Preference for Peers and Educational Inequality: Evidence from School Admission Lotteries*

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September 15, 2026

Abstract

I use data from Chile's centralized school admission system to show that families prefer to enroll children in high schools together with their primary school peers. Leveraging exogenous variation generated by high school admission lotteries, I find that every primary school peer admitted to the same high school increases the probability a family accepts an offer of admission to the school by 0.2 percentage points. To study how a preference to study with peers impacts children's schooling outcomes, I embed it in a structural model of school choice. Since primary school peers tend to live near one another, a preference to study together in high school increases the probability that families apply to nearby schools, where more primary school peers are expected to apply. For families from low-SES backgrounds, who tend to live closer to low-quality schools, this reduces the likelihood of applying to a high-quality high school. Empirically, I find that the preference to study with peers increases the socioeconomic gap in the probability of admission to a highly-rated high school by 19%, and the gap in high school value-added by 18%. To address these gaps, I show that a transport subsidy policy that expands children's access to high-quality high schools can benefit from increasing returns to scale through spillovers within peer networks, while generating minimal negative externalities for other children.

1 Introduction

The choice of high school is among the most consequential decisions that families face. Children who attend higher-quality high schools achieve better grades, continue to tertiary education more frequently, and experience better labor market outcomes (Angrist et al., 2016; Beuermann and Jackson, 2022). Different families, however, systematically choose different schools. Across many

*Inbar Amit: University of Oxford (inbar.amit@economics.ox.ac.uk). I am very grateful for the guidance and helpful comments of Barbara Petrongolo, Alison Andrew, and Romuald Méango. I also thank Áureo de Paula, Anaïs Fabre, Ana Gazmuri, Zach Bleemer, Jack Mountjoy, Rob Garlick, Julio Rodriguez, Marco Pariguana, Giulio Gottardo, Stephen Bond, Mathias Jensen, Howard Smith, Antonella Bancalari, participants at the 2nd TSE Economics of Education Workshop, the Stone Centre Conference on Education and Inequality, the 23rd Nordic Development Conference, the QMUL Economics and Finance Workshop, the Stockholm Uppsala Education Economics Workshop, and seminar participants at the University of Oxford and the Institute for Fiscal Studies for their helpful comments. I also thank the Chilean Ministry of Education (Mineduc) for providing data access and support . A previous version of this manuscript circulated under the title: "Go Your Own Way: Peer Effects, School Choice, and Educational Inequality".

countries, poorer and less educated families disproportionately sort into worse-performing schools, contributing to large socioeconomic gaps in educational achievement (Chetty et al., 2016; Burgess et al., 2015). In Chile, children of high school dropouts score 0.62σ lower on standardized math tests and are twice as likely to drop out of high school as children of graduates. Conditioning on the high school that the child attends cuts these gaps by two-thirds, suggesting that they primarily reflect differences *between* the high schools that children attend, rather than differences in children's underlying academic ability.[1] Understanding why children from poorer backgrounds end up in worse schools is therefore central to understanding the inter-generational persistence of poverty.

Part of the explanation lies in unequal access to high-quality schools. Across many countries, better schools tend to be found in wealthier neighborhoods, where families tend to be more sensitive to quality and have the means to invest in school infrastructure (Nielson, 2021; Chetty and Hendren, 2018). They may also charge tuition fees, making them prohibitively expensive for poorer families, hold competitive admission processes, or directly discriminate against certain families in admissions.[2] As a result, policymakers commonly look to increasing families' choice of schooling options, for instance, by introducing school vouchers, to tackle schooling inequality. However, a growing body of evidence documents that such policies have relatively limited effects on the enrollment patterns of children from low-SES families (Agte et al., 2024; Kutscher et al., 2023; Dustan and Ngo, 2018; Herskovic, 2020).[3]

In this paper, I study the role played by children's social networks in shaping how families choose high schools. Children often form close, long-lasting social ties in primary schools, which influence a large range of their outcomes (e.g., Sacerdote, 2011; Barrios-Fernandez, 2023). I ask whether these social ties lead families to enroll children in high schools together with their primary school peers. Since families tend to enroll their children close to home, and peer networks are often geographically clustered, a preference to study in high schools with peers can further amplify families' tendency to enroll locally. Given the uneven distribution of school quality across neighborhoods, this can make poorer children more likely to apply to lower-quality high schools and wealthier children more likely to apply to higher-quality ones, increasing educational inequality. In other words, since families face unequal access to higher-quality schools, a preference to keep children together can also keep poorer children in worse schools.

Identifying families' preferences to enroll children in high school together with their peers faces the same identification challenges as most studies of peer effects. First, peer groups do not form randomly; primary school peers share similar backgrounds and preferences, which lead them to

[1] The details of this decomposition can be found in Appendix A7.

[2] In contexts where private, profit-seeking schools dominate, monopsonistic providers may also exploit families' preferences, beliefs, or children's ability in ways that advantage wealthier families (Nielson, 2019; Allende, 2021; Bau, 2022).

[3] Kutscher et al. (2023) documents that the introduction of Chile's centralized admission system, which removed schools' ability to discriminate against children, had no effect on socioeconomic diversity in schools. Nielson (2021) documents that the introduction of higher school vouchers for children from low-SES families affected schools' incentives to provide quality, but had relatively small effects on sorting. Herskovic (2020) documents no effect of improved transport links in Chile on school choice, and Dustan and Ngo (2018) document a small effect of metro station openings on choice behavior, concentrated primarily among high-SES families.

become peers in the first place. Moreover, by virtue of studying in the same environment, families of peers are exposed to shared advice from teachers or school counselors, which may generate correlations in their choices.

To identify a preference for enrolling together with peers in high school, I leverage randomization embedded in Chile's centralized school admission system. Whenever a high school is oversubscribed, places are allocated by lottery. This lottery creates (conditionally) random variation in the number of primary school peers admitted to the same high school: some children will be admitted together with more of their primary school peers, while others with fewer. To exploit this variation, I show that it is sufficient to control for the *expected* number of admitted peers, as determined by children's choices and characteristics. Conditional on this expectation, any remaining variation in the *realized* number of peers is driven by the lottery. I use this approach to show that families are more likely to take up a high school place when more of a child's primary school peers are admitted to the same high school.

I find that each primary school peer admitted to the same high school increases the probability a family accepts the offer by approximately 0.2 percentage points. In other words, if all peers in a typical class of 27 were offered admission into the same high school, each would be approximately 5.4 percentage points more likely to accept the offer. Throughout my analysis, I treat the family as a unitary decision maker and do not take a stance on whether the underlying preference for co-enrollment is held by the child, the parent, or both. To shed light on the mechanisms driving this effect, I disentangle the *amenity* value of peers from their *academic-production* value by examining how studying with primary school peers in high school affects a wide range of outcomes related to children's academic performance and well-being. I find no evidence that children who study in high schools with more of their primary school peers achieve better academic outcomes, but I find that they report having better relations with their fellow high school peers, suggesting that primary school peers are primarily an amenity. To confirm this, I examine heterogeneity in the results by the characteristics of children and their peers. I find patterns consistent with friendship networks in primary schools, for instance, girls are more likely to accept an offer at a high school when more girls from their primary school are admitted (McPherson et al., 2001; Currarini et al., 2009; Calvó-Armengol et al., 2009).

This analysis alone does not explain how peer preferences contribute to educational inequality in equilibrium. To better understand this relationship, I build a general-equilibrium school choice model in which the utility of attending a high school depends, in part, on the *expected* number of a child's peers who will be admitted. I show that the relationship between the magnitude of peer preferences and educational inequality depends on the spatial distribution of high school quality. When higher-quality high schools are relatively accessible for both high-SES and low-SES children, peer preferences pull all children *towards* higher-quality schools and away from low-quality schools, reducing educational inequality. Alternatively, when inequality in access to higher-quality high schools is high – i.e. high-SES children have much better access to good high schools relative to low-SES children – peer preferences pull low-SES children *away* from higher-quality schools, and

high-SES children towards higher-quality schools, increasing inequality.

I identify families' preference for peers by leveraging the fact that I observe families make two decisions: which schools to apply to, and conditional on receiving an offer at a particular school, whether to accept the offer. I assume that both decisions depend on the same observable characteristics of schools, such as distance and whether a sibling is already enrolled, as well as the number of primary school peers who are admitted. When choosing where to apply, families do not yet know how many peers will be admitted and instead form an expectation. When deciding whether to accept the offer, on the other hand, they observe the realized number, which may (randomly) differ from its expectation because of the school admission lottery. I use this variation to pin down families' preference for peers relative to their preferences for other school characteristics in the second-stage enrollment decision. I then use the fact that families trade off the same observed characteristics of schools in both decisions to map this preference to the first-stage application decision, where I lack comparable exogenous variation in families' expectations about how many peers will be admitted into each high school.

I find that families place substantial value on enrolling children in high school together with their primary school peers. Although the admission of one additional peer increases enrollment by only 0.2 percentage points, the implied effect on the utility of a school is equivalent to reducing the distance to it by 1.2 km. Using the estimated model, I show that peer preferences significantly contribute to disparities in applications and admissions into higher-quality high schools. Eliminating peer preferences shifts low-SES children's applications to higher-quality schools located farther from their home. Overall, this reduces the gap in school value-added between low- and high-SES children by 18%, and the gap in the probability of being admitted into a school rated as medium- or high-quality by 19%.

The findings of this study have important implications for policy debates on educational inequality. First, to the extent that children's choices influence one another, the elasticity of an individual family's choice with respect to changes in a school's attributes is likely to be low. For instance, families may be less inclined to accept an offer at a new school if it is not convenient for their child's peers. This mechanism may rationalize why targeting supply-side barriers that make it harder for low-SES children to attend higher-quality schools, such as by centralizing admissions or reducing transportation costs, has not significantly reduced educational inequality across many contexts (Dustan and Ngo, 2018; Herskovic, 2020; Kutscher et al., 2023). Moreover, children's revealed preference to study with their peers suggests that while "moving to opportunity" initiatives may have large effects on children's academic and labor market outcomes, their true welfare effects may be lower than those implied by these outcomes alone (e.g., Chetty et al., 2016).

More optimistically, peer preferences can be leveraged to increase the effectiveness of policy aimed at encouraging low-SES families to enroll in better schools. A single child applying to a better school encourages their peers to apply, which suggests that an intervention aimed at reallocating children across schools is likely to have a positive multiplier effect if it has a sufficiently strong effect on individual choice. To study this, I simulate a counterfactual policy in which I offer

families vouchers that reimburse them for the cost of traveling to higher-quality high schools. To explicitly study the role of spillovers, I simulate the effect of targeting the policy to different shares of families in primary schools with predominantly low-SES children.[4] I explicitly account for the general equilibrium effects arising from increased competition across high schools by modeling the entire centralized admission system that maps from families' applications into admissions.

I find that this policy generates both increasing returns to scale on treated families as well as spillovers on control peers, which increase with the scale of the program. Treating 10% of families in a primary school cohort increases the probability that a treated child is admitted to a higher-quality high school by 15% with no effect on control peers. Treating 80% of families, in contrast, increases the probability that a treated child is admitted to a higher-quality school by 18%, while also increasing the probability that a control peer is admitted by 5%. At the same time, the policy generates minimal externalities for children in primary schools that predominantly enroll children from high-SES backgrounds and are therefore never treated. For every 100 treated students admitted, fewer than 12 control students are displaced. Since families prefer that peers study in the same high school, the policy increases applications to higher-quality, but relatively under-subscribed schools where children (and their peers) are *all* more likely to be admitted. As a result, it does not generate large congestion externalities that crowd out control children, suggesting that effective policy can close socioeconomic gaps in school quality without harming children from high-SES families by explicitly taking spillovers within peer networks into account.[5]

This paper contributes to the large body of literature studying the sources of inequality in educational attainment. Studies have highlighted that inequality is the result of multiple interacting factors: low-SES families may have weaker preferences for school quality (Nielson, 2021; Burgess et al., 2015), less accurate beliefs about school performance (Agte et al., 2024), or a preference for enrolling their children with peers of similar socioeconomic background (Allende, 2021); low-SES areas typically provide worse access to higher-quality schools (Chetty et al., 2016; Fabre et al., 2024); and high tuition costs may put higher-quality schools out of reach for poorer children (Hoxby and Avery, 2012).[6] I focus on a novel factor: the role of children's peer network. I document that families prefer to enroll children in high school together with their primary school peers. Given the unequal distribution of school quality, peer preferences result in low-SES children applying to closer but lower-quality high schools. Moreover, while spillovers through peer networks constrain the effectiveness of policy aimed at encouraging low-SES children to attend better schools when

[4]Similar policies may include building schools in central areas within low-SES neighborhoods. If these schools are built in a location that is sufficiently attractive to enough children within a single network, children will *pull in* their peers, generating positive spillovers. Moreover, the finding that primary school peers influence each other's educational trajectories has bearing for the optimal assignment of children into primary schools. In an environment with high inequality in access to primary schools, increasing the socioeconomic diversity of peer groups may help draw in more low-SES children into higher-quality high schools.

[5]See Bennett and Bergman (2021) and Avvisati et al. (2014) for examples of papers documenting multiplier effects of educational interventions.

[6]In contexts where private, profit-seeking schools dominate, monopsonistic providers may also exploit families' preferences, beliefs, or children's ability in ways that advantage wealthier families (Nielson, 2019; Allende, 2021; Bau, 2022).

rolled out at small scale, they can also be exploited to yield high returns at larger scales, with minimal negative externalities on untreated children.

Second, I add to the literature studying the impact of peers on children's educational choices, including which schooling track to choose (Black et al., 2013), whether to enroll in high school (Bobonis and Finan, 2009), or whether to enroll in university (Carrell et al., 2018; Barrios-Fernández, 2022; Chetty et al., 2016).[7] To the best of my knowledge, this is the first paper to study the effect of *cohort peers* on children's choice of school. Prior research has largely examined sequential spillovers, such as younger siblings following the educational paths of older siblings (Dustan, 2018; Gurantz et al., 2020; Altmejd et al., 2021) or neighbors responding to earlier enrollment decisions (Bobonis and Finan, 2009; Barrios-Fernández, 2022).[8] A separate strand analyzes how exposure to peers with particular characteristics – such as ability, gender, race, or disruptive behavior – affects outcomes (Hoxby, 2000; Black et al., 2013; Carrell et al., 2018; Idoux and Corradini, 2024). This distinction is important; I find that joint decision-making reinforces existing inequalities by keeping low-SES children in lower-quality high schools. To the extent that children also impact younger peers, these effects are likely to be amplified.

Finally, I contribute to the growing literature that models school choice. School choice models with rich preference heterogeneity have been used to study private schools in Pakistan (Bau, 2022), voucher schools in Chile (Nielson, 2021; Agte et al., 2024), and charter schools in the United States (Walters, 2018). Closely related, Allende (2021) models families' preferences for children studying with peers from the same socioeconomic group in Peru and shows how these preferences, interacting with schools' profit-maximizing behavior, can generate complex equilibrium dynamics. I complement this literature by embedding families' choice of high school within children's social network: families do not choose schools independently, but instead value them as a function of the number of their children's peers who are expected to attend. Since peers tend to apply to the same schools, failing to account for peer preferences may overstate families' preferences for other school attributes, such as distance.

Methodologically, I develop a novel approach that exploits school admission lotteries to identify the causal effect of peers on high school choice.[9] The method builds on the use of admission lotteries to estimate the value-added of schools on children's outcomes (e.g., Deming, 2014; Angrist et al., 2017).[10] Most closely related, Idoux and Corradini (2024) use a similar strategy to identify the

[7] A number of papers focus on social interactions in job search. Topa (2001) builds a model that explicitly incorporates local interactions and allows agents to exchange information about job openings within their social networks. More recently, Caria et al. (2023) combine a randomized job-search assistance treatment with a social network survey to study how unemployed individuals impact each other's job search, and how information propagates across networks.

[8] A related literature examines the role of peer pressure on simultaneous decisions, showing that children's choices can be shaped by the observability of their actions or by coordination within peer groups (Bursztyn and Jensen, 2015; Bursztyn et al., 2019).

[9] This approach mirrors the use of instruments for peers' outcomes, such as grade cutoffs in university admission (Altmejd et al., 2021), or variation in eligibility rules for cash transfers or loan programs (Bobonis and Finan, 2009; Barrios-Fernández, 2022).

[10] Relatedly, Kirkebøen et al. (2021) leverages admission cutoffs to identify the impact of college enrollment on the probability that college graduates marry other graduates from their institution and field of study.

effect of exposure to Black peers in middle school on families' preferences for high schools with a higher share of Black children. I show that lottery-induced variation in peers' offers can be used to identify the causal effect of peers on families' enrollment choices. I then extend this approach to identify peer preference parameters in a structural model of school choice. While Brock and Durlauf (2007) shows that peer effects in multinomial choice models are generally not separately identified from group-level unobservables, I show that school admission lotteries provide the variation needed for identification.

The rest of this paper is structured as follows. Section 2 describes the education system in Chile and introduces the data and variables used in the analysis. Section 3 presents a number of descriptive facts and a conceptual framework linking peer preferences to inequality. Section 4 discusses how admission lotteries identify a preference for peers in families' second-stage enrollment decision. Section 5 embeds this decision in a structural model of school choice. Section 6 presents the estimated parameters and evaluates the model's fit. Section 7 uses the estimated model to quantify the contribution of peer preferences to inequality in equilibrium and the effectiveness of transport subsidies in reducing it. Section 8 concludes.

2 Setting and Data

In this section, I describe the education system in Chile and introduce the data sources used in the analysis.

2.1 Education in Chile

Schools Chile's education system enrolls approximately 3.5 million children across more than 11,000 schools. Compulsory education is divided into primary school (ages 6-14) and high school (ages 14-18).[11] By law, children must remain in high school until the age of 18, and, in practice, 95% graduate. Children attend one of three types of schools: private voucher schools, which are publicly funded but privately managed and enroll 53% of children; public schools, which are publicly funded and managed by local municipalities and enroll 35%; and private non-voucher schools, which are privately funded and managed and enroll the remaining 12%.[12]

Peer Networks I define a child's *peer network* as the cohort of children who study in the same primary school class in the same year. Children attend primary school for 8 years, during which

[11] Children transition through these stages in either the same institution or in different institutions. 54% of primary schools offer only primary education, and enroll 48% of children, while the remaining institutions offer both primary and secondary education.

[12] Chile's education system underwent a significant reform with the introduction of the Schooling Inclusion Law (Ley de Inclusión Escolar) in 2016. The law aimed to increase fairness in admissions and curb the negative effects of private schools' profit-maximizing behavior through two key reforms. First, it forbade private voucher schools from charging families' fees on top of the voucher amount and required them to restructure as non-profits. Second, it introduced a centralized application system (Sistema de Admisión Escolar, SAE) for admission into all schools that receive funding from the state (public schools and private voucher schools), which made it impossible for schools to discriminate against children.

peers take all their courses together, share teachers, follow the same timetable, and share break times. A typical primary school class has approximately 28 children, and in 74% of primary schools each cohort is composed of a single class. Mobility across primary schools is relatively limited, with 84% of peers having studied together for all eight years by the time they apply to high school.

High School Admission Families choose a high school at the end of Grade 8 through a nationwide centralized admission platform (Sistema de Admisión Escolar, SAE). In 2023, the SAE accounted for admission into 89% of primary schools and 85% of high schools in the country (Agte et al., 2024). The system is characterized by a high degree of school choice: there are no catchment areas restricting where families can apply, and most schools do not charge tuition fees or admit children based on their prior academic achievement. The admission process consists of two rounds: a main round in August and a complementary round in November.[13] Within each round, families face a two-stage decision. In the first-stage application decision, families indicate their preferences over high schools by submitting a rank-ordered list (ROL). There is no cap on list length, and the average list contains 4.09 high schools. Schools rank children based on their priority status, eligibility for special quota seats, and lottery numbers. Priority, in descending order, is given to children who have a sibling at the school, are the child of a school employee, or previously attended the school. Schools also reserve up to 15% of seats for children with special educational needs, 15% for high-achieving children, and 15% for children from low-SES families.[14]

To complete schools' rankings over children, each child receives a randomly drawn lottery number at each school to which they apply. Among children with the same priority and quota eligibility, these lottery numbers serve as tie-breakers. As a result, two children who submit the same ROL and have the same priority and quota eligibility at each school face the same admission probabilities, with differences in their assignments arising from their lottery draws. A child-proposing deferred acceptance (DA) algorithm then assigns children to schools based on their submitted ROLs, quota eligibility, priorities, and lottery draws.[15]

In the second-stage enrollment decision, families observe the school to which their child has been admitted and decide whether to accept the offer or reject it. A family that rejects an offer can then decide whether to participate in the complementary admission round or enroll in an off-platform private school. Approximately 94% of children accept their main-round offer. Of those who

[13]The main round starts in early August for admission the following January, during which applications can be submitted and edited for one month. The complementary round in November allows children who remained unmatched or were dissatisfied with their main-round placement to reapply.

[14]High-achieving children typically correspond to those with grades in the top 30% of their cohort. Quota policies are partly regulated by the Ministry of Education: all schools must reserve at least 15% of seats for special-needs children, while reserving seats for high-achieving children or children from low-SES families is optional and capped at 15% for each group.

[15]The algorithm proceeds sequentially through each quota group and priority level. Children with the highest priority are considered first for the quotas for which they are eligible. Once a quota is filled, remaining children compete for regular seats, again in priority order. Quota groups are themselves ordered, with the highest priority given to special-needs children, followed by children from low-SES families and then high-achieving children. Applicants eligible for multiple quotas are first considered under the highest-priority quota and, if rejected, compete for regular seats.

reject it, 74% re-apply in the complementary round.[16] Importantly, the DA algorithm generates exogenous variation not only in the school to which a child is admitted, but also in the number of their primary school peers admitted to the same school. As a result, two children admitted to the same high school, whose primary school peers make identical application decisions and have identical characteristics, may nevertheless be admitted alongside different numbers of peers because of their peers' lottery draws. Figure 1 illustrates the structure of the admission process.

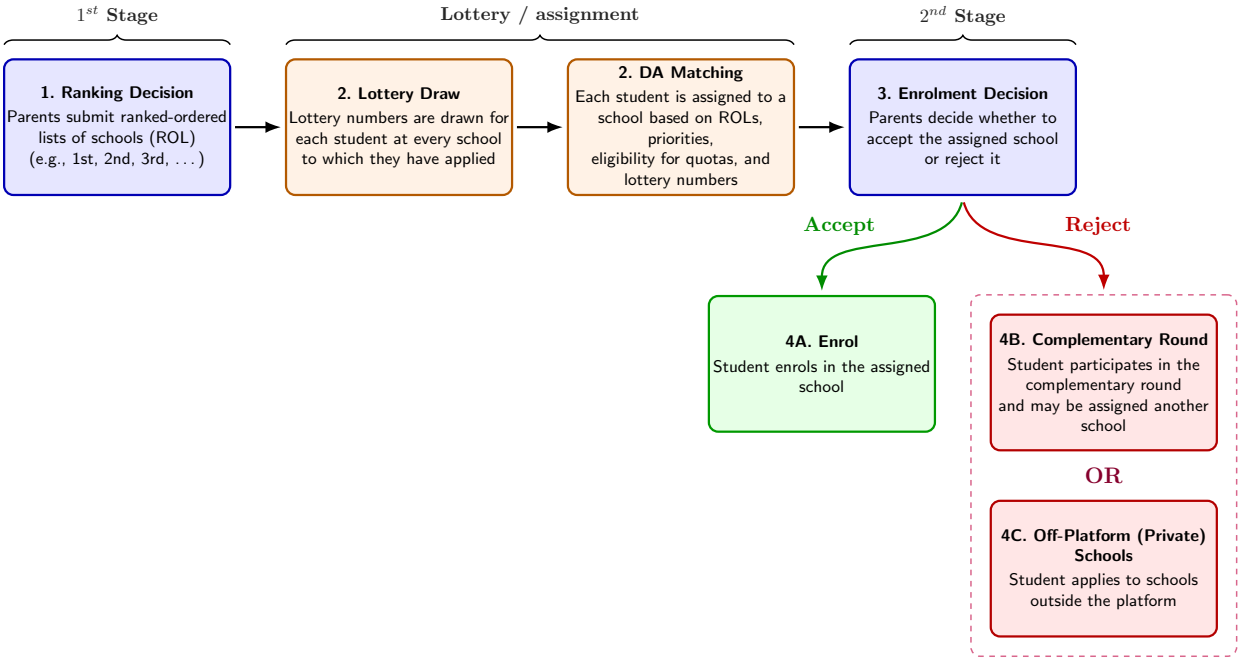


Figure 1: Illustration of the Centralized Admission Process

Notes: The figure illustrates the two-stage admission process. In the first stage, families submit rank-ordered lists of schools. Lottery numbers are then drawn and the deferred acceptance algorithm determines offers of admission on the basis of lists, priorities, quota eligibility, and lottery draws. In the second stage, families observe the realized peer composition of their assigned school and decide whether to enroll, participate in a complementary round, or enroll off-platform.

2.2 Data and Variables

I link several registries maintained by the Chilean Ministry of Education (Mineduc) to create the dataset for this study. All of the datasets include unique and consistent identifiers for children, classes, schools, and teachers, allowing me to perform various linkages across them. Appendix Table A2 describes the variables available in each data source in more detail.

[16] In terms of where they ultimately enroll the following year, 52% are nonetheless observed at the school to which they were initially admitted, 11% at a school they had ranked above their offer (after being admitted from that school's waitlist), and the remaining 34% at another school, including off-platform private schools. Appendix Table A3 reports these outcomes separately for children who accept and reject their main-round offers.

Centralized Admission System Data I begin by obtaining the administrative data from the centralized school admission system (SAE), which includes information on families' ranking over schools, priorities, eligibility for quota seats, and residential location.[17]. In addition, I also observe the (realized) lottery numbers drawn for every child at each school to which they apply, their offer of admission, and whether they accept and enroll in the school. On the school side, I observe the number of available places in each year, including quota seats.

Administrative child Records I link the centralized admission data to administrative child records, which identify the classroom and school attended by each child in every year. I use these records to identify children's primary school peers.

Standardized Exam Records I also link the data to records from the national standardized SIMCE exam. These records include standardized Spanish and Math test scores from exams taken in the 4^{th} grade, while children are in primary school, and in the 10^{th} grade, while children are in high school. In addition, the data include surveys of exam takers and exam takers' families containing detailed information on family characteristics, including income and parental education.[18] Based on these measures, I define families as having a *low-SES* background if children's mother did not complete secondary education. In the 2022-2023 application year, approximately 31% of high school applicants were classified as low-SES.

School Quality I use ratings of school quality from the Agency for Quality in Education (ACE), the primary body responsible for monitoring and evaluating school quality in Chile. ACE classifies schools into four performance categories. I divide schools into 2 bins based on these categories: *higher-quality* schools, which ACE rates as *medium* or *high* quality, and *lower-quality* schools, which it rates as *medium-low* or of *insufficient* quality.[19] These ratings are based on the performance of teachers, personal development indicators, and SIMCE exam results, adjusted for school-level child characteristics.[20] These ratings are publicly available online, and are displayed to families on the school application platform.[21]

[17]For the majority of children, residential location is recorded on the basis of the IP address of the device from which they access the school application portal. For cases in which the location was not retrieved directly from the device, it is based on geolocating the reported addresses of families. To protect children's identity, the location that appears in the administrative files includes a small amount of noise that shifts the true location in a random direction by a median of 150 meters.

[18]My primary measure of family income is reported by families in binned categories, which I convert into deciles.

[19]Nationally, 15% of schools are rated as higher-quality, 55% as medium-quality, 24% as medium-low quality, and 6% as having insufficient quality.

[20]In my empirical analysis, I complement these qualitative ratings with quantitative measures of schools' value-added on the SIMCE math exam. I discuss the construction of these measures in Section 6.2.

[21]The SAE provides several tools to inform families about the characteristics of schools. Since 2016, the SAE application platform has offered the "School Showcase" (Vitrina SAE) website, enabling families to search for schools by name (Correa et al., 2022). The platform displays information on schools' available seats, tuition prices, and academic quality ratings. In 2021, the Ministry of Education introduced a new school explorer platform, Más Información Mejor Educación (MIME), developed by an EdTech NGO and hosted on the government website (Agte et al., 2024). This tool aggregates public data on all schools nationwide and allows families to search for schools on a map rather than by name, enabling the discovery and comparison of nearby schools previously unknown to them. Additionally, MIME

3 Descriptive Evidence and Conceptual Framework

In this section, I present several descriptive facts about schooling inequality in Chile. I then present evidence on families' choice sets, preferences, and the structure of peer groups, which motivates a simple conceptual framework linking a preference to study with peers to schooling inequality.

3.1 Schooling Inequality in Chile

I first document that children from low-SES families are far less likely than their high-SES peers to apply to, and to attend, higher-quality high schools. Figure 2 shows that low-SES children are 8 percentage points less likely to rank a higher-quality high school anywhere on their ROLs, 11 points less likely to place one at the top of it, and 7.5 points less likely to be admitted to one. The socioeconomic gaps at the application stage are larger than the resulting gap in admissions, indicating that disparities arise primarily from differences in the schools families apply to.

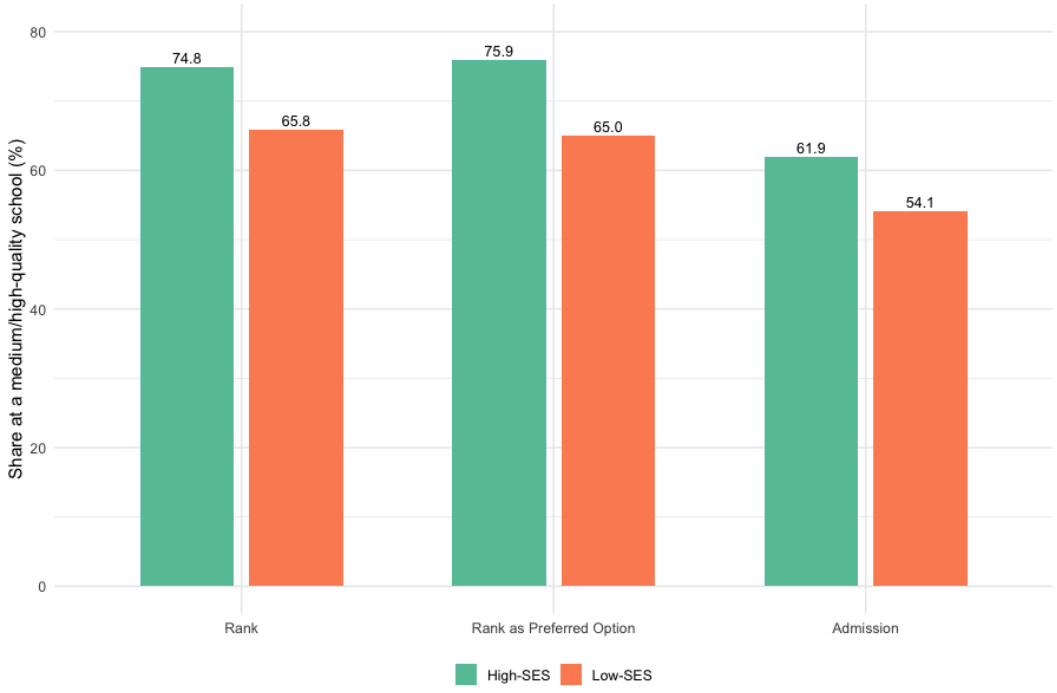


Figure 2: Applications and Admissions to Higher-Quality High Schools

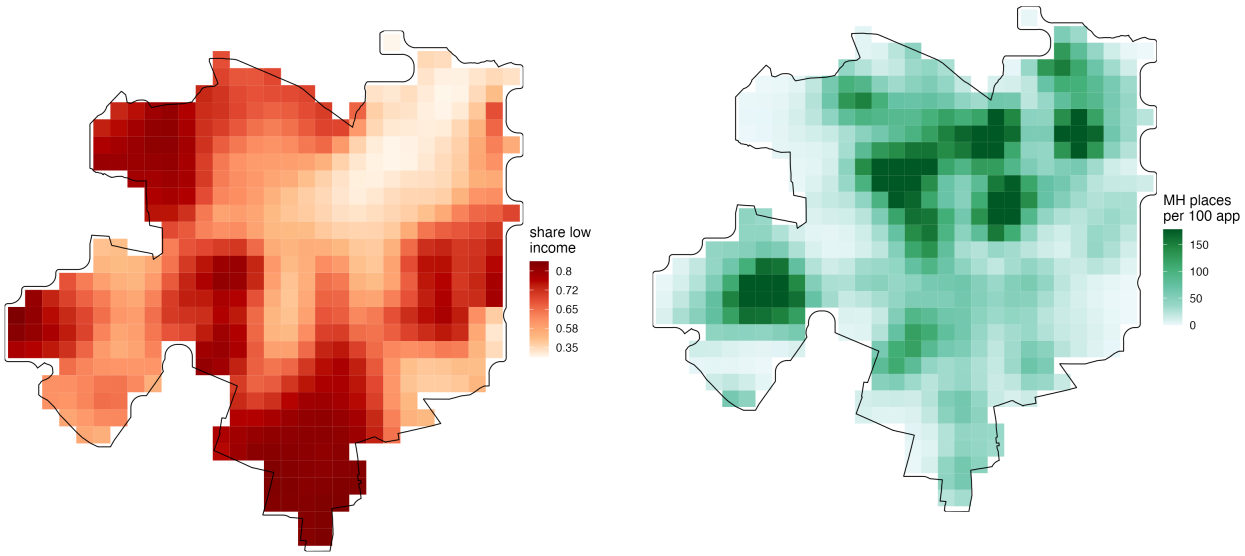
Notes: Each bar corresponds to the probability a family ranks or is admitted to a medium- or high-quality high school. School quality is the rating of the Agency for Quality in Education described in Section 2.2. Teal bars correspond to the mean for children from high-SES families (whose mother completed secondary schooling), and orange bars correspond to the mean for children from low-SES families (whose mother did not complete secondary schooling). The first set of bars corresponds to the probability to rank a medium or high-quality school anywhere in the ROL, the second to rank the school as a family's most preferred option, and the last is the probability to receive an offer of admission to the school. The figure above each pair of bars is the mean of the outcome. Data from the 2023 admission process; all differences are significant at the 1% level.

uses data on children's locations and characteristics to provide tailored information. For more details, see Agte et al. (2024).

3.2 Families' Choice Sets, Preferences, and the Structure of Peer Groups

I begin this section by presenting descriptive evidence linking the spatial distribution of school quality to schooling inequality. I then show how, given the structure of peer groups, a preference to study with peers can amplify schooling gaps generated by geography alone.

Fact 1: Higher-Quality High Schools Are Located Far from Low-SES Children The spatial distribution of higher-quality high schools is highly uneven. Figure 3 maps the share of low-SES children across Santiago, Chile's capital and largest city, alongside the number of seats in higher-quality high schools per hundred applicants. Low-SES families are concentrated in the South and West of Santiago, while high-SES families tend to live in central and northeastern areas of the city, precisely where higher-quality high school places are more abundant. The two maps are nearly mirror images: neighborhoods with the highest concentrations of disadvantaged children have the fewest seats in higher-quality high schools.



(a) Share of Low-SES Children

(b) Seats at Higher-Quality Schools per 100 Applicants

Figure 3: Disadvantage and Access to Higher-Quality Schools across Santiago

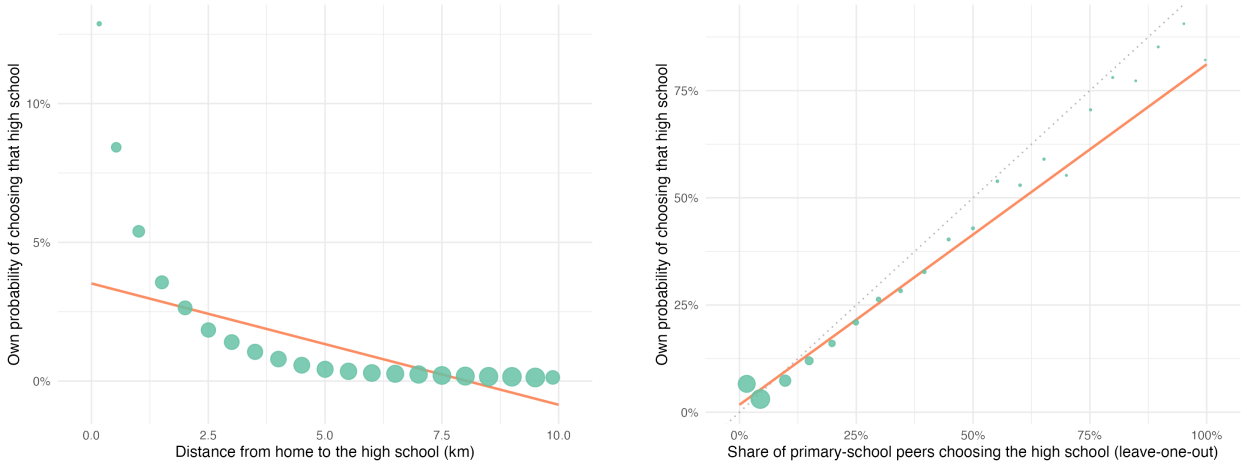
Notes: Both panels cover the Santiago metropolitan area, partitioned into 1 km by 1 km cells, with cell values smoothed across neighboring cells by a Gaussian kernel. Panel (a) reports, in each cell, the share of grade-9 applicants whose mother has at most a secondary education, the measure of low socioeconomic status used throughout. Panel (b) reports the number of seats in medium- or higher-quality high schools within 2 km of the cell, per 100 grade-9 applicants living in the cell. School quality is the rating of the Agency for Quality in Education (Section 2.2). Data from the 2023 admission process.

This pattern is not unique to Santiago. Appendix Table A1 shows that, across the country, the

nearest higher-quality high school is, on average, 165 meters farther from a low-SES child's home than from a high-SES child's. Low-SES children also have access to 19 fewer higher-quality schools, and roughly 1000 fewer seats at these schools, within ten kilometers of their home.

Fact 2: Families Choose Schools Close to Home, Where Their Children's Peers Apply Families rarely look for high schools far from home. The median ranked school is 2.5 kilometers away from a child's home, and the median child is enrolled in a school about 2.3 kilometers from home. Panel (a) of Figure 4 shows how sharply families' applications respond to distance: the probability that a family ranks a given school falls from around 13% for a school less than 1km from their home, to less than 1% for a school 5 km away.

Families also tend to rank schools to which children's peers apply. Panel (b) plots the probability that a child applies to a high school against the share of the child's primary school peers who apply. The relationship is strongly positive: children are more likely to apply to a school when a larger share of their former primary school peers also apply. This pattern is consistent with a preference for attending school alongside one's peers, but does not by itself establish one. In Section 4, I discuss how I identify these preferences.



(a) Ranking Probability by Distance

(b) Ranking Probability by Peer Share

Figure 4: Ranking Probability, Distance, and Peers

Notes: The sample is grade-9 applicants in the 2023 admission process. Panel (a) groups high schools into 0.5 km bins by their straight-line distance from a child's home, and plots, for each bin, the average probability that a family enrolls in a school at that distance. Each dot is a bin, its size is proportional to the number of child–school pairs it contains, and the line is a linear fit. Panel (b) groups child–school pairs by the share of a child's primary school peers who enroll in the school, excluding the child, and plots the average probability that the child also accepts the offer there; each dot is a bin, its size is proportional to the number of pairs, and the line is a linear fit.

Fact 3: Peer Groups Are Geographically Clustered A preference for peers would matter little for schooling inequality if peer groups were geographically diverse. However, children who attend the

same primary school tend to live close to each other. Figure 5 compares the distance between the homes of pairs of children observed in the data. I compare peers, children who attend the same primary school, to children who live in the same commune, Chile's smallest administrative division. Primary school peers tend to live in close proximity to one another: the typical peer lives 1.9 kilometers away, compared to 3.8 kilometers for another child who lives in the same commune, and a quarter of primary school peers live within a kilometer of one another.

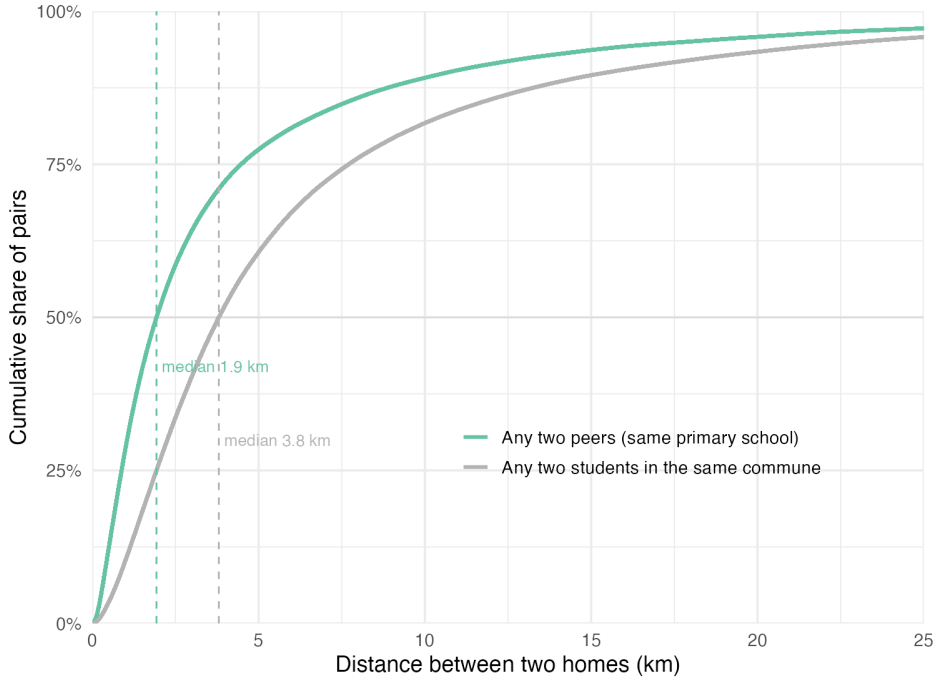


Figure 5: CDF of Distance Between Children

Notes: Peers are children who attended the same primary school in eighth grade. Panel (a) plots the cumulative distribution of the straight-line distance between the homes of two peers (green) and between two children who live in the same commune (grey); dashed lines mark the medians. Panel (b) groups child–school pairs by the share of a child's primary school peers who enroll in the school, excluding the child, and plots the average probability that the child also accepts the offer there; each dot is a bin, its size is proportional to the number of pairs, and the line is a linear fit.

3.3 Conceptual Framework

How does a preference to study with peers interact with the uneven spatial distribution of school quality? The intuition is straightforward. Because children dislike traveling long distances (Fact 2), and primary school peers tend to live in the same area (Fact 3), a preference for peers increases the likelihood of applying to a nearby high school. For low-SES children, who have worse access to higher-quality schools (Fact 1), this may increase the likelihood of applying to a lower-quality school. A low-SES family is therefore less likely to apply to a higher-quality school for two mutually reinforcing reasons: it is farther from home, implying a longer commute, and it is also less likely to

be attended by the child's peers.

The same logic operates in reverse in high-SES neighborhoods. There, peers are more likely to apply to nearby higher-quality schools, so a preference for peers pulls the marginal family toward, rather than away from, higher-quality options. As a result, peer preferences may amplify differences in the choices families from different backgrounds would make, pushing Low- and high-SES children further apart and widening the gap in the quality of schools to which they apply.

A preference for peers, however, does not necessarily amplify school inequality. If higher-quality schools are readily accessible regardless of where children live, and families value quality, they may be more likely to apply to them even absent peer preferences. Peer preferences can then reinforce these choices, pulling additional children in each primary school towards higher-quality schools. In this case, peer preferences increase applications to higher-quality schools across groups and can reduce inequality.

The effect of peer preferences on inequality therefore depends on the spatial distribution of school quality, families' preference for quality, and their discommon preference for distance. Appendix A3 formalizes this intuition in a model with two high schools and two peer groups that differ in their distance to the higher-quality school. When a unique equilibrium exists, there is a cutoff distance to the higher-quality school such that peer preferences increase a group's applications to the higher-quality school if the group lives within the cutoff and reduce it otherwise. When one group lives within the cutoff and the other outside it, peer preferences widen the gap in the probability of applying to the higher-quality school; when both live within it, peer preferences increase that probability for both groups. Appendix Figure A12 illustrates these two cases.

4 Identification of Peer Preferences Using Admission Lotteries

In this section, I discuss the identification of peer preferences using the random tie-breaking built into Chile's centralized school assignment. I develop a framework which focuses on identifying the *causal* effect of primary school peers' admission to the same high school on families' decision to accept the offer at the school.[22] The resulting estimate measures *whether* families value enrolling children in high school with their primary school peers. In Section 5, I develop a structural model of school choice which allows me to identify *how much* families value studying with peers relative to other characteristics of schools, and to recover how peers shape which high schools families rank in the first place, and, as a result, which children ends up in which schools.

4.1 Identification

To identify whether families prefer to enroll children in high schools with their primary school peers, I begin by asking whether families are more likely to accept an offer when more of a child's

[22]The strategy builds on Angrist et al. (2022) that show that the causal effect of a school characteristic can be recovered from variation induced by centralized admission systems by conditioning on the value of that characteristic a child can expect given their application. Idoux and Corradini (2024) adopt the same design to study how the racial composition of a child's school peers shapes their high school choices.

primary school peers are admitted to the same high school. In the ideal experiment, children would be randomly assigned to high schools. If families were more likely to accept an offer when more primary school peers were randomly admitted alongside their child, this would provide evidence of families' preference for enrolling children in high school with their primary school peers. The analysis in this section follows the same logic, leveraging lottery variation embedded within the centralized admission system, but accounting for the fact that admission is only random conditional on children's and peers' applications and characteristics.

Let i denote a family, which I treat as a single decision maker.[23] Let j index a high school, and J_i the high school to which the child of family i is admitted. I am interested in estimating the effect of the admission of m_i of child i's primary school peers into high school J_i, on the probability that family i accepts a high school offer, which I denote by y_{ij}. I formalise this with the following linear model:[24]

$$y_{ij} = \rho_0 m_i + u_{ij} \tag{1}$$

where u_{ij} collects all other determinants of enrollment, observed and unobserved. In this specification ρ_0 represents the average causal effect of the admission of an additional primary school peer to school J_i on enrollment. Identification of ρ_0 by ordinary least squares requires that the number of admitted peers m_i be uncorrelated with other determinants of enrollment:

$$\text{Cov}(m_i, u_{ij}) = 0 \tag{2}$$

Condition (2) generally fails in observational data because the number of primary school peers admitted to the same high school, m_i, ultimately reflects the choices made by their families. Families of primary school peers likely have correlated preferences over high schools. For instance, they may be similar along unobserved dimensions, such as their academic ambition for their children, or share similar sources of information about high schools. As a result, peers tend to apply to the same schools and, consequently, to be admitted together. Accordingly, high schools that admit many of a child's primary school peers (a high value of m_i) are also likely to be schools that the child's family independently prefers (a high value of u_{ij}). A naive regression of enrollment on the number of admitted peers would then conflate the causal effect of peers with the shared backgrounds, neighborhoods, and institutional influences that lead peers to prefer the same schools.

4.1.1 Admission Lotteries as a Source of Exogenous Variation

Following Angrist et al. (2022) and Idoux and Corradini (2024), I isolate variation in the number of i's peers admitted into high school J_i, m_i, that is orthogonal to u_{ij} by exploiting tie-breaking

[23] I do not distinguish between the preferences of children and their guardians.

[24] I work throughout this section with the linear model (1) for two reasons. First, stating the problem for a generic linear model makes clear that the approach is not specific to school choice: it identifies the average effect of peer exposure on any outcome generated in this way. Second, while the model presented in Section 5 is a nonlinear discrete-choice model, I show that peer preferences are identified from a linear model, so that the condition under which peer preferences are identified is exactly the one derived here.

lotteries embedded in Chile's centralized admission system.

To illustrate the approach, I express the number of i's peers admitted into high school J_i, m_i, as follows:

$$m_i = m(X, L) \tag{3}$$

where X corresponds to all children's ROLs as well as their admission-relevant characteristics, and L corresponds to children's lottery draws at every school. $m(\cdot)$ is a function that maps from X and L and produces a count of the number of i's primary school peers who were admitted to school j. Expression 3 makes it clear that the number of admitted primary school peers may vary because of peers' choices, included in X, or because of their lottery draws L.

Now consider the number of primary school peers that, in expectation, would be admitted to high school j across different lottery draws:

$$\mathbb{E}_L[m_i \mid X,\, J_i] \tag{4}$$

where J_i holds fixed child i's own admission to school J_i, so that the expectation is taken over draws that keep a child's outcome constant but vary their peers' offers. The *realized* number of primary school peers admitted into the same high school as child i, m_i, can be decomposed into the expected number, and a residual, r_i, which I refer to as the *peer shock*.

$$m_i = \mathbb{E}_L[m_i \mid X,\, J_i] + r_i \tag{5}$$

The expected number of peers, $\mathbb{E}_L[m_i \mid X,\, J_i]$, is taken over lottery draws it is a function only of the variables included in X. In other words, it summarizes, in a single number, everything about families' choices and characteristics that influences the number of primary school peers admitted into the same high school as child i, other than their lottery draws. As a result, the expected number of peers captures the endogenous component of m_i, while the shock r_i captures the variation induced by the lottery. In Appendix A4, I formally prove the following results:

Theorem 1 (Orthogonality of the peer shock)**.** *If the lottery draws are independent of family's characteristics and preferences:*

$$L \perp\!\!\!\perp (X, u_{ij})$$

Then the peer shock is orthogonal to the unobservable determinants of enrollment:

$$\mathrm{Cov}(r_i, u_{ij}) = 0$$

In practice, Theorem 1 suggests that ρ_0 can be identified from a regression of y_{ij} on the peer shock, r_i, or equivalently, the coefficient on the realized number of peers, m_i, in a regression that controls for the expected number.[25] The appeal of the argument is that it requires neither observing

[25] This follows from Frisch-Waugh-Lovell theorem: r_i is the residual from projecting the realized number of admitted peers on the expected count, so the coefficient on m_i in a regression that controls for the expected number of peers equals the coefficient from regressing the outcome on r_i alone.

nor modeling the unobservable collected in u_{ij}: it is enough to strip from the number of admitted peers the component the inputs predict, which I compute from the admission system, leaving variation that is driven by the lottery alone. Effectively, this approach compares children that face the same expected number of admitted peers, but end up studying with different numbers of peers because of their peers' randomly assigned lottery draws.

4.1.2 Estimating the Expected Number of Admitted Peers

In order to take this approach to the data, I first need to estimate the expected number of i's primary school peers admitted into high school J_i. I estimate its sample counterpart, which I denote by $\bar{m}_i$, using a re-randomization procedure. Fixing children's ROLs, priorities, quota eligibility, and school capacities, I redraw the lottery vector, L, $S = 1{,}000$ times. I restrict attention to the S_{J_i} simulations in which child i is assigned to school J_i.[26] For each simulation s, I record the number of i's primary school peers who are also assigned to J_i, which I denote by $m_i^{(s)}$, and take the sample average. This procedure is feasible because I observe every input required by the DA algorithm, and it recovers the expected number of admitted peers to arbitrary precision as S grows.[27] Formally, I define the sample expected number of admitted peers as:

$$\bar{m}_i = \frac{1}{S_{J_i}} \sum_{s=1}^{S_{J_i}} m_i^{(s)} \tag{6}$$

Validation Identifying ρ_0 requires variation in the peer shock, r_i. That is, children with the same expected number of admitted peers, $\bar{m}_i$, must sometimes end up with different realized number of admitted peers, m_i, because of their lottery draws.[28] Appendix Figure A1 illustrates this variation by plotting the realized number of admitted peers, m_i, against its estimated expectation, $\bar{m}_i$. For approximately 95% of children, the realized number of admitted peers differs from its expected value, and the standard deviation of the resulting peer shock, $\hat{r}_i$, is close to 1.

To confirm that peer shocks are driven by the lottery and therefore orthogonal to children's

[26] For each simulation, I retain the draw only if child i is assigned to school j. This isolates variation that is driven by *peers'* offers, rather than by children's offers of admission. In other words, the variation is driven by changes in the number of peers at the same school, rather than by changes in the school to which a child is admitted, which may have different numbers of peers.

[27] The expected count can also be obtained analytically rather than by simulation. In the large-market limit, the assignment probabilities implied by the mechanism have a closed form that can be tabulated directly from cutoffs and priorities (Abdulkadiroğlu et al., 2017, 2022), and $\bar{m}_i$ is then the corresponding sum of peers' co-assignment probabilities. I use re-randomization because it extends immediately to the count treatment and to the quota and tie-breaking structure of the Chilean mechanism without requiring me to derive that closed form, and because with $S = 1{,}000$ draws the simulation error is negligible.

[28] This variation can arise through two channels. First, high school J_i may be oversubscribed within a given priority group, so that some of child i's peers are admitted to J_i under some lottery realizations but not others. Second, i's peers may rank another oversubscribed school, j', above J_i. Under some lottery realizations, these peers are admitted to j' and therefore never compete for a place at J_i. Under others, they are not admitted to j' and instead compete for admission to J_i, potentially increasing m_i. Thus, even conditional on the expected number of admitted peers, lottery draws generate substantial variation in the number of peers ultimately admitted alongside a child.

predetermined characteristics, I run the following regression:

$$X_{ij}^k = \pi_0^k m_i + \pi_1^k \bar{m}_i + e_{ij} \tag{7}$$

where X_{ij}^k corresponds to a characteristic of child i at high school j. Figure 6 plots the estimated coefficients, π_0^k. Conditional on the expected number of peers admitted to school J_i, the realized number of peers is uncorrelated with every observable characteristic, including those most likely to be related to peer admissions, such as family income, distance to school, and primary school GPA.[29] In contrast, without controlling for the expected count, these same characteristics are strongly correlated with the realized number of admitted peers. This comparison illustrates the role of the expected count: it absorbs the systematic variation in the number of peers admitted, leaving only the lottery-induced variation.

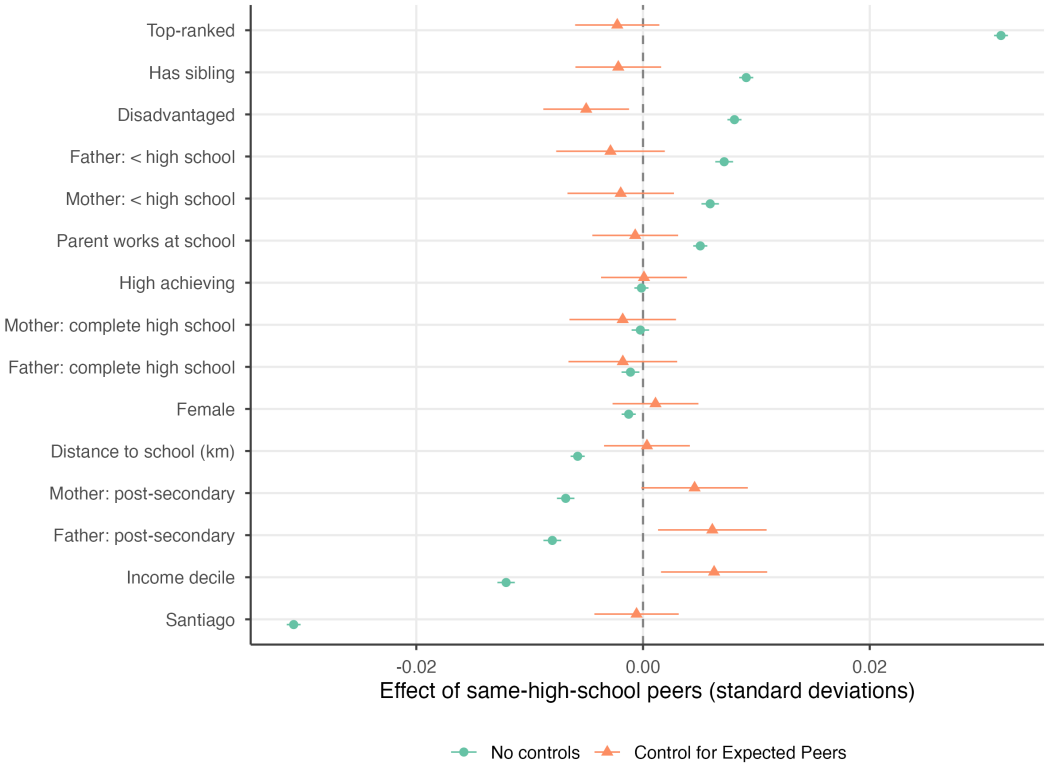


Figure 6: Orthogonality of the Peer Shocks

Notes: The figure plots the estimated coefficient π_k from regression (7) for each observable child characteristic, that is, the correlation between the realized number of admitted peers and that characteristic conditional on the expected count. Error bars are 95% confidence intervals. All coefficients are statistically indistinguishable from zero.

[29] As with the estimand in Corollary A2, regressing X_{ij}^k on the realized number of admitted peers while controlling for the expected count is equivalent, by the Frisch-Waugh-Lovell theorem, to regressing it on the peer shock $r_i = m_i - \bar{m}_i$ alone.

4.2 Evidence for Peer Preferences

In this section, I present evidence that families are more likely to accept an offer at a high school when more primary school peers are randomly admitted. I first discuss the empirical specification, before presenting the results. I conclude with a discussion about the interpretation of these preferences for peers.

4.2.1 Sample and Specification

Sample I use data from the main application round for cohorts that applied to high school between 2022 and 2025. I restrict the sample to children in urban areas who attend primary schools that do not also offer secondary schooling, and for whom there is any variation in the number of admitted peers across lottery realizations.[30] The resulting sample contains 272,683 applicants from 36,283 primary networks applying to 2,445 high schools.[31] I show in Appendix Table A4 that my sample is comparable across most characteristics to the overall population of high school applicants, and the overall population of children.

Empirical Specification I estimate the average effect of an admitted peer on enrollment using the following linear model:

$$y_{ij} = \rho_0 \, m_i + \rho_1 \, \bar{m}_i + u_{ij} \tag{8}$$

where the outcome y_{ij} is an indicator for whether family i accepts their offer of admission. The treatment m_i is the number of the child's primary school peers admitted to the same high school. As a result, ρ_0, the coefficient of interest, is the effect of one additional admitted peer on the probability that i accepts the offer at high school J_i.

4.2.2 Results

Table 1 reports estimates of estimating Equation (8). Column (1) presents the raw correlation between the number of admitted peers and enrollment, without conditioning on the expected count. Column (2) adds the control for the expected count. Columns (3) adds high school fixed effects, and column (4) further controls for a rich set of individual characteristics (family income, distance to school, GPA, and gender).

The raw coefficient in column (1) is 0.299 percentage points per additional admitted peer. Conditioning on the expected count in column (2) reduces the estimate to 0.210 percentage points. In other words, each additional primary school peer admitted to the same high school as a child increases the probability their family accepts the offer by 0.2 percentage points. If all peers in a typical class of 27 were offered admission into the same high school as the family, each would be

[30] I also restrict my sample to children who attend primary schools that do not also offer secondary schooling. Observing these children choosing high schools may primarily reflect family moves or some dissatisfaction with the current high school.

[31] I also exclude children who apply to a high school together with a sibling, as these children likely make a joint decision that is beyond the scope of my framework.

Dependent Variable:	Attendance (p.p.)			
Model:	(1)	(2)	(3)	(4)
Variables				
Admitted peers	0.2991***	0.2104***	0.1958***	0.1951***
	(0.0072)	(0.0375)	(0.0383)	(0.0374)
Expected peers		0.0919**	0.1317***	0.0679*
		(0.0383)	(0.0405)	(0.0394)
Additional Controls	No	No	No	Yes
Fixed-effects				
HS			Yes	Yes
Observations	272,483	272,483	272,421	272,414
R^2	0.00563	0.00565	0.03652	0.06340
Control mean	93.979	93.979	93.980	93.981

Clustered (Primary school x High School) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 1: Peer Effect on Attendance (Percentage Points)

Notes: The table presents estimates from the reduced-form regression. The dependent variable is an indicator for enrolling in the assigned high school, in percentage points. Column (1) reports the coefficient on the number of admitted peers without conditioning on the expected count; column (2) adds a control for the expected count; column (3) further controls for high school fixed effects; column (4) further controls for family income, distance to school, GPA, and gender. The control mean is the mean enrollment rate. Standard errors, clustered at the admitted high school level, are in parentheses. ***, **, * denote significance at the 1, 5, and 10% levels.

approximately 5.4 percentage points more likely to accept the offer. The decline between columns (1) and (2) is itself informative, it reflects exactly the positive selection that motivated the identification strategy. Children admitted to high schools with more peers also tend to be admitted to high schools that, independently, they would have a higher probability of accepting the offer at. Adding the full set of high school fixed effects and individual controls in columns (3) and (4) leaves the estimate essentially unchanged. This validates my approach: conditioning on the expected number of peers already removes the endogenous variation in m_i, so additional controls should not change the estimate.

4.2.3 Discussion

Why Do Peers Matter? Peers could matter for families' decision to accept an offer of admission for a number of reasons. First, families of peers might have some private information about the quality of different schools, which can drive families' decision to enroll. However, as I exploit variation induced by the lottery in the number of peers admitted into each school, this channel is unlikely to drive my results. The admission of more or less peers into a school is driven by a lottery and so should not in itself transmit information about the school that was not known before. As such, I interpret the results as reflecting families' preferences for children to study together.

Second, peers may have an *amenity value*, they may be friends and so valued by families for their effect on child's welfare. Alternatively peers may have an *academic production value*, and may help children adjust better to new high schools and ultimately improve their academic outcomes. I separate the two mechanisms by looking at the effect of the number of peers admitted to the same high school as a child on a range of downstream outcomes relating to children's academic performance and well-being in high school. I plot the estimates in Appendix Figure A2. Overall, I find positive but economically small and statistically insignificant effects on children's math and reading scores. Similarly, I find mostly small and insignificant effects on indices relating to bullying, disruptive behavior, phone use, self-efficacy, attitudes towards school and learning, and team work. I find a significant (p-value = 0.06) effect on an index of children's relationship with their current peers. I interpret these results as evidence that studying with primary school peers does not improve high school children's academic outcomes, suggesting that peers likely represent a non-productive amenity.[32]

Which Peers Matter? I estimate how the effect of an admitted primary school peer on enrollment varies by the characteristics of the child and peer. I first look at how the effects vary by whether a child is a girl, low-SES and high achieving, which I define as a child in the top-30% of their cohort. I plot the results in Appendix Figure A3. Overall, girls appear to respond significantly more to their peers relative to boys, whereas the effect for low-SES and high-achieving children is not statistically distinguishable from that for other children. Appendix Figure A4 further decomposes these effects by both child and peer characteristics. The results reveal a pattern of homophily: children respond most strongly to peers with similar characteristics. Girls respond more to female peers, high-achieving children respond more to high-achieving peers, and low-SES children respond more to other low-SES peers. These patterns are consistent with the results primarily reflecting a preference to keep *friends* together, as friendships in school tend to form disproportionately between children of the same gender and background (McPherson et al., 2001; Currarini et al., 2009; Calvó-Armengol et al., 2009).

Robustness I test the robustness of my results in several ways. First, I show in Table 1 that the results are robust to the addition of a number of controls. Second, I show in Appendix Figure A5 that the results are robust to restricting the sample to children who face more or less variation in the number of admitted peers across simulations.

[32]Studying with primary school peers may also generate direct benefits for parents. For example, having children attend the same school may facilitate coordination among parents around childcare and transportation to school. In addition, the parents of primary school peers may themselves have formed relationships that they wish to maintain. Consistent with this, Appendix Figure A2 shows a positive, though statistically insignificant, effect of studying in high school with more primary school peers on parents' reported relationships with other parents of children attending the same high school.

5 Structural Model

In this section, I develop an empirical model of demand for high schools which incorporates social interactions among primary school peers. My goal is to characterize how preferences for peers affect inequality in admission into high-quality schools, and ultimately, children's academic outcomes. The model links the reduced-form estimates from Section 4, which identify families' value for peers at the enrollment stage – where the lottery supplies exogenous variation – to the role of peers in determining which schools families apply to in the first place, where no comparable variation exists. Finally, I estimate each high school's causal effect on children's academic outcomes to quantify how peer preferences affect inequality in children's academic achievement.

5.1 Set-up

Families make decisions at two stages, $l \in \{1, 2\}$, mirroring the high school admission process in Chile. In the first stage, families apply to high schools by submitting rank-ordered lists of schools. A deferred acceptance algorithm then assigns admission offers based on families' submitted rank-ordered lists, children's priorities, school capacities, and randomly drawn lottery numbers. These lottery draws generate random variation in the number of a child's peers admitted to the same school. In the second stage, corresponding to the decision studied in Section 4, families decide whether to accept a high school place and enroll or reject. After choices are made, schools' effects on children's academic outcomes are realized.

Utility Let i index a child, c a primary school, and j a high school. The utility that family i derives from attending high school j is a linear function of the school's characteristics, the number of peers admitted to the school, and families' unobserved preferences for the school.[33] Preference parameters vary by families socioeconomic status $g \in \{L, H\}$:

$$U_{ij}^{l} = \underbrace{\beta_g' X_{ij}}_{\substack{\text{School} \\ \text{characteristics}}} + \underbrace{\gamma_g \, m_{ij}}_{\text{Peers}} + \underbrace{u_{ij}^{l}}_{\substack{\text{Unobserved} \\ \text{preferences}}} \tag{9}$$

The vector X_{ij} collects observed characteristics of the child-high school pair, such as the distance between each child and a school, and whether a child has a parent or a sibling at the school. To capture additional unobserved reasons why families may prefer school j over other schools in their choice set, I model an unobserved component of utility, u_{ij}.

Unobserved Preferences I allow families' unobserved preferences over high schools to have a primary-by-high school specific component. This captures the fact that families within the same primary school may have correlated preferences over high schools, for instance, because they share

[33] In the multinomial choice literature, this type of peer preference is also referred to as an endogenous peer preference or network externality (Brock and Durlauf, 2007).

similar unobserved background characteristics or are exposed to similar recommendations from teachers. To model this, I decompose the unobserved component into a primary-by-high school common preference, η_{cgj}, which varies by child type, and an idiosyncratic, stage-specific preference, e^l_{ij}:

$$u^l_{ij} = \eta_{cgj} + e^l_{ij} \tag{10}$$

I assume that in each stage, l, corresponding to the first-stage ranking or second-stage enrollment decision, families draw different idiosyncratic preferences from a Type-I Extreme Value distribution:

$$\begin{aligned} e^1_{ij} &\sim \text{i.i.d. Type-I Extreme Value} \\ e^2_{ij} &= \sigma_g \, \tilde{e}^2_{ij}, \quad \tilde{e}^2_{ij} \sim \text{i.i.d. Type-I Extreme Value} \end{aligned} \tag{11}$$

I normalize the scale of unobserved preferences in the first-stage application decision to one, but allow the scale in the second-stage enrollment decision, σ_g, to vary. The assumption that the two stages differ only in scale, rather than in the preference parameters $(\beta_g, \gamma_g, \eta_{cgj})$, imposes that families hold the same preferences over observable school characteristics when ranking schools and when deciding whether to accept the offer. The parameter σ_g captures differences in the dispersion of idiosyncratic preferences across the two stages, which may arise, for example, from new information arriving between the ranking and enrollment stages.

Academic Outcomes I define q_{ij} as high school j's causal effect on child i's tenth-grade SIMCE math score, which I refer to as a school's *overall value-added*.[34] I allow this effect to vary across children from different families by decomposing it into three components:

$$q_{ij} = \underbrace{q^0_j}_{\substack{\text{Common} \\ \text{Value - Added}}} + \underbrace{q_{gj}}_{\substack{\text{Type-Specific} \\ \text{Value-Added}}} + \zeta_{ij}, \tag{12}$$

where $g \in \{L, H\}$ denotes the child's socioeconomic status (low- or high-SES, defined by maternal education). I refer to q^0_j as the school's *common value-added*. Differences in q^0_j differentiate good schools, which are good for all children, from bad schools. I refer to q_{gj} as the school's *type-specific value-added*, capturing how effective the school is at increasing the academic outcomes of children from families of type g. With two types, $q_{Lj} = -q_{Hj}$, so that a single match parameter summarizes whether a school is relatively more effective for children from low- or high-SES families. The last term, ζ_{ij} is a mean-zero error. This specification allows schools to vary in their overall quality, and in how well they serve children of a particular group. In section 7.1, I explore the effect of allowing the value-added of a school to depend on the composition of it's student body.

[34] I treat school supply and quality as exogenous. A large literature studies private schools' incentives to choose prices and quality. For example, Nielson (2021) studies these incentives among voucher schools in Chile, while Allende et al. (2019) examines how private schools target children from different socioeconomic groups in Peru. My setting differs in that I focus on publicly funded schools which, following the 2015 School Inclusion Law, cannot operate for profit and therefore likely face weaker incentives to compete strategically.

5.1.1 First Stage: The Application Decision

In the first stage, families form a belief $\widehat{m}_{ij}$ about the number of peers who will be admitted to each high school. Based on these beliefs, families rank schools according to their (expected) utility.

I assume that families' observed rank-ordered lists (ROLs) reflect their true preferences over schools. This follows from the strategy-proof nature of the child-proposing deferred acceptance (DA) mechanism used in the assignment process (Correa et al., 2022). Under DA, children are assigned to the highest-ranked school on their list with an available seat, so ranking a less-preferred school higher does not increase the chance of admission to a preferred school. Families therefore have no incentive to distort their rankings based on admission probabilities, allowing observed ROLs to be interpreted as direct measures of preference. Peer preferences do not change this property in my framework. Families form beliefs about the share of peers who will be admitted to each high school that are independent of their own choices, so these beliefs enter utility like any other school characteristic. Because a family's actual ranking cannot influence its peers' behavior, peer preferences do not create an incentive to strategically manipulate rankings.[35]

Ranking and Admission Probability The school that family i ranks as their most preferred option, which I denote by $R_i(1)$, is the school that maximizes their utility within their choice set J_i. Since I assume that idiosyncratic preferences can be approximated with an Extreme-Type I distribution, the probability that family i ranks school j as their most preferred option can be written as:

$$\mathbb{P}(R_i(1) = j) = \frac{\exp(\beta_g X_{ij} + \gamma_g \hat{m}_{ij} + \eta_{cgj})}{\sum_{k \in J_i} \exp(\beta_g X_{ik} + \gamma_g \hat{m}_{ik} + \eta_{cgk})} \tag{13}$$

Families may rank as many schools as they like, but they are not required to rank all available schools. For any rank $r \geq 2$, families may select any school that has not been previously ranked or the outside option. To model the decision to only rank schools up to position $r \geq 2$, I introduce an outside option, which represents the choice not to rank any schools, with utility $\bar{V}_g^1$. I model the outside option as having constant value for type g families.

The probability that child i receives an offer of admission to school j, $\mathbb{P}(A_i = j)$ depends on their own ranking, as well as how other families rank schools, their priority at each school, eligibility for a quota, and randomly drawn lottery numbers. Because children submit ROLs and school capacities are limited, the assignment process is shaped by the interactions of all applicants' preferences and priority-quota group. I discuss this in more detail in Appendix A5.1.

Beliefs Following Brock and Durlauf (2007) and Bhattacharya et al. (2024), I model interactions among peers as a game of incomplete information.[36] I assume that families do not know

[35] This stands in contrast to examples such as siblings coordinating their applications. In that case, since families primarily care about studying together and are aware of each other's choices, strategic ranking that accounts for admission probabilities is beneficial.

[36] An alternative information structure would allow families to observe the preferences or intended choices of particular peers. Soetevent and Kooreman (2007), for example, consider a framework in which individual shocks are

one another's choices or offers when ranking schools. Instead, each family i observes its own characteristics, $X_i = \{X_{ij}\}_{j\in\mathcal{J}}$, and idiosyncratic preferences, $e_i^1 = \{e_{ij}^1\}_{j\in\mathcal{J}}$. Families also know the primary-by-high school preferences, $\eta_{cg} = \{\eta_{cgj}\}_{j\in\mathcal{J}}$, the admission probabilities into different high schools, and the distribution of peers' idiosyncratic preferences, and the distribution of their peers' characteristics, which I denote by F_g.[37]

I impose that families' beliefs about the number of peers into each high school correspond to the expected number, given their information set. Let $\mathcal{P}_c$ denote the set of children in primary school c, and let A_i denote the high school to which child i is admitted. Family i's belief about the number of its peers who will be admitted to school j is given by:

$$\widehat{m}_{ij} = \sum_{k\in\mathcal{P}_c\setminus\{i\}} \mathbb{P}(A_k = j \mid X_i, e_i^1, \eta_{cg}, F_g) \qquad \forall i, j \tag{14}$$

Observed ranking data may be consistent with many possible beliefs (Manski, 1995). As such, I impose the following restrictions on families' information sets that discipline how these beliefs are formed:

(**C1**) **Conditional Independence of Peer Characteristics:** Conditional on families' knowledge of common parameters, such as the primary-by-high school common preferences, the distribution of peers' characteristics, F_g, and admission probabilities into different high schools, a family's own characteristics and idiosyncratic preferences contain no information about the characteristics and idiosyncratic preferences of another family:

$$(X_i, e_i^1) \perp\!\!\!\perp (X_k, e_k^1) \mid \eta_{cg}, F_g \qquad \forall i \neq k \in \mathcal{P}_c \tag{15}$$

Condition (C1) implies that a family's private information about itself does not affect its beliefs about another child's offer. Intuitively, although families observe their own characteristics and idiosyncratic preferences, this private information does not help them predict where another child will be admitted.[38] As a result, families in the same primary school share a common belief about each peer's offer. I formally prove the following result in Appendix A5:

observed by other agents but remain unobserved to the econometrician. Such a framework permits agents to condition their choices on the realized preferences of others. Implementing this information structure here would require specifying which families observe which peers' preferences or intended rankings and would substantially increase the dimensionality of the equilibrium problem.

[37] I assume that families have correct information about the primitives of the model, including the admission mechanism and the distribution of characteristics and preferences within their network. This is a common assumption in structural models of school choice (e.g., Bau, 2022; Allende et al., 2019; Nielson, 2021; Walters, 2018). More recent work focusing on primary school and university choice highlights the importance of beliefs and consideration sets (Agte et al., 2024; Fabre et al., 2024).

[38] Condition (C1) does not require families within a primary school to have identical characteristics or preferences. They do, however, rule out family i possessing private information about a particular peer k that helps predict k's choice. For example, the model rules out a family privately knowing that a particular friend intends to rank school j, or knowing characteristics of that friend that are not otherwise incorporated into the distribution F_g and that predict their choice. Common influences on families within the primary school, such as advice from teachers or counselors or a shared preference for a particular high school, can instead be captured by the primary-by-high school component η_{cgj}.

Result 1 (Common Beliefs about Peers): Under Condition (C1), for any $i \neq k$ in primary school c and any high school j,

$$\mathbb{P}(A_k = j \mid X_i, e_i^1, \eta_{cg}, F_g) = \mathbb{P}(A_k = j \mid \eta_{cg}, F_g) \tag{16}$$

Consequently, the common belief about the number of peers admitted to high school j is given by:

$$\widehat{m}_{ij} = \underbrace{(N_c - 1) \cdot \mathbb{P}(A_k = j \mid \eta_{cg}, F_g)}_{=\widehat{m}_{cj}} \tag{17}$$

where N_c corresponds to the number of children in primary school c.

Equilibrium An equilibrium requires families' beliefs about the number of peers admitted to each high school to be consistent with the admission probabilities generated by those beliefs. Because offers of admission depend on families' rankings, and rankings depend on their beliefs whenever $\gamma_g \neq 0$, the admission probability is itself a function of $\widehat{m}_{cj}$. As a result, the right-hand side of Equation 17 can be re-expressed as a *belief-mapping function*, $\Phi(\widehat{m}_{cj})$. An equilibrium belief corresponds to a fixed point of this mapping, satisfying the equality expressed by Equation 17.

$$\widehat{m}_{cj} = \Phi(\widehat{m}_{cj}) \tag{18}$$

Since the belief-mapping function is continuous and maps $[0, N_c]$ into itself, Brouwer's fixed-point theorem guarantees the existence of at least one equilibrium belief. Moreover, if γ_g is sufficiently small, the mapping is a contraction and the equilibrium is unique.[39] I formally prove the following result in Appendix A5:

Result 2 (Equilibrium Existence and Uniqueness): An equilibrium belief always exists. Furthermore, the equilibrium within a primary school cohort is unique if

$$\gamma_g \leq \left(\bar{R} N_c\right)^{-1}$$

where $\bar{R}$ denotes the longest possible ROL and N_c the size of the primary school cohort.

5.1.2 Second Stage: The Enrollment Decision

In the second stage, each family observes their own offer of admission, A_i, and the realized number of peers admitted into the same high school, m_{ij}. Family i accepts the offer at high school j if the realized second-stage utility exceeds the value of rejecting the offer, which I denote by $\bar{V}_g^2$:

$$U_{ij}^2 = \beta_g' X_{ij} + \gamma_g \, m_{ij} + \eta_{cgj} + e_{ij}^2 \;\geq\; \bar{V}_g^2 \tag{19}$$

[39] The condition for uniqueness is sufficient but not necessary: for many parameterizations, a unique equilibrium exists for values of γ_g above $\left(\bar{R} N_c\right)^{-1}$. The result provides a universal bound on γ_g under which the belief mapping is guaranteed to be a contraction and the equilibrium is therefore unique.

5.2 Identification

In this section, I first discuss the identification of the beliefs that enter the first-stage application decision, then the identification of peer preferences using the same lottery variation as in Section 4, and finally the identification of the remaining model parameters.

5.2.1 Identification of Beliefs

Result 2 establishes that an equilibrium belief must exist. In equilibrium, families will be correct about the number of peers admitted into each high school. As such, it is possible to consistently estimate this belief with the sample average number of children who will be admitted into a high school, $\bar{m}_{cj}$.[40] When peer preferences are strong, corresponding to high values of γ_g, there may be multiple different beliefs about the share of children admitted into a high school that constitute an equilibrium within a given primary school. Note that my model is not equipped with any equilibrium selection mechanism. However, given $\bar{m}_{cj}$, X_{ij} and η_{cgj}, there is no need to solve for an equilibrium to predict families' ranking probabilities. This is because these variables uniquely pin down the (deterministic) utility of each school for every family and so it is not necessary to solve the equilibrium system expressed in Equation 17 to predict families' behavior. This is possible since only $\hat{m}_{cj}$ is endogenously determined in equilibrium, and can be consistently estimated using $\bar{m}_{cj}$.[41]

5.2.2 Identification of Peer Preferences

At the application stage, there is no exogenous variation in beliefs about the number of peers admitted to each high school, $\bar{m}_{cj}$, and so γ_g cannot be identified from ranking data alone. To see why this is the case, note that the belief $\bar{m}_{cj}$ is itself a function of the unobserved primary-by-high school preferences, η_{cgj}. As such, it is not possible to separately identify whether a high school is ranked because many peers are expected to attend or because families have strong unobserved preferences for the school.

I address this problem by combining exogenous variation generated by the lottery in families' second-stage enrollment decisions with families' observed trade-offs over school attributes in both stages. The identification argument has three parts. First, I use lottery-induced variation in the *realized* number of admitted peers to identify families' preference for peers in the second-stage enrollment decision. The second-stage estimate identifies γ_g up to an unknown scale parameter, σ_g, that captures the importance of unobserved factors in the second-stage enrollment decision relative to the first-stage application decision. Second, I use families' observed preferences for other school characteristics, such as distance or enrolling with a sibling, in both stages to identify the relative

[40] I compute this expectation in the same way as I do in Section 4, by re-running the admission system $S = 1000$ times, holding families' rankings constant, and measuring the average number of peers admitted into each high school.

[41] A similar approach is adopted by Bhattacharya et al. (2024) to estimate peer preferences in the take up of mosquito nets in Kenya.. An alternative approach relies on fixed-point iteration to endogenously determine beliefs and estimates structural parameters using the simulated beliefs (see, for e.g., Seim, 2006).

scale of unobserved preferences in the second-stage. Finally, I combine the estimate of the scale with the estimate of peer preferences in the second-stage enrollment decision to recover the preference for peers in the first-stage application decision.

Step 1: Peer Preferences up to Scale, from the Enrollment Stage Consider first the enrollment decision expressed by Equation (19). I collect all terms that are common to every child in primary school c who is admitted into high school j to form a new composite second-stage fixed effect ϕ_{cgj}. That is:

$$\sigma_g \, \phi_{cgj} = \gamma_g \, m_{cj} + \eta_{cgj} - \bar{V}_g^2 \tag{20}$$

The probability that family i accepts the offer at high school j can then be written as follows:

$$\mathbb{P}(E_{ij} = 1 \mid A_i = j, X_{ij}) = \Lambda\left(\frac{1}{\sigma_g}\beta_g' X_{ij} + \phi_{cgj}\right) \tag{21}$$

where E_{ij} is a binary indicator for the enrollment of child i in high school j, $A_i = j$ indicates that they are admitted to school j, and $\Lambda(\cdot)$ is the logistic function. Using standard constructive identification arguments, I show in Appendix A5.2.2 that β_g/σ_g and ϕ_{cgj} are identified from the enrollment probability.

The second-stage fixed effect ϕ_{cgj} is just a linear function of the realized number of admitted peers m_{cj} and the unobserved primary-by-high school common preference η_{cgj}. As a result, we can estimate the impact of admitted peers on the preference for high school j using exactly the same approach as in Section 4. Theorem 1 establishes that once we condition on the expected number, the realized number of students from primary school c admitted to high school j is determined by random lottery draws. As a result, variation in m_{cj} identifies γ_g/σ_g in a regression of the estimated second-stage fixed effect, $\hat{\phi}$, on the realized number of admitted children, m_{cj}, controlling for the expected number, $\bar{m}_{cj}$.

Step 2: The Scale, from Repeated Choice The probability of ranking a high school as a family's most-preferred option does not depend on σ_g, the relative variance of the second-stage unobserved preferences. However, it depends on the same preference parameters, (β_g, γ_g), and unobserved primary-by-high school common preferences η_{cgj}. As before, I collect all terms that are common to every child in primary-by-high school cell (c, j) to form a new composite fixed effect ω_{cgj}. That is:

$$\omega_{cgj} = \gamma_g \bar{m}_{cj} + \eta_{cgj} \tag{22}$$

I show by standard constructive identification arguments in Appendix A5.2 that β_g and ω_{cgj} are identified from ranking probabilities. Since school characteristics X_{ij} enter both stages, with coefficient β_g in the application stage and β_g/σ_g in the enrollment stage, the ratio of the coefficients

on any characteristic m identifies the scale:

$$\frac{\beta_{m,g}}{\beta_{m,g}/\sigma_g} = \sigma_g \tag{23}$$

Intuitively, the same attribute, for e.g., distance, shifts utility by $\beta_{m,g}$ in the application stage and by $\beta_{m,g}/\sigma_g$ in the enrollment stage. The shrinkage of the coefficient between the two stages reveals the variance of idiosyncratic preferences in the enrollment stage relative to the application stage. Every characteristic that enters both stages provides a separate estimate of σ_g, so the scale is over-identified. Combining the two steps recovers the peer preference, γ_g:

$$\left(\frac{\gamma_g}{\sigma_g}\right) \cdot \sigma_g = \gamma_g \tag{24}$$

I formally prove in Appendix A5 the following result:

Theorem 2 (Identification of γ_g)**.** *Under random lottery draws, Type-I Extreme Value idiosyncratic preferences, common beliefs, and constant preferences across the two stages, the preference for peers in the application-stage utility, γ_g, is identified.*

I discuss the identification of primary-by-high-school preferences, η_{cgj}, and the second-stage outside option, $\bar{V}_g^2$ in appendix A5.2.

5.2.3 Identification of High School Value-Added

I identify school value-added using the quasi-random variation in admission generated by Chile's centralized school assignment system (Abdulkadiroğlu et al., 2017). I compute, by re-randomization, the probability of admission of each child i into each high school j. I then compare the outcomes of children who face the same probability of admission into the same high schools, but in practice are admitted to different schools by the centralized admission system to identify the *causal* effect on child's test scores of attending a particular high school. I identify the value-added of high schools separately for high- and low-SES children, which I denote by, q_j^H and q_j^L, respectively, and construct measures of common value-added, q_j^0, and type-specific value-added, q_j^g, as follows:

$$\widehat{q}_j^0 = \frac{1}{2}\left(\widehat{q}_j^L + \widehat{q}_j^H\right), \qquad \widehat{q}_j^g = \widehat{q}_{gj} - \widehat{q}_j^0. \tag{25}$$

5.3 Estimation

I estimate the parameters for each stage separately using a two-step procedure, starting from the enrollment-stage parameters. Because both stages involve high-dimensional fixed effects, a maximum likelihood estimator that jointly estimates structural parameters and fixed effects would be subject to the incidental-parameters problem (Neyman and Scott, 1948). I avoid this problem by first estimating the model's structural parameters in each stage using a conditional maximum like-

lihood estimator that eliminates the fixed effects. I then recover the fixed effects at each stage by maximizing a second likelihood which uses the estimated structural parameters from the first step.

5.3.1 Estimation of Second-Stage Enrollment Decision Parameters

Estimation of Structural Parameters I begin by estimating the enrollment stage structural parameters, β_g/σ_g, using the Chamberlain (1980) conditional maximum likelihood approach. I stratify children by primary-by-high school cells, (c, j), and condition on the total number of children who enroll in each cell:

$$S_{cj} \equiv \sum_{i \in (c,j)} E_i$$

I show in Appendix A5.3.1 that S_{cj} is a sufficient statistic for the cell fixed effect ϕ_{cgj}. As a result, conditioning on S_{cj} eliminates ϕ_{cgj} from the likelihood, allowing me to estimate β_g/σ_g without jointly estimating the full set of cell fixed effects. Consequently, this estimator is free of the incidental-parameters bias that would arise from estimating the ϕ_{cgj} directly by maximum likelihood. Intuitively, the conditional likelihood uses variation in *which* children enroll within a cell, holding fixed *how many* children enroll. The latter is informative about the common enrollment propensity ϕ_{cgj}, whereas, conditional on the number of enrollees, differences in enrollment across children identify β_g/σ_g through differences in their observed characteristics X_{ij}. This within-cell comparison avoids the incidental-parameters problem that would arise from estimating a separate ϕ_{cgj} for every cell by joint maximum likelihood. I therefore estimate β_g/σ_g by maximizing the following conditional likelihood:[42]

$$\widehat{\beta_g/\sigma_g} = \arg\max_{\beta_g/\sigma_g} \sum_{(c,j)} \log \mathbb{P}\big(\{E_i\}_{i \in (c,j)} \,\big|\, S_{cj};\, \beta_g/\sigma_g\big) \tag{26}$$

Estimation of Fixed Effects In a second step, I then recover the composite fixed effects parameters by maximizing the likelihood to observe families' second-stage enrollment decisions, given the estimated structural parameters, $\widehat{\beta_g/\sigma_g}$.

$$\widehat{\phi}_{cgj} = \arg\max_{\phi_{cgj}} \sum_{(c,j)} E_i \cdot \log \mathbb{P}\Big(E_i \,\Big|\, \phi_{cgj},\, \widehat{\beta_g/\sigma_g}\Big) + (1 - E_i) \cdot \log(1 - \mathbb{P}\Big(E_i \,\Big|\, \phi_{cgj},\, \widehat{\beta_g/\sigma_g}\Big)\Big) \tag{27}$$

Estimation of Peer Preferences Finally, because the primary-by-high school preferences, ϕ_{cgj}, are linear in the number of admitted peers, I recover γ_g/σ_g by following the same approach as in Section 4. I regress the estimated cell effects on the realized number of admitted peers, controlling for the *expected* number of admitted peers prior to the lottery, $\bar{m}_{cj}$:

$$\widehat{\phi}_{cgj} = \frac{\gamma_g}{\sigma_g} m_{cj} + \lambda_g \bar{m}_{cj} + \nu_{cgj} \tag{28}$$

[42] Only cells containing both enrollees and non-enrollees contribute to this conditional likelihood: cells in which either all or none of the children enroll contain no within-cell variation with which to identify β_g/σ_g and are dropped from the conditional likelihood.

By Theorem 1, conditioning on the expected number of admitted peers, $\bar{m}_{cj}$, renders the realized number of admitted peers m_{cj} exogenous. I discuss the estimation of the second-stage outside option in Appendix A5.3.1.

5.3.2 Estimation of First-Stage Application Decision Parameters

I follow the same approach to estimate the utility parameters in the first-stage application decision using families' observed ROLs.

In the first step, I estimate β_g, families' preferences over individually-varying school characteristics in the application stage, using a conditional likelihood approach. To difference-out the primary-by-high school composite fixed effects, ω_{cgj}, I compute the probability that two families in the same primary school c, rank the same high school, j, in opposite order. I show in Appendix A5.2, that the probability of this event has a closed form solution that does not depend on η_{cgj}. I then estimate β_g by maximizing the likelihood associated with observing this event.

In a second step, given $\widehat{\beta}_g$, I recover the composite effects ω_{cgj} one primary school at a time by maximizing that school's rank-ordered-list likelihood over $\{\omega_{cgj}\}$, holding the preference term $\widehat{\beta}_g$ fixed and normalizing the value of the outside option to zero.

With the parameters from both the first-stage application decision and second-stage enrollment decision estimated, I combine the estimated parameters to identify the scale and the peer preference parameters. I estimate the scale, $\hat{\sigma}_g$, through the ratio of estimated preference for schools with siblings at the enrollment- and rankings-stages. Finally, I estimate the peer preference parameter by multiplying the estimated scale, with the estimated preference for peers in the second-stage enrollment decision: $\widehat{\gamma}_g = \widehat{(\gamma_g/\sigma_g)} \cdot \widehat{\sigma}_g$, as in Equation (24).

5.3.3 Estimation of High School Value-Added

For each child i, I compute the probability they are admitted into high school, j, p_{ij}, by a re-randomization procedure.[43] I then bin these probabilities into 5 bins of 20 percentage points per high school, and collect them in vector, b_i. For children of socioeconomic type $g \in \{L, H\}$, I estimate:

$$Y_i = \sum_{j,g} q_{gj} \mathbf{1}\{J_i = j, g_i = g\} + \sum_{j,b} \varphi_{jbg} \mathbf{1}\{J_i = j, g_i = g, b_i = b\} + u_i \tag{29}$$

where $\mathbf{1}\{J_i = j, g_i = g\}$ is a binary indicator indicating that child i is from group g and was admitted into high school j, and φ_{jbg} are high school-by-probability bin fixed effects. These fixed effects restrict comparisons to children competing for the same school who face similar admission probabilities. Conditional on these school-by-probability bin fixed effects, the remaining variation in admission offers is generated by the lottery. As a result, the coefficients q_{gj} measure the effect

[43] I simulate the admission mechanism S = 1,000 times, and compute the share of times child i is admitted into high school j.

of receiving an offer from school j on achievement for children of type g.[44] Estimating Equation (29) jointly for low- and high-SES children yields two estimates of each school's causal effect on children's academic outcomes, $\widehat{q}_{Lj}$ and $\widehat{q}_{Hj}$. I follow the transformation described in Section 5.2.3 to convert these into estimates of schools' common and type-specific value-added.

A final challenge is that the estimated school effects contain sampling error. I therefore use empirical-Bayes posterior means of school value-added as my preferred measures. The procedure jointly shrinks $(\widehat{q}_{Lj}, \widehat{q}_{Hj})$ toward their respective type means, with more precise school estimates receiving less shrinkage, while exploiting the covariance in value-added across types. This removes sampling variation from the estimated distribution of school effectiveness and stabilizes the decomposition into vertical and type-specific value-added. Appendix A6.5 describes the construction of the assignment propensity scores and the empirical-Bayes shrinkage procedure in detail.

5.3.4 Parameterization, Sample and Inference

Parameterization Within a primary-school-by-school cell, the school attributes that vary across children, and so identify β_g and β_g/σ_g, are the travel distance from the child's geocoded home to the school and an indicator for whether the child has a sibling already enrolled there. The school-level characteristics that are constant within a cell—indicators for whether the school is rated medium- or higher-quality by the ACE and the school's value-added on test scores, along with other time-invariant features of a school—are absorbed into the composite effect ω_{cgj}. The endogenous peer preference γ_g is the coefficient on the number of a child's primary school peers admitted to the school—expected in the application stage and realized in the enrollment stage. I allow for heterogeneity in all parameters, including common primary-by-high school preferences, by socioeconomic status, g.

Sample Because the estimation is computationally demanding, I estimate the model on children living in the urban area around Chile's capital, Santiago. I use data from the 2022-2023 main high school application round.

Standard Errors I compute standard errors using a primary school block bootstrap that resamples primary schools and re-runs every step of the estimation. Because I resample entire primary schools rather than individual children, this procedure is equivalent to a nonparametric cluster bootstrap at the primary school level. It allows for arbitrary correlation among children, cells, and estimation stages within a primary school without imposing a parametric structure on that correlation (Efron, 1979; Cameron et al., 2008; Cameron and Miller, 2015).[45]

[44] In practice, admission offers do not translate one-for-one into school attendance, so q_{gj} in (29) is an intention-to-treat effect of an offer rather than the causal effect of attendance. However, since 94% of children take up the offer of a high school place the ITT and LATE are of equivalent magnitude.

[45] In each of $B = 100$ replications, I draw primary schools with replacement until reaching the original number of schools. I assign fresh child and network identifiers to each draw, so that a primary school drawn multiple times is treated as multiple distinct networks rather than as repeated observations of the same network. I then re-run the entire estimation procedure on the resampled data. I compute the standard error of each parameter as the standard

6 Estimation Results and Model Fit

In this section, I present the estimated model parameters and evaluate the model's fit by comparing predicted and observed ranking patterns.

6.1 Demand Parameter Estimates

	Parameter Estimates			
	Low-SES		High-SES	
	Estimate	WTC	Estimate	WTC
Panel A: Student–School Pair Characteristics				
Distance	−0.186		−0.232	
	(0.011)		(0.010)	
Sibling	2.230	12.009	2.538	10.951
	(0.082)		(0.051)	
Panel B: Peer Preferences				
γ_g	0.229	1.232	0.272	1.174
	(0.101)		(0.100)	
Panel C: School Characteristics				
Medium-Quality	0.362	1.950	0.518	2.234
	(0.022)		(0.024)	
High-Quality	0.937	5.045	1.393	6.011
	(0.046)		(0.044)	
Common VA (q_j^0)	0.002	0.009	0.203	0.875
	(0.032)		(0.033)	
Type-Specific VA (q_{gj})	0.026	0.141	0.030	0.129
	(0.051)		(0.053)	
Panel D: Other Parameters				
σ_g	2.323		3.167	
	(0.515)		(0.508)	
$\bar{V}_g^2$	−0.408		−2.462	
	(0.570)		(0.592)	

Table 2: Structural Parameter Estimates

Notes: Parameters are estimated separately for two socioeconomic groups, defined by whether the student's mother completed high school (Low = did not; High = did). Panel A reports the marginal utility of home-to-school distance (km) and of having a sibling already enrolled at the school; Panel B the endogenous peer preference (the marginal utility of an additional admitted primary-school peer); Panel C the tastes for medium- and high-quality schools (as rated by the ACE) and for a school's value-added; and Panel D the second-stage scale and the outside-option values, $\bar{V}_g^1$ (value of stopping the ranking, normalized to 0) and $\bar{V}_g^2$ (value of rejecting an admission offer). "WTC" is the implied willingness to commute, minus the parameter divided by the distance coefficient, in kilometers. Standard errors, in parentheses, are from a primary-school block bootstrap that resamples primary schools with replacement and re-runs the entire estimation, with the standard error given by the standard deviation across the 100 bootstrap resamples.

Table 2 presents the estimated demand parameters of the structural model, estimated separately for low- and high-SES families. These parameters capture how families trade off different school attributes when applying to high school. Panel (A) reports estimates of preferences for school characteristics that vary at the family level. The estimates confirm that families systematically

deviation of its estimates across bootstrap replications. Because every estimation step is repeated, uncertainty in $\widehat{\beta}_g$, $\widehat{(\beta_g/\sigma_g)}$, $\widehat{\omega}$, $\widehat{(\gamma_g/\sigma_g)}$, and $\widehat{\sigma}_g$ propagates to the reported $\widehat{\gamma}_g$ and implied willingness-to-commute. I provide more details about this procedure in Appendix A5.4.

prefer schools that are closer to home and schools where a sibling already attends. Because the scale of utility is not identified, the magnitudes of these coefficients are not directly interpretable. To facilitate comparisons, I normalize each coefficient by the estimated disutility from distance. This re-parameterization expresses the importance of each attribute in terms of families' *willingness to commute*, the additional distance (in kilometers) that families would be willing to travel to attend a school with a particular characteristic.

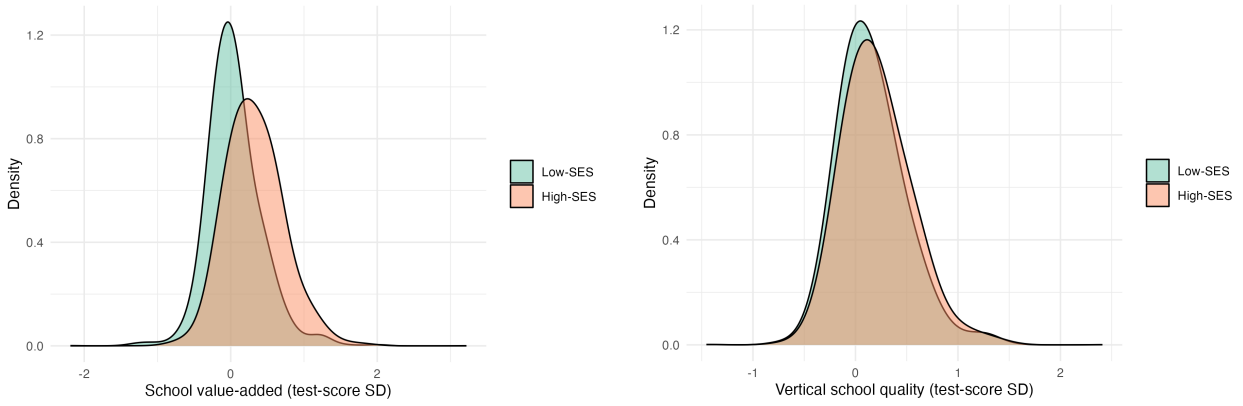
Panel (B) reports the estimated preference for attending school with primary school peers. The estimates indicate that families are highly responsive to their peers' expected choices: on average, a family is willing to travel approximately 1.2 km farther from home for the child to attend high school with one additional peer. Alternatively, studying with 10 peers is has approximately the same impact on the utility of a school as studying with a sibling. This parameter captures the *causal* effect of peers' expected offers on the utility a family derives from a high school.

To study which common characteristics of schools families prefer, Panel (C) project the estimated primary-by-high school fixed effects, $\hat{\eta}_{cgj}$, onto characteristics of high schools. Families systematically prefer schools with higher value-added and higher official quality ratings. In general, high-SES families are more sensitive to quality. High-SES families are significantly more responsive to common school VA. In contrast, I cannot reject that both high- and low-SES families are not sensitive to type-specific VA. As I show in Section 6.2, common school VA is strongly correlated with observable school characteristics, such as its rated quality, and may therefore be easier for families to perceive than type-specific VA.

Finally, Panel (D) reports the remaining model parameters. These include the relative variance of second-stage unobserved preferences, σ_g; the outside option in the first-stage decision, $\bar{V}_g^1$, which is normalized to zero; and the outside option in the second-stage decision, $\bar{V}_g^2$. For both low- and high-SES families, the estimated second-stage outside option is negative. Families are therefore less willing to reject an offered school in the second stage than they are to forgo ranking an additional school in the first stage. This reluctance is particularly pronounced among high-SES families, for whom the estimated second-stage outside option is more negative.

6.2 High School Value-Added

Figure 7 compares the value-added of the high schools attended by low- and high-SES children. The left panel plots the distribution of overall value-added, q_{gj}, while the right panel plots only common school value-added, q_j^0. On average, high-SES children attend schools with 0.27 standard deviations higher value-added and 0.05 standard deviations higher common value-added than low-SES children. These gaps point to both vertical and horizontal sorting: high-SES children attend higher-quality schools, but they also attend schools that are particularly effective for them. Appendix Figure A6 shows that schools' value-added for low- and high-SES children, q_{Lj} and q_{Hj}, is strongly correlated but far from one-to-one. Appendix Table A6 decomposes the resulting variation in value-added and shows that common value-added accounts for 45–48% of the variation across schools, while type-specific value-added accounts for the remainder.



(a) Overall VA (q_{gj})

(b) Common VA, (q_j^0)

Figure 7: High School Value-Added by Child Type

Note: Distribution, across children, of the value-added q_{gj} of the school each child attends (left) and of its common value-added component q_j^0 (right), by child type. Empirical-Bayes estimates, in test-score standard deviations, relative to a reference school.

To validate these estimates, I plot in Appendix Figure A7 how they relate to school ratings from the Agency for Quality in Education (ACE). Schools' common value-added increases strongly and monotonically with its ACE rating, by 0.16 standard deviations per rating category. Type-specific value-added, on the other hand, is largely unrelated to rating. It is positive for high-SES children across the entire distribution and negative for low-SES children, suggesting that high-SES children benefit more from attending *any* school relative to low-SES children, but does not change with the ratings of a school.[46] I also validate these estimates against a simpler measure of school value-added obtained under a selection-on-observables assumption, controlling for a rich set of family characteristics and prior achievement (see, e.g., Nielson, 2021). Appendix Figure A9 compares the lottery-based and selection-on-observables estimates and shows a strong relationship ($\rho = 0.66$) between the two.

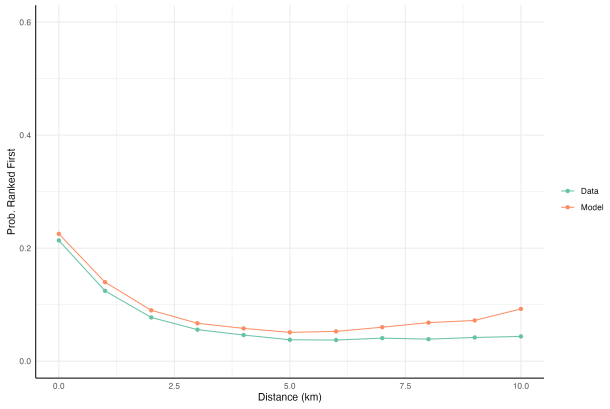
6.3 Model Fit

To simulate rankings over high schools, I compute each school's deterministic utility according to $\hat{\beta}_g$ and $\hat{\gamma}_g$ and $\hat{\eta}_{cgj}$.[47] I assume that families rank all schools whose utility is positive, as the outside option is normalized to 0. To map from ranking into offers, I simulate the child-proposing deferred acceptance algorithm that assigns families to schools based on their ranked preferences, priority and eligibility for a quota, mirroring the Chilean school admission system (SAE). I repeat this process

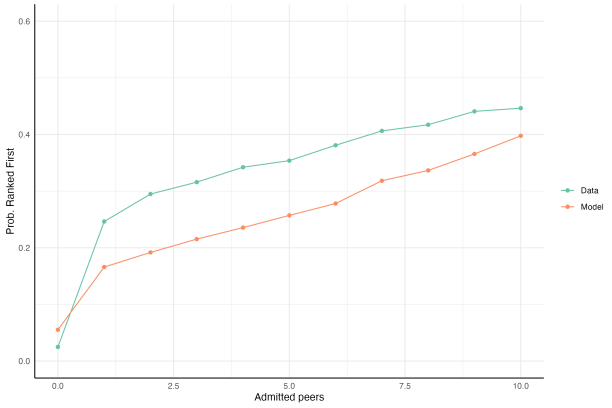
[46] The empirical-Bayes correction has little effect on the results. The relationship between common value-added and the ACE rating is similar before and after shrinkage, with slopes of 0.19 and 0.16, respectively, while the high–low SES value-added gap remains 0.27 standard deviations. The correction primarily reduces the dispersion of the noisier type-specific component. Appendix Figures A8a–A8b compare the raw and empirical-Bayes estimates of both components.

[47] To match the equilibrium observed in the data, I assume that the expected number of peers admitted into each school matches the observed equilibrium. I relax this assumption in the counterfactuals I present in Section 7.

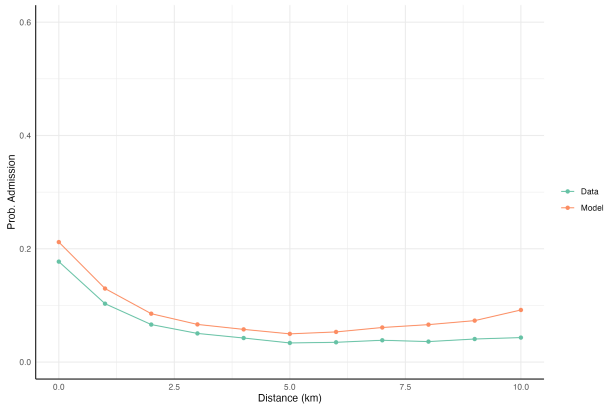
100 times, and average across simulations to obtain the average probability that each family ranks each high school and their child is admitted to it. I discuss the algorithm in more detail in Appendix A5.1.2.



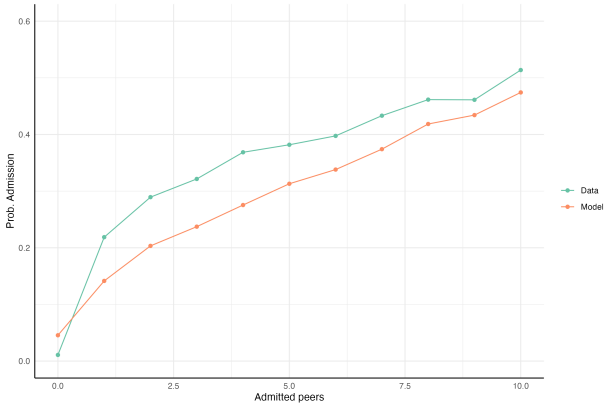
(a) Ranking Probability and Distance



(b) Ranking Probability and Share of Peer Admissions



(c) Admission Probability and Distance



(d) Admission Probability and Share of Peer Admissions

Figure 8: Model Fit

Note: The top two figures correspond to two moments that are implicitly targeted in the estimation. Plot (a) corresponds to the probability that a family ranks a school as their most preferred option at every percentile of distance. Plot (b) corresponds to the probability that a family ranks a school as their most preferred option at every percentile of the share of peers admitted to the school. Plot (c) corresponds to the probability that a child is admitted to a school at every percentile of distance. Plot (d) corresponds to the probability that a child is admitted to a school at every percentile of the share of peers admitted to the school. The teal line corresponds to the true data, whereas the orange line corresponds to the simulated probability, based on the model with the estimated parameters.

As a first test of the validity of the model, I compare its predictions to the actual ranking patterns observed in the data. Panel (a) of Figure 8 examines how the probability of ranking a school as families' preferred choice varies with distance. The observed data and the model predictions align closely, showing a strong negative relationship – families are significantly less likely to apply to

schools that are farther away. Panel (b) examines how ranking probabilities vary with the number of a child's peers who are admitted into a school. As expected, since families prefer to attend high school with their primary school peers, the probability to rank a school increases monotonically with the number of peers who attend. Again, the predicted probability tracks the observed probability relatively closely.

I also evaluate the fit of the model using actual admission probabilities, which were not targeted in estimation, rather than ranking probabilities. Panel (c) of Figure 8 examines how the probability of being admitted into a school varies with distance. As before, I group schools into twenty bins based on their distance from families' homes. Panel (d) examines how admission probabilities vary with the share of peers who are admitted into each school. As expected, the probability of being admitted into a school decreases with distance and increases with the number of peers who are admitted. In both cases the predicted probability tracks the observed probability relatively closely.

For the model to be useful in discussing socioeconomic gaps in school quality, it should be able to replicate the distribution of quality among the schools to which low- and high-SES families are admitted. To assess this, I plot in Appendix Figure A10 the probability that children will rank, and be admitted to, high schools rated as having higher-quality across the family socioeconomic spectrum and compare it to the true probability. The model predictions closely match observed shares: as children's mothers' level of education increases, families are more likely to rank and attend a school rated as *medium* or *high* quality and less likely to rank and attend a school rated as *low* or of *insufficient* quality.

7 Counterfactuals

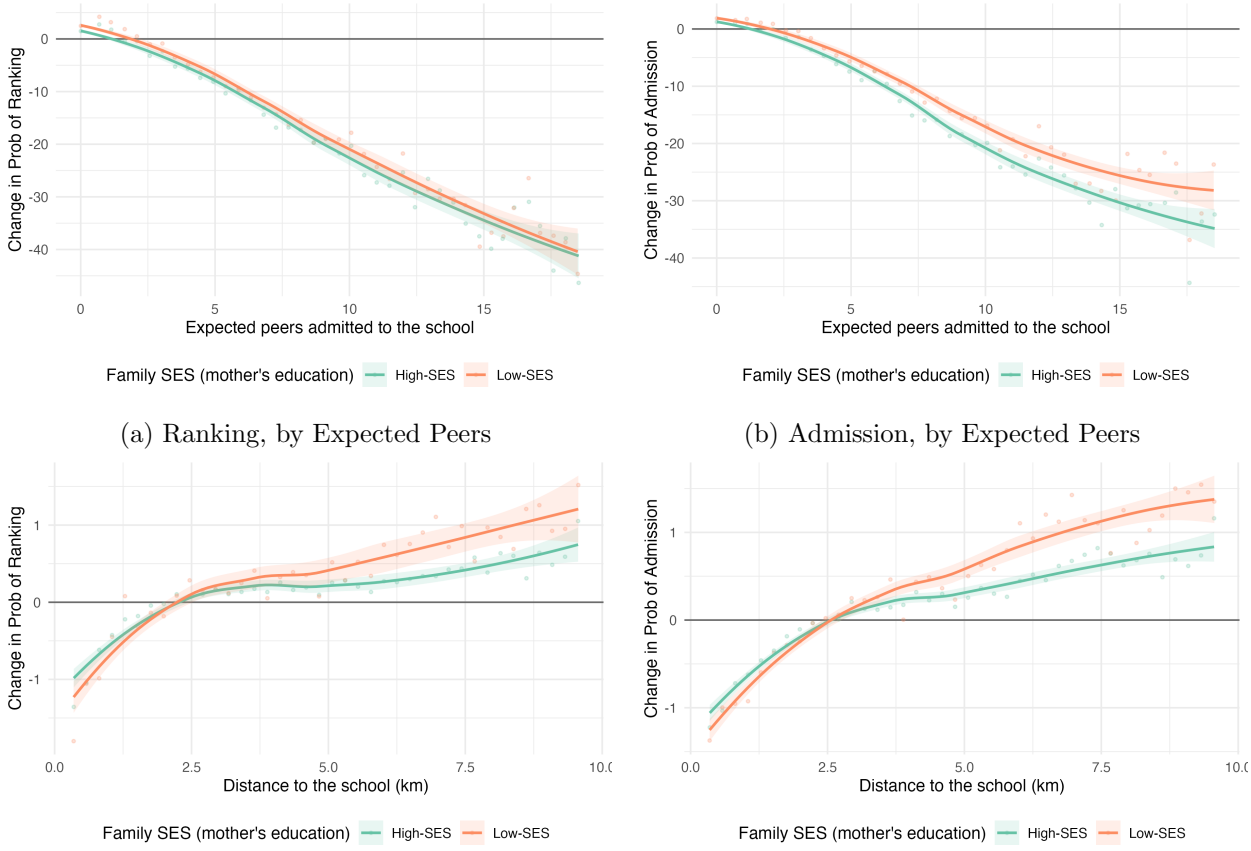
In this section, I first use the model to quantify how peer preferences interact with the uneven spatial distribution of school quality to generate educational inequality. To do so, I simulate a counterfactual in which I remove peer preferences, holding all other factors constant. I then use the model to assess the effects of expanding access to higher-quality schools using transport vouchers.

7.1 Peer Preferences and Educational Inequality

I use the estimated model to quantify how peer preferences shape socioeconomic inequality in education. To isolate the role of a preference for peers, I compare two simulations of the full application and admission process. First, I simulate families' application decisions and offers with all parameters held at their estimated values. I then model families' application decisions as if they placed no values on peers, by setting the peer preference parameter, γ_g, to zero, holding all other preferences and the admission mechanism fixed.

Figure 9 summarizes how families' rankings and admissions change. Panels (a) and (b) plot the change in ranking and admission probabilities by the (baseline) expected share of peers that are admitted into a high school. Reassuringly, removing peer preferences encourages families to rank schools where fewer of their peers are expected to be admitted. Panels (c)-(d) plot the change in

ranking and admission probabilities by the distance of the school from a child's home. Consistent with the evidence that peer groups tend to be geographically clustered presented in Section 3, removing peer preferences encourages families to apply to, and be admitted to, high schools further away from their home. Since families also value school quality, and there are fewer higher-quality schools near low-SES families' homes, removing peer preferences encourages particularly low-SES children to apply to schools far away from home.



(a) Ranking, by Expected Peers

(b) Admission, by Expected Peers

(c) Ranking, by Distance

(d) Admission, by Distance

Figure 9: Impact of Peer Preferences on Applications

Note: The plots show the change in the probability of ranking a school as a child's preferred option (Panels a and c) and of being admitted to a school (Panels b and d), between the simulated model without peer preferences and the estimated model with peer preferences. A positive change indicates that the probability is higher in the model without peer preferences. Panels (a)–(b) plot the change against the expected share of peers admitted to the school; Panels (c)–(d) plot it against the distance of the school from the child's home. Each panel shows separate lines for low- and high-SES children.

Effect on Individual Gaps I evaluate the impact of peer preferences on schooling inequality by examining how removing peer preferences impacts the quality of the high schools high- and low-SES families rank and are admitted to. I measure school quality along three dimensions: overall value-added, common value-added, and whether a school is rated as having medium or high-quality

by the Chilean Agency for Quality in Education. To quantify the effect of the counterfactual on each outcome and assess whether this effect differs by socioeconomic status, I estimate the following regression:

$$q_{is} = \beta_0 LowSES_i + \beta_1 Counterfactual_s + \beta_2 Counterfactual_s \times LowSES_i + u_{is} \tag{30}$$

where $LowSES_i$ is a dummy equal to 1 if a child is classified as low-SES, and $Counterfactual_s$, is a dummy equal to 1 if the observation is for the counterfactual, rather than baseline, simulation. β_2 captures how removing peer preferences reduces gaps in outcomes between high-SES and low-SES children.

I report the results of estimating Equation (30) in Table 3. Each column is a difference-in-differences that stacks the baseline and the counterfactual. The constant corresponds to the high-SES baseline level; the coefficient on *low-SES* corresponds to the baseline high–low gap; the coefficient on *Counterfactual* corresponds to the change in outcome for high-SES families when peer preferences are removed; and the interaction-term, *Counterfactual* × *low-SES*, corresponds to the additional change for low-SES families, that is, the change in the SES gap.

Table 3: Peer Preferences and Socioeconomic Inequality in School Quality

	Overall VA (SD)		Common VA (SD)		High-Quality Rating (pp)	
	Ranking	Admission	Ranking	Admission	Ranking	Admission
Constant	0.375***	0.327***	0.243***	0.198***	76.02***	63.20***
	(0.007)	(0.007)	(0.007)	(0.006)	(0.63)	(0.79)
Low-SES	−0.331***	−0.303***	−0.074***	−0.051***	−9.89***	−6.53***
	(0.007)	(0.007)	(0.005)	(0.005)	(0.58)	(0.63)
Counterfactual	0.009***	−0.007***	0.009***	−0.005***	1.55***	−1.73***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.34)	(0.25)
Counterfactual × Low-SES	0.004	0.010***	0.005*	0.009***	1.56***	1.27***
	(0.004)	(0.002)	(0.002)	(0.002)	(0.26)	(0.22)
Observations	130,108	131,192	130,108	131,192	135,574	133,934

Notes: Each column is a difference-in-differences from the estimated model, stacking the baseline simulation, in which families rank and enroll with peer preferences, and the peers-off counterfactual, in which families place no value on peers. The outcome is a family's expected school value-added (empirical Bayes) or school quality (its vertical/permanent component, empirical Bayes), each in school-level standard deviations, or its probability of a high-quality school (ACE category 3 or 4), in percentage points, at the first-ranked school (Ranking) and the admitted school (Admission). *Low-SES* equals one if the student's mother did not complete high school and gives the baseline high-low gap. *Counterfactual* equals one in the counterfactual and gives the change for high-SES families. *Counterfactual* × *Low-SES* is the additional change for low-SES families, that is, the narrowing of the gap; a positive value means the gap shrinks. Standard errors, clustered by primary school, are in parentheses. Significance: $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

At baseline, low-SES children are admitted to high schools that raise their test scores by 0.303 SD less than the schools to which high-SES children are admitted. Removing peer preferences narrows this gap by 0.010, or 3 % of the baseline difference. The corresponding change at the application stage is statistically indistinguishable from zero (Column 1). Similarly, at baseline, low-SES children are admitted into schools with a 0.05 standard deviation lower value-added.

Removing peer preferences narrows this gap by 0.009, approximately 18% of the gap. Finally, at baseline, high-SES families rank a school rated as having high quality 9.9 percentage points more often than low-SES families (Column 5), and are admitted to one 6.5 percentage points more often (Column 6). Removing peer preferences narrows both gaps: the ranking gap falls by 1.6 percentage points and the admission gap by 1.3 percentage points, each precisely estimated. Relative to the baseline gaps, this closes 16 % of the high–low gap in ranking a higher-quality school, from 9.9 to 8.3 percentage points, and 19 % of the gap in admission to one, from 6.5 to 5.3 percentage points. Appendix Figure A11 shows that removing removing peer preferences monotonically increases the quality of schools families rank and are admitted to across the full range of mother's education. Note that while peer preferences increase gaps in high school quality, they also increase the high-school quality of high-SES students, consistent with my conceptual framework.

Role of Primary School Composition Since peer preferences widen inequality by tying children to the high schools they expect their peers to be admitted to, the counterfactual change should be greater for children with more disadvantaged peers. To study this, Figure 10 presents the impact of removing peer effects on the quality of schools that families rank and are admitted to, by the socioeconomic composition of their children's peers. Consistent with this prediction, the effects of removing peer preferences on the quality of schools families rank and are admitted to are significantly stronger for children in peer groups with an above-median share of low-SES children. Appendix Table A7 shows the result of re-estimating the regression expressed in Equation 30 replacing a child's own socioeconomic status with the share of their peers that are classified as low-SES.

Robustness A primary concern is that the counterfactual may not account for general equilibrium effects on school quality from reallocating children across schools. In particular, admitting more low-SES children to higher-performing schools could reduce their effectiveness if school value-added depends on the composition of the child body.[48] To account for these general equilibrium effects, I examine how school value-added responds to lottery-induced shocks to the socioeconomic composition of its child body. Appendix A8 presents the results. I find no statistically significant effect of an increase in the share of low-SES children on either overall value-added or type-specific value-added. I provide details on the estimation strategy in Appendix A6.4 and additional robustness exercises. These results suggest that changes in school effectiveness induced by the reallocation of low-SES children are unlikely to be quantitatively important for the counterfactual exercise.

[48] Jackson (2013) exploits exogenous secondary-school assignments in Trinidad and Tobago and finds that short-run variation in peer achievement accounts for a relatively small share of school value-added on average, although peer effects are larger among highly selective schools. Harker and Tymms (2004) find evidence of socioeconomic compositional effects on child achievement, particularly in mathematics, but show that their magnitude and statistical significance are sensitive to model specification, controls for prior achievement, and measurement issues, highlighting the difficulty of interpreting such compositional effects causally.

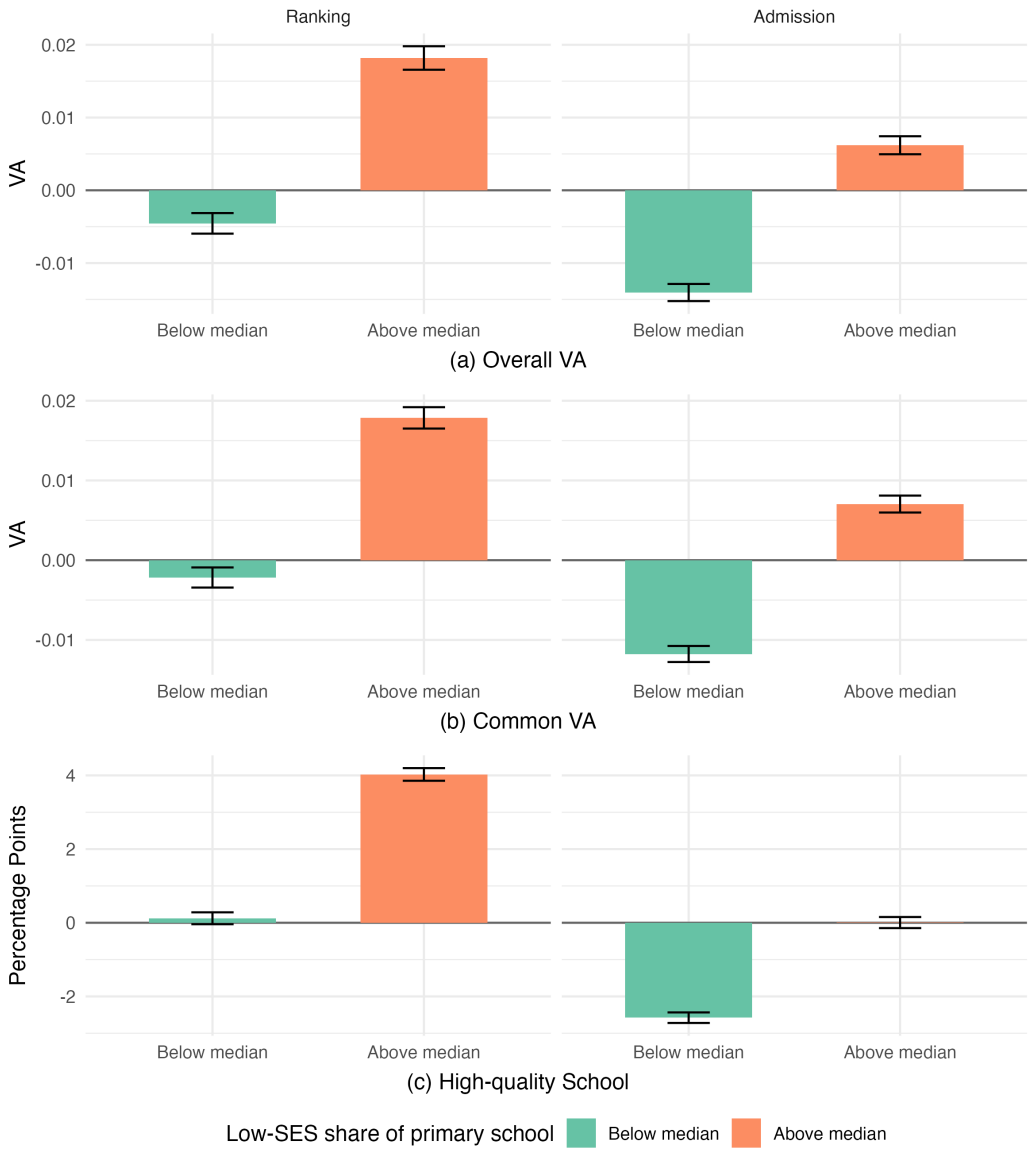
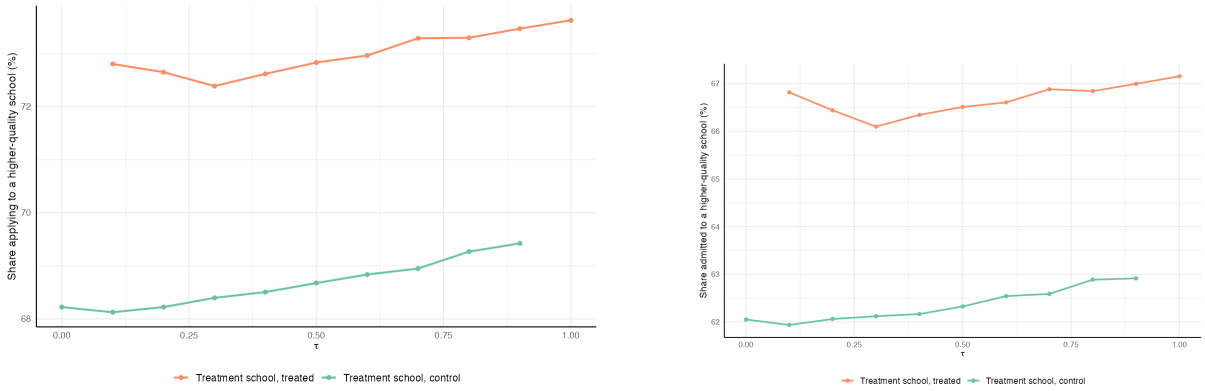


Figure 10: Counterfactual Change by Composition of Peer Group

Note: Each bar is the average change in a family's expected school outcome when peer preferences are removed—the peers-off counterfactual minus the baseline—for families whose peer group has a below-median (green) versus above-median (orange) share of low-SES children. Rows report three measures of the school a family reaches: (a) its overall value-added q_{gj} and (b) its common (vertical) value-added component q_j^0, both in test-score standard deviations; and (c) the probability that it is a high-quality school (ACE category 3 or 4), in percentage points. Columns correspond to the first-ranked school (Ranking) and the admitted school (Admission). Whiskers are 95% confidence intervals, with standard errors clustered by primary school. Removing peer preferences raises the quality of the schools families reach by more in primary schools with a larger low-SES share, indicating that peer preferences most constrain children in low-SES-dominated networks.

7.2 Policy Spillovers Through Peer Networks

Equalizing educational opportunities for high- and low-SES children is often cited as a key policy objective. A common lever to achieve this goal is to directly target the uneven spatial distribution of school quality, either by building higher-quality schools in low-SES areas, or by making it easier for lower-SES children to access higher-quality schools, such as through transport vouchers. The presence of peer preferences, however, implies that these interventions can have complicated equilibrium consequences and may have increasing returns to scale. For instance, if enrollment decisions are interdependent, families may not accept an offer at a new school that is accessible to them but not their children's peers. Conversely, a policy may generate positive spillover effects if it targets enough families within a peer network, as one family's decision to accept an offer at a better school can induce similar choices by peers. To study this trade-off, I simulate offering families vouchers which reimburse the costs associated with travel to higher-quality high schools.[49] To understand the equilibrium dynamics of this policy, I assign vouchers to families studying in deprived primary schools, which I identify as primary schools where the share of children from low-SES families is above the median, and vary the fraction, τ, of families who are offered the voucher.[50]



(a) Applications to Higher-Quality Schools

(b) Admissions to Higher-Quality Schools

Figure 11: Impact of Transport Vouchers

Note: This figure corresponds to a counterfactual simulation in which different shares of families, τ, in schools with an above-median share of children from low-SES families are offered transport vouchers to attend higher-quality schools. Panel (a) plots the probability a family ranks a high school defined as medium- or high-quality by ACE as their most preferred option. Panel (b) plots the probability a child is admitted into a medium- or high-quality school. The orange line corresponds to treated families, while the teal line corresponds to control families.

[49] To do this, I offset the utility-cost associated with travel to a higher-quality school. Consistent with assumption (C1), I assume that families take into account that the distribution of their peers' characteristics has changed, however, they do not know which peer received the subsidy.

[50] Since my parameter estimates suggest that multiple equilibria are possible, I simulate choices starting from 100 randomly chosen starting values for children's beliefs about the share of their peers who will attend each high school, and average outcomes across the simulations.

Spillovers Figure 11 presents the effect of the policy on the probability that families rank and are admitted into a higher-quality high school. The policy has a strong effect on families who receive the subsidy. When 10% of children are treated, treated children become 15% more likely to be admitted into higher-quality school relative to control children. This nearly halves the gap in the likelihood children in deprived and non-deprived primary schools are admitted into a higher-quality high school. As the share of treated children increases so does the effect of the treatment. When 80% of children are treated, treated children become 18% more likely to be admitted into a higher-quality school relative to the baseline with no children targeted. Since most children already attend higher-quality schools, treated peers induce each other to apply, increasing the effectiveness of the policy. Similarly, the policy spills over to control peers. When 10% of families are treated, the effect on control peers is negligible. On the other hand, when 80% of families are treated, control peers become 4% more likely to be admitted into a higher-quality school, as they are pulled in by their treated peers. Appendix Figure 11 shows similar results for the value-added of the high schools families rank and are admitted to.

Displacement While transport vouchers increase the share of low-SES children in higher-quality schools, their effectiveness partly depends on whether compliers displace untreated children. To study this, Table 4 presents the number of treated and control children admitted to higher-quality schools when 80% of children in treated schools receive a transport voucher. Overall, the policy increases the number of treated children admitted to higher-quality schools by 1,867, relative to baseline. The policy also increases the number of their peers who do not receive the voucher – control children in treatment schools – who are admitted to higher-quality schools by 77, suggesting that every treated complier increases the number of untreated peers in higher quality schools by 0.04. The number of children in control primary schools admitted to higher quality high schools drops by 281, or by about 0.15 per treated child. Overall, the policy increases the number of children admitted to medium- or high-quality schools by 1,663, or by 0.89 per treated complier.

Student Type	School Type	Baseline ($\tau = 0$)	Transport Vouchers ($\tau = 0.8$)	Change	Change per Treated Complier
Treat	Treat	13,195	15,062	$+1,867$	1.000
Control	Treat	3,257	3,334	$+77$	0.041
Control	Control	17,346	17,065	-281	-0.151
All	All	33,799	35,461	$+1,663$	0.891

Table 4: Voucher Effects on Admission to Higher-Quality Schools by Group

Notes. Each group is defined by its treatment status *at* $\tau = 0.8$ (the voucher is given to a random 80% of eligible treatment-school children; the assignment is nested across τ). The Baseline ($\tau = 0$) and Transport Vouchers ($\tau = 0.8$) columns count the SAME fixed population of children, so the change is a within-children comparison. 'Control Children, Treatment Schools' are the eligible children *not* selected for the voucher; they are untreated in both columns, so their change is a spillover from their treated classmates – not a treatment or displacement effect. 'Change per treated complier' divides each group's change by the change for treated children (those the policy moves into a medium/high-quality school).

To better understand why so few control students are displaced by the policy, Figure 12 plots the change in the number of applications at each high school by its pre-policy competitiveness, which I define as the difference between the number of families who rank the school as their most preferred option and available places. As expected, the policy reduces applications to lower-quality schools at all percentiles of competition. On the other hand, the policy increases applications to the most competitive higher-quality schools, but has almost no impact on applications to the most competitive schools. Appendix Table A5 confirms that this pattern is robust to controlling for a large number of high school characteristics which may be correlated with its pre-policy competitiveness. I interpret this pattern as consistent with peers' preference to study together: the policy leads families to apply to higher-quality but relatively under-subscribed schools, where the probability of their children being admitted with their peers is high. Consequently, the policy generates minimal externalities for control children, whose chances of admission to higher-quality schools remain largely unchanged.

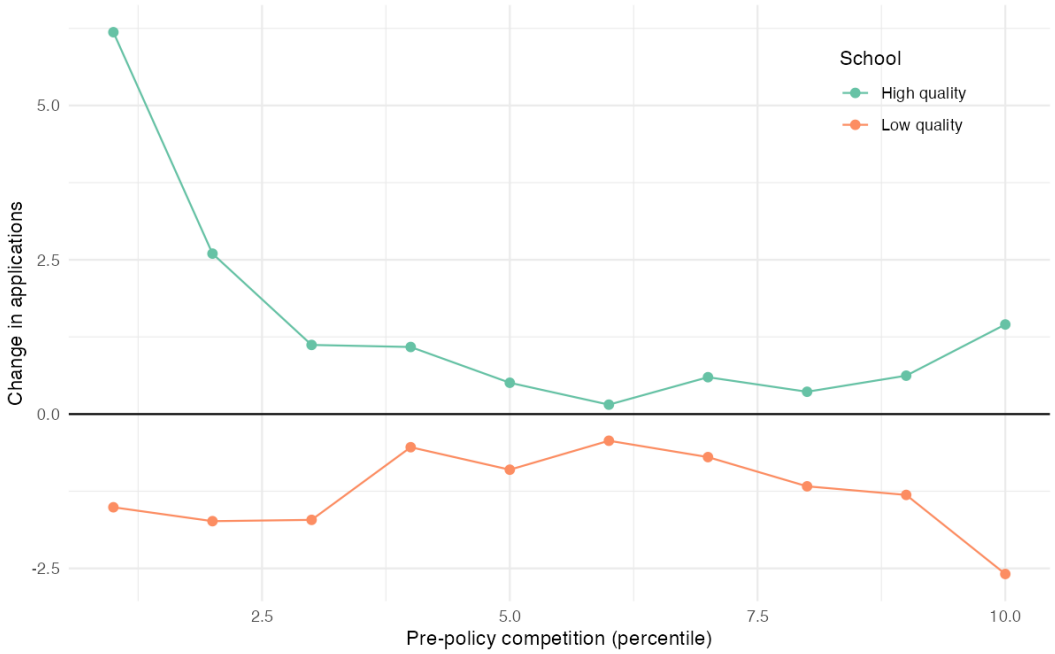


Figure 12: Impact of Transport Vouchers by High School Competitiveness

Note: This figure corresponds to the change in applications to different schools when $\tau = 0.8$. The x-axis corresponds to the pre-policy competitiveness, measured by the difference between applicants (families ranking the school as their preferred option) and available seats. The y-axis corresponds to the change in the number of applications. The teal line corresponds to higher-quality high schools, defined as those having *medium* or *high* quality by ACE. The orange line corresponds to low-quality high schools, defined as those having *insufficient* or *low* quality by ACE.

8 Conclusion

This paper shows that primary school peers play a crucial role in shaping children's choice of high school. Using administrative data from Chile's centralized school admission system, I provide evidence that increasing the number of a child's primary school peers admitted to the same high school increases the probability that the child accepts the high school place. To quantify the equilibrium impact of these social interactions, I incorporate peer preferences into a structural model of school choice. I find that social interactions have a significant impact on the equilibrium allocation of children to schools. If children were to make decisions independently of their peers, the gap in high school value-added between low- and high-income children would shrink by 18%.

A key limitation of my study is the lack of specialized network data. I assume that children care about all of their peers equally, whereas in reality, the choices of some peers are almost surely more important than others. Data that explicitly maps social connections would allow for more precise identification of peer preferences and a better understanding of which peers matter most in shaping school choices, expanding the scope of feasible policy instruments, such as targeting the behavior of *key players* (Ballester et al., 2006). Similarly, the lack of data on families' beliefs requires me to make strong assumptions on families' choice sets and belief formation. These assumptions almost certainly do not hold in practice and may bias my results.

My results suggest that interventions which take advantage of peer networks can have meaningful impacts on inequality in education. Increasing access to higher-quality schools in under-served areas – whether by expanding transportation options or building new schools – may benefit from significant spillover effects within peer networks, with minimal negative externalities on untreated children. Recognizing that school choice is not an isolated decision but one embedded in a social context is crucial for designing policies that effectively address educational inequality.

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Appendix

A1 Appendix Figures

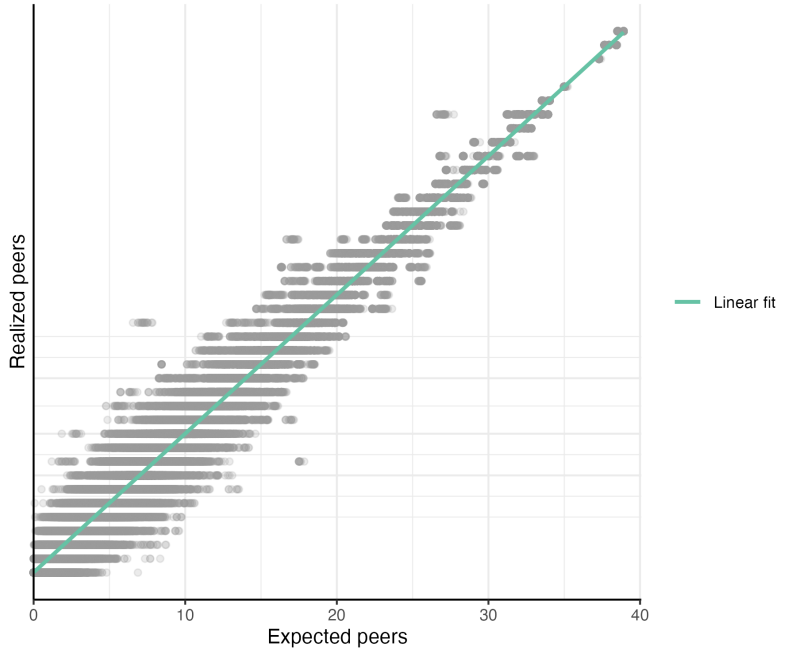


Figure A1: Variation in Peer Shocks

Notes: The figure documents the lottery-induced variation in the number of admitted peers that identifies the reduced-form peer effect. Each point is a single child. The vertical axis is the realized number of the child's primary-school peers admitted to the same high school, m_i, and the horizontal axis is the expected number across 1,000 re-drawn lottery realizations, $\bar{m}_i$, computed while holding the child's own admission fixed. Points off the 45-degree line have a nonzero peer shock $r_i = m_i - \bar{m}_i$, the variation the design exploits: for roughly 95% of children the realized count differs from its expectation, and the standard deviation of the shock is about one peer. Data are from the SAE centralized admission system (2022–2025 main rounds).

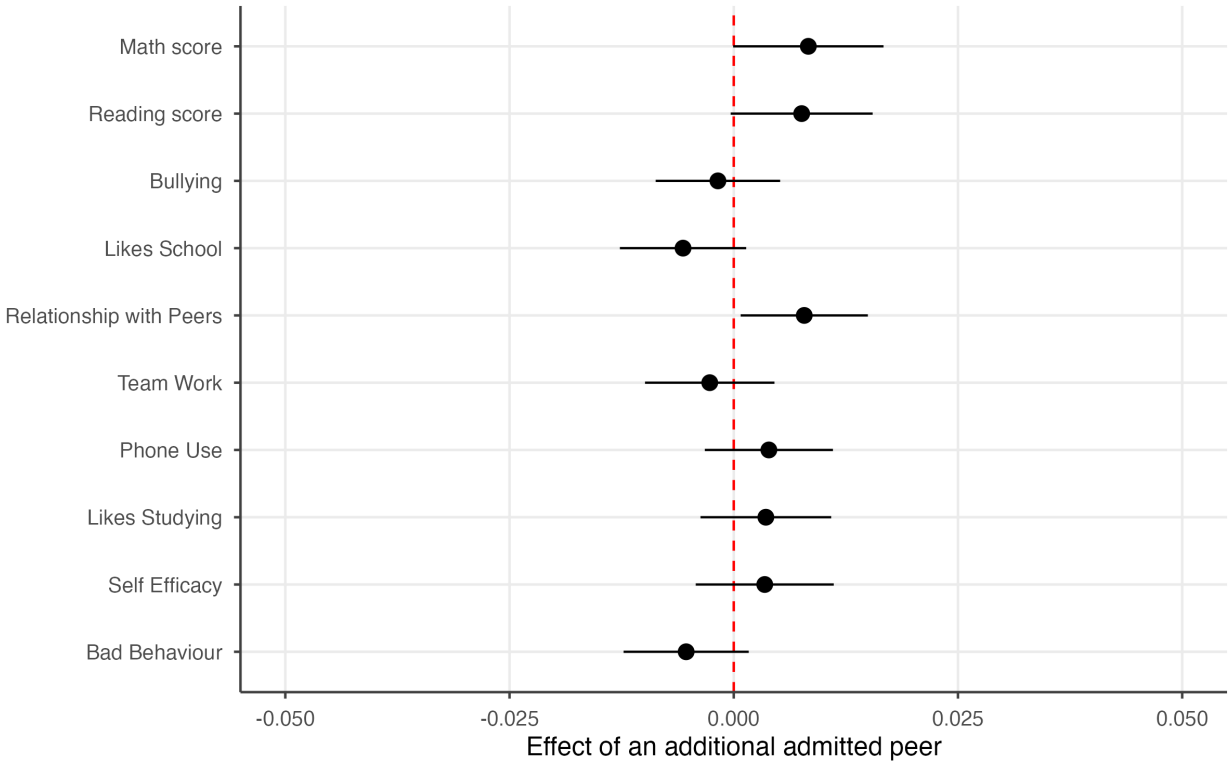


Figure A2: Effect of Admitted Peers on Multiple Outcomes

Notes: The figure asks whether studying with more primary-school peers improves children's academic and well-being outcomes, in order to separate the *amenity* value of peers from an *academic-production* value. Each point is the estimated coefficient on the number of admitted peers from the reduced-form regression in Equation (8), estimated separately for each outcome and controlling for the expected number of admitted peers; error bars are 95% confidence intervals. Outcomes include tenth-grade math and reading scores and indices of bullying, disruptive behavior, phone use, self-efficacy, attitudes toward school and learning, teamwork, and relationships with current high school peers. The effects on academic outcomes are small and statistically insignificant, while the effect on peer relationships is positive, suggesting that primary-school peers are primarily a non-productive amenity. Outcomes are measured in the SIMCE assessments and their accompanying surveys.

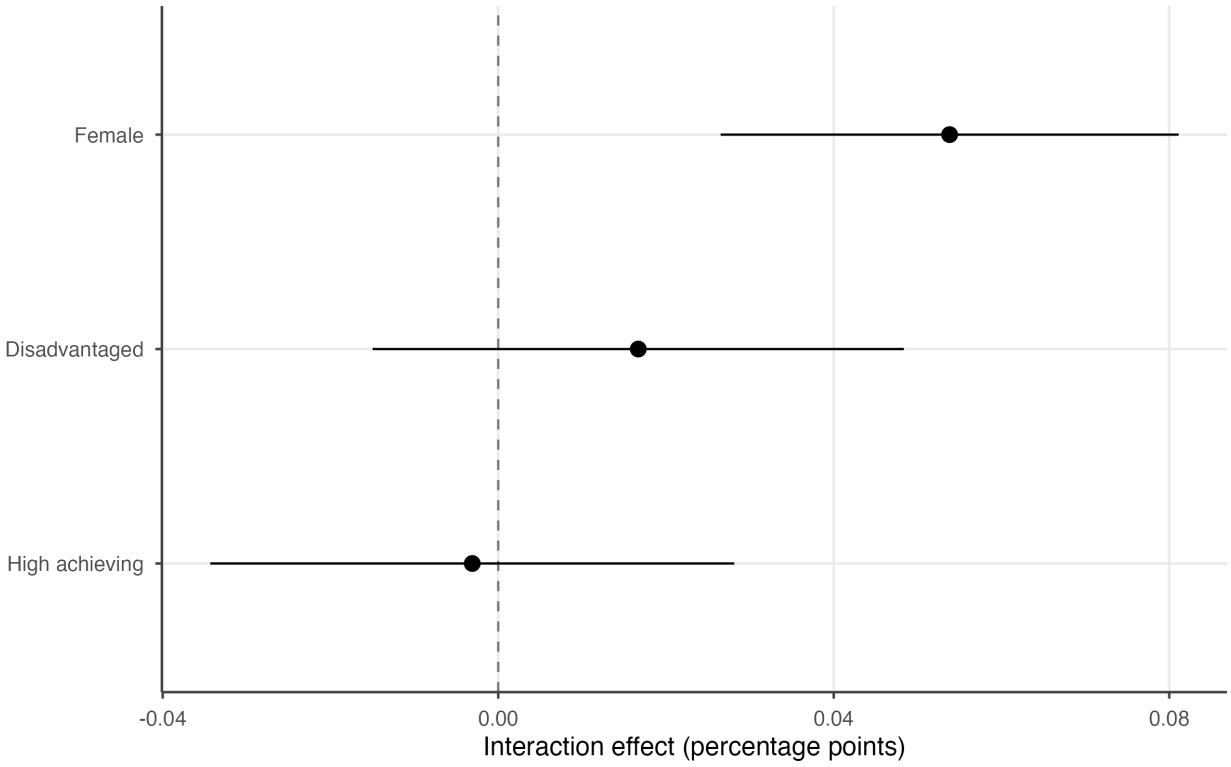


Figure A3: Heterogeneity in Peer Preferences by Child Type

Notes: The figure reports how the enrollment response to an admitted primary-school peer varies with the responding child's own characteristics. Each point is the estimated coefficient on the number of admitted peers, ρ_0, from the reduced-form regression in Equation (8), estimated separately within subgroups defined by the child's gender, socioeconomic status, and whether the child is high-achieving (in the top 30% of their primary-school cohort); the expected number of admitted peers is controlled for throughout. Error bars are 95% confidence intervals, with standard errors clustered at the admitted high school. Girls respond significantly more to their peers than boys, whereas the responses of low-SES and high-achieving children are not statistically distinguishable from those of other children. Data are from the SAE admission system linked to administrative and SIMCE records.

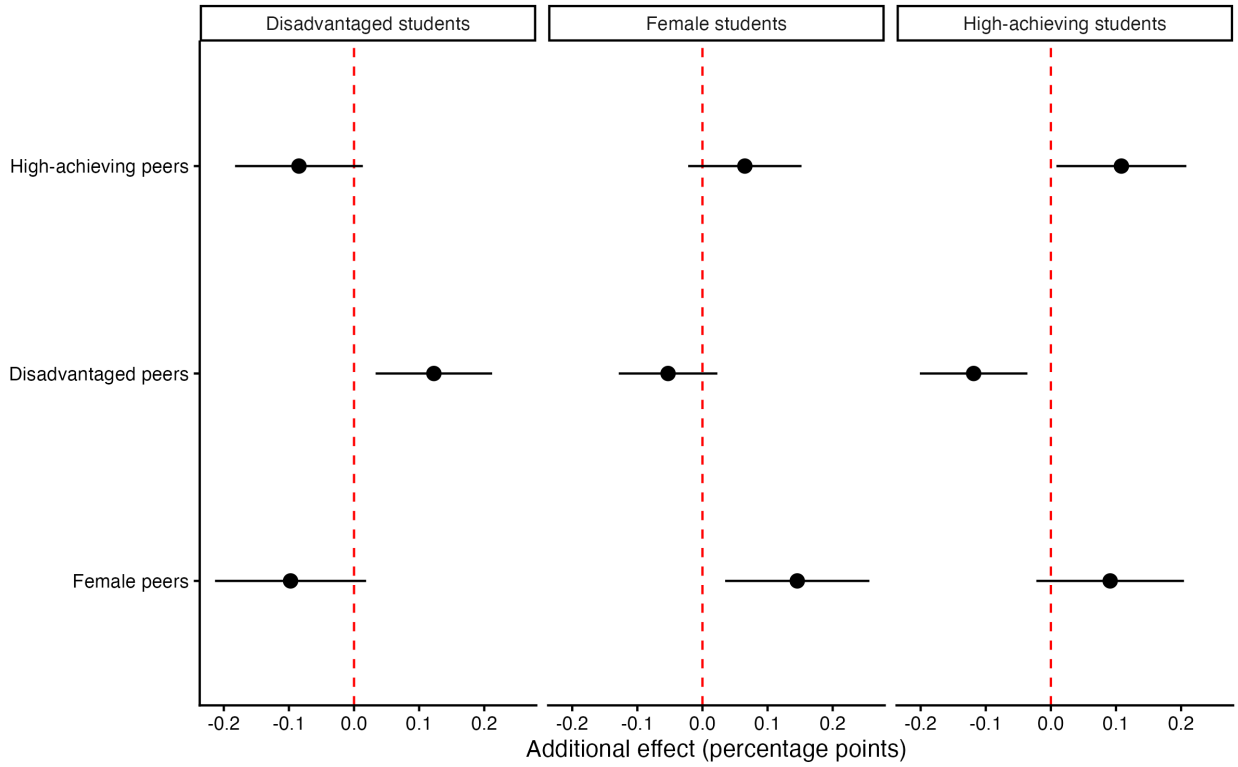


Figure A4: Heterogeneity by Child and Peer Income (Joint)

Notes: The figure decomposes the enrollment response to admitted peers by both the responding child's type (rows) and the admitted peer's type (columns). Each point is the estimated coefficient on the number of admitted peers of a given type, obtained from the reduced-form regression in Equation (8) with the number of admitted peers interacted with child and peer characteristics (gender, socioeconomic status, and high-achieving status), controlling for the expected number of admitted peers. Error bars are 95% confidence intervals, with standard errors clustered at the admitted high school. The pattern is one of homophily: children respond most strongly to peers who share their characteristics—girls to girls, high-achievers to high-achievers, and low-SES children to low-SES peers—consistent with a preference to attend high school with friends. Data are from the SAE admission system linked to administrative and SIMCE records.

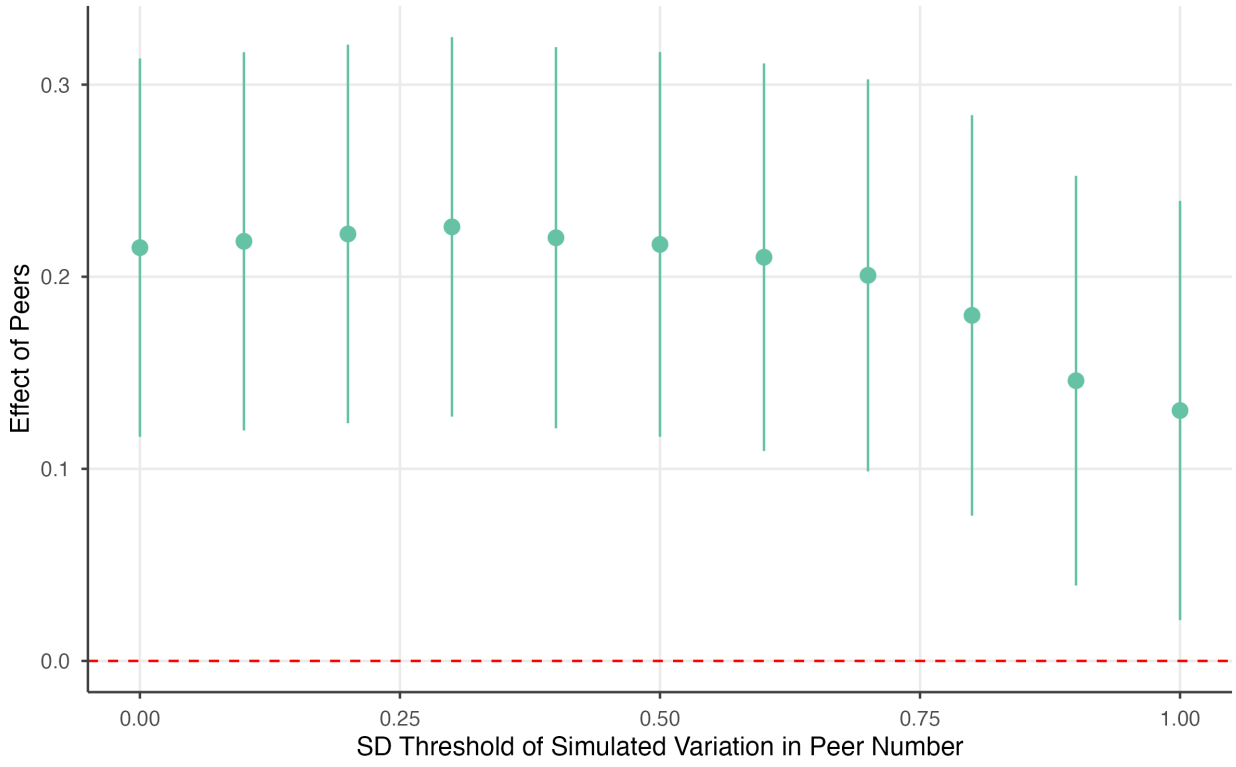


Figure A5: Sensitivity to the Variation Threshold

Notes: The figure shows that the estimated peer effect is robust to the sample restriction that generates the identifying variation. Each point is the estimated coefficient on the number of admitted peers from the reduced-form regression in Equation (8), re-estimated as the minimum required standard deviation of a child's simulated peer-count distribution is varied along the horizontal axis; error bars are 95% confidence intervals. Higher thresholds retain only children who face more lottery-induced variation in their number of admitted peers, trading sample size for stronger identifying variation. The estimate is stable across thresholds, indicating that the result is not driven by children with little or much exposure to the lottery. Data are from the SAE centralized admission system.



Figure A6: Value-Added for Low- vs. High-SES Children, $\widehat{q}_{Lj}$ vs. $\widehat{q}_{Hj}$.

Note: Each point is a high school; the axes are its empirical-Bayes value-added for low-SES children ($\widehat{q}_{Lj}$, horizontal) and for high-SES children ($\widehat{q}_{Hj}$, vertical), in test-score standard deviations. The dashed line is the 45-degree line and the solid line is the linear fit. The two are strongly but imperfectly correlated (disattenuated correlation 0.46), so a school's effectiveness differs across the two groups. The sample is the schools with both low- and high-SES admitted test-takers.

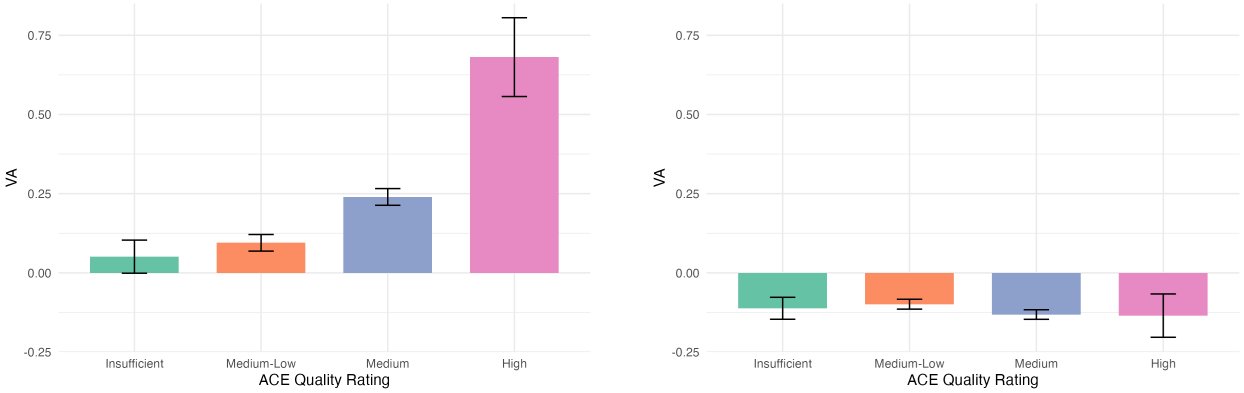
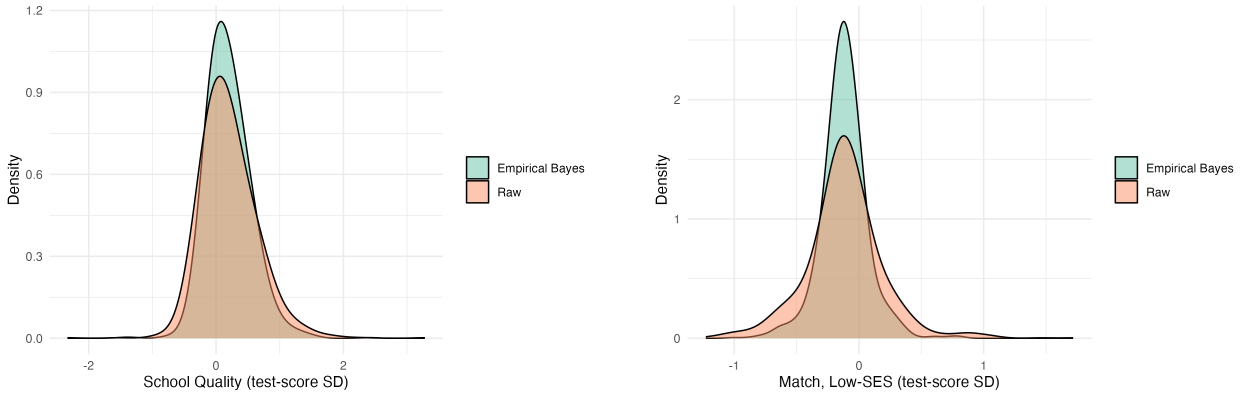


Figure A7: School Value-Added by ACE Quality Rating

Note: Each bar is the mean of a value-added component across schools within an ACE performance-rating category, with 95% confidence intervals; both panels share a common vertical scale, in test-score standard deviations. The left panel plots common (vertical) value-added q_j^0; the right panel plots the low-SES type-specific value-added q_j^L (its high-SES counterpart is $q_j^H = -q_j^L$). Estimates are empirical Bayes. The ACE rating (Agencia de Calidad de la Educación) classifies schools as Insufficient, Medium-Low, Medium, or High. Common value-added rises steeply and monotonically with the rating, whereas the type-specific component is essentially flat, so the external rating loads on the vertical component and is orthogonal to the match. The sample is the schools with both low- and high-SES admitted test-takers that are matched to an ACE rating.



(a) School Quality q_j^0

(b) Type-Specific Value-Added q_{gj}

Figure A8: School Value-Added: Raw vs. Empirical Bayes

Notes: Kernel densities, across schools, of school quality q_j^0 (Panel A) and type-specific value-added q_{gj} (Panel B), before (raw) and after the empirical-Bayes correction, in test-score standard deviations. The empirical-Bayes correction shrinks each school's estimate toward the group mean in proportion to its sampling noise. It changes the location of q_j^0 little and mainly reduces its dispersion. Because q_{gj} is constructed from two noisy type-specific estimates, it is shrunk more heavily. The sample consists of schools for which both types are estimated.

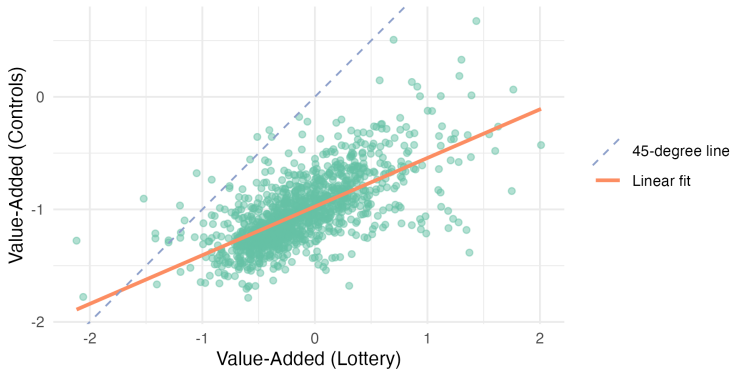
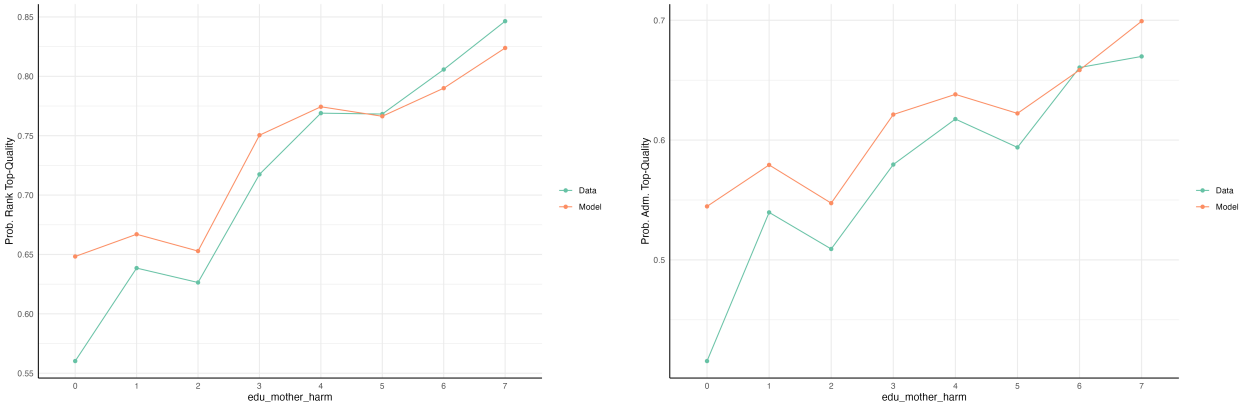


Figure A9: Lottery vs. Selection-on-Observables Value-Added.

Note: Each point is a high school. The horizontal axis is the lottery-based (pooled) value-added estimate; the vertical axis is a value-added estimate constructed under a selection-on-observables assumption, obtained by regressing test scores on a rich set of household and prior-achievement controls together with school fixed effects (Appendix A6.5). The dashed line is the 45-degree line and the solid line is the linear fit. The two measures are strongly related (correlation 0.66), validating the lottery-based estimates. The sample is the schools estimated by both methods, in test-score standard deviations.



(a) Ranking Probability and Mother's Education (b) Admission Probability and Mother's Education

Figure A10: Model Fit by Mother's Education

Note: The top two figures correspond to two moments that are implicitly targeted in the estimation. Plot (a) corresponds to the probability that a family ranks a medium- or higher-quality school as their most preferred option by mother's education. Plot (b) corresponds to the probability that a child is admitted to a medium- or higher-quality school by mother's education. The categories of mother's education are the following: (1) primary school, (2) some high school, (3) complete high school, (4) some post-secondary, (5) technical education, (6) undergraduate degree, (7) post-graduate degree. The orange line corresponds to the model-simulated probability, whereas the teal line corresponds to the true data. Ratings of school quality are obtained from the Agency for Quality in Education.

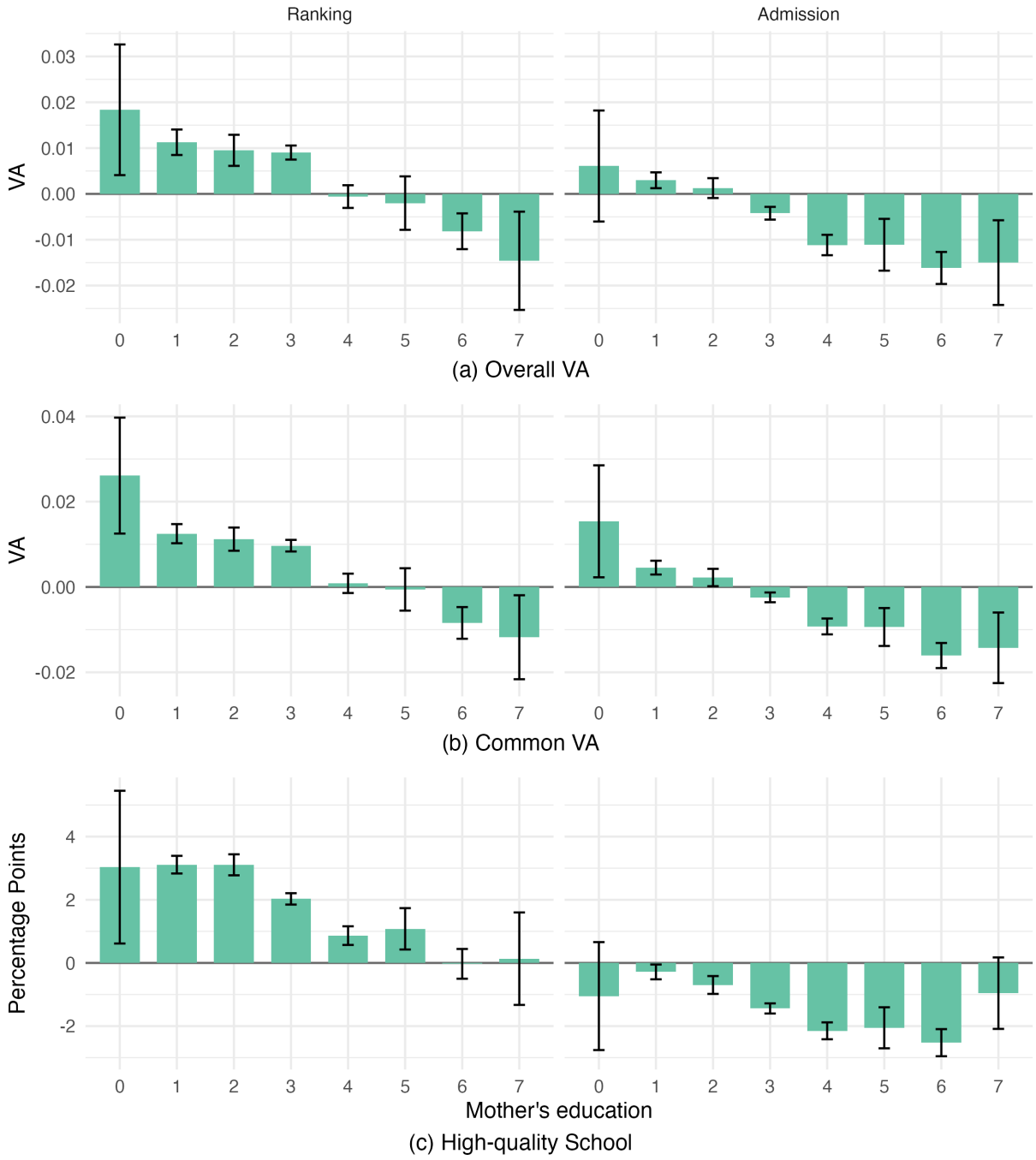


Figure A11: Change in Outcomes by Mother's Education

Note: The plots on the LHS correspond to changes in the characteristics of schools that families rank as their most preferred option. The plots on the RHS correspond to changes in the characteristics of schools to which families are admitted. The top two plots correspond to changes in the value-added of schools, whereas the bottom two plots correspond to changes in the quality of schools. Ratings of school quality are obtained from the Agency for Quality in Education. The categories of mother's education are the following: (1) primary school, (2) some high school, (3) complete high school, (4) some post-secondary, (5) technical education, (6) undergraduate degree, (7) post-graduate degree. The orange line corresponds to the model-simulated probability, whereas the teal line corresponds to the true data.

A2 Appendix Tables

	Distance		Schools		Seats	
	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Constant	0.954		72.4		3,656.2	
	(0.007)		(0.383)		(20.6)	
Bottom-6 deciles	0.165	0.069	-19.0	-1.31	-980.8	-79.0
	(0.009)	(0.009)	(0.497)	(0.437)	(26.7)	(23.8)
Fixed-effects						
Commune	No	Yes	No	Yes	No	Yes
Fit statistics						
Observations	107,832	107,034	110,391	109,585	110,391	109,585
R^2	0.00293	0.21431	0.01299	0.65557	0.01205	0.63818

Notes: The table reports coefficients from regressing three measures of access to medium- or higher-quality high schools on a low-SES indicator. Columns (1)–(2): distance (km) to the nearest such school. Columns (3)–(4): number of such schools within 10 km. Columns (5)–(6): seats available in such schools within 10 km. Even-numbered columns include commune fixed effects. Data from 2023. All coefficients significant at the 1 percent level.

Table A1: Access to Higher-Quality High Schools by Income

Dataset	Key variables
SAE (Centralized Admission System) records	• Rank-ordered lists • Geolocated addresses • Priorities and eligibility for quotas at schools • Admission responses and outcomes
Administrative child Records	• Primary school and class group • Child characteristics (e.g., age, sex) • Non-standardized grades, attendance, and class progression
SIMCE exam data	• Standardized test scores (Grades 4, 8, and 10) • Family characteristics (e.g., income, parental education) • Qualitative data on child wellbeing, aspirations, and beliefs

Table A2: Data Sources

Note: The table lists the administrative and survey datasets used in the analysis and their key variables. The centralized admission system (SAE) provides families' rank-ordered lists, geocoded home addresses, priorities and quota eligibility, and admission offers and responses; the administrative child records link each child to their primary school and class group and give demographics and school progression; and the SIMCE assessments provide standardized test scores in grades 4, 8, and 10 together with family background and survey measures of child wellbeing, aspirations, and beliefs. The datasets are linked at the child level.

Main-round response	N	Applied complement.	At offered school	At Waitlisted school	Other School
Accept	103,762	0.00	87.45	1.57	9.40
Reject	8,711	73.96	52.06	11.36	34.19

Table A3: High School Admission Outcomes in 2023

Sample: grade-9 applicants who received a main-round assignment. "Applied complement." is a separate (overlapping) share; the other five columns are mutually exclusive 2023-enrollment outcomes summing to 100%. "At offered school" = ever enrolled at a school offered in the main (initial or post-waitlist) or complementary round. "Waitlisted school" = enrolled at a school ranked above their best main-round offer (admitted off that school's waitlist). "Other" = a platform school that is neither offered nor ranked above the offer. "Off-platform" = a school never in the SAE system (not in A1/A2). Accept = codes 1, 2, 5 (incl. no response); Reject = 3, 4.

Variable	Sample	Applicants	Students
Female	0.480	0.485	0.487
Santiago (student region)	0.281	0.336	0.386
Grade 8 GPA (1–7)	5.910	5.912	5.903
Grade 8 attendance (%)	89.197	88.934	89.314
Disadvantaged	0.708	0.689	
High achieving	0.262	0.262	
Father: < high school	0.389	0.369	
Father: complete high school	0.427	0.418	
Father: post-secondary	0.184	0.213	
Mother: < high school	0.327	0.310	
Mother: complete high school	0.439	0.427	
Mother: post-secondary	0.234	0.263	
Income decile	4.378	4.532	
Distance to school (km)	6.176	7.726	
SIMCE math, 4th grade (primary)	226.340	227.635	233.250
SIMCE reading, 4th grade (primary)	235.885	237.509	242.641
SIMCE math, 10th grade	251.252	251.538	262.329
SIMCE reading, 10th grade	262.699	263.383	273.190
Observations	61,610	129,255	264,895

Table A4: Balance: 2022 analysis sample vs. all applicants and all students

Notes: The table reports mean characteristics for students in the analysis sample, all applicants to Chile's centralized school admission system, and all students. *Female* is an indicator for female students. *Santiago* indicates that the student lives in the Santiago Metropolitan Region. *Grade 8 GPA* is the student's average eighth-grade grade on Chile's 1–7 grading scale, and *Grade 8 attendance* is the percentage of school days attended in eighth grade. *Disadvantaged* and *High achieving* indicate students classified as socioeconomically disadvantaged (bottom 6-deciles of the household income distribution) and high achieving (top 30% of cohort), respectively. Father's and mother's education report the share of students whose respective parent has less than a high school education, completed high school, or attained post-secondary education. *Income decile* is the decile of the student's household income distribution. *Distance to school* is the distance, in kilometers, between the student's residence and their primary school. *SIMCE math* and *SIMCE reading* are standardized national assessment scores in mathematics and reading, respectively, measured in fourth grade at the student's primary school and in tenth grade. Blank cells indicate that the corresponding characteristic is unavailable for the full student population. The final row reports the number of observations in each sample.

Dependent Variable:	Change in Admission Probability (p.p.)
Model:	(1)
Variables	
Constant	-2.37***
	[-2.67; -2.07]
Competition (pre-policy)	-0.008***
	[-0.010; -0.006]
Distance (km)	0.325***
	[0.284; 0.365]
Expected admitted peers (pre-policy)	0.008
	[-0.024; 0.039]
Sibling	-0.501**
	[-0.881; -0.120]
Parent	-0.744
	[-2.46; 0.976]
Low quality school	-0.189*
	[-0.387; 0.008]
Medium quality school	2.23***
	[1.97; 2.49]
High quality school	1.75***
	[1.47; 2.03]
Fit statistics	
Observations	292,414
R^2	0.05038

Clustered (primary_school_id) co-variance matrix, 95% confidence intervals in brackets
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A5: Change in Admission Probability: School-Level Regression

Notes: Estimates from regressing the policy-induced change in each school's application probability (at $\tau = 0.5$, relative to baseline) on school characteristics. Pre-policy competition is applicants minus available seats. Standard errors clustered at the primary school level; 95% confidence intervals in brackets.

	low-SES	high-SES
School quality (q^0)	45%	48%
type-specific value-added (q^g)	55%	52%

Table A6: Variance Decomposition of School Value-Added (Share of Signal Variance).

Notes: The table decomposes the cross-school variance of value-added into a common (vertical) component q_j^0 and a type-specific component q_{gj}, and reports each as a share of the signal (noise-corrected) variance, separately for the low- and high-SES estimates. Because the two type-specific estimates are computed from disjoint sets of children, their sampling errors are independent, so their cross-type covariance identifies the common-quality variance $\text{Var}(q^0)$ with no noise bias; subtracting the average sampling variance from each type's total variance gives its signal variance, and the type-specific share is the residual (Equation (A44)). Equivalently, the common-quality share equals the disattenuated correlation between $\widehat{q}_{Lj}$ and $\widehat{q}_{Hj}$, which is 0.46 (raw 0.33). The sample is the $n = 1{,}260$ schools with both low- and high-SES admitted test-takers.

Table A7: Inequality and the Composition of the Peer Group

	Overall VA (SD)		Common VA (SD)		High-Quality Rating (pp)	
	Ranking	Admission	Ranking	Admission	Ranking	Admission
Constant	0.428^{***}	0.363^{***}	0.297^{***}	0.232^{***}	80.72^{***}	65.92^{***}
	(0.013)	(0.012)	(0.013)	(0.011)	(1.11)	(1.41)
Share Low-SES	-0.491^{***}	-0.412^{***}	-0.236^{***}	-0.154^{***}	-24.14^{***}	-14.76^{***}
	(0.030)	(0.028)	(0.029)	(0.026)	(2.85)	(3.50)
Counterfactual	-0.008^{*}	-0.020^{***}	-0.006	-0.018^{***}	-0.63	-3.53^{***}
	(0.004)	(0.003)	(0.004)	(0.003)	(0.56)	(0.42)
Counterfactual × Share Low-SES	0.051^{***}	0.049^{***}	0.049^{***}	0.047^{***}	8.14^{***}	6.74^{***}
	(0.012)	(0.008)	(0.011)	(0.008)	(1.27)	(1.01)
Observations	130,108	131,192	130,108	131,192	135,574	133,934

Notes. Each column is a difference-in-differences from the estimated model, stacking the baseline simulation, in which families rank and enroll with peer preferences, and the peers-off counterfactual, in which families place no value on peers. The outcome is a family's expected school value-added (empirical Bayes) or school quality (its vertical/permanent component, empirical Bayes), each in school-level standard deviations, or its probability of a high-quality school (ACE category 3 or 4), in percentage points, at the first-ranked school (Ranking) and the admitted school (Admission). *Low-SES* equals one if the student's mother did not complete high school and gives the baseline high-low gap. *Counterfactual* equals one in the counterfactual and gives the change for high-SES families. *Counterfactual* × *Low-SES* is the additional change for low-SES families, that is, the narrowing of the gap; a positive value means the gap shrinks. Standard errors, clustered by primary school, are in parentheses. Significance: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. This specification interacts the counterfactual with the share of low-SES students in the family's primary school. *Counterfactual* × *Share low-SES peers* is the additional change per unit of that share, that is, moving from an all-high-SES to an all-low-SES primary school.

	Overall VA	Common VA	Low-SES Specific VA
Panel A: Peers SES			
Realized share high-SES	0.014	0.036	−0.022
	(0.049)	(0.045)	(0.025)
Expected share high-SES	0.075	0.065	0.010
	(0.049)	(0.045)	(0.025)
Panel B: Peers Income			
Realized average income	0.007	0.012	−0.005
	(0.051)	(0.046)	(0.026)
Expected average income	0.095*	0.100**	−0.005
	(0.051)	(0.046)	(0.026)
Observations	1,260	1,260	1,260

Table A8: School Value-Added and Peer Socioeconomic Composition

Notes: Each column regresses a school-level value-added measure on the socioeconomic composition of its admitted cohort. The outcomes are the school's overall value-added for low-SES children, its common (vertical) component q_j^0, and its low-SES type-specific component q_j^L (so that Overall = Common + Low-SES-Specific). Panel A uses the share of high-SES peers and Panel B their average income; each panel includes *both* the realized composition and its expected value under the lottery, so that, conditional on the expected composition, the coefficient on the realized composition isolates the lottery-induced shock to who is admitted. All regressors are standardized to unit standard deviation, so coefficients are in test-score standard deviations per one-standard-deviation change in the peer characteristic. The sample is the schools with both types estimated; standard errors are in parentheses ($^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$). The realized composition has no statistically significant effect on any measure.

A3 Conceptual Framework

To see why peer preferences interact with spatial access, consider a child i in primary school s choosing between a higher-quality high school H (quality normalized to 1) and a low-quality school L (quality 0). For simplicity assume no capacity constraints, so every child attends their preferred school.[51] Let the utility of school j be

$$U_{ij} = \alpha q^j - \beta d_i^j + \gamma\, m_s^j + \nu_i^j \tag{A1}$$

where q^j is quality, d_i^j is the distance from i's home to j, m_s^j is the expected share of i's peers attending j, and ν_i^j is an i.i.d. Type-I Extreme Value shock. There are two groups of children, from primary schools A and B, that differ in their distance to the higher-quality school: $d_B^H > d_A^H$. Children form rational beliefs about their peers' behavior, so the share of children from primary school s attending H is the fixed point

$$m_s^H = \frac{\exp(\alpha - \beta d_s^H + \gamma m_s^H)}{\exp(\alpha - \beta d_s^H + \gamma m_s^H) + \exp(\beta d_s^L + \gamma(1 - m_s^H))}, \qquad s \in \{A, B\} \tag{A2}$$

Each child's belief about their peers is consistent with the average behavior those beliefs induce; this is the same equilibrium logic, in stylized form, that the full model imposes. The effect of increasing peer preferences, γ, on the share attending H depends on how far the group lives from H.

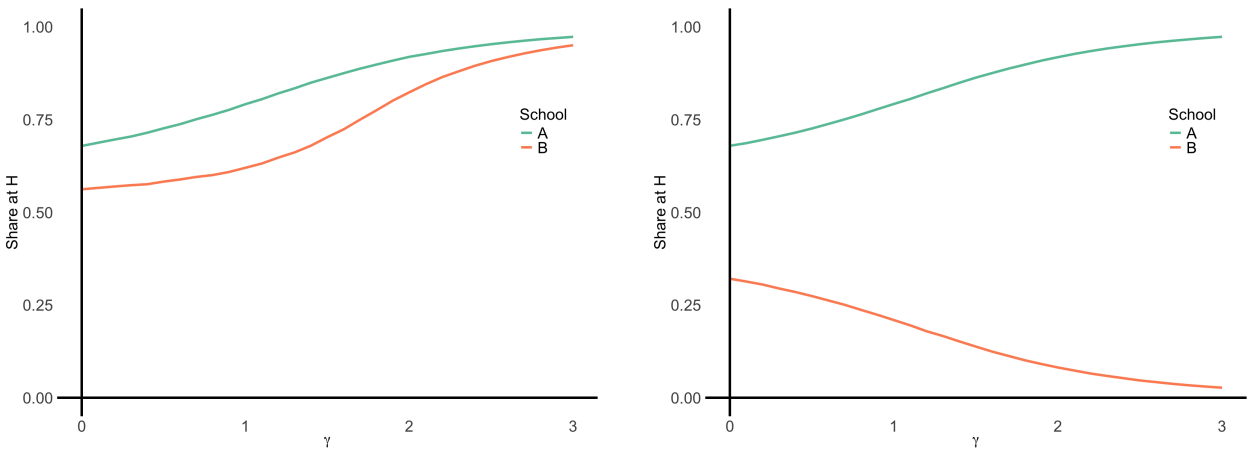
Result A1 (Peer Preferences and Inequality)**.** *When m_s^H is unique, there exists a cut-off distance $\bar{d}$ such that strengthening peer preferences increases the share of children from primary school s attending the higher-quality school if they live closer than $\bar{d}$, and decreases it otherwise:*

$$\frac{\partial m_s^H}{\partial \gamma} \begin{cases} > 0 & \text{if } d_s^H < \bar{d}, \\ < 0 & \text{otherwise.} \end{cases}$$

The cut-off $\bar{d}$ is the distance at which $m_s^H = 0.5$. Consequently, when $d_A^H < \bar{d} < d_B^H$, increasing peer preferences widens *the gap in the share of children from A and B attending the higher-quality school.*

The intuition is that peer preferences amplify whatever sorting would occur in their absence. In a primary school where, absent peer preferences, most children already attend H (because they live close, $d_s^H < \bar{d}$), peer preferences make H even more attractive and pull the marginal child in. In a primary school where most children attend L (because they live far, $d_s^H > \bar{d}$), peer preferences instead reinforce attendance at L. Figure A12 illustrates both cases. When both groups live close (panel a, "low inequality"), increasing peer preferences raises the share attending H for both, and is equalizing. When group B lives far (panel b, "high inequality"), the groups diverge as peer preferences strengthen, and inequality widens.

[51] I relax this assumption in the full structural model of Section 5.1, where admission is rationed through the deferred acceptance mechanism.



(a) Low inequality

(b) High inequality

Figure A12: Simulated Share of Children Attending the Higher-Quality School

Notes: The figure plots the simulated equilibrium share of children from two primary schools, A (orange, closer to H) and B (teal, farther from H), attending the higher-quality school as the peer preferences parameter γ increases from zero. Panel (a): both groups have $m_s^H > 0.5$ at $\gamma = 0$; peer preferences benefit both. Panel (b): group B has $m_B^H < 0.5$ at $\gamma = 0$; peer preferences widen the gap.

Because children from low-SES families live systematically farther from higher-quality schools (Table A1), many of them are in the "far" regime $d_s^H > \bar{d}$, while children from high-SES families are in the "near" regime $d_s^H < \bar{d}$. If spatial inequality is severe enough relative to children's preference for quality and disutility from distance, then a preference to study with peers increases the probability that children from low-SES families attend low-quality schools and that children from high-SES families attend higher-quality ones, widening the gap in high school quality between rich and poor. The following corollary states this formally.

Corollary A1 (Inequality amplification)**.** *If school quality is sufficiently unequally distributed across space, so that $d_A^H \leq \bar{d} \leq d_B^H$, then increasing peer preferences increases the expected gap in school quality between groups A and B:*

$$\frac{\partial \left[\mathbb{E}(q \mid A) - \mathbb{E}(q \mid B)\right]}{\partial \gamma} \geq 0$$

Proof of Result A1. Write the equilibrium share attending H from (A2) as the fixed point $m_s^H = \Lambda\big(\Delta_s + \gamma(2m_s^H - 1)\big)$, where $\Lambda(\cdot)$ is the logistic function and $\Delta_s := \alpha - \beta(d_s^H - d_s^L)$ collects the non-peer utility difference. Differentiating implicitly with respect to γ,

$$\frac{\partial m_s^H}{\partial \gamma} = \frac{\Lambda'(\cdot)\,(2m_s^H - 1)}{1 - 2\gamma\,\Lambda'(\cdot)}$$

When the equilibrium is unique the denominator is positive (this is the contraction condition), and $\Lambda'(\cdot) > 0$, so the sign of $\partial m_s^H/\partial\gamma$ equals the sign of $(2m_s^H - 1)$. Hence $\partial m_s^H/\partial\gamma > 0$ iff $m_s^H > 1/2$. Since m_s^H is strictly decreasing in d_s^H, there is a unique cut-off distance $\bar{d}$ at which $m_s^H = 1/2$; groups closer than $\bar{d}$ have $m_s^H > 1/2$ and are pushed toward H, while groups farther than $\bar{d}$ have $m_s^H < 1/2$ and are pushed toward L. When $d_A^H < \bar{d} < d_B^H$, strengthening γ raises m_A^H and lowers

m_B^H, widening the gap. Corollary A1 follows because expected quality is increasing in the share attending H. □ □

A4 Reduced-Form Proofs

This appendix collects the formal identification results used in the body. I first prove the orthogonality of the peer shock (Theorem 1) and the identification of the average effect in the linear model (Corollary A2). I then work through the identification of the full structural model of Section 5, parameter by parameter. Throughout, c indexes a child's primary school (equivalently, peer group), $\bar{m}_i = \mathbb{E}[m_i \mid X, J_i]$ denotes the expected number of admitted peers, and I maintain two assumptions.

Assumption A1 (Lottery independence)**.** *The lottery vector is independent of covariates and unobservables,* $L \perp\!\!\!\perp (X, u_{ij})$ *for all* i, j*.*

Assumption A1 is the design assumption. It requires that the draw used to ration oversubscribed seats be independent of everything about children and their preferences. It does not require the number of admitted peers to be independent of preferences (that number depends on the whole profile of submitted lists, which is not random) but only that, holding that profile fixed, the resolution of the rationing is random. It holds by construction of the SAE lottery.

Assumption A2 (Overlap)**.** *There is residual variation in the peer shock,* $\mathrm{Var}(r_i) > 0$*; equivalently, among children admitted to the same school with the same expected number of admitted peers, the realized peer count still varies.*

Assumption A2 is the support condition that gives the design its power. It requires that children admitted to the same school with the same expected number of peers actually experience different realized counts. It does not restrict preferences in any way; it is a property of the admission environment, and Figure A1 shows that it holds throughout the support.

A4.1 Orthogonality of the Peer Shock

The first result is that, conditional on the inputs, the unobservable is independent of the realized number of admitted peers.

Lemma A1. *Under Assumption A1,* $u_{ij} \perp\!\!\!\perp m_i \mid X, J_i$*.*

Proof. The realized number of admitted peers is a deterministic function of the inputs and the lottery draw, $m_i = m(X, L)$. Conditional on X, it therefore varies only with L, and Assumption A1 makes L independent of (X, u_{ij}). Conditioning on m_i in addition to X thus provides no further information about u_{ij}, which is the stated independence. □

Proof of Theorem 1. By Lemma A1, the unobservable is mean-independent of the number of admitted peers given the inputs, $\mathbb{E}[u_{ij} \mid m_i, X, J_i] = \mathbb{E}[u_{ij} \mid X, J_i]$. Since $\mathbb{E}[r_i \mid X, J_i] = 0$, the shock has mean zero and its covariance with the unobservable equals the cross-moment, $\mathrm{Cov}(r_i, u_{ij}) = \mathbb{E}[r_i\, u_{ij}]$. Substituting $r_i = m_i - \bar{m}_i$ and taking iterated expectations over the inputs,

$$\begin{aligned}\mathrm{Cov}(r_i, u_{ij}) &= \mathbb{E}_X\big\{\mathbb{E}[m_i\, u_{ij} \mid X, J_i] - \bar{m}_i\, \mathbb{E}[u_{ij} \mid X, J_i]\big\} \\ &= \mathbb{E}_X\big\{\bar{m}_i\, \mathbb{E}[u_{ij} \mid X, J_i] - \bar{m}_i\, \mathbb{E}[u_{ij} \mid X, J_i]\big\} = 0\end{aligned}$$

where the second line uses $\mathbb{E}[m_i\, u_{ij} \mid X, J_i] = \bar{m}_i\, \mathbb{E}[u_{ij} \mid X, J_i]$, which holds because u_{ij} is mean-independent of m_i given X and $\bar{m}_i = \mathbb{E}[m_i \mid X, J_i]$. □

A4.2 Identification of the Average Effect

Corollary A2 (Identification of the average effect)**.** *Under the linear model* (1) *and Assumptions A1–A2, the average causal effect is identified and equals* $\rho_0 = \mathbb{E}[r_i\, y_{ij}]/\operatorname{Var}(r_i)$.

Proof. Under the linear model (1) and Theorem 1,

$$\mathbb{E}[r_i\, y_{ij}] = \rho_0\, \mathbb{E}[r_i\, m_i] + \mathbb{E}[r_i\, u_{ij}] = \rho_0\, \operatorname{Var}(r_i)$$

where the last equality uses $\mathbb{E}[r_i\, m_i] = \mathbb{E}\big[r_i(r_i + \bar{m}_i)\big] = \operatorname{Var}(r_i)$, because r_i is orthogonal to $\bar{m}_i$ by construction (as $\mathbb{E}[r_i \mid X] = 0$), and $\mathbb{E}[r_i\, u_{ij}] = 0$ by Theorem 1. Under Assumption A2, $\operatorname{Var}(r_i) > 0$, so $\rho_0 = \mathbb{E}[r_i\, y_{ij}]/\operatorname{Var}(r_i)$ is identified; it is the estimand of an instrumental-variables regression using r_i as an instrument for the number of admitted peers. Equivalently, by the Frisch-Waugh-Lovell theorem, ρ_0 is the coefficient on m_i in a regression of the outcome on the peer count that controls linearly for the expected count $\bar{m}_i$. □

A5 Model Appendix

A5.1 Equilibrium and Computation

This appendix collects the components of the model deferred from Section 5.1: the admission-probability mapping, the equilibrium existence and uniqueness result, and the algorithm used to compute equilibrium choice probabilities in estimation and counterfactuals.

Admission Probability A child's admission to a given high school depends not only on their own ranking but also on how other families rank schools, their priority at each school, and eligibility for a quota. Because children submit ROLs and school capacities are limited, the assignment process is shaped by the interactions of all applicants' preferences and priority-quota group. Letting R_i denote the ROL of a child, let all possible rankings of schools by child i be denoted by $\mathcal{R}_i$. Correspondingly, let the rankings submitted by all other children be denoted by $\tilde{R}_{-i} = \{R_1, ..., R_N\}$ and the set of all possible rankings submitted by other children by $\tilde{\mathcal{R}}_{-i}$.

Let $\phi_{ij}(R_i, \tilde{R}_{-i})$ denote the probability that child i is admitted into school j if they submit ranking R_i when other children submit rankings $\tilde{R}_{-i}$. The centralized admission system differentiates between children based on their priority-quota group at a high school. As a result, two children who submit the same rankings, have the same priority, and eligibility for a quota, will therefore have the same probability of being admitted into a school. I therefore write $\phi_{ij}(R_i, \tilde{R}_{-i}) = \phi_{pgj}(R_i, \tilde{R}_{-i})$, where p denotes the priority-quota group of a child at school j.

Using the law of total probability, the probability that a child who submits ranking R_i is admitted into a school can be re-written by taking the expectation over all possible rankings submitted by other children:

$$\mathbb{P}(A_i = j|R_i) = \sum_{\tilde{R}_{-i} \in \tilde{\mathcal{R}}_{-i}} \phi_{pgj}(R_i, \tilde{R}_{-i}) \mathbb{P}(\tilde{R}_{-i}|R_i) \tag{A3}$$

where the sum is taken across all possible permutations of rankings submitted by all children other than i. Note that since children react to their peers' *expected* behavior, rather than realized rankings, it follows that, $\mathbb{P}(\tilde{R}_{-i}|R_i) = \mathbb{P}(\tilde{R}_{-i})$. For the same reason, this probability is equivalent to the product of individual ranking probabilities:

$$\mathbb{P}(\tilde{R}_{-i}) = \prod_{k \neq i} \mathbb{P}(R_k) \tag{A4}$$

Putting this together, I write the unconditional probability that a child is admitted into a high school as follows:

$$\begin{aligned} \mathbb{P}(A_i = j) &= \sum_{R_i \in \mathcal{R}} \mathbb{P}(A_i = j | R_i) \mathbb{P}(R_i) \\ &= \sum_{R_i \in \mathcal{R}} \sum_{\tilde{R}_{-i} \in \tilde{\mathcal{R}}_{-i}} \phi_{pgj}(R_i, \tilde{R}_{-i}) \left(\prod_{k \neq i} \mathbb{P}(R_k) \right) \mathbb{P}(R_i) \end{aligned} \tag{A5}$$

where the sum is taken across all possible rankings that (1) a child, and (2) all other children can submit.

Equilibrium Existence and Uniqueness Beliefs about the number of peers admitted to each school solve the fixed-point (belief-mapping) equation

$$\Phi(\widehat{m}_{cj}) = N_c \int \mathbb{P}(A_i = j)\, dF_g(X_{ij}) \qquad \forall\, c, j \tag{A6}$$

This mapping is continuous and maps $[0, N_c]$ into itself, so by Brouwer's theorem it has at least one fixed point. The following result gives a sufficient condition for uniqueness.

Result A2 (Equilibrium Existence and Uniqueness)**.** *An equilibrium belief always exists. It is unique within a primary school cohort if* $\gamma_g \leq \left(\bar{R} \cdot |G_c|\right)^{-1}$*, where* $\bar{R}$ *is the longest admissible ROL and* $|G_c|$ *is the cohort size.*

The condition is sufficient but not necessary; for many parameterizations uniqueness obtains for larger γ_g. Importantly, estimation does not require selecting an equilibrium: given $\widehat{m}_{cj}$, X_{ij}, and η_{cgj}, choice probabilities are fully determined, and $\widehat{m}_{cj}$ is consistently estimated by the observed admitted share $\bar{m}_{cj} = |G_c|^{-1} \sum_{i \in G_c} \mathbf{1}\{A_i = j\}$, following the approach of Bhattacharya et al. (2024).

Proof of Result A2 Existence follows from Brouwer's theorem, as noted above. For uniqueness, by the contraction mapping theorem it suffices to show that the belief-mapping operator Φ in (A6) is a contraction, that is, that $|d\Phi(\widehat{m}_{cj})/d\widehat{m}_{cj}| < 1$. Substituting the admission probability (A5) into Φ and differentiating under the integral and the sums by the product rule, the derivative has three terms, one for each of ϕ_{pgj}, $\mathbb{P}(\tilde{R}_{-i})$, and $\mathbb{P}(R_i)$. Conditional on all children's rankings the admission probabilities are constant, so $\partial \phi_{pgj}/\partial \widehat{m}_{cj} = 0$ and the first term vanishes. The other two are controlled by two lemmas.

Lemma 1. The derivative of the probability of a rank-ordered list R_i with respect to $\widehat{m}_{cj}$ is bounded by $\gamma_g \bar{R}\, \mathbb{P}(R_i)$, where $\bar{R}$ is the maximum list length. This follows because, differentiating the rank-ordered logit $\mathbb{P}(R_i) = \prod_r \mathbb{P}(R_i(r) \mid S_r)$ with respect to the utility V_{ij},

$$\frac{\partial \mathbb{P}(R_i)}{\partial V_{ij}} = \mathbb{P}(R_i) \sum_{r=1}^{\bar{R}} \big(\mathbf{1}\{j_r = j\} - \mathbb{P}(R_i(r) = j \mid S_r) \big)$$

whose absolute value is at most $\bar{R}\, \mathbb{P}(R_i)$ (school j can occupy at most one rank); since $\partial V_{ij}/\partial \widehat{m}_{cj} = \gamma_g$, the claim follows.

Lemma 2. The derivative of the joint probability of the other children's lists $\mathbb{P}(\tilde{R}_{-i}) = \prod_{k \neq i} \mathbb{P}(R_k)$ with respect to $\widehat{m}_{cj}$ is bounded by $\gamma_g \bar{R} |G_c| \mathbb{P}(\tilde{R}_{-i})$, because $\widehat{m}_{cj}$ affects only the lists of the $|G_c|$ children in the same primary school, each contributing a term bounded as in Lemma 1.

Combining the two lemmas, the surviving two terms of the derivative are bounded by

$$\left| \frac{d\Phi(\widehat{m}_{cj})}{d\widehat{m}_{cj}} \right| \leq \gamma_g \bar{R} \left(|G_c| + 1 \right) \int \mathbb{P}(A_i = j) \, dF_g(X_{ij}) \leq \gamma_g \bar{R} \, |G_c|$$

where the last step uses that the integral is a convex combination of probabilities, hence at most one, and that $|G_c| + 1$ is the cohort size. Therefore $\gamma_g \leq (\bar{R} \, |G_c|)^{-1}$ makes the derivative strictly less than one, so Φ is a contraction and the equilibrium is unique. □

A5.1.1 Simulating Equilibrium Choice Probabilities

In the counterfactuals, where the observed admitted shares are no longer valid, I implement a fixed-point algorithm to determine the equilibrium peer distribution, where the probability of each child applying to a school is updated iteratively. The core of the algorithm lies in solving for the stable set of probabilities P_{ij}. These probabilities represent the likelihood that child i in primary school c applies to school j and are influenced by both the school's characteristics and the decisions of other children in the same peer group.

The algorithm begins by initializing $P_{ij}^{(0)}$ for each child and school using uniform probabilities. I then compute $m_{ij}^{(1)}$, the average *predicted* number of peers who rank high school j as their most preferred option, for every primary school:

$$m_{ij}^{(1)} = \frac{1}{N_c} \sum_{k \in \mathcal{G}_i} P_{kj}^{(0)}$$

where the summation is over all children k in the peer group of child i, $\mathcal{G}_i$. Using these updated values of $m_{ij}^{(l)}$, I compute the next iteration of $P_{ij}^{(l+1)}$ as:

$$P_{ij}^{(1)} = \Lambda(X_{ij}, m_{ij}^{(1)}, \theta, \eta_{cgj})$$

The algorithm iterates between recalculating $m_{ij}^{(l)}$ and updating $P_{ij}^{(l+1)}$ until convergence. Convergence is achieved when the difference between successive iterations of $P_{ij}^{(l)}$ falls below a predefined tolerance level:

$$\max_{i,j} \left| P_{ij}^{(l+1)} - P_{ij}^{(l)} \right| < \varepsilon$$

where ε is a small positive number. Since each iteration of $P_{ij}^{(l)}$ implies a particular $m_{ij}^{(l)}$, the algorithm inherently captures the feedback loop between individual probabilities and the peer distribution. Since the probability function is continuous and monotonic in m_{ij}, the existence of a fixed point is guaranteed under standard conditions.

A5.1.2 Simulating Admission Probabilities

In this section, I provide a detailed description of the child-proposing Deferred Acceptance algorithm used to assign children to schools based on their ranked preferences and school priorities. This implementation closely follows the structure of Chile's centralized school admission system (SAE).

To begin, I first generate rank-ordered lists (ROLs), which I denote by $\hat{R}_i$, which represent families' preferences over schools. In each simulation, I draw a vector of idiosyncratic preferences,

ϵ, for each family over each school as well as the outside option. I then compute the utility for each option based on the estimated structural parameters $\{\hat{\beta}_g, \hat{\gamma}_0\}$ and primary school by high school fixed effects, $\hat{\eta}_{cgj}$, as follows:

$$\hat{U}_{ij} = \begin{cases} X_{ij}\hat{\beta}_g + \bar{m}_{ij}\hat{\gamma}_0 + \hat{\eta}_{cgj} + \epsilon_{ij} & \text{if } j \in J_i \\ \hat{V}_o + \epsilon_{ij} & \text{if } j = \emptyset, \end{cases} \tag{A7}$$

where X_{ij} represents observable school characteristics, $\bar{m}_{ij}$ instruments for families' beliefs, and ϵ_{ij} follows a Type-I extreme value distribution. I then construct a ranking, $\hat{R}_i$, by sorting schools based on their computed utility values $\hat{U}_{ij}$. Formally, the ranking $\hat{R}_i$ is constructed by ordering the set of schools J_i and the outside option $\emptyset$ in descending order of utility:

$$\hat{R}_i = \arg\operatorname{sort}_{j \in J_i \cup \{\emptyset\}} \hat{U}_{ij}, \quad \text{such that} \quad \hat{U}_{ij_1} \geq \hat{U}_{ij_2} \geq \cdots \geq \hat{U}_{ij_{|J_i|}} \tag{A8}$$

Given $\hat{R}_i$, I simulate a child-proposing Deferred Acceptance algorithm, which assigns children to schools based on their ranked choices and school-specific priority. Children first apply to their highest ranked school, $\hat{R}_i(1)$, and schools tentatively accept children according to their priority rankings $\pi_j(i)$. Priorities are defined to match those in the Chilean school admission system, so top priority is given to children whose siblings study at the school, followed by children whose families work at the school. If the number of applicants exceeds a school's capacity q_j, the lowest-ranked children are rejected and must apply to their next preferred school. If a school is oversubscribed within a priority group, children are assigned random lottery numbers L_i and those with lottery numbers lower than the number of remaining seats are accepted. Rejected children remove the rejected school from their preference list and apply to their next highest ranked school. The following provides an overview of the algorithm:

1. **Initialization:** All children start unmatched:

$$A_i = \emptyset, \quad \forall i \in \mathcal{I} \tag{A9}$$

   where A_i denotes the current assignment of child i (or $\emptyset$ if unmatched).

2. **Proposals:** Each unmatched child applies to their highest-ranked available school:

$$\mathcal{P}_j = \{i \in \mathcal{I} \mid A_i = \emptyset, \hat{R}_i(1) = j\} \tag{A10}$$

   where $\mathcal{P}_j$ represents the set of children applying to school j in the current round.

3. **Evaluation:** Each school ranks all applicants based on their priority order $\pi_j(i)$, using random lottery numbers L_i to break ties when necessary. Formally, let $\mathcal{G}_{pj}$ correspond to all applicants within priority group p at school j:

$$\mathcal{G}_{pj} = \{i \in \mathcal{P}_j \mid \pi_j(i) = p\}.$$

   Within each priority group, schools rank all applicants based on random lottery draws L_i for tie-breaking. The lottery numbers are assigned as a random permutation over the applicants:

$$L : \mathcal{G}_{pj} \to \{1, 2, \ldots, |\mathcal{G}_{pj}|\} \tag{A11}$$

   Formally, the position of child i in schools' preference ranking is given by:

$$\mathcal{A}_j = \operatorname{sort}_{i \in \mathcal{P}_j} (\pi_j(i), L_i) \tag{A12}$$

   Let $\mathcal{A}_j(i)$ correspond to the rank of child i within the school's preference list. That is:

$$i \succ_j \tilde{i} \iff \mathcal{A}_j(i) < \mathcal{A}_j(\tilde{i}) \tag{A13}$$

4. **Admission & Rejection:** Schools accept the top q_j children in their ranked list, $\mathcal{A}_j$. Formally,

$$A_i = \begin{cases} j, & \text{if } \mathcal{A}_j(i) \leq q_j \\ \emptyset, & \text{otherwise.} \end{cases} \tag{A14}$$

children in the first priority group are automatically admitted if the size of the priority group is below the size of the school. If a school is oversubscribed, there will be a marginal priority group, consisting of children whose priority level places them at the boundary of the school's remaining available seats. Within the marginal priority group, children will be admitted if their lottery number is lower than the remaining number of seats.

5. **Reapplications:** Rejected children remove the school that rejected them from their preference list and apply to their next most preferred school:

$$\hat{R}_i \leftarrow \hat{R}_i \setminus \{j\}, \quad \text{where } j = \hat{R}_i(1), \quad \forall i \text{ rejected} \tag{A15}$$

6. **Termination Condition:** The process repeats until no children are rejected in a round, ensuring that all unmatched children have either been assigned to a school or have exhausted their preference lists.

I repeat this process $S = 100$ times and then compute the average probability that a family ranks a school in positions 1–3 as follows:

$$\bar{\mathbb{P}}(R_i(r) = j) = \frac{1}{S} \sum_s \mathbf{1}\{R_i(r) = j\},$$

and the average probability that a child is admitted to a school as follows:

$$\bar{\mathbb{P}}(A_i = j) = \frac{1}{S} \sum_s \mathbf{1}\{A_i = j\},$$

where s corresponds to a simulation draw and S to the total number of simulations. When multiple equilibria exist, I initialize at the observed shares and report the equilibrium to which the iteration converges, which is the one closest to the data.

A5.2 Identification

For notational simplicity, I first prove that parameters are identified in the first-stage application decision. I then prove that parameters are identified in the second-stage enrollment decision.

A5.2.1 Identification in the First-Stage Application Decision

Consider the following utility function for the first-stage application decision:

$$U_{ij} = \beta_g' X_{ij} + \omega_{cgj} + e_{ij}^1$$

As before, X_{ij} corresponds to characteristics of school j that are specific to child i, and ω_{cgj} is a composite parameter that varies at the primary-by-high school cell, (c, j).

I claim that the probability that a family ranks a high school as their most preferred option point-identifies the vector of parameters $\theta = \{\beta_g, \omega_{cgj}\}$. In other words if:

$$\mathbb{P}(R_i(1) = j|\beta_g, \omega_{cgj}) = \mathbb{P}(R_i(1) = j|\tilde{\beta}_g, \tilde{\omega}_{cgj})$$

then:

$$\beta_g = \tilde{\beta}_g, \omega_{cgj} = \tilde{\omega}_{cgj}$$

I show that this will be the case under our model assumptions together with a technical assumption on the distribution of children's observable characteristics within a school.

> **Non-degenerate distribution of child-school characteristics (NSD):** The distribution of children's observable characteristics, $F_g(X_{ij})$, is not degenerate.

Identification of β_g First consider the identification of β_g. Without loss of generality, consider the set of children in primary school s_0 considering whether to apply to some high school j_0. For these children ω_0 is just a constant value as the expected number of peers who are admitted into a given high school does not vary within a primary school cohort. Consider some alternative $\tilde{\omega}_0$ and $\tilde{\beta}_g$. Assume that within this set of children:

$$\Lambda(\omega_0 + \beta_g X_{ij}) = \Lambda(\tilde{\omega}_0 + \tilde{\beta}_g X_{ij})$$

where $\Lambda(\cdot)$ corresponds to the probability to rank a school as a family's preferred option. As defined in Equation 13 this is simply given by the multinomial choice probabilities. Since Λ is strictly monotonic, this implies that:

$$\omega_0 + \beta_g X_{ij} = \tilde{\omega}_0 + \tilde{\beta}_g X_{ij}$$

Because we observe the choice probability for at least two different children in every class, it must then be the case that:

$$\omega_0 + \beta_g X_{1j_0} = \tilde{\omega}_0 + \tilde{\beta}_g X_{1j_0}$$
$$\omega_0 + \beta_g X_{2j_0} = \tilde{\omega}_0 + \tilde{\beta}_g X_{2j_0}$$

Subtracting one equation from the other:

$$\beta_g(X_{1j_0} - X_{2j_0}) = \tilde{\beta}_g(X_{1j_0} - X_{2j_0})$$

Under Assumption NSD we can always find two children in a class such that $X_{1j_0} \neq X_{2j_0}$. As such, this equation can only hold if $\beta_g = \tilde{\beta}_g$.

Identification of ω_{cgj} By the same argument as before, strict monotonicity implies that if the choice probability for two sets of fixed effects are the same, then:

$$\beta_g X_{ij} + \omega_{cgj} = \beta_g X_{ij} + \tilde{\omega}_{cgj}$$

which can only be satisfied if:

$$\omega_{cgj} = \tilde{\omega}_{cgj}$$

□

A5.2.2 Identification in the Second-Stage Enrollment Decision

The identification argument for the second-stage enrollment decision follows directly from the argument above. Conditional on admission to school j, the probability that family i accepts the offer admission and enrolls is given by:

$$\mathbb{P}(E_i = 1 \mid A_{ij} = 1, X_{ij}) = \Lambda\left(\frac{1}{\sigma_g}\beta_g X_{ij} + \phi_{cgj}\right) \tag{A16}$$

where $\Lambda(\cdot)$ is the logistic function. As in the application stage, the choice probability is strictly monotonic in the underlying utility index.

Suppose that two sets of parameters generate the same enrollment probabilities:

$$\Lambda\left(\frac{\beta_g}{\sigma_g}X_{ij} + \phi_{cgj}\right) = \Lambda\left(\frac{\widetilde{\beta_g}}{\widetilde{\sigma_g}}X_{ij} + \widetilde{\phi}_{cgj}\right) \tag{A17}$$

Strict monotonicity implies

$$\frac{\beta_g}{\sigma_g}X_{ij} + \phi_{cgj} = \frac{\widetilde{\beta_g}}{\widetilde{\sigma_g}}X_{ij} + \widetilde{\phi}_{cgj} \tag{A18}$$

The remainder of the argument is identical to the application-stage argument. Consider two children in the same primary-by-high school cell (c, j). Because ϕ_{cgj} is constant within the cell, subtracting their utility indices gives

$$\frac{\beta_g}{\sigma_g}(X_{1j} - X_{2j}) = \frac{\widetilde{\beta_g}}{\widetilde{\sigma_g}}(X_{1j} - X_{2j}) \tag{A19}$$

Under Assumption NSD, there exist two children for whom $X_{1j} \neq X_{2j}$, so this equality can only hold if

$$\frac{\beta_g}{\sigma_g} = \frac{\widetilde{\beta_g}}{\widetilde{\sigma_g}} \tag{A20}$$

Thus, enrollment probabilities identify β_g/σ_g.

Given identification of β_g/σ_g, strict monotonicity also implies

$$\phi_{cgj} = \widetilde{\phi}_{cgj} \tag{A21}$$

Therefore, the enrollment probabilities identify both β_g/σ_g and ϕ_{cgj}. □

A5.2.3 Identification of School Characteristics

I now consider the identification of η_{cgj}. The argument has two steps. I begin by establishing that two alternative sets of parameters, η_{cgj} and $\tilde{\eta}_{cgj}$, that yield the same probability to observe schools ranked as families' most preferred option must also yield the same expectation over the number of peers at different schools. I then show that, as a result, this means that they must be equal to each other.

Lemma A2. *If two sets of parameters, η and $\tilde{\eta}$, yield the same probability over rankings, they must yield the same beliefs over the number of peers at different high schools*

Proof. Recall from Equation A5 that the number of peers admitted into a school can be written as:

$$\begin{aligned}\tilde{m}_{cj}(\tilde{\eta}) &= N_c \int \sum_{R \in \mathcal{R}} \phi_{pgj}(R_i)\mathbb{P}(R_i|\tilde{\eta})dF_g(X_{ij}) \\ &= N_c \int \sum_{R \in \mathcal{R}} \phi_{pgj}(R_i)\mathbb{P}(R_i|\eta)dF_g(X_{ij}) \\ &= \hat{m}_{cj}(\eta)\end{aligned} \tag{A22}$$

where the equality between the first line and the second is given by the fact that the probability to observe each ranking remains unchanged under both sets of parameters. □

I now proceed to prove the identification of η_{cgj}. Note that I have proved in Appendix A5.2.1 that the probability to rank a school as a family's most preferred option identifies ω_{cgj}. Then identification requires that for two values of η_{cgj} and $\tilde{\eta}_{cgj}$:

$$\omega_{cgj}(\eta_{cgj}) = \omega_{cgj}(\tilde{\eta}_{cgj})$$
$$\eta_{cgj} + \gamma_g \hat{m}_{cj}(\eta) = \tilde{\eta}_{cgj} + \gamma_g \hat{m}_{cj}(\tilde{\eta})$$

By Lemma 2, this is equivalent to:

$$\eta_{cgj} + \gamma_g \hat{m}_{cj} = \tilde{\eta}_{cgj} + \gamma_g \hat{m}_{cj}$$

Re-arranging:

$$\eta_{cgj} - \tilde{\eta}_{cgj} = \gamma_g[\hat{m}_{cj} - \hat{m}_{cj}]$$

$$\eta_{cgj} - \tilde{\eta}_{cgj} = 0$$

$$\eta_{cgj} = \tilde{\eta}_{cgj}$$

□

A5.3 Estimation

A5.3.1 Estimation of Second-Stage Enrollment Decision Parameters

The estimation proceeds in three steps. First, I estimate the structural parameters of the second-stage enrollment decision, $\frac{\beta_g}{\sigma_g}$, using a conditional likelihood approach, where I remove the composite fixed effects ϕ_{cgj}. I then estimate the composite ϕ_{cgj}, by maximizing the likelihood to observe the second-stage enrollment decisions, using the estimated structural parameters, $\frac{\beta_g}{\sigma_g}$. Finally, I estimate $\frac{\gamma_g}{\sigma_g}$, by regressing the fixed effects estimates $\hat{\phi}_{cgj}$ on the realized number of admitted peers, controlling for the expected number.

Conditional Maximum Likelihood Estimation for Structural Parameters This section derives the conditional likelihood used to estimate β_g/σ_g. Consider a primary-by-high school cell (c, j). For each child i in the cell, enrollment is binary, $E_i \in \{0, 1\}$, and the enrollment logit (21) implies

$$\Pr(E_i = 1 \mid X_{ij}, \phi_{cgj}) = \frac{\exp\Big(X'_{ij}\beta_g/\sigma_g + \phi_{cgj}\Big)}{1 + \exp\Big(X'_{ij}\beta_g/\sigma_g + \phi_{cgj}\Big)} \tag{A23}$$

Equivalently, the probability of the realized binary outcome E_i can be written as

$$\Pr(E_i \mid X_{ij}, \phi_{cgj}) = \frac{\exp\Big[E_i\Big(X'_{ij}\beta_g/\sigma_g + \phi_{cgj}\Big)\Big]}{1 + \exp\Big(X'_{ij}\beta_g/\sigma_g + \phi_{cgj}\Big)} \tag{A24}$$

Conditional on the covariates and the cell fixed effect, enrollment decisions are independent across children. The joint probability of the observed enrollment configuration in cell (c, j) is therefore

$$\begin{aligned}
&\Pr\big(\{E_i\}_{i\in(c,j)} \,\big|\, X, \phi_{cgj}\big) \\
&\quad= \prod_{i\in(c,j)} \frac{\exp\Big[E_i\Big(X'_{ij}\beta_g/\sigma_g + \phi_{cgj}\Big)\Big]}{1 + \exp\Big(X'_{ij}\beta_g/\sigma_g + \phi_{cgj}\Big)} \\
&\quad= \frac{\exp\Big(\sum_{i\in(c,j)} E_i X'_{ij}\beta_g/\sigma_g\Big)\exp\Big(\phi_{cgj}\sum_{i\in(c,j)} E_i\Big)}{\prod_{i\in(c,j)}\big[1 + \exp\big(X'_{ij}\beta_g/\sigma_g + \phi_{cgj}\big)\big]}.
\end{aligned} \tag{A25}$$

Define the total number of enrollees in the cell as

$$S_{cj} \equiv \sum_{i\in(c,j)} E_i \tag{A26}$$

Equation (A25) can then be written as

$$\Pr\big(\{E_i\}_{i\in(c,j)} \,\big|\, X, \phi_{cgj}\big) = \frac{\exp\Big(\sum_{i\in(c,j)} E_i X'_{ij}\beta_g/\sigma_g\Big)\exp(S_{cj}\phi_{cgj})}{\prod_{i\in(c,j)}\big[1 + \exp\big(X'_{ij}\beta_g/\sigma_g + \phi_{cgj}\big)\big]}. \tag{A27}$$

Thus, conditional on the covariates, the enrollment outcomes enter the part of the likelihood involving ϕ_{cgj} only through S_{cj}. Hence S_{cj} is a sufficient statistic for the cell fixed effect.

To construct the conditional likelihood, suppose that the observed number of enrollees in cell (c, j) is $S_{cj} = s$. Let

$$\mathcal{A}_{cj}(s) \equiv \left\{ (a_i)_{i\in(c,j)} : a_i \in \{0,1\},\ \sum_{i\in(c,j)} a_i = s \right\} \tag{A28}$$

denote the set of all possible binary enrollment configurations containing exactly s enrollees. Here, $(E_i)_{i\in(c,j)}$ denotes the observed enrollment configuration, while $(a_i)_{i\in(c,j)}$ indexes the alternative configurations over which the conditional probability is computed.

By the definition of conditional probability,

$$\begin{aligned} &\Pr\big(\{E_i\}_{i\in(c,j)} \,\big|\, S_{cj} = s, X, \phi_{cgj}\big) \\ &\quad = \frac{\Pr\big(\{E_i\}_{i\in(c,j)} \mid X, \phi_{cgj}\big)}{\displaystyle\sum_{a\in\mathcal{A}_{cj}(s)} \Pr\big(\{a_i\}_{i\in(c,j)} \mid X, \phi_{cgj}\big)}. \end{aligned} \tag{A29}$$

Substituting (A27) into (A29) gives

$$\begin{aligned} &\Pr\big(\{E_i\}_{i\in(c,j)} \,\big|\, S_{cj} = s, X, \phi_{cgj}\big) \\ &\quad = \frac{\dfrac{\exp\Big(\sum_i E_i X_{ij}'\beta_g/\sigma_g\Big)\exp(s\phi_{cgj})}{\prod_i\Big[1+\exp\Big(X_{ij}'\beta_g/\sigma_g+\phi_{cgj}\Big)\Big]}}{\displaystyle\sum_{a\in\mathcal{A}_{cj}(s)} \frac{\exp\Big(\sum_i a_i X_{ij}'\beta_g/\sigma_g\Big)\exp(s\phi_{cgj})}{\prod_i\Big[1+\exp\Big(X_{ij}'\beta_g/\sigma_g+\phi_{cgj}\Big)\Big]}}. \end{aligned} \tag{A30}$$

Every configuration in $\mathcal{A}_{cj}(s)$ contains exactly s enrollees. Consequently, the factor $\exp(s\phi_{cgj})$ is common to the observed configuration and every alternative configuration in the denominator. The logit denominator

$$\prod_{i\in(c,j)} \big[1+\exp\big(X_{ij}'\beta_g/\sigma_g+\phi_{cgj}\big)\big]$$

is also common to all configurations. Both terms therefore cancel from the conditional probability. We obtain

$$\Pr\big(\{E_i\}_{i\in(c,j)} \,\big|\, S_{cj} = s, X\big) = \frac{\exp\Big(\sum_{i\in(c,j)} E_i X_{ij}'\beta_g/\sigma_g\Big)}{\displaystyle\sum_{a\in\mathcal{A}_{cj}(s)} \exp\left(\sum_{i\in(c,j)} a_i X_{ij}'\beta_g/\sigma_g\right)}. \tag{A31}$$

The cell fixed effect ϕ_{cgj} no longer appears in (A31). Conditioning on the number of enrollees therefore eliminates the fixed effect exactly.

Writing b for a candidate value of β_g/σ_g, the resulting conditional log-likelihood is

$$\begin{aligned} \ell_c(b) &= \sum_{(c,j)} \log\Pr\big(\{E_i\}_{i\in(c,j)} \,\big|\, S_{cj}; b\big) \\ &= \sum_{(c,j)} \left[\sum_{i\in(c,j)} E_i X_{ij}'b - \log\left\{\sum_{a\in\mathcal{A}_{cj}(S_{cj})} \exp\left(\sum_{i\in(c,j)} a_i X_{ij}'b\right)\right\}\right]. \end{aligned} \tag{A32}$$

The conditional maximum likelihood estimator is consequently

$$\widehat{(\beta_g/\sigma_g)} = \arg\max_b \ell_c(b) \tag{A33}$$

This likelihood identifies β_g/σ_g from differences in covariates between enrollees and non-enrollees within the same (c, j) cell. If $S_{cj} = 0$ or $S_{cj} = N_{cj}$, where N_{cj} denotes the number of children in the cell, there is only one enrollment configuration consistent with S_{cj}. The corresponding conditional probability is one, so the cell contributes zero to the conditional log-likelihood. Identification therefore comes from cells with $0 < S_{cj} < N_{cj}$ and sufficient within-cell variation in the covariates.

Maximum Likelihood Estimation for Fixed Effects After estimating the structural parameters, I estimate the fixed effects by maximizing the following likelihood:

$$\widehat{\phi}_{cgj} = \arg\max_{\phi_{cgj}} \sum_{i\in(c,j)} \left[E_i \log P\left(E_i = 1 \mid \widehat{\beta_g/\sigma_g}, \phi_{cgj}\right) + (1 - E_i) \log\left(1 - P\left(E_i = 1 \mid \widehat{\beta_g/\sigma_g}, \phi_{cgj}\right)\right)\right] \tag{A34}$$

Using $\Lambda' = \Lambda(1 - \Lambda)$, each summand differentiates to $E_i(1 - p_i) - (1 - E_i)p_i = E_i - p_i$, so

$$\frac{\partial \ell_{cj}}{\partial \phi_{cgj}} = \sum_{i\in(c,j)} \left(E_i - \Lambda(\widehat{\beta_g/\sigma_g}' X_{ij} + \phi_{cgj})\right)$$

Setting it to zero equates the observed number of enrollees, $\sum_i E_i$, to the expected number, $\sum_i \Lambda(\cdot)$. That is:

$$\sum_{i\in(c,j)} \left[E_i - \Lambda(\widehat{\beta_g/\sigma_g}' X_{ij} + \phi_{cgj})\right] = 0. \tag{A35}$$

Because Λ is strictly increasing, the left-hand side is strictly decreasing in ϕ_{cgj}, so the root is unique whenever it exists. Writing $k_{cj} = \sum_{i\in(c,j)} E_i$ and n_{gj} for the cell size, the left-hand side runs from k_{cj} (as $\phi_{cgj} \to -\infty$) to $k_{cj} - n_{gj}$ (as $\phi_{cgj} \to +\infty$), so a finite root exists exactly for *interior* cells, $0 < k_{cj} < n_{gj}$. Corner cells — all admitted children enroll, or none do — have $\phi_{cgj} \to \pm\infty$ and are dropped, exactly the cells the conditional logit already excludes. I solve (A35) cell by cell with a one-dimensional root-finder.

Second-Stage Outside Option Value As I show in Section A5.2, the second-stage outside option can be formed as follows:

$$\widehat{\bar{V}}_g^2 = \hat{\gamma}_g\,(m_{cj} - \widehat{m}_{cj}) + \hat{\omega}_{cgj} - \sigma_g\,\hat{\phi}_{cgj} \tag{A36}$$

Note that $\gamma_g(m_{cj} - \widehat{m}_{cj})$ is present because ω_{cgj} is built from the belief while ϕ_{cgj} is built from the realized count. Because $\gamma_g, \sigma_g, \omega_{cgj}$ and ϕ_{cgj} are estimated, the right-hand side of (A36) is a noisy estimate of the same $\bar{V}_g^2$ in each cell, and I take the average over the interior cells $\mathcal{C}$ (those in which some but not all admitted children enroll, so that ϕ_{cgj} is finite),

$$\widehat{\bar{V}}_g^2 = \frac{1}{|\mathcal{C}|} \sum_{(c,j)\in\mathcal{C}} \left[\widehat{\gamma}_g\,(m_{cj} - \widehat{m}_{cj}) + \widehat{\omega}_{cgj} - \widehat{\sigma}_g\,\widehat{\phi}_{cgj}\right]. \tag{A37}$$

A5.3.2 Estimation of First-Stage Application Decision Parameters

Estimation of parameters in the first-stage application decision proceeds following the same structure as the parameters for the second-stage enrollment decision. First, I estimate the structural parameters, β_g, using a conditional likelihood approach, where I remove the composite fixed effects ω_{cgj}. I then estimate the composite ω_{cgj}, by maximizing the likelihood to observe families' rank-ordered lists, using the estimated structural parameters, β_g.

Maximum Likelihood Estimation for the Ranking Decision This section derives the conditional likelihood used to estimate β_g in the first-stage application decision. The argument proceeds in two steps: I first turn the problem from a multinomial choice problem into a binary choice problem, by comparing the probability to rank one high school above another. In a second step, I compare this probability across two families, within the same primary school, to eliminate the primary-by-high school fixed effect.

Fix a primary school c, and child i, and compare the probability that an arbitrary high school j is ranked above another high school j'. This probability is given as follows:

$$\mathbb{P}(U_j > U_j') = \frac{\exp(\beta_g' X_{ij} + \omega_{cgj})}{\exp(\beta_g' X_{ij} + \omega_{cgj}) + \exp(\beta_g' X_{ij'} + \omega_{cj'})}$$

Define the within-child differences

$$\Delta X_i^{jj'} := X_{ij} - X_{ij'}, \qquad \Delta\omega_{cg}^{jj'} := \omega_{cgj} - \omega_{cj'}$$

Then we can write the pairwise ranking probability as follows:

$$\mathbb{P}(U_j > U_j') = \Lambda\left(\beta_g' \Delta X_i^{jj'} + \Delta\omega_{cg}^{jj'}\right) \tag{A38}$$

where $\Lambda(\cdot)$ is the logistic function. By comparing two schools j and j', I have turned the multinomial choice problem into a binary choice problem. As a result, I follow the same approach as in the second-stage enrollment decision to difference out the remaining nuisance term, $\Delta\omega_{cg}^{jj'}$, which is common to children from the same primary school who face the same pair of high schools.

To eliminate this term, consider two children i and i' in the same primary school c. Consider the event that the families rank the two schools differently. Without loss of generality consider the case that family i ranks school j above j', while family i' ranks school j' above j. Using (A38), I can write this as follows:

$$\mathbb{P}(U_{ij} > U_{ij'}, U_{i'j'} > U_{i'j}) = \Lambda\left(\beta_g' \Delta X_i^{jj'} + \Delta\omega_{cg}^{jj'}\right) \cdot \left[1 - \Lambda\left(\beta_g' \Delta X_{i'}^{jj'} + \Delta\omega_{cg}^{jj'}\right)\right] \tag{A39}$$

Write $A = \beta_g' \Delta X_i^{jj'} + \Delta\omega_{cg}^{jj'}$ and $B = \beta_g' \Delta X_{i'}^{jj'} + \Delta\omega_{cg}^{jj'}$, so this joint probability is $\Lambda(A)\,[1 - \Lambda(B)]$. Conditioning on the two families ranking the pair in opposite orders divides it by $\Lambda(A)\,[1 - \Lambda(B)] + [1 - \Lambda(A)]\,\Lambda(B)$, whereupon the fixed-effect difference $\Delta\omega_{cg}^{jj'}$ cancels from the resulting odds ratio. Hence,

$$\mathbb{P}\big(U_{ij} > U_{ij'} \,\big|\, i, i' \text{ disagree}\big) = \Lambda\left[\beta_g'\left(\Delta X_i^{jj'} - \Delta X_{i'}^{jj'}\right)\right] \tag{A40}$$

The resulting index contains only β_g and variation in relative covariates across the two children. In particular, any component common to children from primary school c for a given high school—which is absorbed by ω_{cgj}—drops out.

Equation (A40) is the conditional-logit argument of Chamberlain (1980). For a fixed pair (j, j'), the two children play the role of two observations sharing the nuisance intercept $\Delta\omega_{cg}^{jj'}$. Conditioning on the children giving different pairwise rankings eliminates this common intercept and identifies β_g from differences across children in their relative covariates. Formally, we require the following technical assumption to identify β_g.

Assumption A3 (Within-primary schoolvariation)**.** *There exist at least one pair of children,* (i, i')*, within the same primary school, and two high schools* (j, j') *such that* $\Delta X_i^{jj'} - \Delta X_{i'}^{jj'} \neq 0$*.*

The estimator, $\hat{\beta}_g$ maximizes the following conditional log-likelihood:

$$\hat{\beta}_g = \arg\max_{\beta_g} \sum_{i,i',j,j'} \log \Lambda \left[\beta_g' \left(\Delta X_i^{jj'} - \Delta X_{i'}^{jj'} \right) \right] \tag{A41}$$

where the summation is taken across all pairs of children i and i', that disagree about the ranking of high schools j and j'. Note that this can also include schools that a child chooses not to rank, as an unranked school is revealed to be less preferred than a ranked school.

Maximum Likelihood Estimation for Fixed Effects I recover the primary-by-high school composite fixed effects in the application decision by maximizing the pooled log-likelihood over the whole vector $\omega_{cg} = \{\omega_{cgj}\}_j$, holding constant the estimated parameters, $\hat{\beta}_g$.

$$\{\widehat{\omega}_{cgj}\}_j = \arg\max_{\{\omega_{cgj}\}_j} \sum_{k \in g} \log P(R_k \mid \{\omega_{cgj}\}_j, \hat{\beta}_g), \tag{A42}$$

Where $P(R_k)$ is given by Equation **??**. Note that the log-likelihood (A42) is globally concave in $\{\omega_{cgj}\}_j$, as it is a sum of log-concave rank-ordered-logit terms. As a result the maximizer is unique. A school that no member of c ever lists carries no ranking information; its $\omega_{cgj} \to -\infty$. These *corner cells* are excluded from the optimization and recorded separately.

A5.4 Estimation of Standard Errors

This appendix details the block bootstrap used for the standard errors reported in Section 5.3. Because the tetrad estimator of β_g is a composite likelihood whose tetrads are not independent, and because the remaining parameters are recovered in sequence, I do not have valid analytic standard errors; I obtain them by resampling primary schools and re-running the entire estimation. Resampling whole primary schools makes this a nonparametric cluster (pairs) bootstrap with the primary school as the cluster, so the standard errors are robust to arbitrary dependence among the children, cells, and estimation stages within a primary school (Efron, 1979; Cameron et al., 2008; Cameron and Miller, 2015).

Let the sample contain G primary schools, and let $\widehat{\theta}$ collect the estimated parameters, namely β_g, β_g/σ_g, γ_g/σ_g, σ_g, γ_g, the school-characteristic coefficients, and the outside-option value $\bar{V}_g^2$. For each replication $b = 1, \ldots, B$, with $B = 100$:

1. **Resample primary schools.** Draw G primary schools with replacement from the G observed ones. A given primary school may be drawn zero, one, or several times.

2. **Relabel duplicated draws as distinct networks.** Give each drawn primary school a fresh network identifier and give fresh child identifiers to all of its children. A primary school drawn

k times therefore enters the bootstrap sample as k separate networks with disjoint children, rather than as k copies that share identifiers. This keeps each network's internal structure intact—the same children, cells, rank-ordered lists, and enrollment decisions—while treating repeated draws as independent networks, as the block bootstrap requires.

3. **Re-run the whole estimation.** On the resampled data, repeat every step of Section 5.3: the conditional cell logit for β_g/σ_g in (26); the cell-effect inversion for ϕ_{cgj} in (27); the regression of the cell effects on the realized and expected number of admitted peers for γ_g/σ_g in (28); the tetrad logit for β_g; the rank-ordered-list inversion for ω_{cgj}; and the cross-stage combination that returns σ_g, γ_g, the school-characteristic coefficients, and $\bar{V}_g^2$. Store the resulting estimate $\widehat{\theta}^{(b)}$.

4. **Discard failed replications.** I discard a replication if any step fails to converge—for example, a resample with too few interior cells to identify a coefficient—and keep the $B' \leq B$ successful replications.

The bootstrap standard error of each parameter is the standard deviation of its estimate across the retained replications,

$$\widehat{\mathrm{se}}\big(\widehat{\theta}_p\big) = \sqrt{\frac{1}{B'-1}\sum_{b=1}^{B'}\big(\widehat{\theta}_p^{(b)} - \bar{\theta}_p\big)^2}, \qquad \bar{\theta}_p = \frac{1}{B'}\sum_{b=1}^{B'}\widehat{\theta}_p^{(b)}$$

computed parameter by parameter. Because each replication re-runs the entire pipeline, the standard error of a downstream parameter such as $\gamma_g = (\gamma_g/\sigma_g)\cdot\sigma_g$ automatically incorporates the sampling variation in all of the inputs that produce it, together with their covariation. The willingness-to-commute figures, which are ratios of estimated coefficients, are treated in the same way.

A6 Value-Added

A6.1 Estimation

The estimating equation (29) regresses the outcome on assigned-school-by-admission indicators and risk-set fixed effects. The SAE breaks ties with a single lottery number, so each type faces an admission probability p_i at its assigned school. Abdulkadiroğlu et al. (2017) show $\{Y_{ij}(1), Y_{ij}(0)\} \perp D_i \mid p_i$: conditional on the propensity score, offers are independent of potential outcomes, so the risk-set controls in (29) make D_i as good as random and q_{gj} causal.

A6.2 Empirical Bayes Correction

Write $\widehat{q}_{gj} = q_{gj} + u_{gj}$ with errors independent across types, $\mathrm{Var}(u_{gj}) = s_{gj}^2 = \mathrm{Var}(\xi)/n_{gj}$ for n_{gj} admitted type-g children. With Σ the estimated signal covariance of (q_{Lj}, q_{Hj}), $R_j = \mathrm{diag}(s_{Lj}^2, s_{Hj}^2)$, and m the type means, the posterior mean is

$$\big(\widehat{q}_{Lj}^{\,\mathrm{EB}}, \widehat{q}_{Hj}^{\,\mathrm{EB}}\big)' = m + \Sigma\,(\Sigma + R_j)^{-1}\big((\widehat{q}_{Lj}, \widehat{q}_{Hj})' - m\big)$$

and I form $\widehat{q}_j^{\,0,\mathrm{EB}}, \widehat{q}_j^{\,g,\mathrm{EB}}$ from it as in (25).

A6.3 Variance Decomposition

Substituting $q_{gj} = q_j^0 + q_{gj}$ into $\widehat{q}_{gj} = q_{gj} + u_{gj}$ gives

$$\widehat{q}_{Lj} = q_j^0 + q_j^L + u_{Lj}, \qquad \widehat{q}_{Hj} = q_j^0 + q_j^H + u_{Hj}$$

I use three assumptions: (i) the common and type-specific components are uncorrelated, $\mathrm{Cov}(q^0, q^g) = 0$; (ii) the type-specific components are uncorrelated across types, $\mathrm{Cov}(q^L, q^H) = 0$; and (iii) the estimation errors are uncorrelated with the components and with each other across types, $\mathrm{Cov}(u_{Lj}, u_{Hj}) = 0$. Assumption (iii) is the crucial one and holds by construction: $\widehat{q}_{Lj}$ and $\widehat{q}_{Hj}$ are estimated from *disjoint* sets of children, so their errors cannot covary.

Under (i)–(iii) the cross-type covariance isolates the common (school-quality) variance, because every other term vanishes:

$$\mathrm{Cov}\big(\widehat{q}_{Lj}, \widehat{q}_{Hj}\big) = \mathrm{Var}(q^0) + \underbrace{\mathrm{Cov}(q^L, q^H)}_{=0 \text{ (ii)}} + \underbrace{\text{terms in } q^0, q^g}_{=0 \text{ (i)}} + \underbrace{\mathrm{Cov}(u_{Lj}, u_{Hj})}_{=0 \text{ (iii)}} = \mathrm{Var}(q^0). \tag{A43}$$

The estimation error—which inflates each type's own variance—drops out of the covariance because it is independent across types; this is what makes the covariance a clean, noise-free measure of school quality. Each type's total variance is in turn

$$\mathrm{Var}\big(\widehat{q}_{gj}\big) = \mathrm{Var}(q^0) + \mathrm{Var}(q^g) + \overline{s_g^2}, \qquad s_{gj}^2 = \frac{\mathrm{Var}(\xi)}{n_{gj}}$$

where $\mathrm{Var}(\xi)$ is the within-school child-level variance of the score and n_{gj} the number of admitted type-g children. Subtracting the average sampling variance $\overline{s_g^2}$ gives the signal variance $\mathrm{Var}(q^0) + \mathrm{Var}(q^g)$, so the match variance is the residual

$$\mathrm{Var}(q^g)\big|_g = \big[\mathrm{Var}\big(\widehat{q}_{gj}\big) - \overline{s_g^2}\big] - \mathrm{Var}(q^0). \tag{A44}$$

Table A6 reports $\mathrm{Var}(q^0)$ and $\mathrm{Var}(q^g)$ as shares of the signal variance. Equivalently, the school-quality share equals the *disattenuated* correlation between a school's value-added for its two types,

$$\frac{\mathrm{Cov}(\widehat{q}_L, \widehat{q}_H)}{\sqrt{\big(\mathrm{Var}\,\widehat{q}_L - \overline{s_L^2}\big)\big(\mathrm{Var}\,\widehat{q}_H - \overline{s_H^2}\big)}} = 0.46$$

whereas the raw correlation, 0.33, is biased toward zero by exactly the estimation error $\overline{s_g^2}$ that (A43) removes.

A6.4 School Value-Added and Peer Composition

I assess whether the socioeconomic composition of a school's admitted cohort shapes its value-added by relating each component—common value-added q_j^0 and the low-SES match q_j^L—to the realized and expected share of high-SES peers, and, in a separate specification, to their average income. Including *both* the realized and the expected composition is key: conditional on the expected share, variation in the realized share is generated only by the admission lotteries, so the coefficient on the realized share isolates a lottery-induced shock to who is admitted, purged of the selection that ordinarily ties composition to quality. Table A8 reports the estimates; the realized composition has no statistically significant effect on either common value-added or type-specific value-added.

A6.5 Selection-on-Observables Benchmark

As a validation benchmark for the lottery-based value-added estimates described above, I also compute school value-added using a conventional selection-on-observables approach. The objective is to measure differences across schools in child achievement after adjusting for differences in the characteristics of children who attend each school. This approach follows the value-added literature, which interprets regression-adjusted differences in child outcomes as school effects under the assumption that, conditional on a sufficiently rich set of predetermined child characteristics, children do not systematically sort across schools on unobserved determinants of achievement (Deming, 2014; Chetty et al., 2014a; Angrist et al., 2017a, 2023).

Let $Y_i(j)$ denote the potential test-score outcome of child i if she were to attend school j, and let D_{ij} indicate that child i attends school j. I assume an additively separable potential-outcomes model,

$$Y_i(j) = X_i'\beta + \delta_j + \varepsilon_i, \tag{A45}$$

where X_i is a vector of predetermined child characteristics, δ_j captures the contribution of school j to child achievement, and ε_i collects determinants of achievement that are unobserved by the econometrician. The causal effect of attending school j rather than school k is therefore

$$Y_i(j) - Y_i(k) = \delta_j - \delta_k \tag{A46}$$

Equation (A45) imposes constant school effects: the effect of attending j rather than k does not vary across children. The observed outcome can consequently be written as

$$Y_i = X_i'\beta + \sum_{j=1}^{J} \delta_j D_{ij} + \varepsilon_i \tag{A47}$$

Because each child attends exactly one school, I impose that school-fixed effects must average zero,

$$\frac{1}{J}\sum_{j=1}^{J} \delta_j = 0 \tag{A48}$$

The identifying assumption underlying OLS estimation of (A47) is *selection on observables*. Specifically, I assume:

$$E[\varepsilon_i \mid X_i, D_{i1}, \ldots, D_{iJ}] = E[\varepsilon_i \mid X_i] = 0 \tag{A49}$$

In order to make this credible, I include in X a large set of individual child characteristics, including the level of education obtained by their mother and father, their family income, their area of residence, their gender and age, and, importantly, their standardized test scores from exams taken in primary school. Prior achievement is particularly valuable because it summarizes both earlier educational inputs and persistent determinants of academic performance.

Angrist et al. (2017a) and Angrist et al. (2024)show how admissions lotteries, which generate variation in admission, can be used to obtain school value-added measures. In principle, this approach is possible in my setting as well. However, since not all schools are over-subscribed, this approach would limit the amount of schools for which I can get value-added estimates. Luckly Deming (2014) shows that several conventional school VAM specifications with rich prior achievement information successfully predict lottery-induced achievement effects.

I obtain my school value-added measures by estimating (A47) by OLS. For ease of interpretation and comparison across specifications, I standardize the resulting school effects, δ_j, using the cross-school distribution of estimated value-added:

$$VA_j = \frac{\widehat{\delta}}{\sigma_{\hat{\delta}}} \tag{A50}$$

A7 Schools and Educational Inequality

This section reviews my framework for decomposing differences in the raw means of educational outcomes between groups into differences in the average 'quality' of schools children attend and differences in the average match-effect and 'advantage' of children. Let Y_{ij} denote the potential outcomes of child i were they to attend school $j \in \mathcal{J}$. We can decompose Y_{ij} into three components:

$$Y_{ij} = \underbrace{\alpha_i}_{\text{child effect}} + \underbrace{v_j}_{\text{School effect}} + \underbrace{\epsilon_{ij}}_{\text{Match effect}} \tag{A51}$$

where α_i is child i's average potential outcome across all schools; it vertically differentiates children, reflecting traits such as ability and ambition, but also families' ability to support their children. v_j corresponds to school effects, which capture each school j's average causal value-added on children's outcomes. Finally, ϵ_{ij} captures the quality of the match between child i and school j; it corresponds to the causal effect of attending school j for child i. This specification is similar to the specification commonly adopted in the value-added literature, but is more flexible as it does not restrict the value-added of schools to be homogeneous across individuals (see, for example, Abowd et al., 1999; Chetty et al., 2014b; Angrist et al., 2016, 2017b).[52]

Differences in outcomes between different groups of children can represent differences in each of these dimensions. Poorer children are likely to attend worse schools and, at the same time, have lower potential outcomes on average. Letting $S_i = j$ indicate that child i attends school j, and g_i the group that child i belongs to, we can decompose the raw mean outcomes between children in groups g_1 and g_0 as follows:

$$\underbrace{\mathbb{E}[Y_{ij}|g_1] - \mathbb{E}[Y_{ij}|g_0]}_{\substack{\text{Difference in raw means} \\ := \Delta Y}} = \underbrace{\mathbb{E}[\alpha_i|g_1] - \mathbb{E}[\alpha_i|g_0]}_{\substack{\text{Difference in average} \\ \text{child potential outcomes} \\ := \Delta\alpha}} + \underbrace{\mathbb{E}[v_j|g_1] - \mathbb{E}[v_j|g_0]}_{\substack{\text{Difference in school} \\ \text{vertical quality} \\ := \Delta v}} + \underbrace{\mathbb{E}[\epsilon_{ij}|g_1] - \mathbb{E}[\epsilon_{ij}|g_0]}_{\substack{\text{Difference in school} \\ \text{match quality} \\ := \Delta\epsilon}} \tag{A52}$$

Without imposing any restrictions on sorting, we cannot identify $\Delta\alpha + \Delta\epsilon$ using a fixed effects estimator. However, one way to overcome selection issues is to take the mean of school-level comparisons between different groups of children. The idea is that while any comparison may be biased due to selection, by the law of iterated expectations, the global average should not be influenced by selection (even if different groups select differently). To see this note that,

$$\begin{aligned} E_j\{E_i[Y_{ij}|g_1, j] - E_i[Y_{ij}|g_0, j]\} &= \\ &= E_j\{E_i[\alpha_i|g_1, j] + E_i[\epsilon_{ij}|g_1, j] + v_j - (E_i[\alpha_i|g_0, j] + E_i[\epsilon_{ij}|g_0, j] + v_j)\} \\ &= E_j\{E_i[\alpha_i|g_1, j] - E_i[\alpha_i|g_0, j] + E_i[\epsilon_{ij}|g_1, j] - E_i[\epsilon_{ij}|g_0, j]\} \\ &= E_i[\alpha_i|g_1] - E_i[\alpha_i|g_0] + E_i[\epsilon_{ij}|g_1] - E_i[\epsilon_{ij}|g_0] \\ &= \Delta\alpha + \Delta\epsilon, \end{aligned} \tag{A53}$$

where the law of iterated expectations is invoked to move from the third line to the fourth line.

[52] See Kirkebøen et al. (2021), Bonhomme et al. (2019), Lamadon et al. (2019), Hull (2020), Abdulkadiroglu et al. (2020), and Goldsmith-Pinkham et al. (2021) for recent approaches relaxing value-added homogeneity.

Estimation We can estimate $E_j\{E_i[Y_{ij}|g_1, j] - E_i[Y_{ij}|g_0, j]\}$, the average school-level difference in outcomes, directly using the following estimator:

$$\hat{\mu} = \frac{1}{J}\sum_j \left[\frac{1}{N_j^1} \sum_{\substack{G_i=g_1 \\ S_i=j}} Y_{ij} - \frac{1}{N_j^0} \sum_{\substack{G_i=g_0 \\ S_i=j}} Y_{ij} \right] \tag{A54}$$

where J corresponds to the total number of schools and $N_j^{G_i}$ corresponds to the number of children of type G_i in school j. The variance of this estimator is given by:

$$Var(\hat{\mu}) = \frac{1}{J^2}\sum_j \left[\frac{\sigma_{1,j}^2}{N_j^1} + \frac{\sigma_{0,j}^2}{N_j^0} \right] \tag{A55}$$

where $\sigma_{G_i,j}^2$ corresponds to the variance of outcomes of children of type G_i in school j. This estimator, however, requires full treatment support, which in our context means there should be children of each group in every school. Without further assumptions on heterogeneity, we require at least 2 children of each type in every school. Under the assumption of homogeneous variance within each group, we only require 1 child of each type in every school.

I apply the method described above to decompose the role of schools in generating gaps in standardized test scores. The SIMCE is a standardized exam that children take during the second year of high school (when children are typically 15–16 years old). It is graded on a scale running from 0 to 500, where the mean and median are, respectively, 264 and 258 points. In 2018, children whose mother had a high school education, constituting 70.7% of test-takers, scored, on average, 277 points, whereas children whose mother had less than a high school education scored only 239 points, corresponding to a difference of 0.6 SD. Table A9 presents the breakdown of standardized test scores to identify schools' influence on the achievement gap. Column (1) compares raw means between high- and Low-SES children, defined on the basis of maternal education. Column (2) provides the estimate of the difference in a regression that includes school fixed effects, and suggests that schools explain 72% of the achievement gap. Column (3) corresponds to the mean within-school average gap; using this approach, schools appear to explain 66% of the achievement gap. Overall, the analysis indicates that schools significantly contribute to explaining the achievement gap between low- and high-SES children (over 60% across all specifications) and suggests non-symmetric selection patterns into schools across socioeconomic groups: either high-SES children with higher average potential scores are more likely to select into better schools, or high-SES children enjoy greater match effects at schools.

	Mathematics Test scores		
	Base	FE	Within-school comparison
	(1)	(2)	(3)
$\Delta\hat{Y}$	32.46		
	[31.70, 33.22]		
$\Delta\hat{\alpha} + \Delta\hat{\epsilon}$		9.08	11.14
		[8.44, 9.69]	[10.03, 12.24]
$(1 - (\Delta\hat{\alpha} + \Delta\hat{\epsilon})/\Delta\hat{Y})$		72.03%	65.58%
*100 %		[65.50, 78.56]	[60.88, 70.28]
N	149,016	149,016	149,016
J	2,498	2,498	2,498

Note: The table corresponds to the decomposition of Maths test scores into a between-school and within-school component. The first row corresponds to the raw gap in scores between high- and low-SES children, defined based on whether a child's mother completed high school. The second row corresponds to estimates of the average within-school difference in test scores estimated using the approach outlined in this section. The third row corresponds to estimates of the average between-school component, obtained by subtracting the within-school estimate from the raw gap and normalizing by the size of the gap. Confidence intervals correspond to the 95% confidence level.

Table A9: Decomposition of Standardized Exam Scores

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