SCHOOL VOUCHER DESIGN AND STRATEGIC PRICING: EVIDENCE FROM INDIA*

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This paper uses detailed government records from India to study the world's largest voucher system for primary education, in which voucher levels are linked to private school tuition. Lottery results show that voucher recipients benefit from improved achievement measures and lower tuition payments. However, private schools respond to the tuition-linked voucher design by raising tuition fees up to 15%, with only modest improvements in quality. These strategic responses affect the 95% of children who do not receive vouchers. Using an empirical model of the education market, welfare estimates based on revealed preference suggest the program's benefits exceed its costs. Failing to account for school responses, however, would have overstated the benefit-cost ratio by a factor of two. An alternative voucher design – which pays a fixed amount regardless of tuition charged – would eliminate the distortionary price incentives and increase the benefit-cost ratio by 40%.

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I. Introduction

More than 350 million children around the world pay out of pocket to attend private schools (UNESCO 2021). Vouchers – which provide government subsidies for private tuition fees – have the promise of equalizing access to these schools and facilitating greater competition in education markets (Friedman 1955). Indeed, a large literature has shown that vouchers can not only improve the outcomes of recipients by expanding choice, but also non-recipients by creating incentives for private schools to improve their quality (Epple, Romano, and Urquiola 2017). Of course, schools may also respond to a subsidy by adjusting the prices they charge, affecting a potentially large number of students without vouchers. While there is much evidence on the equilibrium effects of vouchers on school quality, there is limited research of their impacts on school pricing.

India, which has the world's largest voucher program for primary school, is an ideal setting to study private school responses. Private schools educate nearly half of all students in the country and are required to reserve 25% of their primary seats for a nationwide voucher system.[1] The program provides full tuition subsidies to over a million disadvantaged children each year (Indus Action 2021). For each voucher student, the government pays schools their listed tuition fee up to a maximum voucher cap. This "tuition-linked" design is common across the world and allows private schools who are below the cap to collect additional payments by raising their tuition.[2]

This paper examines the consequences of India's voucher program accounting for not only quality but also price adjustment by private schools. To do so, the paper brings together new government records that cover the universe of students and schools in the state of Madhya Pradesh, home to more than 10 million primary school children and the largest voucher system within India. The analysis leverages voucher assignment lotteries and the rollout of the policy across markets to study its impacts on recipients and school responses. Then, it estimates an empirical model of the education market that accounts for these responses and performs policy counterfactuals.

There are three primary findings. First, voucher assignment lotteries show that students who receive vouchers – 5% of the market – benefit from greater choice, consistent with prior studies.[3] Students apply for vouchers with a rank-ordered list of private schools, receive one offer through a Deferred Acceptance mechanism, and choose whether to take the free offer or enroll in a different school at market prices. If seats are oversubscribed, a lottery determines who wins an offer (Abdulkadiroğlu et al. 2017). This provides random variation in whether students win their top-choice offer, a powerful instrument for whether they accept ("takeup") the offer. Among these top-choice compliers, voucher takeup delivers meaningful improvements in measures of achievement and choice.[4] This includes a 0.17σ increase in GPA; a 9pp increase in English instruction; and a \$77 reduction in tuition fees paid, roughly 6% of household income at the poverty line.[5]

1. Eligibility depends on poverty status (BPL) and social caste (SC/ST).
2. Programs in the US and Australia share this design feature. See Table AI for a global overview of voucher systems.
3. Only 15% of eligible students apply. In a neighboring state, Romero and Singh 2022 find information gaps about the policy and costs in acquiring documentation for the application.
4. Compliers are those who would have accepted their top-choice offer but rejected their second or worse choice.
5. GPA is not standardized. Figure AIII plots mean GPA against standardized test scores across schools (ρ=0.42).

Second, private schools respond to the tuition-linked voucher design by raising prices and modestly raising quality, affecting millions of students without vouchers – 95% of the market. Because voucher students pay nothing, schools below the cap can raise tuition and collect additional payments without losing voucher demand. Those above the cap, whose vouchers are fixed, have no such incentive. To study this empirically, the analysis leverages policy changes that expanded voucher eligibility and introduced an online application portal, dramatically increasing the number of applicants. This difference-in-differences design compares markets with greater versus lower exposure, before versus after the policy changes. Consistent with theory, schools below the cap respond to increased voucher applications by raising tuition fees up to 15%; those above the cap see little change. The price hikes come with modest increases in quality measures below the cap, including GPA value-added and teacher-student ratios, as schools compete to capture the subsidy. There are little quality changes above the cap, which may suggest constraints to adjustment.[6]

Third, an empirical model of the education market suggests the program is cost-effective, but the strategic responses lower its overall efficiency. On the demand-side, students decide to apply for vouchers; submit private school rankings; receive a voucher offer; and enroll in a school. Utility for schools depends on distance, quality, and price (Berry, Levinsohn, and Pakes 1995). On the supply-side, private schools are imperfectly competitive and set quality and price to maximize profit given demand and the tuition-linked voucher.[7] The model is identified using a new approach that combines high-stakes choices with exogenous variation from lotteries. Private school rankings are submitted by each student and help pin down their preferences across schools. Then, voucher lotteries randomize the price each student faces and help pin down their price sensitivities.

Estimates reveal two key distortions in the market: (1) private schools have higher quality and lower cost than public schools, but (2) they charge markups of over 40%. The policy helps correct each distortion by shifting some students from public to private and capping the voucher amount. This yields a benefit-cost ratio (BCR) of 1.5 to 1.[8] However, tuition hikes caused by the design harm millions of students who are price sensitive and without vouchers. This substantially reduces cost-effectiveness: ignoring school responses would have overstated the BCR by nearly a factor of two (2.9 to 1). Switching instead to a "flat" design – which pays the maximum voucher regardless of tuition – would remove the perverse pricing incentive and raise the BCR by 40% (2.1 to 1).[9]

Other common designs – such as voluntary school participation, extra "top-up" fees, or distance-based voucher assignment – substantially reduce the benefits for recipients and result in fewer voucher applications. Across the many designs on the table, voucher programs can generate benefit-cost ratios that range from less than 1 to more than 2. Importantly, ignoring school responses would have suggested the most cost-effective design is in fact the least cost-effective.

6. There is little evidence of impacts on public schools or entry/exit decisions. Government schools face little threat of shut down and teachers are unionized with strong tenure protection, consistent with work in similar contexts that document poor incentives to compete (Duflo, Hanna, and Ryan 2012; Bau 2022)

7. A quality adjustment constraint is added to the model match the limited effects we see in the reduced-form analysis.

8. In terms of social integration, voucher-eligible students increase private school enrollment by 13% and school segregation falls by 2.5%. Segregation is measured using a "multigroup entropy" index (Reardon and Firebaugh 2002).

9. A flat voucher continues to increase the BCR under program expansion and greater school quality adjustment.

This paper contributes to several strands of literature. First and foremost, it improves our understanding of the supply-side impacts of school vouchers. Prior work has largely studied the quality responses of private and public schools.[10] This paper provides some of the first theory and evidence that schools may also respond by adjusting *prices*.[11] Two sets of influential studies are closely related. First, Muralidharan and Sundararaman 2015 and Arcidiacono et al. 2021 study an experiment in India, which weakly benefits recipients via choice and non-recipients via price discounts. This paper shows that, under common designs, scaled-up policy can *harm* non-recipients via price hikes. Second, Neilson 2021 and Sanchez 2023 study school responses in Chile, where vouchers are not linked to prices but schools can charge extra top-up fees. While neither tests price effects in the data, the latter shows how top-ups for recipients change in counterfactuals. This paper shows that, under a price-linked design, schools may adjust prices for *non-recipients*.

This paper also adds to the demand-side literature, providing the largest lottery-based study on recipient outcomes. The most similar of these is Romero and Singh 2022, which studies India's policy in the neighboring state of Chattisgarh. The study administers standardized phone-based exams to estimate impacts on recipients. It also evaluates an experiment to increase application rates by providing information. Beyond the supply-side analysis, this paper adds to this study in three ways. First, it estimates effects on new outcomes including GPA, promotion rates, English instruction, proximity, and tuition expenses. Second, it shows how the benefits to recipients respond to different designs using estimates of willingness-to-pay based on revealed preference.[12] Third, its framework allows us to quantify the gains of reducing application frictions in equilibrium, which can be set against the costs of potential programs (e.g. information campaigns).

This paper builds on top of several studies that use structural models to estimate the equilibrium effects of voucher policies in Chile (Allende 2019; Neilson 2021; Sanchez 2023). First, it provides the first such analysis of India's voucher program, an important policy with a very different design. Second, it develops a new approach to identification that makes use of students' rank-ordered lists and price variation from voucher assignment lotteries, avoiding typical "BLP" instruments. Third, the model includes the decision to apply for the voucher program, which creates a new form of equilibrium adjustment in response to policy counterfactuals. For example, allowing top-up fees for voucher students can reduce overall effectiveness by lowering application volume.

Finally, this paper adds to the broader development economics literature on education, particularly studies that examine the rapidly growing private school sector in low income countries.[13] Vouchers are among the most common interventions that economists and policymakers continue to debate in these settings (World Bank 2023). This paper advances our knowledge of the strategic responses of private schools and offers insights on how to improve policy designs.

10. Epple, Romano, and Urquiola 2017 and Neal 2018 review the evidence on the impacts of voucher programs.
11. Hungerman and Rinz 2016 and Arcidiacono et al. 2021 find price effects, but do not provide an explicit model.
12. Two ongoing studies also estimate the welfare impact of vouchers on recipients (Arcidiacono et al. 2021; Kamat and Norris 2023). This paper builds on these by (1) adding a supply-side model accounts for spillovers to non-recipients from school adjustment and (2) studying how the equilibrium impacts depend on voucher design.
13. See Bedi and Garg 2000 in Indonesia; Andrabi, Das, and Khwaja 2017, Carneiro, Das, and Reis 2022, Bau 2022, and Andrabi et al. 2023 in Pakistan; Wamalwa and Burns 2018 in Kenya; Romero, Sandefur, and Sandholtz 2020 in Liberia.

II. Background

India has the largest education system in the world, with nearly 2 million schools, across half a million villages and cities, educating nearly a third of a billion students per year (U-DISE 2021). While government (public) schools still educate the majority of the population, low-cost private schools have grown quickly and acquired a substantial share of students. Over the past two decades, India has seen a staggering growth in the market share of private schools, nearly doubling from roughly 25% in 2005 to more than 47% today.

This paper studies the education system in the state of Madhya Pradesh (MP), which contains the largest number of voucher students in the country (Indus Action 2021). MP is the fifth largest of 36 Indian states, with a population exceeding 85 million people and per-capita income of roughly $1,700 per year. Across states, MP is relatively underachieving: it is the fourth lowest in the UN Human Development Index and the sixth lowest in the UN Quality Education Index.

II.A. India's Primary School Voucher System

In a landmark 2009 legislation, India passed the Right to Education Act (RTE), with the intention of substantially raising school standards and ensuring "free and compulsory education to all children in India" (Government of India 2009). In one of its clauses, Section 12(1)(c) or the "25% Reservation", RTE mandated that every private school in India must reserve 25% of its seats for a new voucher program targeted to disadvantaged students.

For each voucher student, the government pays the school its tuition fee up to a maximum voucher cap. The cap is set annually and is equal to the average per-child expenditure in each state's public school system. Importantly, the students themselves cannot be asked to "top-up" and pay any out-of-pocket fees. That is, for these children, private schools would have to cover any differences between its own per-child expenditure and that of the public schools.

The program is implemented at the state-level, and eligibility depends on state-specific income thresholds ("Below Poverty Line" or BPL) or social caste categories.[14] States are mandated to have a centralized application process where eligible students apply for vouchers, which are assigned using a state-specific allocation mechanism. Students apply for class 1 (first grade) or earlier and receive a single voucher offer for one school, which they can use until class 8.

This policy has a specific design, some features of which are shared by other programs around the world. Table AI summarizes the largest programs in the world that public fund private tuition for primary education. For example, most programs in the US and Australia also have a "tuition-linked" design, where voucher payments are based on school tuition fees. Overall, there is a substantial amount of heterogeneity in voucher designs implemented across countries, with few sharing the exact same design package. By enrollment, India has the largest program in the world. The setting of this paper, Madhya Pradesh, has the third largest.

14. For example, in this paper, Scheduled Caste (SC) and Scheduled Tribes (ST) are eligible in Madhya Pradesh, but Other Backwards Castes (OBC) are not. In other states like Gujarat and Rajasthan, all three are eligible.

1. The Voucher Application Process. MP first implemented the RTE voucher program at in 2013. Eligibility is restricted to children who are lower-caste (Scheduled Tribe or Scheduled Caste) or whose household is below the poverty line (BPL).[15] Hence, upper-caste ("General") children are eligible if they are BPL, and lower-caste children are eligible regardless of income.[16] Roughly half of all children in MP are eligible for the program (Table I).

Eligible students apply to one of four classes based on age criteria: Nursery, KG-I, KG-II, and Class 1. These are the four years of schooling up to and including the first grade, which begins typically at age 5 or 6. The application proceeds in three stages. First, students apply with up to 10 rank-ordered preferences over private schools.[17] Each parent identifies their village and are then given choices to rank schools as far as their "Extended Neighborhood" (adjacent villages of all adjacent villages), with a minimum number of three ranks.[18] Second, through an assignment mechanism, they are offered a single voucher to enroll in one of their ranked private schools. Third, they choose whether to enroll in this voucher school for free, pay out of pocket for a different private school, or enroll in a public school for free. Students apply in May during the summer break after academic year t and receive offers and enroll 1 month later in June of academic year $t + 1$.

The voucher assignment mechanism is Deferred Acceptance (DA), where students are prioritized by schools according to proximity. The mechanism is strategy-proof, incentivizing truthful reporting of rank-ordered lists (Abdulkadiroğlu and Sönmez 2003). There are three priority groups for student-school pairs: (1) the same village, (2) the same "Neighborhood" (the set of adjacent villages), and (3) the same "Extended Neighborhood" (the Neighborhood of the Neighborhood). During the DA assignment mechanism, if the number of students assigned to a school exceeds its capacity, these over-subscribed seats are randomly assigned to students with a single tie-breaker.

III. Data Description and Construction

Through independent partnerships, comprehensive administrative records were obtained on applications, student outcomes, and schools from the education departments in the Government of India and the state Government of MP. The MP data is new, capturing the universe of voucher applications, enrollment and achievement measures for every child (including those outside the voucher system), and annual private school tuition fees. These data are linked with unique student and school identifiers maintained by the state and national governments, respectively.

15. The poverty line is roughly the 30th percentile of annual household income: $1,130 (rural) or $1,310 (urban).
16. Parents submit credentials during the application process which are then reviewed by government officials and checked against administrative records.
17. Between 2013 and 2016, applications were filed using paper forms. Starting in 2016 applications were moved online, with offline applications still available for those without internet access. Paper forms are submitted to local block officers, who manually enter these applications in the main online portal.
18. In 2016, the year online application data begins, the minimum requirement was one rank instead of three.

III.A. Voucher Applications and Centralized Lotteries

Applications for vouchers are observed for academic years 2016-17 to 2018-19. These nearly 700,000 applications include up to 10 rank-ordered preferences across private schools for each applicant. Students' priorities relative to the schools ranked are also observed, which, together with each school's voucher capacity (25% of prior year's total enrollment), comprise all the information used in the voucher assignment mechanism. Finally, applications provide the name of students' home village, which are geocoded to compute school distances.

Figure AV presents statistics on submitted lists, offers, and takeup by year of application. A majority of applicants submit three ranked schools, the minimum number required, with considerable variation.[19] Roughly 90% of students win their first choice offer, while 10% win their second or lower choice offers. Submitted rankings are therefore high stakes and (because the mechanism is strategy-proof) assumed to be truthful. Indeed, those who win their top choice offer have a substantially higher probability enrolling in the school for which they were offered ("takeup"). The analysis below will exploit lottery variation in whether students' receive a top choice offer, which will serve as a power instrument for voucher takeup.[20]

III.B. Student Characteristics and Outcomes

Panel data on the characteristics and outcomes of every school-enrolled child in MP are observed, both applicants and non-applicants, from 2013 to 2018 for class 1 to 8. Characteristics include gender, caste, and poverty status. Outcomes include grade point average (GPA), class promotion, and enrollments (which school the child attends). This comprises the largest individual-level dataset on student outcomes in India, covering roughly 10 million children over 6 years.

GPA is computed using end-of-year exams administered by schools.[21] This averages across Math, Hindi, and (if offered) English. GPA is transformed to have mean zero and unit variance for each class and year. Importantly, GPA is not standard across schools – the only standardized exam scores available are at the school-level with coarse measures (i.e. fraction scoring above the 60th percentile) and only exists for class 5 and above. Figure AIII plots GPA against this standardized measure averaged at the school level. The correlation is high at 0.42, which suggests GPA may capture learning outcomes as opposed to curved grading within classes.

Finally, class promotion (grade promotion) is computed by tracking students' enrollment over time: whether or not students continue from class k in year t to class $k+1$ in year $t+1$. This provides an important extensive margin of educational performance that complements intensive margins such as exam scores or GPA.[22]

19. Some students may select fewer than three under either of two conditions: (1) they are applying in 2016, where the minimum was one rank or (2) there are fewer than three schools in their choice set.

20. There are very few applicants who are rejected from all their ranked choices, and thus receive no offers (3% of all applications). These students are not observed and are thus excluded from the analysis.

21. The department of education in Madhya Pradesh releases class-specific assessment tests for all teachers to use, but only public schools are mandated to use them.

22. Primary school promotion rates are lowest in the earliest years (roughly 85% among applicants in class 1 or below)

1. Data Availability. Voucher applications are linked to student outcomes for one to three years after application. This panel covers roughly 200,000 students (34% of all applicants). Because enrollment is only observed from classes 1 to 8, the individuals that are not observed are largely those in early classes (such as Nursery or KG) that do not enter class 1 by the year after application.

To assess differential attrition in the data, Table AIV reports summary statistics of applicant characteristics between all applicants and those for which either school enrollment or GPA outcomes is observed. We see that differences are small in student demographics such as gender, poverty status, and social caste categories. Observed students tend to have slightly higher rates of poverty and live in areas that are less urban, have lower private school market shares, and have lower average education expenditure. Differences are even smaller between observed enrollment and GPA groups. However, observed groups have a much higher share of early applicants in 2016 and smaller share of later applicants in 2018. They also have a lower share of nursery applicants and higher share of class 1 applicants. This is consistent with outcome data capturing those in later years, as opposed to selective reporting by student demographics.

III.C. School Characteristics

The Unified District Information System for Education (U-DISE), an annual census administered by the Government of India, collects hundreds of characteristics for more than 1.5 million registered schools in the country (U-DISE 2021). This includes a rich, high-dimensional panel from 2000 to 2015, including school inputs such as English instruction, playground access, number of teachers, number of computers, etc. Separately, precise locations of each school are scraped from an online web portal hosted by U-DISE – these are used together with applicant locations to impute kilometer distances between applicants and schools.

To validate this approach, Figure AIV plots the distribution of distances computed using the imputation method versus distances from the 75th round of the National Sample Survey (NSS), a representative sample of Indian families in 2018. The distribution of final enrollment distances imputed in the sample closely resembles that of the broader MP population.

Finally, data on private school prices (annual tuition fees for each school, class, and year) for classes 1-8 and academic years 2013-14 to 2018-19 is obtained from administrative data provided by the MP Government.[23] Figure AI presents the distribution of school-specific mean prices – the average annual tuition fee for each school across classes 1 to 8 and academic years 2016-17 to 2018-19, the rounds for which applications are observed.

and are substantially higher in later years (roughly 98% after class 1). Between class 1 and 8, more than 10% of students would have been held back at least once.

23. By law, Madhya Pradesh requires private schools to submit an annual registration in order to provide education services, which are audited by local offers. This includes the fee structure charged by schools, which must be the same for all students.

III.D. Summary of Data

Madhya Pradesh has a large and diverse education market, with more than 130,000 schools, 600,000 teachers, and 16 million students (U-DISE 2021). The primary school system (classes 1 to 5) comprises roughly 50% of the market, with nearly 8 million children. Table I reports summary statistics of primary students and schools across MP. Panel A reports mean characteristics across different subgroups of primary school students. Among those in class 1, one-fifth belong to families that are below the state's poverty line. Moreover, only 12% belong to the "upper-caste" General category and nearly half belong to "lower-caste" groups including Scheduled Castes (SC) and Scheduled Tribes (ST), with the remaining belonging to Other Backward Castes (OBC). Based on their residential area ("block"), these children live in blocks that are (on average) 38% urbanized, have a 34% private school market share, and pay $28 per year on tuition fees.

Across students, GPA is strongly correlated with socio-economic status (SES). Table AII presents OLS estimates of individual GPA on observables. Without additional controls, we see that: compared to males, females have 0.04σ higher GPA; compared to those above the poverty line, those below have 0.12σ lower GPA; and compared to general caste students, OBC, SC, and ST students have 0.24σ, 0.40σ, and 0.59σ lower GPA, respectively. After including granular fixed effects (including school, class, year, and religion) and lagged GPA, differences fall but remain large.[24]

Roughly 57% of class 1 students are eligible for the voucher policy (BPL or lower-caste). In comparison to the overall population, we see that those that are eligible have higher rates of poverty and are disproportionately lower-caste. In addition, these students live in blocks that are (on average) less urban, have lower private market share, spend less on education, and live in locations with a 0.15σ lower average GPA.

However, among those eligible, only 12.5% apply for vouchers, despite roughly 30% attending private school. Compared to those eligible and even others, applicants come from richer areas (more urban, higher private market share, higher education expenditure, higher GPAs), but have substantially higher rates of poverty (77% compared to 37% among those eligible and 21% overall). Applicants have a comparatively higher share of General caste students and comparatively lower share of ST students, the most historically disadvantaged group. This suggests that, among those eligible, the voucher program attracts applications from relatively low-income and upper-caste families in richer areas. When examining these characteristics for students in lower classes, the block-level differences are even starker. This is consistent with the theory that those who enroll in pre-school (such as Nursery or KG) come from more affluent areas.[25]

24. In subsequent analysis, SES is grouped using a combination of caste and poverty status: "low" (SC or ST and below the poverty line), "middle" (SC or ST and above the poverty line), and "high" (OBC or general caste). The groups are increasing in average GPA in Table AII and comprise roughly 25%, 25%, and 50% of applicants, respectively.

25. Romero and Singh 2022 find that in Chhattisgarh, a neighboring state to MP, voucher applicants also come from more affluent areas than the eligible population. However, the study's survey data finds that applicants come from families that are wealthier and more educated, while data from this paper suggests that applicants have higher rates of poverty. This may reflect differences in the policy implementation across states. Relative to Chhattisgarh, MP's voucher system is relatively more mature, with more than 5 times as many voucher applicants in aggregate, and 2 times more applications per capita.

Panel B reports summary statistics of public and private primary schools in MP. The private school market share sits at 35% in 2015, having undergone significant growth in the last two decades consistent with India broadly. On average, private schools are larger and better-equipped, with more teachers and facilities per student, and a much higher likelihood of offering English instruction. For class 1 students, this comes at price of roughly $53 (2019USD) per year on average, roughly 4% of the state's per-capita income. Figure AI reports the distribution of annual tuition fees across private schools in MP averaged across classes 1 to 8 from 2016 to 2018. We see a substantial dispersion in prices, with some schools charging as low as $20 per year and as much as $400, with a mean of $88. Meanwhile, the per-child cost in the public education system is roughly $74. Despite differences in resources, private schools operate with lower labor costs, with average teacher wages of $160 per year compared to $400 in the public school system. In addition, private schools are more likely to be located in blocks that are (on average) more urban, have higher private market share, spend more on education, and have higher GPAs.

Geographically, schools are located across rural and urban regions of the state. Figure AII plots public and private schools that teach class 1 across MP. The grey dots plot roughly 35,000 public schools; the black and red dots plot roughly 15,000 private schools; and the red dots plot roughly 13,000 private schools that receive at least 1 voucher application from 2016 to 2018. We see that public schools cover nearly every corner of the state. Private schools are more sparse, but cover both major cities (indicated by blue stars) as well as more remote areas. Most students in this setting thus face both public and private options. The voucher system, which is mandatory, attracts applications from nearly 90% of all private schools.

IV. The Effects of Voucher Takeup on Recipient Outcomes

Oversubscription lotteries in the assignment of vouchers provide random variation in whether applicants win their first choice offer. The analysis begins by estimating the effects of taking up the voucher, using first choice offers as an instrument for voucher takeup. This follows a large literature that uses lotteries generated by centralized assignment mechanisms to estimate the effects of school choice programs (Rouse 1998; Deming et al. 2014; Abdulkadiroğlu et al. 2017; Abdulkadiroğlu, Pathak, and Walters 2018). Because outcomes are observed for up to three years after treatment, this panel setting allows for estimation of the effects of voucher takeup pooled over all years as well as for each year after application.

Consider outcomes for applicant i in treatment period t years after application:

$$\begin{aligned} y_{it} &= \beta \text{Takeup}_{it} + R_{it}'\delta + X_i'\gamma + \epsilon_{it}, \\ \text{Takeup}_{it} &= \alpha \text{First Choice Offer}_i + R_{it}'\delta^{FS} + X_i'\gamma^{FS} + \epsilon_{it}^{FS}, \end{aligned} \tag{1}$$

where y_{it} is a student outcome in treatment period t (e.g. GPA, promotion, or enrolled school characteristics); Takeup_{it} is whether applicant i accepts their voucher offer, enrolling in the voucher

school in period t; First Choice Offer$_i$ is whether applicant i received a voucher offer for their first choice school; R_{it} is a vector of "lottery" fixed effects; and X_i is a vector of demographics.[26]

The lottery fixed effects R_{it} are narrow bins that allow comparisons between applicants who win versus lose lotteries for their (oversubscribed) first choice schools. Conditional on R_{it}, the instrument is exogenous and excluded: first choice voucher offers are randomly assigned via lotteries and only affect outcomes if students accept the offers.[27] Thus, estimates of β reflect the local average treatment effect (LATE) of voucher takeup (enrolling in a voucher school) on student outcome y pooled over all years after application. The LATE is the average treatment effect of voucher takeup for compliers: those who would accept the voucher if they received their first choice, but reject it if they received second or lower choices.[28] All estimates stack data across entry year cohorts (2016, 2017, and 2018).[29]

Because outcomes are observed for multiple years, the specification in equation (1) can be extended to estimate effects of voucher takeup for each year after treatment:

$$y_{it} = \sum_{\tau \in \{1,2,3\}} \beta_\tau \text{Takeup}_{i\tau} \times 1\{t = \tau\} + R'_{it}\delta + X'_i\gamma + \epsilon_{it}, \tag{2}$$

$$\text{Takeup}_{i\tau} \times 1\{t = \tau\} = \sum_{\tau \in \{1,2,3\}} \alpha_\tau \text{First Choice Offer}_i \times 1\{t = \tau\} + R'_{it}\delta^{FS} + X'_i\gamma^{FS} + \epsilon^{FS}_{it}.$$

Here, β_τ reflects the LATE of voucher takeup on student outcome y in year τ after application. In all specifications, controls R_{it} and X_i are fully interacted with treatment period τ.

IV.A. Estimation with Lottery Fixed Effects

There are two approaches to specifying the lottery fixed effects R_{it}. The first is "Full Conditioning" which bins students exactly into groups under which first choice offers are randomly assigned (i.e. the full rank-ordered list and corresponding priorities). Given the mechanism, this approach includes granular fixed effects for each {outcome year, entry year, entry class, first choice school, first choice priority, second choice school, second choice priority, ...} stratum. Two students in the same stratum have the same probability of winning their first choice school. Conditional on these fixed effects, the first choice offer instrument is randomly assigned.

The second is the "DA p-Score" approach that exploits propensity scores of first choice assignment π_{ij_1} given the DA mechanism. This approach, developed by Abdulkadiroğlu et al. 2017, leverages lotteries in school assignments that occur both across and within the fully conditioned

26. Demographic controls include fixed effects for observed student characteristics (poverty status by caste by religion by gender; birth year; and village cluster).

27. Because there is two-sided non-compliance, the monotonicity assumption is that there are no *deniers*: those who would accept their offer if they won their second or worse choice but reject their offer if they won their first choice.

28. Alternatively, the reduced-form effects of winning a first choice voucher offer are reported in Table AVII. As expected, the effects are scaled down in magnitude but qualitatively similar.

29. This results in a sample of more than 100,000 observations (depending on the outcomes), after excluding those who submit at least two choices and are thus exposed to first-choice randomization. These one-rank students are common in 2016 as there was no minimum number of choices required. In 2017, the minimum was set to three choices.

strata.[30] Two students with the same first choice propensity score π_{ij_1} have the same probability of winning their first choice offer. Conditional on these (coarser) propensity scores for each round of the lottery, first choice offers are randomly assigned (Rosenbaum and Rubin 1983). Thus, this approach includes fixed effects for each {outcome year, entry year, entry class, π_{ij_1t}} stratum and each first choice school.

Given the observed applicant rankings and school capacities, propensity scores can be estimated for each applicant-school pair π_{ij} by simulating the DA assignment mechanism 10,000 times. Figure AVII plots estimated propensity scores (rounded to 0.001) against observed probabilities of assignment, with a strong correlation of 0.90 and slope of 0.97. Table AVI shows balance across individual characteristics between winning and losing first choice offers after including both types of lottery fixed effects. After either full or DA p-Score conditioning, differences shrink and become statistically insignificant. The DA p-Score approach has considerably more power, with a third the number of fixed effects used in the estimation.

Because the effects are estimated using first-choice winners versus losers for each propensity score, only "non-degenerate" propensity scores strictly between 0 and 1 are used for estimation. Table AV reports characteristics of schools depending on their application and lottery status. We see that out of nearly 26,000 private primary schools in MP, nearly 20,000 of them receive at least one voucher application, and roughly 11,000 are non-degenerate. Both application and non-degenerate groups cover the vast majority of the state's roughly 300 blocks. Compared to all schools, those who receive voucher applications tend to be younger, slightly better resourced, more expensive, and are located in slightly higher achieving blocks. Similarly, compared to all schools applied, those that are non-degenerate are more likely to offer English and charge higher fees, and are located in blocks that are more urban, have higher private market share, and are higher achieving. While the set of non-degenerate schools is large and diverse – covering a majority of blocks, roughly half the schools, and 80% of applications – LATE estimates are interpreted as relative to these schools and not all schools. After these restrictions, the estimation sample over all years after application comprises roughly 80,000 to 140,000 student-year observations depending on the outcome variable.

IV.B. Results

Table II reports first-stage estimates of the effect of winning a first choice voucher offer on voucher takeup for each year after application and overall, conditioning on the preferred DA p-Score lottery fixed effects. The instrument is strong, delivering a 33 percentage point (pp) increase in takeup over all rounds. The first choice offer instrument is notably weaker in the third year after application, increasing takeup by 17pp. In 2016, the entry year cohort for which three-year effects can be

30. Consider students 1, 2, 3, and 4 and schools A, B, and C with capacities 2, 1, and 1. Preferences are: $A \succ_1 B \succ_1 \emptyset$, $A \succ_2 \emptyset$, $B \succ_3 A \succ_3 \emptyset$, $A \succ_4 C \succ_4 \emptyset$. Student 3 has priority at A and student 1 has priority at B, all others are tied. All students first propose their top choice. Because 1, 2, and 4 are tied for A, they enter into a lottery with 2/3 probability of tentatively winning. If 1 loses A, then she wins B as she has priority over 3, who will win A because she has priority over 2 and 4. Then, 2 and 4 will enter into a lottery for the remaining seat with probability 1/2 each. Thus, we have the following top-choice propensity scores: $\pi_{1A} = \pi_{3B} = 2/3, \pi_{2A} = \pi 4A = 1/2$. Full conditioning would include zero students, but simply top choice and top priority would incorrectly pool 1, 2, and 4 (Narita 2020).

estimated, the application system allowed students to submit a single school. Thus, for this year, the effect reflects selection in who submitted more than one choice. This may reduce the effect of winning a first choice offer on takeup because those who submit more than one choice may have weaker preferences for their first choice school.

Table III reports LATE estimates of voucher takeup on various outcomes for each year after application and overall, compared to the Control Complier Mean (CCM).[31] Panel A reports estimates on the two proxies for student achievement: class promotion and school GPA. We see that the effect of voucher takeup on class promotion is roughly 3.3pp in the first year (stat. insig.), 3.9pp in the second year (stat. sig.), and 0pp in the third year (stat insig.). Overall, voucher takeup increases class promotion by 3.3pp over all years, statistically significant at the 5% level. This effect is meaningful, closing the promotion gap among control compliers by roughly 25%. For student GPA, we see increases of 0.04σ in the first year after voucher takeup (stat. insig.), 0.23σ two years after (stat. sig.), and 0.43σ three years after (stat. insig.). Overall, voucher takeup increases GPA by 0.17σ pooled over all years, statistically significant at the 1% level.[32]

These effects on proxies of student achievement are qualitatively similar to prior and ongoing work on voucher effectiveness in developing countries. For test scores, Angrist et al. 2002 study voucher policy in Colombia and find that vouchers increase standardized test scores by 0.20σ. Muralidharan and Sundararaman 2015 study a voucher experiment in south India and find no changes in test scores from vouchers, but note that private schools have lower per-student costs. For class promotion, Angrist et al. 2002 find increases of 5-6pp.

In ongoing work in India, Damera 2017, Dongre, Sarin, and Singhal 2019, and Romero and Singh 2022 collect survey data to compare lottery winners and losers in the states of Gujarat, Karnataka, and Chhattisgarh, respectively. Compared to Madhya Pradesh, these voucher systems are in relatively early stages – the largest, Karnataka, has 40% fewer voucher enrollments (Indus Action 2021). Damera 2017 finds effects of 0.11σ on test scores of girls (no effects for boys). Romero and Singh 2022 finds effects of 0.19σ on standardized test scores during COVID-19, potentially reflecting differences in access to virtual learning between public and private schools. The three studies do not evaluate effects over time or impacts to class promotion (due to lack of panel data).

Panel B of Table III reports LATE estimates of voucher takeup on school characteristics. Pooling over all years, takeup increases access to private school by 12pp (stat. sig.), compared to a control complier mean of 88pp. This suggests that a majority of first-choice compliers would have enrolled private school if they had not received a voucher. This is also consistent with prior voucher studies in India (Damera 2017; Dongre, Sarin, and Singhal 2019; Romero and Singh 2022), which find effects of 7pp–12pp on private school enrollment. This indicates that many applicants are inframarginal to private school choice, consistent with selection in application.

31. The CCM is computed by subtracting the LATE estimate from the mean outcome of takers: those that win first choice offers and takeup their voucher offer.

32. Alternatively, the reduced-form effects of winning a first choice voucher offer are reported in Table AVII. As expected, the effects are scaled down in magnitude but qualitatively similar. For robustness, Table AVIII reports LATE estimates across specifications depending on additional controls and type of lottery fixed effects. As expected, estimates are qualitatively similar, but have greater precision under the DA p-Score approach compared to full conditioning.

Next, we see that takeup increases access to schools that offer English by 9pp and have 0.06σ higher GPA value-added, and decrease distance traveled by 0.4 kilometers.[33] Thus, by enabling access to more preferred schools, vouchers may deliver a larger vector of output than achievement alone. Indeed, Damera 2017 finds that while vouchers in Karnataka, India do not improve test score measures overall, they improve measures of self-efficacy by 0.11σ. Consistent with this, Miller 2022 finds that private schools in India may increase self-efficacy and self-esteem.

Finally, voucher takeup dramatically reduces tuition fees paid by nearly $80 per year. This reduction in expenses amounts to roughly 6% of household income at the state's poverty line. This is consistent with applicants selecting private schools counterfactually, and thus incurring substantial cost savings by availing vouchers.

Overall, these lottery results suggest that vouchers enable students to move from less preferred schools at cost to more preferred schools for free. This delivers academic gains through cognitive and non-cognitive benefits of enrolling in preferred schools, but also non-trivial financial benefits through avoiding tuition fees otherwise paid. Using a revealed preference approach, the demand framework developed below is able to aggregate across these multiple dimensions of impact.

Patterns of heterogeneity are intuitive. Appendix AIII. shows that academic gains are concentrated in poorer markets (proxied by education spending) who are more likely to attend lower quality public schools absent the voucher. Meanwhile, financial gains are concentrated in richer markets who are more likely attend expensive private schools, and thus avoid tuition spending.

However, beyond recipients, the voucher policy may also have aggregate impacts through equilibrium responses of schools. Indeed, the policy's design provides voucher payments to schools that are tied to their tuition fees. We next turn to reduced-form evidence on how the policy, and this particular feature of its design, may affect private school behavior.

V. The Effects of the Voucher Policy on School Behavior

Because of the voucher's payment design, there is potential scope for private schools to strategically respond by adjusting the tuition fees they charge or the quality they provide. In particular, for each voucher student, private schools receive reimbursements equal to their tuition fees up to a voucher cap of roughly $74. Figure AI shows that many schools have tuition fees that are below and above this cap. This offers a natural experiment in design: schools below the cap face a voucher equal to their tuition levels, while those above the cap face a "flat" voucher regardless of their price. This allows us to study how schools may respond depending on what design they face.

The analysis exploits the voucher policy's rollout over time to estimate the effects of voucher applications on school behavior. In 2015, the program was expanded to students under six years old. In 2016, an online portal was introduced that centrally collected applications and assigned vouchers.[34] Figure Ia shows how the number of voucher applications increased by over 15% from

33. School-specific value-added is estimated using individual-level panel data on GPA. See Appendix AII. for details on value-added estimation and Appendix AII.B. for tests of forecast unbiasedness using voucher lotteries.

34. Prior to 2016, applications had to be filled out on paper forms and submitted to offers at local "block" headquarters,

2014 to 2015 when the age minimum was changed and over 30% from 2015 to 2016 after launching the online portal. This growth in applications occurred unequally across regions of the state, motivating a difference-in-differences analysis of this policy variation.

An instrument is developed that exploits variation in regions ("blocks") that were at greater versus lower exposure to these policy changes. A candidate instrument is the fraction of voucher-eligible students in each block that were enrolled in private school before the policy changes. These students – who are already in private school and eligible for vouchers – are greatly incentivized to apply and may thus respond disproportionately to the policy changes. This private share of eligible students *ex ante* is used as an instrument for the volume of voucher applications in a "fuzzy" difference-in-differences (DID) specification:

$$\begin{aligned} y_{jbt} &= \beta \text{App}_{bt} + \eta_{jb} + \delta_t + \epsilon_{jbt}, \\ \text{App}_{bt} &= \alpha z_b \times 1\{t > 2014\} + \eta_{jb}^{FS} + \delta_t^{FS} + \epsilon_{jbt}^{FS}, \end{aligned} \tag{3}$$

where y_{jbt} is an outcome for school j in block b in year t; App_{bt} is number of voucher applications in school j's block in year t; z_b is the share of voucher eligible students who enroll in private schools in 2014, before the policy changes; and η and δ are unit and year fixed effects. Estimates of β capture the effect of additional voucher applications in a block on school outcomes.

Importantly, we can estimate how the voucher policy affects school decisions, depending on whether their tuition fees are below or above the voucher cap (and thus, what design they face). To assess the role of this payment structure, the specification in equation (3) is estimated for narrow ($10-width) bins of *ex ante* prices in 2014. This allows estimation of β across the distribution of school prices, both below and above the voucher cap.

In this approach, both the first stage and reduced form are DID specifications with continuous treatment (z_b) in a single period (post 2014). The common trends assumption is, within tuition fee bins, trends in both applications and outcomes are parallel across instrument doses of z_b. Because there were no changes to the application system prior to 2015, we may expect this to hold.[35]

Outcomes include price and quality margins that are observed and that schools can adjust: sticker prices, teacher hiring, and entry/exit decisions. To measure downstream consequences of these adjustments, effects on schools' mean indirect utility (estimated from the demand model below) and school GPA value-added are also estimated.[36]

after which vouchers were assigned. After, while a majority of applications were submitted online, the government had a mechanism in place for those who could not access internet to submit paper forms to local officials as were done previously. The local officials would then manually upload materials to the online system.

35. Note that if z_b were binary-valued, the 2SLS estimator of equation (3) is equivalent to the 2 group 2 period "Wald DID" estimator presented in Chaisemartin and D'HaultfŒuille 2017, with additional fixed effects for the school, year, and tuition fee bin. This fuzzy design requires additional assumptions including stable treatment levels for the control group and stable treatment effects over time (conditional on the fixed effects). As reported in Figure AX, estimates are qualitatively robust to (1) several binary versions of z_b and (2) an alternative exposure variable: the average distance between schools and block headquarters where applications were filed. The preferred exposure variable z_b delivers the largest first-stage.

36. See Section VI.A. for details on estimating mean indirect utility. School and time varying value-added is estimated using individual-level panel data on GPA. See Appendix AII. for details on value-added estimation and Appendix AII.B.

V.A. Results

To provide intuition, Figure Ib shows the reduced form effect on school tuition fees for those in the modal 2014 price bin ($54-64) using a discrete version of the instrument. Compared to areas that had below-median exposure in 2014, above-median areas exhibited price increases that occurred after the policy changes in 2015 and 2016 but not before. Importantly, trends (and levels) are similar between above- and below-median areas *ex ante*.[37] Overall, this suggests that these schools responded to increased voucher applications by raising their tuition.

Figure II plots estimates of β, the (re-scaled) effect of 1,000 additional voucher applications on school tuition fees, for each bin of prices in 2014. We see that effects are larger and positive for schools that were priced *below* the voucher cap in 2014 and smaller or zero for those above. For example, those whose 2014 prices were less than $34 raise their sticker prices by roughly 15% for every 1,000 additional applications in their block. This effect falls steadily for larger 2014 price bins, but falls sharply between the bin immediately below versus above the voucher cap, where schools no longer face vouchers linked to their tuition levels. The effects remain small and statistically insignificant until the largest price bin of >$124. This estimate is small, at roughly 2% of mean prices compared to 15% for the smallest price bin.

This response is qualitatively robust to (1) several binary versions of z_b and (2) an alternative exposure variable: the average distance between schools and block headquarters where applications are filed by paper. Across all specifications, estimates in Figure AX show an increase in prices for schools below the cap and a near zero response above the cap. The preferred exposure variable z_b delivers the largest first-stage.

In addition to effects on prices, schools also respond to the voucher policy by modestly adjusting quality. Table AX reports estimates by 2014 price bins across several measures of private school quality. We see that effects on prices are large and statistically significant, while effects on quality outcomes are modest and marginally statistically significant. Pooling across bins, for those below the cap, we see that an additional 1,000 voucher applications in a school's block increases schools' GPA value-added by 0.03σ (stat. sig. at the 10% level), teachers per 10 pupils by 0.16 (stat. insig.), school mean utility by 0.87% (stat. sig. at the 10% level), and exit rates by 0.25pp (stat. insig.). For those above the cap, the effects are -0.01σ, -0.10, 0.35%, and 0.52pp (all stat. insig.), respectively.[38]

In contrast to private schools, public schools in India face little threat of shut down and teachers have strong unions and tenure protection. Consequently, there is little incentive to adjust in response to competition. Table AXI presents analogous DID results on public school outcomes,

for tests of forecast unbiasedness using voucher lotteries.

37. Figure AIX shows the first-stage effect of exposure on the number of applications, which depicts a similar relationship of parallel trends before the policy changes and greater increases in application volume for the above-median exposure group after the policy changes.

38. The analysis is restricted to schools who exist in 2014 (and can be assigned to 2014 price bins). Thus, we cannot use school-specific data to examine effects on entry. Table AXII reports results from an analogous difference-in-differences analysis on village-level aggregate school counts, by bins of average village prices in 2014. While there is some evidence of reduced private school entry for villages in the 10th decile of mean prices, there is limited evidence overall of impacts on net entrants for either private or public schools.

for bins of distance to the nearest private school. There is little evidence of the policy's effect on public school entry, exit, or quality measures. This is particularly true for those closer to private schools that would presumably face greater competition from the voucher program. This is consistent with work in similar contexts that documents poor government school incentives and limited response to private entry (Duflo, Hanna, and Ryan 2012; Bau 2022).

Overall, these empirical findings are consistent with private schools raising prices and modestly upgrading quality below the cap, where they face a tuition-linked voucher, but limited adjustment above, where they face a flat voucher. This has two important implications. First, because the market has a high private school market share, these adjustments have the potential to impact millions of students who do not receive vouchers. This raises questions on whether the benefits to recipients documented above are potentially outweighed by consequences to non-recipients, and how these impacts to students weigh against government costs and school profit. Second, the asymmetry in school responses below versus above the cap suggests the policy's payment design is responsible for how the schools choose to adjust, and the downstream consequences of these adjustments. To the extent alternative designs would change these effects is unclear.

To this end, the paper next develops a framework of supply and demand to (1) quantify the total surplus generated by the voucher system across the education market; and (2) examine how this surplus changes if school adjustment were ignored and in response to different voucher designs.

VI. Demand and Supply in the Education Market

In order to quantify how various voucher designs would affect school behavior and student enrollments, we require a tractable model of demand and supply for education. The model captures several considerations of both students and schools. For students, this includes whether to apply for vouchers, forming expectations of offer probabilities within a deferred acceptance assignment mechanism, and the decision of which schools to attend. For schools, they strategically set price and quality with knowledge of multiple channels through which these choices affect enrollment.[39] This includes how their actions may affect enrollment directly, but also indirectly through changes in application behavior and voucher assignment probabilities.

The framework builds upon a growing literature that estimates empirical models of demand and supply to study education policy (Allende 2019; Barahona, Dobbin, and Otero 2021; Dinerstein, Neilson, and Otero 2022; Dinerstein and Smith 2021; Neilson 2021). The models are adapted in order to accommodate and leverage unique features of this setting that allow for identification of model parameters. A stylized version of the demand model is first introduced for illustration, followed by a detailed parametrization of the full model. Then, a supply-side model is introduced which endogenizes price and quality decisions given demand.

39. Public schools are assumed non-strategic. Government schools in India face little threat of shut down and teachers are unionized with strong tenure protection. This administrative structure is consistent with work in similar contexts (Duflo, Hanna, and Ryan 2012; Bau 2022). As presented in Table AXI, there is little evidence of the policy's effect on public school behavior.

Students are denoted by i, schools are denoted by j, and years are denoted by t. Schools are divided into a set of markets denoted by m. In these markets – or choice sets – students have choice over schools and schools face competition with each other. Markets $m(i,t)$ and $m(j,t)$ denote those within which student i and school j belong in year t.

VI.A. Demand Framework

Consider first a stylized version of student i's utility u_{ijt} for enrolling in school j in year t, that depends on prices, proximity, a vertical quality measure, and idiosyncratic preferences:

$$u_{ij} = \alpha_i p_{ijt} + \lambda_i D_{ij} + \delta_{jt} + \epsilon_{ijt}, \tag{4}$$

where price p_{ijt} denotes the annual tuition fee student i pays to enroll in school j (USD); D_{ij} captures the (log) distance between i's residence and school j (KM); δ_{jt} captures school j's mean indirect utility in year t (a vertical quality measure fixed across students including school/teacher value-added, curriculum, facilities, etc.); and ϵ_{ijt} represent idiosyncratic or "match" preferences of student i for school j in year t.

The relative magnitudes of parameters δ_{jt}, α_i, and λ_i reflect trade-offs students make when choosing between school-specific preferences, proximity, and prices. Importantly, α_i captures how sensitive students are to school tuition fees. By comparing other parameters to α_i, we can estimate how studens' value other characteristics in terms of dollars. For example, λ_i/α_i reflects the willingness-to-pay (WTP) in dollars for a 1 log reduction in distance to school.

Importantly, prices are student-specific and depend on voucher offers:

$$p_{ijt} = p_{jt} \cdot (1 - v_{ijt}), \tag{5}$$

where p_{jt} is the sticker price charged by school j in year t (zero for public schools); and v_{ijt} is 1 if student i receives a voucher offer to enroll in school j in year t and 0 otherwise.

When making binary school enrollment decisions $e_{ijt} \in \{0,1\}$, students choose schools in their choice sets $m(i,t)$ to maximize utility:

$$e_{ijt} = 1\left\{ j = \underset{j' \in m(i,t)}{\text{argmax}}\, u_{ij't} \right\}. \tag{6}$$

Given the institutional setting, students can freely choose any school to enroll as long as they can pay tuition fees (for private schools) or are within reasonable proximity (for public schools).[40]

We next turn to how vouchers affect student welfare through the lens of this stylized model.

40. By law, both public and private schools cannot selectively admit students. Anecdotal evidence suggests this is true in practice, with few schools selecting students due to other criteria, such as student achievement or capacity constraints.

1. The Effects of Voucher Takeup on Recipient Welfare. Suppose student i takes her voucher offer for school j_1 at zero price, earning utility $\tilde{u}_{ij_1t}$. Absent the voucher, she would have enrolled in some counterfactual non-voucher option j_0 at its sticker price p_{j_0t}, earning utility u_{ij_0t}. The impact of voucher takeup on consumer welfare is thus the difference in these utilities:[41]

$$\tilde{u}_{ij_1t} - u_{ij_0t} = \underbrace{-\alpha_i p_{j_0t}}_{\text{Monetary}} + \underbrace{(\lambda_i(D_{ij_1} - D_{ij_0}) + \delta_{j_1t} - \delta_{j_0t})}_{\text{Non-Monetary}} + \underbrace{(\epsilon_{ij_1t} - \epsilon_{ij_0t})}_{\text{Match}}. \tag{7}$$

This welfare effect accounts for multiple dimensions of how vouchers may benefit recipients.[42] The "monetary" component captures how students avoid paying tuition fees for their outside option p_{j_0t}. If students' outside options are expensive private schools, the voucher may deliver large welfare gains by defraying this expenditure for families. Meanwhile, if students would have enrolled in public schools absent the voucher, the welfare impacts would be purely non-monetary.

The "non-monetary" component captures how vouchers enable students to sort to more preferred schools. Changes in δ_{jt} reflect impacts to all dimensions of school preferences that are fixed across students. This may include quality of instruction (e.g. value-added or class size), type of curriculum (e.g. English instruction), or access to resources (e.g. textbooks or computers). Changes in D_{ij} capture the utility impacts of changing proximity to school.

Lastly, the "match" component captures changes in idiosyncratic preferences for optimal schools under the subsidy. While price subsidies weakly increase the value of enrolling in any particular school overall, they may induce distortions by giving students an incentive to enroll in schools they would otherwise not attend. Thus, changes in ϵ_{ijt} capture any distortion in individual preferences that may occur from offering a price subsidy.

This decomposition clarifies the potential impacts of vouchers on recipients' welfare. For example, examining lottery results on achievement (e.g. standardized exams or GPA) captures how vouchers may move students from low to high value-added schools. This is akin to focusing on a single component of δ_{jt}, potentially missing monetary or other non-monetary impacts. Finally, by dividing both sides by α_i, we can compute a money-metric version of welfare, which provides an estimate of the total consumer surplus earned for each student.

This stylized school choice model captures how vouchers impact students conditional on receiving them. Voucher receipt itself is an endogenous outcome, which depends on the decision students make to apply for vouchers and what rank-ordered lists they submit during the application. The model is thus expanded to incorporate these additional decisions students face, thereby endogenizing voucher applications and offers.

41. See Appendix AIV. for details.

42. Because these students are children entering primary school, financial decision makers in the household are likely to be caregivers and not students themselves. Thus, the model may be interpreted as capturing parental or familial welfare. To the extent student utility enters the family's utility optimization, estimates of student-specific welfare may either be smaller or larger. Importantly, absent students themselves making financial decisions, such an estimate is infeasible to compute. Alternatively, absent long-run labor market outcomes, an analysis focused exclusively on achievement outcomes such as test scores may miss other dimensions of student welfare and prohibits a calculation of benefit-cost ratios.

2. Model. The model proceeds in three stages: (1) eligible students choose whether to apply for vouchers given application costs and projected offer probabilities; (2) conditional on applying, they then submit rank-ordered lists over private schools as a part of the voucher application; (3) finally, eligible students' voucher offers are realized given the DA mechanism and they then choose, along with ineligible students, in which to schools to enroll. Stages are described in reverse.

i. Enrollment Stage. At the enrollment stage, vouchers offers v_{ijt} are realized (non-applicants receive zero offers by default) and students receive utility u^e_{ijt} from enrolling in school j in year t:

$$u^e_{ijt} = \alpha_i p_{ijt} + \lambda_i D_{ij} + \delta_{jt} + \epsilon^e_{ijt}, \tag{8}$$

where prices p_{ijt} depend on voucher offers v_{ijt} and sticker prices p_{jt}:

$$p_{ijt} = p_{jt} \cdot (1 - v_{ijt}). \tag{9}$$

Students choose the school j in their choice set $m(i,t)$ that maximizes utility:

$$e_{ijt} = 1\left\{ j = \underset{j' \in m(i,t)}{\text{argmax}}\ u_{ij't} \right\}. \tag{10}$$

ii. Ranking Stage. When ranking schools for the voucher application, utility $\tilde{u}^r_{ijt}$ for student i to enroll in school j in year t is composed only of non-price components of private schools, as these ranks are made assuming students will win a voucher and thus face a zero price:

$$\tilde{u}^r_{ijt} = \lambda_i D_{ij} + \delta_{jt} + \epsilon^r_{ijt}. \tag{11}$$

Because the DA mechanism is strategy-proof (Abdulkadiroğlu and Sönmez 2003), students are assumed to submit truthful rank-ordered lists R_{it} over private schools in i's market $m^{\text{Priv}}(i,t)$:[43]

$$R_{it} = \left\{ j_k \in m^{\text{Priv}}(i,t) : \tilde{u}^r_{ij_1t} > \cdots > \tilde{u}^r_{ij_{10}t} \right\}. \tag{12}$$

Once ranks are submitted, the assignment mechanism determines voucher offer draws:

$$v_{ijt} \sim \text{Bernoulli}(q^o_{ijt}(\theta, \epsilon^r_t)), \tag{13}$$

where $q^o_{ijt}(\theta, \epsilon^r_t)$ is the probability of student i winning a voucher offer at school j in year t. This depends on utility parameters θ and unobservables $\epsilon^r_t = \{\epsilon^r_{ijt}\}$. This is precisely the DA propensity score, determined by the ranks and priorities of all students together with school capacities.

43. Lists are required to be ten or less schools. There is little concern for list-length restrictions affecting truthful reporting as more than 99% of applicants rank less than ten private schools.

iii. Application Stage. Eligible students choose to apply for vouchers if the returns to applying exceed application costs. To compute expected returns, students consider their rank-ordered lists of private schools and project the expected value of applying using offer probabilities of each rank given the DA mechanism. This is then compared to the value of the non-voucher option, the highest utility school at market prices. Application costs are heterogeneous, and depend on student observables and an unobserved shock.

At the application stage, eligible student i has utility u^a_{ijt} for enrolling in school j in year t:

$$u^a_{ijt} = \alpha^x_i p_{jt} + \lambda_i D_{ij} + \delta_{jt} + \epsilon^a_{ijt}. \tag{14}$$

where α^x_i is the component of α_i that depends on observables.[44] When considering application, students form hypothetical rankings R^a_{it} over private schools based on non-price utility $\tilde{u}^a_{ijt}$:

$$\tilde{u}^a_{ijt} = \delta_{jt} + \lambda_i D_{ij} + \epsilon^a_{ijt}, \tag{15}$$

$$R^a_{it} = \left\{ j_k \in m^{\text{Priv}}(i,t) : \tilde{u}^a_{ij_1t} > \cdots > \tilde{u}^a_{ij_{10}t} \right\}. \tag{16}$$

Regardless of the offer student i receives, they may reject it in favor of another school without an offer. This non-voucher option j_0 is the highest utility school at sticker prices in year t:

$$u^a_{ij_0t} = \max_{j \in m(i,t)} u^a_{ijt}. \tag{17}$$

They then calculate the expected returns of applying had they submitted the hypothetical rankings:

$$\Delta_{it}(\theta, \epsilon^a_t) = \sum_{j_k \in R^a_{it}} q^o_{ij_kt}(\theta, \epsilon^a_t) \max(\tilde{u}^a_{ij_kt}, u^a_{ij_0t}) - u^a_{ij_0t}, \tag{18}$$

where $q^o_{ij_kt}(\theta, \epsilon^a_i)$ is the offer probability using application-stage utilities, determined by the ranks and priorities of all students together with school capacities. The first term on the right-hand side of equation (18) is the expected value conditional on applying: the max term reflects that at each rank, students may reject their offer j_k in favor of the non-voucher option j_0. The second term is the value of not applying (the non-voucher option).

Finally, an eligible student i applies for a voucher in year t if the expected return from applying Δ_{it} exceeds application costs τ_{it}:

$$a_{it} = 1\{\Delta_{it}(\theta, \epsilon^a_t) > \tau_{it}\}. \tag{19}$$

44. Taste heterogeneity for prices is parametrized below as:

$$\alpha_i = X_i' \alpha_x + \nu_i,$$

where X_i is a vector of observables and ν_i is a random unobservable. Thus, in the application stage, $\alpha^x_i = X_i' \alpha_x$, the fixed component of α_i. This assumes there is no selection into application based on unobserved price heterogeneity, which allows for a tractable, separate estimation of taste and application parameters below.

iv. Heterogeneity. The demand system accommodates rich observed and unobserved preference heterogeneity (Berry, Levinsohn, and Pakes 1995). Tastes for price and distance parameters are time-invariant, but allowed to vary along a rich vector of student demographics X_i. In addition, there is unobserved heterogeneity in the price coefficient:

$$\alpha_i = X_i'\alpha_x + \nu_i, \tag{20}$$

$$\lambda_i = X_i'\lambda_x, \tag{21}$$

where $\nu_i \sim N(0, \sigma_\alpha)$ and is independent of other unobservables. The vector X_i includes three indicators of socio-economic status (SES). First, an indicator of household SES, by partitioning poverty status and social caste into three groups: low – Below Poverty Line and Lower Caste (SC or ST), middle – Above Poverty Line and Lower Caste, and high – Upper Caste (OBC or General).[45] Second, an indicator for gender. Third, an indicator for an observed applicant vs. non-applicant.

Application costs τ_{it} have heterogeneity along individual demographics W_{it}, an exogenous cost shifter Z_i, and an unobserved cost shock κ_{it}:

$$\tau_{it} = W_{it}'\tau_w + \tau_z Z_i + \kappa_{it}, \tag{22}$$

where $\kappa_{it} \sim$ Logistic and is independent of all other unobservables. The vector W_{it} includes SES, gender, and market-by-year fixed effects; and Z_i is the distance between i and the nearest application office (block center). Prior to 2016, applicants were required to verify credentials and submit forms by visiting regional offices. In 2016 the system was moved online but offices remained available for those without internet access. The distance to the office Z_i thus serves as a shifter of application costs that is excluded from the ranking and enrollment decisions.[46]

v. Persistence. Because the observed takeup of voucher offers is high (70% for first-choice offers), it is important to capture persistence in idiosyncratic preferences for schools between the stages. To do so, idiosyncratic terms in each stage are parametrized as follows:

$$\begin{aligned} \epsilon^a_{ijt} &= \eta^a_{ijt}, \\ \epsilon^r_{ijt} &= \psi_{ijt} + \eta^r_{ijt}, \\ \epsilon^e_{ijt} &= \bar{q}^o_{ijt}(\theta, \epsilon^r_t)'\phi + \psi_{ijt} + \eta^e_{ijt}. \end{aligned} \tag{23}$$

where $\bar{q}^o_{ijt}(\theta, \epsilon^r_t)$ is the observed offer probability (DA propensity score) for student i receiving a voucher offer for school j in year t; and $\psi_{ijt}, \eta^a_{ijt}, \eta^r_{ijt}, \eta^e_{ijt}$ are independent T1EV draws. The final

45. These groupings are chosen to be parsimonious but also useful in capturing variation in social and economic advantage. Table AII reports OLS estimates of GPA on student demographics, which shows low, middle, and high SES students have increasing levels of GPA, even with restrictive fixed effects and controls for lagged test scores. The groups contain roughly 25%, 25%, and 50% of students respectively.

46. The Z_i captures one dimension of application costs, a distance penalty, that is observable in the data. Counterfactuals will assess how removing this distance penalty would impact equilibrium outcomes.

unobservables η^a, η^r, η^e have scale parameter 1 and the persistent term ψ has unknown scale β_ψ.

Idiosyncratic preferences from ranking ϵ^r to enrollment ϵ^e are correlated via two channels: (1) through ψ, a persistent preference shock; and (2) through $\bar{q}^o(\theta, \epsilon^r_t)$, which is a direct function of utilities at the ranking stage. This propensity score $\bar{q}^o$ is a specific function of the observed rankings and parameters of the DA acceptance mechanism (e.g. school capacities), entering into ϵ^e as a fixed effect.[47] The reason for its inclusion is to capture additional persistence from ranking to enrollment and to provide identification of the price coefficient, discussed in detail below.

Given these assumptions, the timing can be interpreted as follows. First, before applying, students draw unobserved application costs κ and an idiosyncratic preference shock η^a. They then make application decisions. Second, they draw new preference shocks ψ, η^r, of which ψ carries on into the enrollment stage. They then submit rank-ordered lists to the voucher assignment mechanism. Third, voucher offers v are drawn from the mechanism and students draw an unobserved taste shock for prices ν and a final preference shock η^e. They then make enrollment decisions.

Finally, because unobservables at the application stage are uncorrelated with those at future stages, selection into application is random conditional on observables. This assumption is justified on the following grounds: (1) to apply, families must procure government documents (caste and poverty certifications) well in advance to prove eligibility, such that the application decision is made months before rankings are submitted; (2) a rich vector of observables are included (via W_{it}) to capture selection on intuitive dimensions (e.g. individual and geographic characteristics). This assumption enables a tractable estimation procedure described below: in the first step, tastes are estimated using the ranking and enrollment decisions; in the second step, application costs are estimated using application decisions and the previously estimated taste parameters.

3. Estimation. Parameters of the demand system include tastes θ (coefficients on price and distance; school-specific intercepts; fixed effects for the propensity scores; and variance parameters of the random terms) and application costs τ:

$$\begin{aligned} \theta &= \left\{\alpha_x, \lambda_x, \{\delta_{jt}\}, \phi, \sigma_\alpha, \beta_\psi\right\}, \\ \tau &= \{\tau_w, \tau_z\}. \end{aligned} \tag{24}$$

Estimation proceeds in two steps. In the first step, taste parameters θ are estimated using the two sets of rich choice data: (1) rank-ordered lists over private schools submitted by voucher applicants and (2) final enrollment decisions of voucher applicants and non-applicants. In the second step, data on eligible students' decisions to apply together with taste estimates $\hat{\theta}$ enables estimation of application costs τ.

47. Note that this function $\bar{q}^o$ corresponds to the *observed* propensity scores – the offer probabilities given the distribution of rankings and capacities observed in the data. This is in contrast to the general q^o function which is defined for any given application environment. In counterfactuals, the set of rankings may endogenously change, affecting the application decisions and final offer probabilities by changing expected and realized competition for voucher seats. However, the function $\bar{q}^o$ in ϵ^e will remain unchanged.

Parameters are estimated by maximum simulated likelihood (MSL). We can write the conditional likelihood of the data given parameters and unobservable draws, and then integrate over the draws to find the unconditional likelihood.[48] This unconditional likelihood is estimated with simulation over 300 draws of the unobservables, and maximized using a tractable algorithm.[49]

4. Identification.

i. Identification of Tastes θ. In general, the distribution of α_i and school mean utilities δ_{jt} are not separately identified due to two mechanisms through which prices faced by students p_{ij} are endogenous.[50] The first channel is the typical price endogeneity concern common to empirical models of demand for differentiated products in the industrial organization literature (Berry and Haile 2016). Sticker prices p_{jt} are likely correlated with school-specific fixed preferences δ_{jt}. For example, more expensive schools (high p_{jt}) may provide better resources and teachers for students, which may be preferred by students (high δ_{jt}). In general, we expect prices to be *positively* correlated with measures of quality, such that estimates of α are biased toward zero. Typical approaches to this endogeneity concern involve constructing market- or firm-level instruments such as cost-shifters (e.g. teacher wage shocks across locations) that impact prices but not quality (Allende 2019; Neilson 2021).

The second source of price endogeneity is that voucher offers v_{ijt} are also endogenous and directly affect prices faced by students p_{ijt} via equation (9). In particular, students are more likely to win voucher offers for schools when they are ranked higher. Thus, non-price preferences for schools (δ_{jt} and ϵ^e_{ijt}) are correlated with winning a voucher offer and thus prices faced by students. Through this channel, we would expect prices to be *negatively* correlated with school quality. While typical sticker price endogeneity would bias the magnitude of α downward, this voucher offer endogeneity would bias it upward, such that the net bias is ambiguous. Further, this source of endogeneity occurs at the student-level, rendering typical firm-level instruments insufficient as they do not address non-random variation in prices through voucher assignment.

Two unique features of the setting can be exploited to address these concerns. The first is the randomization of voucher offers induced by lotteries in the DA assignment mechanism. In particular, note that conditional on the propensity scores of voucher assignment π_{ijt}, winning or losing an offer is randomly assigned and therefore uncorrelated with all unobserved preferences:

$$v_{ijt} \perp \psi_{ijt}, \eta^e_{ijt} \mid \pi_{ijt}. \tag{25}$$

48. See Appendix AV. for likelihood functions.

49. The parameter space is large, involving a very large set of fixed effects (one for each school-year and propensity score) in addition to random parameters. For tractability, a minorization technique is adapted from Chen et al. 2022 to estimate the multinomial logit model with high-dimensional fixed effects. This is embedded in an EM algorithm which allows for estimation of additional random coefficient parameters (Train 2007; James 2017). See Appendix AV.B. for details.

50. Given low rates of migration in India and the focus on school choice in early primary years, distance is assumed to be exogenous within students' choice sets. This assumption is consistent with prior work on estimating models of school choice in the education literature.

Thus, when estimating the model in equation (4), fully saturated fixed effects for each propensity score π_{ijt} specific to each student-school pair are included.[51] Because voucher assignment is school- and student-specific, each school has some students that randomly win voucher offers and face zero prices; and each student has some schools they randomly win voucher offers for and whose prices switch to zero. This approach thus leverages lottery variation in prices within student across schools and within school across students.

The second feature is the ranking decision made by applicants before choosing in which school to enroll. This separately identifies school-specific preferences δ_{jt}. During the DA assignment mechanism, students submit rank-ordered preferences over schools that are assumed truthful (Abdulkadiroğlu and Sönmez 2003). These rankings are submitted before vouchers offers are realized, and are thus made assuming prices are zero. Thus, when submitting rankings over schools R_{it}, students only rank their preferences for non-price attributes of schools $\tilde{u}^r_{ijt}$ as in equation (12). The rank ordered lists R_{it} thus provide additional choice data that allow for separate identification of δ_{jt}. This is advantageous because conditional on all non-price components of school-specific preferences δ_{jt}, school-specific sticker prices p_{jt} must be as good as random:

$$p_{jt} \perp \psi_{ijt}, \eta^e_{ijt} \mid \delta_{jt}. \tag{26}$$

This approach is similar to Dinerstein, Neilson, and Otero 2022, which estimates models of demand for schools in the Dominican Republic, and includes additional choices from surveys that capture students' hypothetical preferences for second choice schools as if prices were zero. Similarly, students in this setting make zero-price choices, but they are high-stakes as rankings are used directly for the assignment of private school vouchers.

ii. Identification of Application Costs τ. The returns from applying depend only on the fixed ("linear") taste parameters in θ. Any residual variation in the application choice is due to application costs. Once tastes θ are estimated, we can estimate the costs τ as a residual.[52] The costs that vary with demographics W_{it} capture a variety of frictions that are correlated with student types, markets, and time. These characteristics are left unchanged in counterfactuals. In contrast, Z_i captures one dimension of application costs, a distance penalty, that is observable and excluded from tastes θ. Counterfactuals will assess how removing this friction affects equilibrium outcomes.

51. This is included in the model as an additional source of persistence from the ranking unobservable ϵ^r to the enrollment unobservable ϵ^e in equation (23).

52. In Allende 2019, a model of application is included to correct for selection in a school choice model that is conditional on application. In particular, an instrument that exogenously shifts application behavior allows us to separately identify tastes of applicants versus non-applicants. In this setting, the identification strategy above allows us to estimate tastes θ for the full population. Further, selection into application is random conditional on observables, because the final unobservables $\kappa, epsilon^a$ are uncorrelated with ranking and enrollment unobservables $\nu, \epsilon^r, \epsilon^e$. Here, the application is incorporated to capture endogenous changes under voucher design counterfactuals. The Z_i serves not as an instrument for identification, but as one dimension of application costs, a distance penalty, that is observable in the data and excluded from tastes θ. Counterfactuals will assess how removing this distance penalty would impact equilibrium outcomes.

5. Data Restrictions and Parameter Estimates.

i. Data Restrictions. The school choice data includes non-applicants' enrollment decisions from 2016-2018; and voucher applicants' ranking and enrollment decisions across all entry years 2016-2018 for which enrollment decisions are observed.[53] For tractability, the following restrictions are made in the estimation sample: a 10% sub-sample of non-applicants and a random sample of 200 markets.[54] Outside options are set as the school-year with the lowest market share in each market.[55] This results in roughly 1M rank and enrollment choices for 30K students and 10K schools.

ii. Parameter Estimates. Table IV presents demand estimates. Panel A reports price parameters α_i, where observed applicants, lower SES, and female students have higher price sensitivity. There is modest unobserved heterogeneity, with an estimated σ_α of roughly 15% of the intercept. Panel B reports distance parameters λ_i, where applicants and female students have modestly higher distance sensitivity. Panel C reports estimated school-specific preferences δ_{jt}. We see that private schools have on average higher values than public schools. This is consistent with more resources and higher value-added in the private sector.[56] Schools are highly differentiated, with a standard deviation of roughly 50% of the mean. Panel D reports estimates of persistence parameters. The mean ϕ is roughly 0.7, which suggests schools with positive propensity scores (that are submitted in the application) have higher preferences than others. The unobservable ψ has an estimated scale parameter of roughly 0.9, suggesting substantial persistence from ranking to enrollment.

Finally, Panel E reports estimates of application cost parameters τ. We see that lower SES and female students have larger application costs, consistent with patterns of selection we observe among applicants. In addition, the estimate of τ_z is negative and statistically significant, suggesting students that live farther from application centers have larger application costs. Finally, there is substantial variation in mean application costs across years t (where costs fall over time) and markets m (where lower SES regions have higher costs).

Taken together, the model of demand is rich: parameters capture diverse tastes for price and distance along several dimensions of observed and unobserved individual heterogeneity, unrestricted school-specific preferences across thousands of schools, persistence across students' decisions, and heterogenous application costs. With parameters in hand, the model is able to determine how counterfactuals may change students' application, ranking, and enrollment decisions and how these changes impact consumer surplus.

53. Time-varying parameters including school-year mean indirect utility δ_{jt} and market-by-year application costs τ_{mt} are extrapolated by exploiting the model's remaining time-invariant tastes and a log-inversion procedure. See Appendix 2. and Appendix 2. for more details.

54. Table AXIII reports that this randomization is effective: student and school charactersitics are statistically insignificant predictors of being assigned into the estimation sample.

55. There are no clear school districts within which students must select schools, and so students regularly commute across district or block boundaries. For tractability, an algorithm is developed to construct markets in a parsimonious fashion. Demand estimates are robust to more traditional administrative boundaries ("pincodes"). See Appendix AVI. for details on market construction.

56. Indeed, Figure AXI plots the strong relationship between GPA value-added and school mean utilities.

VI.B. Supply Framework

While the demand model quantifies how schools' price and quality affects enrollments and utility, the supply framework quantifies how voucher policies would affect school behavior, endogenizing the price and quality faced by students. While prices are observed, quality is unobserved. Models of school behavior commonly use measures of test-score value-added (VA) as a proxy for quality (Neilson 2021; Allende 2019). If students value other school characteristics beyond VA, a single measure may miss other adjustments schools may make that affect student welfare. To capture this explicitly, we can use demand-side estimates of school-specific preferences δ_{jt} (or mean indirect utility) as a measure of perceived school quality. This allows quality to be defined in terms of student preferences, without imposing priors on how students value schools.

Private schools face imperfect, Bertrand-Nash competition and set prices p_{jt} and quality δ_{jt} to maximize expected profits Π_{jt}, which are a sum of profits from non-voucher and voucher students:

$$\max_{p_{jt},\delta_{jt}} \Pi_{jt} = [p_{jt} - mc_{jt}(\delta_{jt})]\mathbb{E}[N_{jt}^{nv}] + [v(p_{jt}) - mc_{jt}(\delta_{jt})]\mathbb{E}[N_{jt}^{v}], \tag{27}$$

where p_{jt} is the sticker price; $mc_{jt}(\delta_{jt})$ is the quality-specific marginal cost for an additional student; $v(p_{jt})$ is the reimbursement paid to schools by the government for each voucher student; and $\mathbb{E}[N_{jt}^{nv}]$ and $\mathbb{E}[N_{jt}^{v}]$ denote the school's expected enrollment from the non-voucher and voucher market, respectively. Schools are assumed to have no capacity constraints and must admit all students that are willing to pay the sticker price or are admitted through the voucher system.[57]

Marginal costs depend (linearly) on quality chosen (Neilson 2021):

$$mc_{jt}(\delta_{jt}) = \gamma_{jt}\delta_{jt} + c_{jt}, \tag{28}$$

where $\gamma_{jt} > 0$ reflects the marginal effect of quality upgrading on marginal cost and c_{jt} is an unobserved cost shock. This introduces a revenue-cost trade-off for investing in quality: increasing quality raises expected enrollment and revenue, but also raises cost.

Enrollment depends on demand parameters (θ, τ), student and school characteristics (suppressed for brevity), and unobservables $\epsilon = \{\nu, \psi, \eta^r, \eta^a\}$.[58] Expected voucher enrollment for school j includes those that apply with probability q^a, receive an offer for j with probability q_j^o, and enroll given the offer with probability $q_j^{e|o}$. This is aggregated across covariate groups g in market $m(j,t)$ with population counts $w_{gt}^{m(j,t)}$ (dropping m for brevity):

$$\mathbb{E}[N_{jt}^{v}] = \sum_{gt} w_{gt} \int_{\epsilon} \underbrace{q_{gt}^{a}(\epsilon) q_{gjt}^{o}(\epsilon) q_{gjt}^{e|o}(\epsilon)}_{\text{Apply, Offer, Enroll | Offer}} \, dF_{\epsilon}. \tag{29}$$

57. In practice, voucher-oversubscribed schools at time t expand their class sizes at time $t+1$ to admit non-voucher students who are willing to pay. This suggests schools have substantial excess capacity and do not face constraints on average. By law, schools cannot discriminate in admissions or deny admitted voucher students.

58. See Appendix AV. for full expressions of enrollment levels.

Non-voucher enrollment includes (1) those who do not apply (or are ineligible) and enroll in j; (2) those who apply, but receive no offers with probability $1 - q^o$, and enroll in j; and (3) those who apply, receive a non-j offer with probability q_j^{o-}, but enroll in j anyway with probability $q_j^{e|o-}$:

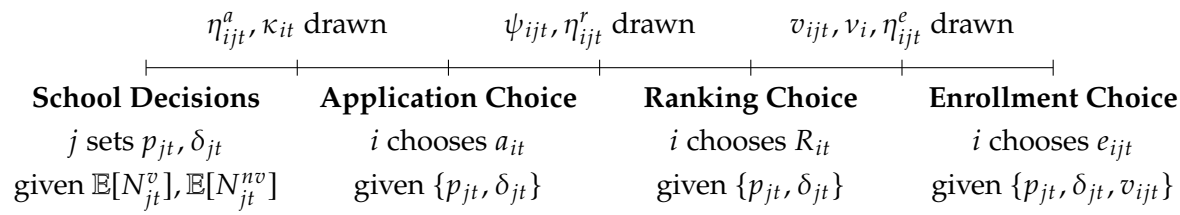
$$\mathbb{E}[N_{jt}^{nv}] = \sum_{gt} w_{gt} \int_{\epsilon} \underbrace{(1 - q_{gt}^a(\epsilon))q_{gjt}^e(\epsilon)}_{\text{No Apply, Enroll}} + \underbrace{q_{gt}^a(\epsilon)(1 - q_{gt}^o(\epsilon))q_{gjt}^e(\epsilon)}_{\text{Apply, No Offer, Enroll}} + \underbrace{q_{gt}^a(\epsilon)q_{gjt}^{o-}(\epsilon)q_{gjt}^{e|o-}(\epsilon)}_{\text{Apply, Other Offer, Reject}} \, dF_\epsilon. \quad (30)$$

Based on the policy's design, the school's marginal revenue for each student admitted in the voucher program $v(p_{jt})$ is the minimum of the school's sticker price p_{jt} and the government's voucher cap $\bar{v}_t$ (the per-student cost in the public school system in year t):

$$v(p_{jt}) = \min\{p_{jt}, \bar{v}_t\}. \quad (31)$$

This kink in the reimbursement function implies different first-order conditions depending on whether schools' sticker prices p_{jt} are above or below this voucher cap $\bar{v}_t$.

1. Timing and Equilibrium. The game proceeds as follows. First, schools make price and quality decisions forming expectations of enrollment across both voucher and non-voucher sectors. Second, after application-stage unobservables are drawn, students make application decisions given the observed school price and quality decisions. Third, once ranking-stage unobservables are drawn, student submit rank-ordered lists given observed price and quality. Fourth, voucher offers are drawn given students' rank-ordered lists and enrollment-stage unobservables are drawn. Then, students make final enrollment decisions given observed price and quality.



The *equilibrium* is a set of prices, qualities, and enrollments $\{p_{jt}^*, \delta_{jt}^*, \mathbb{E}[N_{jt}^{v*}], \mathbb{E}[N_{jt}^{nv*}]\}$ such that:[59]

1. All schools are maximizing profit as in equation (27):

$$p_{jt}^*, \delta_{jt}^* = \underset{p_{jt}, \delta_{jt}}{\text{argmax}} \, \Pi_{jt}\big|_{p_t^*, \delta_t^*} \quad (32)$$

59. Existence and uniqueness are assumed but not guaranteed. However, in the range of counterfactuals studied, the estimated model converges to the same equilibrium across multiple starting values in relatively few iterations.

2. All students are maximizing utility as in equations (29) to (30):

$$\mathbb{E}[N_{jt}^{v*}] = \mathbb{E}[N_{jt}^{v}]\Big|_{p_t^*,\delta_t^*} \qquad (33)$$
$$\mathbb{E}[N_{jt}^{nv*}] = \mathbb{E}[N_{jt}^{nv}]\Big|_{p_t^*,\delta_t^*}$$

2. Optimal Price Setting Under the Status-Quo Design. First-order conditions (FOCs) suggest prices should equal marginal cost plus a markup due to imperfect competition. Markups depend on market shares and price elasticities of demand. Importantly, voucher students' demand is essentially inelastic to prices:

$$\frac{\partial \mathbb{E}[N_{jt}^{v}]}{\partial p_{jt}} \approx 0. \qquad (34)$$

This is apparent as N_{jt}^{v} is composed of (1) application rates, (2) offer probabilities, and (3) enrollment conditional on offers. For (3), the enrollment probability conditional on receiving a voucher $q_{ijt}^{e|o}$ sets p_{jt} to zero. This is because given a voucher offer at school j, the probability of enrolling in j depends only on the non-price attributes of j and the attributes of other schools $-j$. For (1) and (2), the application rates and offer probabilities may also be influenced by prices, but indirectly. For example, if a school raises its price this would raise the returns of applying for vouchers by inflating the potential tuition savings. However, if schools are small relative to their market, we may expect one school's price to only minimally change market-level application rates or offer probabilities (as only non-price attributes matter for rankings).[60]

FOCs depend on whether schools are above or below the voucher cap $\bar{v}_t$. For schools below the voucher cap ($p_{jt} < \bar{v}_t$), the FOC for the status-quo design (sq) is:

$$p_{jt-}^{sq} \approx mc_{jt}(\delta_{jt}) + \frac{\mathbb{E}[N_{jt}^{nv}] + \mathbb{E}[N_{jt}^{v}]}{-\frac{\partial \mathbb{E}[N_{jt}^{nv}]}{\partial p_{jt}}}, \qquad (35)$$

where the denominator only includes the non-voucher price sensitivity given equation (34). The right hand side is the sum of marginal cost and a markup term. The markup term depends on the total expected enrollment (numerator) divided by the sensitivity of non-voucher enrollment to prices (denominator). Schools that have low price elasticities of demand take advantage of market power and charge higher prices through higher markups above marginal cost.

For above-cap schools ($p_{jt} > \bar{v}_t$), we have that $v(p_{jt}) = \bar{v}_t$, so that the marginal revenue from each voucher student is fixed and does not depend on sticker prices. Together with equation (34) this implies that the voucher market drops out completely from the school's first-order condition,

60. The empirical analysis will allow for and estimate how schools' price and quality would affect application and offer rates. These elasticities are low because (1) schools are small relative to their market and (2) application costs are high and prevent even relatively large schools from shifting application rates via adjustment. See Appendix AV. for full expressions of enrollment levels and price and quality gradients that are used in estimation.

which yields an optimal pricing equation that is only sensitive to the non-voucher market:

$$p_{jt+}^{sq} \approx mc_{jt}(\delta_{jt}) + \frac{\mathbb{E}[N_{jt}^{nv}]}{-\frac{\partial \mathbb{E}[N_{jt}^{nv}]}{\partial p_{jt}}}. \tag{36}$$

This markup depends only on the enrollment and price sensitivity of the non-voucher market.

i. Predicted Effects of India's Voucher Policy on Prices. In the absence of a voucher system (nv), all schools (both above and below the voucher reimbursement cap) will set optimal prices considering both the voucher and non-voucher market. This results in an adjusted first-order condition:

$$p_{jt}^{nv} = mc_{jt}(\delta_{jt}) + \frac{\mathbb{E}[N_{jt}^{nv}] + \mathbb{E}[N_{jt}^{v}]}{-\left[\frac{\partial \mathbb{E}[N_{jt}^{nv}]}{\partial p_{jt}} + \frac{\partial \mathbb{E}[N_{jt}^{v}]}{\partial p_{jt}}\right]}. \tag{37}$$

For below-cap schools, the voucher system reduces the magnitude of the denominator of the markup term in equation (35) by switching the price elasticity of demand of voucher students to near zero, which would raise optimal prices (holding quality fixed). Intuitively, without vouchers, schools are incentivized to balance a "revenue-demand" trade-off: raising prices to increase revenue or lowering prices to attract students through price elasticities of demand. Under vouchers, a portion of their students' demand no longer responds to prices, shutting off the demand channel. There is now a strong incentive collect additional revenue by raising prices without losing demand. At the margin, while non-voucher students are still price responsive, this tips the revenue-demand trade-off in favor of the revenue channel, raising optimal sticker prices overall.

For above-cap schools, however, the price under the voucher system given by equation (36) is not clearly higher or lower than the no-voucher price in equation (37). Impacts depend on the relative enrollments and price sensitivities between the voucher and non-voucher market. For example, if the voucher system draws relatively price elastic students, expanding vouchers would also change the price elasticities by reducing the magnitude of $\frac{\partial \mathbb{E}[N_{jt}^{v}]}{\partial p_{jt}}$ and increasing markups. If the voucher students are relatively price inelastic, this mechanism would reduce markups. Thus, the direction of the price effect for these schools depends on demand parameters.

Overall – conditional on quality – the theory suggests a strong incentive for schools below the cap to raise prices, but no direct incentive for those above the cap. This is consistent with reduced-form findings of price increases for those below the cap, but not above.

3. Optimal Quality Setting Under the Current Design. Optimal quality is set to the competitive level (where marginal revenue equals marginal cost) minus a quality mark*down*. Similar to markups, markdowns are the ratio between expected enrollment and the sensitivity of expected enrollment to quality. Unlike price, however, both non-voucher *and* voucher demand are elastic to quality.

For below-cap schools ($p_{jt} < \bar{v}_t$), the optimal quality choice is:

$$\delta^{sq}_{jt-} = mc^{-1}_{jt}(p_{jt}) - \frac{\mathbb{E}[N^{nv}_{jt}] + \mathbb{E}[N^{v}_{jt}]}{\frac{\partial \mathbb{E}[N^{nv}_{jt}]}{\partial \delta_{jt}} + \frac{\partial \mathbb{E}[N^{v}_{jt}]}{\partial \delta_{jt}}}, \tag{38}$$

where the competitive level of quality is when marginal cost equals marginal revenue (price):

$$mc^{-1}_{jt}(p_{jt}) = \frac{p_{jt} - c_{jt}}{\gamma_{jt}} \tag{39}$$

For the marginal student, below-cap schools receive their sticker price regardless of whether students come from the voucher sector. Thus, marginal revenue equals price for both sectors.

Above-cap schools ($p_{jt} > \bar{v}_t$), however, face lower marginal revenue due to the voucher payment cap. Their optimal quality choice is:

$$\delta^{sq}_{jt+} = mc^{-1}_{jt}(\tilde{p}_{jt}) - \frac{\mathbb{E}[N^{nv}_{jt}] + \mathbb{E}[N^{v}_{jt}]}{\frac{\partial \mathbb{E}[N^{nv}_{jt}]}{\partial \delta_{jt}} + \frac{\partial \mathbb{E}[N^{v}_{jt}]}{\partial \delta_{jt}}}, \tag{40}$$

where $\tilde{p}_{jt}$ is the *effective* marginal revenue:

$$\tilde{p}_{jt} = w^{nv}_{\delta} p_{jt} + (1 - w^{nv}_{\delta})\bar{v}_t, \tag{41}$$

the weighted average of the sticker price p_{jt} (marginal revenue for non-voucher students) and the voucher cap $\bar{v}_t$ (marginal revenue for voucher students).[61] For above-cap schools, the effective marginal revenue $\tilde{p}_{jt}$ is necessarily *less* than sticker prices p_{jt} as the voucher cap $\bar{v}_t$ is less than sticker prices p_{jt} and the weights sum to one.

i. Predicted Effects of India's Voucher Policy on Quality. In the absence of a voucher system, all schools (both above and below the voucher reimbursement cap) have marginal revenue equal to price. Thus, the optimal quality choice is:

$$\delta^{nv}_{jt} = mc^{-1}_{jt}(p_{jt}) - \frac{\mathbb{E}[N^{nv}_{jt}] + \mathbb{E}[N^{v}_{jt}]}{\frac{\partial \mathbb{E}[N^{nv}_{jt}]}{\partial \delta_{jt}} + \frac{\partial \mathbb{E}[N^{v}_{jt}]}{\partial \delta_{jt}}}. \tag{42}$$

For below-cap schools, the quality FOC is unchanged holding price fixed. However, the discussion above predicts price increases in response to vouchers. Because $\gamma_{jt} > 0$, mc^{-1}_{jt} is increasing in p_{jt} by equation (39), so we expect optimal quality to *increase* for these schools. Facing excess profits from higher markups, schools competitively upgrade quality to capture these profits.

For above-cap schools, the effective marginal revenue $\tilde{p}_{jt}$ falls when the voucher policy is

61. The weights are proportional to market size and quality sensitivities: $w^{nv}_{\delta} = \frac{\partial \mathbb{E}[N^{nv}_{jt}]}{\partial \delta_{jt}} \Big/ \left[\frac{\partial \mathbb{E}[N^{nv}_{jt}]}{\partial \delta_{jt}} + \frac{\partial \mathbb{E}[N^{v}_{jt}]}{\partial \delta_{jt}}\right]$

introduced due to the cap on voucher payments (which is less than sticker prices). Given mc_{jt}^{-1} is increasing in p_{jt}, we expect optimal quality to *decrease* for these schools. These schools face profit reductions from reduced marginal revenue, which results in quality downgrading.

Overall, we see incentives for schools below the cap to "compete-up" in quality to capture excess profits and those above the cap to "compete-down" to avoid losses. However, the reduced-form analysis finds modest quality adjustment among low tuition schools below the cap, but not above. This suggests there may be potential constraints that prevent quality adjustment, such that a model where schools are able to adjust quality freely may be inappropriate.[62] To address this, the model includes an additional parameter to allow for potential constraints in quality adjustment.

4. Quality Adjustment Threshold. The model assumes schools may freely adjust quality below a marginal cost *threshold*. This threshold reflects several imperfections that would prevent schools from changing perceived quality δ_{jt} beyond a certain point (e.g. credit constraints, market access, information, or quality stickiness). This is also consistent with highly convex technology, where it is prohibitively expensive to change quality beyond a given level of investment. In addition, the threshold is allowed to vary by year, so as to capture how these constraints may relax over time.

In particular, given an exogenous, time-varying threshold $\overline{mc}_t$, schools solve:

$$\begin{aligned} &\max_{p_{jt},\delta_{jt}} \Pi_{jt} \quad \text{if} \quad mc_{jt} < \overline{mc}_t \\ &\max_{p_{jt}} \Pi_{jt} \quad \text{if} \quad mc_{jt} \geq \overline{mc}_t, \end{aligned} \tag{43}$$

so that schools whose marginal costs are below the threshold can freely choose price and quality but those above may only choose price.

The threshold is parametrized parsimoniously as a function of time:

$$\overline{mc}_t = \omega \cdot \text{arcsinh}(t), \tag{44}$$

where $t = 1$ is the first period of the policy and ω captures the marginal cost threshold in the first period and the rate at which it grows each (log) year. This is an additional supply-side parameter that governs which schools may adjust quality over time. Importantly, the model nests both zero quality adjustment ($\omega = 0$) and full quality adjustment ($\omega = \infty$) as special cases.[63]

5. Estimation. Given demand-side parameters, school conduct assumptions identify all supply-side parameters except for ω. Because application, ranking, offer, and enrollment probabilities are known, we can estimate price markups and quality markdowns in equations (35) to (36) and equations (38) to (40). Marginal costs mc_{jt} and the competitive quality level mc_{jt}^{-1} can be obtained

62. Muralidharan and Sundararaman 2015 finds little evidence of spillover effects on student achievement in a cluster-randomized trial of private school vouchers in south India.

63. If $\omega = 0$, then $\overline{mc}_t = 0$ and all schools are above the threshold and not allowed to adjust quality. If $\omega = \infty$, then $\overline{mc}_t = \infty$ and all schools are below the threshold and allowed to adjust.

by inverting these FOCs given price and quality. The FOCs also place restrictions on the quality coefficient γ_{jt} in the marginal cost function (for schools below the quality threshold):

$$\gamma_{jt} = \frac{\tilde{\mu}^p_{jt}}{\tilde{\mu}^\delta_{jt}}, \tag{45}$$

where $\tilde{\mu}^p_{jt}$ and $\tilde{\mu}^\delta_{jt}$ are (effectively) school price markup and quality markdown terms.[64] The structural error c_{jt} is obtained as a residual: $c_{jt} = mc_{jt} - \gamma_{jt}\delta_{jt}$.

To estimate the threshold parameter ω, the same instrumental variable (IV) above is exploited, which delivers variation in voucher applications across markets and time. The variation is then orthogonal to unobserved cost shocks and provides moment conditions that depend on ω, which can be used for estimation via Generalized Method of Moments (GMM).

The IV is constructed as in Section V. :

$$z_{jt} = \tilde{z}_j \times 1\{t > 2014\}, \tag{46}$$

where $\tilde{z}_j$ is the share of voucher eligible students who enroll in private schools in 2014. This is assumed to be orthogonal to the structural cost errors (net of school and year fixed effects):

$$\begin{aligned} \mathbb{E}[\Delta z_{jt} \cdot \Delta c_{jt}] &= 0 \\ \mathbb{E}[\Delta z_{jt} \cdot \Delta mc_{jt}] &= 0, \end{aligned} \tag{47}$$

where the difference operator Δ removes school and year means:

$$\Delta x_{jt} = x_{jt} - \mathbb{E}_t[x_{jt}] - \mathbb{E}_j[x_{jt}]. \tag{48}$$

Using schools' first-order conditions, this implies the following single moment condition, whose sample analogue can be estimated with the data:[65]

$$\mathbb{E}\left[\Delta z_{jt} \cdot [\Delta p_{jt} - \Delta\mu^p_{jt} - 1\{mc_{jt} < \omega \cdot \text{arcsinh}(t)\}\Delta\gamma_{jt}\delta_{jt}]\right] = 0, \tag{49}$$

where t is years relative to year before the policy (2012) and μ^p_{jt} is the school price markup.

The instrument, by increasing application rates, serves as a shifter of schools' price and quality decisions that is orthogonal to unobserved cost shocks. Given any candidate threshold, the moment conditions place restrictions on how markups μ^p and quality-related marginal cost $\gamma\delta$ would have changed in response to the instrument. These restrictions are such that net of markups and quality adjustments, prices should be uncorrelated with the instrument. The estimation procedure selects the threshold which minimizes these disturbances.

64. See Appendix AVII. for more details.

65. Thus, the moment condition used for estimation equation (49) is a slightly weaker condition than equation (47). See Appendix AVII.F. for details.

6. Parameter Estimates. Figure III reports supply-side parameter estimates. Panels A and B show the distribution of price markups and quality markdowns among private schools. Schools have significant market power, with markups that are roughly 40% of prices on average. There is considerable variation, some with markups of more than 75%. This reflects the variation in price sensitivity, where schools in richer markets with low price sensitivity take advantage by raising markups. Similarly, schools markdown quality by roughly 20% on average with sizable variation.

Figure AXII shows the sample moment conditions against candidate quality adjustment threshold parameters ω, with the density of marginal costs shown below. A value of zero would imply no adjustment (as all schools are above the threshold) while a very large value (e.g. 100) would imply full adjustment (as all schools are below the threshold). We see that the sample moment condition is minimized at roughly $\omega = 13$, which implies a model rejection of either no adjustment or full adjustment. A model of no adjustment is a better fit than full adjustment, consistent with reduced-form estimates of the modest impact of vouchers on observed measures of quality.

Panel C of Figure III shows the distribution of marginal costs over time, where the vertical lines denote the estimated adjustment threshold $\overline{mc}_t$ in each year. We see that marginal costs steadily increase over time, but the adjustment threshold increases faster. This results in a greater fraction of private schools whose marginal costs are below the threshold in later years than in earlier years. In that sense, the estimated model allows for greater quality adjustment over time.

VII. The Equilibrium Consequences of Voucher Design

The estimated supply and demand framework allows us to perform policy counterfactuals, including a no-voucher scenario and alternative voucher designs. Each policy regime will change schools' price and quality decisions, affecting students' sorting across schools and generating surplus for consumers, producers, and the government. Because schools form correct expectations of demand, the choices of students are consistent with the beliefs of schools in equilibrium. Counterfactual equilibria are computed with standard methods (Berry, Levinsohn, and Pakes 1995).[66]

VII.A. Consumer, Producer, and Government Surplus

Each voucher design will lead to an equilibrium vector of prices, qualities, and voucher offers $(p_t, \delta_t, v_t) = \{(p_{jt}, \delta_{jt}, v_{ijt})\}$. Given this vector, students of group g in market m will then choose schools to maximize enrollment-stage utility. This generates money-metric consumer surplus CS^m_{gt} (student welfare) over the distribution of unobservables ϵ:

$$CS^m_{gt}(p_t, \delta_t, v_t) = \int_\epsilon \frac{1}{\alpha_g} \max_{j \in m} u^e_{gjt}(p_t, \delta_t, v_t)\, dF_\epsilon. \tag{50}$$

66. Schools' first-order conditions are iteratively updated until convergence. See Appendix AVII.G. for more details. Existence and uniqueness are assumed but not guaranteed. However, in counterfactuals, the estimated model converges to the same equilibrium across multiple starting values in relatively few iterations given the voucher's small scale relative to the market.

Based on the enrollment decisions of both non-voucher and voucher students, schools then generate producer surplus PS_{jt} (school profits) given by the profit expression in equation (27):

$$PS_{jt}(p_t, \delta_t, v_t) = [p_{jt} - mc_{jt}(\delta_{jt})] \cdot \mathbb{E}[N^{nv}_{jt}](p_t, \delta_t, v_t) + [v(p_{jt}) - mc_{jt}(\delta_{jt})] \cdot \mathbb{E}[N^{v}_{jt}](p_t, \delta_t, v_t). \tag{51}$$

This is then aggregated to compute total consumer and producer surplus:

$$CS(p_t, \delta_t, v_t) = \sum_{gt,m} w^m_{gt} CS^m_{gt}(p_t, \delta_t, v_t)$$
$$PS(p_t, v_t) = \sum_{jt} PS_{jt}(p_t, \delta_t, v_t). \tag{52}$$

Depending on voucher takeup and public school enrollment, this affects government surplus (cost):

$$GS(p_t, \delta_t, v_t) = -\bar{v}_t \cdot \mathbb{E}(N^{nv}_{0t})(p_t, \delta_j, v_t) + \sum_{jt} -v(p_{jt}) \cdot \mathbb{E}[N^{v}_{jt}](p_t, \delta_t, v_t), \tag{53}$$

where the first term on the right hand side captures the per-student cost in the public school system $\bar{v}_t$ times the number of students enrolled in public school; and the right hand side captures the total expenditure of the voucher reimbursements to private schools. Finally, total surplus from any design can be compared against a no-voucher counterfactual to compute its benefit-cost ratio.[67]

VII.B. The Equilibrium Impacts of India's Voucher Policy

Figure IV shows how the equilibrium distribution of price and quality change as a result of the voucher policy. We see that, consistent with the reduced-form results and theoretical predictions, there are marked price increases for schools below the voucher cap (roughly \$74), and little price adjustment above this cutoff. We see that schools below the cap experience a modest increase in quality (at most roughly 5%) and schools above the cap experience relatively no change in quality. This is also consistent with reduced-form results, which finds modest quality adjustment below the cap and little above.

Table V presents the equilibrium effects of the status-quo voucher system on total surplus. Panel A reports impacts among the voucher recipient market. We see that for each voucher recipient, the policy delivers an additional \$106 of welfare per year. This is due to these students enrolling in voucher schools, delivering non-monetary benefits (by enrolling in schools with lower D, higher δ, and higher ϵ) and monetary benefits (by avoiding tuition fees otherwise paid). This is consistent with lottery results that report gains in achievement measures and reductions in tuition payments.

However, this benefit is offset by losses to school profit of roughly \$54 per student, from admitting voucher students whose reimbursements are below marginal cost on average. This

67. See Appendix AVIII. for details.

suggests that the voucher causes students to sort to relatively expensive private schools, which benefit students via higher quality but harm schools via profit losses. Finally, the voucher system is costly, as it pays vouchers for students that would have potentially enrolled in other private schools anyway, increasing government expenditure by roughly $18 per student.

There is substantial heterogeneity across students. Compared to those in the bottom quartile of price sensitivity α_i, the top quartile sees smaller gains in student welfare, a smaller reduction in profits, and a smaller increase in government costs. This is because price-elastic students are more likely to have counterfactually attended public schools. Thus, their relative benefits are small because (1) their counterfactual fees are zero, and (2) their willingness-to-pay to quality improvements is low. This also reduces the cost of the policy as the government would have incurred public school expenditure. In addition, these price-sensitive students are more likely to reside in low income areas, such that their voucher school is relatively inexpensive and thus suffers lower losses from admitting voucher students.

Panels B reports effects on those outside the voucher system: applicants who do not takeup vouchers and those who do not apply in the first place. Because schools raise prices and modestly raise quality under vouchers, this causes heterogeneous welfare impacts across the education system. For students that are relatively price-elastic, they either pay more for their education or decide to leave for lower quality schools. As a result, we see a $0.20 reduction in welfare per student. Schools face slightly reduced profits and the government faces increased expenditure from some students switching out from private to public schools.

For relatively price-inelastic students, the effects are opposite. These students benefit from below-cap schools raising quality as they are willing to pay the price hikes for the quality upgrade. By shifting from other schools to these, some students "downgrade" from expensive private schools, which modestly reduces profit. Other students decide to "upgrade" from the public sector, saving the government from these public school expenses.

Aggregating surplus across the market, the policy delivers total benefits that exceed total costs with a benefit-cost ratio of 1.5 to 1. The policy is relatively successful by addressing two market distortions. First, private schools are imperfectly competitive and charge markups that are roughly 40% of tuition fees on average. By placing a cap on voucher payments, the policy reduces school profits and acts to effectively lower the higher-priced schools' market power. Second, compared to private schools, public schools are inefficient: they provide roughly half the quality at twice the marginal cost. Because the public sector is fully subsidized, this results in an over-provision of public schooling. By providing a voucher that is capped at public school costs, the policy shifts students from a less efficient public sector to a more efficient private sector. However, because the existing policy draws many students from private schools, the first channel dominates.

Despite these improvements, the tuition-linked voucher design introduces a new distortion, inadvertently causing some schools to raise their prices and thus their effective market power. This dramatically reduces its efficiency: a failure to account for school adjustment in the model would have overstated the benefit-cost ratio by a factor of two (2.9 to 1).

This adjustment is also regressive: for relatively price-inelastic students, the overall BCR is substantially higher, as they benefit from the school responses, while relatively price-elastic students are harmed. Ignoring adjustment, we would have concluded the opposite: the policy is relatively more cost-effective for price-sensitive recipients as the government incurs lower expenditure by sending *ex ante* public school students to voucher schools.

1. Distributional Outcomes One of the planner's objectives may be to improve socio-economic mixing of students within private schools that have been historically dominated by richer, upper-caste children. Figure V shows how the social integration of private schools changes upon the introduction of India's voucher policy. Panel A reports the impacts on the composition of voucher eligible student within school. Each bar is the fraction of students that are voucher eligible (lower caste or below the poverty line) for each bin of school tuition fees, for the status-quo against the no-voucher counterfactual. We see that, in the no-voucher scenario, there is a negative relationship. For example, in public schools, 60% of students are voucher eligible. In schools that charge above median tuition fees, roughly 30% are voucher eligible. If the school system was fully integrated, these shares would be equal to the population composition of 50%.

We see that the status-quo voucher system increases this measure of integration across the school price distribution. The voucher/no-voucher difference is largest for more expensive schools where voucher students are more likely to enroll. On average, India's voucher system increases this measure of school integration by roughly 22% across all private schools.

Panel B shows the impact on multigroup entropy (MGE), an index of segregation. This captures, for a given market, the difference in student composition between schools and the broader population (Reardon and Firebaugh 2002).[68] An MGE of 1 corresponds to full integration, where all schools have the same mix as the market overall. An MGE of 0 corresponds to full segregation, where schools are homogenous with zero mixing. The figure shows the distribution across markets of MGE for low, middle, and high SES groups. Without vouchers, the mean is roughly 0.55 suggesting substantial segregation in SES. In the status-quo, the entire distribution shifts left, reducing the mean by roughly 2.5%. By enabling voucher students to attend private schools, the policy is able to modestly reduce overall segregation in the education system.

Figure AXIII shows the impact of the status-quo voucher system on welfare (CS) and enrolled school quality (δ) for students in each socio-economic group. The status-quo voucher system increases welfare and quality for all SES groups, but the largest for the lowest SES group. This reduces the gap in education quality between low and high SES groups by roughly 20%. This is accomplished by the explicit targeting of the voucher system toward lower caste and poverty populations. This demonstrates that the policy is able to increase the overall efficiency of the education system (by delivering a benefit-cost ratio that exceeds 1) while also making progress toward equity goals (by increasing school integration and reducing educational inequality).

68. See Appendix AIX. for details.

VII.C. Voucher Design Counterfactuals

While India's program is relatively successful, the analysis suggests its performance is determined by several design choices. In particular, there may be scope for improvement by reforming the tuition-linked payments. Four alternative designs are considered: additional top-up fees, voluntary school participation, distance-based voucher assignment, and a flat voucher payment design. Each change will affect the distribution of surplus through schools' price and quality decisions, changes in fiscal costs, as well as students' sorting between the voucher, private, and public sector.[69]

Table VI reports the equilibrium welfare consequences of the various designs against a no voucher counterfactual. Panel A compares the status quo in India against alternate designs *ceterus paribus*. We see that, compared to a no voucher counterfactual, the status-quo voucher system raises prices by 3% and quality by 1% on average. Introducing top-up fees increases prices substantially more, creating additional incentives for those above the cap to raise prices from increased voucher demand. In addition, because applicants now face fees, they rank lower-priced schools higher, shifting the voucher sector toward low fee schools which raise prices given the payment design. This raises consumer surplus relatively less (by +1% compared to +4% in the status-quo) and substantially reduces school profit losses (−7% compared to −30%). Because some students are priced out of their top-choice voucher offers, the top-up policy shrinks the voucher sector by reducing applications (13% compared to 15%). This lowers voucher expenditure, but also reduces effects on school integration (raising voucher eligible enrollment private school by 7.7% compared to 21.9%). On net, introducing a top-up design would lower the benefit-cost ratio to 0.6, such that benefits no longer justify costs.

Allowing for voluntary school participation results in about 20% of schools dropping out of the voucher system who would face profit losses from participating. Relative to the status-quo, price and quality impacts are relatively unchanged. The schools who exit have relatively high quality and sticker prices, which reduces voucher applications as many students no longer find the policy attractive. In addition, voucher recipients face reductions in surplus as they lose high quality voucher options. Similar to top-ups, this reduces benefits to consumers but reduces losses to schools. The shrunken voucher program causes a modest reduction in voucher expenses and similarly reduces gains in school integration. On net, the BCR falls to 0.8.

The next design counterfactual considers a system – implemented in the neighboring states of Gujarat and Maharashtra – in which students cannot submit rank-ordered lists and are instead assigned voucher offers by distance. We see that this mechanism reduces the overall benefits of the voucher for recipients compared to the status-quo, lowering the application rate and gains in consumer surplus from a misallocation of voucher seats to students. Finally, because disadvantaged students live farther away from high quality schools, this reduces profit losses but substantially reduces equity gains. The net BCR falls to just below 1.

In light of the pricing distortions that arise from the existing tuition-linked voucher, the final design counterfactual considers a system that no longer links voucher payments to tuition fees.

69. See Appendix AX. for details on how each design would change schools' first-order conditions on price and quality.

This "flat voucher" pays all schools the current reimbursement cap (roughly $74) regardless of the sticker price they charge. This alternative design removes the distortionary incentives for schools to raise prices. Price hikes fall modestly to 2% from 3%, but gains in quality are unchanged. This results in similar changes in consumer and producer surplus. Critically, the policy raises voucher expenditure (by increasing reimbursements to below-cap schools) but lowers public school expenditure (by removing price distortions that cause students to shift to the public sector) so that net costs fall.This results in an overall BCR of 2.1, roughly 40% higher than the existing system, and doubles the impact on total surplus from 0.5% to 1.0%. By avoiding the regressive price hikes that fall on price-sensitive students, the flat voucher also improves integration outcomes.

In sum, the cost and benefits of voucher policy depend greatly on voucher design, with benefit-cost ratios ranging from 0.6 to 2.1. Design also matters for equity outcomes, an important objective for policymakers. Impacts on the composition of voucher eligible children in private school range from 8% to 24% depending on voucher design. Importantly, within any particular voucher design, ignoring school adjustment leads to dramatic changes in the corresponding cost-effectiveness: no-adjustment BCRs are between 1.3 to 9.7 times higher. In fact, a failure to account for school responses would have suggested the most cost-effective design is in fact the least cost-effective.

VII.D. Longer-Run Counterfactuals

Panel B reports three potential counterfactuals that expand vouchers and allow for greater school quality adjustment. The first is raising the quota of voucher seats available in the assignment mechanism. Expanding the quota from 25% to 50% would only increase applications modestly to 16% given the high application costs. Further, because many schools are currently undersubscribed, raising the quota would only have impacts for students at oversubscribed schools. Nevertheless, by increasing the volume of seats at the most preferred schools, this allows more voucher students to win their top choice and increases consumer surplus by 6% (compared to 4%). However, this comes with greater profit losses and higher voucher spending. On net, the increased gains to students outweigh costs, raising the BCR to 1.8. Additionally, as expected, increased voucher enrollment improves equity outcomes substantially.

Instead of raising the quota, an alternative is to increase the 15% application rate among eligible students. While application costs are not observed, the parameter τ_z captures how distance to application centers influences application choice, net of the projected returns to applying. This instrument is excluded from tastes and serves as a shifter of application costs. The second counterfactual in Panel B shuts down this distance penalty, which raises application rates substantially to 26%. By attracting students from lower SES areas (where application costs are high), equity outcomes are improved. Because they are more price sensitive, despite a larger voucher population, consumer surplus is relatively unchanged relative to raising the quota. However, because these price-sensitive students are more likely to have attended other public schools counterfactually, this reduces voucher spending. On net, the BCR increases to 3.0 and impact on total surplus increases to 1.5%, providing a benchmark with which to compare the costs of reducing application frictions.

Third, the policy's eligibility may be expanded to all students, not just those that are disadvantaged. This "universal" voucher dramatically increases applications (and application rates by attracting students from areas with low application costs). This boosts consumer surplus, raises government expenses, and nearly eliminates school profit. For schools, this leads to (1) price hikes for those below the cap as before and (2) price reductions for those above the cap to deter applications by lowering the potential returns. Despite overall welfare gains, this comes at a modest loss to integration as some disadvantaged students are crowded out by the new advantaged applicants.

The design counterfactuals generate large losses in profit but face constraints in downward quality adjustment. In the long run, we may expect schools to adjust even more, potentially reducing the returns of the policy. The fourth counterfactual shows how welfare impacts may evolve with greater quality adjustment. This is accomplished by extrapolating the marginal cost threshold to its level in 2100 as given by equation (44). Given the estimate of ω, this threshold rises from roughly \$32 in 2018 (25th percentile of marginal costs) to \$67 in 2100 (75th percentile). Increased quality adjustment causes schools above the cap to lower price and quality. This has two consequences: first, as higher quality schools fall quality, fewer eligible students find the voucher policy attractive, lowering application rates and reducing voucher expenditure; second, by allowing quality adjustment, higher quality schools avoid profit losses. Across both the status-quo and flat voucher scenarios, this shrinks the voucher sector, reducing equity gains but raising the BCR from reduced costs and profit losses.

Across all of these scenarios, the flat voucher continues to outperform the status-quo design by removing distortionary price incentives. However, the size of this voucher (in this case equal to the existing voucher cap) may not be optimal. Figure VI presents the impact of flat vouchers across different sizes, under this 2100-level of quality adjustment. We see that as voucher levels increase, there is greater price and quality adjustment upward, as firms compete to capture profits from attracting voucher students. As levels decrease, equilibrium price and quality falls. Higher vouchers increase consumer surplus at first, but then these start to fall as some of the quality adjustment is distortionary – price elastic students would have preferred a bundle with lower price and lower quality. As expected, producer surplus rises and government surplus falls with the size of the voucher payment. For low voucher levels, the government incurs cost savings, as some students still shift to the private sector and the government avoids voucher expenditure.

On net, the total surplus of the policy and integration gains are maximized at a voucher level that is roughly \$100. However, because the government incurs cost savings, the benefit-cost ratio is higher (and even infinite) at lower voucher levels. This presents an equity-efficiency tradeoff: high voucher levels raise equilibrium quality and integration, but have lower benefits per dollar spent. The optimal voucher will thus depend on planners' budget constraints as well as preference weights across school integration, levels of education quality, and welfare.

VIII. Discussion

This paper examines the consequences of India's primary school voucher system – the largest in the world – accounting for both strategic quality and price adjustment by private schools. The policy delivers benefits to voucher recipients but private schools respond to its tuition-linked voucher design by raising prices and modestly upgrading quality. These strategic responses have spillovers to millions of non-recipients and dramatically reduce the policy's overall cost-effectiveness. Switching the program's payment design to a flat voucher would eliminate the harmful incentives for schools to raise tuition and increase its overall efficiency.

Other design features beyond the payment design – such as allowing top-fees, voluntary participation, and the assignment mechanism – are also consequential. Depending on design choices, the policy could deliver a benefit-cost ratio ranging from 0.6 to 2.1. This is especially important given the substantial variation in voucher designs across the world and continued debate on voucher effectiveness in the backdrop of a rapidly growing private school sector.

These conclusions are limited in important ways. This paper is focused on the first six years of the policy, for which data is available. With limited evidence of short run quality adjustment, the parsimonious adjustment model may not correctly predict how quickly and which schools may start to adjust over time. These quality adjustments may be at the intensive margin through investment in a vertical quality measure, as modeled in this paper, or the extensive margin through entry and exit decisions. In particular, we may expect (1) the entry of relatively inexpensive schools to capture higher profits that accrue to schools below the voucher cap; and (2) the exit of relatively expensive schools to avoid profit losses that are incurred by schools above the cap. The consequences of these entry-exit decisions would act to increase equilibrium quality for below-cap schools and reduce equilibrium quality for above-cap schools. This provides an additional mechanism that would reinforce the existing incentives for school quality adjustment. In the short run, this channel may be limited – the reduced-form analysis finds no statistically significant effects of the voucher system on school entry or exit. In the longer run, we may see more adjustment along these extensive margins. Over time, optimal policy design may involve raising voucher payment levels to prevent losses to private schools and lower equilibrium quality.

The University of Chicago, United States

Appendix

AI. Evidence of Deferred Acceptance

Figure AVI reports data from the assignment mechanism that is consistent with DA as opposed to the common Boston Mechanism (BM). Under BM, rank-ordered lists are not strategy-proof, and it would be a mistake to list an oversubscribed school as a second choice, as that choice would be wasted (Abdulkadiroglu et al. 2006). If the mechanism were BM, we would expect a sharp drop in applications from the first to the second choice in the probability of submitting an application to an oversubscribed school. Panel A reports the share of applications who apply to an oversubscribed school by rank order. We see that across multiple definitions of oversubscribed schools (in the previous year, current year, and both), there is no disproportionate decline in the share from the first to the second choice.

In addition to this mistake, under BM it is impossible to lose a school's seat to a student who ranked the school lower. In DA, which first respects students' distance priorities, this is possible if the student who submitted a lower rank has higher priority. Panel B reports the fraction of applicants that lost a voucher offer for a given rank to another applicant who ranked the same school lower, conditional on losing an offer at the given rank. We see that 15% of students who do not win their first choice school, lose their seat to someone with who ranked the school second or lower. The share is substantial, and is consistent with a DA mechanism as opposed to BM or other first-choice maximizers.

Finally, Figure AVII plots the strong relationship between observed probabilities and estimated propensity scores given the DA mechanism (Abdulkadiroğlu et al. 2017). We see that the correlation is strong at 0.90 with an OLS coefficient of 0.97, which suggests the underlying offer probabilities are likely generated by a DA mechanism.

AII. School Value-Added

Using panel data on GPA at the individual-level, we can estimate school value-added models to capture an observed proxy for school quality. School GPA value-added is estimated from school-by-year fixed effects q_{jt} in the following OLS specification that controls for lagged GPA for individual i in school j and year t:

$$y_{ijt} = q_{jt} + \rho y_{ij,t-1} + X'_{it}\gamma, + \epsilon_{ijt} \tag{A1}$$

where y_{ijt} is student i's GPA (normalized to have mean zero and unit variance in each year and class) and X_{it} is a vector of student characteristics including gender, poverty status, caste, and class of enrollment. All controls are included as fixed effects and the model is estimated on a 10% sample of all students in the state from 2013 to 2018. Preferred estimates are presented in column (2) of Table AII.

AII.A. Empirical Bayes Shrinkage

We may correct for sampling error in estimation of VA by employing a parametric empirical bayes shrinkage estimator as in Kane and Staiger 2008. We assume

$$\begin{aligned} q_{jt} &\sim^{iid} N(0, \sigma_q), \\ \epsilon_{ijt} &\sim^{iid} N(0, \sigma_\epsilon). \end{aligned} \tag{A2}$$

Then, construct

$$\tilde{y}_{ijt} = q_{jt} + \epsilon_{ijt}, \tag{A3}$$

where q_{jt} is estimated as above and ϵ_{ijt} as the residual. Then compute its school-by-year mean:

$$\bar{\tilde{y}}_{jt} = \frac{1}{N_{jt}} \sum_i \tilde{y}_{ijt}, \tag{A4}$$

where N_{jt} are the number of students who enroll in school j in year t. Then, compute the shrunken estimate:

$$q_{jt}^{EP} = \bar{\tilde{y}}_{jt} \cdot \frac{\sigma_q^2}{\sigma_q^2 + \sigma_\epsilon^2 / N_{jt}}., \tag{A5}$$

where we estimate the variance terms from their empirical counterparts:

$$\begin{aligned} \hat{\epsilon}_\epsilon^2 &= \text{Var}(\tilde{y}_{ijt} - \bar{\tilde{y}}_{jt}), \\ \hat{\sigma}_q^2 &= \text{Var}(\tilde{y}_{ijt}) - \hat{\epsilon}_\epsilon^2. \end{aligned} \tag{A6}$$

AII.B. Validation of Value-Added Estimates Using Voucher Lotteries

Because voucher lotteries provide random variation in student-school assignments (via randomized voucher offers), we can leverage them to assess the validity of school value-added (VA) estimates (Andrabi et al. 2022, Deming 2014). Specifically, those who (randomly) win their first choice offer are more likely to enroll in higher value-added schools. We can use this variation to estimate the effect of enrolled school VA on student GPA and test against forecast unbiasedness.

We construct the following IV specification akin to equation (1):

$$\begin{aligned} y_{ijt} &= \beta q_{jt} + R_{it}' \delta + X_i' \gamma + \epsilon_{ijt}, \\ q_{jt} &= \alpha \text{First Choice Offer}_i + R_{it}' \delta^{FS} + X_i' \gamma^{FS} + \epsilon_{ijt}^{FS}, \end{aligned} \tag{A7}$$

where school value-added q_{jt} is estimated using the procedure above; R_{it} are lottery fixed effects using the DA p-score approach; and X_i are individual-specific demographics. Here β reflects the effect of a 1 unit increase in school VA on student GPA. Importantly, the variation in VA used to estimate this comes from comparing otherwise similar students who won their first versus second choice voucher offer, and are thus more likely enrolled in higher VA schools.

Note that this estimate is the effect of school VA after 1 to 3 years of enrollment post voucher receipt, so we may not expect the estimate of β to equal 1. To correct for years since treatment, the following specification is also estimated:

$$\begin{aligned} y_{ijt} &= \beta q_{jt} \times \tau + R'_{it}\delta + X'_i\gamma + \epsilon_{ijt}, \\ q_{jt} \times \tau &= \alpha \text{First Choice Offer}_i \times \tau + R'_{it}\delta^{FS} + X'_i\gamma^{FS} + \epsilon^{FS}_{ijt}, \end{aligned} \tag{A8}$$

where τ is years since voucher receipt. Here β is now the effect of a 1 unit increase in school VA for 1 additional year on subsequent GPA.

1. Results. Table AIII shows estimates of β for both specifications and for both standard and empirical bayes shrinkage estimates of VA. For standard VA, the coefficient estimates are roughly 1.62 (stat. sig.), and 0.86 (stat sig.) after correcting for years since treatment. This suggests being randomly assigned to a higher value-added school indeed raises student GPA, as expected. We fail to reject the coefficients equal 1 up to the 40% and 74% level, respectively. However, estimates are relatively noisy and the instrument is relatively weak (first stage F-statistics are 12.3 and 17.0, respectively). Empirical bayes shrinkage estimates are slightly larger in magnitude, and are more noisy. Overall, we fail to reject forecast unbiasedness, but caution our results due to noise.

AIII. Heterogeneity in the Effects of Voucher Takeup on Recipients

While vouchers may benefit recipients on average, there may be considerable heterogeneity across individuals. Indeed, theory and evidence suggests that more disadvantaged populations – whose choices are the most constrained – have the largest to gain from school choice policy (e.g. Abdulkadiroğlu et al. 2011; Howell et al. 2002). While the policy was targeted to disadvantaged students, the state of Madhya Pradesh is large and diverse with considerable variation in levels of consumption across markets. While data on earnings and total consumption is only available at the district-level (n=51), a proxy for regional socioeconomic status (SES) is constructed by computing the average student expenditure on school fees using enrollment and tuition data at the block-level (n=317). This has a mean of roughly \$33 per year, but has substantial variation with a standard deviation of roughly \$20 across blocks. Table AIX reports regression results of average annual school expenditure on block- and district-level measures of SES. Across several measures, OLS coefficients are statistically significant and the correlation is strong. For example, average school expenditure has a correlation of 0.44 with urban-rural status, 0.39 with fraction lower caste, and 0.50 with district-level average income.

To assess how effects may vary across markets, the analysis can be extended to include interac-

tions with individual characteristics $h(i)$ such as SES:

$$y_{it} = \sum_h \beta_h \text{Takeup}_{ih} \times 1\{h(i) = h\} + R'_{it}\delta + X'_i\gamma + \epsilon_{it}, \tag{A9}$$
$$\text{Takeup}_{i\tau} \times 1\{h(i) = h\} = \sum_h \alpha_h \text{First Choice Offer}_i \times 1\{h(i) = h\} + R'_{it}\delta^{FS} + X'_i\gamma^{FS} + \epsilon^{FS}_{it}.$$

Here, β_h reflects the LATE of voucher takeup on student outcome y for individuals with characteristic $h(i) = h$ for all years after application.

Figure AVIII shows the LATE of voucher takeup on student outcomes across this proxy for SES. We see that the academic benefits of vouchers are concentrated in poorer regions. For example, in markets at the bottom-quartile of average school expenditure, voucher takeup increases promotion by 9pp, GPA by 0.33σ, and private school enrollment by 21pp (all stat. sig.). In markets at the top-quartile, effects are 2.5pp, 0.15σ, and 5.1pp, respectively (all stat. insig.). However, tuition savings are concentrated among the richer markets, which exhibit a larger probability of enrolling private school *ex ante*. Markets in the bottom-quartile benefit from roughly \$59 of saved tuition fees, while those at the top-quartile benefit from \$106 of savings. Together, these results suggest vouchers benefit the poor academically and the rich financially.

AIV. The Effects of Voucher Takeup on Recipient Welfare

The model can used to study how winning a voucher impacts the utility of recipients. Suppose individual i receives a single voucher offer for school j_1. Denote v^v_{it} as the vector of voucher offers across schools for individual i in year t under this counterfactual:

$$v^v_{ijt} = \begin{cases} 1 & j = j_1 \\ 0 & \text{otherwise.} \end{cases} \tag{A10}$$

Given equations (4) and (5), student i would receive utility $u_{ijt}(p_{jt}, v^v_{ijt})$ from each school j that depends on sticker prices p_{jt} and voucher offers v^v_{ijt}:

$$u_{ijt}(p_{jt}, v^v_{ijt}) = \alpha_i p_{jt}(1 - v^v_{ijt}) + \lambda_i D_{ij} + \delta_{jt} + \epsilon_{ijt}. \tag{A11}$$

Suppose individual i takes up the voucher offer, and enrolls in the voucher school j_1: $e_{ij_1t} = 1$.[70] Thus, j_1 is i's utility maximizing school under the voucher offer:

$$j_1 = \arg\max_{j' \in m(i,t)} u_{ij't}(p_{j't}, v^v_{ij't}), \tag{A12}$$

70. Note that if the student does not take up the voucher, their optimal school is a non-voucher school. Because price subsidies weakly increase utility of enrolling in the subsidized school, the student would enroll in the same non-voucher school absent the voucher as this school gives even higher utility. In this case, the voucher would have no impact on the student's utility, as they would enroll in the same school (and receive the same utility) whether or not they received the voucher offer.

and i receives utility $u_{ij_1t}(p_{j_1t}, v^v_{ij_1t})$ for enrolling in the voucher school for free:

$$\begin{aligned} u_{ij_1t}(p_{j_1t}, v^v_{ij_1t}) &= \alpha_i p_{j_1t}(1 - v^v_{ij_1t}) + \lambda_i D_{ij_1} + \delta_{j_1t} + \epsilon_{ij_1t} \\ &= \lambda_i D_{ij_1t} + \delta_{j_1t} + \epsilon_{ij_1t}. \end{aligned} \tag{A13}$$

Here, the voucher offer $v^v_{ij_1t} = 1$, so that j_1's tuition fee faced by i is zero and drops out from the utility expression. Thus, the student receives utility based on only school-specific preferences δ_{j_1t}, proximity D_{ij_1}, and the idiosyncratic match preference ϵ_{ij_1t}.

Instead, suppose i did not receive a voucher offer at any school. Denote v^{nv}_{it} as the vector of voucher offers across schools for individual i in year t under this counterfactual:

$$v^{nv}_{ijt} = 0 \ \forall j. \tag{A14}$$

In this case, i would enroll in the highest utility school, say j_0, under no voucher offers:

$$j_0 = \arg\max_{j' \in m(i,t)} u_{ij't}(p_{j't}, v^{nv}_{ij't}), \tag{A15}$$

and receive utility $u_{ij_0t}(p_{j_0t}, v^{nv}_{ij_0t})$ for enrolling in this "non-voucher option":

$$\begin{aligned} u_{ij_0t}(p_{j_0t}, v^{nv}_{ij_0t}) &= \alpha_i p_{j_0t}(1 - v^v_{ij_0t}) + \lambda_i D_{ij_0t} + \delta_{j_0t} + \epsilon_{ij_0t} \\ &= \alpha_i p_{j_0t} + \lambda_i D_{ij_0t} + \delta_{j_0t} + \epsilon_{ij_0t}. \end{aligned} \tag{A16}$$

Here, the voucher offer $v^{nv}_{ij_0t} = 0$, so that j_0's tuition fee faced by i is the sticker price p_{j_0t}. Thus, the student receives utility based on both non-price and price preferences for school j_0.

The effect of taking up the voucher on student i's welfare is thus the difference in realized utility between the voucher and no voucher counterfactual:

$$u_{ij_1t}(p_{j_1t}, v^v_{ij_1t}) - u_{ij_0t}(p_{j_0t}, v^{nv}_{ij_0t}) = \underbrace{-\alpha_i p_{j_0t}}_{\text{Monetary}} + \underbrace{(\lambda_i(D_{ij_1} - D_{ij_0}) + \delta_{j_1t} - \delta_{j_0t})}_{\text{Non-Monetary}} + \underbrace{(\epsilon_{ij_1t} - \epsilon_{ij_0t})}_{\text{Match}}. \tag{A17}$$

AV. Demand Model Estimation Details

AV.A. Likelihood Functions

1. Conditional Likelihood. Given θ, draws ν, ψ, and the T1EV distributional assumptions on η, the conditional probabilities of student i in year t submitting a rank-ordered list $R_{it} = \{j_1, \ldots, j_{10}\}$

and enrollment at a particular school j are:

$$q^R(R_{it}|\theta,\nu,\psi) = \prod_k \frac{\exp(\lambda_i D_{ij_k} + \delta_{j_k t} + \psi_{ij_k t})}{\sum_{k' \geq k} \exp(\lambda_i D_{ij'_k t} + \delta_{j'_k} + \psi_{ij'_k t})}, \tag{A18}$$

$$q^e_{ijt}(\theta,\nu,\psi) = \frac{\exp(\alpha_i p_{ijt} + \lambda_i D_{ij} + \delta_{jt} + \pi'_{ijt}\phi + \psi_{ijt})}{\sum_{j' \in m(i,t)} \exp(\alpha_i p_{ij't} + \lambda_i D_{ij'} + \delta_{j't} + \pi'_{ijt}\phi + \psi_{ij't})}, \tag{A19}$$

where observed propensity scores are written $\pi_{ijt} = \bar{q}^o_{ijt}(\theta, \epsilon^r_t)$.

Given τ, θ, draws η^a, and the logistic distributional assumptions on κ, the conditional probability of eligible student i submitting a voucher application is:

$$q^a_{it}(\tau,\theta,\eta^a) = \frac{\exp(\Delta_{it}(\theta,\eta^a_i) + W'_{it}\tau_w + Z'_i\tau_z)}{1 + \exp(\Delta_{it}(\theta,\eta^a_i) + W'_{it}\tau_w + Z'_i\tau_z)}. \tag{A20}$$

2. Unconditional Likelihood. Given θ and unobservable distributions $F_\nu(\sigma_\alpha)$ and $F_\psi(\beta_\psi)$, the unconditional, joint likelihood of the observed ranking and enrollment choice is thus:

$$L(e_{ijt}, R_{it}|\theta) = \int_\psi \int_\nu q^e_{ijt}(\theta,\nu,\psi)^{e_{ijt}} \cdot q^R(R_{it}|\theta,\nu,\psi)\, dF_\nu(\sigma_\alpha)\, dF_\psi(\beta_\psi). \tag{A21}$$

In the first step, MSL maximizes the simulated analogue of this joint likelihood across all students and years:

$$\hat{\theta} = \underset{\theta}{\operatorname{argmax}} \prod_{it} \hat{L}(e_{ijt}, R_{it}|\theta). \tag{A22}$$

Once $\hat{\theta}$ is estimated, given τ and the unobservable distribution F_{η^a}, the unconditional likelihood of the application choice is thus:

$$L(a_{it}|\tau,\hat{\theta}) = \int_{\eta^a} q^a_{it}(\tau,\hat{\theta},\eta^a)^{a_{it}}\, dF_{\eta_a}. \tag{A23}$$

In the second step, MSL maximizes the simulated analogue of this likelihood across all students and years:

$$\hat{\tau} = \underset{\tau}{\operatorname{argmax}} \prod_{it} \hat{L}(a_{it}|\tau,\hat{\theta}). \tag{A24}$$

AV.B. Step 1: Estimate Taste Parameters θ

The model is estimated with maximum simulated likelihood. However, the parameter space for the demand system is large, involving tens of thousands of fixed effects in a non-linear model (one for each school-year and propensity score). For tractability, a minorization technique is adapted from Chen et al. 2022 to estimate the multinomial logit model with high-dimensional fixed effects. This is embedded in an EM algorithm which allows for estimation of additional random coefficient parameters (Train 2007; James 2017).

In particular, denote the choice-setting level indirect utility v_{ij} (suppressing t) as:

$$v_{ij}(\nu, \psi, \theta^l) = \begin{cases} \alpha_i p_{ij} + \lambda_i D_{ij} + \delta_j + \pi'_{ij}\phi + \psi_{ij} & \text{if } i \in E \\ \lambda_i D_{ij} + \delta_j + \psi_{ij} & \text{if } i \in R, \end{cases} \tag{A25}$$

where E is the set individuals in the enrollment choice setting and R are those in the ranking choice setting;[71] $\psi_{ij} \sim T1EV(\beta_\psi)$ is the persistent preference term; price and distance heterogeneity are as follows:

$$\alpha_i = X'_i \alpha_x + \nu_i, \tag{A26}$$

$$\lambda_i = X'_i \lambda_x, \tag{A27}$$

where X_i are observed characteristics and $\nu_i \sim N(0, \sigma_\alpha)$; and the entire parameter vector θ is:

$$\theta = \left\{ \underbrace{\alpha_x, \lambda_x, \{\delta_j\}, \phi}_{\theta^l}, \underbrace{\sigma_\alpha, \beta_\psi}_{\theta^{nl}} \right\}, \tag{A28}$$

where θ^l and θ^{nl} are fixed ("linear") and random ("non-linear") parameters, respectively.

Given (ν, ψ, θ^l), the probability of observing i make choice j is

$$q_{ij}(\nu, \psi, \theta^l) = \frac{\exp(v_{ij}(\nu, \psi, \theta^l))}{\sum_{j'} \exp(v_{ij'}(\nu, \psi, \theta^l))}, \tag{A29}$$

and the individual (conditional) likelihood can be written:

$$L_i(\nu, \psi, \theta^l) = \prod_j q_{ij}(\nu, \psi, \theta^l)^{y_{ij}}, \tag{A30}$$

where y_{ij} is the observed choice: e_{ij} if $i \in E$ and r_{ij} if $i \in R$.

Given i.i.d. draws of $\{\nu^r, \psi^r\}$ from $N(0, \sigma_\alpha)$ and $T1EV(\beta_\psi)$, we aim to maximize the following simulated (unconditional) log-likelihood:

$$SLL(\theta) = \sum_i \sum_r \ln[L_i(\nu^r, \psi^r, \theta^l)]. \tag{A31}$$

Alternatively, there exists an EM surrogate function $Q(\theta|\theta^k)$ such that iteratively maximizing over θ given the previous maximum θ^k converges to the maximum of $SLL(\theta)$ (Train 2007):

$$\theta^{k+1} = \text{argmax}_\theta Q(\theta|\theta^k) \ \rightarrow^k \ \text{argmax}_\theta SLL(\theta). \tag{A32}$$

71. For $i \in E$, if i did not apply for vouchers, distances to each school D_{ij} are not observed. Thus, for non-applicants, distances are drawn from the empirical CDF of observed distances F_D (Figure AIV) and treated like an additional unobservable in the estimation procedure below. This is suppressed in notation for brevity.

This surrogate function Q takes the form:

$$Q(\theta|\theta^k) = \sum_i \sum_r w_i^{r,k} \ln[L_i(\nu^{r,k}, \psi^{r,k}, \theta^l) f(\nu^{r,k}, \psi^{r,k}|\theta^{nl})], \tag{A33}$$

where

$$w_i^{r,k} = \frac{L_i(\nu^{r,k}, \psi^{r,k}, \theta^{l,k})}{\sum_{r'} L_i(\alpha^{r',k}, \psi^{r',k}, \theta^{l,k})}. \tag{A34}$$

This formulation is advantageous as it can be additively separated into maximizations of linear and non-linear parameters (James 2017):

$$Q(\theta|\theta^k) = \underbrace{\sum_i \sum_r w_i^{r,k} \ln[L_i(\nu^{r,k}, \psi^{r,k}, \theta^l)]}_{Q^l(\theta^l|\theta^k)} + \underbrace{\sum_i \sum_r w_i^{r,k} \ln[f(\nu^{r,k}, \psi^{r,k}|\theta^{nl})]}_{Q^{nl}(\theta^{nl}|\theta^k)}. \tag{A35}$$

Maximizing Q^{nl} is straightforward as it is simply the (weighted) sample analogue of the corresponding parameter:

$$\sigma_\alpha^{k+1} = \sqrt{\frac{\sum_{i,r} w_i^{r,k} (\alpha_i^{r,k} - \overline{\alpha^k})^2}{|I| - 1}}, \tag{A36}$$

$$\beta_\alpha^{k+1} = \frac{1}{\pi^2/6} \cdot \frac{\sum_{i,j,r} w_i^{r,k} (\psi_{ij}^{r,k} - \overline{\psi^k})^2}{|IJ| - 1}. \tag{A37}$$

Maximizing Q^l, however, is challenging as it is equivalent to a standard multinomial logit with a large number of fixed effects. To aid estimation, we define another surrogate function S as:

$$S(\theta^l|\theta^k) = g(\theta^k) - \frac{1}{2} \sum_{ijr} w_i^{r,k} \left[[v_{ij}(\nu^{r,k}, \psi^{r,k}, \theta^{l,k}) - (y_{ij} - q_{ij}(\nu^{r,k}, \psi^{r,k}, \theta^{l,k}))] - v_{ij}(\nu^{r,k}, \psi^{r,k}, \theta^l) \right]^2, \tag{A38}$$

where

$$g(\theta^k) = Q^l(\theta^{l,k}|\theta^k) + \frac{1}{2} \sum_{ijr} w_i^{r,k} \left[y_{ij} - q_{ij}(\nu^{r,k}, \psi^{r,k}, \theta^{l,k}) \right]. \tag{A39}$$

Then, because S is a minorization of Q^l, the step-wise maximum of S converges to the maximum of Q^l (Chen et al. 2022):

$$\theta^{l,k+1} = \text{argmax}_{\theta^l} S(\theta^l|\theta^k) \ \rightarrow^k \ \text{argmax}_{\theta^l} Q^l(\theta^l|\theta^k). \tag{A40}$$

Importantly, note that conditional on θ^k, the minorization S is a least-squares objective in parameters θ^l, weighted by $w_i^{r,k}$. Thus, each maximization of S is a fast OLS estimation. It follows that by updating θ^l in this manner and θ^{nl} by their weighted sample analogues, we are guaranteed to increase the overall surrogate Q, and thereby the overall simulated log-likelihood

SLL. The procedure starts with a guess of θ^0 and iterates until $|Q^{k+1} - Q^k| < \kappa$. The current estimation uses 300 draws of the unobservables (using Halton sequences) with $\kappa = 10^{-4}$.

1. Standard Errors. Analytic standard errors are estimated using standard techniques. Following Ruud 1991, the Fisher information matrix is evaluated at the parameter estimate $\hat{\theta}$ and computed using the score functions:

$$I(\hat{\theta}) = \sum_i \frac{\partial \ln[L_i(\hat{\theta})]}{\partial \theta} \frac{\partial \ln[L_i(\hat{\theta})]}{\partial \theta}' . \tag{A41}$$

The simulated scores are estimated as follows (Train 2007; James 2017):

$$\frac{\partial \ln[L_i(\theta)]}{\partial \alpha_x} = \sum_j p_{ij} X_i (y_{ij} - q_{ij}^w(\theta)), \tag{A42}$$

$$\frac{\partial \ln[L_i(\theta)]}{\partial \lambda_x} = \sum_j D_{ij} X_i (y_{ij} - q_{ij}^w(\theta)), \tag{A43}$$

$$\frac{\partial \ln[L_i(\theta)]}{\partial \delta_j} = \sum_{j'} 1\{j' = j\} (y_{ij'} - q_{ij'}^w(\theta)), \tag{A44}$$

$$\frac{\partial \ln[L_i(\theta)]}{\partial \phi_\pi} = \sum_j 1\{\pi_{ij} = \pi\} (y_{ij} - q_{ij}^w(\theta)), \tag{A45}$$

$$\frac{\partial \ln[L_i(\theta)]}{\partial \sigma_\alpha} = \sum_r w_i^r(\theta) \left[\frac{\alpha_{ir}}{\sigma_\alpha^3} - \frac{1}{\sigma_\alpha^2} \right], \tag{A46}$$

$$\frac{\partial \ln[L_i(\theta)]}{\partial \beta_\psi} = \sum_{jr} w_i^r(\theta) \left[\frac{\psi_{ijr}(1 - \exp(-\psi_{ijr}/\beta_\psi)) - \beta_\psi}{\beta_\psi^2} \right], \tag{A47}$$

where

$$q_{ij}^w(\theta) = \sum_r w_i^r(\theta) q_{ij}(\nu^r, \psi^r, \theta^l). \tag{A48}$$

Finally, standard errors are computed as:

$$\hat{\text{se}}(\hat{\theta}) = \sqrt{\text{diag}(I(\hat{\theta})^{-1})}. \tag{A49}$$

2. Extrapolating δ_{jt}. While δ_{jt} are not directly estimated for years outside the estimation sample, they can be extrapolated by using estimated time-invariant tastes for price and distance ($\hat{\alpha}_i$ and $\hat{\lambda}_i$) and observed school market shares for non-applicants s_{jt}^{na}. In particular, given the multinomial logistic specification for non-applicants, we can perform a fixed point routine using log inversion to recover the mean school utilities (Berry, Levinsohn, and Pakes 1995):

$$\delta_{jt}^{k+1} = \delta_{jt}^k + \log(s_{jt}^{na}) - \log\left(\sum_{gt} w_{gt} \int_{\psi,\nu} \frac{\exp((\hat{\alpha}_g + \nu) p_{j't} + \hat{\lambda}_g D_{ij} + \delta_{jt}^k)}{\sum_{j' \in m_{jt}} \exp((\hat{\alpha}_g + \nu) p_{j't} + \hat{\lambda}_g D_{ij} + \delta_{j't}^k)} \, dF_\nu \, dF_\psi \right), \tag{A50}$$

where the integral on the right had side is estimated using draws of ν from $N(0, \hat{\sigma}_\alpha)$ and ψ from $T1EV(\beta_\psi)$.[72]

AV.C. Step 2: Estimate Application Cost Parameters τ

Once taste parameters θ are estimated, application costs are more straightforward to estimate as there remain only the "linear" parameters τ. Given i.i.d. draws of $\{\eta^{a,r}\}$ from $T1EV(1)$, we aim to maximize the following simulated (unconditional) log-likelihood (dropping t-subscripts):

$$SLL(\tau) = \sum_i \sum_r \ln[L_i(a_i|\tau, \eta^{a,r})]. \tag{A51}$$

Similar to step 1, we again define an EM surrogate function with its linear/non-linear decomposition (Train 2007):

$$Q(\tau|\tau^k) = \underbrace{\sum_i \sum_r w_i^{r,k} \ln[L_i(a_i|\tau, \eta^{a,r})]}_{Q^l(\tau|\tau^k)} + \underbrace{\sum_i \sum_r w_i^{r,k} \ln[\hat{f}(\eta^{a,r})]}_{Q^{nl}}, \tag{A52}$$

where

$$w_i^{r,k} = \frac{L_i(a_i|\tau^k, \eta^{a,r})}{\sum_{r'} L_i(a_i|\tau^k, \eta^{a,r'})}, \tag{A53}$$

and $\hat{f}$ is the joint PDF of the unobservables using their estimated variance parameters.

Because Q^{nl} is not a function of τ, it drops out completely from the maximization (there are no random parameters to estimate here). It remains to maximize Q^l, which is simply a standard weighted logit.

1. Standard Errors. Following the same procedure for taste parameters, analytic standard errors for $\hat{\tau}$ are computed using the information matrix:

$$I(\hat{\tau}) = \sum_i \frac{\partial \ln[L_i(\hat{\tau})]}{\partial \tau} \frac{\partial \ln[L_i(\hat{\tau})]}{\partial \tau}', \tag{A54}$$

with score functions:

$$\frac{\partial \ln[L_i(\tau)]}{\partial \tau_w} = W_i(a_i - q_i^w(\tau)), \tag{A55}$$

$$\frac{\partial \ln[L_i(\tau)]}{\partial \tau_z} = Z_i(a_i - q_i^w(\tau)), \tag{A56}$$

72. As noted in the estimation procedure, distance to schools D_{ij} are unobserved for non-applicants. To compute this integral, they are thus drawn from the empirical CDF of observed distances $\{D_{ij}\}$ (Figure AIV).

where

$$q_i^w(\tau) = \sum_r w_i^r(\tau) q_i^a(\tau, \theta, \eta^{a,r}). \tag{A57}$$

Finally, standard errors are computed as:

$$\hat{\text{se}}(\hat{\tau}) = \sqrt{\text{diag}(I(\hat{\tau})^{-1})}. \tag{A58}$$

2. *Extrapolating* τ_{mt}. We can perform a similar routine to extrapolate market and year fixed effects given s^a_{mt}, the share of eligible students that apply for vouchers from market m in year t:

$$\tau_{mt}^{k+1} = \tau_{mt}^k + \log(s^a_{mt}) - \log\left(\sum_{it} \int_{\eta^a} \frac{\exp(\Delta_{it}(\hat{\theta}, \eta^a) + \tilde{X}'_{it}\hat{\tau}_{\tilde{x}} + Z'_i\hat{\tau}_z + \tau_{mt})}{1 + \exp(\Delta_{it}(\hat{\theta}, \eta^a) + \tilde{X}'_i\hat{\tau}_{\tilde{x}} + Z'_i\hat{\tau}_z + \tau_{mt})} \, dF_{\eta^a}\right), \tag{A59}$$

where $\tilde{X}_i$ are individual SES and gender and $\hat{\tau}_{\tilde{x}}$ are the corresponding estimated application cost parameters. The integral on the right had side is estimated using draws of η^a from $T1EV(1)$.[73]

AVI. Market Construction

Students in this context exhibit a substantial degree of choice. Within the state, there are no clear school districts within which students must select schools, and so students regularly commute across district or block boundaries. The choice of market size has a computational tradeoff: with larger choice sets, demand estimation and counterfactuals are more computationally intensive, but the model accounts for greater potential choices. However, because distance is a strong predictor of choices, choice probabilities go to zero very quickly for very far schools. In light of these concerns, markets (or choice sets) are constructed using a parsimonious k-means clustering algorithm for school locations. The number of clusters is disciplined by rank-ordered lists submitted by students and the school which they ultimately attend, which provides unique data on students' actual choice sets. For any given k, markets $\{m^k\}$ are formed by selecting k groups of schools to maximize distance between any two markets. Students are then assigned the market $m^k(i,t)$ which contains the school they attend. Finally, the following objective is computed: the fraction of schools in the student i's rank-ordered list R_{it} that belong to market $m^k(i,t)$. As k rises this objective falls, highlighting the tradeoff. Finally, the largest k is selected that covers at least 90% of all ranked schools. This results in $k^* = 1,350$ markets across the state, with roughly 50 schools each and roughly 90% of ranked schools falling within the markets of enrolled schools.[74]

Once markets are formed and students are assigned to each market, distances between students and schools are computed. First, "nodes" are constructed using village locations, and comprise the

73. As noted in the estimation procedure, distance to schools D_{ij} are unobserved for non-applicants. To compute this integral for non-applicants, they are thus drawn from the empirical CDF of observed distances $\{D_{ij}\}$ (Figure AIV).

74. Demand estimates are robust to several different values of k and more traditional administrative boundaries ("pincodes").

unique set of roughly 50,000 points upon which students may live. For voucher applicants, their village location is reported in the application, and they are assigned the corresponding node. For non-applicants, their village location is not observed, only the school in which they enroll. For any enrolled school, nodes are sampled using the distribution of distances travelled to school (from the 2016 round of the National Sample Survey).[75] Once nodes are assigned to each student, distances between students' nodes and schools D_{ij} are computed for each school in the student's market.

AVII. Supply Model Estimation Details

School j faces Bertrand-Nash competition and sets price and quality to maximize profit (suppressing t-subscripts):

$$\max_{p_j,\delta_j} \; [p_j - mc_j(\delta_j)]\mathbb{E}[N_j^{nv}] + [\min(p_j, \bar{v}) - mc_j(\delta_j)].\mathbb{E}[N_j^{v}].$$

First-order conditions reveal that optimal prices are set to marginal cost plus markups, which depend on whether schools are priced above or below the reimbursement level $\bar{v}$:

$$p_{j-} = mc_j(\delta_j) + \frac{\mathbb{E}[N_j^{nv}] + \mathbb{E}[N_j^{v}]}{-\left[\frac{\partial \mathbb{E}[N_j^{nv}]}{\partial p_j} + \frac{\partial \mathbb{E}[N_j^{v}]}{\partial p_j}\right]}, \tag{A60}$$

$$p_{j+} = mc_j(\delta_j) + \frac{[\bar{v} - mc_j(\delta_j)]\frac{\partial \mathbb{E}[N_j^{v}]}{\partial p_j} + \mathbb{E}[N_j^{nv}]}{-\frac{\partial \mathbb{E}[N_j^{nv}]}{\partial p_j}}, \tag{A61}$$

and quality is set to competitive levels minus markdowns:

$$\delta_{j-} = mc_j^{-1}(p_j) - \frac{\mathbb{E}[N_j^{nv}] + \mathbb{E}[N_j^{v}]}{\frac{\partial \mathbb{E}[N_j^{nv}]}{\partial \delta_j} + \frac{\partial \mathbb{E}[N_j^{v}]}{\partial \delta_j}}, \tag{A62}$$

$$\delta_{j+} = mc_j^{-1}(\tilde{p}_j) - \frac{\mathbb{E}[N_j^{nv}] + \mathbb{E}[N_j^{v}]}{\frac{\partial \mathbb{E}[N_j^{nv}]}{\partial \delta_j} + \frac{\partial \mathbb{E}[N_j^{v}]}{\partial \delta_j}}. \tag{A63}$$

where

$$mc_j(\delta_j) = \gamma_j \delta_j + c_j, \tag{A64}$$

$$\tilde{p}_j = w_\delta^{nv} p_j + (1 - w_\delta^{nv})\bar{v}, \tag{A65}$$

$$w_\delta^{nv} = \frac{\frac{\partial \mathbb{E}[N_j^{nv}]}{\partial \delta_j}}{\frac{\partial \mathbb{E}[N_j^{nv}]}{\partial \delta_j} + \frac{\partial \mathbb{E}[N_j^{v}]}{\partial \delta_j}}. \tag{A66}$$

75. See Figure AIV for the distribution of observed distances.

The price and quality FOCs together imply the following cost coefficient:

$$\gamma_{j-} = \frac{\tilde{\mu}^p_{j-}}{\tilde{\mu}^\delta_{j-}},$$
$$\gamma_{j+} = \frac{\tilde{\mu}^p_{j+}}{\tilde{\mu}^\delta_{j+}},$$

where the $\tilde{\mu}$-terms are (effectively) markups and markdowns:

$$\tilde{\mu}^p_{j-} = \frac{\mathbb{E}[N^{nv}_j] + \mathbb{E}[N^v_j]}{-\left[\frac{\partial \mathbb{E}[N^{nv}_j]}{\partial p_j} + \frac{\partial \mathbb{E}[N^v_j]}{\partial p_j}\right]},$$
$$\tilde{\mu}^p_{j+} = \frac{\mathbb{E}[N^{nv}_j]}{-\left[\frac{\partial \mathbb{E}[N^{nv}_j]}{\partial p_j} + \frac{\partial \mathbb{E}[N^v_j]}{\partial p_j}\right]},$$
$$\tilde{\mu}^\delta_{j-} = \tilde{\mu}^\delta_{j+} = \frac{\mathbb{E}[N^{nv}_j] + \mathbb{E}[N^v_j]}{\frac{\partial \mathbb{E}[N^{nv}_j]}{\partial \delta_j} + \frac{\partial \mathbb{E}[N^v_j]}{\partial \delta_j}}.$$

We first estimate markups, markdowns, and the cost coefficients γ_j by computing enrollments and their price and quality gradients. Then, given markups, we compute marginal costs by inverting the price FOCs. Finally, given marginal costs and cost coefficients γ_j, we can back out structural cost errors c_j. It thus remains to compute enrollments and their price and quality gradients.

Define expected enrollment from each sector:

$$\mathbb{E}[N^v_j] = \sum_i \int q^a_i(\eta^a) \cdot q^o_{ij}(\psi + \eta^r, \eta^a) \cdot q^{e|o}_{ij}(\nu, \psi)\, dF_{\nu,\psi,\eta^a,\eta^r}, \tag{A67}$$

$$\mathbb{E}[N^{nv}_j] = \sum_i \int (1 - q^a_i(\eta^a) q^o_i(\psi + \eta^r, \eta^a)) \cdot q^e_{ij}(\nu, \psi) + q^a_i(\eta^a) \cdot q^{o_-,e}_{ij}(\nu, \psi, \eta^r, \eta^a)\, dF_{\nu,\psi,\eta^a,\eta^r}, \tag{A68}$$

where

$$q^o_i(\psi + \eta^r, \eta^a) = \sum_j q^o_{ij}(\psi + \eta^r, \eta^a), \tag{A69}$$

$$q^{o_-,e}_{ij}(\nu, \psi, \eta^r, \eta^a) = \sum_{j' \neq j} q^o_{ij'}(\nu, \psi + \eta^r, \eta^a) \cdot q_i^{e_j|o_{j'}}(\nu, \psi). \tag{A70}$$

Collecting unobservables into $\epsilon = \{\nu, \psi, \eta^a, \eta^r\}$, we know the following choice probabilities:

$$q_i^a(\epsilon) = \frac{\exp(\Delta_i(\epsilon) - k_i)}{1 + \exp(\Delta_i(\epsilon) - k_i)}, \tag{A71}$$

$$q_{ij}^{e|o}(\epsilon) = \frac{\exp(\tilde{u}_{ij}^e(\epsilon))}{\exp(\tilde{u}_{ij}^e(\epsilon)) + \sum_{j' \neq j} \exp(u_{ij'}^e(\epsilon))}, \tag{A72}$$

$$q_i^{e_j|o_{j'}}(\epsilon) = \frac{\exp(u_{ij}^e(\epsilon))}{\exp(\tilde{u}_{ij'}^e(\epsilon)) + \sum_{k \neq j'} \exp(u_{ik}^e(\epsilon))}, \tag{A73}$$

$$q_{ij}^e(\epsilon) = \frac{\exp(u_{ij}^e(\epsilon))}{\sum_{j'} \exp(u_{ij'}^e(\epsilon))}, \tag{A74}$$

where

$$\Delta_i(\epsilon) = \sum_{j \in R_i} q_{ij}^o(\epsilon) \tilde{\Delta}_{ij}(\epsilon), \tag{A75}$$

$$R_i = \{j_k \in m^{\text{Priv}}(i) : \tilde{u}_{ij_1} > \cdots > \tilde{u}_{ij_{10}}\}, \tag{A76}$$

$$\tilde{\Delta}_{ij}(\epsilon) = \max(\tilde{u}_{ij}(\epsilon), u_i^m(\epsilon)) - u_i^m(\epsilon), \tag{A77}$$

$$u_i^m(\epsilon) = \max_j u_{ij}(\epsilon), \tag{A78}$$

$$\tilde{u}_{ij}(\epsilon) = \lambda_i D_{ij} + \delta_j + \epsilon_{ij}, \tag{A79}$$

$$u_{ij}(\epsilon) = \alpha_i p_j + \lambda_i D_{ij} + \delta_j + \epsilon_{ij}, \tag{A80}$$

$$\tilde{u}_{ij}^e(\epsilon) = \tilde{u}_{ij}(\epsilon) + \bar{q}_{ij}^o(\psi + \nu_r)'\phi, \tag{A81}$$

$$u_{ij}^e(\epsilon) = u_{ij}(\epsilon) + \bar{q}_{ij}^o(\psi + \nu_r)'\phi, \tag{A82}$$

where $\bar{q}_{ij}^o$ is the observed propensity score: the offer probability given i's ranks where cutoffs (capacities and others' ranks) are fixed at their observed levels. It remains to compute offer probabilities.

AVII.A. Approximating Offer Probabilities

The offer probability q_{ij}^o is known given the DA mechanism, but analytic gradients do not exist and numeric gradients are infeasible. A simple linear approximation can be estimated using simulations of DA propensity scores under various application environments:

$$\hat{q}_{ij}^o(\epsilon_1, \epsilon_2) = \alpha^o \tilde{\pi}_{ij}(\epsilon_1) + \beta^o A(\epsilon_2) + X_{ij}^{o'} \gamma^o, \tag{A83}$$

where

$$\tilde{\pi}_{ij}(\epsilon) = \frac{\exp(\tilde{u}_{ij}(\epsilon))}{\sum_{j' \in R_i} \exp(\tilde{u}_{ij'}(\epsilon))}, \tag{A84}$$

$$A(\epsilon) = \frac{1}{N} \sum_i \log \frac{q_i^a(\epsilon)}{1 - q_i^a(\epsilon)}, \tag{A85}$$

$$X_{ij}^{o'} = [\text{Priority}_{ij} \;\; \text{Capacity}_j]. \tag{A86}$$

This approximation captures the main drivers of voucher offer probabilities: students' non-price preferences for schools via $\tilde{\pi}$, the volume of total voucher applications via A, and the priorities and capacities of schools via X^o. Note that q_{ij}^o is the probability of receiving an offer at school j for a marginal application – holding fixed the set of applicants observed.

However, there is simultaneity between application rates in equation (A71) and offer probabilities in equation (A83) at the time of application ($\epsilon_1 = \epsilon_2 = \eta^a$). Higher offer probabilities will increase the returns to applying via Δ_i in equation (A75), causing application rates to increase. Higher application rates will in turn reduce offer probabilities because of oversubscription via $\beta^o A$.

Thus, we require an instrument for application volume A to estimate β^o. Because the offer probabilities are a known function of the application environment, we can compute a new vector of counterfactual application probabilities by exogenously changing the number of applications. In particular, the original set of applications used to compute the observed propensity scores is halved (by drawing a 50% random sub-sample), resulting in new propensity scores $q_{ijh}(\epsilon)$ and application volume $A_h(\epsilon)$.[76] Together with the full sample propensity scores $q_{ijf}(\epsilon)$ and application volume $A_f(\epsilon)$, we stack both and include the following first stage for $g \in \{h, f\}$:

$$A_g(\epsilon) = \beta_0^{FS} 1\{g = h\} + \alpha_0^{FS} \tilde{\pi}_{ijg}(\epsilon) + X_{ij}^{o'} \gamma_{FS}^o + \epsilon_{FS}^o. \tag{A87}$$

Because the only difference in propensity scores is driven by application volume, g is a valid instrument for A, and we can estimate β^o.

Once β^o is estimated, the linear approximation allows us to solve for the "reduced-form" of q_{ij}^o by plugging equation (A83) into equation (A71). In particular, this simplifies to

$$A(\epsilon) = \frac{\alpha^o \sum_{ij} \tilde{\Delta}_{ij}(\epsilon) \tilde{\pi}_{ij}(\epsilon) + \sum_i k_i}{N - \beta^o \sum_{ij} \tilde{\Delta}_{ij}(\epsilon)}. \tag{A88}$$

Now, plugging equation (A88) into equation (A83), we can solve for $\hat{q}_{ij}^o(\epsilon)$. Thus, we can compute

76. This exercise requires us to compute propensity scores under two different application environments: a full and a halved sample. To do so, we follow an approach by Abdulkadiroğlu et al. 2017 that uses an analytic version of the DA propensity score. For any random number assigned to students, "cutoffs" determine whether students are admitted to any particular school. These cutoffs are generated using the distribution of rankings, priorities, and school capacities in the market. We first compute cutoffs for each set of ranks g that are submitted, second simulate the marginal rank-ordered list R_{itg} by drawing unobservables ϵ, and third compute $q_{ijg}^o(\epsilon)$ for a given draw using the analytic DA propensity score given the cutoffs.

all components necessary to estimate expected enrollment in equations (A67) to (A69). It remains to compute their gradients.

AVII.B. Enrollment Gradients

Given several draws of unobservables $\{\nu, \psi, \eta^a, \eta^r\}$ estimated enrollments are computed as:

$$\hat{\mathbb{E}}[N_j^v] = \sum_i \sum_{\nu,\psi,\eta^a,\eta^r} q_i^a(\eta^a) \cdot q_{ij}^o(\psi + \eta^r, \eta^a) \cdot q_{ij}^{e|o}(\nu, \psi), \tag{A89}$$

$$\begin{aligned}\hat{\mathbb{E}}[N_j^{nv}] = \sum_i \sum_{\nu,\psi,\eta^a,\eta^r} &(1 - q_i^a(\eta^a) q_i^o(\psi + \eta^r, \eta^a)) \cdot q_{ij}^e(\nu, \psi) \\ &+ q_i^a(\eta^a) \cdot q_{ij}^{o_-,e}(\nu, \psi, \eta^r, \eta^a),\end{aligned} \tag{A90}$$

where the following are now approximated:

$$q_{ij}^o(\psi + \eta^r, \eta^a) = \alpha^o \tilde{\pi}_{ij}(\psi + \eta^r) + \beta^o A(\eta^a) + X_{ij}^{o'} \gamma^o, \tag{A91}$$

$$q_i^o(\psi + \eta^r, \eta^a) = \sum_j q_{ij}^o(\psi + \eta^r, \eta^a), \tag{A92}$$

$$q_{ij}^{o_-,e}(\nu, \psi, \eta^r, \eta^a) = \sum_{j' \neq j} q_{ij'}^o(\psi + \eta^r, \eta^a) \cdot q_i^{e_j|o_{j'}}(\nu, \psi). \tag{A93}$$

Then, gradients are:

$$\begin{aligned}\frac{\partial \hat{\mathbb{E}}[N_j^v]}{\partial y_j} = \sum_i \sum_{\nu,\psi,\eta^a,\eta^r} &\frac{\partial q_i^a(\eta^a)}{\partial y_j} \cdot q_{ij}^o(\psi + \eta^r, \eta^a) \cdot q_{ij}^{e|o}(\nu, \psi) \\ &+ q_i^a(\eta^a) \cdot \frac{\partial q_{ij}^o(\psi + \eta^r, \eta^a)}{\partial y_j} \cdot q_{ij}^{e|o}(\nu, \psi) \\ &+ q_i^a(\eta^a) \cdot q_{ij}^o(\psi + \eta^r, \eta^a) \cdot \frac{\partial q_{ij}^{e|o}(\nu, \psi)}{\partial y_j},\end{aligned} \tag{A94}$$

$$\begin{aligned}\frac{\partial \hat{\mathbb{E}}[N_j^{nv}]}{\partial y_j} = \sum_i \sum_{\nu,\psi,\eta^a,\eta^r} &(1 - q_i^a(\eta^a) q_i^o(\psi + \eta^r, \eta^a)) \cdot \frac{\partial q_{ij}^e(\nu, \psi)}{\partial y_j} \\ &- q_{ij}^e(\nu, \psi) \cdot \left[\frac{\partial q_i^a(\eta^a)}{\partial y_j} q_i^o(\psi + \eta^r, \eta^a) + q_i^a(\eta^a) \frac{\partial q_i^o(\psi + \eta^r, \eta^a)}{\partial y_j} \right] \\ &+ q_i^a(\eta^a) \cdot \frac{\partial q_{ij}^{o_-,e}(\nu, \psi, \eta^r, \eta^a)}{\partial y_j} + q_{ij}^{o_-,e}(\nu, \psi, \eta^r, \eta^a) \cdot \frac{\partial q_i^a(\eta^a)}{\partial y_j}.\end{aligned} \tag{A95}$$

Gradients for q^e_{ij} and $q^{e|o}_{ij}$ are:

$$\frac{\partial q^{e|o}_{ij}(\epsilon)}{\partial y_j} = q^{e|o}_{ij}(\epsilon) \cdot (1 - q^{e|o}_{ij}(\epsilon)) \cdot \frac{\partial \tilde{u}^e_{ij}(\epsilon)}{\partial y_j}, \tag{A96}$$

$$\frac{\partial q^{e}_{ij}(\epsilon)}{\partial y_j} = q^{e}_{ij}(\epsilon) \cdot (1 - q^{e}_{ij}(\epsilon)) \cdot \frac{\partial u^e_{ij}(\epsilon)}{\partial y_j}. \tag{A97}$$

Note that u^e consists of observed propensity score fixed effects, which are not estimated for the full support of possible values $[0, 1]$. To address this, a 2nd order polynomial approximation f is estimated with OLS:

$$\bar{q}^o_{ij}(\psi + \nu_r)'\phi = \underbrace{\phi_1 \bar{q}^o_{ij}(\psi + \nu_r) + \phi_2 \bar{q}^o_{ij}(\psi + \nu_r)^2}_{f(\bar{q}^o_{ij}(\psi+\nu_r))} + \epsilon^{\bar{q}}_{ij}, \tag{A98}$$

Thus, the utility gradients are now

$$\frac{\partial \tilde{u}^e_{ij}(\epsilon)}{\partial y_j} = \frac{\partial \tilde{u}_{ij}(\epsilon)}{\partial y_j} + f'(\bar{q}^o_{ij}(\psi + \nu_r)) \frac{\partial \bar{q}^o_{ij}(\psi + \nu_r)}{\partial y_j}, \tag{A99}$$

$$\frac{\partial u^e_{ij}(\epsilon)}{\partial y_j} = \frac{\partial u_{ij}(\epsilon)}{\partial y_j} + f'(\bar{q}^o_{ij}(\psi + \nu_r)) \frac{\partial \bar{q}^o_{ij}(\psi + \nu_r)}{\partial y_j}, \tag{A100}$$

where $f'(\bar{q}^o_{ij}(\psi + \nu_r)) = \phi_1 + 2\phi_2 \bar{q}^o_{ij}(\psi + \nu_r)$. The non-$p$-score utilities on the left-hand side have simple gradients:

$$\frac{\partial \tilde{u}_{ij}(\epsilon)}{\partial p_j} = 0, \tag{A101}$$

$$\frac{\partial \tilde{u}_{ij}(\epsilon)}{\partial \delta_j} = 1, \tag{A102}$$

$$\frac{\partial u_{ij}(\epsilon)}{\partial p_j} = \alpha_i, \tag{A103}$$

$$\frac{\partial u_{ij}(\epsilon)}{\partial \delta_j} = 1. \tag{A104}$$

For the right-hand side, we apply the offer probability approximation to the observed propensity score:

$$\bar{q}^o_{ij}(\psi + \nu_r) = \alpha^o \tilde{\pi}_{ij}(\psi + \eta^r) + \beta^o \bar{A} + X^{o'}_{ij} \gamma^o, \tag{A105}$$

where $\bar{A}$ is fixed to the observed application propensity. It remains to compute gradients of this approximation, the offer probabilities q^o, and application probabilities q^a.

AVII.C. Gradients of the Offer Probabilities

Given the approximation and simplification of q^o_{ij} in equation (A83), its gradient reduces to:

$$\frac{\partial q^o_{ij'}(\epsilon_1, \epsilon_2)}{\partial y_j} = \alpha^o \frac{\partial \tilde{\pi}_{ij'}(\epsilon_1)}{\partial y_j} + \beta^o \frac{\partial A(\epsilon_2)}{\partial y_j}, \tag{A106}$$

and (because $\bar{A}$ is fixed) the gradient of the observed propensity score in equation (A105) reduces to:

$$\frac{\partial \bar{q}^o_{ij}(\psi + \nu_r)}{\partial y_j} = \alpha^o \frac{\partial \tilde{\pi}_{ij}(\psi + \eta^r)}{\partial y_j}, \tag{A107}$$

where

$$\frac{\partial \tilde{\pi}_{ij'}(\epsilon)}{\partial y_j} = \begin{cases} \tilde{\pi}_{ij}(\epsilon)(1 - \tilde{\pi}_{ij}(\epsilon)) \frac{\partial \tilde{u}_{ij}(\epsilon)}{\partial y_j} & \text{if } j = j', \\ 0 & \text{otherwise,} \end{cases} \tag{A108}$$

$$\frac{\partial A(\epsilon)}{\partial y_j} = \frac{A_D(\epsilon)\beta^o(-\sum_{ij'} \frac{\partial \tilde{\Delta}_{ij'}}{\partial y_j}) - A_N(\epsilon)\alpha^o \left(\sum_{ij'} \tilde{\Delta}_{ij'} \frac{\partial \tilde{\pi}_{ij'}(\epsilon)}{\partial y_j} + \frac{\partial \tilde{\Delta}_{ij'}}{\partial y_j} \tilde{\pi}_{ij'}(\epsilon) \right)}{A_D(\epsilon)^2}, \tag{A109}$$

$$A_D(\epsilon) = N - \beta^o \sum_{ij} \tilde{\Delta}_{ij}(\epsilon), \tag{A110}$$

$$A_N(\epsilon) = \alpha^o \sum_{ij} \tilde{\Delta}_{ij}(\epsilon) \tilde{\pi}_{ij}(\epsilon) + \sum_i k_i, \tag{A111}$$

$$\frac{\partial \tilde{\Delta}_{ij'}}{\partial y_j} = \begin{cases} -\frac{\partial u_{ij}(\epsilon)}{\partial y_j} & \text{if } u_{ij} = u^m_i, \\ \frac{\partial \tilde{u}_{ij}(\epsilon)}{\partial y_j} & \text{if } u_{ij} \neq u^m_i \text{ and } \tilde{u}_{ij} > u^m_i \text{ and } j = j', \\ 0 & \text{otherwise.} \end{cases} \tag{A112}$$

Finally, the gradient of the total offer probability is:

$$\frac{\partial q^o_i(\epsilon)}{\partial y_j} = \sum_{j'} \frac{\partial q^o_{ij'}(\epsilon)}{\partial y_j}. \tag{A113}$$

AVII.D. Gradients of the Application Probabilities

We have that

$$\frac{\partial q^a_i(\epsilon)}{\partial y_j} = q^a_i(\epsilon)(1 - q^a_i(\epsilon)) \frac{\partial \Delta_i(\epsilon)}{\partial y_j}, \tag{A114}$$

where

$$\frac{\partial \Delta_i(\epsilon)}{\partial y_j} = \sum_{j'} q^o_{ij'}(\epsilon) \frac{\partial \tilde{\Delta}_{ij'}}{\partial y_j} + \frac{\partial q^o_{ij'}(\epsilon)}{\partial y_j} \tilde{\Delta}_{ij'}. \tag{A115}$$

AVII.E. Gradients of the Enrollment Probabilities Given Other Offers

We have that

$$\frac{\partial q_{ij}^{o_-,e}(\nu, \psi, \eta^r, \eta^a)}{\partial y_j} = \exp(u_{ij}(\nu, \psi)) B_{ij}(\nu, \psi, \eta^r, \eta^a) + q_{ij}^{o_-,e}(\nu, \psi, \eta^r, \eta^a) \frac{\partial u_{ij}(\nu, \psi)}{\partial y_j}, \tag{A116}$$

where

$$\begin{aligned} B_{ij}(\nu, \psi, \eta^r, \eta^a) = &\left[\beta^o \frac{\partial A(\eta^a)}{\partial y_j} + q_{ij}^{o_-,e}(\nu, \psi, \eta^r, \eta^a) \frac{\partial u_{ij}(\nu, \psi)}{\partial y_j} \right] \\ &\times \sum_{j' \neq j} \frac{1}{\exp(\tilde{u}_{ij'}(\nu, \psi)) + \sum_{k \neq j'} \exp(u_{ik}(\nu, \psi))}. \end{aligned} \tag{A117}$$

AVII.F. Moment Conditions for Estimating the Quality Adjustment Threshold

The school first-order condition on price implies:

$$p_{jt} - \mu^p_{jt} = mc_{jt}(\delta_{jt}). \tag{A118}$$

Applying the difference operator reduces to:

$$\Delta p_{jt} - \Delta \mu^p_{jt} = 1\{mc_{jt} < \overline{mc}_t\}(\Delta \gamma_{jt} \delta_{jt} + \Delta c_{jt}) + 1\{mc_{jt} \geq \overline{mc}_t\} \Delta mc_{jt}, \tag{A119}$$

$$\Delta p_{jt} - \Delta \mu^p_{jt} - 1\{mc_{jt} < \overline{mc}_t\} \Delta \gamma_{jt} \delta_{jt} = 1\{mc_{jt} < \overline{mc}_t\} \Delta c_{jt} + 1\{mc_{jt} \geq \overline{mc}_t\} \Delta mc_{jt}. \tag{A120}$$

Multiplying by the IV reduces to:

$$\Delta z_{jt}[\Delta p_{jt} - \Delta \mu^p_{jt} - 1\{mc_{jt} < \overline{mc}_t\} \Delta \gamma_{jt} \delta_{jt}] = 1\{mc_{jt} < \overline{mc}_t\} \Delta z_{jt} \Delta c_{jt} + 1\{mc_{jt} \geq \overline{mc}_t\} \Delta z_{jt} \Delta mc_{jt}. \tag{A121}$$

Taking expectations and inserting moment conditions in equation (47) implies:

$$\mathbb{E}\left[\Delta z_{jt}[\Delta p_{jt} - \Delta \mu^p_{jt} - 1\{mc_{jt} < \overline{mc}_t\} \Delta \gamma_{jt} \delta_{jt}] \right] = 0, \tag{A122}$$

$$\mathbb{E}\left[\Delta z_{jt}[\Delta p_{jt} - \Delta \mu^p_{jt} - 1\{mc_{jt} < \omega \cdot \text{arcsinh}(t)\} \Delta \gamma_{jt} \delta_{jt}] \right] = 0. \tag{A123}$$

AVII.G. Counterfactual Equilibria

For any counterfactual, equilibrium is reached using standard methods (Berry, Levinsohn, and Pakes 1995). The algorithm starts by initializing the prices and qualities observed in the current

equilibrium. Given a counterfactual policy represented by v', the algorithm updates new first-order conditions for school prices and qualities, $FOC_p(v')$ and $FOC_\delta(v')$, defined in Appendix AX. These functions depend on all prices and qualities in the market, and require iteration to converge.

The main loop of the algorithm continues until certain convergence conditions are met. Within the loop, for each school j, the algorithm updates the school's price p_{jt} based on the first-order condition $FOC_p(v')$. If the school's marginal cost mc_{jt} is less than the exogenous threshold $\overline{mc}_t$, it further updates the school's quality δ_{jt} using $FOC_\delta(v')$ and updates mc_{jt} based on the quality update and exogenous cost parameters. These updates require computing various demand shares and gradients described above. This iterative process continues until the convergence criteria for school prices and qualities are satisfied. All counterfactuals set the convergence threshold $\kappa = 10^{-4}$ and use the same 300 pre-draws of ϵ (using Halton sequences) for all policies.

Algorithm 1: Computing Counterfactual Equilibria

Given policy v', define new first-order conditions for price $FOC_p(v')$ and quality $FOC_\delta(v')$;
Initialize $k = 0$ to the prices and qualities observed in current equilibrium $\{p_{jt}^0, \delta_{jt}^0\}$;
while $\{\|p_{jt}^k - p_{jt}^{k-1}\| < \kappa \text{ and } \|\delta_{jt}^k - \delta_{jt}^{k-1}\| < \kappa\}$ *or* $k < 1$ **do**
  for $j = 1, \ldots, J$ **do**
    Update price p_{jt}^k using first-order conditions $FOC_p(v')$ and $\{p_t^{k-1}, \delta_t^{k-1}\}$;
    if $mc_{jt}^{k-1} < \overline{mc}_t$ **then**
      Update quality δ_{jt}^k using first-order conditions $FOC_\delta(v')$ and $\{p_t^{k-1}, \delta_t^{k-1}\}$;
      Update marginal cost mc_{jt}^k given new δ_{jt}^k;
    end
    Update $k = k + 1$;
  end
end

AVIII. Benefit-Cost Ratio

Under the status-quo voucher policy, prices, qualities, and vouchers are set to their observed distribution, which generates consumer, producer, and government surplus determined by equations (50) to (53):

$$\begin{aligned} &p_t^{sq} = p_t,\ \delta_t^{sq} = \delta_t,\ v_t^{sq} = v_t \\ &\Rightarrow \{CS(p_t^{sq}, \delta_t^{sq}, v_t^{sq}), PS(p_t^{sq}, \delta_t^{sq}, v_t^{sq}), GS(p_t^{sq}, \delta_t^{sq}, v_t^{sq})\}. \end{aligned} \tag{A124}$$

Under a no voucher counterfactual, voucher offers are set to zero. In addition, prices and qualities are determined by solving the adjusted firms' first-order conditions given by equations (37)

and (42).[77] This new distribution of prices and vouchers under the no voucher counterfactual also generates consumer, producer, and government surplus:

$$\begin{aligned} & p_t^{nv},\ \delta_t^{nv},\ v_t^{nv} = 0 \\ & \Rightarrow \{CS(p_t^{nv}, \delta_t^{nv}, v_t^{nv}), PS(p_t^{nv}, \delta_t^{nv}, v_t^{nv}), GS(p_t^{nv}, \delta_t^{nv}, v_t^{nv})\}. \end{aligned} \tag{A125}$$

Thus, the voucher policy acts to move the distribution of sticker prices, qualities, and voucher offers from $(p_t^{sq}, \delta_t^{sq}, v_t^{sq}) \rightarrow (p_t^{nv}, \delta_t^{nv}, v_t^{nv})$, which generates potential changes in surplus. By taking differences, we can compute the impacts of the voucher policy on different dimensions of total surplus:

$$\begin{aligned} \Delta CS &= CS(p_t^{sq}, \delta_t^{sq}, v_t^{sq}) - CS(p_t^{nv}, \delta_t^{nv}, v_t^{nv}), \\ \Delta PS &= PS(p_t^{sq}, \delta_t^{sq}, v_t^{sq}) - PS(p_t^{nv}, \delta_t^{nv}, v_t^{nv}), \\ \Delta GS &= GS(p_t^{sq}, \delta_t^{sq}, v_t^{sq}) - GS(p_t^{nv}, \delta_t^{nv}, v_t^{nv}). \end{aligned} \tag{A126}$$

Finally, by interpreting $|\Delta GS|$ as total government cost of the policy, these estimates can be used to compute the annual benefit-cost ratio BCR of the voucher policy across the education market:[78]

$$\text{BCR} = \frac{\Delta CS + \Delta PS}{|\Delta GS|}. \tag{A127}$$

To understand the source of welfare impacts, students are grouped into voucher recipients and non-recipients. For welfare estimation under each counterfactual, averages of each market segment are computed over 300 draws of unobservables.

AIX. Multigroup Entropy

For any given market m, multigroup entropy MGE_m is defined as follows (Reardon and Firebaugh 2002):

$$MGE_m = \sum_j \frac{N_j}{N_m} \cdot \frac{(E_m - E_j)}{E_m},$$

where N_j is the total enrollment in school j; N_m is the total enrollment in market m; and E_j and E_m are entropy "scores" of school j and market m.

77. To find this new equilibria, schools iteratively solve the new first-order conditions until differences in price and quality between iterations are sufficiently small across all schools.

78. If $\Delta GS > 0$ then the BCR is infinite.

The entropy scores describe the diversity of enrollment within each respective unit:

$$E_j = \sum_l s_{lj} \log\left(\frac{1}{s_{lj}}\right),$$
$$E_m = \sum_l s_{lm} \log\left(\frac{1}{s_{lm}}\right).$$

where s_{lj} is the fraction of enrollment in school j that belongs to group l; and s_{lm} is the fraction of market m that belongs to group l.

This measure is computed for all markets using $l \in$ {Low SES, Middle SES, High SES}, where low SES are those that are lower caste (SC/ST) and below the poverty line (BPL); middle SES are lower caste and above the poverty line; and high SES are upper caste.

AX. Voucher Design and Optimal Private School Behavior

AX.A. Top-Up Fees

The status-quo voucher allows students to attend private schools at zero cost. Some systems (e.g. Australia and France) allow schools to charge "top-up" fees above the voucher amount $\bar{v}$ to cover the difference between sticker prices p_{jt} and the voucher amount $\bar{v}$.[79] Under this top-up policy, schools below the cap face a status-quo, tuition-linked voucher and would thus set price and quality as in the current voucher system. Those above the cap, however, face demand from voucher students who now must pay additional top-ups. Thus, schools under a top-up system will set price and quality $\{p^{tu}_{jt}, \delta^{tu}_{jt}\}$ that solve schools' adjusted first-order conditions:

$$\begin{aligned}
p^{tu}_{jt-} &= p^{sq}_{jt-}(.), \\
p^{tu}_{jt+} &= mc_{jt}(\delta_{jt}) + \frac{\mathbb{E}[N^{nv}_{jt}] + \mathbb{E}(N^{v}_{jt}; p^{tu}_{jt} - \bar{v})}{-\left[\frac{\partial \mathbb{E}[N^{nv}_{jt}]}{\partial p_{jt}} + \frac{\partial \mathbb{E}(N^{v}_{jt}; p^{tu}_{jt} - \bar{v})}{\partial p_{jt}}\right]}, \\
\delta^{tu}_{jt-} &= \delta^{sq}_{jt-}(.), \\
\delta^{tu}_{jt+} &= mc^{-1}_{jt}(\tilde{p}_{jt}) - \frac{\mathbb{E}[N^{nv}_{jt}] + \mathbb{E}(N^{v}_{jt}; p^{tu}_{jt} - \bar{v})}{\frac{\partial \mathbb{E}[N^{nv}_{jt}]}{\partial \delta_{jt}} + \frac{\partial \mathbb{E}(N^{v}_{jt}; p^{tu}_{jt} - \bar{v})}{\partial \delta_{jt}}}.
\end{aligned} \tag{A128}$$

For schools below the cap, the first-order conditions on price and quality are identical to the status-quo system, which would predict substantial price increases and limited quality adjustment (modulo equilibrium responses to the price/quality adjustments of above-cap schools).

79. Some systems (e.g. Chile) allows schools to charge a top-up that is different for voucher students than just the difference between sticker prices and the flat voucher. Because price discrimination is not allowed in this setting, this design is not feasible. If it were implemented, because voucher-eligible students are more price elastic, this would lead to smaller voucher top-ups, raising the policy's BCR modestly.

For those above the cap, the price and quality responses are more complex. For prices, because voucher students must pay top-ups, schools consider the voucher market when setting prices (unlike the current system). Here, the voucher demand will be larger than that without vouchers as they face discounts, potentially increasing markups. Thus, this top-up policy may raise prices for schools above the cap as well. For quality, because students have to pay additional fees, the voucher demand will be smaller under top-ups than under the status-quo. This creates an additional mechanism for above-cap schools to reduce quality by increasing markdowns.

For consumers, voucher students will now face non-zero prices $p_{jt} - \bar{v}$ for schools above the voucher cap. This will cause these students to potentially reject their voucher offer or take-up but at potentially high cost.[80] This would reduce the welfare benefits of the policy for recipients. Non-voucher students will face the adjusted equilibrium price and quality vector under the new rule, with unclear net effects. For producers, the top-up policy will ensure no profit losses by guaranteeing marginal revenue equals price. This is expected to thus increase profits by raising total demand via the price subsidy. The government will continue to face marginal expenses $v(p_{jt})$ for each voucher student as in the existing system. However, voucher students may select less expensive private schools (due to top-up fees), reducing voucher expenses for the government.

These changes will generate a new distribution of consumer, producer, and government surplus and sorting of students to schools. We expect this policy to potentially be weaker for equity outcomes, as voucher recipients may be priced out from enrolling in their top school.

AX.B. Voluntary School Participation

The status-quo policy mandates that all schools must participate in the voucher system. Many systems instead make participation voluntary that allows schools to opt-out (e.g. Pakistan and France). Under this scheme, schools choose to participate if profits weakly increase from admitting voucher students. The counterfactual assumes schools follow a simple condition for exiting the system – if the voucher they receive would be lower than their marginal cost:

$$v(p_{jt}) < mc_{jt}. \tag{A129}$$

Because $mc_{jt} < p_{jt}$, all schools below the cap have marginal revenue unchanged $v(p_{jt}) = p_{jt}$ and benefit from the increased markups, so they will thus always participate. For schools above the cap, they would receive $\bar{v} < p_{jt}$ from each voucher student – if their marginal costs exceed this, they would face losses from each voucher student, and would thus exit the program.[81]

Schools' first-order conditions under voluntary participation for price and quality $\{p_{jt}^{vp}, \delta_{jt}^{vp}\}$

80. In counterfactuals, the rank-ordered lists submitted in voucher applications may also adjust as some schools have positive prices. This is accounted for by submitting synthetic rankings based on total utility. Then, counterfactual voucher offers v_{ijt}^{tu} are drawn based on estimated propensity scores from these new lists.

81. This condition is necessary but not sufficient. For those above the cap but have marginal costs that are lower than $\bar{v}$, they face a more complex entry-exit decision that depends on how entry would change their profits. If they participate they face lower marginal revenue but higher demand. **sanchez21** studies this entry problem in detail. Counterfactuals assume these schools always participate. Assuming they always exit further reduces the policy's BCR.

will be unchanged from the existing system, except for those that choose to exit the voucher sector. These exiting schools (who are above the cap) will set price and quality according to the non-voucher only:

$$
\begin{aligned}
p^{vp}_{jt-} &= p^{sq}_{jt-}(.), \\
p^{vp}_{jt+} &= p^{sq}_{jt+}(.), \\
p^{vp}_{jt+,e} &= mc_{jt}(\delta_{jt}) + \frac{\mathbb{E}[N^{nv}_{jt}]}{-\frac{\partial \mathbb{E}[N^{nv}_{jt}]}{\partial p_{jt}}}, \\
\delta^{vp}_{jt-} &= \delta^{sq}_{jt-}(.), \\
\delta^{vp}_{jt+} &= \delta^{sq}_{jt+}(.), \\
\delta^{vp}_{jt+,e} &= mc^{-1}_{jt}(p_{jt}) - \frac{\mathbb{E}[N^{nv}_{jt}]}{\frac{\partial \mathbb{E}[N^{nv}_{jt}]}{\partial \delta_{jt}}}.
\end{aligned}
\tag{A130}
$$

We should therefore expect a similar change in the distribution of price and quality as the status-quo system upon allowing for voluntary school participation.

For consumers, voluntary participation in the voucher sector will reduce consumer surplus as students will have reduced choice in voucher offers.[82] In particular, the most expensive (and highest quality schools) exit the voucher sector, reducing the potential returns to receiving vouchers. However, because profit-losing schools are those that exit, the rule may increase producer surplus by avoiding these losses. The government may face reduced expenses as more expensive schools exit the voucher sector, which would have demanded larger reimbursements at the cap. Like the top-up policy, this policy would shift surplus away from consumers toward producers, so that equity outcomes would be worse than under the status-quo.

AX.C. Distance-based Assignment

The assignment mechanism for voucher offers in Madhya Pradesh follows deferred acceptance, where students propose rank-ordered lists of private schools. Other states, including Gujarat and Maharashtra, have mechanisms in which students cannot list ranked preferences. In particular, schools are first selected and then ranked according to students' distances to schools. Schools continue to have distance-based priority over students. Thus, in these distance-based assignment mechanisms, the effective rank-ordered lists are then:

$$
R^{d}_{it} = \left\{ j_k \in m^{\text{Priv}}(i,t) : D_{ij_1} < \cdots < D_{ij_{10}} \right\}. \tag{A131}
$$

82. In counterfactuals, the rank-ordered lists submitted in voucher applications may also adjust as some schools opt-out, causing lists to be reduced in size. This is accounted for by submitting synthetic rankings of previously un-ranked schools such that the total list sizes are kept identical. Then, the assignment mechanism is run with the new lists and counterfactual voucher offers are assigned v^{vp}_{ijt}.

If the system were switched to this mechanism, students would have a higher probability of receiving voucher offers from schools that are closer as opposed to those for which they have higher overall preferences (including quality and idiosyncratic utility). Thus, this mechanism may reduce the overall benefits of the voucher for recipients compared to the status-quo (which may lower applications) and result in a misallocation of voucher seats to students. In addition, because disadvantaged students may live farther away from high quality schools, this would lead to smaller improvements in social integration. On the supply-side, we may expect this change to lower schools' incentives to change quality and affect voucher offer probabilities, which are now de-linked from quality δ_{jt}. This would reduce the incentive for low cost schools to raise quality and high cost schools to lower quality.

AX.D. Flat Voucher Payments

Theoretical results suggest that the "tuition-linked" payment design of the status-quo voucher system creates incentives for schools to raise prices below the cap but not above, where reimbursements are "flat" and no longer linked to tuition. It is therefore intuitive to construct a flat voucher counterfactual, in which all schools would receive a single voucher reimbursement $\bar{v}$ regardless of what price they charge. Under flat vouchers, all schools set price and quality $\{p^f_{jt}, \delta^f_{jt}\}$ exactly as the status-quo "above-cap" schools do (who face a flat voucher):

$$\begin{aligned} p^f_{jt-} &= p^f_{jt+} = p^{sq}_{jt+}(.), \\ \delta^f_{jt-} &= \delta^f_{jt+} = \delta^{sq}_{jt+}(.). \end{aligned} \tag{A132}$$

Here, all schools set prices and quality decisions as above-cap schools in the status-quo voucher system (who currently face a flat voucher). When setting prices, they only consider the non-voucher market. When setting quality, they set markdowns below a competitive level which depends on the effective marginal revenue $\tilde{p}_{jt}$. This term is higher than p_{jt} for schools below $\bar{v}$, who now see increased reimbursements and lower than p_{jt} for schools above $\bar{v}$, whose reimbursements continue to be below their price.

The flat voucher system's price setting rule is identical to those above the cap in the status-quo rule, which creates no direct incentive to raise prices. Conditional on quality, prices will only change through changes in enrollment and price elasticities between the voucher and non-voucher market. Quality will adjust asymmetrically depending on the school's price relative to the reimbursement level $\bar{v}$. For more (less) expensive schools who face lower (higher) marginal revenue, we expect quality decreases (increases). This would change marginal costs causing additional changes in sticker prices through quality adjustment. Importantly, these impacts reflect changes in costs as opposed to markups, and so would not be interpreted as distortionary. On net, given a limited quality adjustment, we should expect prices to adjust less than the status-quo by removing the tuition-linked payment incentive to raise prices.

Finally, under this new rule, the government will now incur marginal expenditure $\bar{v}$ for all

voucher students regardless of school tuition fees. This should cause voucher payments to increase relative to the status-quo, as previously below-cap schools now see increased reimbursements. Given the flat voucher amount $\bar{v}$ and equilibrium price and quality $\{p^f_{jt}, \delta^f_{jt}\}$, this will yield a new vector of consumer, producer, and government surplus that can be compared to that under the no-voucher counterfactual. In terms of sorting patters, because the prices faced by voucher recipients remain zero, we expect a flat voucher policy to deliver similar gains in school integration.

References

Abdulkadiroğlu, Atila, Joshua D. Angrist, Susan M. Dynarski, Thomas J. Kane, and Parag A. Pathak. 2011. " Accountability and Flexibility in Public Schools: Evidence from Boston's Charters And Pilots *." *The Quarterly Journal of Economics* 126, no. 2 (May): 699–748.

Abdulkadiroğlu, Atila, Joshua D. Angrist, Yusuke Narita, and Parag A. Pathak. 2017. "Research Design Meets Market Design: Using Centralized Assignment for Impact Evaluation." *Econometrica* 85 (5): 1373–1432.

Abdulkadiroglu, Atila, Parag Pathak, Alvin E Roth, and Tayfun Sonmez. 2006. *Changing the Boston School Choice Mechanism.* Working Paper, Working Paper Series 11965. National Bureau of Economic Research.

Abdulkadiroğlu, Atila, Parag A. Pathak, and Christopher R. Walters. 2018. "Free to Choose: Can School Choice Reduce Student Achievement?" *American Economic Journal: Applied Economics* 10 (1): 175–206.

Abdulkadiroğlu, Atila, and Tayfun Sönmez. 2003. "School Choice: A Mechanism Design Approach." *American Economic Review* 93 (3): 729–747.

Allende, Claudia. 2019. *Competition under Social Interactions and the Design of Education Policies.* Working Papers.

Andrabi, Tahir, Natalie Bau, Jishnu Das, Naureen Karachiwalla, and Asim Ijaz Khwaja. 2023. *Crowding in Private Quality: The Equilibrium Effects of Public Spending in Education.* Working Paper.

Andrabi, Tahir, Natalie Bau, Jishnu Das, and Asim Ijaz Khwaja. 2022. *Heterogeneity in School Value-Added and the Private Premium.* Working Paper, Working Paper Series 30627. National Bureau of Economic Research.

Andrabi, Tahir, Jishnu Das, and Asim Ijaz Khwaja. 2017. "Report Cards: The Impact of Providing School and Child Test Scores on Educational Markets." *The American Economic Review* 107 (6): 1535–1563.

Angrist, Joshua, Eric Bettinger, Erik Bloom, Elizabeth King, and Michael Kremer. 2002. "Vouchers for Private Schooling in Colombia: Evidence from a Randomized Natural Experiment." *American Economic Review* 92 (5): 1535–1558.

Angrist, Joshua, Eric Bettinger, and Michael Kremer. 2006. "Long-Term Educational Consequences of Secondary School Vouchers: Evidence from Administrative Records in Colombia." *American Economic Review* 96 (3): 847–862.

Arcidiacono, Peter, Karthik Muralidharan, Eun-young Shim, and John D Singleton. 2021. *Experimentally Validating Welfare Evaluation of School Vouchers: Part I.* Working Paper, Working Paper Series 29077. National Bureau of Economic Research.

Barahona, Nano, Caue Dobbin, and Sebastian Otero. 2021. *Affirmative action in centralized college admission systems: Evidence from Brazil*. Working Papers.

Bau, Natalie. 2022. "Estimating an Equilibrium Model of Horizontal Competition in Education." *Journal of Political Economy* 130 (7): 1717–1764.

Bedi, Arjun S, and Ashish Garg. 2000. "The effectiveness of private versus public schools: The case of Indonesia." *Journal of Development Economics* 61 (2): 463–494.

Berry, Steven, and Philip Haile. 2016. "Identification in Differentiated Products Markets." *Annual Review of Economics* 8 (1): 27–52.

Berry, Steven, James Levinsohn, and Ariel Pakes. 1995. "Automobile Prices in Market Equilibrium." *Econometrica* 63 (4): 841–890.

Carneiro, Pedro, Jishnu Das, and Hugo Reis. 2022. "The Value of Private Schools: Evidence from Pakistan." *The Review of Economics and Statistics* (September): 1–45.

Chaisemartin, C de, and X D'HaultfŒuille. 2017. "Fuzzy Differences-in-Differences." *The Review of Economic Studies* 85, no. 2 (August): 999–1028.

Chen, Mingli, Marc Rysman, Shuang Wang, and Krzysztof Wozniak. 2022. *An MM algorithm for Fixed Effects in Multinomial Models with an Application to Payment Choice in Grocery Stores.* Working Papers.

Damera, Vijay. 2017. *Choice for the poor or poor choice? Experimental evidence from implementation of India's school choice policy.* Working Papers.

Deming, David J. 2014. "Using School Choice Lotteries to Test Measures of School Effectiveness." *American Economic Review* 104 (5): 406–11.

Deming, David J., Justine S. Hastings, Thomas J. Kane, and Douglas O. Staiger. 2014. "School Choice, School Quality, and Postsecondary Attainment." *American Economic Review* 104 (3): 991–1013.

Dinerstein, Michael, Christopher A. Neilson, and Sebastian Otero. 2022. *The Equilibrium Effects of Public Provision in Education Markets: Evidence from a Public School Expansion Policy.* Working Papers.

Dinerstein, Michael, and Troy D. Smith. 2021. "Quantifying the Supply Response of Private Schools to Public Policies." *American Economic Review* 111 (10): 3376–3417.

Dongre, Ambrish, Ankur Sarin, and Karan Singhal. 2019. *Can a Mandate for Inclusion Change School Choices for Disadvantaged Parents? – Evidence from Urban India.* Working Papers.

Duflo, Esther, Rema Hanna, and Stephen P. Ryan. 2012. "Incentives Work: Getting Teachers to Come to School." *American Economic Review* 102 (4): 1241–78.

Epple, Dennis, Richard E. Romano, and Miguel Urquiola. 2017. "School Vouchers: A Survey of the Economics Literature." *Journal of Economic Literature* 55 (2): 441–92.

Figlio, David, and Cassandra M. D. Hart. 2014. "Competitive Effects of Means-Tested School Vouchers." *American Economic Journal: Applied Economics* 6 (1): 133–56.

Figlio, David, and Krzysztof Karbownik. 2016. *Evaluation of Ohio's EdChoice Scholarship Program: Selection, Competition, and Performance Effects.* Washington, DC: Thomas B. Fordham Foundation.

Friedman, Milton. 1955. *The Role of Government in Education.* Edited by Robert A. Solow. New Brunswick, New Jersey: Rutgers University Press.

Government of India. 2009. *The Right of Children to Free and Compulsory Education Act.* Ministry of Law & Justice.

Howell, William G., Paul E. Peterson, Patrick J. Wolf, and David E. Campbell. 2002. *The Education Gap: Vouchers and Urban Schools.* 2nd ed. Brookings Institution Press.

Hoxby, Caroline Minter. 2003. "School Choice and School Productivity. Could School Choice Be a Tide that Lifts All Boats?" In *The Economics of School Choice,* 287–342. University of Chicago Press.

Hsieh, Chang-Tai, and Miguel Urquiola. 2006. "The effects of generalized school choice on achievement and stratification: Evidence from Chile's voucher program." *Journal of Public Economics* 90 (8): 1477–1503.

Hungerman, Daniel M, and Kevin Rinz. 2016. "Where does voucher funding go? How large-scale subsidy programs affect private-school revenue, enrollment, and prices." *Journal of Public Economics* 136:62–85.

Indus Action. 2021. *Bright Spots Report 2021: Status of Inclusion through the Lens of RTE Section 12(1)(c).* Indus Action.

James, Jonathan. 2017. "MM Algorithm for General Mixed Multinomial Logit Models." *Journal of Applied Econometrics* 32 (4): 841–857.

Kamat, Vishal, and Samuel Norris. 2023. *Estimating Welfare Effects in a Nonparametric Choice Model: The Case of School Vouchers.* Working Paper. arXiv.

Kane, Thomas J, and Douglas O Staiger. 2008. *Estimating Teacher Impacts on Student Achievement: An Experimental Evaluation.* Working Paper, Working Paper Series 14607. National Bureau of Economic Research.

Miller, Ray. 2022. "The Effect of Private Schools on Measures of Socioemotional Development in Adolescence: Evidence from India." *Journal of Human Capital* 16 (2): 303–331.

Muralidharan, Karthik, and Venkatesh Sundararaman. 2015. " The Aggregate Effect of School Choice: Evidence from a Two-Stage Experiment in India *." *The Quarterly Journal of Economics* 130, no. 3 (February): 1011–1066.

Narita, Yusuke. 2020. *A Theory of Quasi-Experimental Evaluation of School Quality.* Working Papers 2020-085. Human Capital and Economic Opportunity Working Group, December.

Neal, Derek A. 2018. *Information, Incentives, and Education Policy.* Cambridge, MA and London, England: Harvard University Press.

Neilson, Christopher A. 2021. *Targeted Vouchers, Competition Among Schools, and the Academic Achievement of Poor Students.* Working Papers. Princeton University.

Rao, Gautam. 2019. "Familiarity Does Not Breed Contempt: Generosity, Discrimination, and Diversity in Delhi Schools." *American Economic Review* 109 (3): 774–809.

Reardon, Sean F., and Glenn Firebaugh. 2002. "Measures of Multigroup Segregation." *Sociological Methodology* 32:33–67.

Romero, Maurcio, and Abhijit Singh. 2022. *The Incidence of Affirmative Action: Evidence from Quotas in Private Schools in India.* Working Papers.

Romero, Mauricio, Justin Sandefur, and Wayne Aaron Sandholtz. 2020. "Outsourcing Education: Experimental Evidence from Liberia." *American Economic Review* 110 (2): 364–400.

Rosenbaum, Paul R., and Donald B. Rubin. 1983. "The Central Role of the Propensity Score in Observational Studies for Causal Effects." *Biometrika* 70 (1): 41–55.

Rouse, Cecilia Elena. 1998. "Private School Vouchers and Student Achievement: An Evaluation of the Milwaukee Parental Choice Program*." *The Quarterly Journal of Economics* 113, no. 2 (May): 553–602.

Ruud, Paul A. 1991. "Extensions of estimation methods using the EM algorithm." *Journal of Econometrics* 49 (3): 305–341.

Sanchez, Christian. 2023. *Equilibrium Consequences of Vouchers Under Simultaneous Extensive and Intensive Margins Competition.* Working Papers.

Train, Kenneth E. 2007. "A Recursive Estimator for Random Coefficient Models."

U-DISE. 2021. *Report on the Unified Information System for Education Plus.* Department of School Education & Literacy, Government of India.

UNESCO. 2021. *Global Education Monitoring Report 2021/2: Non-state actors in education: Who chooses? Who loses?* Paris, France: UNESCO.

Wamalwa, Fredrick M., and Justine Burns. 2018. "Private schools and student learning achievements in Kenya." *Economics of Education Review* 66:114–124.

Wolf, Patrick, Babette Gutmann, Michael Puma, Brian Kisida, Lou Rizzo, Nada Eissa, and Matthew Carr. 2010. *Evaluation of the DC Opportunity Scholarship Program: Final Report.* Washington, DC: National Center for Education Evaluation / Regional Assistance, Institute of Education Sciences, U.S. Department of Education.

World Bank. 2023. *Designing Effective Public-Private Partnerships in Education.* Education for Global Development.

Table I
The Primary School Market in Madhya Pradesh, India

Panel A: Primary School Students (2016–2018)

	All Students	Voucher Eligible	Voucher Applicants	
	Class 1	Class 1	Class 1	All
Female	0.48	0.48	0.42	0.43
Below Poverty Line	0.21	0.37	0.77	0.75
Caste				
General Class	0.12	0.03	0.10	0.11
Other Backward Class	0.43	0.16	0.42	0.42
Scheduled Caste	0.18	0.32	0.32	0.33
Scheduled Tribe	0.28	0.49	0.16	0.14
Block Characteristics				
Urban	0.38	0.35	0.42	0.47
Private Share	0.34	0.30	0.37	0.42
Avg. School Exp. (USD)	28.04	25.81	31.81	37.38
Avg. GPA ($\mu_B = 0, \sigma_B = 1$)	0.00	–0.15	0.13	0.28
No. Students	3,075,527	1,724,905	214,352	659,246

Panel B: Primary Schools (2015)

	Public Schools	Private Schools
Age (Years)	35.99	15.81
Inputs		
Offers English	0.06	0.41
Has Playground	0.60	0.86
Computers Per 10 Pupils	0.03	0.21
Teachers Per 10 Pupils	0.57	0.90
Achievement		
Fraction High Marks	0.49	0.66
GPA ($\mu_I = 0, \sigma_I = 1$)	–0.18	0.41
Financials		
Class 1 Annual Fees (USD)	0.00	53.01
Teacher Wage (USD)	397.19	159.92
Block Characteristics		
Urban	0.33	0.48
Private Share	0.29	0.46
Avg. School Exp. (USD)	24.04	37.80
Avg. GPA ($\mu_B = 0, \sigma_B = 1$)	–0.17	0.36
No. Schools	83,135	25,688
No. Class 1 Students	897,074	712,805

Notes: This table presents summary statistics for students and schools in Madhya Pradesh, India (MP). Panel A reports mean characteristics across different subgroups of primary school students across MP from 2016 to 2018. "Voucher Eligible" refers to students who are eligible to apply for voucher (Below Poverty Line or SC or ST caste groups). "Voucher Applicants" is the set of Nursery, KG1, KG2, or Class 1 voucher applicants from 2016 to 2018. "Class 1" refers to students who were in class 1 between 2016 and 2018. Panel B reports mean characteristics in 2015 across primary schools in MP that have positive class 1 enrollment. "Fraction High Marks" refers to the fraction of class 5 and 8 students who score higher than 60% in standardized exams. "GPA" refers to individual end of year exam scores averaged across all subjects, normalized to mean zero and unit variance across students I. "Block Characteristics" refers to mean characteristics of the "block" (sub-district) in which students or schools are located. "Avg. GPA" refers to the average GPA across students in the block, normalized to have mean zero and unit variance across blocks B. "Avg School Exp." refers to the average per-student expenditure on tuition fees in the district. School characteristics come from the 2015 round of the Unified District Information System for Education (U-DISE) and teacher wages come from the 2018 round of the Periodic Labour Force Survey (PLFS).

TABLE II
FIRST STAGE ESTIMATES OF FIRST CHOICE OFFERS ON VOUCHER TAKEUP

Dependent Variable:	1{Voucher Takeup}			
	1 Year After	2 Years After	3 Years After	All Years After
First Choice Offer	0.35***	0.35***	0.17***	0.33***
	(0.01)	(0.01)	(0.03)	(0.01)
Lottery FE	Yes	Yes	Yes	Yes
Student Char. FE	Yes	Yes	Yes	Yes
Control Mean Takeup	0.23	0.20	0.30	0.23
Application Year Range	2016–2018	2016–2017	2016	2016–2018
No. Observations	237,720	127,804	26,363	137,976

Notes: This table presents separate OLS estimates of the effects of winning a first choice offer on voucher takeup for each year after application (columns), as specified by equations (1) to (2). "All Years After" denotes estimates pooled for all years after application. All estimates (1) pool across all application year and class cohorts; (2) include lottery fixed effects (application class by application year by DA propensity score and first choice school); (3) include student characteristic fixed effects (poverty status by caste by religion by gender by birth year, and if GPA, then also by class); and (4) are clustered at the application level. All controls (lottery fixed effects and student characteristics) are interacted by treatment period. DA propensity scores are estimated from 10,000 simulations of the Deferred Acceptance assignment mechanism for each year and rounded to 0.001.

*10%, **5%, and ***1% significance level.

Table III
The Effects of Voucher Takeup on Student Outcomes

Panel A: The Effect of Voucher Takeup on Student-Specific Outcomes

	1 Year After		2 Years After		3 Years After		All Years After	
	CCM	Effect	CCM	Effect	CCM	Effect	CCM	Effect
Class Promotion (pp)	56.62	3.35	93.46	3.90**	100.20	−0.80	86.63	3.30**
		(7.74)		(1.71)		(3.26)		(1.54)
GPA ($\mu_I = 0, \sigma_I = 1$)	−0.00	0.04	0.14	0.23***	0.10	0.43	0.07	0.17***
		(0.08)		(0.08)		(0.28)		(0.06)
Application Year Range	2016–2018		2016–2017		2016		2016–2018	
First Stage F-Stat Range	100–782		485–649		257–440		1,094–1,985	
No. Obs. Range	21,723–41,659		46,832–51,739		9,840–10,351		83,813–98,331	

Panel B: The Effect of Voucher Takeup on Enrolled School Characteristics

	1 Year After		2 Years After		3 Years After		All Years After	
	CCM	Effect	CCM	Effect	CCM	Effect	CCM	Effect
Private	0.89	0.11***	0.88	0.12***	0.87	0.13	0.88	0.12***
		(0.02)		(0.03)		(0.09)		(0.02)
Offers English	0.25	0.08***	0.26	0.09***	0.40	0.15	0.26	0.09***
		(0.03)		(0.03)		(0.11)		(0.03)
GPA Value−Added	0.14	0.06*	0.20	0.03	−0.02	0.23*	0.15	0.06**
		(0.03)		(0.04)		(0.14)		(0.03)
Distance (KM)	2.29	−0.27	2.25	−0.31	3.28	−1.33*	2.34	−0.36*
		(0.24)		(0.29)		(0.80)		(0.22)
Price Paid (USD)	76.40	−76.40***	72.40	−72.40***	120.26	−120.26***	77.48	−77.48***
		(3.08)		(4.02)		(19.21)		(3.03)
Application Year Range	2016–2018		2016–2017		2016		2016–2018	
First Stage F-Stat Range	882–1,268		699–945		497–596		2,305–3,178	
No. Obs. Range	58,118–75,782		40,328–51,791		8,342–10,401		106,788–137,974	

Notes: This table presents LATE estimates of the effects of voucher takeup on student outcomes (rows) for each year after application and over all years (columns), using first choice offer as an instrument specified by equations (1) to (2). Panel A reports estimates for impacts on student-specific outcomes and Panel B reports estimates for impacts on enrolled school characteristics. "All Years After" denotes estimates pooled for all years after application. "CCM" denotes the Control Complier Mean and "Effect" denotes the estimated impact of voucher takeup with standard errors in parentheses. "Class Promotion" is whether individuals continued to the next class from the year prior. "GPA" refers to individual end of year exam scores averaged across all subjects, normalized to mean zero and unit variance across students I. "GPA Value-Added" is estimated as described in Appendix AII. School characteristics come from the 2015 round of the Unified District Information System for Education (U-DISE). All estimates (1) pool across all application year and class cohorts; (2) include lottery fixed effects (year after application by application class by application year by DA propensity score and first choice school); (3) include student characteristic fixed effects (poverty status by caste by religion by gender; birth year; and village cluster); and (4) are clustered at the application level. DA propensity scores are estimated from 10,000 simulations of the Deferred Acceptance assignment mechanism for each year and rounded to 0.001.

*10%, **5%, and ***1% significance level.

TABLE IV
DEMAND MODEL ESTIMATES

Parameter	Estimate	Standard Error
Panel A: Price Parameters (α_i)		
Price (10USD)	-0.367^{***}	0.003
× Observed Applicant	-0.088^{***}	0.013
× Low SES	-0.142^{***}	0.007
× Middle SES	-0.114^{***}	0.004
× Female	-0.045^{***}	0.003
σ_α	0.060^{***}	0.000
Panel B: Distance Parameters (λ_i)		
Log Distance (KM)	-0.982^{***}	0.015
× Observed Applicant	-0.314^{***}	0.056
× Low SES	-0.002	0.029
× Middle SES	-0.021	0.018
× Female	-0.032^{*}	0.017
Panel C: School Mean Utility Parameters (δ_{jt})		
Mean Public	3.917	
Mean Private	7.847	
Standard Deviation	2.004	
Panel D: Persistence Parameters (ϕ, β_ψ)		
Mean ϕ	0.774	
Standard Deviation ϕ	0.385	
β_ψ	0.934^{***}	0.000
Panel E: Application Cost Parameters (τ)		
Low SES	-3.443^{***}	0.657
Middle SES	-12.902^{***}	0.603
Female	-1.412^{***}	0.504
Log Distance to Application Center (KM)	-1.564^{***}	0.340
Mean τ_t	1.184	
Standard Deviation τ_t	0.351	
Mean τ_m	-1.796	
Standard Deviation τ_m	1.795	

Notes: This table presents parameter estimates from the demand model as described in Section 3. "Low SES" denotes children who are lower caste and below the poverty line; "Middle SES" denotes children who are lower caste and above the poverty line; and the excluded group is those who are upper caste. Estimates come from applicants' rank-ordered lists, and application and enrollment decisions of applicants and a 10% sub-sample of non-applicants. Initial estimation is restricted to a random sample of 200 markets from 2016 to 2018. School mean utilities δ_{jt} and application costs τ_t, τ_m are then estimated for other markets and years before 2016. See Appendix AV. for details of the estimation and extrapolation procedure.

*10%, **5%, and ***1% significance level.

TABLE V
THE IMPACTS OF VOUCHER POLICY ON CONSUMER, PRODUCER, AND GOVERNMENT SURPLUS

	Effect of Voucher Policy (2019USD Per Student Per Year)		
		Price Coefficient (α_i)	
	All	Bottom Quartile	Top Quartile
Panel A: Voucher Recipients (5.2%)			
Consumer Surplus	+105.9	+63.4	+194.9
(Fraction Monetary)	(20.5%)	(11.8%)	(29.3%)
Producer Surplus	–54.1	–28.1	–112.2
Government Surplus	–17.6	–9.0	–32.9
Panel B: Voucher Non-Recipients (94.8%)			
Consumer Surplus	+0.1	–0.2	+0.8
Producer Surplus	–1.3	–0.7	–0.1
Government Surplus	–0.1	–0.7	+0.5
Benefit-Cost Ratio	1.5	1.5	5.6
(Without School Adjustment)	(2.9)	(4.6)	(2.4)

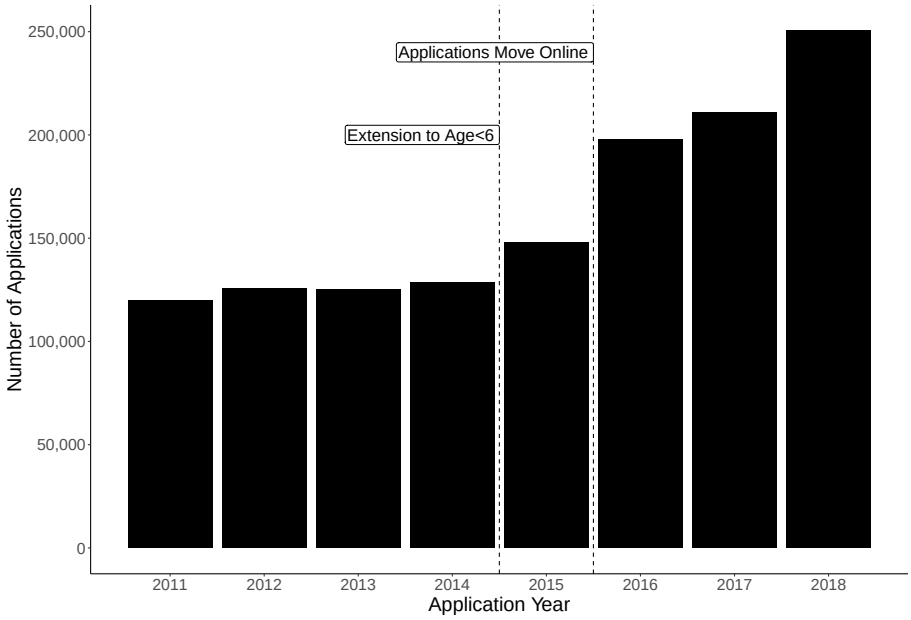
Notes: This table presents estimates of the effects of India's voucher policy on welfare as described in Section VII. Panels A and B reports estimates for voucher recipients (applicants who receive voucher offers,) and voucher non-recipients (applicants who receive no voucher offers or those who do not apply for vouchers), respectively. Estimates are restricted to a random sample of 200 markets in 2018.

TABLE VI
THE EQUILIBRIUM CONSEQUENCES OF VOUCHER DESIGN

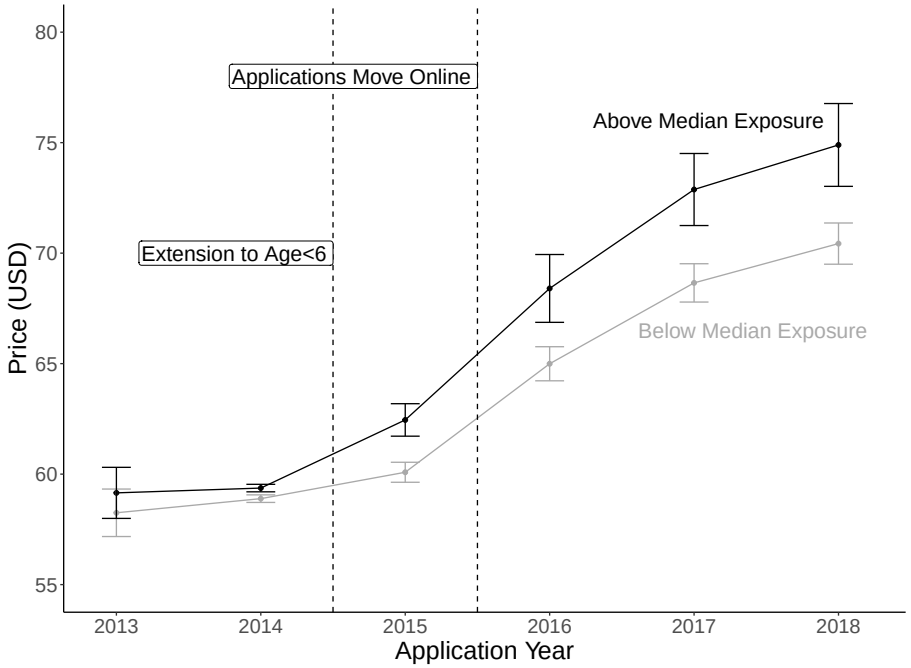
	App. Rate (%)	Impact of Policy on: (%)								Benefit-Cost Ratio	
		Price	Quality	CS	PS	GS	TS	Integration		School Adjustment	
								Private	Entropy	Yes	No
Panel A: Voucher Design Counterfactuals											
Status Quo	14.9	+2.7	+1.2	+4.2	–29.6	–2.1	+0.5	+21.9	–2.5	1.5	2.9
Top-Up Fees	12.8	+3.8	+1.2	+1.2	–7.2	–2.1	–0.4	+7.7	–0.2	0.6	5.2
Voluntary Participation	12.9	+3.0	+1.2	+1.4	–8.7	–1.8	–0.2	+10.7	–0.4	0.8	5.2
Distance-based Assignment	12.8	+2.1	+0.9	+1.9	–14.1	–1.2	–0.0	+11.9	–1.6	1.0	4.2
Flat Voucher ($74)	14.9	+2.1	+1.2	+4.3	–28.7	–1.7	+1.0	+23.8	–2.7	2.1	2.7
Panel B: Longer-Run Counterfactuals											
Raise Quota (25%→50%)	15.6	+2.9	+1.2	+5.3	–35.9	–2.6	+0.9	+27.6	–3.0	1.7	2.9
Flat Voucher ($74)	15.6	+2.2	+1.2	+5.4	–34.7	–2.1	+1.5	+29.9	–3.1	2.3	2.6
Lower Application Costs ($\tau_z = 0$)	25.9	+2.4	+1.2	+6.2	–39.8	–1.9	+1.9	+36.8	–3.5	3.0	3.0
Flat Voucher ($74)	25.9	+1.5	+1.1	+6.3	–38.8	–1.6	+2.4	+39.0	–3.8	3.9	2.7
Expand Eligibility (Universal)	24.6	+1.0	+0.6	+17.4	–94.1	–5.1	+8.0	+21.8	–2.4	4.0	3.0
Flat Voucher ($74)	24.6	–1.9	+0.0	+17.5	–92.7	–4.7	+8.5	+24.9	–2.7	4.5	2.7
Greater Quality Adjustment ($\overline{mc}_{2100}$)	13.8	+2.0	+1.1	+2.7	–24.4	–0.7	–0.2	+15.5	–2.0	0.6	2.9
Flat Voucher ($74)	13.8	+1.7	+1.1	+2.8	–21.4	–0.5	+0.5	+16.5	–2.1	2.8	2.7

Notes: This table presents the estimated impacts of various voucher designs as described in Section VII.C. Panel A compares the status quo in India which pays schools their price up to a voucher cap (on average $74) to alternate designs. "With Top-Ups" additionally allows schools above the cap to charge additional fees equaling the difference between sticker prices and the cap; " With Voluntary Part." is a system that allows schools to opt-out of the voucher system; "Distance-based Assignment" is a system in which students choose 10 private schools but are ranked according to distance instead of preferences and submitted to the DA mechanism (Gujarat/Maharashtra); and"Flat Voucher" is a voucher with a fixed amount equal to the current cap in the status-quo ($74). Panel C expands the voucher system by raising the quota level from 25% to 50% or lowering application costs by shutting off the distance penalty. Panel D allows for greater quality adjustment, raising the threshold to 2100 levels ($\overline{mc}_{2100}$). For integration measures, "Private" denotes the fraction of private school enrollment that comprise voucher eligible children (lower caste or below the poverty line) and "Entropy" is a multigroup entropy index that captures the degree of segregation across individual SES (low, middle, and high) within schools compared to the market's overall composition (see Appendix AIX. for details). "CS" denotes consumer surplus; "PS" denotes producer surplus; "GS" denotes government surplus; and "TS" denotes total surplus. For the benefit-cost ratios, "CS" denotes the benefit-cost ratio considering only consumer surplus and "CS+PS" considers both consumer and government surplus. Estimates are restricted to a random sample of 200 markets in 2018.

(A) Application Growth

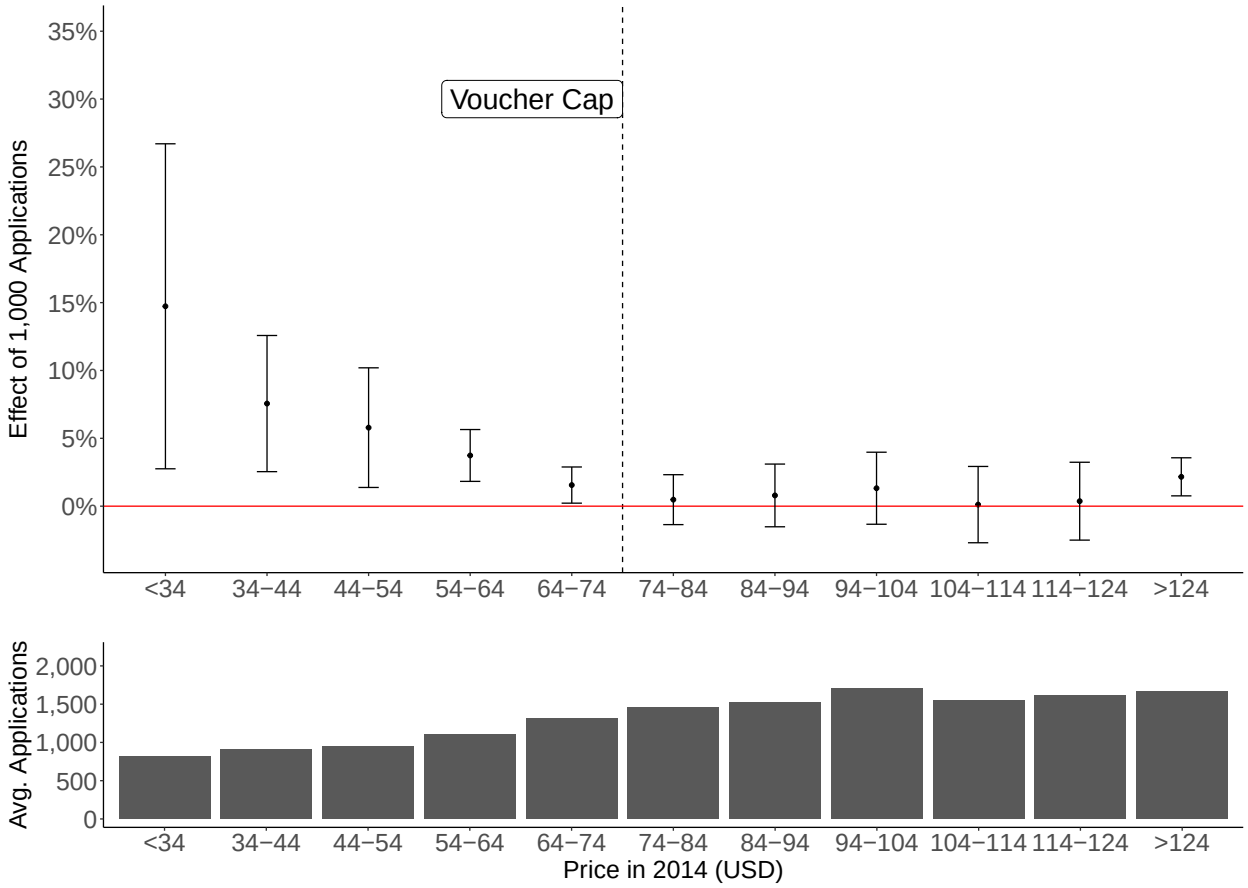


(B) Effects of Application Growth Exposure on School Tuition Fees



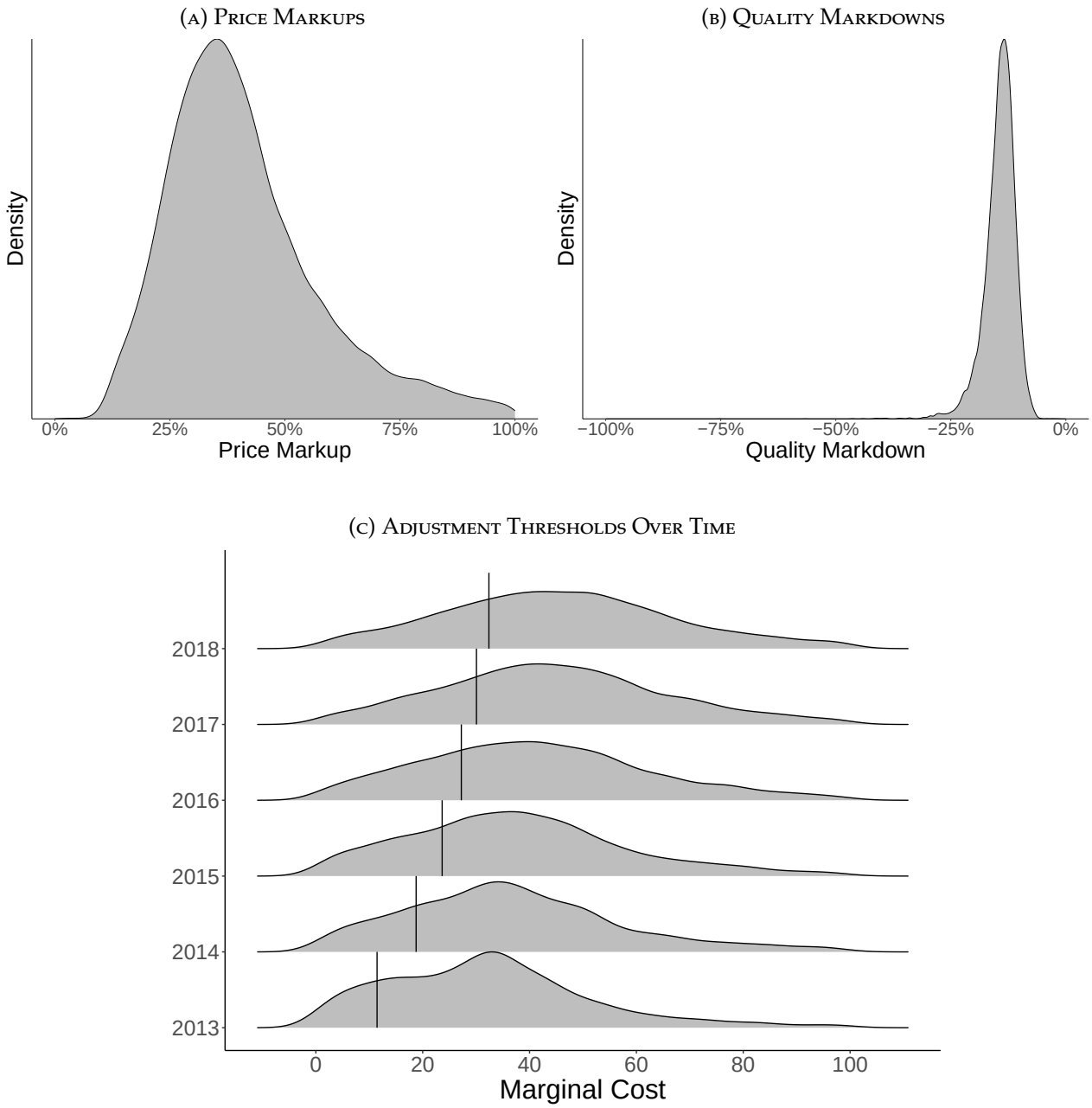
Notes: This figure presents data on application volume and school prices over time. Panel A reports the total number of applications for the Madhya Pradesh voucher system from 2011 to 2018. Panel B presents the average prices charged by schools over time grouped by *ex ante* exposure to application growth: blocks with greater or less than the median private market share for voucher eligible students (black versus grey). Panel B is restricted to schools in the modal bin of 2014 prices: \$54 to \$64 (2019USD). The dashed vertical lines denotes that the policy was extended to children under age 6 in 2015 and applications moved from an offline to an online system in 2016, substantially increasing application volume by 15% and 30%, respectively. The dashed horizontal line denotes the average voucher cap over the sample period 2016 to 2018 of \$74.47.

Figure I
Voucher Application Growth and Price Responses



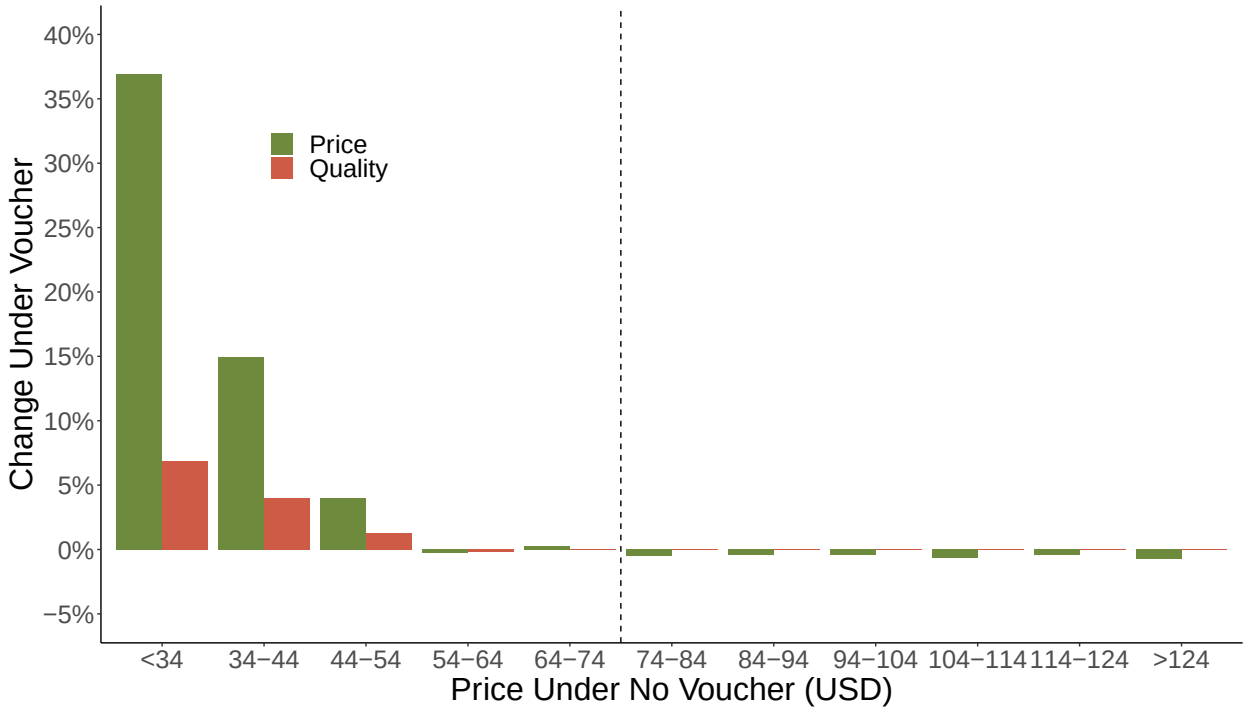
Notes: This figure presents IV difference-in-difference estimates of the impacts of local voucher demand on school prices as specified by equation (3), for various bins of sticker prices in 2014. For each bin (x-axis), points (y-axis) denote the difference-in-differences coefficient of block-level application volume divided by the mean price in the bin, instrumented by block-level private market share of voucher eligible students interacted with post-2014; intervals denote 95% confidence intervals. The dashed vertical line denotes the average voucher cap over the sample period of $74.47. The bottom panel reports the average number of block-level applications in each bin over the sample period. Estimates (1) are re-scaled to reflect the impact of 1,000 additional applications on school prices; (2) include all schools between 2013 and 2018 and classes 1-8; (3) include year and school-by-class fixed effects, and (4) are clustered by block, the level of treatment assignment. First stage F-stats range from 2,257 to 27,447.

FIGURE II
THE EFFECTS OF VOUCHER APPLICATIONS ON SCHOOL TUITION FEES



Notes: This figure presents estimates from the supply-side model as described in Section VI.B. Panel A plots the kernel density estimate (KDE) of price markups (as a fraction of school tuition fees) and Panel B plots the KDE of quality markdowns (as a fraction of estimated school quality). Panel C plots the KDE of marginal costs over time, with vertical lines denoting the estimated quality adjustment threshold in each year. Estimates are reported for all markets from 2013 to 2018.

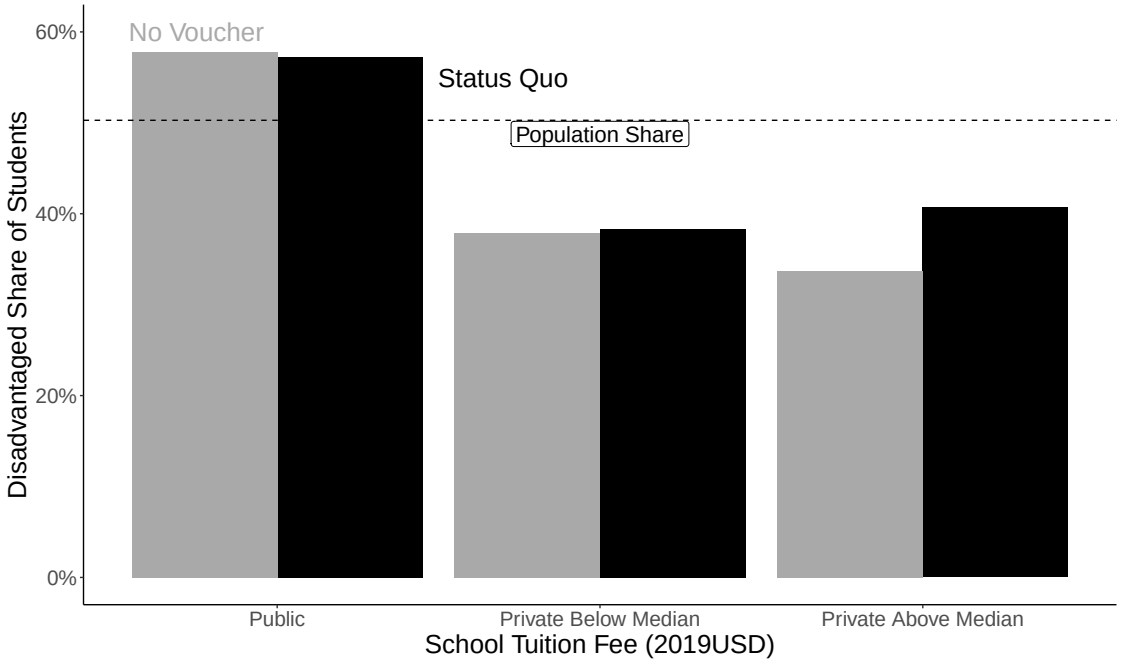
Figure III
Supply Model Estimates



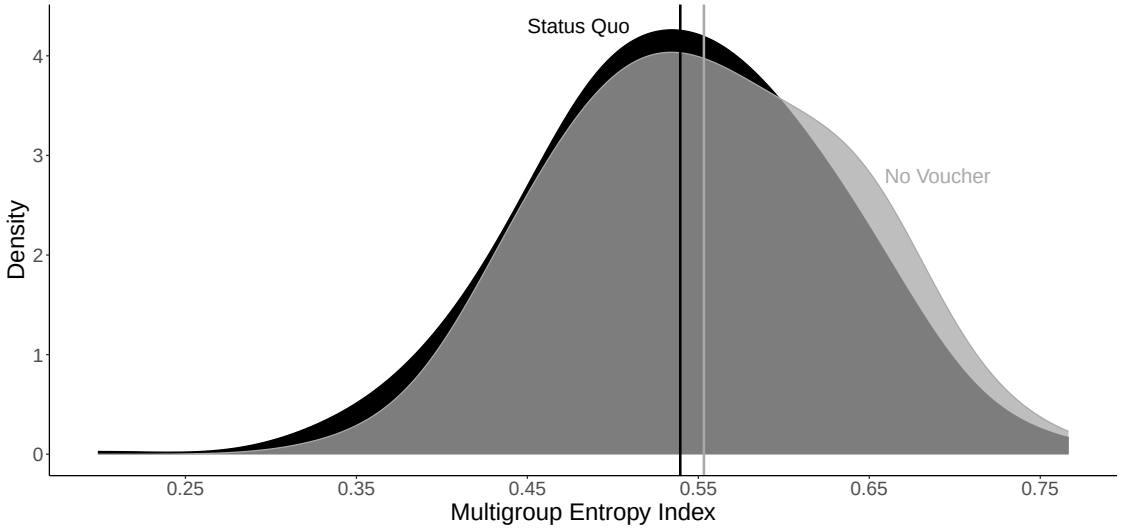
Notes: This figure presents the impact of India's voucher system on equilibrium prices and quality. Each bar (y-axis) reports, for each bin of private school prices under the no voucher system (x-axis), the average percent change in school prices and quality (green and red, respectively) of moving from the no voucher counterfactual to the status-quo voucher system as described in Appendix AVIII. The dashed vertical line denotes the average voucher cap over the sample period 2016 to 2018 of $74.47. Estimates are restricted to a random sample of 200 markets in 2018.

FIGURE IV
THE IMPACT OF VOUCHER POLICY ON EQUILIBRIUM PRICE AND QUALITY

(A) School Composition of Voucher Ellgible Students

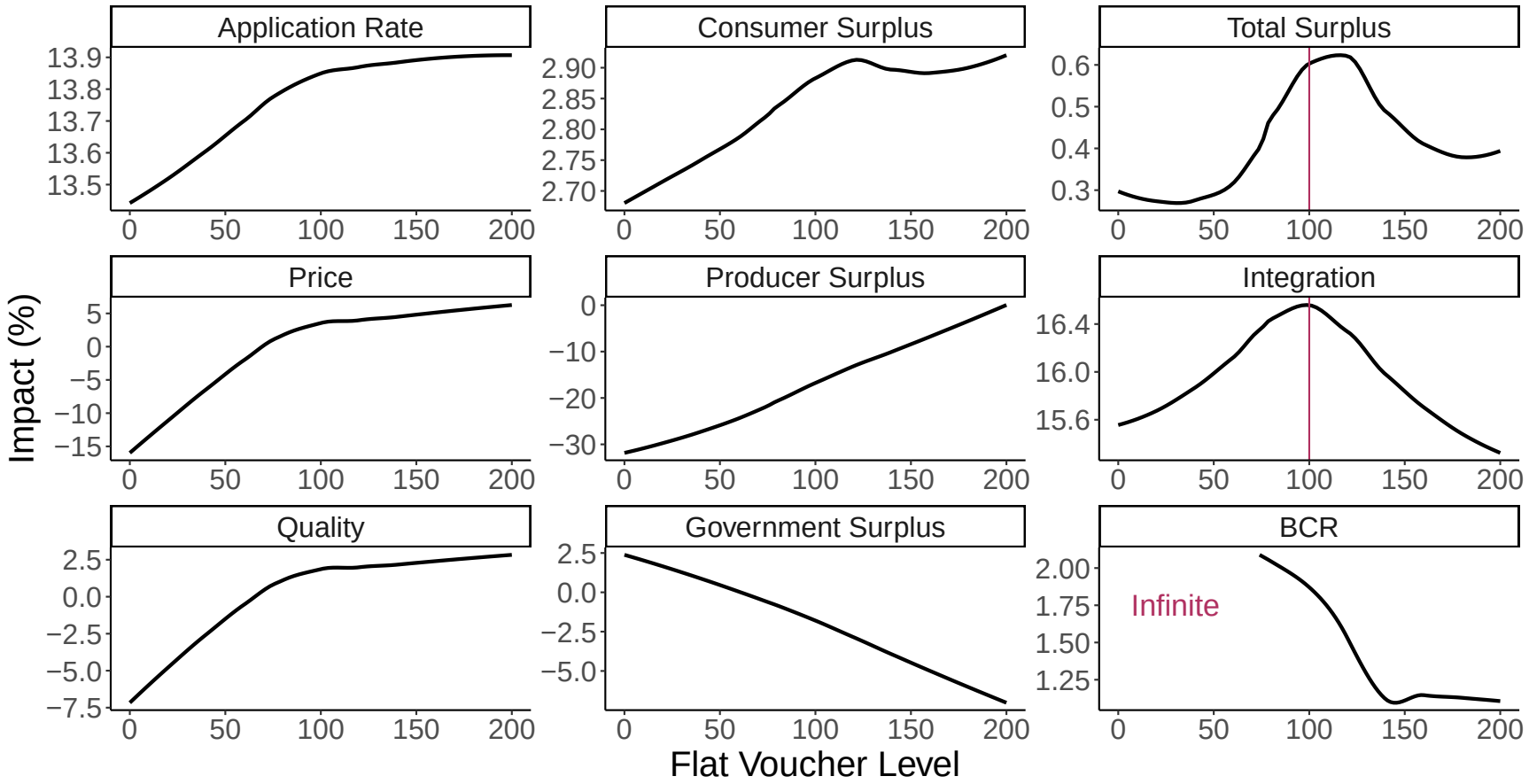


(B) Index of School Segregation Across Markets



Notes: This figure presents the impacts of India's voucher system on school integration. In Panel A, each bar is the fraction of school enrollment that comprise voucher-eligible children (y-axis) against bins of school tuition fees (x-axis). The black color denotes the status-quo voucher system and the grey denotes the no-voucher counterfactual as described in Appendix AVIII. In Panel B, the black distribution plots the kernel density estimate (KDE) of multigroup entropy across markets in the status quo voucher system. The entropy index captures the degree of segregation across individual SES (low, middle, and high) within schools compared to the market's overall composition (see Appendix AIX. for details). The grey distribution is the KDE of entropy across markets for the no voucher counterfactual. Vertical lines denote means of each distribution. Estimates are restricted to a random sample of 200 markets in 2018.

Figure V
The Impacts of Voucher Policy on School Integration



Notes: This figure presents the estimated impact of flat vouchers depending on the size of the voucher payment. Counterfactual impacts are based on greater quality adjustment, raising the cost threshold to 2100 levels ($\overline{mc}_{2100}$). Effects are computed for voucher levels from \$0 to \$200 in increments of \$20 (x-axis) for various outcomes relative to a no voucher scenario (y-axis). The black lines present smoothed impacts over the range of voucher levels. Red lines denote the voucher level which maximizes the corresponding outcome. For the BCR panel, "infinite" denotes that the range of missing voucher levels deliver an infinite benefit-cost ratio.

FIGURE VI

THE IMPACTS OF FLAT VOUCHER LEVELS UNDER GREATER QUALITY ADJUSTMENT

TABLE AI
PUBLIC FUNDING FOR PRIVATE PRIMARY EDUCATION AROUND THE WORLD

Region	Period	System	Participation	Top-Up Fees	Voucher Level	Enrollment
India	2009 –	Targeted	Mandatory	No	Tuition-Linked	4,130,000
Pakistan	2005 –	Targeted	Voluntary	No	Flat	1,200,000
M.P. (India)	2009 –	Targeted	Mandatory	No	Tuition-Linked	1,120,00
Netherlands	1917 –	Universal	Mandatory	No	Flat	800,000
Australia	1964 –	Universal	Mandatory	Yes	Tuition-Linked	670,000
France	1959 –	Universal	Voluntary	Yes	Cost-Linked	650,000
Indonesia	2008 –	Targeted	Mandatory	Yes	Flat	640,000
Chile	1981 –	Universal	Voluntary	Yes	Flat	470,000
Belgium	1914 –	Universal	Mandatory	No	Cost-Linked	440,000
Chile	2008 –	Targeted	Voluntary	No	Flat	300,000
Germany	1949 –	Universal	Mandatory	Yes	Flat	150,000
United States	1990 –	Targeted	Voluntary	Yes	Tuition-Linked[†]	140,000
Sweden	1990 –	Universal	Mandatory	No	Flat	90,000
New Zealand	1975 –	Universal	Mandatory	Yes	Flat	60,000
Denmark	1855 –	Universal	Mandatory	No	Flat	60,000
Colombia	1995 –	Targeted	Voluntary	Yes	Flat	30,000

Notes: This table describes government programs that publicly fund private primary schools around the world. This includes either full or partial government subsidies for primary school students to attend private schools. "Targeted" refers to programs that have eligibility limited by social and/or economic criteria. "Universal" refers to programs where all students are eligible. "Mandatory" refers to a system where private schools must participate, while under a "Voluntary" they can opt-out of the voucher system. "Top-Up Fees" refers to fees schools may charge students above any voucher amount. "Tuition-Linked" refers to a payment design where vouchers are paid to schools according to their tuition levels, while "Cost-Linked" is paid according to anticipated costs. "Flat" refers to payments of a fixed voucher amount to all schools regardless of tuition or cost structures. Where possible, estimates of enrollment size are reported for primary school children enrolled in private voucher schools in 2018. Enrollment estimates are computed using author calculations (Indus Action 2021 for India) and are rounded to the nearest 10,000.
[†]Programs in New Hampshire and Wisconsin have "Flat" voucher payments.

TABLE AII
SOCIO-ECONOMIC STATUS, GPA, AND VALUE-ADDED ESTIMATION

	GPA_{it} ($\mu_I = 0, \sigma_I = 1$)			
	(1)	(2)	(3)	(4)
Female	0.04***	0.06***	0.04***	0.06***
	(0.00)	(0.00)	(0.00)	(0.00)
Below Poverty Line (BPL)	–0.12***	–0.06***		
	(0.00)	(0.00)		
Other Backward Caste (OBC)	–0.24***	–0.06***		
	(0.01)	(0.00)		
Scheduled Caste (SC)	–0.40***	–0.12***		
	(0.01)	(0.00)		
Scheduled Tribes (ST)	–0.59***	–0.18***		
	(0.01)	(0.00)		
Middle SES (SC/ST & Not BPL)			–0.31***	–0.08***
			(0.00)	(0.00)
Low SES (SC/ST & BPL)			–0.44***	–0.15***
			(0.00)	(0.00)
School × Year FE	No	Yes	No	Yes
$GPA_{i,t-1}$ FE	No	Yes	No	Yes
Religion FE	No	Yes	No	Yes
$Class_{it}$ FE	No	Yes	No	Yes
$Class_{i,t-1}$ FE	No	Yes	No	Yes
Observations	1,741,356	1,741,356	1,741,356	1,741,356
Adjusted R^2	0.04	0.41	0.03	0.41

Notes: This table presents OLS estimates of student-level GPA on characteristics. GPA_{it} is the grade point average of student i in year t and is normalized to have mean zero and unit variance in the broader MP student population in each year. Estimation is restricted to a 10% random sample of students in primary school (class 1 to 8) from 2013 to 2018. Standard errors are clustered at the school level. Value-added is recovered using the preferred specification in column (2) following the procedure described in Appendix AII.

*10%, **5%, and ***1% significance level.

TABLE AIII
TEST OF VALUE-ADDED FORECAST UNBIASEDNESS USING VOUCHER LOTTERIES

	GPA_{ijt} ($\mu_I = 0, \sigma_I = 1$)			
	Standard		Empirical Bayes	
	(1)	(2)	(3)	(4)
Value-Added$_{jt}$	1.62**		2.37**	
	(0.74)		(1.18)	
Value-Added$_{jt}$ × Years Treated		0.86**		1.27*
		(0.42)		(0.69)
Lottery FE	Yes	Yes	Yes	Yes
p-value (Coefficient = 1)	0.40	0.74	0.24	0.70
First-Stage F-Stat	12.33	16.97	9.72	13.15
No. Obs.	87,114	87,114	87,105	87,105

Notes: This table presents LATE estimates of standardized student-level GPA on the value-added of school attended, which is instrumented by winning a first-choice offer as described in Appendix AII.B. First two columns use standard VA estimates as in Appendix AII. and latter two columns use VA estimates with empirical bayes shrinkage as in Appendix AII.A. The "Value-Added × Years Treated" row corrects for years since voucher receipt. Data is restricted to those schools and applicants for which school characteristics are observed. All estimates (1) pool across all application year and class cohorts; (2) include lottery fixed effects (application class by application year by DA propensity score and first-choice school fixed effects); and (3) are clustered at the application level. DA propensity scores are estimated from 10,000 simulations of the Deferred Acceptance assignment mechanism for each year and rounded to 0.001.
*10%, **5%, and ***1% significance level.

Table AIV
Voucher Applicant Data Availability

	Voucher Applications 2016–2018		
	All	Attendance Observed	GPA Observed
Female	0.43	0.42	0.42
Below Poverty Line	0.75	0.77	0.77
Caste			
General Class	0.11	0.10	0.10
Other Backward Class	0.42	0.42	0.42
Scheduled Caste	0.33	0.32	0.32
Scheduled Tribe	0.14	0.16	0.16
Application Year			
2016	0.30	0.47	0.48
2017	0.32	0.32	0.32
2018	0.38	0.21	0.20
Application Class			
Nursery	0.33	0.05	0.05
KG1	0.37	0.49	0.47
KG2	0.10	0.14	0.14
Class 1	0.20	0.31	0.33
Block Characteristics			
Urban	0.47	0.42	0.42
Private Share	0.42	0.37	0.37
Avg. School Exp. (USD)	37.38	31.62	31.70
Avg. GPA ($\mu_B = 0, \sigma_B = 1$)	0.28	0.12	0.12
No. Students	659,246	222,787	199,872

Notes: This table presents summary statistics on data availability of voucher applicants. Each column reports mean characteristics across different subgroups of students between 2016 and 2018."Voucher Applicants" is the set of Nursery, KG1, KG2, or Class 1 applicants for the voucher policy from 2016 to 2018. "Attendance Observed" refers to applicants whose school enrollments are observed for at least 1 year after application. "GPA Observed" refers to applicants whose GPA is also observed for at least 1 year after application. "Block Characteristics" refers to mean characteristics of the "block" (sub-district) in which students or schools are located. "Avg. GPA" refers to the average GPA across students in the block, normalized to have mean zero and unit variance across blocks B. "Avg School Exp." refers to the average per-student expenditure on tuition fees in the block.

TABLE AV
PRIVATE SCHOOLS BY APPLICATION AND LOTTERY STATUS

	Private Schools 2015		
	All	Received Voucher App.	Non-Degenerate
Age (Years)	15.81	14.58	15.13
Inputs			
Offers English	0.41	0.42	0.51
Has Playground	0.86	0.87	0.89
Computers Per 10 Pupils	0.21	0.19	0.23
Teachers Per 10 Pupils	0.90	0.84	0.81
Achievement			
Fraction High Marks	0.66	0.68	0.67
GPA ($\mu_I = 0, \sigma_I = 1$)	0.42	0.42	0.44
Financials			
Class 1 Annual Fees (USD)	53.01	64.88	73.18
Block Characteristics			
Urban	0.48	0.47	0.52
Private Share	0.46	0.45	0.48
Avg. School Exp. (USD)	37.80	38.40	42.17
Avg. GPA ($\mu_B = 0, \sigma_B = 1$)	0.35	0.38	0.45
No. Blocks	319	319	312
No. Schools	25,688	19,410	11,921
No. Voucher Applicants	600,367	600,367	483,373

Notes: This table presents summary statistics for private primary schools in Madhya Pradesh, India (MP). Each column reports mean characteristics for different school subgroups in 2015 that have positive class 1 enrollment. "Received Voucher App." denotes private schools listed in at least 1 voucher application. "Non-Degenerate" refers to private schools which, in addition, have a DA p-score that lies strictly between 0 and 1. "Fraction High Marks" refers to the fraction of class 5 and 8 students who score higher than 60% in standardized exams."GPA" refers to individual end of year exam scores averaged across all subjects, normalized to mean zero and unit variance across students I. "Block Characteristics" refers to mean characteristics of the "block" (sub-district) in which schools are located. "Avg. GPA" refers to the average GPA across students in the block, normalized to have mean zero and unit variance across blocks B. "Avg. School Exp." refers to the average per-student expenditure on tuition fees in the block. Data is restricted to those schools and applicants for which school characteristics are observed. School characteristics come from the 2015 round of the Unified District Information System for Education (U-DISE).

Table AVI
First Choice Offer and Individual Characteristics

		Effect of First Choice Offer		
			Lottery Fixed Effects	
	Control Mean	No FEs	Full Conditioning	DA p-Score
Female	0.45	0.01	0.01	−0.00
		(0.00)	(0.03)	(0.01)
Below Poverty Line	0.72	0.04***	0.02	0.01
		(0.00)	(0.02)	(0.01)
Caste				
General Class	0.12	−0.02***	−0.00	−0.00
		(0.00)	(0.01)	(0.01)
Other Backward Class	0.41	0.01	0.01	0.00
		(0.00)	(0.02)	(0.01)
Scheduled Caste	0.36	−0.03***	0.01	0.01
		(0.00)	(0.02)	(0.01)
Scheduled Tribe	0.11	0.04***	−0.01	−0.01
		(0.00)	(0.02)	(0.00)
Block Characteristics				
Urban	0.55	−0.11***	−0.00	−0.00
		(0.00)	(0.00)	(0.00)
Private Share	0.50	−0.10***	0.00	−0.00
		(0.00)	(0.00)	(0.00)
Avg. School Exp. (USD)	42.98	−10.95***	−0.00	−0.00
		(0.20)	(0.00)	(0.00)
Avg. GPA ($\mu_B = 0, \sigma_B = 1$)	0.38	−0.27***	−0.00	−0.00
		(0.01)	(0.00)	(0.00)
No. FE Range		0	74,758−75,481	23,722−23,963
No. Obs. Range		103,990−104,971	103,990−104,971	96,728−97,630

Notes: This table presents OLS estimates of the effects of winning a first choice voucher offer on individual characteristics (rows) across specifications (columns). "Full Conditioning" denotes estimates with fixed effects for the full rank-ordered list submitted by application class by application year. "DA p-Score" denotes estimates with application class by application year by DA propensity score and first-choice school fixed effects. "Block Characteristics" refers to mean characteristics of the "block" (sub-district) in which students are located. "Avg. GPA" refers to the average GPA across students in the block, normalized to have mean zero and unit variance across blocks B. "Avg. School Exp." refers to the average per-student expenditure on tuition fees in the block. Data is restricted to those schools and applicants for which school characteristics are observed. All estimates (1) pool across all application year and class cohorts and (2) are clustered at the application level. DA propensity scores are estimated from 10,000 simulations of the Deferred Acceptance assignment mechanism for each year and rounded to 0.001.

*10%, **5%, and ***1% significance level.

Table AVII
The Effects of First Choice Voucher Offers on Student Outcomes

Panel A: The Effect of Winning a First Choice Voucher Offer on Student-Specific Outcomes

	1 Year After		2 Years After		3 Years After		All Years After	
	CM	Effect	CM	Effect	CM	Effect	CM	Effect
Class Promotion (pp)	90.02	0.59	98.17	1.36**	99.34	−0.13	97.20	0.95**
		(1.32)		(0.61)		(0.54)		(0.45)
GPA ($\mu_I = 0, \sigma_I = 1$)	0.20	0.01	0.28	0.08***	0.49	0.08	0.29	0.06***
		(0.03)		(0.03)		(0.05)		(0.02)
Application Year Range	2016–2018		2016–2017		2016		2016–2018	
No. Obs. Range	21,767–41,659		46,832–51,757		9,840–10,353		83,877–98,331	

Panel B: The Effect of Winning a First Choice Voucher Offer on Enrolled School Characteristics

	1 Year After		2 Years After		3 Years After		All Years After	
	CM	Effect	CM	Effect	CM	Effect	CM	Effect
Private	0.73	0.04***	0.76	0.04***	0.85	0.02	0.76	0.04***
		(0.01)		(0.01)		(0.02)		(0.01)
Offers English	0.41	0.03***	0.47	0.03**	0.61	0.03	0.46	0.03***
		(0.01)		(0.01)		(0.02)		(0.01)
GPA Value−Added	0.12	0.02*	0.11	0.01	0.14	0.04*	0.12	0.02**
		(0.01)		(0.01)		(0.03)		(0.01)
Distance (KM)	2.71	−0.10	2.71	−0.11	2.57	−0.27*	2.69	−0.12*
		(0.08)		(0.10)		(0.16)		(0.07)
Price Paid (USD)	49.25	−26.34***	58.40	−25.63***	65.22	−21.94***	54.86	−25.63***
		(1.30)		(1.69)		(4.15)		(1.22)
Application Year Range	2016–2018		2016–2017		2016		2016–2018	
No. Obs. Range	58,118–75,782		40,328–51,791		8,342–10,401		106,788–137,974	

Notes: This table presents reduced-form estimates of the effects of receiving a first choice voucher offer on student outcomes (rows) for each year after application and over all years (columns). Panel A reports estimates for impacts on student-specific outcomes and Panel B reports estimates for impacts on enrolled school characteristics. "All Years After" denotes estimates pooled for all years after application. "CM" denotes the Control Mean (those who did not win their first choice) and "Effect" denotes the estimated impact of winning a first choice offer with standard errors in parentheses. "Class Promotion" is whether individuals continued to the next class from the year prior. "GPA" refers to individual end of year exam scores averaged across all subjects, normalized to mean zero and unit variance across students I. "GPA Value-Added" is estimated as described in Appendix AII. School characteristics come from the 2015 round of the Unified District Information System for Education (U-DISE). All estimates (1) pool across all application year and class cohorts; (2) include lottery fixed effects (year after application by application class by application year by DA propensity score and first choice school); (3) include student characteristic fixed effects (poverty status by caste by religion by gender; birth year; and village cluster); and (4) are clustered at the application level. DA propensity scores are estimated from 10,000 simulations of the Deferred Acceptance assignment mechanism for each year and rounded to 0.001.

*10%, **5%, and ***1% significance level.

Table AVIII
The Effects of Takeup on Student Outcomes: Robustness Across Specifications

Panel A: The Effect of Voucher Takeup on Student-Specific Outcomes

	Full Conditioning				DA Propensity Score			
	(1)		(2)		(3)		(4)	
	CCM	Effect	CCM	Effect	CCM	Effect	CCM	Effect
Class Promotion (pp)	85.96	3.97	85.89	4.04	86.28	3.65**	86.63	3.30**
		(3.43)		(3.43)		(1.54)		(1.54)
GPA ($\mu_I = 0, \sigma_I = 1$)	0.07	0.17*	0.08	0.15	0.04	0.19***	0.07	0.17***
		(0.10)		(0.10)		(0.06)		(0.06)
Additional Controls	No		Yes		No		Yes	
First Stage F-Stat Range	1,133–2,050		1,092–1,967		1,105–1,975		1,094–1,984	
No. Obs. Range	89,808–105,144		89,808–105,144		83,813–98,331		83,813–98,331	

Panel B: The Effect of Voucher Takeup on Enrolled School Characteristics

	Full Conditioning				DA Propensity Score			
	(1)		(2)		(3)		(4)	
	CCM	Effect	CCM	Effect	CCM	Effect	CCM	Effect
Private	0.88	0.12***	0.87	0.13***	0.88	0.12***	0.88	0.12***
		(0.04)		(0.04)		(0.02)		(0.02)
Offers English	0.33	0.02	0.33	0.02	0.27	0.08***	0.26	0.09***
		(0.04)		(0.04)		(0.03)		(0.03)
GPA Value−Added	0.20	0.01	0.20	0.02	0.17	0.05*	0.15	0.06**
		(0.04)		(0.04)		(0.03)		(0.03)
Distance (KM)	2.43	−0.45	2.44	−0.45	2.31	−0.33	2.34	−0.36*
		(0.32)		(0.32)		(0.22)		(0.22)
Price Paid (USD)	63.91	−63.91***	63.74	−63.74***	77.62	−77.62***	77.48	−77.48***
		(3.93)		(3.93)		(3.08)		(3.03)
Additional Controls	No		Yes		No		Yes	
First Stage F-Stat Range	2,587–3,795		2,572–3,605		2,311–3,161		2,305–3,177	
No. Obs. Range	113,954–147,094		113,954–147,094		106,788–137,974		106,788–137,974	

Notes: This table presents LATE estimates of the effects of voucher takeup on student outcomes all years after application (rows) for different lottery fixed effect specifications (columns), using first-choice offer as an instrument specified by equation (1). Panel A reports estimates for impacts on student-specific outcomes and Panel B reports estimates for impacts on enrolled school characteristics. "CCM" denotes the Control Complier Mean and "Effect" denotes the estimated impact of voucher takeup for all years after application, with standard errors in parentheses. "Class Promotion" is whether individuals continued to the next class from the year prior. "GPA" refers to individual end of year exam scores averaged across all subjects, normalized to mean zero and unit variance across students I. "GPA Value-Added" is estimated as described in Appendix AII. School characteristics come from the 2015 round of the Unified District Information System for Education (U-DISE). "Full Conditioning" denotes estimates with fixed effects for the full rank-ordered list submitted by application class by application year. "DA p-Score" denotes estimates with application class by application year by DA propensity score and first-choice school fixed effects. "Additional Controls" denote student characteristic fixed effects (poverty status by caste by religion by gender by birth year, and if GPA, then also by class). All controls (lottery fixed effects and student characteristics) are interacted by treatment period. All estimates (1) pool across all application years, application classes, and treatment periods; and (2) are clustered at the application level. DA propensity scores are estimated from 10,000 simulations of the Deferred Acceptance assignment mechanism for each year and rounded to 0.001.

*10%, **5%, and ***1% significance level.

TABLE AIX
MARKET SCHOOL EXPENDITURE AND CHARACTERISTICS

Dependent Variable:	Block Avg. Annual School Expenditure (USD)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Block Characteristics							
Urban	31.22***						
	(3.60)						
Private Share		84.12***					
		(3.23)					
Avg. GPA ($\mu_B = 0, \sigma_B = 1$)			13.16***				
			(0.86)				
Fraction Below Poverty Line				−29.03*			
				(16.72)			
Fraction SC or ST					−40.24***		
					(5.40)		
District Characteristics							
Avg. Years of Schooling						6.59**	
						(2.55)	
Avg. Annual Income (USD)							0.06***
							(0.01)
No. Observations	319	319	319	319	319	319	319
Adjusted R^2	0.19	0.68	0.42	0.01	0.15	0.10	0.25

Notes: This table reports OLS regression estimates of market average school expenditure on other characteristics. "Block Characteristics" refers to mean characteristics of the "block" (sub-district) across the entire population of class 1 to 8 students in Madhya Pradesh. The dependent variable is the average per-student expenditure on annual tuition fees at the block-level, using administrative data on school enrollment and tuition fees. "Avg. GPA" refers to the average GPA across students in the block, normalized to have mean zero and unit variance across blocks B. "SC" and "ST" refer to Scheduled Castes and Scheduled Tribes, the two most disadvantaged social groups. District characteristics come from the 2016-17 round of the Periodic Labour Force Survey. Estimates are weighted by block-level student population and standard errors are clustered at the district-level.

*10%, **5%, and ***1% significance level.

Table AX
The Effects of Voucher Applications on Private School Outcomes

	Effect of Block-Level Application Volume (1,000)					Range of Fit Statistics	
2014 Price (USD)	Price (%)	GPA Value-Added (σ)	Teachers per 10 Pupils	School Mean Utility (%)	School Exit (pp)	First Stage F-Stat	No. Obs.
<$34	14.73**	0.05	0.60	−0.06	−0.63	617–11,941	6,889–56,837
	(6.11)	(0.07)	(0.47)	(1.38)	(0.72)		
$34–$44	7.56***	0.04	0.42	2.48**	0.79	704–14,006	7,227–57,753
	(2.56)	(0.05)	(0.40)	(1.20)	(1.05)		
$44–$54	5.79**	0.10**	0.14	0.21	−0.02	1,207–15,402	8,954–71,004
	(2.25)	(0.05)	(0.37)	(0.82)	(0.49)		
$54–$64	3.74***	0.01	0.18	1.04*	0.05	2,864–34,299	17,053–144,397
	(0.97)	(0.03)	(0.24)	(0.62)	(0.17)		
$64–$74	1.55**	0.02	−0.08	0.58	0.68	1,743–23,796	10,839–100,298
	(0.68)	(0.02)	(0.13)	(0.46)	(0.47)		
$74–$84	0.48	0.00	0.05	0.17	0.79	1,063–15,515	6,144–56,775
	(0.94)	(0.02)	(0.22)	(0.38)	(0.52)		
$84–$94	0.79	0.02	0.21	0.20	0.64	833–10,374	4,017–39,012
	(1.18)	(0.03)	(0.41)	(0.31)	(0.46)		
$94–$104	1.32	−0.06*	−0.23	1.09*	0.90	514–5,850	1,874–19,902
	(1.35)	(0.04)	(0.28)	(0.55)	(0.75)		
$104–$114	0.12	−0.00	−0.33	−0.00	−0.25	313–5,033	1,672–19,175
	(1.43)	(0.05)	(0.30)	(0.57)	(0.52)		
$114–$124	0.37	0.00	0.01	−0.02	0.26	131–2,810	766–9,662
	(1.46)	(0.05)	(0.28)	(0.83)	(0.39)		
>$124	2.16***	−0.02	−0.39	0.65	0.19	572–14,323	1,414–46,278
	(0.72)	(0.03)	(0.44)	(0.63)	(0.41)		
Below Voucher Cap	4.20***	0.03*	0.16	0.87*	0.25	7,242–99,569	50,962–430,289
	(1.20)	(0.02)	(0.19)	(0.51)	(0.29)		
Above Voucher Cap	1.29	−0.01	−0.10	0.35	0.52	3,418–53,706	16,447–190,804
	(0.86)	(0.01)	(0.14)	(0.26)	(0.37)		

Notes: This table presents IV difference-in-difference estimates of the impacts of application volume on school outcomes as specified by equation (3), for various bins of sticker prices in 2014. For each outcome and bin, effects denote the difference-in-differences coefficient of block-level application volume, instrumented by block-level private market share of voucher eligible students interacted with post-2014. Standard errors are in parentheses, clustered by block. "Price" denotes the impact on school tuition fees for classes 1-8 (expressed as a percentage of the mean in each bin); "GPA Value-Added" is estimated as described in Appendix AII.; "Teachers per 10 Pupils" denotes the impact to teacher-student ratios in class 1; 'School Mean Utility" denotes impacts on mean school utility (expressed as a percentage of the mean in each bin); and "School Exit" denotes impact to whether schools shut down (no longer report prices to the government as per regulations). The average voucher cap is $74.47. Estimates are (1) re-scaled to reflect the impact of 1,000 additional applications on school outcomes; and (2) include year and school fixed effects (school-by-class for "Price").

*10%, **5%, and ***1% significance level.

Table AXI
The Effects of Voucher Applications on Public School Outcomes

	Effect of Block-Level Application Volume (1,000)				Range of Fit Statistics	
Private School Distance	GPA Value-Added (σ)	Teachers per 10 Pupils	School Mean Utility (%)	School Exit (pp)	First Stage F-Stat	No. Obs.
Decile 1 (0.0KM – 0.1KM)	−0.01	−0.03	−0.44	0.00	2,138–6,709	13,927–34,979
	(0.03)	(0.16)	(0.70)	(0.01)		
Decile 2 (0.1KM – 0.6KM)	−0.01	−0.06	−0.35	−0.01	4,739–10,272	24,057–50,837
	(0.02)	(0.08)	(0.47)	(0.01)		
Decile 3 (0.6KM – 1.4KM)	−0.00	−0.13	−0.56	−0.01	3,092–5,605	31,534–50,822
	(0.02)	(0.14)	(0.82)	(0.01)		
Decile 4 (1.4KM – 2.1KM)	−0.03	−0.38	1.07	0.01	1,229–2,536	32,060–50,716
	(0.04)	(0.29)	(1.14)	(0.01)		
Decile 5 (2.1KM – 2.7KM)	0.14	−0.28	−0.53	0.00	425–1,287	32,891–50,759
	(0.11)	(0.42)	(1.56)	(0.01)		
Decile 6 (2.7KM – 3.3KM)	0.04	−0.13	1.33	0.00	653–1,369	32,658–50,688
	(0.08)	(0.39)	(1.88)	(0.01)		
Decile 7 (3.3KM – 4.1KM)	0.03	−0.14	−0.39	0.01	354–947	32,960–50,757
	(0.12)	(0.48)	(2.38)	(0.01)		
Decile 8 (4.1KM – 5.2KM)	0.23	1.08	−2.34	0.00	393–809	33,333–50,840
	(0.19)	(0.83)	(3.48)	(0.01)		
Decile 9 (5.2KM – 7.1KM)	0.38	−0.48	−1.93	0.02	413–923	33,446–50,907
	(0.27)	(0.63)	(4.46)	(0.02)		
Decile 10 (>7.1KM)	0.26*	0.14	−0.48	−0.01	1,240–2,001	33,721–50,826
	(0.15)	(0.40)	(2.89)	(0.02)		
All	0.02	−0.09	−0.29	−0.00	20,187–42,663	304,131–492,131
	(0.02)	(0.11)	(0.56)	(0.01)		

Notes: This table presents IV difference-in-difference estimates of the impacts of application volume on public school outcomes as specified by equation (3), for deciles of distance to the nearest private school. For each outcome and bin, effects denote the difference-in-differences coefficient of block-level application volume, instrumented by block-level private market share of voucher eligible students interacted with post-2014. Standard errors are in parentheses, clustered by block. "GPA Value-Added" is estimated as described in Appendix AII.; "Teachers per 10 Pupils" denotes the impact to teacher-student ratios in class 1; 'School Mean Utility" denotes impacts on mean school utility (expressed as a percentage of the mean in each bin); and "School Exit" denotes impact to whether schools shut down (no longer report prices to the government as per regulations). Estimates are (1) re-scaled to reflect the impact of 1,000 additional applications on school outcomes; and (2) include year and school fixed effects.

*10%, **5%, and ***1% significance level.

Table AXII
The Effects of Voucher Applications on Village-Level Entry and Exit

	Effect of Block-Level Application Volume (1,000)						Fit Statistics	
	Private Schools			Public Schools				
2014 Avg. Village Price	Entrants	Exiters	Net Entrants	Entrants	Exiters	Net Entrants	First Stage F-Stat	No. Obs.
Decile 1 ($3 – $36)	−0.08	0.39	−0.47	0.00	−0.15	0.15	111	3,237
	(0.15)	(0.26)	(0.32)	(0.05)	(0.15)	(0.16)		
Decile 2 ($36 – $45)	−0.07	0.31	−0.38	0.04	−0.17	0.21	152	3,263
	(0.18)	(0.24)	(0.29)	(0.10)	(0.19)	(0.15)		
Decile 3 ($45 – $51)	−0.03	0.05	−0.07	−0.03	−0.42	0.39	171	3,651
	(0.25)	(0.23)	(0.19)	(0.10)	(0.33)	(0.26)		
Decile 4 ($51 – $55)	0.07	0.08	−0.01	−0.00	−0.27	0.26	253	3,225
	(0.16)	(0.19)	(0.11)	(0.07)	(0.27)	(0.27)		
Decile 5 ($55 – $60)	0.08	0.06	0.02	0.02	0.01	0.02	478	2,942
	(0.10)	(0.12)	(0.11)	(0.05)	(0.07)	(0.08)		
Decile 6 ($60 – $64)	0.17	0.17	0.00	0.09	−0.04	0.13	299	2,903
	(0.13)	(0.17)	(0.17)	(0.09)	(0.11)	(0.15)		
Decile 7 ($64 – $71)	−0.17	0.06	−0.22	−0.07	−0.15	0.08	380	3,448
	(0.21)	(0.20)	(0.22)	(0.10)	(0.22)	(0.23)		
Decile 8 ($71 – $77)	−0.17	−0.20	0.03	0.01	−0.01	0.02	573	2,872
	(0.19)	(0.22)	(0.10)	(0.04)	(0.10)	(0.11)		
Decile 9 ($77 – $92)	−0.17	0.10	−0.28	−0.01	0.05	−0.06	484	3,068
	(0.15)	(0.21)	(0.24)	(0.05)	(0.09)	(0.07)		
Decile 10 (>$92)	−0.37***	−0.02	−0.35	−0.04	−0.06	0.03	512	2,874
	(0.12)	(0.19)	(0.26)	(0.05)	(0.13)	(0.12)		
No Private School	−0.00	−0.01	0.00	0.03	−0.01	0.03	7,210	183,290
	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.03)		
All	−0.06	0.01	−0.07	0.01	−0.03	0.04	12,200	214,773
	(0.06)	(0.07)	(0.05)	(0.02)	(0.05)	(0.05)		

Notes: This table presents IV difference-in-difference estimates of the impacts of block-level application volume on village-level outcomes as specified by equation (3), for various bins of average private school sticker prices in 2014. For each outcome and bin, effects denote the difference-in-differences coefficient of block-level application volume, instrumented by block-level private market share of voucher eligible students interacted with post-2014. Standard errors are in parentheses, clustered by block. "Entrants" denotes impact on the number of schools that start enrolling students for the first time; "Exiters" denotes impact on the number of schools that shut down (no longer report enrollment to the government as per regulations); "Net Entrants" denote the difference between entrants and exiters. Estimates are (1) re-scaled to reflect the impact of 1,000 additional applications on school outcomes; and (2) include year and village fixed effects.

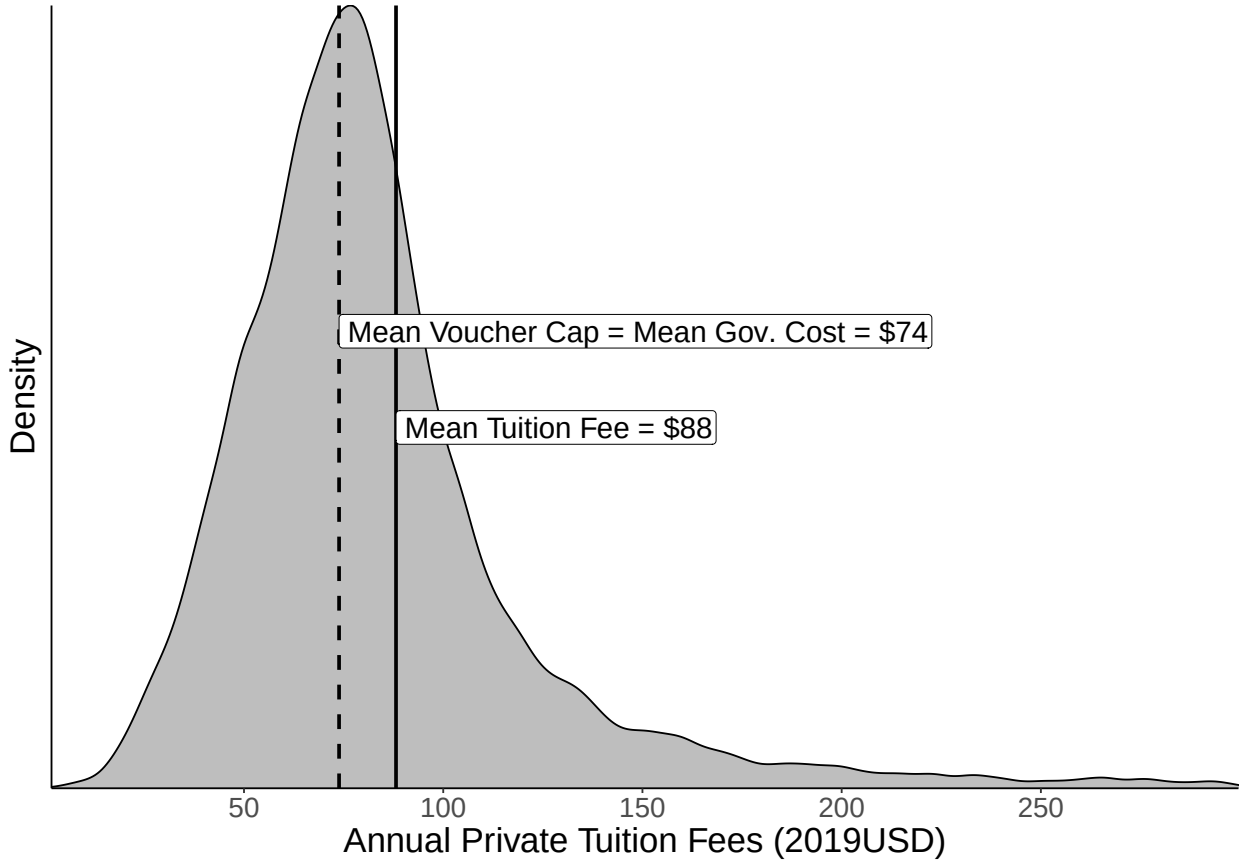
*10%, **5%, and ***1% significance level.

Table AXIII
Demand Estimation Sample versus Overall Sample

	1{Estimation Sample}
	(1)
(Intercept)	0.12***
	(0.04)
Low SES	0.01
	(0.01)
Middle SES	–0.00
	(0.02)
Female	–0.00
	(0.00)
School Tuition Fee (USD)	0.00
	(0.00)
Log Distance (KM)	0.02
	(0.01)
Voucher Offer Probability	0.03
	(0.03)
Observations	13,987,899
Adjusted R^2	0.00

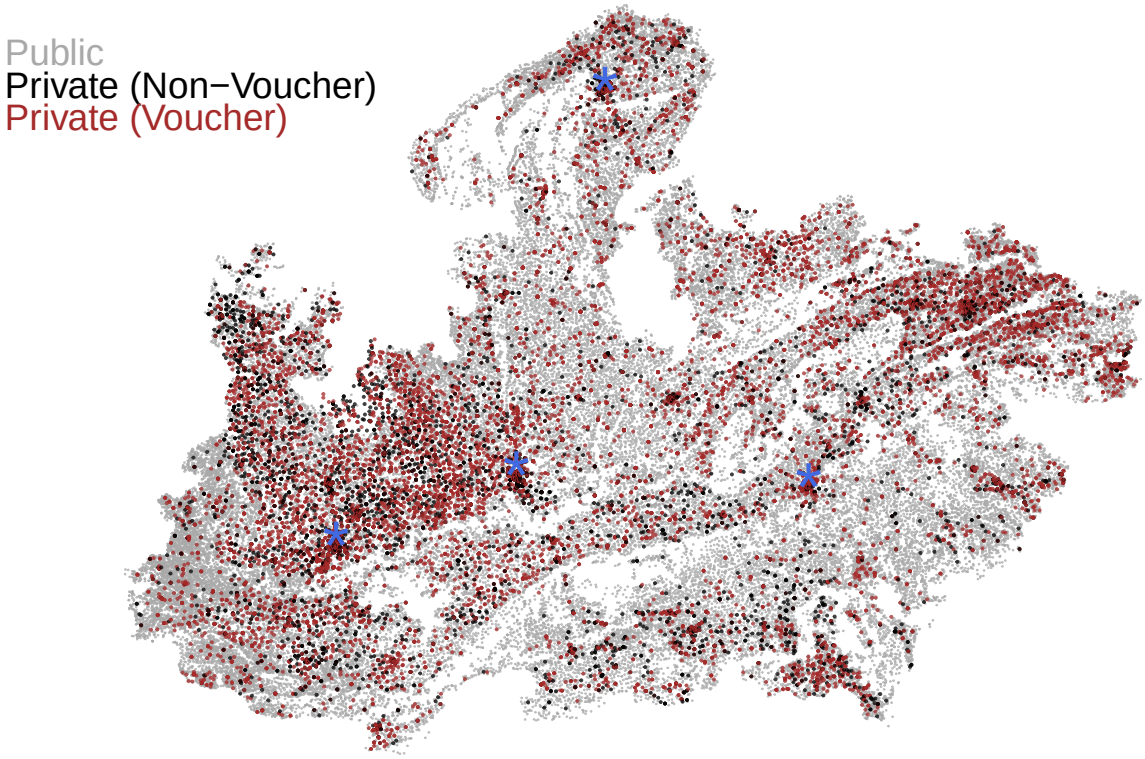
Notes: This table presents OLS estimates of an indicator of whether an observation is included in the demand estimation sample on student and school characteristics. The demand estimation sample is a random sample of 200 markets. Each observation is a student-school pair in a given year, and characteristics correspond to the SES and gender of the student; the tuition fee of the school; and the distance and voucher offer probability of the student-school pair. "Low SES" denotes children who are lower caste (SC or ST) and below the poverty line; "Middle SES" denotes children who are lower caste and above the poverty line; and "High SES" denotes children who are upper caste. "Voucher Offer Probability" is the computed propensity score from 10,000 simulations of the DA assignment mechanism. Estimates are clustered at the market level, the unit at which observations were randomly assigned for demand estimation.

*10%, **5%, and ***1% significance level.



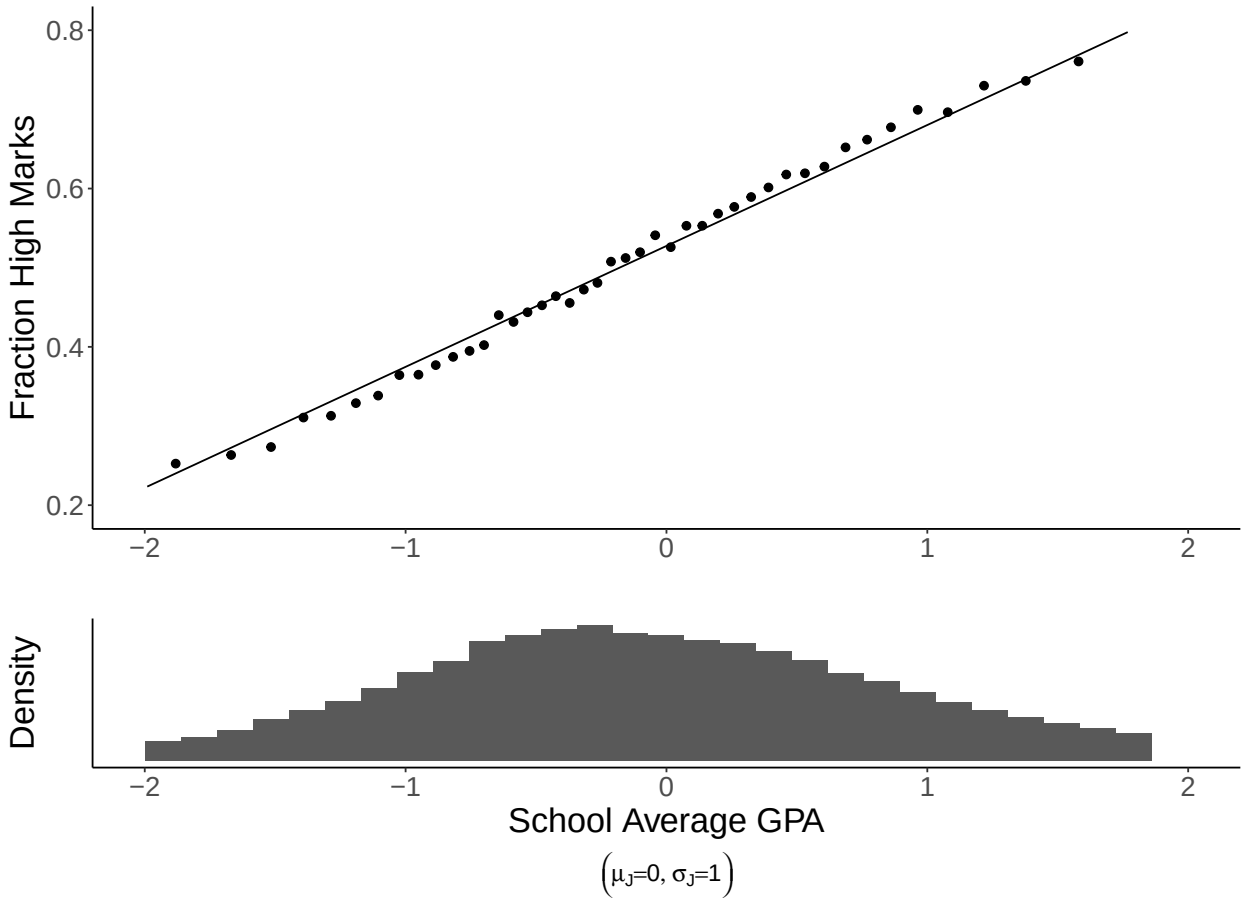
Notes: This figure presents the distribution of annual private school fees faced by students in Madhya Pradesh (MP) averaged across classes 1 to 8 from 2016 to 2018. The solid vertical line depicts the mean tuition fee. The dotted vertical line depicts the mean voucher cap, which is the average per-child expenditure among primary government schools in MP from 2016 to 2018.

FIGURE AI
DISTRIBUTION OF PRIVATE SCHOOL TUITION FEES



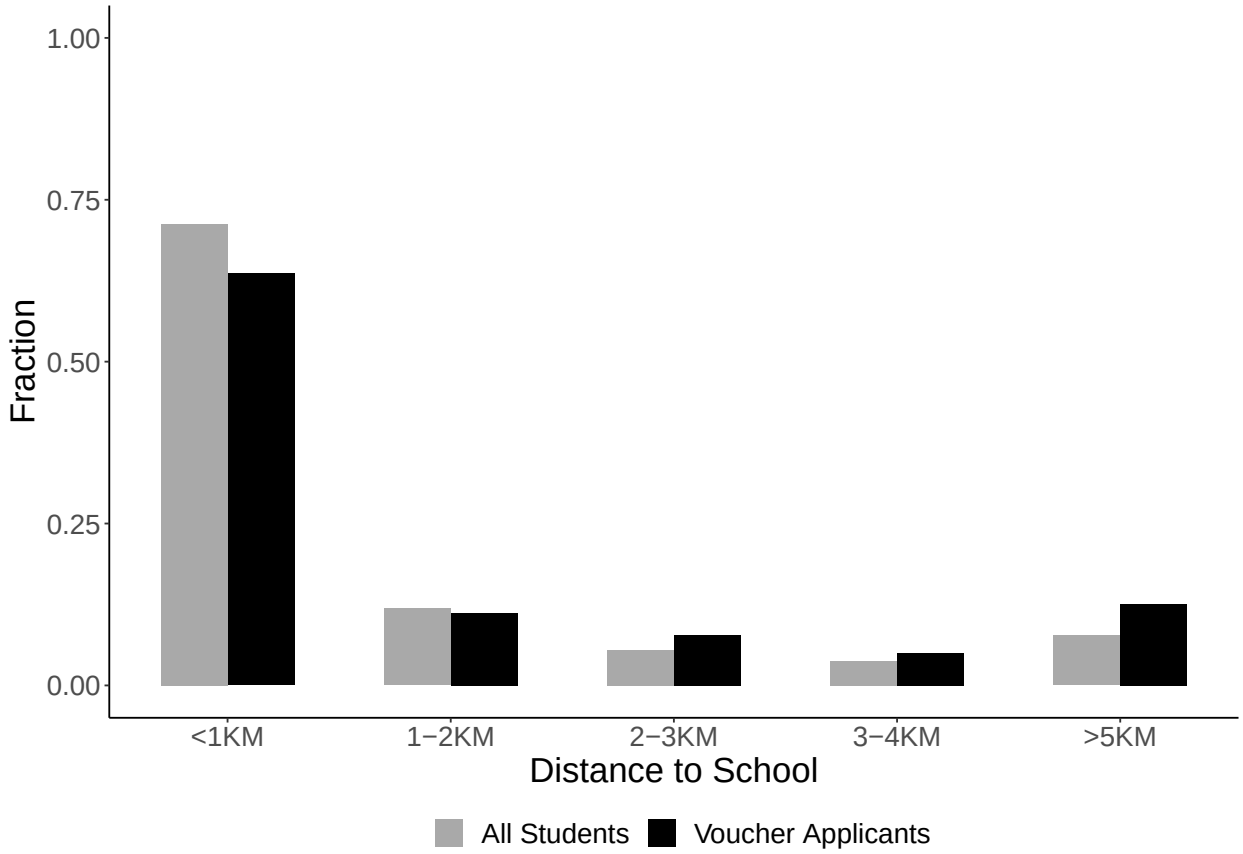
Notes: This figure shows a map of primary schools across Madhya Pradesh, restricted to those that offer class 1 instruction. The grey dots plot roughly 35,000 public schools; the black and red dots plot roughly 15,000 private schools; and the red dots plot roughly 13,000 private schools that receive at least 1 voucher application in the sample period from 2016 to 2018. Blue stars indicate the top four most populated cities (Bhopal, Indore, Jabalpur, and Gwalior).

FIGURE AII
PRIMARY SCHOOLS ACROSS MADHYA PRADESH, INDIA



Notes: This figure describes the relationship between reported student GPA (x-axis) and standardized exam performance (y-axis) in 2015. The top panel presents a binscatter across schools and the bottom panel presents the distribution of average GPA across schools. "School Average GPA" refers to individual end of year exam scores averaged across all subjects and all students in a given school, normalized to have mean zero and unit variance across schools J and winsorized at the 1% level. "Fraction High Marks" refers to the fraction of class 5 and 8 students who score higher than 60% in standardized exams. Correlation at the school-level is 0.42. Data is restricted to 72,024 schools for which at least 1 student appeared for standardized exams. Standardized exam performance comes from the 2015 round of the Unified District Information System for Education (U-DISE).

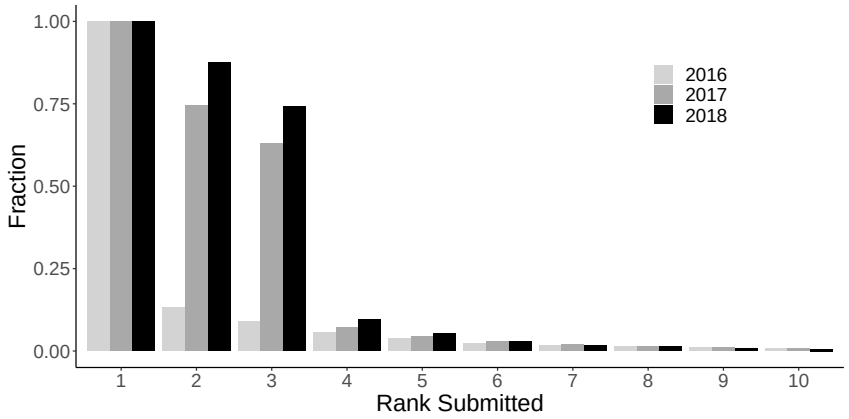
FIGURE AIII
SCHOOL GPA AND STANDARDIZED EXAM PERFORMANCE



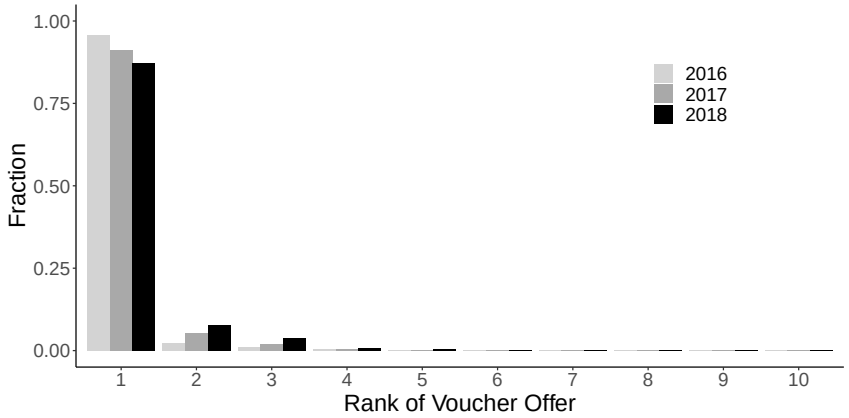
Notes: This figure reports the fraction of students who live a given distance from their school of attendance. Grey bars denote the fraction of all primary school students across Madhya Pradesh whose kilometer distance to school is within the given distance bin. Black bars denote the same fraction as predicted by the distance imputation method for those in the study sample who apply for the voucher policy. Data for all students comes from the 75th round of the Indian National Sample Survey in 2018.

FIGURE AIV
DISTRIBUTION OF DISTANCE TO SCHOOL

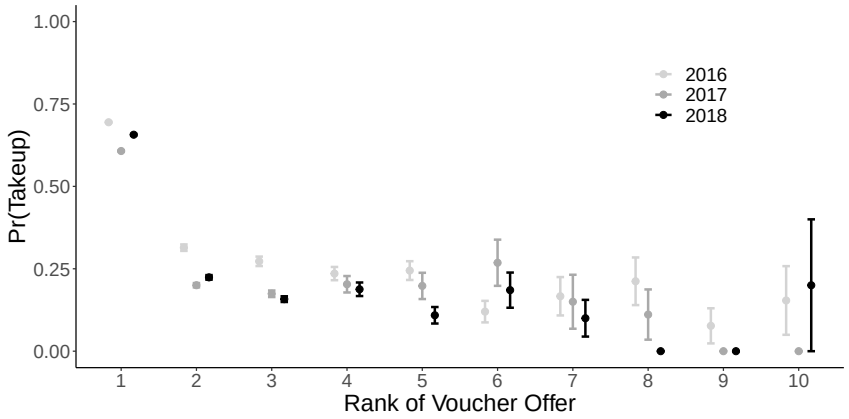
(A) Rank Submitted



(B) Rank of Voucher Offer



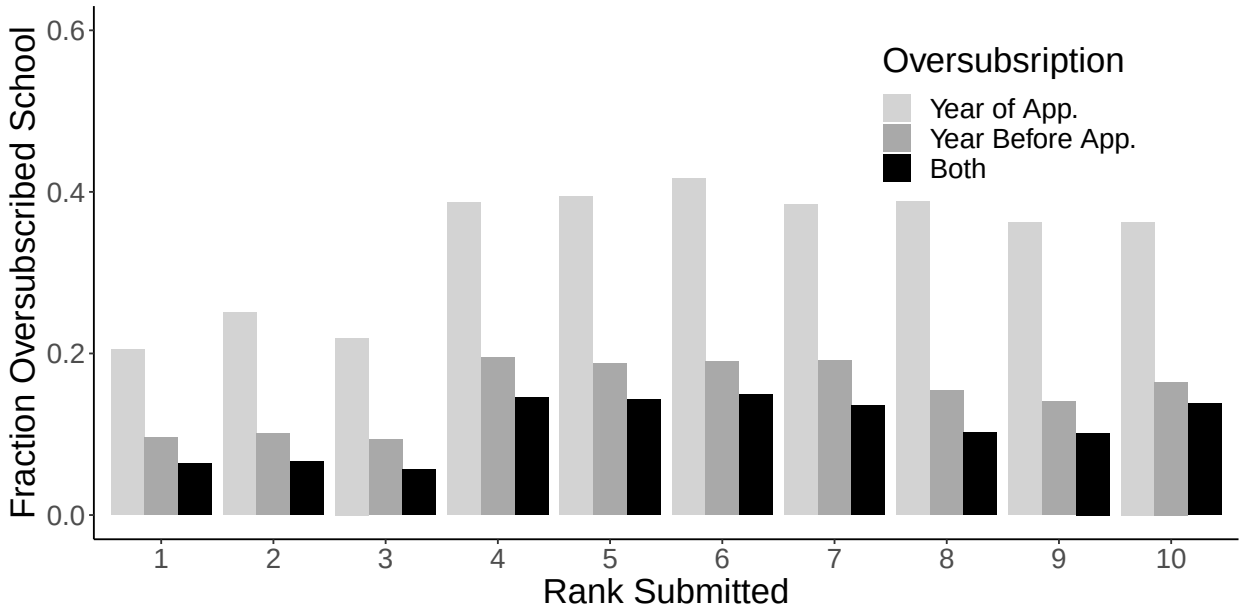
(C) Voucher Takeup by Rank of Voucher Offer



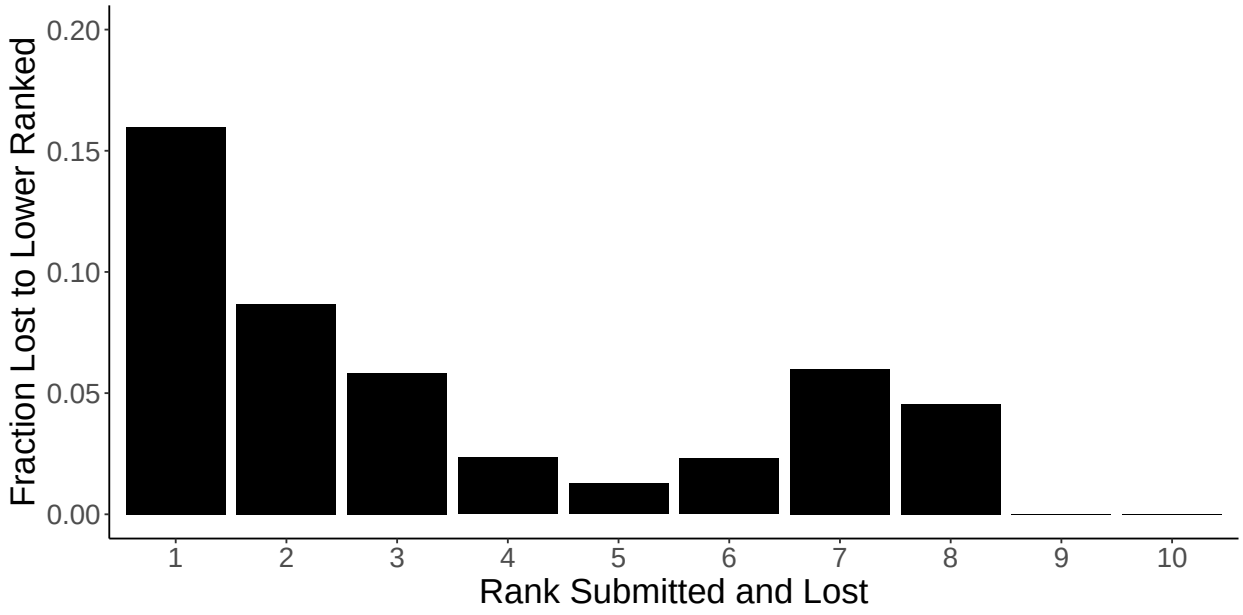
Notes: This figure presents data on rank-ordered lists, offers, and takeup for voucher applications for each application year from 2016 to 2018. Panel A reports the fraction of who applicants who submit a school for a given rank. In 2016, applicants could submit lists of any size. Starting in 2017 onward, applicants were required to submit at least 3 ranks if schools were available. Panel B reports the distribution of the rank of voucher offers received. Panel C reports, for each rank offered, the fraction of offers that were accepted by applicants ("Pr(Takeup)"). Intervals denote standard errors. Data is restricted to 220,388 applicants whose school enrollments are observed for at least 1 year after application.

Figure AV
Rank-Ordered Lists, Offers, and Takeup

(a) Ranking Oversubscribed Schools

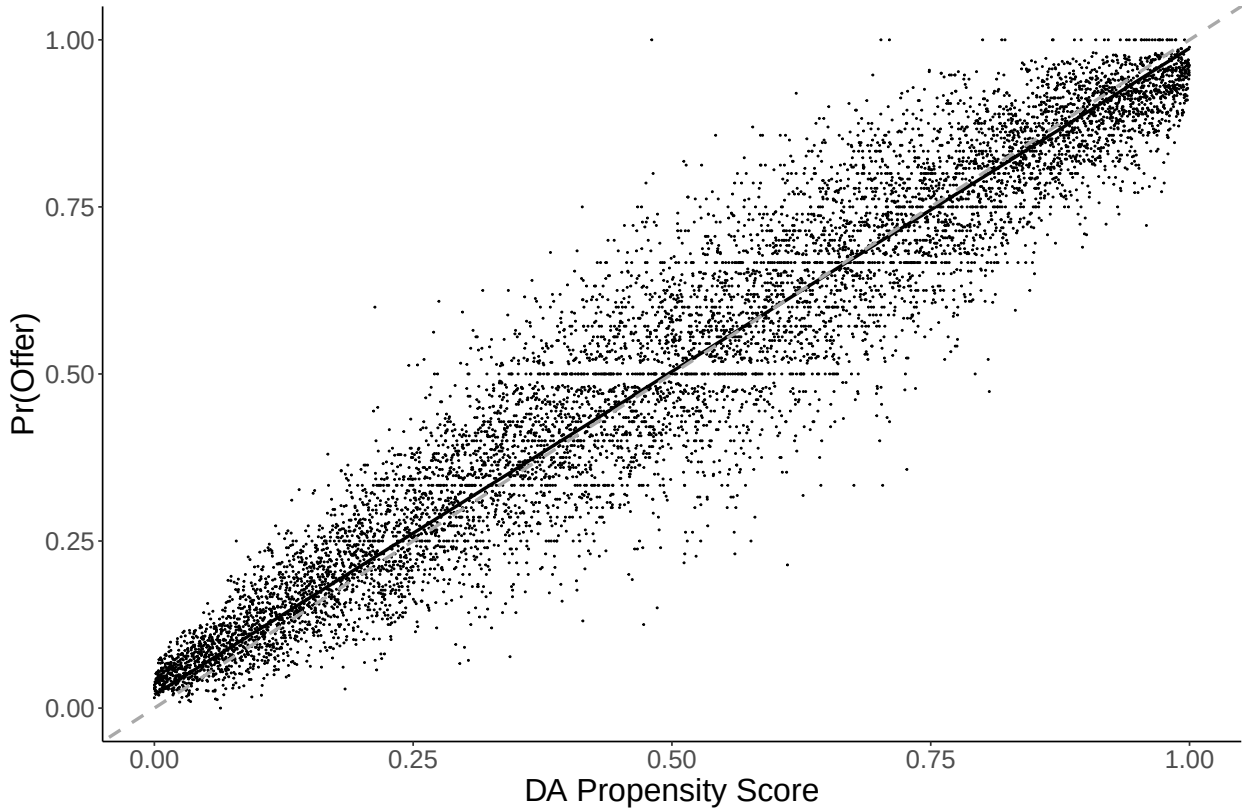


(b) Losing to Lower Ranked Applicants



Notes: This figure presents evidence of the Deferred Acceptance assignment mechanism. Panel A reports the fraction of applicants who applied to an oversubscribed school with the given rank, conditional on submitting a rank-ordered list of the given size or greater. Light grey bars denote the fraction of applications who applied to schools that were oversubscribed in the year of the application; dark grey bars denote schools oversubscribed the year before the application; and black bars denote schools oversubscribed in both year. Panel B reports the fraction of applicants that lost a voucher offer for a given rank to another applicant who ranked the same school lower, conditional on losing an offer at the given rank. Data is restricted to voucher applications from 2016 to 2018 who are applying for Class 1 entry. The set of oversubscribed and lower-rank winning schools is specific to each application year.

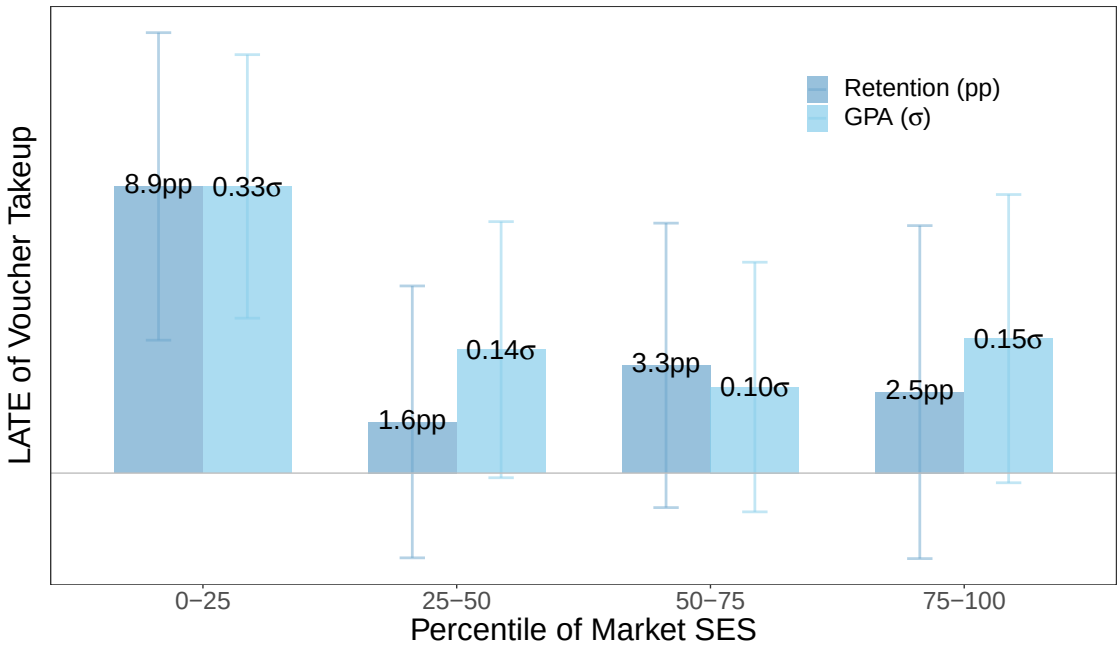
Figure AVI
Evidence of Deferred Acceptance Assignment



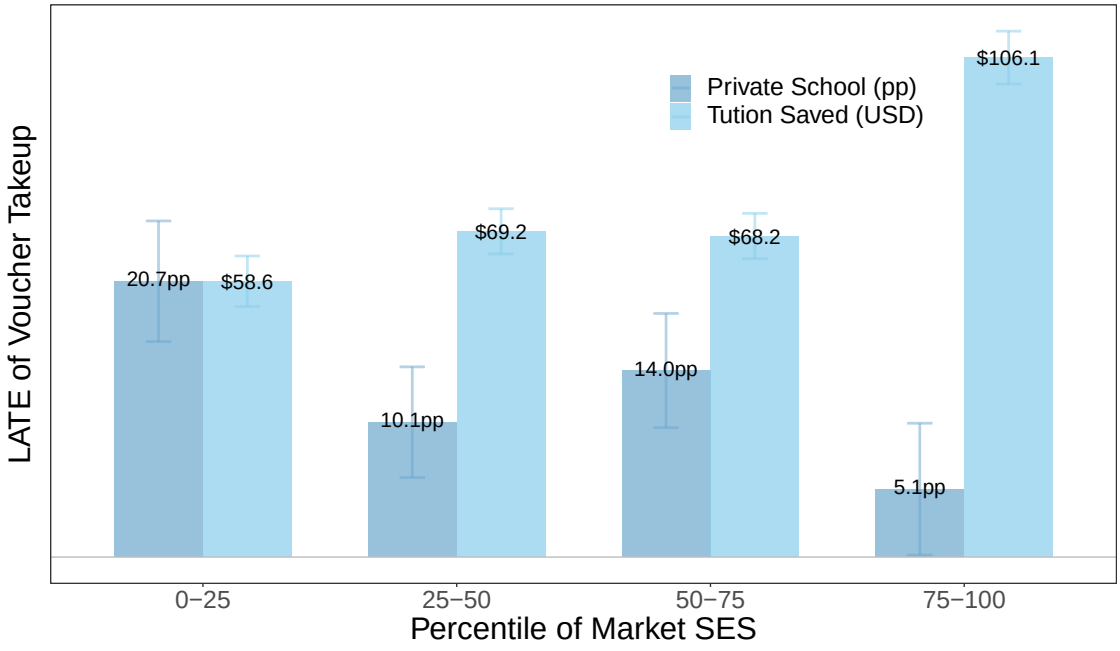
Notes: This figure describes the relationship between the simulated Deferred Acceptance (DA) propensity score (x-axis) and probability of winning a voucher offer (y-axis) across all applications from 2016 to 2018. For each propensity score π, each point denotes the fraction of applicant-school pairs with propensity score π that resulted in a voucher offer ("Pr(Offer)"). The solid black line denotes the best fit line (coefficient of 0.97 and correlation of 0.90) and the dashed grey line denotes the 45° line. Propensity scores are computed from 10,000 simulations of the DA mechanism.

FIGURE AVII
VOUCHER OFFER PROBABILITIES AND DA PROPENSITY SCORES

(A) The Effect of Voucher Takeup on Student-Specific Outcomes

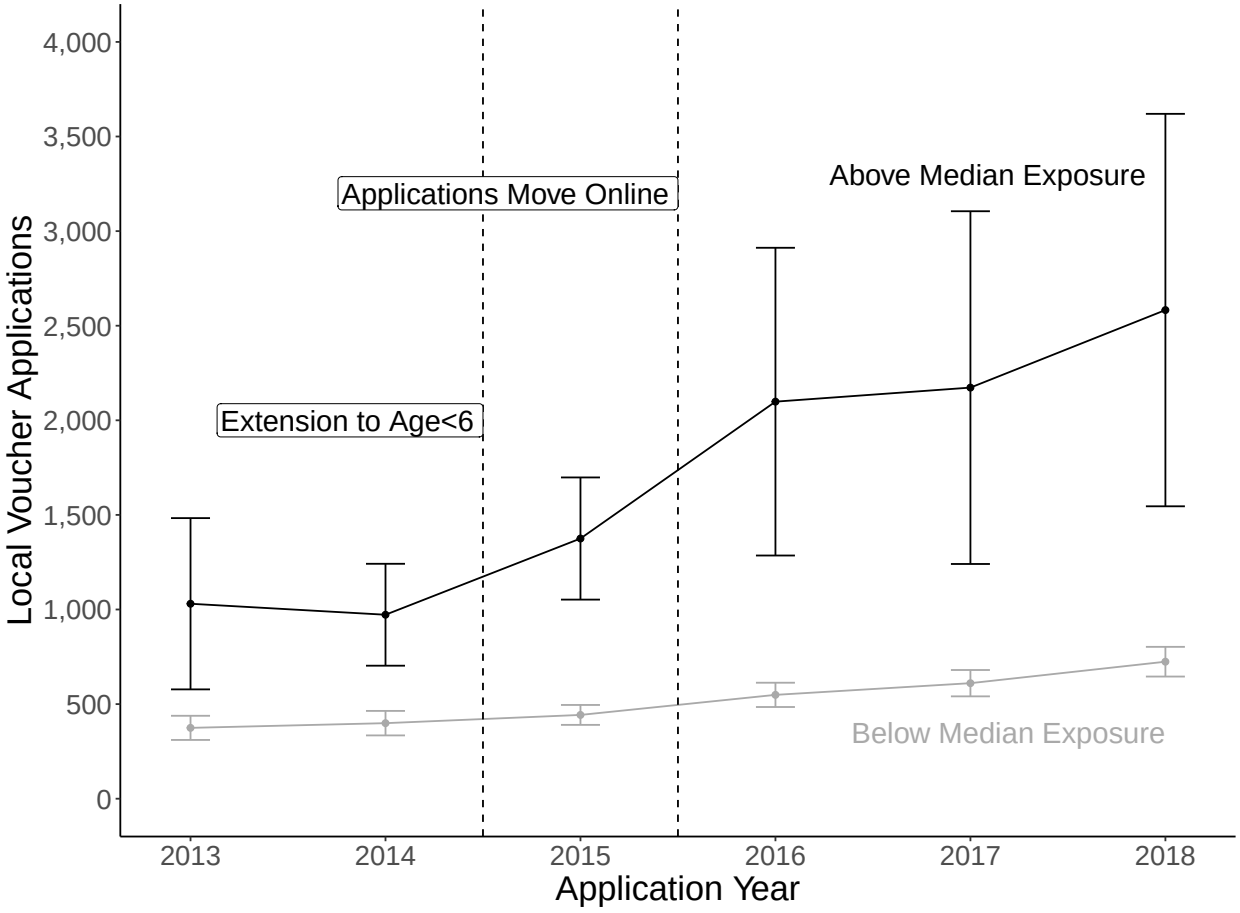


(B) The Effect of Voucher Takeup on Enrolled School Characteristics



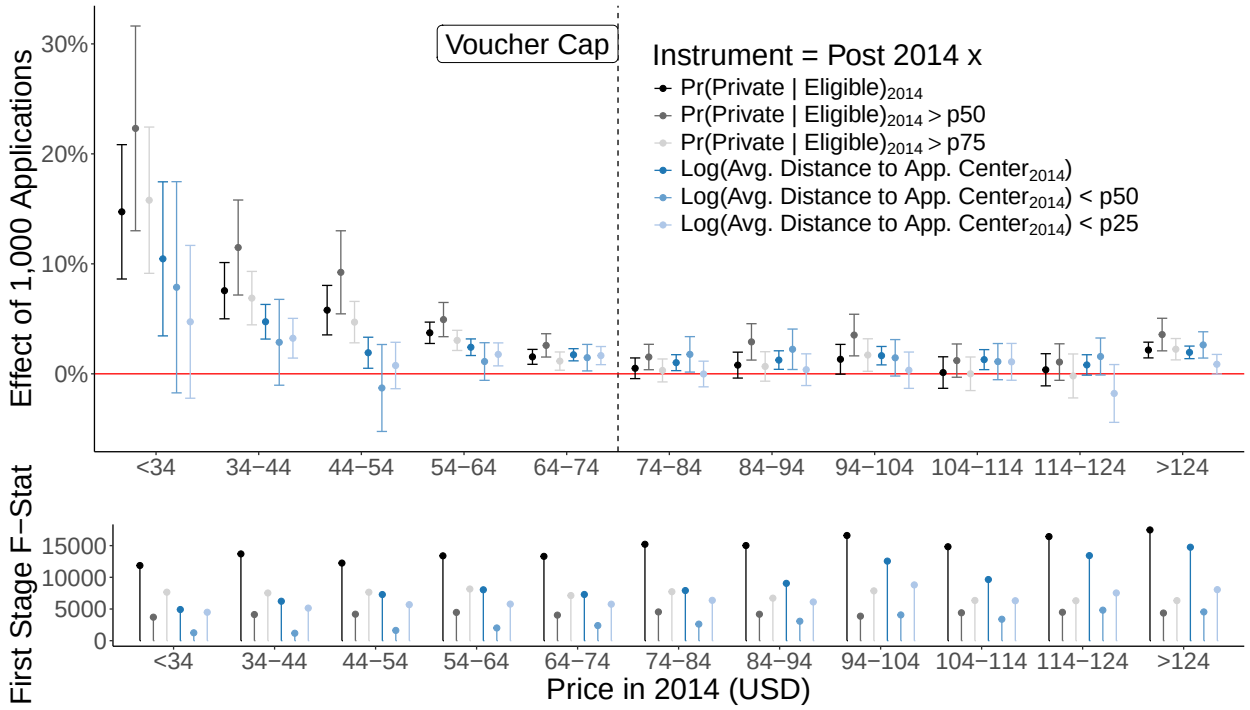
Notes: This figure presents LATE estimates of voucher takeup on student outcomes over all years after application with additional interactions between takeup and market covariates as specified by equation (A9). Market covariates include binary indicators for four percentile bins of the average annual school expenditure in each block (x-axis). Panel A reports impacts on student achievement outcomes (promotion and GPA) and Panel B reports impacts on school outcomes (private enrollment and tuition fees saved). Intervals denote 90% confidence intervals on LATE estimates.

Figure AVIII
The Effects of Takeup on Student Outcomes: Market Heterogeneity



Notes: This figure presents the block-level average number of applications over time grouped by *ex ante* exposure to application growth: blocks with greater or less than the median private market share for voucher eligible students (solid versus dashed). Panel B is restricted to schools in the modal bin of 2014 prices: $54 to $64 (2019USD). The dashed vertical lines denotes that the policy was extended to children under age 6 in 2015 and applications moved from an offline to an online system in 2016, substantially increasing application volume by 15% and 30%, respectively.

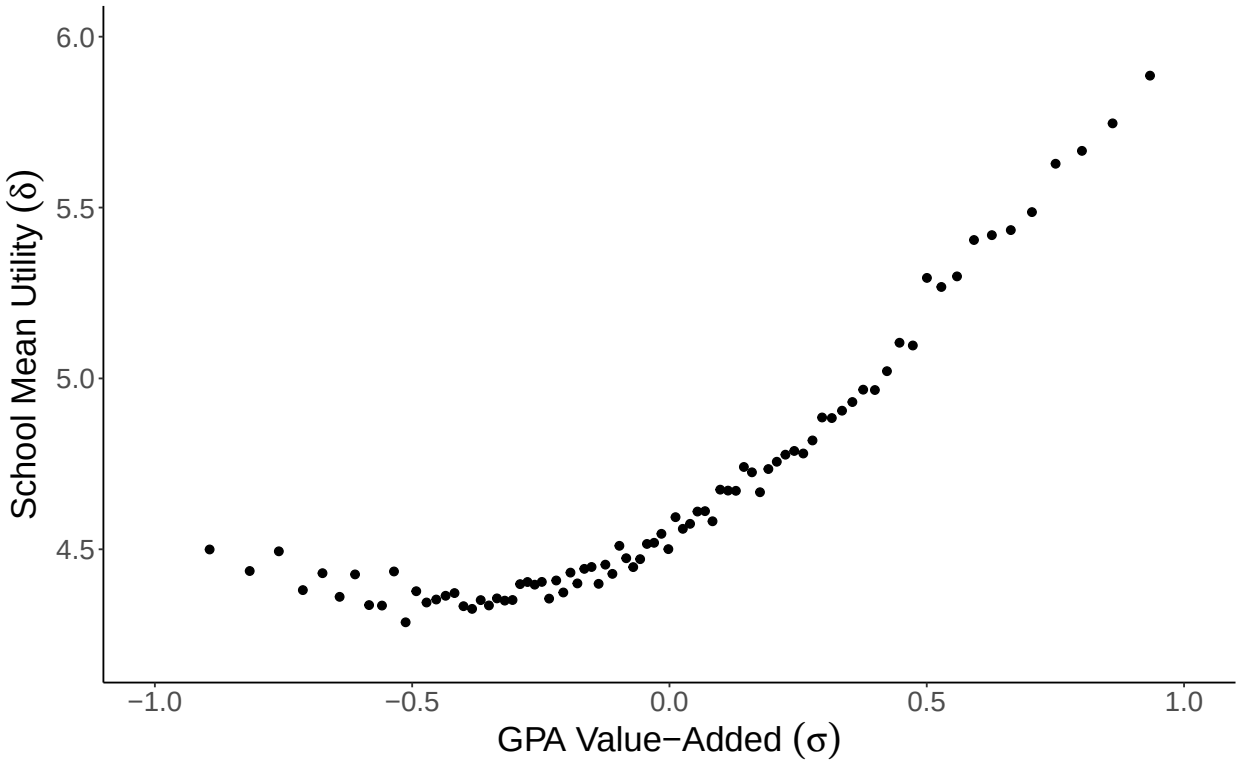
FIGURE AIX
EX ANTE EXPOSURE AND APPLICATION GROWTH



Notes: This figure presents IV difference-in-difference estimates of the impacts of local voucher demand on school prices as specified by equation (3), for various bins of sticker prices in 2014 and across different IV specifications. For each bin (x-axis), points (y-axis) denote the difference-in-differences coefficient of block-level application volume the mean price in the bin, instrumented by the given block-level instrument interacted with post-2014; intervals denote 95% confidence intervals. "Pr(Private | Eligible)$_{2014}$" denotes, for each block in 2014, the fraction of voucher-eligible students who are enrolled in private school; "Avg. Distance to App. Center$_{2014}$" denotes, for each block in 2014, the average kilometer distance between private schools and block headquarters, where written voucher applications can be filed; and "p25", "p50", and 'p75" denote the 25th, 50th, and 75th percentiles of the given variable, respectively. The dashed vertical line denotes the average voucher cap over the sample period of $74.47. Estimates (1) are re-scaled to reflect the impact of 1,000 additional applications on school prices; (2) include all schools between 2013 and 2018 and classes 1-8; (3) include year and school-by-class fixed effects, and (4) are clustered by block, the level of treatment assignment. The bottom panel presents the first stage F-statistics corresponding to each estimation.

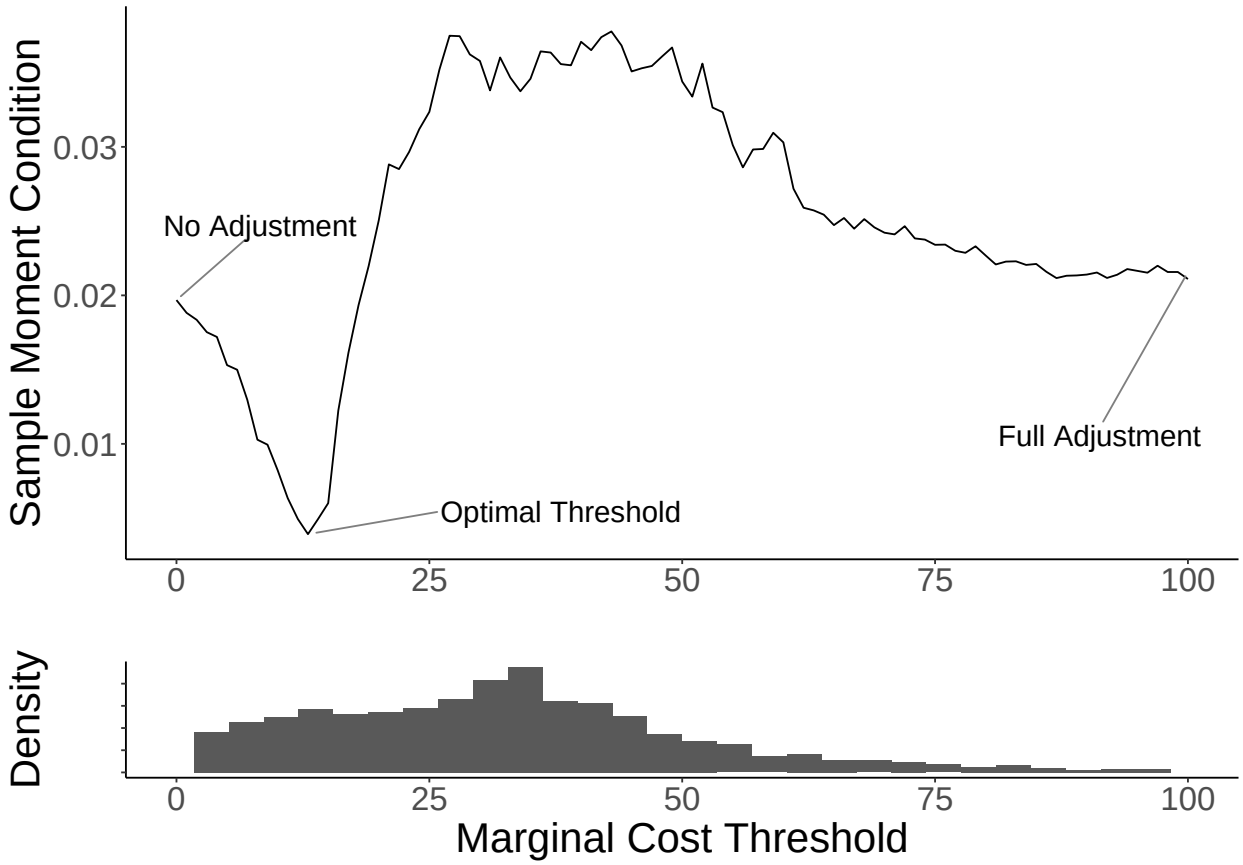
FIGURE AX

THE EFFECTS OF VOUCHER APPLICATIONS ON PRICES: ROBUSTNESS ACROSS SPECIFICATIONS



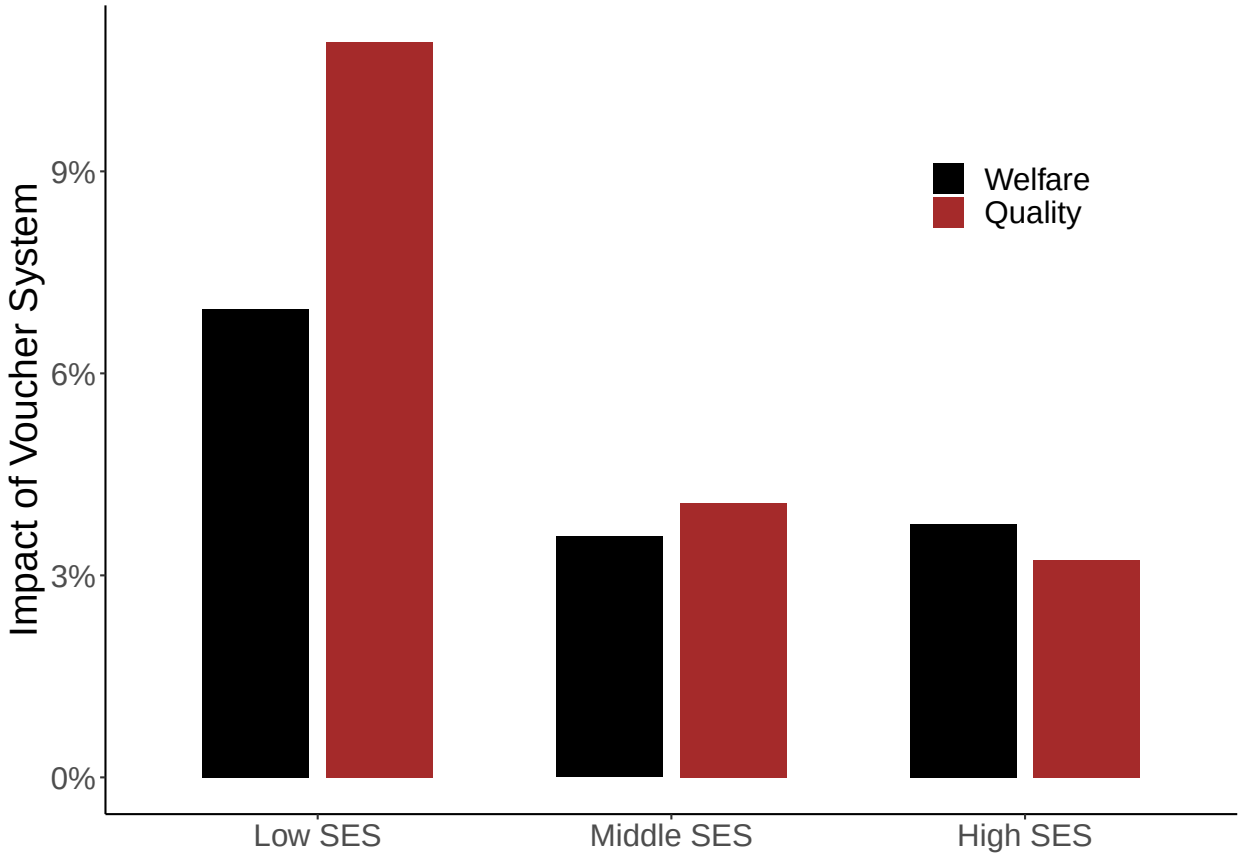
Notes: This figure plots a binscatter of school mean utilities (δ_{jt}) from the demand model as described in Section 3. against GPA value-added (q_{jt}) as described in Appendix AII. Initial estimation is restricted to a random sample of 200 markets from 2016 to 2018. School mean utilities δ_{jt} and application costs τ_t, τ_m are then estimated for other markets and years before 2016. See Appendix AV. for details of the estimation and extrapolation procedure.

FIGURE AXI
SCHOOL MEAN UTILITY AND GPA VALUE-ADDED



Notes: This figure presents sample moment conditions against candidate quality adjustment parameters as described in Section 4. The top panel plots the sample analogue to the moment condition (y-axis) for small increments of candidate threshold parameters ω (x-axis). The bottom panel plots a histogram of the distribution of private school marginal costs. The left-most parameter $\omega = 0$ denotes a model with no adjustment as all private schools are above the threshold. The right-most parameter $\omega = 100$ denotes a model with full adjustment as (nearly) all private schools are below the threshold. Finally, candidate parameter $\omega = 13$ is the optimal threshold which minimizes the sample moment condition. Estimates are restricted to a random sample of 200 markets from 2013 to 2018.

FIGURE AXII
QUALITY ADJUSTMENT THRESHOLDS AND SAMPLE MOMENT CONDITIONS



Notes: This figure presents estimates of the effects of India's voucher policy on student welfare CS and quality δ (y-axis), along the children's socio-economic status (x-axis). Black bars denote the percent change in consumer surplus from the status quo voucher system as described Section VII. and red bars denote the percent change in quality of the enrolled school. "Low SES" denotes children who are lower caste (SC or ST) and below the poverty line; "Middle SES" denotes children who are lower caste and above the poverty line; and "High SES" denotes children who are upper caste. Estimates are restricted to a random sample of 200 markets in 2018.

FIGURE AXIII
HETEROGENEITY IN IMPACTS OF VOUCHER POLICY ON WELFARE AND SCHOOL QUALITY