e^{-06} within a reasonable time, which is not small enough to rule out consequential numerical error.

Simulation of the enrollment probabilities: Simulated probabilities are computed using the formula in equation (10). Each probability involves two levels of integration: The first level is the integration of the

[52] Charter schools were authorized in North Carolina only in 1997.

random coefficients; The second level is the integration of the residential draws.

To integrate the random coefficients on quality, classroom segregation, and school racial composition within each student-by-residential-draw unit, I use three-dimensional nested quadrature with Gaussian weights, choosing the accuracy level so as to integrate polynomials of degree 15 or less (Heiss and Winschel, 2008).

I then integrate the residential draws within every student. The NCERDC has no residential address on record for CMS students before the school year 2006-2007: As explained in the "Technical Report #5: Geocoding Addresses and Assigning MastIDs" made available by the NCERDC, this is because the information was not at all collected in the Transportation Information Management System databases from which the NCERDC obtains the addresses. In what follows, I explain how I impute students' addresses (at the Census block group level) for the school years 1999-2000 and 2004-2005.

As for the school year 2004-2005, 84% of the students in my sample have a CMS address on record for 2006-2007: For these students, I make the assumption that they do not move between 2000 and 2007 and assign probability 1 to the 2007 Census block group of residence. For the remaining 16% of the sample, I randomly draw 20 Census block groups within CMS. To each student-by-residential-draw observation, I then assign a weight equal to the fraction of students from the same race-by-SES group living in that Census block group before the reform (i.e., in the school year 1999-2000). I anchor the weights to the pre-reform residential densities to mimimize the potential bias stemming from residential re-sorting in response to the introduction of open enrollment.

As for the school year 1999-2000, I proceed in three steps. First, for the 83% of the students attending a zoned school (i.e., a school that shows up in the 2000 official map of the catchment areas and is, therefore, assigned a default pool of students based on residential proximity), I rely on the institutional knowledge that before the reform, attending a zoned school without residing within the catchment area was only possible in special (and likely rare) circumstances. Hence, I assign to each of these students all the Census block groups falling within the catchment area of his or her school. Every draw receives equal weight. Second, for the students left out with a CMS residential address on record for 2006-2007 (11% of the sample), I make the assumption that they do not move between 2005 and 2007 and assign probability 1 to the 2007 Census block group of residence. Third, for the remainder of the students (6% of the sample), I randomly draw 20 Census block groups within CMS and assign weights following the procedure illustrated above for 2004-2005.

Summary statistics on the fraction of students attending the zoned school and home-school distance as implied by my imputation strategy are reported in Table D.3 in the paper. As discussed in Section 5.3, these statistics seem reasonable in light of the reform provisions described in Section 2 and the summary statistics reported by other papers in the literature (in particular Hastings et al., 2009 for CMS and Gilraine et al., 2022 for urban areas in North Carolina).

Minimization: I minimize the negative of the log-likelihood function (rescaled by sample size; equation (24)) using a gradient-based search algorithm.[53] I find that the function, which theoretically is continuously differentiable, exhibits local kinks. I attribute these kinks to either numerical issues or the correlation between the endogenous dimensions that enter the demand model. To ensure that the solution is an actual minimum, I minimize the function using the numerical gradient: While computing the numerical gradient requires many more function evaluations per iteration compared to the analytical gradient, it has the advantage of indulging the local kinks and preventing the algorithm from getting stuck at points that are not actual minima. The gradient at the solution meets my optimality threshold ($E-03$ for the first order optimality as computed by *MATLAB*'s *fmincon*). To further ensure that I can find no point at which the function takes a smaller value, I also:

1. Profile the function along each dimension, i.e., vary one parameter at a time on a coarse grid centered *around* the solution while holding the other parameters fixed *at* the solution;

2. Run the gradient-free *MATLAB*'s *patternsearch* algorithm around the solution.

The outcome of the first exercise confirms that moving any parameter away from the solution while holding fixed the other parameters leads to a larger function value. As for the second exercise, hundreds of function evaluations with *patternsearch* find no point at which the function takes a smaller value.

B.3 GMM

This section provides details on the estimation of the linear preference parameters θ_1 and cost parameters θ_3 via generalized method of moments.

Instrument relevance: Tables B.1, B.2, and B.3 list my instruments for the within-school change in classroom segregation and academic quality and schools' mean utilities: These are the endogenous variables that I use along with the instruments to construct moments off restrictions 25, 26, and 27. Evaluating relevance through linear regressions may not be informative or sufficient, especially when the endogenous objects are non-linear functions of the parameters (Berry and Haile, 2021), and needs to be complemented with diagnostics like profiling that ensure that the GMM function is steep around the estimated parameters (Stock and Wright, 2000).

Estimator and minimization: The GMM estimator is defined in Section 5.2. I assume independence across the three blocks of moments (Neilson, 2021). W is the identity matrix. I can therefore treat the

[53] I use *MATLAB fmincon* with the interior point algorithm.

Table B.1: Excluded instruments for ΔD: First stage regression

VARIABLES	(1) Within-School Change In Classroom Segregation
Competitive pressure	0.201***
	(0.053)
Differentiation at baseline, q - I	-0.505***
	(0.105)
Differentiation at baseline, q - II	0.334***
	(0.107)
Differentiation at baseline, q - III	0.266***
	(0.078)
Differentiation at baseline, q - IV	-0.196***
	(0.073)
Differentiation at baseline, D - I	-1.309***
	(0.180)
Differentiation at baseline, D - II	-0.138**
	(0.060)
Observations	78
R-squared	0.658
F-statistic on excluded instruments	19.23

Notes: See Section 5 for further details on the instruments.

minimization problem as a non-linear least square problem and use *knitro* as a solver. Standard errors are computed using the standard GMM formula.

Constraint: For four of the 78 schools in the estimation sample, the constraint in 15 is binding in either time period. For these schools, the cost shocks that I back out in estimation (equations 25 and 26) may therefore differ from the true ones. Future versions of the paper will address this issue via parametric extrapolation or by adjusting the moment conditions so as to accommodate censored data in the presence of endogenous regressors and fixed effects, using the method proposed by Honoré and Hu (2004)[54].

B.4 Computing The Model Equilibrium

Algorithm 1 illustrates how I solve for the 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 update the vectors of academic quality and classroom segregation using the first-order conditions derived from the school problem (equations 18 and 19) and forcing the values of classroom segregation to lie between 0 and 1. I feed the first-order conditions with the vectors of academic quality, classroom segregation, and shares of white students at the school level from the previous iteration. The outer loop terminates upon

[54]On the relation between *corner solution model* and censored regression model, see also Wooldridge, 2002; Greene, 2011

Table B.2: Excluded instruments for Δq: First stage regression

VARIABLES	(1) Within-School Change In Academic Quality
Equity Plus Indicator	0.285***
	(0.054)
Differentiation at baseline, q - V	-13.015***
	(2.321)
Differentiation at baseline, q - VI	-5.544***
	(1.399)
Differentiation at baseline, q - VII	4.757***
	(1.224)
Differentiation at baseline, q - VIII	12.080***
	(2.331)
Differentiation at baseline, q - IX	-0.337***
	(0.121)
Differentiation at baseline, q - X	-0.195***
	(0.071)
Median teacher experience (# years) at baseline	-0.005***
	(0.002)
Observations	78
R-squared	0.612
F-statistic on excluded instruments	13.38

Notes: See Section 5 for further details on the instruments. Not reported is the coefficient on the share of economically disadvantaged students at the school level (i.e., the running variable).

Table B.3: Excluded instruments for $\widehat{\delta}$: First stage regression

VARIABLES	(1) Mean Utility (Estimated In Step 1)
Pupil-to-Teacher ratio	0.072***
in previous period (or P2T at $t-1$)	(0.016)
P2T at $t-1$ x	-0.071***
Competitive pressure	(0.014)
P2T at $t-1$ x	0.072***
2000 neighborhood share of graduates	(0.021)
Observations	171
R-squared	0.4380
F-statistic on excluded instruments	35.89

Notes: See Section 5 for further details on the instruments. Not reported are the coefficients on the year and magnet dummies.

convergence of the values of academic quality and classroom segregation (provided that sufficient conditions for optimality under inequality constraints on classroom segregation are met by all schools). Within each iteration of the outer loop, the inner loop solves for the vector of shares of white students at the school level that are consistent with the vectors of academic quality and classroom segregation being considered in that iteration. The shares are computed using the fixed point equation in 17. The inner loop is necessary as the shares are determined at equilibrium in response to schools setting their academic quality and classroom segregation: Households' choices depend on schools' *expected* racial composition, which in turn depends on households' choices. The inner loop stops upon convergence of the vector of shares.[55]

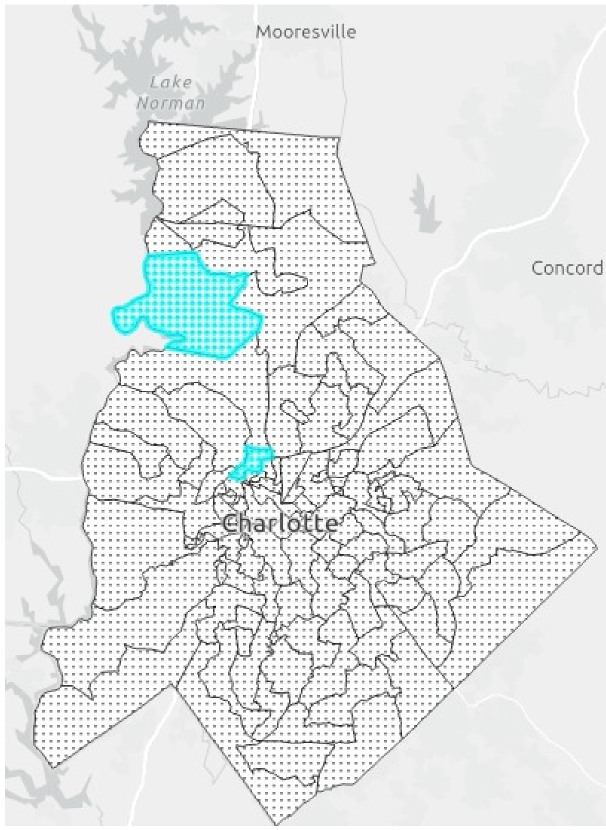
Initial guess: $\{q_t^0, D_t^0, W_t^{0,0}\}$
for $r = 0, 1, ..., R$
while $||q_t^{r+1} - q_t^r||_\infty > \epsilon$ *or* $||D_t^{r+1} - D_t^r||_\infty > \epsilon$ **do**
  for $\psi = 0, 1, ..., \Psi_r$
  while $||W_t^{r,\psi+1} - W_t^{r,\psi}||_\infty > \epsilon$ **do**
    Compute matrix of individual 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 (17)
  end
  Compute q_t^{r+1} as function of $(q_t^r, D_t^r, W_t^{r,\Psi_r})$ using equation (18)
  Compute D_t^{r+1} as function of $(q_t^r, D_t^r, W_t^{r,\Psi_r})$ using equation (19)
  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

[55]The fact that the equilibrium shares of white students at the school level enter parental demand implies that multiple equilibria are theoretically possible in my model. However, I have not encountered any multiple equilibria in the simulations that I have conducted.

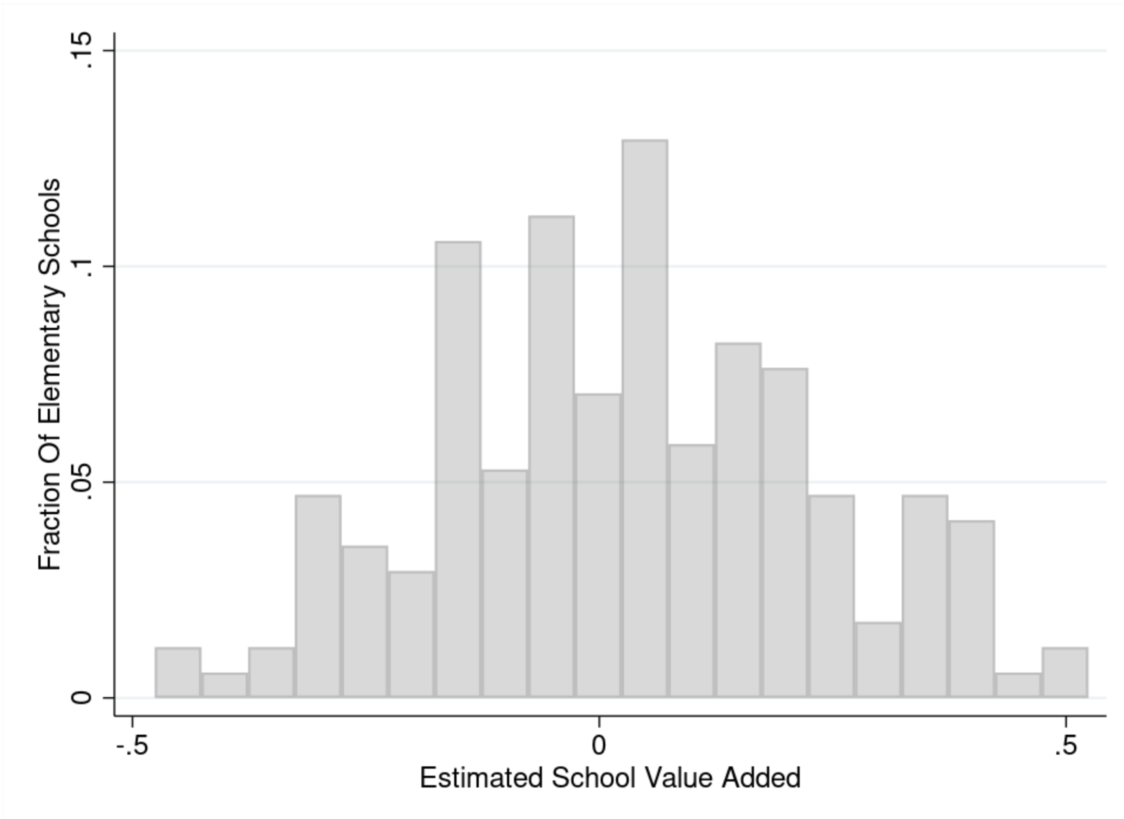
C Additional Figures

Figure C.1: Example of a Satellite Zone under Mandatory Busing



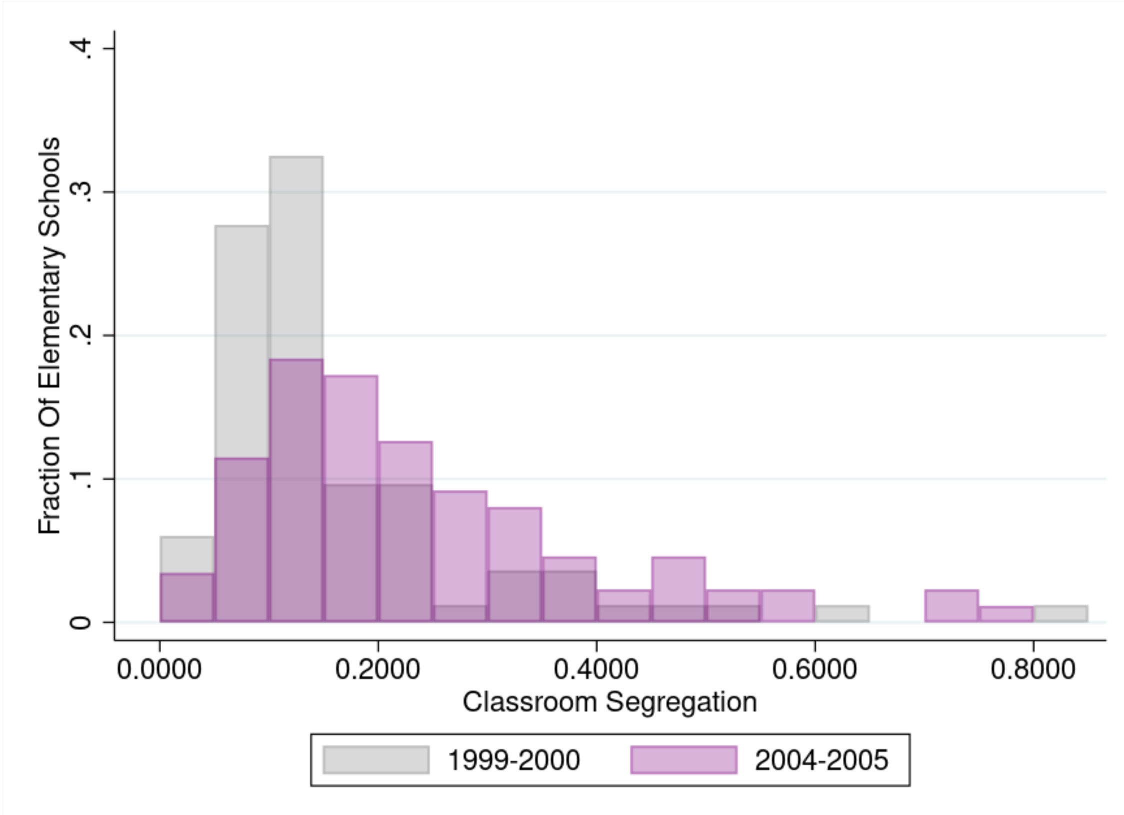
Notes: This figure shows the CMS district subdivided into its elementary school catchment areas for the school year 1999-2000. The school zone colored in light blue is the one for Long Creek Elementary School. Students residing in the small "satellite" zone in the urban heart of Charlotte were bused to the northern suburbs. Upon the elimination of mandatory busing and the introduction of choice in the Fall of 2002, the share of white students enrolled at Long Creek Elementary increased from 57 to 74%.

Figure C.2: Estimated value-added at CMS elementary schools in 2005



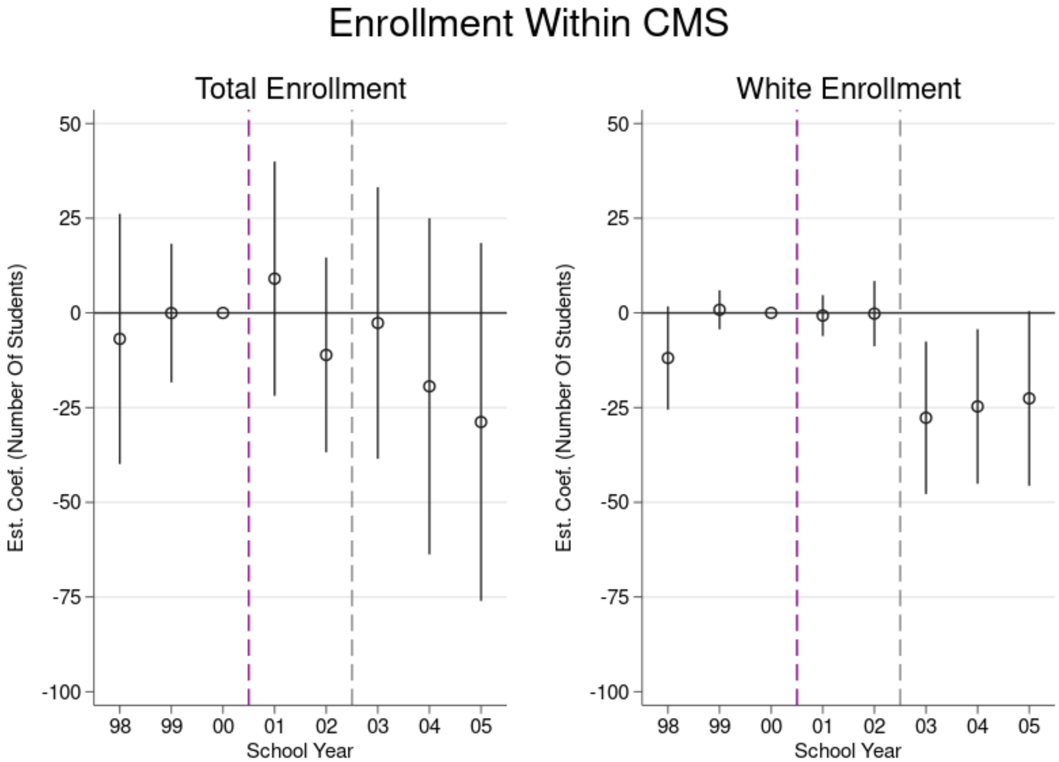
Notes: This figure plots the distribution of estimated value-added for CMS elementary schools in CMS. Estimates are obtained from specification 3 and then shrunk via empirical Bayes. See Section 3.1 for details.

Figure C.3: Distribution of classroom segregation before and after the reform



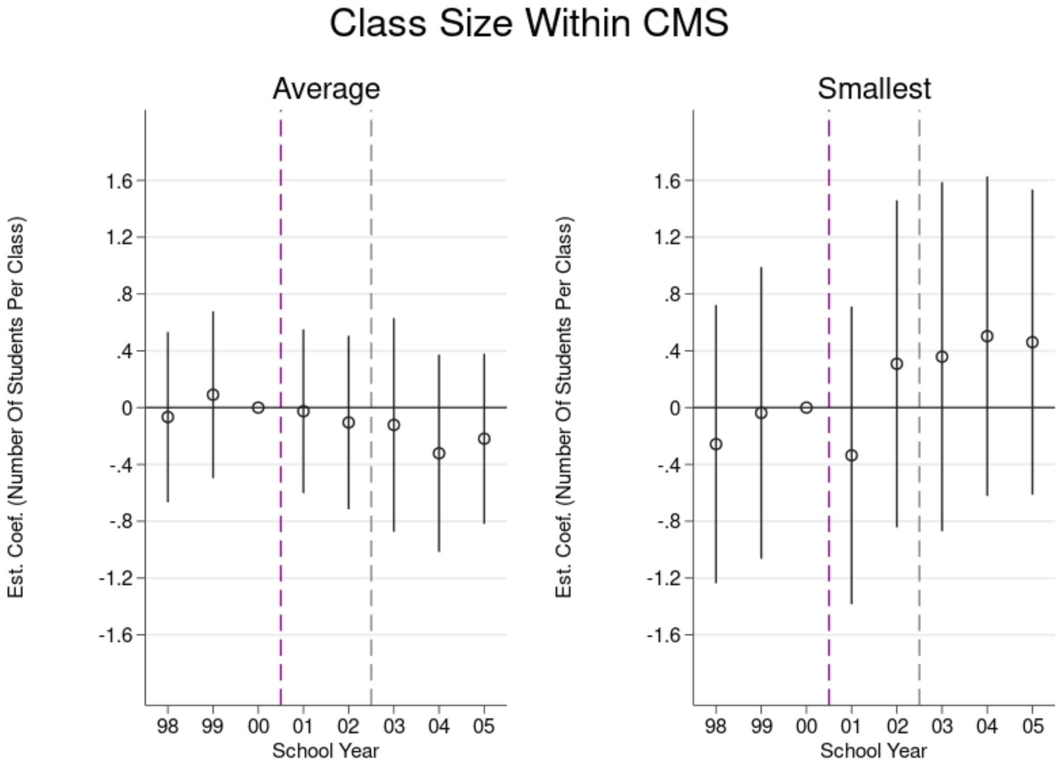
Notes: Classroom segregation is computed according to equation (1).

Figure C.4: No effect of competitive announcement of enrollment



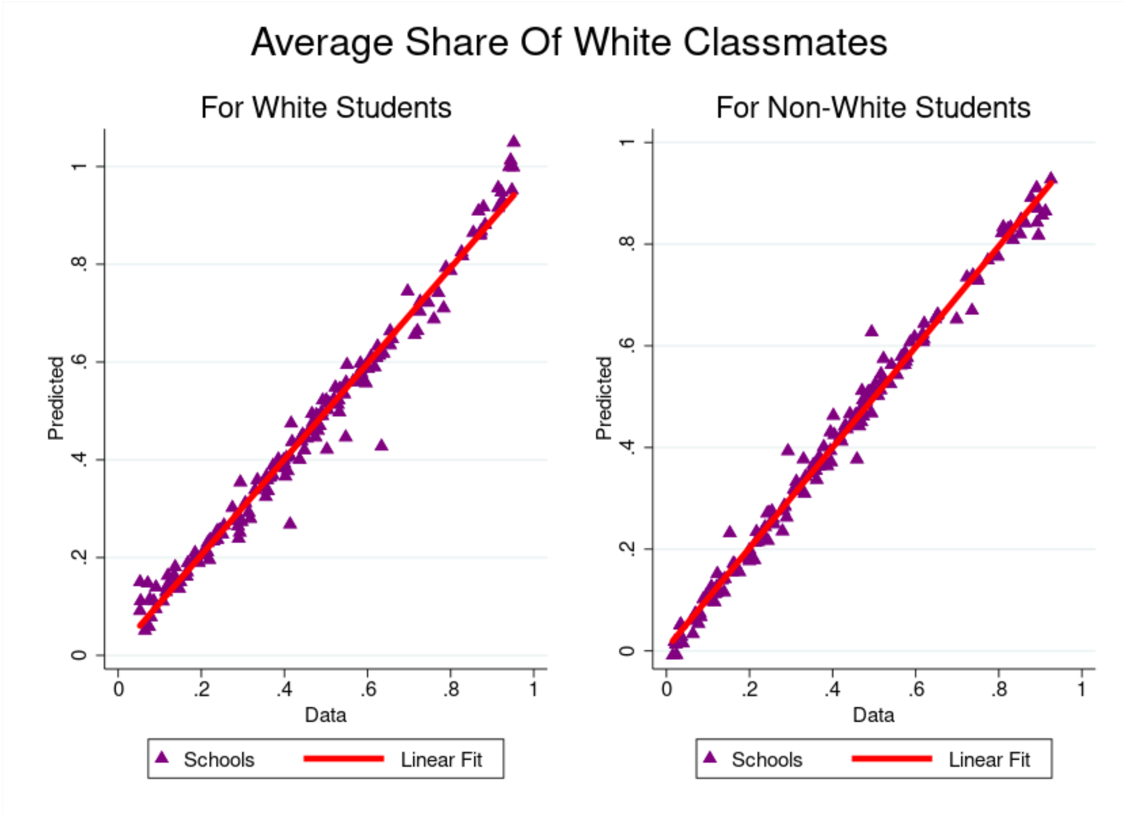
Notes: Estimates obtained from estimating specification 4 (B). The sample is restricted to CMS schools. *Left panel*: the dependent variable is the total number of students enrolled at the school level 1. *Right panel*: the dependent variable is the number of white students enrolled at the school level 2, and total enrollment is a control variable in the regression. Enrollment levels are calculated off the classroom records used to compute the dissimilarity index used in Figure 6. Standard errors are clustered at the school level. N = 758.

Figure C.5: No effect of competitive announcement on class size



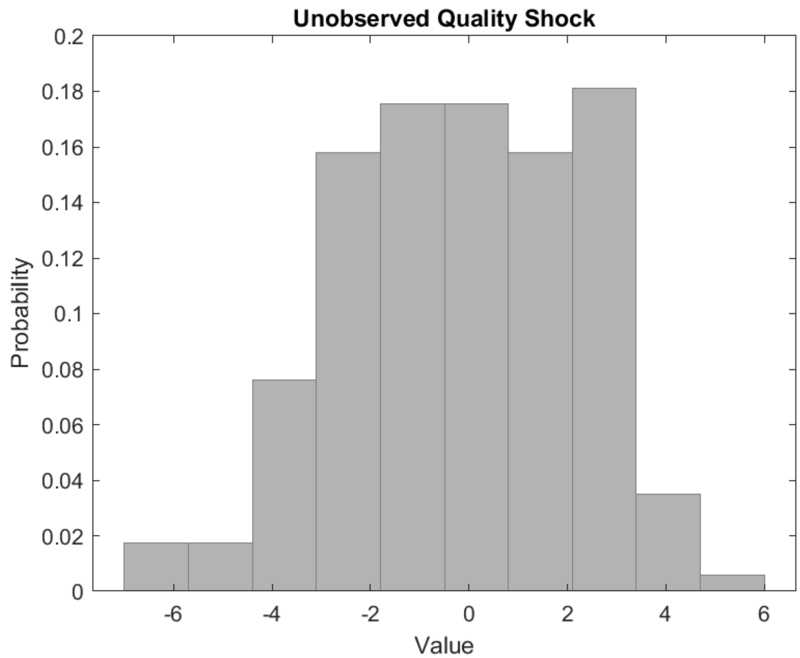
Notes: Estimates obtained from estimating specification 4 (B). The sample is restricted to CMS schools. *Left panel*: the dependent variable is the average class size at the school-grade level, averaged within schools across grades one to four. *Right panel*: the dependent variable is the smallest class size at the school-grade level, averaged within schools across grades one to four. Standard errors are clustered at the school level. N = 758.

Figure C.6: Approximation for expected share of white classmates



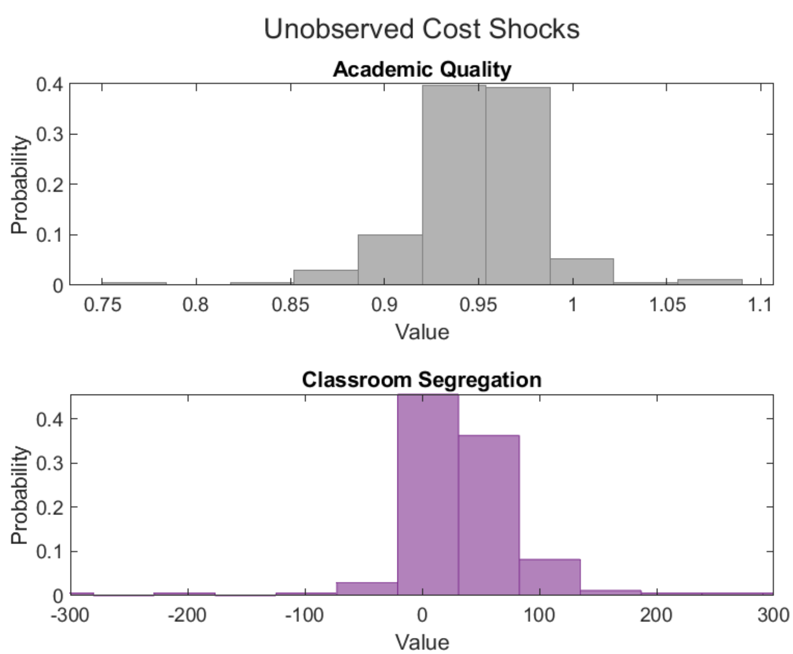
Notes: This figure shows how well I can predict the average share of white classmates at the school level through a simple function of classroom segregation D_{st} (equation (2)) and the share of white students at the school level W_{st}. In either panel, a triangle represents a school. *Left panel*: On the horizontal axis I report the share of white classmates to which white students are exposed, computed as a weighted average on the real data. On the vertical axis, I report the values predicted by the linear regression $y^W_{st} = \alpha + \beta D_{st} + \gamma W_{st} + \delta D_{st} \times W_{st} + \epsilon_{st}$, where $\widehat{\alpha} = 0.03$, $\widehat{\beta} = 0.10$, $\widehat{\gamma} = 0.92$, and $\widehat{\delta} = 0.19$. The R-squared of the regression is 98%. The red line is the linear fit. *Right panel*: On the horizontal axis I report the share of white classmates to which non-white students are exposed, computed as a weighted average on the real data. On the vertical axis, I report the values predicted by the linear regression $y^N_{st} = \alpha' + \beta' D_{st} + \gamma' W_{st} + \delta' D_{st} \times W_{st} + \nu_{st}$, where $\widehat{\alpha'} = 0.01$, $\widehat{\beta'} = -0.02$, $\widehat{\gamma'} = 1.02$, and $\widehat{\delta'} = -0.31$. The R-squared of the regression is 99%. The red line is the linear fit. The sample includes CMS elementary schools in the school years 1999-2000 and 2004-2005, grades 3 and 4. N = 170.

Figure C.7: Estimated unobservable quality shocks



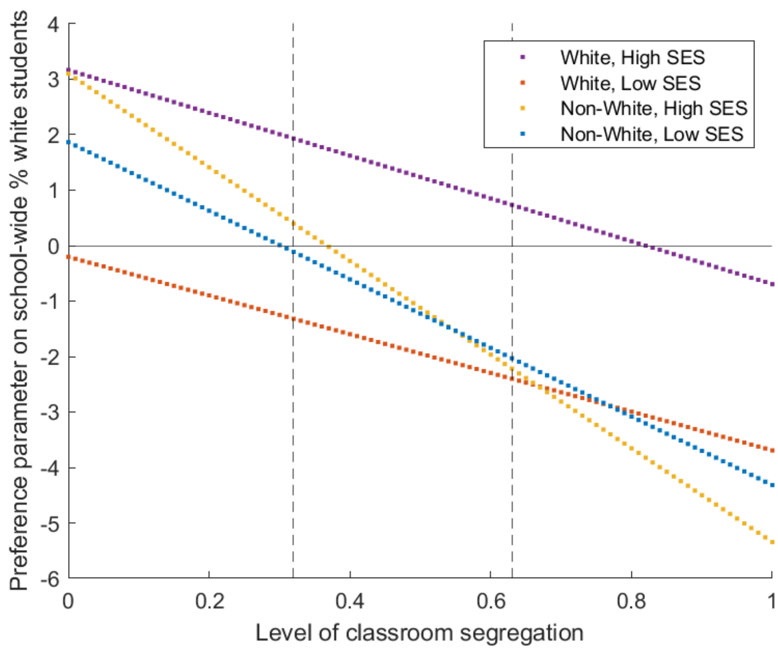
Notes: The histogram plots the estimated unobserved quality shocks ξ. The shocks are backed out from the expression for the mean utilities (equation (12)) at the parameter estimates.

Figure C.8: Estimated unobservable cost shocks



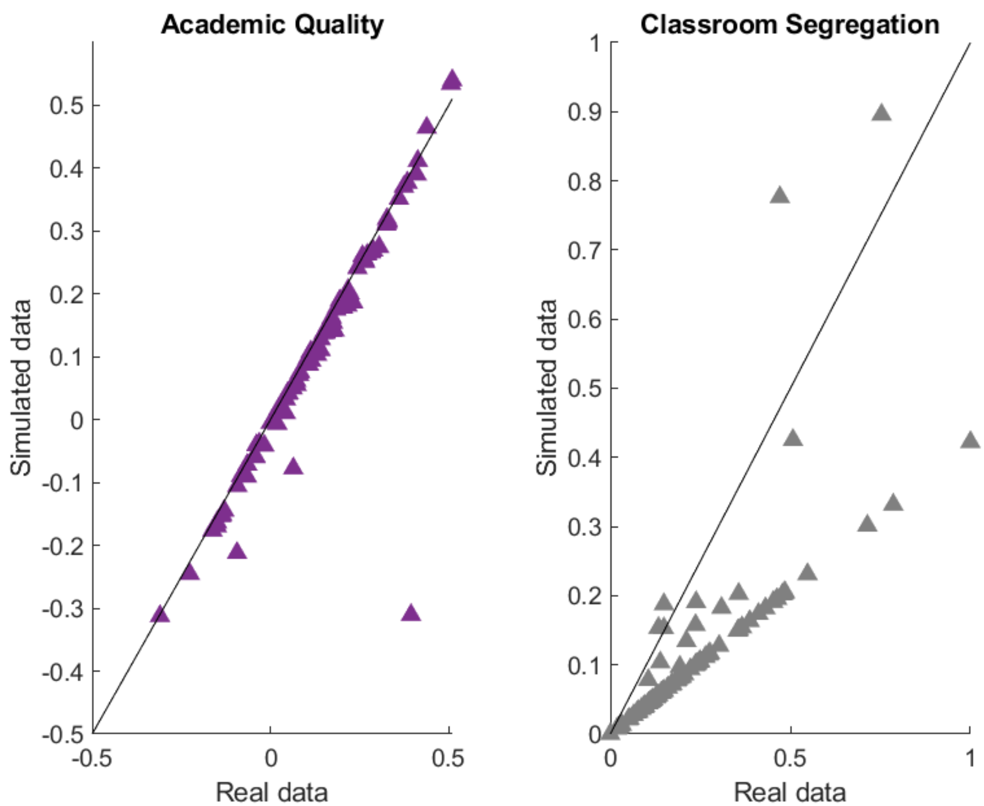
Notes: The histograms plot the estimated unobserved cost shocks ω^q and ω^D. The shocks are backed out from the first-order conditions derived from the school problem (equations 18 and 19) at the parameter estimates. The bottom panel excludes a handful of schools with estimated values that fall off the range on the horizontal axis.

Figure C.9: Estimated preference parameters on the share of white students at the school level



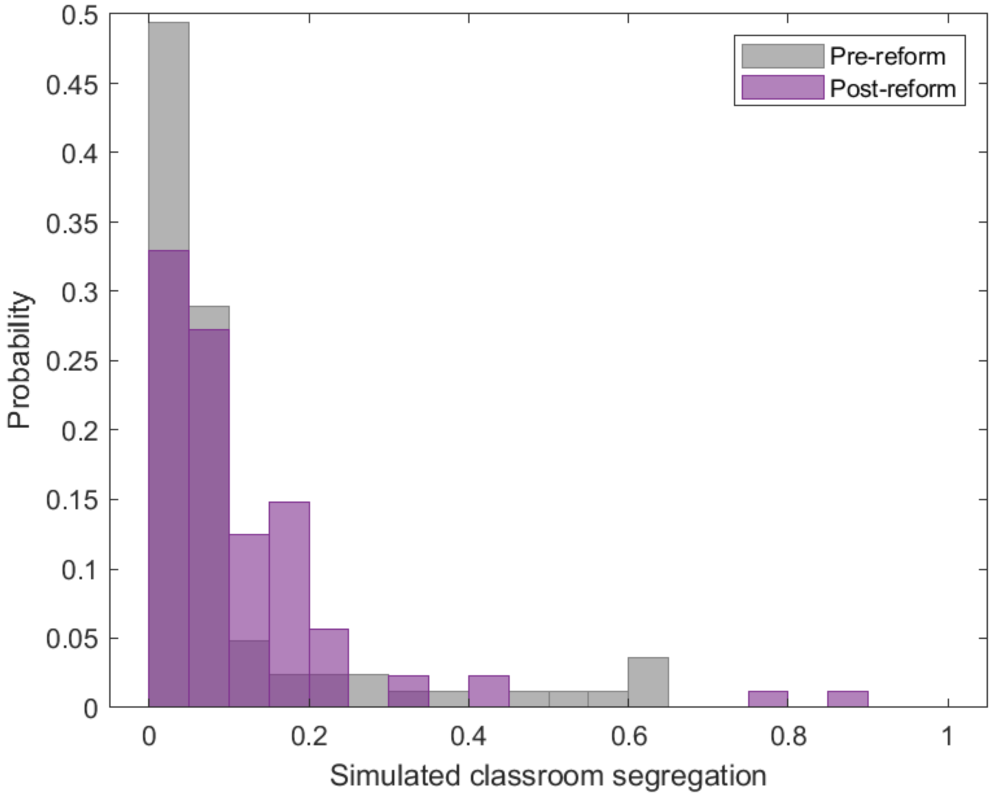
Notes: The figure plots the estimated average preference parameter on the share of white students at the school level against the school level of classroom segregation. It does so separately for the four observable types across which preferences are allowed to vary. Within each observable type, the random coefficient is set at the average value of zero. The estimates are reported in tables 4 and 5.

Figure C.10: Simulated equilibrium under school choice: fit



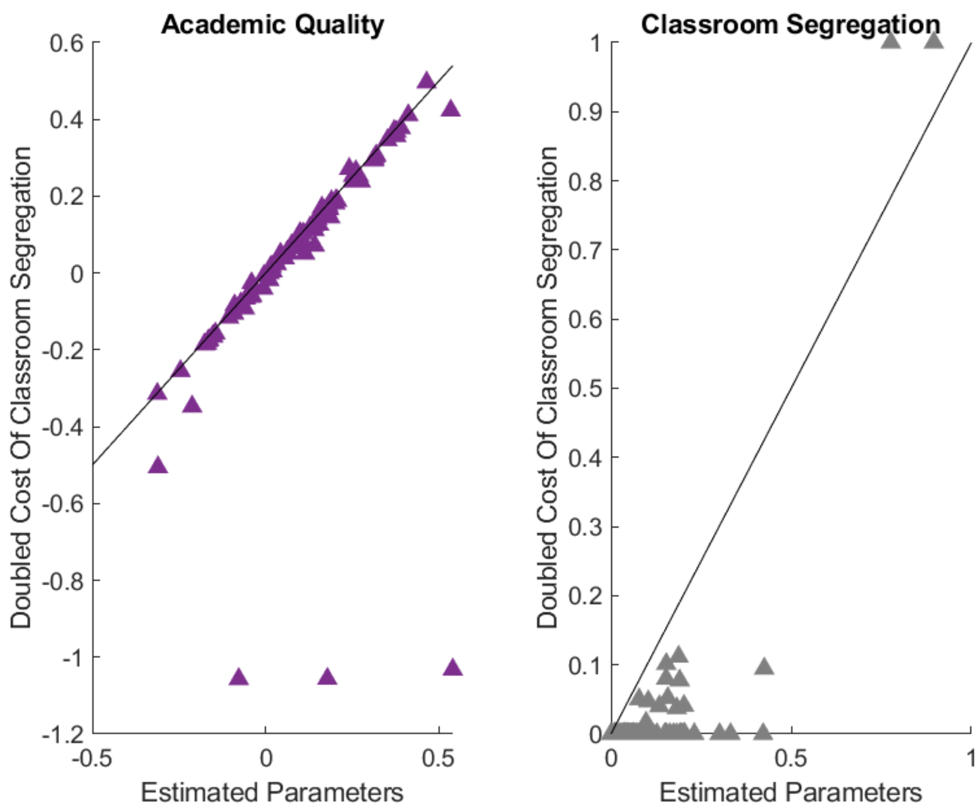
Notes: This figure describes how my model fits the real data. The left panel is for academic quality, while the right panel is for classroom segregation. In both panels, the horizontal axis reports values observed in the real data and the vertical axis reports simulated data. Values for the post-reform market (i.e., school year 2004-2005) are plotted. The algorithm used to compute the model equilibrium is illustrated in Section 7.1. I simulate using the 10% random sample of students used in estimation.

Figure C.11: Simulated distribution of classroom segregation before and after the reform



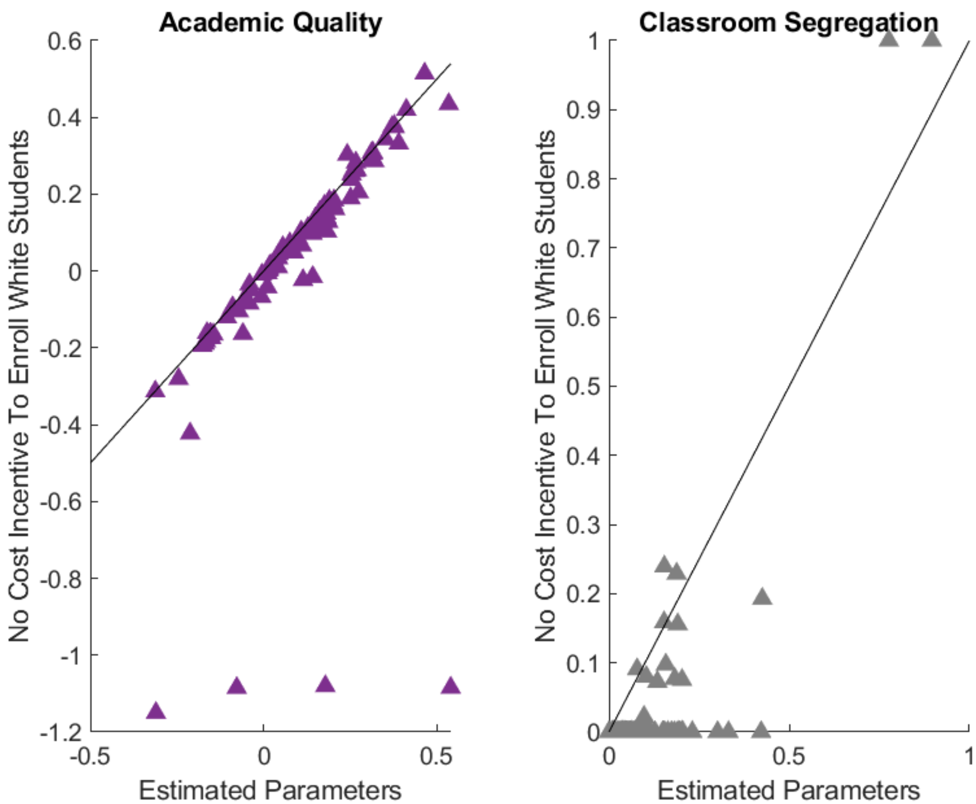
Notes: This figure plots the distribution of classroom segregation predicted by my model, separately for the pre-reform market (in gray) and the post-reform market (in violet).

Figure C.12: Simulated equilibrium under school choice: doubled cost of classroom segregation vs. baseline



Notes: This figure plots the values of academic quality (left panel) and classroom segregation (right panel) simulated under a counterfactual scenario where schools face a twice as large cost parameter on the quadratic term in classroom segregation (i.e, $\alpha = \widehat{\alpha} \times 2$ in equation (16)). The values simulated under the counterfactual scenario are reported on the vertical axis and plotted again the values simulated under the estimated parameters and reported on the horizontal axis. The equilibria are simulated using Algorithm 1. I simulate using the 10% random sample of students used in estimation.

Figure C.13: Simulated equilibrium under school choice: no cost incentive to white-skim vs. baseline



Notes: This figure plots the values of academic quality (left panel) and classroom segregation (right panel) simulated under a counterfactual scenario where schools face no cost incentive to enroll white students (i.e, $\zeta = 0$ in equation (16)). The values simulated under the counterfactual scenario are reported on the vertical axis and plotted again the values simulated under the estimated parameters and reported on the horizontal axis. The equilibria are simulated using Algorithm 1. I simulate using the 10% random sample of students used in estimation.

D Additional Tables

Table D.1: Student-teacher match quality does not respond to competitive incentives

VARIABLES	(1) Teacher VA Advantage With White Students	(2) 1(Teacher VA Advantage With White Students > 0)
1(Student is White)	0.009	-0.011
	(0.009)	(0.022)
1(Student is White) x 1(Post-reform)	-0.015	0.052
	(0.016)	(0.041)
School FE	Y	Y
Grade FE	Y	Y
Year FE	Y	Y
Observations	19,994	19,994
R-squared	0.186	0.169

Notes: This table reports results obtained from estimating regressions at the student level to explore whether student-teacher match quality responds to competitive incentives. The dependent variable in column 1 is the difference between the teacher's effectiveness at teaching white students and the teacher's effectiveness at teaching non-white students. Teacher effectiveness is estimated through a teacher value-added model which closely resembles the school value-added model illustrated in Section 3.1, except for the fact that teacher-year fixed effects are being estimated rather than school-year fixed effects. The dependent variable in column 2 is a dummy that takes value 1 if the teacher is more effective with white students than with non-white students, 0 otherwise. On the right hand side, I interact an indicator that takes value 1 if the student is white with an indicator for the school years following the introduction of open enrollment in CMS. I include in the specification school, grade, and year fixed effects. The sample is restricted to CMS students enrolled in grade 3 to 5 in school years 1997-1998 to 2004-2005.

Table D.2: Summary statistics for the value-added estimation sample

Student Characteristics	Sample Mean
Math test score (σ)	0.0257
Reading test score (σ)	0.0158
Lagged math test score (σ)	0.0157
Lagged reading test score (σ)	0.0151
% White	62.34%
% Economically disadvantaged	34.57%
% High parental education	25.21%
% English learners	2.46%
% Gifted and talented	10.34%
% With disability	11.90%
N. students	862,127
N. observations (student-year)	1,491,457

Notes: The sample includes North Carolina public school students in grades 3 or 4 in school years 1997-1998 through 2004-2005. High parental education is defined as at least one parent having a college degree.

Table D.3: Summary statistics for estimation sample

Students	**1999-2000**		**2004-2005**	
	Full	10% Random	Full	10% Random
% White high-SES	41.97	42.92	35.91	37.88
% White low-SES	7.32	6.06	6.78	7.25
% Non-white high-SES	14.44	14.29	14.84	15.13
% Non-white low-SES	36.27	36.73	42.47	39.74
% Attending zoned school (for at least some residential draws)	81.97	82.68	57.03	58.20
White	82.11	82.20	68.73	72.22
Non-white	81.83	83.15	48.32	46.67
Distance to school of attendance (in miles)				
Q1	1.68	1.67	1.28	1.28
Median	2.89	2.73	2.77	2.69
Q3	4.20	4.21	7.17	6.92
Number of students	16,452	1,617	18,626	1,890
Number of student-by-address observations	240,391	23,899	74,638	6,887

Schools	**1999-2000**	**2004-2005**
Estimated value-added	-0.071 (0.179)	0.127 (0.176)
Classroom segregation (as defined in eq. 1)	0.166 (0.136)	0.244 (0.159)
Fraction of feasible classroom segregation attained (as defined in eq. 2)	0.162 (0.157)	0.221 (0.187)
Share of white students at the school level	0.459 (0.201)	0.367 (0.284)
Market share	0.012 (0.004)	0.011 (0.005)
Number of schools	83	88

Notes: This Table reports summary statistics for the estimation sample by year. *Students* panel: The statistics in columns (1) and (3) are computed on the full student sample, whereas columns (2) and (4) are calculated within the 10% random sub-sample used to estimate the model. The full sample includes the third- and fourth-graders attending a traditional public school in CMS and living therein. Appendix Section B.2 illustrates how I deal with missing residential addresses. *Schools* panel: Only CMS elementary traditional public schools are included. Market shares are calculated on the full student sample but are identical on average to those computed on the 10% random sub-sample. The sets of schools differ across years due to closings and openings: 76 schools belong to both sets. Three more schools appear active in 2000 and 2005 in the original data but are excluded from the 2000 set as their 2000 location is missing.