The Welfare Implications of School Voucher Design: Evidence from India

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Abstract

While school voucher policies are common, their design varies dramatically across the world. This paper studies the impact of these design choices on students, schools, and overall welfare using novel data from India – the largest primary school voucher program in the world – where schools must participate, cannot charge extra fees, and receive payments linked to their tuition. Voucher lotteries suggest recipients benefit from lower tuition expenses and greater school choice. However, because school payments are linked to tuition, schools respond by raising tuition fees, impacting millions of children who do not receive vouchers. To understand the policy's full equilibrium impact, the paper develops a model of demand and supply in which students' enrollment choices and schools' price and quality decisions are endogenous to voucher design. On net, welfare estimates based on revealed-preference show that the policy's benefits exceed costs (1.5 to 1), while also reducing measures of segregation. A failure to account for the impacts to non-recipients, however, would have overstated the benefit-cost ratio by a factor of two (2.9 to 1). Finally, changing the policy design has large implications: allowing schools to charge extra fees or opt out would substantially reduce its net benefits, while switching to a "flat" voucher would substantially increase them.

1 Introduction

More than 300 million children around the world pay out of pocket to attend private school, comprising nearly a quarter of the global market for K-12 education.[1] While privatization offers alternatives to resource-constrained public schools, it may also leave out students who cannot afford to pay. Vouchers, which provide tuition subsidies, are increasingly utilized to balance these equity and efficiency concerns (Friedman 1955). In practice, however, there remains substantial variation in how voucher programs are designed and their ultimate effectiveness.[2] Design features can include whether eligibility is universal or targeted, whether private school participation is mandatory or voluntary, whether schools are allowed to charge additional "top-up" fees, and how schools are reimbursed for each voucher student. These design choices present important trade-offs between government expenditure, school profits, and student welfare. While much evidence exists on the effects of individual voucher programs, there is limited research on how specific design elements can impact the overall equity and efficiency of the education system.

This paper offers new evidence from India, home to the world's largest voucher system for primary education, which has several key design features: schools must participate, cannot charge extra fees, and receive payments linked to their tuition.[3] The paper leverages new data on the largest voucher program within India, including voucher assignment lotteries and the policy's rollout, to estimate its effects on recipients and non-recipients. Then, using this policy variation, an empirical model of supply and demand is developed to estimate the equilibrium impacts of voucher design. The paper reaches three main conclusions: (1) while voucher recipients benefit from greater choice, the tuition-linked payments incentivize schools to raise prices with limited changes in quality, impacting millions of children who do not receive vouchers; (2) welfare estimates based on revealed-preference show that the policy's benefits exceed costs, while also reducing measures of segregation; and (3) alternative voucher designs have substantial impacts: allowing top-up fees or voluntary exit would virtually eliminate its efficiency and equity gains, while switching to a "flat" voucher – which pays all schools a fixed amount – would improve them. These findings are robust to policy expansion and the potential for greater quality adjustment over time.

India is at the frontier of school privatization: 47% of K-12 students attend private school, but rates are substantially lower for disadvantaged students (U-DISE 2021). In 2009, the Right to Education Act mandated all private primary schools in the country to participate in a voucher system targeted to these students.[4] Private schools must reserve 25% of their seats for the program: they

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1. In developing countries, private school market share is even higher. For example, the private share of enrollment is 47% in India; 34% in Pakistan, 24% in Bangladesh, 23% in Indonesia, 22% in Thailand, 30% in Ghana, and 43% in the Congo (World Bank).

2. For example, Abdulkadiroğlu, Pathak, and Walters 2018 finds negative effects of vouchers in Louisiana, which they attribute to voluntary school participation that incentivized entry of low quality private schools into the voucher system. Neilson 2021 finds positive effects in Chile's targeted voucher system, attributed to eliminating top-up fees for low income students, which induced greater quality investment in low income areas.

3. See Table A1 for an overview of programs that publicly fund private primary schools around the world.

4. In the study setting, households must belong to any of the following three groups: Below Poverty Line (BPL; earning less than $1,130 (rural) or $1,310 (urban) per year), Scheduled Caste (SC), or Scheduled Tribe (ST).

cannot charge additional fees or opt out. For each voucher student, the government pays schools their tuition fee up to a "voucher cap" (the per-child cost for public schools). The counterfactual analysis is focused on three of these design elements: top-up fees, school participation, and the voucher payment structure. Students apply for vouchers with a rank-ordered list of private schools, receive one offer through a Deferred Acceptance (DA) assignment mechanism, and choose whether to take the free offer or enroll in a different school with potential cost. The paper leverages newly collected government records that cover the universe of voucher applications, students, and schools across Madhya Pradesh (MP), India's fifth largest state with more than 10 million primary school children and the largest voucher system in the country (Indus Action 2021).

The paper proceeds in three steps. The first step documents how the existing policy affects the outcomes of voucher recipients by analyzing results from centralized lotteries. The second step estimates how the tuition-linked payment design impacts school behavior by studying the program's rollout across markets. These reduced-form results demonstrate that the existing policy has benefits to recipients that may come at the cost of others, which are driven in part by particular features of the voucher design. To infer the welfare consequences of alternative designs, the third step develops and estimates a framework of demand and supply for schooling using individual-level choice data and price variation from voucher lotteries. This is then used to compute the overall cost-effectiveness and sorting patterns of the existing policy against alternate voucher schemes.

The paper begins by documenting how vouchers benefit those who receive them by leveraging lotteries. Within the DA assignment mechanism, if a student's top choice school is oversubscribed, seats are assigned via lotteries: this serves as a powerful instrument for voucher takeup (Abdulkadiroğlu et al. 2017). We can then estimate the Local Average Treatment Effect (LATE) of voucher takeup on the outcomes of more than 100,000 students. This includes two student-level outcomes (Grade Point Average (GPA) and class promotion) and several characteristics of the schools which students attend (e.g. subjects offered, GPA value-added, distance traveled, and tuition fees paid).[5]

Vouchers allow recipients to access more preferred schools and improve academic outcomes. Voucher takeup delivers a modest 12 percentage point (pp) increase in the probability of enrolling in private school, pooled over three years from voucher receipt. This implies that vouchers change school choices, but many applicants would have enrolled in private school absent a voucher. In response to the changes, voucher takeup increases recipients' GPA by 0.17σ and class promotion by 3.3pp, a quarter of the mean failure rate. These magnitudes are similar to prior estimates in similar contexts.[6] In addition, vouchers enable recipients to enroll in schools that have a 9pp

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5. GPA captures end-of-year exam scores administered by schools and is averaged across subjects, including Math, Hindi, and (if offered) English. While GPA is not standardized across schools, Fig. A3 plots the strong relationship between average school GPA and standardized exam performance at the school level. The correlation is high at 0.42. Class promotion captures whether students successfully continue from one grade into the next.

6. For test scores, Angrist et al. 2002 study voucher policy in Colombia and find effects of 0.20σ. Muralidharan and Sundararaman 2015 study a voucher experiment in rural India and find no changes in test scores, but note that private schools teach more subjects (including English) and have lower costs. Damera 2017 and Romero and Singh 2022 study India's voucher system in other states: the former finds effects of 0.11σ for girls (null for boys), but improvements in self-efficacy measures; the latter finds effects of 0.19σ during COVID-19, potentially reflecting differences in virtual learning environments. For promotion, Angrist et al. 2002 find increases of 5-6pp; the studies in India do not examine

higher chance of offering English instruction, have a 0.10σ higher GPA value-added, and are 0.4 kilometers closer in proximity. Finally, voucher takeup reduces tuition expenses by nearly \$80 per year – about 6% of household income at the poverty line. These several different benefits to recipients may be driven in part by two design choices: (1) schools cannot opt-out, which allows access to high quality schools and amplifies academic gains; and (2) schools cannot charge extra fees, which avoids any tuition payments and amplifies financial gains. Using a revealed preference approach, the framework developed below is able to aggregate across these multiple dimensions of impact and assess the extent to which they depend on design.

After examining recipients, the paper then studies how the voucher system affects school behavior, which may cause spillovers to non-recipients. A simple model of profit-maximizing, imperfectly competitive private schools predicts that the tuition-linked voucher payments generate strong incentives for schools to raise tuition fees. Schools whose sticker prices are below the voucher reimbursement cap can raise tuition and receive additional payments without losing voucher demand; those above the cap have no such incentive. Differing incentives below versus above the cap provide a natural experiment to study how design influences school behavior. To study this empirically, the paper exploits policy changes that expanded voucher eligibility and introduced online applications, dramatically increasing application volume. A difference-in-differences approach that compares markets with greater or lower exposure, before and after policy changes, suggests that the voucher program causes private schools to raise their tuition fees. Consistent with theoretical predictions, this response is asymmetric, with tuition increases concentrated among schools whose sticker prices were below the voucher cap. This market response imposes financial costs to students outside the voucher program, which comprise more than 90% of the market. In contrast to effects on school tuition, there are limited impacts on measures of school quality (i.e. GPA value-added, teacher-student ratio, and entry/exit) or school-specific preferences (i.e. mean indirect utility).[7]

In total, the policy delivers a complex patchwork of impacts across the education system driven in part by the policy's design: benefits to recipients via greater choice and cost savings, but also impacts to non-recipients via school adjustment. This raises questions on whether total benefits exceed costs, and the extent to which they depend on design. With this in mind, a model of supply and demand for education is developed that captures several channels through which voucher design affects student and school decisions. On the demand-side, students decide whether to apply for vouchers given the chances of winning each offer and potential application costs. Once they receive offers, they decide which school to attend. On the supply-side, private schools strategically set price and quality to maximize profits, with knowledge of how their decisions would affect how students apply for vouchers and enroll in schools. Critically, their incentives to set price and

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promotion. The studies in Colombia (Angrist et al. 2002) and in India (Damera 2017; Dongre, Sarin, and Singhal 2019; Romero and Singh 2022) document how many recipients would enroll in private school absent the voucher.

7. Estimates suggest a modest increase in teacher-student ratios, GPA value-added, and mean indirect utility for schools below the cap, but little change above. There are is little evidence of impacts on entry/exit decisions or public school behavior. Similarly, Muralidharan and Sundararaman 2015 finds little evidence of spillover effects on student achievement in a cluster-randomized trial of private school vouchers. Impacts on school tuition are not studied.

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quality depend on the voucher's design. The estimated model allows us to calculate the policy's dollar-equivalent impact on student welfare, school profits, and government expenditure net of equilibrium responses and compute its overall benefit-cost ratio (BCR). The BCR of the status-quo policy can then be compared to that of alternative voucher designs.

The demand framework captures how, given their preferences, students choose whether to apply for the voucher and in which school to enroll. These preferences reflect the trade-offs student must make between academic concerns (e.g. school quality and proximity) and tuition fees.[8] The application model captures how, given DA assignment probabilities, students weigh the expected benefits of receiving a voucher offer against exogenous application costs.[9] After receiving offers, students then choose schools based on the prices they now face. Given a particular voucher design and the resulting distribution of school prices and qualities, the demand model captures the sorting of students into the voucher system and across schools, and quantifies the total consumer surplus or Willingness to Pay (WTP) for these enrollment decisions. Two unique features of this setting are not commonly found in other contexts and allow for identification of model parameters. First, applicants initially receive voucher offers, then later choose which schools to attend. In this later enrollment choice, the initial voucher lotteries from oversubscription deliver random variation in prices students face, which is orthogonal to all other dimensions of school preferences. Second, during the DA assignment mechanism, students submit rank-ordered preferences over schools, which are assumed truthful and strategy-proof (Abdulkadiroğlu and Sönmez 2003). Importantly, these rankings are submitted before vouchers offers are realized, and are thus made assuming prices are zero. This allows for separate identification of the non-price dimensions of school preferences. These two elements of the voucher system enable credible estimation of the demand model without relying on typical firm-level instruments (Berry and Haile 2016).

The supply framework captures how private schools set price and quality to maximize profits under imperfect competition.[10] Schools charge prices above marginal cost and set quality below a competitive level depending on their local market power. The voucher payment design determines the marginal revenue received from voucher students, and in turn changes the optimal price and quality setting rule. Under the status-quo system, schools' marginal revenue from voucher students equals their price up to the voucher cap and is a fixed amount thereafter. This predicts that linking voucher payments to schools' prices creates a distortionary incentive for schools to raise tuition fees below the cap, but no such incentive above the cap. Because the policy generates excess profits

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8. Building on standard frameworks in the empirical industrial organization literature, the model accommodates unrestricted school mean utilities, rich dimensions of observed heterogeneity in tastes for price and distance by student demographics, and unobserved heterogeneity in tastes for price (Berry, Levinsohn, and Pakes 1995).

9. Roughly 15% of those that are eligible for the policy apply for vouchers, suggesting the that application costs are large. Romero and Singh 2022 find large gaps in knowledge about the policy and frictions in accessing required documentation for the application.

10. Public schools are assumed to be 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). In this setting, there is little evidence of the policy's effect on public school entry, exit, or quality measures.

(losses) below (above) the cap, this creates incentives for schools to raise (lower) quality.[11] Given the estimated demand parameters, the supply-side model can then be used to compute schools' equilibrium price, quality, and profit under various voucher schemes. A model of limited quality adjustment is adapted to capture the muted effects on school quality we see in the reduced-form. Finally, the estimated supply model is able to replicate the asymmetric price and quality response from the difference-in-differences analysis of the policy's roll out.

Together, the demand and supply framework allows us to estimate the consumer, producer, and government surplus under the status-quo voucher program against counterfactual designs (including no vouchers). For recipients, the program delivers roughly $106 of additional utility per student per year. This impacts producer surplus asymmetrically: profits increase for lower marginal cost schools who benefit from voucher reimbursements, but fall for higher cost schools whose payments are capped. On average, profits fall by roughly $54 for each voucher recipient. Finally, the government incurs costs of roughly $18 per recipient, as many applicants would have attended private school counterfactually. However, these impacts in the voucher sector are set against complex spillovers in the non-voucher sector. The policy causes welfare gains for price-insensitive students that benefit from schools that modestly upgrade quality, but causes welfare losses for price-sensitive students from schools that substantially raise prices. These spillovers lower profits and raise public school enrollment, reducing total surplus for the non-voucher sector.

Aggregating across the market, the policy remains relatively successful and delivers benefits that exceed costs (1.5 to 1). However, a failure to account for the impacts to non-recipients from school adjustment would have overstated the BCR by a factor of two (2.9 to 1). By examining the sorting of students across schools, the framework suggests the voucher policy is also successful in improving social integration within schools, increasing the private school composition of voucher eligible students by 13% and reducing measures of overall school segregation by 2.5%.[12]

Several features of the existing voucher policy design and market structure enable the policy's relative success. First, the policy does not allow schools to charge additional top-up fees to students. This means prices are zero under vouchers but remain at their sticker-prices under a no voucher counterfactual, such that cost savings for recipients are large. In contrast, fiscal costs remain small as reimbursements paid to schools are capped. Second, compliance with the voucher system is mandatory for private schools. This ensures higher quality (and thus higher cost) schools remain available for voucher students to access. Third, schools exhibit substantial market power, charging markups that are roughly 40% of tuition fees on average. Schools above the reimbursement cap – which is the 80th percentile of marginal costs – continue operating without raising prices. The policy therefore reduces school profits and acts to effectively lower the higher-priced schools' market power. Fourth, because the policy design explicitly targeted children in poverty or lower

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11. The model captures how private schools may adjust along intensive margins of price and quality. Because the policy impacts profit, it may also cause adjustment along the extensive margin including entry and exit (Dinerstein and Smith 2021). However, there is little evidence of this in the reduced-form analysis. See Section 9 for more discussion.

12. This is measured using a "multigroup entropy" index, that captures how the socio-economic composition of students within school differs from the market's overall composition (Reardon and Firebaugh 2002).

caste groups, it was able to increase socio-economic diversity within private schools. These features enable benefits to recipients to remain large while containing negative spillovers to others.

While the existing policy is cost-effective, there remain substantial distortions from the tuition-linked payment design, suggesting scope for improvement. The supply model predicts that switching instead to a flat voucher system – which pays all schools a fixed amount – would remove the direct incentive for schools to raise prices. However, it would also increase voucher expenditure relative to the status-quo by raising payments for schools that were below the cap *ex-ante*. On balance, benefits from correcting the pricing distortion outweigh costs from increased voucher spending: the flat voucher system increases the benefit-cost ratio (BCR) by 40% from 1.5 to 2.1. Moreover, this modestly improves equity outcomes by avoiding the distortionary tuition hikes that harm price-sensitive students. However, schools may avoid profit losses by lowering quality over time, presenting an equity-efficiency trade-off between high versus low voucher amounts.

Counterfactuals beyond the payment design – such as school participation and top-up fees – also have large welfare implications. Allowing schools to charge top-up fees raises voucher students' tuition expenses but cushions school profit. Similarly, allowing schools to voluntarily participate causes voucher students to lose access to high quality schools who exit the program to avoid profit losses. Further, by reducing the benefits to those who apply for vouchers, these policies cause an endogenous reduction in voucher applications as the returns fall. The overall consequences for students exceed savings for private schools, resulting in BCRs that fall below 1. Moreover, by shrinking the voucher sector, benefits to school integration are all but eliminated.

Finally, the framework allows us to test the impacts of a potential expansion of the policy. Raising the voucher quota from 25% to 50% results in improved outcomes for voucher recipients by enabling offers from more preferred schools. This also attracts more voucher students and on net raises equity outcomes with no loss in efficiency. However, expanding the policy by reducing application costs is more effective. By attracting voucher students from lower SES areas (where application costs are high), these price sensitive students are more likely to have attended other public schools, reducing voucher spending and improving equity outcomes. Across all of these counterfactuals, the results illustrate how design choices are critical in determining the ultimate equity and efficiency implications of voucher programs. Depending on design specifics, vouchers can generate benefit-cost ratios that range from less than 1 to more than 2.

This paper contributes to several strands of literature. First, there is a large body of empirical evidence on the effects of individual voucher programs. On the demand-side, several studies have found positive, null, and negative effects on the education outcomes of voucher recipients around the world.[13] This paper adds to this evidence by providing the largest lottery-based study of the effects of vouchers on student outcomes. This is consistent with work in similar contexts that show a large component of benefits come through reduced tuition that would otherwise be paid

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13. Positive effects: Angrist et al. 2002 and Angrist, Bettinger, and Kremer 2006 in Colombia; Rouse 1998 in the US; Damera 2017 and Romero and Singh 2022 in India. Null effects: Hsieh and Urquiola 2006 in Chile; Wolf et al. 2010 in the US; Muralidharan and Sundararaman 2015 in India. Negative effects: Figlio and Karbownik 2016 and Abdulkadiroğlu, Pathak, and Walters 2018 and in the US. See Epple, Romano, and Urquiola 2017 and Neal 2018 for a review.

(Angrist et al. 2002; Damera 2017; Dongre, Sarin, and Singhal 2019; Romero and Singh 2022). On the supply-side, a smaller set of studies have found both positive and null effects on the education outcomes of non-recipients through equilibrium school responses.[14] While these studies largely focus on schools' quality responses, this paper provides some of the first empirical evidence that vouchers may have *negative* consequences through design-related school tuition increases.[15]

Second, there is a smaller literature that studies how features of voucher design may affect their overall impacts. This includes theoretical and empirical models that analyze the role of specific program elements such as school participation, policy targeting, and top-up fees in the US and Chile (Nechyba 2000; Epple and Romano 2008; Neilson 2021; Sanchez 2021). This paper innovates on this work along two dimensions. First, this paper studies a new element of voucher design: how linking voucher payments to school tuition affects welfare through equilibrium school adjustment. Second, more broadly, the paper provides a single consistent framework to assess how multiple voucher design features separately affect equity and efficiency. This includes a welfare measure based on revealed-preference that quantifies both non-monetary and monetary dimensions of consumer surplus for recipients and non-recipients, which can then be set against government and producer surplus to calculate the total benefit-cost ratio of various voucher schemes.[16] This demonstrates that one particular feature – voucher payment design – is quantitatively important relative to other features previously studied. The framework clarifies how the social planner may choose from a large set of possible designs depending on equity and efficiency goals.

Third, this paper is related to a growing body of work that uses structural models to estimate the equilibrium effects of education policy more broadly (Allende 2019; Barahona, Dobbin, and Otero 2021; Dinerstein and Smith 2021; Neilson 2021; Sanchez 2021). In addition to a focus on welfare, this paper builds on these models by making voucher applications endogenous, allowing for a new dimension of equilibrium adjustment. This reveals that when applications are costly, policy designs have the potential to shape application behavior and thus overall impacts.

Finally, this paper adds to the broader development economics literature on education, particularly the body of work that examines the growing private school sector in low income countries.[17] Given limited state capacity, these non-state alternatives may provide higher quality education, but may leave behind students who cannot afford to pay. Vouchers are among the most common interventions that economists and policymakers continue to debate in these settings (World Bank 2023). This paper improves our understanding of how to design these policies to be more effective, and provides benefit-cost ratios that policymakers can set against other development interventions.

14. Hoxby 2003 and Figlio and Hart 2014 in the US; Muralidharan and Sundararaman 2015 and Rao 2019 in India; Hsieh and Urquiola 2006 and Neilson 2021 in Chile. See Epple, Romano, and Urquiola 2017 and Neal 2018 for a review.

15. One exception is Hungerman and Rinz 2016 that uses state-level variation in US voucher programs to show that some systems cause increases in per-student revenue. A model of school price setting is not provided.

16. Two ongoing studies also use revealed-preference approaches to estimate the welfare impact of vouchers on recipients (Arcidiacono et al. 2021; Kamat and Norris 2023). This paper builds on these by adding a supply-side model that allows us to study impacts on recipients as well as non-recipients net of equilibrium school responses.

17. For example, 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.

2 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. Over the past two decades, India (along with many other developing countries) 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. Across states, MP is relatively underachieving: the fourth lowest in the UN Human Development Index and the sixth lowest in the UN Quality Education Index. It is therefore an important context in which to study the effects of policy that aims to expand access to education.

2.1 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.

With the aim of revenue neutrality, for each voucher student admitted into a school, the government pays the school its tuition fee up to a voucher cap: 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 low-caste social categories.[18] States are mandated to have a centralized application process where eligible students apply for vouchers with a state-specific allocation mechanism. Students apply for class 1 (first grade) or earlier and receive a voucher offer for one school, which they can use until class 8.

This policy has specific features, some of which are shared by programs around the world that subsidize private school education. In particular, it is "targeted" to disadvantaged students and is free of charge for recipients, such that schools are not allowed to charge "top-up" fees above the voucher cap. In addition, private school participation is mandatory. Table A1 describes government programs across countries that publicly fund private primary school enrollment. Several countries have programs that have some elements in common, but very few have the exact

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18. 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.

same design. India, whose design package is different from all others, has the largest such program in the world. The setting of this paper, Madhya Pradesh, is the third largest.

The Voucher Application Process. Similar to other states, MP first implemented the RTE voucher program at a serious basis 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).[19] Hence, upper-caste ("General") children are eligible if they are BPL, and lower-caste children are eligible regardless of income.[20] Eligibility is generous, covering about 50% of all MP children (Table 1).

Eligible students choose to apply to one of four classes based on age criteria: Nursery, KG-I, KG-II, and Class 1, which 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.[21] 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.[22] Second, through an assignment mechanism, they are offered a voucher to enroll in a single private school. 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 Gale-Shapley Deferred Acceptance (DA), where students are prioritized by schools based on proximity. The mechanism is strategy-proof, incentivizing truthful reporting of students' 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.

3   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 in the state as well as data on the enrollment and learning outcomes for every child in the state, including those outside the voucher system. They are linked together with unique student and school identifiers maintained by the state and national governments, respectively.

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19. The poverty line is set to roughly the 30th percentile of household income: $1,130 (rural) or $1,310 (urban) per year.

20. Parents submit credentials during the application process which are then reviewed by government officials and checked against administrative records.

21. Between 2013 and 2016, applications were filed using paper forms. Starting in 2016 applications were moved online, with offline applications are still available for those without internet access. Paper forms are submitted to local sub-district officers, who manually enter these applications in the main online portal.

22. In 2016, the year of online application data, the minimum requirement was one rank instead of three.

3.1 Voucher Applications

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 during the DA voucher assignment mechanism. Finally, applications provide the name of students' home village, which are geocoded to compute school distances.

Fig. A5 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.[23] 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 of DA) assumed to be strategy-proof. Those who win their first choice offer have a substantially higher probability of taking up the voucher (enrolling in the school for which they were offered) relative to those who do not. The analysis below will exploit lottery variation in the rank which students' receive, which will serve as an instrument for voucher takeup.[24]

3.2 Student Characteristics and Outcomes

Panel data on characteristics and outcomes of every school-enrolled child in MP are observed, both applicants and non-applicants, from 2013 to 2018, from class 1 to 8. Characteristics includes 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 scores on exams administered by schools.[25] 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. Fig. A3 plots GPA against this standardized measure averaged at the school level. The correlation is high at 0.42, which suggests GPA may capture achievement outcomes as opposed to curved grading within class.

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 measure of educational attainment provides an important extensive margin of achievement that complements intensive margins of educational performance metrics such as GPA.[26]

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23. 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.

24. 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.

25. The department of education in Madhya Pradesh releases class-specific assessment tests for all teachers to use, but are not mandated across schools.

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

Data Availability.   After linking voucher applications with student outcomes between one and three years after application, this results in outcomes of roughly 200,000 students (34% of all applicants). Because enrollment outcomes are observed only from classes 1 to 8, the individuals that are not observed are largely those in early application 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 A3 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.

3.3   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 of characteristics from 2000 to 2015, including inputs such as english instruction, playground access, number of teachers, number of computers, etc. These characteristics allow me to assess which types of schools students prefer enrolling, and what resources they provide to students. 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, Fig. A4 plots the distribution of distances computed using the imputation method versus distances from MP subset of 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 resemble that of 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.[27] Fig. A1 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.

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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.

27. 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.

3.4 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 1 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 zone ("block"), these children live in blocks that are (on average) 38% urbanized, have a 34% private school market share, pay $28 per year on tuition fees.

Across students, GPA is strongly correlated with socio-economic status (SES). Table A2 presents regression 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, 0.4σ, 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.[28]

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 0.15σ a 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.[29]

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28. In subsequent analysis, SES is grouped into "low" (SC or ST and below the poverty line), "middle" (SC or ST and above the poverty line), and "high" (OBC or general caste), which show increasing GPA in Table A2. These comprise roughly 25%, 25%, and 50% of applicants respectively.

29. 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. Fig. A1 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 teachers 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. Fig. A2 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.

4   The Effects of Voucher Takeup on Observed Outcomes

Oversubscription lotteries in the assignment of vouchers provides random variation in whether applicants win their first choice offers. 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:

$$y_{it} = \beta \text{Takeup}_{it} + R'_{it}\delta + X'_i\gamma + \epsilon_{it}, \tag{1}$$
$$\text{Takeup}_{it} = \alpha \text{First Choice Offer}_i + R'_{it}\delta^{FS} + X'_i\gamma^{FS} + \epsilon^{FS}_{it},$$

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.[30]

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.[31] 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.[32] All estimates stack data across entry year cohorts (2016, 2017, and 2018).[33]

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

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

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

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.

4.1 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 instruments are randomly assigned.

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

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

31. 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.

32. Alternatively, the reduced-form effects of winning a first choice voucher offer are reported in Table A6. As expected, the effects are scaled down in magnitude but qualitatively similar.

33. 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.

fully conditioned strata.[34] 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.

To estimate these propensity scores, the full set of information needed to replicate the DA assignment mechanism is observed. Given applicant rankings and school capacities, propensity scores can be estimated for each applicant-school pair π_{ijt} by simulating the DA assignment mechanism 10,000 times. Fig. A7 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 A5 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 A4 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.

4.2 Results

Table 2 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,

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34. 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: $\pi_{1A} = \pi_{3B} = 2/3$, $\pi_{2A} = \pi4A = 1/2$. Full conditioning would include zero students, but simply top choice and top priority would incorrectly pool 1, 2, and 4 (Narita 2020).

increasing takeup by 17pp. In 2016, the entry year cohort for which three-year effects can be 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 likely have weaker preferences for their first choice school.

Table 3 reports LATE estimates of voucher takeup on various outcomes for each year after application and overall, compared to the Control Complier Mean (CCM).[35] 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%. LATE estimates suggest voucher takeup increases student GPA by 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.[36]

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 3 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

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35. 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.

36. Alternatively, the reduced-form effects of winning a first choice voucher offer are reported in Table A6. As expected, the effects are scaled down in magnitude but qualitatively similar. For robustness, Table A7 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.

inframarginal to private school choice, consistent with selection in application.

Next, we see that takeup increases access to schools that offer english by 9pp and have 0.10σ higher GPA value-added, and decrease distance traveled by 0.4 kilometers.[37] 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 enrolling 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 voucher 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 A3 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.

Two features of the existing voucher design may have a role in delivering these benefits. First, the voucher system requires participation by all private schools. Thus, students have access to high quality schools that may otherwise find it privately sub-optimal to provide vouchers. Second, the top-ups of additional fees are not allowed. This means that vouchers enable students to attend schools at zero cost, delivering marked financial benefits. This calls for an explicit analysis of how design influences these impacts.

However, beyond recipients, the voucher policy may also have aggregate impacts through equilibrium responses of schools. Indeed, the policy's design sets 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 design, may affect private school behavior.

5   The Effects of the Voucher Policy on School Behavior

While public schools have administrative protections that limit incentives to adjust, private schools are profit-maximizing and do not face the same protections.[38] Because of the direct financial

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37. School-specific value-added is estimated using individual-level panel data on GPA. See Appendix Appendix A2 for details on value-added estimation.

38. Indeed, 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). In this setting, there is little evidence of the policy's effect on public school entry, exit, or quality measures.

implications of the voucher system, 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 student admitted through the voucher program, private schools receive reimbursements equal to their tuition fees up to a fixed voucher cap of roughly $74. As we see in Fig. A1, many schools have annual tuition fees that are below and above this cap, offering 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 tuition levels. This allows us to study how schools may respond depending on what design they face.

The analysis exploits the evolution of the voucher policy over time to estimate the effects of increased voucher applications on school behavior. In 2015, the government expanded the policy's eligibility to students under six years old. In 2016, an online system was introduced, which centrally collected applications and assigned vouchers.[39] Fig. 1a shows that the number of applications for the voucher program increased by over 15% from 2014 to 2015 when the policy was extended to younger children and over 30% from 2015 to 2016 after the online system was introduced. This provides substantial variation in application growth with which to estimate school responses to increased voucher demand.

An instrument paired with a difference-in-differences specification is developed to identify the effects of local voucher demand on school behavior. The instrument exploits variation in regions ("blocks") that were at greater vs. lower exposure to the growth in voucher applications. In particular, a candidate instrument is the fraction of voucher eligible students in the block who enroll in private schools in 2014. These students who already enroll in private schools and are eligible for the voucher policy 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:

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

where y_{jbt} is some 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 (in units of 1,000); z_b is the share of voucher eligible students who enroll in private schools in 2014; and η and δ are unit and year fixed effects. Estimates of β capture the effect of 1,000 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 Eq. (3) is estimated for narrow ($10-width) bins of *ex-ante* prices in 2014. This allows estimation of β across the distribution of

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

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 assumption is, within tuition fee bins, trends in both application and outcomes are parallel across instrument doses of z_b in the pre-period.[40] Because there were no changes to the application system prior to 2015, we may expect this to hold.

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 studied.[41]

5.1 Results

To provide intuition, Fig. 1b shows the reduced form effect on school sticker prices 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 (private share of eligible students), above-median exposure 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 exposure areas before the policy changes.[42] Overall, this suggests that these schools responded to increased voucher applications by raising their sticker prices.

Fig. 2 plots estimates of β, the effect of 1,000 additional voucher applications on school sticker prices, 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 20% 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 20% for the smallest price bin.

In comparison to effects on prices, there is comparatively less evidence that schools respond to the voucher policy by adjusting quality. Table A9 reports estimates by 2014 price bins across several measures of private school quality.[43] We see that effects on prices are large and statistically significant, but effects on other outcomes are small and (largely) statistically insignificant across price bins. Pooling across bins, for those below the cap, we see that an additional 1,000 voucher

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40. Chaisemartin and D'HaultfŒuille 2017 notes that, with a discrete-valued instrument, additional assumptions – including stable treatment levels – are also required, proposing alternative estimators to relax these. Estimates are qualitatively robust to several discretized versions of z_b and these alternative estimators.

41. See Section 6.1 for details on estimating mean indirect utility. School and time varying value-added is estimated using individual-level panel data on GPA. See Appendix Appendix A2 for details on value-added estimation.

42. Fig. A9 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.

43. There is little evidence of the policy's effect on public school entry, exit, or quality measures. See Table A10 for estimates of the voucher policy on public school outcomes at the village-level.

applications in a school's block increases schools' GPA value-added by 0.05σ (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.

Overall, these empirical findings are consistent with schools raising prices and (modestly) upgrading quality below the cap, where they face a tuition-linked voucher, and limited adjustment above, where they face a flat voucher. This has two important implications. First, because the market has 43% 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.

With this in mind, the paper next develops a framework of supply and demand that (1) is able to quantify the total surplus generated by the voucher system across the education market; and (2) endogenizes the behavior of students and schools with respect to voucher design.

6   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.[44] 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 model of supply is introduced which endogenizes price and quality decisions given demand.

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44. 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). In this setting, there is little evidence of the policy's effect on public school entry, exit, or quality measures. See Table A10 for estimates of the voucher policy on public school outcomes at the village-level.

Environment. 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. The market $m(i, t)$ is the set of schools over which i chooses in year t.

6.1 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, and school-specific 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 – all observed and unobserved preferences fixed across students specific to school j and year t (e.g. value-added, teacher quality, curriculum, resources, 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:

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

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).[45]

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

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

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45. 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.

some counterfactual non-voucher option j_0 at its sticker price $p_{j_0 t}$, earning utility $u_{ij_0 t}$. The impact of voucher takeup on consumer welfare is thus the difference in these utilities:[46]

$$\tilde{u}_{ij_1 t} - u_{ij_0 t} = \underbrace{-\alpha_i p_{j_0 t}}_{\text{Monetary}} + \underbrace{(\lambda_i (D_{ij_1} - D_{ij_0}) + \delta_{j_1 t} - \delta_{j_0 t})}_{\text{Non-Monetary}} + \underbrace{(\epsilon_{ij_1 t} - \epsilon_{ij_0 t})}_{\text{Match}}. \tag{7}$$

This welfare effect accounts for multiple dimensions of how vouchers may benefit recipients.[47] The "monetary" component captures how students avoid paying tuition fees for their outside option $p_{j_0 t}$. 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. 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 test scores 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 consumer surplus for each student depending on the distribution of prices faced. We next turn to estimation and identification of model parameters in order to estimate welfare.

6.1.1 Model

The stylized school choice model above 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 appli-

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46. See Appendix A4 for details.

47. 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.

cation. The model is thus expanded to incorporate these additions decisions students may face, thereby endogenizing voucher applications and offers. 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 ranks submitted and they then choose, along with ineligible students, in which to schools to enroll. Stages are described in reverse.

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

$$u_{ijt}^e = \alpha_i p_{ijt} + \lambda_i D_{ij} + \delta_{jt} + \epsilon_{ijt}^e, \tag{8}$$

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:

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

Ranking Stage. When ranking schools for the voucher application, utility $\tilde{u}_{ijt}^r$ 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:

$$\tilde{u}_{ijt}^r = \lambda_i D_{ij} + \delta_{jt} + \epsilon_{ijt}^r. \tag{11}$$

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 $m^{\text{Priv}}(i, t)$:[48]

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

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

$$v_{ijt} \sim \text{Bernoulli}(q_{ijt}^o(\theta, \epsilon_t^r)), \tag{13}$$

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

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48. 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.

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

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

$$u_{ijt}^a = \alpha_i^x p_{jt} + \lambda_i D_{ij} + \delta_{jt} + \epsilon_{ijt}^a. \tag{14}$$

where α_i^x is the component of α_i that depends on observables only.[49] When considering whether to apply, students predict their rankings over private schools based on non-price utility $\tilde{u}_{ij}^a$:

$$\tilde{u}_{ij}^a = \delta_j + \lambda_i D_{ij} + \epsilon_{ij}^a, \tag{15}$$

and construct a hypothetical rank-ordered list R_i^a:

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

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:

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

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

$$\Delta_{it}(\theta, \epsilon_t^a) = \sum_{j_k \in R_{it}^a} q_{ij_kt}^o(\theta, \epsilon_t^a) \max(\tilde{u}_{ij_kt}^a, u_{ij_0t}^a) - u_{ij_0t}^a, \tag{18}$$

where $q_{ij_kt}^o(\theta, \epsilon_i^a)$ 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 Eq. (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

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49. 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, $\alpha_i^x = X_i' \alpha_x$, the fixed component of α_i. This assumes there is no selection into application based on unobserved price heterogeneity, allowing for a separate estimation of taste and application parameters below.

Δ_{it} exceeds application costs τ_{it}:

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

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 observable characteristics 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 all other unobservables. The vector X_i includes three indicators of socio-economic status (SES) at the individual level. 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). These comprise roughly 25%, 25%, and 50% of applicants respectively.[50] Second, a separate indicator is included for the gender of student. Third, there is an additional indicator for an observed voucher applicant vs. non-applicant. Therefore, there are a total of 10 price and distance coefficients, in addition to unobserved heterogeneity in the price coefficient.

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.[51]

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

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50. These groupings are chosen to be parsimonious (to ensure power within each group) but also useful in capturing variation in social and economic advantage. Table A2 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.

51. 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.

do so, idiosyncratic terms in each stage are parametrized as follows:

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

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 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.[52] 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 next 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 the estimated tastes and application decisions.

6.1.2 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

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52. 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.

terms) and application costs τ:

$$\theta = \left\{ \alpha_x, \lambda_x, \{\delta_{jt}\}, \phi, \sigma_\alpha, \beta_\psi \right\},$$ (24)

$$\tau = \{\tau_w, \tau_z\}.$$

Estimation proceeds in two steps. In the first step, taste parameters θ are estimated using the latter 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. This provides two stages of choice that aids identification. In the second step, data on eligible students' decisions to apply together with taste estimates $\hat{\theta}$ enables estimation of application costs τ.

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.[53] This unconditional likelihood is estimated with simulation over 300 draws of the unobservables, and maximized using a tractable algorithm.[54]

6.1.3 Identification

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.[55] 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 (reflected by p_{jt}) may provide better resources and teachers for students, which may be preferred by students (reflected by 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 Eq. (9). In particular, students are more likely to win voucher offers for schools when they are ranked higher. Thus, non-price preferences for schools (reflected in δ_{jt}, D_{ij} 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

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53. See Appendix A5 for likelihood functions.

54. The parameter space is large, involving a very large set of fixed effects (one for each school 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 A5.1 for details.

55. 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.

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 exploits 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:

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

Thus, when estimating the model in Eq. (4), fully saturated fixed effects for each propensity score π_{ijt} specific to each student-school pair are included.[56] 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 approach exploits additional choices made by applicants before choosing which school to enroll in that separately identify 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). Importantly, these rankings are submitted before vouchers offers are realized, and are thus excluded from school prices. This allows for identification of the non-price dimensions of school preferences. In particular, when submitting rankings over schools R_{it}, students only rank their preferences for non-price attributes of schools $\tilde{u}^r_{ijt}$ as in Eq. (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. In this setting, students make similar zero-price choices, but they are high-stakes as choices are used directly for the assignment of private school vouchers.

Identification of Application Costs τ. The returns from applying for vouchers depend only on the fixed ("linear") taste parameters in θ. Any residual variation in the application decision is thus due to application costs. Once tastes θ are estimated, we can estimate application costs τ as

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56. 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 Eq. (23).

a residual.[57] The application 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 distance penalty would impact equilibrium outcomes.

6.1.4 Data Restrictions and Parameter Estimates

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.[58] 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.[59] Outside options are set as the school with the lowest market share in each market.[60] This results in roughly 1M rank and enrollment choices for 30K students and 10K schools.

Parameter Estimates. Table 4 presents demand estimates. Panel A reports price parameters α_i, which show substantial heterogeneity across student demographics. Observed applicants, lower SES, and female students show higher sensitivity to prices. Further, there is modest unobserved heterogeneity, with an estimated σ_α at roughly 15% of the α_i intercept. Panel B reports distance parameters λ_i, which show modestly higher distance sensitivity for observed applicants and female students. Panel C reports the distribution of estimated school-specific preferences. We see that private schools have on average higher δ_{jt} than public schools, reflecting overall preferences for enrolling in private over public schools. This is consistent with private schools having more resources and higher value-added.[61] There is substantial heterogeneity, with a standard deviation at roughly 50% of the mean, suggesting schools are highly differentiated so that students' fixed preferences vary greatly across schools. Panel D reports estimates of persistence parameters. The mean ϕ is roughly 0.7, which suggests schools with positive propensity scores (that are submitted

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57. 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.

58. 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 A5.1.2 and Appendix A5.2.2 for more details.

59. Table A11 reports that this randomization is effective: student and school charactersitics are statistically insignificant predictors of being assigned into the estimation sample.

60. 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 A6 for details on market construction.

61. Indeed, Fig. A10 plots the strong relationship between GPA value-added and school mean utilities.

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.

6.2 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 these price and quality decisions. 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} is the 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. 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.[62]

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62. 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.

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 schools: increasing quality raises expected enrollment (and revenue), but also raises cost.

Expected enrollment depends on all demand parameters θ, τ along with student and school characteristics (suppressed for brevity) and unobservable draws. Collecting unobservables into $\epsilon = \{\nu, \psi, \eta^a, \eta^r\}$, enrollment that j expects from the voucher system depends on (1) the probability of applying; (2) the probability receiving an offer for school j; and (3) the probability accepting the offer. These are aggregated across covariate groups g in market $m(j,t)$ with population counts $w_{gt}^{m(j,t)}$. Thus, expected voucher enrollment for school j in year t is (dropping m for brevity):

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

Non-voucher enrollment in school j includes (1) those who do not (or cannot) apply and enroll in school j; (2) those who apply but receive no offers and enroll in school j without a voucher; and (3) those who apply, receive an offer for a different school, but reject it in favor of school j:

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

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):

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

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 $\bar{v}_t$.

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.

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$\eta^a_{ijt}, \kappa_{it}$ drawn	ψ_{ijt}, η^r_{ijt} drawn	$v_{ijt}, v_i, \eta^e_{ijt}$ drawn

School Decisions	**Application Choice**	**Ranking Choice**	**Enrollment Choice**
j sets p_{jt}, δ_{jt}	i chooses a_{it}	i chooses R_{it}	i chooses e_{ijt}
given $\mathbb{E}[N^v_{jt}], \mathbb{E}[N^{nv}_{jt}]$	given $\{p_{jt}, \delta_{jt}\}$	given $\{p_{jt}, \delta_{jt}\}$	given $\{p_{jt}, \delta_{jt}, v_{ijt}\}$

The *equilibrium* is a set of prices, qualities, and enrollments $\{p^*_{jt}, \delta^*_{jt}, N^{v*}_{jt}, N^{nv*}_{jt}\}$ such that:[63]

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

$$p^*_{jt}, \delta^*_{jt} = \underset{p_{jt}, \delta_{jt}}{\mathrm{argmax}}\ \Pi_{jt}\Big|_{p^*_t, \delta^*_t} \tag{32}$$

2. All students are maximizing utility as in Eq. (29) and Eq. (30):

$$\mathbb{E}[N^{v*}_{jt}] = \mathbb{E}[N^v_{jt}]\Big|_{p^*_t, \delta^*_t} \tag{33}$$

$$\mathbb{E}[N^{nv*}_{jt}] = \mathbb{E}[N^{nv}_{jt}]\Big|_{p^*_t, \delta^*_t}$$

6.2.1 Optimal Price Under the Current Design

First-order conditions (FOCs) on price depend on whether prices are above or below the voucher cap $\bar{v}_t$, and suggest prices should equal marginal cost plus a markup due to limited competition. Markups depend on market shares and price elasticities of demand. Importantly, we see that voucher students' demand is essentially inelastic to prices:

$$\frac{\partial \mathbb{E}[N^v_{jt}]}{\partial p_{jt}} \approx 0. \tag{34}$$

This is apparent as N^v_{jt} 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 $q^{e|o}_{ijt}$ 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 schools' price to only minimally change market-level application rates or offer probabilities (as only non-price attributes matter for rankings).[64]

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63. 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.

64. The empirical analysis will allow for and estimate how schools' price and quality would affect application and offer rates. These elasticities are very small as schools being small relative to their market, and the existence of large application costs that prevent even relatively large schools from shifting application rates via adjustment. See Appendix A5 for full expressions of enrollment levels and price and quality gradients that are used in estimation.

For schools below the voucher cap ($p_{jt} < \bar{v}_t$), the FOC for the status-quo design (sq) is:

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

where the denominator only includes the non-voucher price sensitivity given Eq. (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 Eq. (34) this implies that the voucher market drops out completely from the school's first-order condition, which yields an optimal pricing equation that is only sensitive to the non-voucher market:

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

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

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:

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

For below-cap schools, the voucher system reduces the magnitude of the denominator of the markup term in Eq. (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. Thus, for these students, there is a strong incentive to raise prices to capture additional revenue without losing demand. In aggregate, 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 Eq. (36) is not clearly higher or lower than the no-voucher price in **??**. 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.

6.2.2   Optimal Quality Under the Current Design

Optimal quality is set to the competitive level (where marginal revenue equals marginal cost) minus a quality mark*down* due to limited competition. 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:

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

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

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

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, may face lower marginal revenue due to the voucher reimbursement cap. Their optimal quality choice is:

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

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

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

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).[65] 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.

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:

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

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_{jt}^{-1} is increasing in p_{jt} by Eq. (39), so we expect optimal quality to *increase* for these schools. These schools face excess profits from increased markups, which results in quality upgrading to capture these profits.

For above-cap schools, the effective marginal revenue $\tilde{p}_{jt}$ falls when the voucher policy is introduced due to the cap on the voucher payments (which are 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.[66] To address this, the model adds an additional parameter to allow for potential constraints in quality adjustment.

6.2.3   Quality Adjustment Threshold

To parametrize potential constraints to quality adjustment, the model assumes schools may freely adjust quality below a marginal cost *threshold*. This threshold reflects a variety of 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

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65. The weights are proportional to market size and quality sensitivities:

$$w_{\delta}^{nv} = \frac{\frac{\partial \mathbb{E}[N_{jt}^{nv}]}{\partial \delta_{jt}}}{\frac{\partial \mathbb{E}[N_{jt}^{nv}]}{\partial \delta_{jt}} + \frac{\partial \mathbb{E}[N_{jt}^{v}]}{\partial \delta_{jt}}}$$

66. 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.

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:

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

$$\max_{p_{jt}} \Pi_{jt} \quad \text{if} \quad mc_{jt} \geq \overline{mc}_t,$$

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.[67]

6.2.4 Estimation

Together with the estimated demand parameters, the supply side conduct assumptions identify all supply-side parameters except for the quality adjustment parameter ω. In particular, because all application, ranking, offer, and enrollment probabilities are known, we can compute empirical estimates of price markups and quality markdowns in the respective first-order conditions Eq. (35)-Eq. (36) and Eq. (38)-Eq. (40). Marginal costs mc_{jt} and the competitive quality level mc_{jt}^{-1} can be estimated by inverting these first order conditions given observed prices and quality. Finally, parameters of the marginal cost function are identified from the first-order conditions (for schools below the quality threshold), which together place restrictions on the quality coefficient:

$$\gamma_{jt} = \frac{\mu_{jt}^{p}}{\mu_{jt}^{\delta}}, \tag{45}$$

where $\mu_{jt}^{p} > 0$ is the school price markup term (the right hand side expression of Eq. (35)-Eq. (36)) and $\mu_{jt}^{\delta} > 0$ is the school quality markdown term (the right hand side expression of Eq. (38)-Eq. (40)). The structural error $c_{jt} = mc_{jt} - \gamma_{jt}\delta_{jt}$ is obtained as a residual.

In order to estimate the threshold, the same instrumental variable (IV) above is exploited that captures exposure to policy changes that led to increased voucher applications in some markets but not others. The assumption is that the exposure instrument is orthogonal to unobserved cost

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67. 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.

shocks. In practice, this implies moment conditions that depend on the threshold parameter ω which can be used for estimation via Generalized Method of Moments (GMM).

The IV is constructed as in Section 5:

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

where $\tilde{z}_j$ is the share of voucher eligible students who enroll in private schools in 2014.

An intuitive assumption is that (after differencing school and time fixed effects) the instrument is orthogonal to the structural cost errors:

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

where the difference operator removes school and year means:

$$\Delta x_{jt} = x_{jt} - \bar{x}_j - \bar{x}_t. \tag{48}$$

Using schools' first-order conditions, this implies the following single moment condition, whose sample analogue can be estimated with the data:[68]

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

where t is years relative to the initial period (2013) and μ_{jt}^p 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 unaffected by the instrument. The estimation procedure selects the threshold which minimizes these disturbances.

6.2.5 Parameter Estimates

Fig. 3 reports supply-side parameter estimates. Panels A and B show the distribution of estimated price markups and quality markdowns among private schools. Schools exhibit substantial market power, with markups that are roughly 40% of prices on average. There is considerable variation, with schools charging 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 considerable variation.

Fig. A11 shows the sample moment conditions against candidate quality adjustment threshold

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68. Thus, the moment condition used for estimation Eq. (49) is a slightly weaker condition than Eq. (47). See Appendix A7.7 for details.

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 lowest sample moment condition is 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 little impact of vouchers on observed measures of quality.

Panel C of Fig. 3 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.

7 The Welfare Impacts of India's Voucher Policy

With both supply and demand models in hand, we can then compute how counterfactuals affect aggregate welfare. Each design counterfactual will change schools' price and quality decisions affecting students' sorting across schools and generating consumer, producer, and government surplus. By aggregating these different dimensions of surplus across the market, we can evaluate the total welfare impact of each counterfactual, and compute benefit-cost ratios.

Counterfactual Equilibria. For any counterfactual, equilibrium is reached using standard methods (Berry, Levinsohn, and Pakes 1995).[69] On the supply-side, voucher design will directly affect the profit function (via the marginal revenue from voucher students by changing payment levels or the expected voucher enrollment by adding top-up fees) and thus influence schools' decisions by changing first-order conditions.

On the demand-side, given schools' price-quality decisions and unobservables $\{v, \psi, \eta\}$, students make application and ranking decisions by maximizing utility according to the demand model. The voucher offers $\{v_{ijt}\}$ are realized given the submitted ranks, and final enrollment choices are made. These choices may also be affected by the particulars of the voucher design (e.g. allowing top-up fees or changing application costs). Because schools form correct expectations of demand, the choices of students are consistent with the beliefs of schools in equilibrium.

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_{gt}^m (student welfare) over the distribution of

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69. Schools' first-order conditions are iteratively updated until convergence. See Appendix A7.6 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.

unobservables ϵ:

$$CS_{gt}^m(p_t, \delta_t, v_t) = \int_\epsilon \frac{1}{\alpha_g} \max_{j \in m} u_{gjt}^e(p_t, \delta_t, v_t) \, dF_\epsilon. \tag{50}$$

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 Eq. (27):

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

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

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

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

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

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, surplus from any design can be compared against a no-voucher counterfactual to compute its benefit-cost ratio.[70]

7.1 Results

Fig. 4 shows how the equilibrium distribution of price and quality change as a result of the voucher policy. Panel A reports the change in prices from the no-voucher counterfactual to the status-quo voucher system for each bin of school prices. These price impacts are grouped by year of the policy, with 2013 being the first and 2018 being the last observed. 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. The adjustment is substantially more pronounced as the program expands from 2013 to 2018, with a 35% increase in prices for schools who charge less than \$34 per year in 2018.

Panel B shows changes in equilibrium school quality. 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. In counterfactuals, the quality adjustment (especially for more expensive schools) appears in future years as the adjustment threshold

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70. See Appendix A8 for details.

increases, which allows for more schools to adjust quality.

Table 5 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). 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 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 these students, that are more price elastic, are more likely to have counterfactually attended public schools. Thus, their relative benefits are smaller because (1) their counterfactual fees are zero, and (2) their willingness-to-pay to quality improvements is small. 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 the relatively elastic students, this causes a $0.20 reduction in student welfare as some of them are potentially priced out from their preferred school. These students may switch schools as a result of price increases. As a result, schools face slightly reduced profits and the government faces increased expenditure from some students switching from private to public schools. For relatively inelastic students, the effects are opposite. These students benefit from lower quality schools raising quality, which tips the quality-price tradeoff in their favor. By shifting from other schools to these, this results in a modest reduction in profit as some students "downgrade" from expensive private schools. Importantly, this also causes some students to "upgrade" from the public sector, saving the government from these public school expenses.

On net, the benefit-cost ratio (BCR) is roughly 1.5 across the market, which suggests the benefits to voucher recipients exceed the costs to others. However, a failure to account for the impacts to non-recipients would have led to a BCR that is nearly two times larger at 2.9. This underscores the role of equilibrium school response in shaping the policy's overall cost-effectiveness.

Note that among the price insensitive students, the overall BCR is substantially higher, as they benefit from the school responses, while the price sensitive students are harmed by them.

Ignoring non-recipients, the policy is relatively more cost-effective for price sensitive students as the government incurs lower expenditure by sending ex-ante public school students to voucher schools. For insensitive students, however, the policy is more costly as many students are inframarginal.

7.2 Distributional Outcomes

While the BCR captures how the policy balances aggregate costs and benefits, the framework allows us to examine how vouchers affect student sorting across schools and the distribution of welfare. Indeed, 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.

Fig. 5 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 13% 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).[71] 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.

Fig. A12 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).

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71. See Appendix A9 for details.

8 Voucher Design and Welfare

While India's voucher system is relatively successful from an equity and efficiency perspective, the analysis suggests some of its impacts may be driven by specific design choices. The demand and supply framework allows us to infer the equilibrium welfare consequences of changing features of the voucher design. Three alternative voucher schemes are considered: additional top-up fees, voluntary school participation, and a flat voucher payment design. Finally, counterfactuals that expand the policy and allow for greater quality adjustment are also examined. 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.[72]

8.1 Results

Voucher Design. Table 6 reports the equilibrium welfare consequences of the various designs against a no voucher counterfactual. Panel A reports estimates under the status quo (tuition-linked payments below the voucher cap) and two alternatives: a design with top-ups allowed for schools above the cap and a design that allows voluntary school participation. 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 reduces voucher expenses, but virtually eliminates effects on school integration (raising voucher eligible enrollment private school by 3% compared to 13%). On net, introducing a top-up design would reduce 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.

Panel B reports estimates for flat voucher systems. Shifting to a flat voucher set to the current reimbursement cap (roughly $74) reduces price hikes (2% compared to 3%). This highlights how removing the link between voucher payments and school tuition levels removes the distortionary

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72. See Appendix A10 for details on how each design would change schools' first-order conditions on price and quality.

incentives for schools to adjust their prices that is present in the status-quo system. 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. There are similar positive impacts to school integration as the benefits to voucher recipients are relatively unchanged. This results in an overall BCR of 2.1, substantially higher than the existing system, and doubles the impact on total surplus from 0.5% to 1.0%.

Reducing the flat voucher payment level to the median marginal cost (roughly $51) has three effects. First, for those below the cap, there is downward quality adjustment as schools face reduced marginal revenue, causing reductions in price and quality. Second, there are greater profit losses for schools that receive lower reimbursements. Third, the government incurs substantially lower expenditure from reduced voucher levels. On net, by reducing voucher expenditure, the policy ends up increasing government surplus resulting in an infinite BCR.

In sum, the cost and benefits of voucher policy depend greatly on voucher design, with total benefit-cost ratios ranging from 0.6 to 2.1 (and even infinity). Moreover, within any particular voucher design, ignoring producer surplus leads to significant changes in the corresponding cost-effectiveness, with consumer-only BCRs ranging from 1.5 to 6.7. Finally, design also matters for equity outcomes, an important objective for policy makers. Impacts on the composition of voucher eligible children in private school ranges from 3% to 16% depending on voucher design.

Policy Expansion. The policy's performance suggests scope for expansion. This can be achieved in several ways. Panel C reports two potential counterfactuals that grow the voucher sector.

The first is raising the quota of voucher seats available in the assignment mechanism. Currently, schools are mandated to allocate 25% of their seats. Expanding the quota to 50% would raise voucher applications modestly to 16%. This is because many of schools are currently under-subscribed, such that raising the quota would only have impacts for the (relatively few) 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 expanding voucher seats, an alternative is to expand the applicant pool. There are large application costs such that only 15% of eligible students apply for the voucher system. While costs are not observed, the parameter τ_z captures how students' distance to application centers influences application choice, net of the projected returns from applying. This instrument, which is excluded from tastes, serves as a shifter of application costs. The second counterfactual in Panel C shuts down this distance penalty, which raises application rates substantially to 26%. By attracting voucher 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, spending falls compared to raising the quota, increasing the BCR to 3.0. Overall, these findings suggest scope for policy expansion and provide a benchmark with which to compare the costs of reducing application frictions.

Quality Adjustment Over Time. The flat voucher that pays the lowest amount delivers an infinite BCR, but generates the largest losses in profit and downward quality adjustment. In the long run, we may expect schools to adjust even more, potentially reducing the returns of the policy.

Panel D shows how the welfare impacts of counterfactual voucher policies may evolve with greater quality adjustment. This is accomplished by extrapolating the marginal cost threshold to its level in 2100 as given by Eq. (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 all three designs, this shrinks the voucher sector, reducing equity gains but raising the BCR from reduced costs and profit losses.

Importantly, the flat voucher programs continue to outperform the status-quo policy, even under substantially higher quality adjustment over time. While the lower flat voucher still has an infinite BCR, compared to the higher flat voucher, it causes substantial quality reductions from the reduced voucher level and increases total surplus by 0.5% compared to 1.2%.

In the long run, there may thus be tradeoffs from lower vs. higher voucher levels. Fig. 6 presents the impact of flat vouchers depending on the size of voucher payments, 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 voucher 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. Importantly, for low voucher levels, the government has net 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 is maximized at a voucher level that is roughly equal to the current per-capita public school cost of $74. However, impacts on socio-economic integration are maximized at a higher voucher level of roughly $90. Finally, because the government incurs cost savings, the benefit-cost ratio is infinite for sufficiently low voucher levels. This presents an equity-efficiency tradeoff: high voucher levels raise equilibrium quality and integration, but are costly from an efficiency perspective. The optimal voucher will thus depend on planners' preferences and the relative weights on school integration, levels of education quality, and welfare.

9 Discussion

Using detailed administrative records, this paper develops an empirical framework to quantify the total welfare consequences of India's primary school voucher system – the largest in the world – against alternative voucher designs. The policy delivers a complex patchwork of individual- and market-level impact across the education system, including a distortionary price response due to the tuition-linked payment design. The framework is able to aggregate these various impacts in money-metric terms and set them against government costs. This reveals that India's current voucher policy is able to increase the overall efficiency of the education system, while also improving equity outcomes.

However, the policy's efficiency could be substantially improved by switching its design to a flat voucher system, which eliminates the harmful incentives for schools to raise tuition. Alternative voucher designs that allow private schools to charge additional fees or exit the system shift surplus from consumers to producers and lead to poor equity and efficiency outcomes. This exercise suggests that the many design choices made when developing voucher systems are not innocuous, and have large impacts on policy effectiveness. This is especially important given continued debate on the efficacy of voucher programs around the world 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 observed. 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, 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, voucher systems may cause changes along intensive margins of quality investment as well as extensive margins of entry and exit. As discussed above, optimal policy design in the long run may involve raising voucher payments to prevent losses to private schools and downward quality adjustment.

Table 1: 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 2: 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 Eq. (1) and Eq. (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 3: The Effects of Voucher Takeup on Student and School Outcomes

Panel A: The Effect of Voucher Takeup on Student 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 School Outcomes

	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	0.28	0.11***	0.33	0.08**	0.29	0.12	0.30	0.10***
		(0.03)		(0.04)		(0.11)		(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***
		(3.10)		(4.04)		(19.25)		(3.03)
Application Year Range	2016–2018		2016–2017		2016		2016–2018	
First Stage F-Stat Range	882–1,157		699–945		497–563		2,305–3,010	
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 and school outcomes (rows) for each year after application and over all years (columns), using first choice offer as an instrument specified by Eq. (1) and Eq. (2). Panel A reports estimates for impacts to student achievement and Panel B reports estimates for impacts to assigned 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 Appendix A2. 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.

Figure 1: Voucher Application Growth and Price Responses

(a) Application Growth

(b) Effects of Application Growth Exposure on School Prices
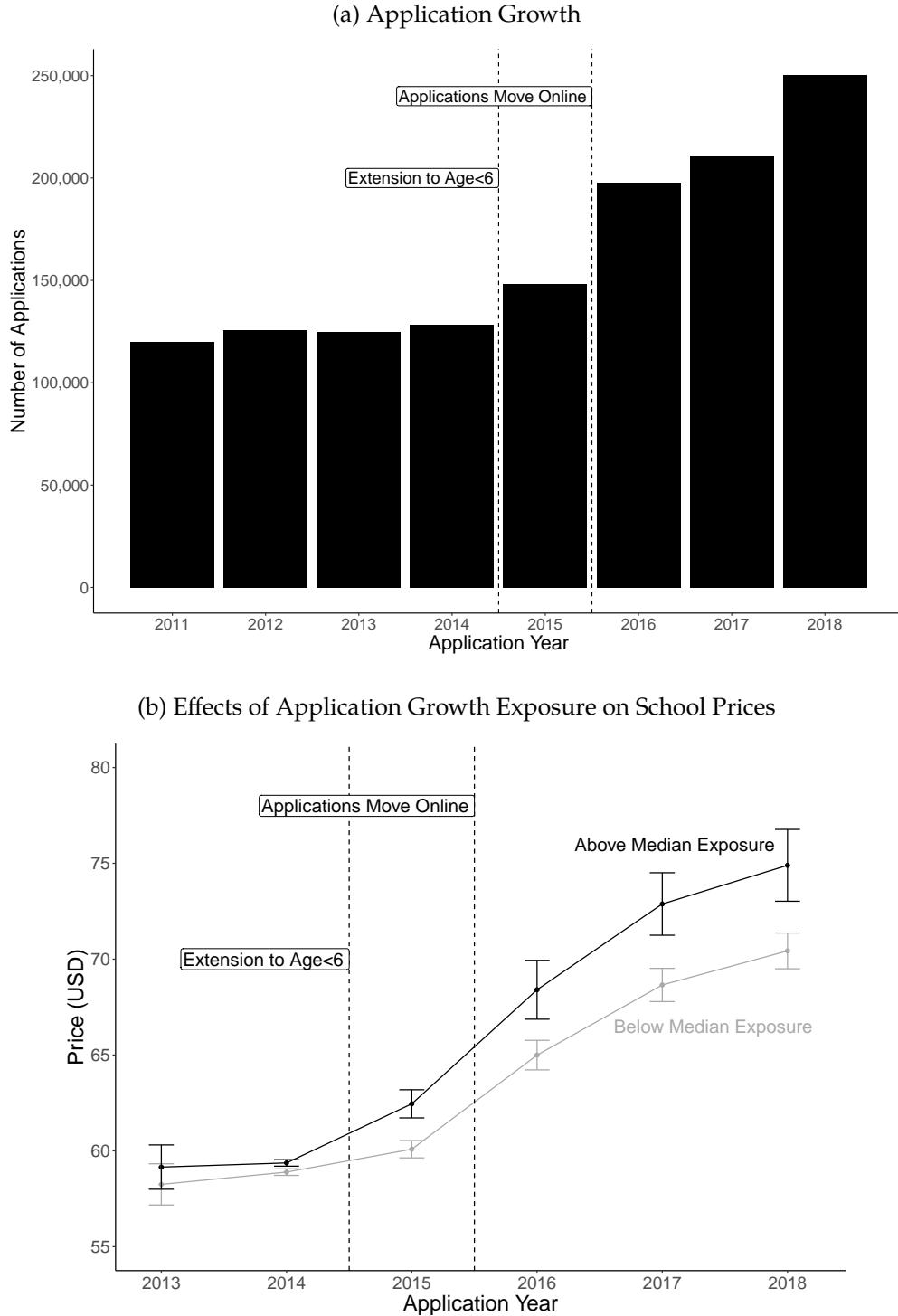
Notes: This figure presents data on application volume and school prices over time. Panel A reports the total number of applications for the Madhya Pradesh voucher system from 2011 to 2018. Panel B presents the average prices charged by schools over time grouped by ex-ante exposure to application growth: 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 2: The Effects of Voucher Expansion on School Prices
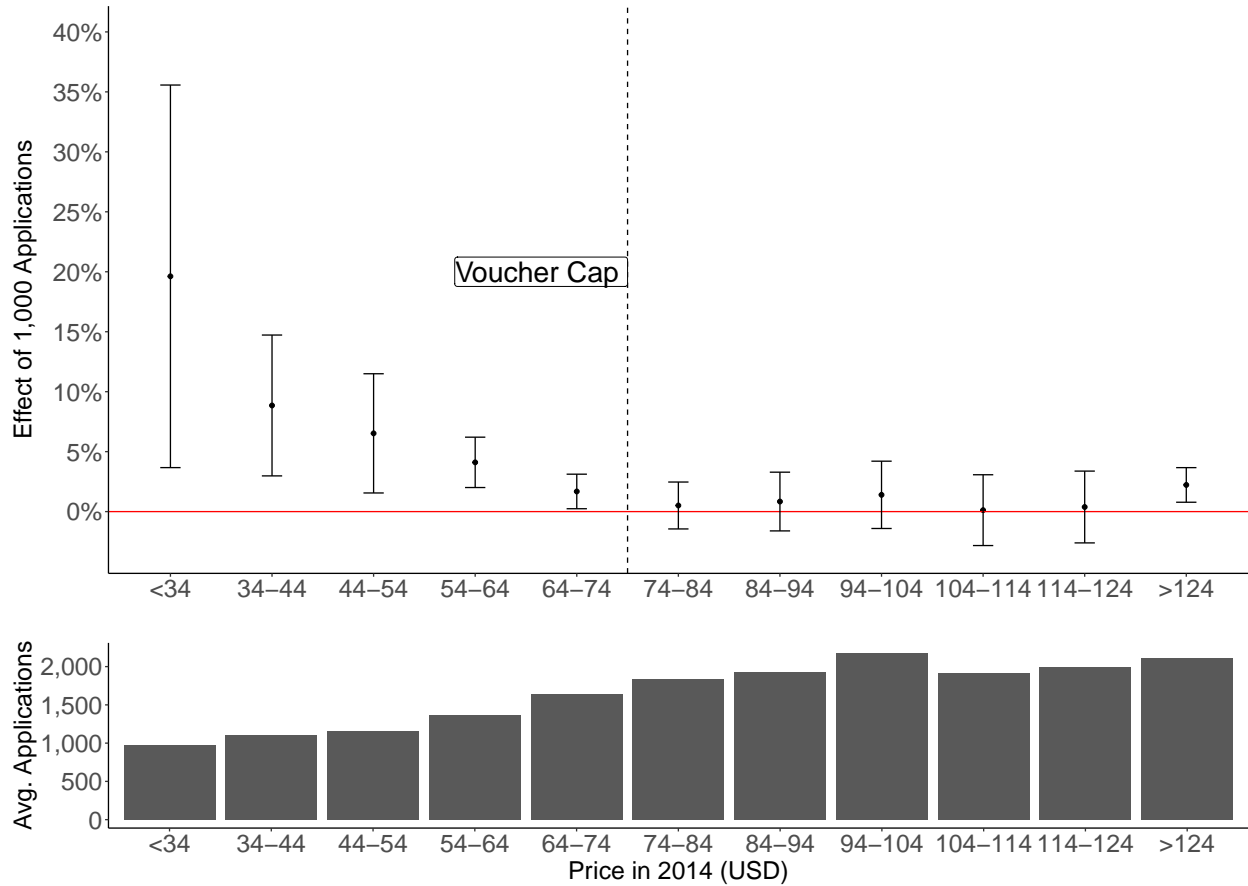
Notes: This figure presents IV difference-in-difference estimates of the impacts of local voucher demand on school prices as specified by Eq. (3), for various bins of sticker prices in 2014. For each bin (x-axis), points (x-axis) denote the difference-in-differences coefficient of block-level application volume divided by the mean 2014 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 2016 to 2018 of \$74.47. Estimates are (1) re-scaled to reflect the impact of 1,000 additional applications on school prices; (2) include year and school-by-class fixed effects, and (3) are clustered by block, the level of treatment assignment. First stage F-stats range from 2,257 to 27,447.

Table 4: 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 6.1.2. "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 A5 for details of the estimation and extrapolation procedure.

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

Figure 3: Supply Model Estimates

(a) Price Markups

(b) Quality Markdowns

(c) Adjustment Thresholds Over Time
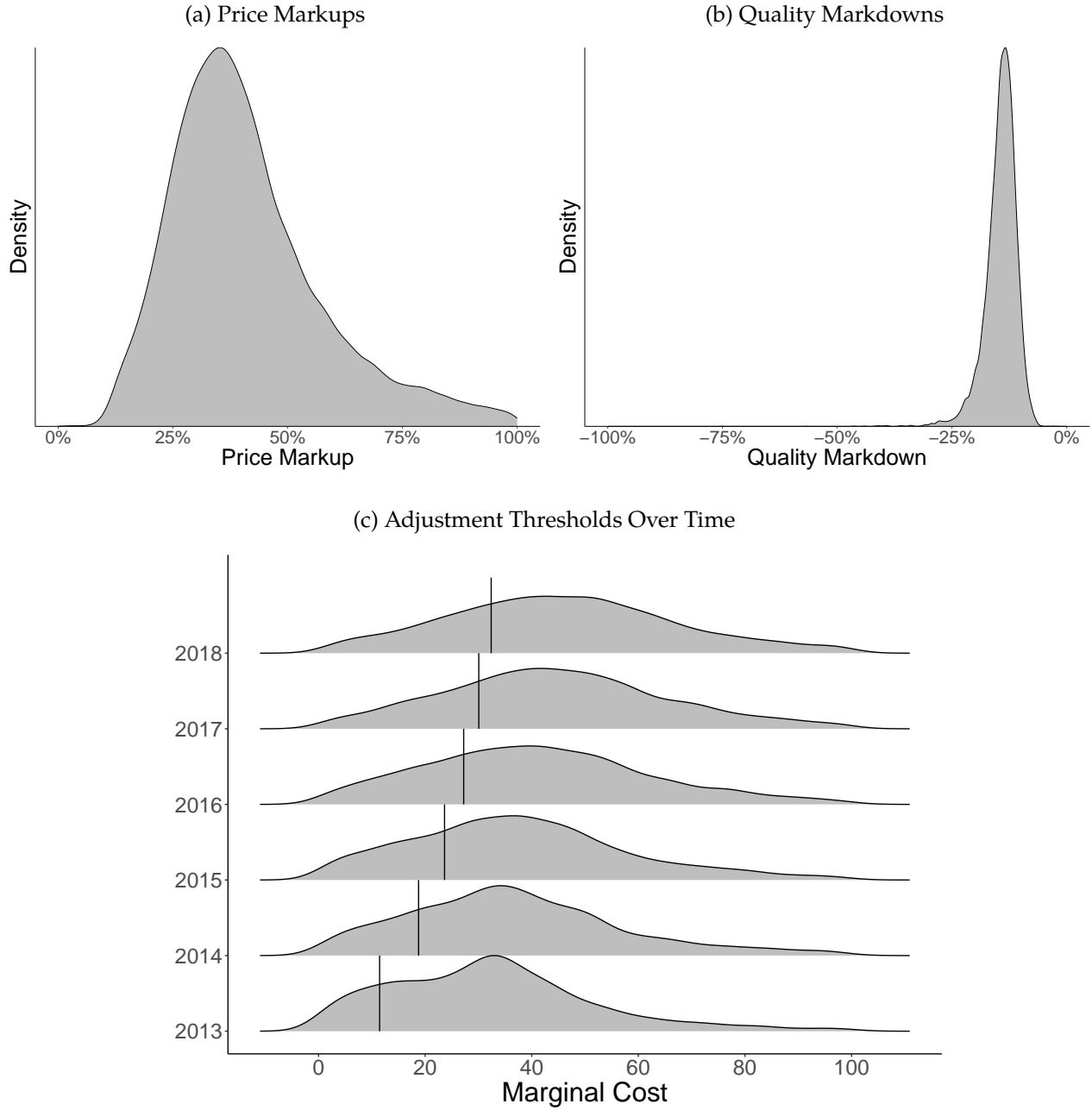
Notes: This figure presents estimates from the supply-side model as described in Section 6.2. Panel A plots the kernel density estimate (KDE) of price markups (as a fraction of school tuition fees) and Panel B plots the KDE of quality markdowns (as a fraction of estimated school quality). Panel C plots 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 4: The Impact of Vouchers on Equilibrium Price and Quality

(a) Equilibrium Price Response

(b) Equilibrium Quality Response
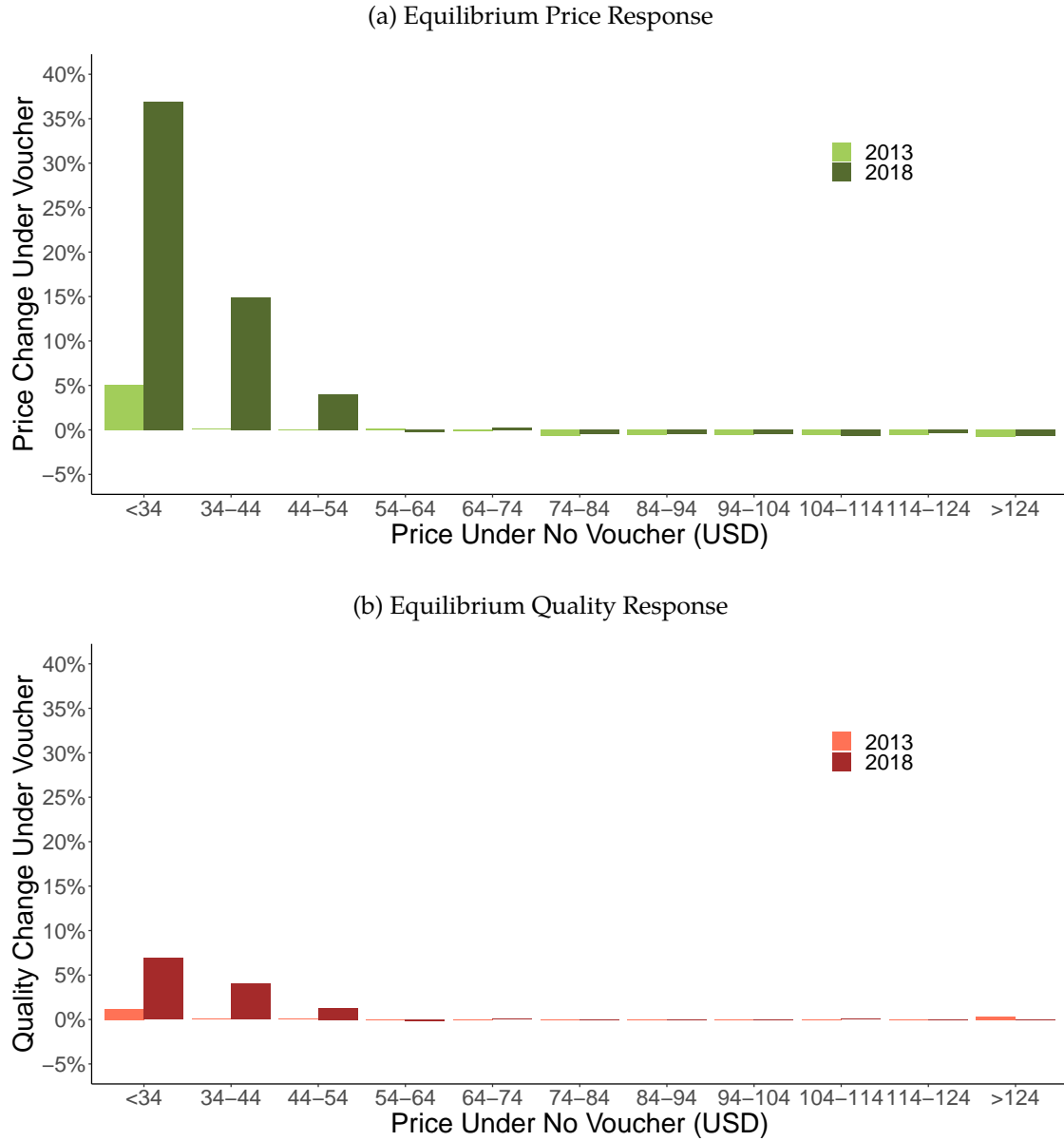
Notes: This figure presents the impact of India's voucher system on equilibrium prices and quality. Panel A shows for each bin of private school prices under the no voucher system (x-axis), the average percent change in school prices (y-axis) of moving from the no voucher counterfactual to the status-quo voucher system as described in Appendix A8. Panel B shows the same but for impacts on school quality. Lighter colors denote effects for the year 2013 and darker for the year 2018. Estimates are restricted to a random sample of 200 markets from 2013 to 2018.

Table 5: The Welfare Impacts of Voucher Policy Across the Education Market

| | Effect of Voucher Policy (2019USD Per Student Per Year) | | |
		Price Sensitivity	
	All	Top Quartile	Bottom Quartile
Panel A: Voucher Recipients			
Consumer Surplus (Student Welfare)	+105.9	+63.4	+194.9
Producer Surplus (School Profit)	–54.1	–28.1	–112.2
Government Surplus (Cost)	–17.6	–9.0	–32.9
Panel B: Voucher Non-Recipients			
Consumer Surplus (Student Welfare)	+0.1	–0.2	+0.8
Producer Surplus (School Profit)	–1.3	–0.7	–0.1
Government Surplus (Cost)	–0.1	–0.7	+0.5
Benefit-Cost Ratio	1.5	1.5	5.6
Ignoring Non-Recipients	2.9	3.9	2.5

Notes: This table presents estimates of the effects of India's voucher policy on welfare as described in Section 7. Panels A and B reports estimates for voucher recipients (applicants who takeup their voucher offer,) and voucher non-recipients (applicants who deny their voucher offer and those who do not apply for vouchers), respectively. Estimates are restricted to a random sample of 200 markets from 2013 to 2018.

Figure 5: The Impacts of Voucher Policy on School Integration

(a) School Composition of Voucher Ellgible Students
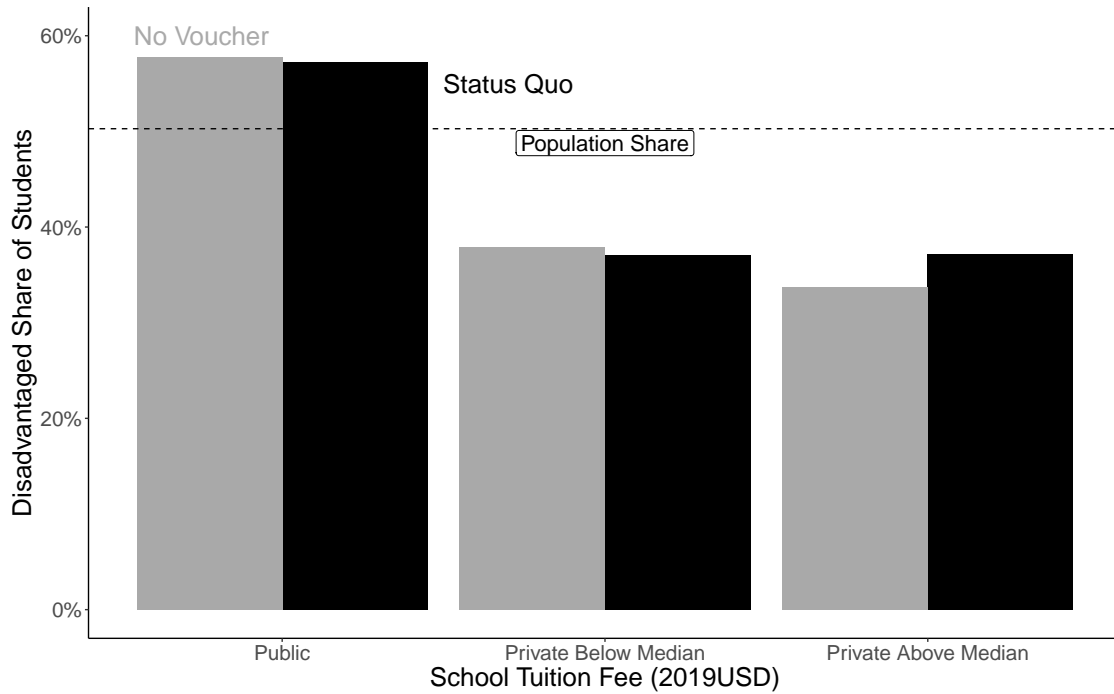
(b) Index of School Segregation Across Markets
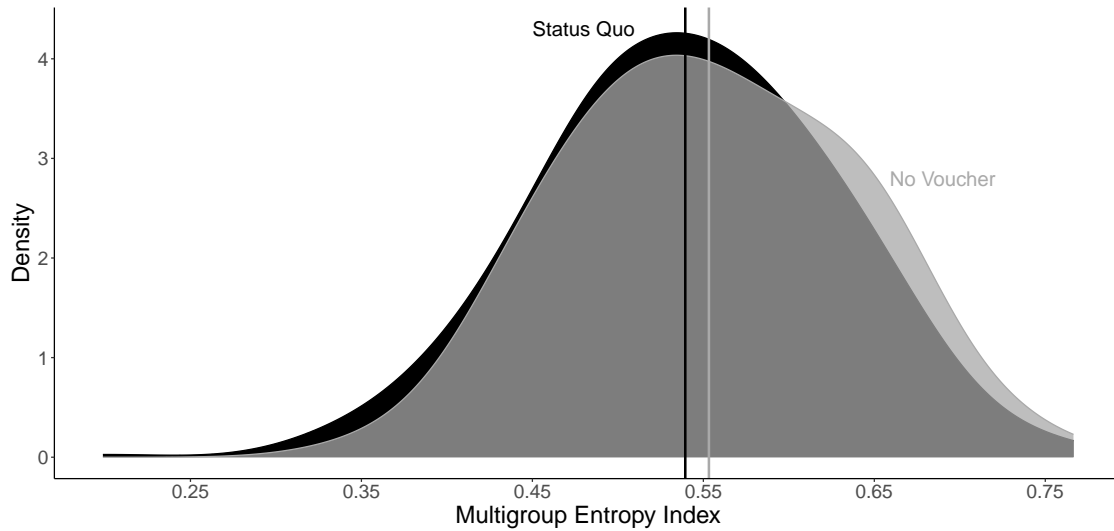
Notes: This figure presents the impacts of India's voucher system on school integration. In Panel A, each bar is the fraction of school enrollment that comprise voucher-eligible children (y-axis) against bins of school tuition fees (x-axis). The black color denotes the status-quo voucher system and the grey denotes the no-voucher counterfactual as described in Appendix A8. 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 A9 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.

Table 6: Voucher Design, Welfare, and School Integration

	App. Rate (%)	Price	Quality	CS	PS	GS	TS	Integration		Benefit-Cost Ratio	
								Private	Entropy	CS	CS + PS
Panel A: Tuition-Linked Voucher Below Cap											
Status Quo	14.9	+2.7	+1.2	+4.2	−29.6	−2.1	+0.5	+13.1	−2.5	5.4	1.5
With Top-Ups	12.8	+3.8	+1.2	+1.2	−7.2	−2.1	−0.4	+3.1	−0.2	1.5	0.6
With Voluntary Part.	12.9	+3.0	+1.2	+1.4	−8.7	−1.8	−0.2	+5.9	−0.5	2.1	0.8
Panel B: Flat Voucher											
High (Current Cap = $74)	14.9	+2.1	+1.1	+4.3	−28.7	−1.7	+1.0	+15.0	−2.7	6.7	2.1
Low (Median MC = $51)	14.8	+0.9	+0.7	+4.3	−34.7	+0.3	+1.1	+15.6	−2.8	Inf	Inf
Panel C: Status Quo Policy Expansion											
Raise Quota (25%→50%)	16.2	+2.9	+1.2	+6.4	−42.2	−3.1	+1.2	+20.1	−3.3	5.5	1.8
Lower App. Cost ($\tau_z \to 0$)	25.9	+2.4	+1.2	+6.2	−39.8	−1.9	+1.9	+25.3	−3.5	8.7	3.0
Panel D: Greater Quality Adjustment (2100 Threshold)											
Status Quo	13.8	+2.0	+1.2	+2.9	−22.9	−0.7	+0.3	+10.0	−2.0	11.6	2.0
Flat High	13.8	+1.7	+1.1	+3.2	−19.7	−0.6	+1.2	+10.6	−1.9	13.9	4.9
Flat Low	13.7	−3.2	−1.1	+2.9	−24.8	+0.3	+0.5	+10.7	−2.0	Inf	Inf

Notes: This table presents the estimated impacts of various voucher designs as described in Section 8. Panel A is the status quo in India which pays schools their price up to a voucher cap (on average $74); "With Top-Ups" additionally allows schools above the cap to charge additional fees equaling the difference between sticker prices and the cap; and " With Voluntary Part." is a system that allows schools to opt-out of the voucher system. Panel B is a system that pays all schools a fixed amount regardless of sticker prices. "Current Cap" is a flat voucher where the fixed amount is equal to the current voucher cap in the status-quo ($74) and "Median MC" is the same but the level is equal to the median private school marginal cost ($51). Panel C expands the voucher system by raising the quota level from 25% to 50% or lower application costs by shutting off the distance penalty. Panel D allows for greater quality adjustment, raising the threshold to 2100 levels ($\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 A9 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.

Figure 6: Voucher Levels and Welfare in the Long Run
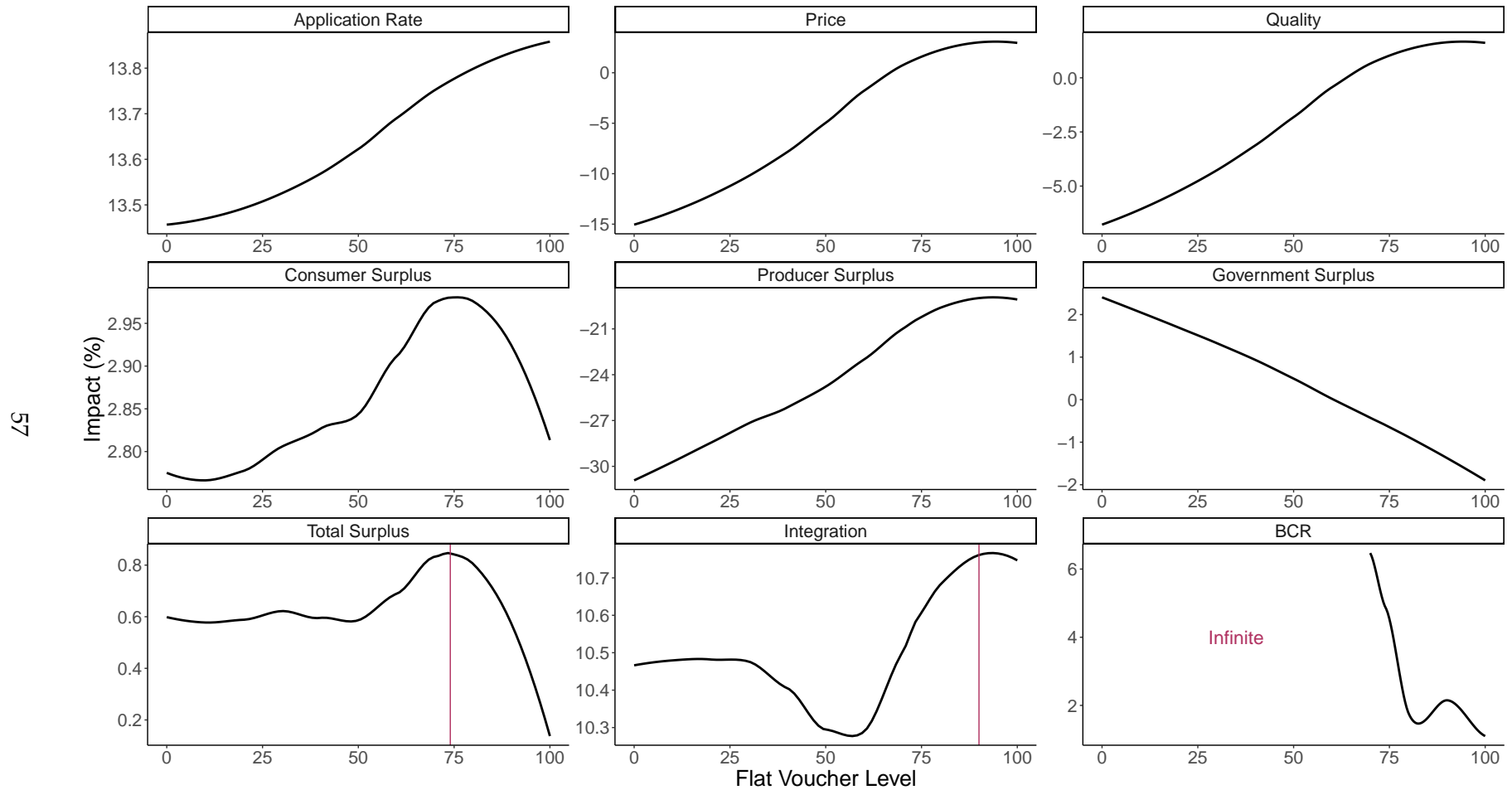
Notes: This figure presents the estimated impact of flat vouchers depending on the size of the voucher payment. Counterfactual impacts are based on greater quality adjustment, raising the cost threshold to 2100 levels ($\overline{mc}_{2100}$). Effects are computed for voucher levels from $0 to $100 in increments of $10 (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 third panel, "infinite" denotes that the range of missing voucher levels deliver an infinite benefit-cost ratio.

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Appendix for:
The Welfare Implications of School Voucher Design:
Evidence from India

Harshil Sahai

Contents

A1 Evidence of Deferred Acceptance

Fig. A6 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 was 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 sharp decline in the share from first to second choice (and beyond).

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.

A2 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 fixed effects q_j in the following value-added model that controls for lagged GPA for individual i in school j and year t:

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

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 A2.

For estimating the supply-side response, this can be extended to estimate time-varying value-added by instead including school-by-year fixed effects q_{jt}.

A3 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

A1

choices are the most constrained – have the largest to gain from school choice policy (e.g. Ab-dulkadiroğlu 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 A8 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 interactions with individual characteristics $h(i)$ such as SES:

$$y_{it} = \sum_h \beta_h \text{Takeup}_{ih} \times 1\{h(i) = h\} + R'_{it}\delta + X'_i\gamma + \epsilon_{it}, \tag{A2}$$

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

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.

Fig. A8 shows the LATE of voucher takeup on student and school 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.

A4   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:

$$v^v_{ijt} = \begin{cases} 1 & j = j_1 \\ 0 & \text{otherwise.} \end{cases} \tag{A3}$$

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

$$u_{ijt}(p_{jt}, v_{ijt}^v) = \alpha_i p_{jt}(1 - v_{ijt}^v) + \lambda_i D_{ij} + \delta_{jt} + \epsilon_{ijt}. \tag{A4}$$

Suppose individual i takes up the voucher offer, and enrolls in the voucher school j_1: $e_{ij_1t} = 1$.[73] Thus, j_1 is i's utility maximizing school under the voucher offer:

$$j_1 = \arg\max_{j' \in m(i,t)} u_{ij't}(p_{j't}, v_{ij't}^v), \tag{A5}$$

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

$$u_{ij_1t}(p_{j_1t}, v_{ij_1t}^v) = \alpha_i p_{j_1t}(1 - v_{ij_1t}^v) + \lambda_i D_{ij_1} + \delta_{j_1t} + \epsilon_{ij_1t} \tag{A6}$$
$$= \lambda_i D_{ij_1t} + \delta_{j_1t} + \epsilon_{ij_1t}.$$

Here, the voucher offer $v_{ij_1t}^v = 1$, 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_{it}^{nv} as the vector of voucher offers across schools for individual i in year t under this counterfactual:

$$v_{ijt}^{nv} = 0 \ \forall j. \tag{A7}$$

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

$$j_0 = \arg\max_{j' \in m(i,t)} u_{ij't}(p_{j't}, v_{ij't}^{nv}), \tag{A8}$$

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

$$u_{ij_0t}(p_{j_0t}, v_{ij_0t}^{nv}) = \alpha_i p_{j_0t}(1 - v_{ij_0t}^v) + \lambda_i D_{ij_0t} + \delta_{j_0t} + \epsilon_{ij_0t} \tag{A9}$$
$$= \alpha_i p_{j_0t} + \lambda_i D_{ij_0t} + \delta_{j_0t} + \epsilon_{ij_0t}.$$

Here, the voucher offer $v_{ij_0t}^{nv} = 0$, 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

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73. 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.

utility between the voucher and no voucher counterfactual:

$$u_{ij_1t}(p_{j_1t}, v^v_{ij_1t}) - u_{ij_0t}(p_{j_0t}, v^{nv}_{ij_0t}) = \underbrace{-\alpha_i p_{j_0t}}_{\text{Monetary}} + \underbrace{(\lambda_i(D_{ij_1} - D_{ij_0}) + \delta_{j_1t} - \delta_{j_0t})}_{\text{Non-Monetary}} + \underbrace{(\epsilon_{ij_1t} - \epsilon_{ij_0t})}_{\text{Match}}. \quad \text{(A10)}$$

A5   Demand Model Estimation Details

Conditional Likelihood.   Given θ, draws v, 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:

$$q^R(R_{it}|\theta, v, \psi) = \prod_k \frac{\exp(\lambda_i D_{ij_k} + \delta_{j_k t} + \psi_{ij_k t})}{\sum_{k' \geq k} \exp(\lambda_i D_{ij'_k} + \delta_{j'_k} + \psi_{ij'_k t})}, \quad \text{(A11)}$$

$$q^e_{ijt}(\theta, v, \psi) = \frac{\exp(\alpha_i p_{ijt} + \lambda_i D_{ij} + \delta_{jt} + \pi'_{ijt}\phi + \psi_{ijt})}{\sum_{j' \in m(i,t)} \exp(\alpha_i p_{ij't} + \lambda_i D_{ij'} + \delta_{j't} + \pi'_{ijt}\phi + \psi_{ij't})}, \quad \text{(A12)}$$

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:

$$q^a_{it}(\tau, \theta, \eta^a) = \frac{\exp(\Delta_{it}(\theta, \eta^a_i) + W'_{it}\tau_w + Z'_i\tau_z)}{1 + \exp(\Delta_{it}(\theta, \eta^a_i) + W'_{it}\tau_w + Z'_i\tau_z)}. \quad \text{(A13)}$$

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

$$L(e_{ijt}, R_{it}|\theta) = \int_\psi \int_v q^e_{ijt}(\theta, v, \psi)^{e_{ijt}} \cdot q^R(R_{it}|\theta, v, \psi) \, dF_v(\sigma_\alpha) \, dF_\psi(\beta_\psi). \quad \text{(A14)}$$

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

$$\hat{\theta} = \underset{\theta}{\operatorname{argmax}} \prod_{it} \hat{L}(e_{ijt}, R_{it}|\theta). \quad \text{(A15)}$$

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

$$L(a_{it}|\tau, \hat{\theta}) = \int_{\eta^a} q^a_{it}(\tau, \hat{\theta}, \eta^a)^{a_{it}} \, dF_{\eta_a}. \quad \text{(A16)}$$

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

$$\hat{\tau} = \underset{\tau}{\operatorname{argmax}} \prod_{it} \hat{L}(a_{it}|\tau, \hat{\theta}). \quad \text{(A17)}$$

A5.1 Step 1: 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:

$$v_{ij}(v, \psi, \theta^l) = \begin{cases} \alpha_i p_{ij} + \lambda_i D_{ij} + \delta_j + \pi'_{ij}\phi + \psi_{ij} & \text{if } i \in E \\ \lambda_i D_{ij} + \delta_j + \psi_{ij} & \text{if } i \in R \end{cases} \tag{A18}$$

where E is the set individuals in the enrollment choice setting and R are those in the ranking choice setting;[74] $\psi_{ij} \sim T1EV(\beta_\psi)$ is the persistent preference term; price and distance heterogeneity are as follows:

$$\alpha_i = X'_i \alpha_x + v_i \tag{A19}$$

$$\lambda_i = X'_i \lambda_x \tag{A20}$$

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

$$\theta = \left\{ \underbrace{\alpha_x, \lambda_x, \{\delta_j\}, \phi,}_{\theta^l} \underbrace{\sigma_\alpha, \beta_\psi}_{\theta^{nl}} \right\} \tag{A21}$$

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

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

$$q_{ij}(v, \psi, \theta^l) = \frac{\exp(v_{ij}(v, \psi, \theta^l))}{\sum_{j'} \exp(v_{ij'}(v, \psi, \theta^l))} \tag{A22}$$

and the individual (conditional) likelihood can be written:

$$L_i(v, \psi, \theta^l) = \prod_j q_{ij}(v, \psi, \theta^l)^{y_{ij}} \tag{A23}$$

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 $\{v^r, \psi^r\}$ from $N(0, \sigma_\alpha)$ and $T1EV(\beta_\psi)$, we aim to maximize the following

---

74. 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 (Fig. A4) and treated like an additional unobservable in the estimation procedure below. This is suppressed in notation for brevity.

simulated (unconditional) log-likelihood:

$$SLL(\theta) = \sum_i \sum_r \ln[L_i(\nu^r, \psi^r, \theta^l)] \tag{A24}$$

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):

$$\theta^{k+1} = \text{argmax}_\theta Q(\theta|\theta^k) \rightarrow^k \text{argmax}_\theta LL(\theta) \tag{A25}$$

This surrogate function Q takes the form:

$$Q(\theta|\theta^k) = \sum_i \sum_r w_i^{r,k} \ln[L_i(\nu^{r,k}, \psi^{r,k}, \theta^l) f(\nu^{r,k}, \psi^{r,k}|\theta^{nl})] \tag{A26}$$

where

$$w_i^{r,k} = \frac{L_i(\nu^{r,k}, \psi^{r,k}, \theta^{l,k})}{\sum_{r'} L_i(\alpha^{r',k}, \psi^{r',k}, \theta^{l,k})} \tag{A27}$$

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

$$Q(\theta|\theta^k) = \underbrace{\sum_i \sum_r w_i^{r,k} \ln[L_i(\nu^{r,k}, \psi^{r,k}, \theta^l)]}_{Q^l(\theta^l|\theta^k)} + \underbrace{\sum_i \sum_r w_i^{r,k} \ln[f(\nu^{r,k}, \psi^{r,k}|\theta^{nl})]}_{Q^{nl}(\theta^{nl}|\theta^k)} \tag{A28}$$

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

$$\sigma_\alpha^{k+1} = \frac{\sum_{i,r} w_i^{r,k}(\alpha_i^{r,k} - \overline{\alpha^k})^2}{|I| - 1} \tag{A29}$$

$$\beta_\alpha^{k+1} = \frac{1}{\pi^2/6} \cdot \frac{\sum_{i,j,r} w_i^{r,k}(\psi_{ij}^{r,k} - \overline{\psi^k})^2}{|IJ| - 1} \tag{A30}$$

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:

$$S(\theta^l|\theta^k) = g(\theta^k) - \frac{1}{2} \sum_{ijr} w_i^{r,k} \left[[v_{ij}(\nu^{r,k}, \psi^{r,k}, \theta^{l,k}) - (y_{ij} - q_{ij}(\nu^{r,k}, \psi^{r,k}, \theta^{l,k}))] - v_{ij}(\nu^{r,k}, \psi^{r,k}, \theta^l) \right]^2, \tag{A31}$$

where

$$g(\theta^k) = Q^l(\theta^{l,k}|\theta^k) + \frac{1}{2} \sum_{ijr} w_i^{r,k} \left[y_{ij} - q_{ij}(\nu^{r,k}, \psi^{r,k}, \theta^{l,k}) \right] \tag{A32}$$

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):

$$\theta^{l,k+1} = \text{argmax}_{\theta^l} S(\theta^l|\theta^k) \rightarrow^k \text{argmax}_{\theta^l} Q^l(\theta^l|\theta^k) \tag{A33}$$

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 $\kappa = 10^{-4}$.

A5.1.1 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:

$$I(\hat{\theta}) = \sum_i \frac{\partial \ln[L_i(\hat{\theta})]}{\partial \theta} \frac{\partial \ln[L_i(\hat{\theta})]}{\partial \theta}' \tag{A34}$$

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

$$\frac{\partial \ln[L_i(\theta)]}{\partial \alpha_x} = \sum_j p_{ij} X_i (y_{ij} - q_{ij}^w(\theta)) \tag{A35}$$

$$\frac{\partial \ln[L_i(\theta)]}{\partial \lambda_x} = \sum_j D_{ij} X_i (y_{ij} - q_{ij}^w(\theta)) \tag{A36}$$

$$\frac{\partial \ln[L_i(\theta)]}{\partial \delta_j} = \sum_{j'} 1\{j' = j\}(y_{ij'} - q_{ij'}^w(\theta)) \tag{A37}$$

$$\frac{\partial \ln[L_i(\theta)]}{\partial \phi_\pi} = \sum_j 1\{\pi_{ij} = \pi\}(y_{ij} - q_{ij}^w(\theta)) \tag{A38}$$

$$\frac{\partial \ln[L_i(\theta)]}{\partial \sigma_\alpha} = \sum_r w_i^r(\theta) \left[\frac{\alpha_{ir}}{\sigma_\alpha^3} - \frac{1}{\sigma_\alpha^2} \right] \tag{A39}$$

$$\frac{\partial \ln[L_i(\theta)]}{\partial \beta_\psi} = \sum_{jr} w_i^r(\theta) \left[\frac{\psi_{ijr}(1 - \exp(-\psi_{ijr}/\beta_\psi)) - \beta_\psi}{\beta_\psi^2} \right] \tag{A40}$$

where

$$q_{ij}^w(\theta) = \sum_r w_i^r(\theta) q_{ij}(v^r, \psi^r, \theta^l) \tag{A41}$$

Finally, standard errors are computed as:

$$\hat{se}(\hat{\theta}) = \sqrt{\text{diag}(I(\hat{\theta})^{-1})} \tag{A42}$$

A5.1.2 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):

$$\delta_{jt}^{k+1} = \delta_{jt}^k + \log(s_{jt}^{na}) - \log\left(\sum_{gt} w_{gt} \int_{\psi,\nu} \frac{\exp((\hat{\alpha}_g + \nu)p_{j't} + \hat{\lambda}_g D_{ij} + \delta_{jt}^k)}{\sum_{j' \in m_{jt}} \exp(\hat{\alpha}_g + \nu)p_{j't} + \hat{\lambda}_g D_{ij} + \delta_{j't}^k} \, dF_\nu \, dF_\psi \right), \quad \text{(A43)}$$

where the integral on the right had side is estimated using draws of ν from $N(0, \hat{\sigma}_\alpha)$ and ψ from $T1EV(\beta_\psi)$.[75]

A5.2 Step 2: 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):

$$SLL(\tau) = \sum_i \sum_r \ln[L_i(a_i|\tau, \eta^{a,r})] \quad \text{(A44)}$$

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

$$Q(\tau|\tau^k) = \underbrace{\sum_i \sum_r w_i^{r,k} \ln[L_i(a_i|\tau, \eta^{a,r})]}_{Q^l(\tau|\tau^k)} + \underbrace{\sum_i \sum_r w_i^{r,k} \ln[\hat{f}(\eta^{a,r}]}_{Q^{nl}} \quad \text{(A45)}$$

where

$$w_i^{r,k} = \frac{L_i(a_i|\tau^k, \eta^{a,r})}{\sum_{r'} L_i(a_i|\tau^k, \eta^{a,r'})} \quad \text{(A46)}$$

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

Because the distributions of the random parameters are estimated, Q^{nl} is no longer a function of τ and drops out from the maximization. It remains to maximize Q^l, which is simply a standard weighted logit.

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75. 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 $\{D_{ij}\}$ (Fig. A4).

A5.2.1 Standard errors

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

$$I(\hat{\tau}) = \sum_i \frac{\partial \ln[L_i(\hat{\tau})]}{\partial \tau} \frac{\partial \ln[L_i(\hat{\tau})]'}{\partial \tau} \tag{A47}$$

with score functions:

$$\frac{\partial \ln[L_i(\tau)]}{\partial \tau_w} = W_i(a_i - q_i^w(\tau)) \tag{A48}$$

$$\frac{\partial \ln[L_i(\tau)]}{\partial \tau_z} = Z_i(a_i - q_i^w(\tau)) \tag{A49}$$

where

$$q_i^w(\tau) = \sum_r w_i^r(\tau) q_i^a(\tau, \theta, \eta^{a,r}) \tag{A50}$$

Finally, standard errors are computed as:

$$\hat{\mathrm{se}}(\hat{\tau}) = \sqrt{\mathrm{diag}(I(\hat{\tau})^{-1})} \tag{A51}$$

A5.2.2 Extrapolating τ_{mt}

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

$$\tau_{mt}^{k+1} = \tau_{mt}^k + \log(s_{mt}^a) - \log\left(\sum_{it} \int_{\eta^a} \frac{\exp(\Delta_{it}(\hat{\theta}, \eta^a) + \tilde{X}_{it}'\hat{\tau}_{\tilde{x}} + Z_i'\hat{\tau}_z + \tau_{mt})}{1 + \exp(\Delta_{it}(\hat{\theta}, \eta^a) + \tilde{X}_i'\hat{\tau}_{\tilde{x}} + Z_i'\hat{\tau}_z + \tau_{mt})} \, dF_{\eta^a}\right), \tag{A52}$$

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 $T1EV(1)$.[76]

A6 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,

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76. 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 $\{D_{ij}\}$ (Fig. A4).

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.[77]

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 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).[78] 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.

A7 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 optimal prices are set to marginal cost plus markups, which depend on whether schools are priced above or below the reimbursement level $\bar{v}$:

$$p_j^- = mc_j + \frac{\mathbb{E}[N_j^{nv}] + \mathbb{E}[N_j^v]}{-\left[\frac{\mathbb{E}[N_j^{nv}]}{\partial p_j} + \frac{\mathbb{E}[N_j^v]}{\partial p_j}\right]} \tag{A53}$$

$$p_j^+ = mc_j + \frac{(\bar{v} - mc_j)\frac{\mathbb{E}[N_j^v]}{\partial p_j} + \mathbb{E}[N_j^{nv}]}{-\frac{\mathbb{E}[N_j^{nv}]}{\partial p_j}} \tag{A54}$$

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

78. See Fig. A4 for the distribution of observed distances.

and quality is set to competitive levels minus markdowns:

$$\delta_j^- = mc_j^{-1}(p_j) - \frac{\mathbb{E}[N_j^{nv}] - \mathbb{E}[N_j^v]}{\frac{\mathbb{E}[N_j^{nv}]}{\partial \delta_j} + \frac{\mathbb{E}[N_j^v]}{\partial \delta_j}} \tag{A55}$$

$$\delta_j^+ = mc_j^{-1}(\tilde{p}_j) - \frac{\mathbb{E}[N_j^{nv}] - \mathbb{E}[N_j^v]}{\frac{\mathbb{E}[N_j^{nv}]}{\partial \delta_j} + \frac{\mathbb{E}[N_j^v]}{\partial \delta_j}} \tag{A56}$$

where

$$\tilde{p}_j = w_\delta^{nv} p_j + (1 - w_\delta^{nv})\bar{v} \tag{A57}$$

$$w_\delta^{nv} = \frac{\frac{\mathbb{E}[N_j^{nv}]}{\partial \delta_j}}{\frac{\mathbb{E}[N_j^{nv}]}{\partial \delta_j} + \frac{\mathbb{E}[N_j^v]}{\partial \delta_j}} \tag{A58}$$

It is therefore required to compute enrollments and their price and quality gradients in order to estimate marginal costs, markups, and markdowns.

Define expected enrollment from each sector:

$$\mathbb{E}[N_j^v] = \sum_i \int q_i^a(\eta^a) \cdot q_{ij}^o(\psi + \eta^r, \eta^a) \cdot q_{ij}^{e|o}(v, \psi) \, dF_{v,\psi,\eta^a,\eta^r} \tag{A59}$$

$$\mathbb{E}[N_j^{nv}] = \sum_i \int (1 - q_i^a(\eta^a)q_i^o(\psi + \eta^r, \eta^a)) \cdot q_{ij}^e(v, \psi) \tag{A60}$$

$$+ q_i^a(\eta^a) \cdot q_{ij}^{o-,e}(v, \psi, \eta^r, \eta^a) \, dF_{v,\psi,\eta^a,\eta^r}$$

where

$$q_i^o(\psi + \eta^r, \eta^a) = \sum_j q_{ij}^o(\psi + \eta^r, \eta^a) \tag{A61}$$

$$q_{ij}^{o-,e}(v, \psi, \eta^r, \eta^a) = \sum_{j' \neq j} q_{ij'}^o(v, \psi + \eta^r, \eta^a) \cdot q_i^{e_j|o_{j'}}(v, \psi) \tag{A62}$$

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

$$q_i^a(\epsilon) = \frac{\exp(\Delta_i(\epsilon) - k_i)}{1 + \exp(\Delta_i(\epsilon) - k_i)} \tag{A63}$$

$$q_{ij}^{e|o}(\epsilon) = \frac{\exp(\tilde{u}_{ij}^e(\epsilon))}{\exp(\tilde{u}_{ij}^e(\epsilon)) + \sum_{j' \neq j} \exp(u_{ij'}^e(\epsilon))} \tag{A64}$$

$$q_i^{e_j|o_{j'}}(\epsilon) = \frac{\exp(u_{ij}^e(\epsilon))}{\exp(\tilde{u}_{ij'}^e(\epsilon)) + \sum_{k \neq j'} \exp(u_{ik}^e(\epsilon))} \tag{A65}$$

$$q_{ij}^e(\epsilon) = \frac{\exp(u_{ij}^e(\epsilon))}{\sum_{j'} \exp(u_{ij'}^e(\epsilon))} \tag{A66}$$

where

$$\Delta_i(\epsilon) = \sum_{j \in R_i} q_{ij}^o(\epsilon) \tilde{\Delta}_{ij}(\epsilon) \tag{A67}$$

$$R_i = \{j_k \in m^{\text{Priv}}(i) : \tilde{u}_{ij_1} > \cdots > \tilde{u}_{ij_{10}}\} \tag{A68}$$

$$\tilde{\Delta}_{ij}(\epsilon) = \max(\tilde{u}_{ij}(\epsilon), u_i^m(\epsilon)) - u_i^m(\epsilon) \tag{A69}$$

$$u_i^m(\epsilon) = \max_j u_{ij}(\epsilon) \tag{A70}$$

$$\tilde{u}_{ij}(\epsilon) = \lambda_i D_{ij} + \delta_j + \epsilon_{ij} \tag{A71}$$

$$u_{ij}(\epsilon) = \alpha_i p_j + \lambda_i D_{ij} + \delta_j + \epsilon_{ij} \tag{A72}$$

$$\tilde{u}_{ij}^e(\epsilon) = \tilde{u}_{ij}(\epsilon) + \bar{q}_{ij}^o(\psi + v_r)'\phi \tag{A73}$$

$$u_{ij}^e(\epsilon) = u_{ij}(\epsilon) + \bar{q}_{ij}^o(\psi + v_r)'\phi, \tag{A74}$$

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.

A7.1 Approximating offer probabilities

The offer probability q_{ij}^o is known 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:

$$\hat{q}_{ij}^o(\epsilon_1, \epsilon_2) = \alpha^o \tilde{\pi}_{ij}(\epsilon_1) + \beta^o A(\epsilon_2) + X_{ij}^{o'} \gamma^o \tag{A75}$$

where

$$\tilde{\pi}_{ij}(\epsilon) = \frac{\exp(\tilde{u}_{ij}(\epsilon))}{\sum_{j' \in R_i} \exp(\tilde{u}_{ij'}(\epsilon))} \tag{A76}$$

$$A(\epsilon) = \frac{1}{N} \sum_i \log \frac{q_i^a(\epsilon)}{1 - q_i^a(\epsilon)} \tag{A77}$$

$$X_{ij}^{o'} = [\text{Priority}_{ij} \quad \text{Capacity}_j] \tag{A78}$$

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. Thus, for estimation, we compute cutoffs associated with the observed ranks that are submitted, simulate the marginal rank-ordered list by drawing unobservables ϵ, and compute $q_{ij}^o(\epsilon)$ for a given draw using the analytic DA propensity score given the cutoffs.

However, there is simultaneity between application rates in Eq. (A63) and offer probabilities in Eq. (A75) at the time of application ($\epsilon_1 = \epsilon_2 = \eta^a$). Higher offer probabilities will increase the returns to applying via Δ_i in Eq. (A67), 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 $q_{ih}(\epsilon)$ and application volume A_h from the halved sample. Together with the full sample propensity scores $q_{ih}(\epsilon)$ and application volume A_f, we stack both and include the following first stage for $g \in \{h, f\}$:

$$A_g(\epsilon) = \beta_0^{FS} \mathbf{1}\{g = h\} + \alpha_0^{FS} \tilde{\pi}_{ijg}(\epsilon) + X_{ij}^{o'} \gamma_{FS}^o + \epsilon_{FS}^o \tag{A79}$$

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 Eq. (A75) into Eq. (A63). In particular, this simplifies to

$$A(\epsilon) = \frac{\alpha^o \sum_{ij} \tilde{\Delta}_{ij}(\epsilon) \tilde{\pi}_{ij}(\epsilon) + \sum_i k_i}{N - \beta^o \sum_{ij} \tilde{\Delta}_{ij}(\epsilon)} \tag{A80}$$

Now, plugging Eq. (A80) into Eq. (A75), we can solve for $\hat{q}_{ij}^o(\epsilon)$. Thus, we can compute all components necessary to estimate expected enrollment in Eq. (A59)-Eq. (A61). It remains to compute their gradients.

A13

A7.2 Enrollment gradients

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

$$\hat{\mathbb{E}}[N_j^v] = \sum_i \sum_{\nu,\psi,\eta^a,\eta^r} q_i^a(\eta^a) \cdot q_{ij}^o(\psi + \eta^r, \eta^a) \cdot q_{ij}^{e|o}(\nu, \psi) \tag{A81}$$

$$\hat{\mathbb{E}}[N_j^{nv}] = \sum_i \sum_{\nu,\psi,\eta^a,\eta^r} (1 - q_i^a(\eta^a) q_i^o(\psi + \eta^r, \eta^a)) \cdot q_{ij}^e(\nu, \psi) \tag{A82}$$

$$+ q_i^a(\eta^a) \cdot q_{ij}^{o-,e}(\nu, \psi, \eta^r, \eta^a) \tag{A83}$$

where the following are now approximated:

$$q_{ij}^o(\psi + \eta^r, \eta^a) = \alpha^o \tilde{\pi}_{ij}(\psi + \eta^r) + \beta^o A(\eta^a) + X_{ij}^{o'} \gamma^o \tag{A84}$$

$$q_i^o(\psi + \eta^r, \eta^a) = \sum_j q_{ij}^o(\psi + \eta^r, \eta^a) \tag{A85}$$

$$q_{ij}^{o-,e}(\nu, \psi, \eta^r, \eta^a) = \sum_{j' \neq j} q_{ij'}^o(\psi + \eta^r, \eta^a) \cdot q_i^{e_j|o_{j'}}(\nu, \psi) \tag{A86}$$

Then, gradients are:

$$\frac{\partial \hat{\mathbb{E}}[N_j^v]}{\partial y_j} = \sum_i \sum_{\nu,\psi,\eta^a,\eta^r} \frac{\partial q_i^a(\eta^a)}{\partial y_j} \cdot q_{ij}^o(\psi + \eta^r, \eta^a) \cdot q_{ij}^{e|o}(\nu, \psi) \tag{A87}$$

$$+ q_i^a(\eta^a) \cdot \frac{\partial q_{ij}^o(\psi + \eta^r, \eta^a)}{\partial y_j} \cdot q_{ij}^{e|o}(\nu, \psi) \tag{A88}$$

$$+ q_i^a(\eta^a) \cdot q_{ij}^o(\psi + \eta^r, \eta^a) \cdot \frac{\partial q_{ij}^{e|o}(\nu, \psi)}{\partial y_j}$$

$$\frac{\partial \hat{\mathbb{E}}[N_j^{nv}]}{\partial y_j} = \sum_i \sum_{\nu,\psi,\eta^a,\eta^r} (1 - q_i^a(\eta^a) q_i^o(\psi + \eta^r, \eta^a)) \cdot \frac{\partial q_{ij}^e(\nu, \psi)}{\partial y_j} \tag{A89}$$

$$- q_{ij}^e(\nu, \psi) \cdot \left[\frac{\partial q_i^a(\eta^a)}{\partial y_j} q_i^o(\psi + \eta^r, \eta^a) + q_i^a(\eta^a) \frac{\partial q_i^o(\psi + \eta^r, \eta^a)}{\partial y_j} \right]$$

$$+ q_i^a(\eta^a) \cdot \frac{\partial q_{ij}^{o-,e}(\nu, \psi, \eta^r, \eta^a)}{\partial y_j} + q_{ij}^{o-,e}(\nu, \psi, \eta^r, \eta^a) \cdot \frac{\partial q_i^a(\eta^a)}{\partial y_j}$$

Gradients for q_{ij}^e and $q_{ij}^{e|o}$ are:

$$\frac{\partial q_{ij}^{e|o}(\epsilon)}{\partial y_j} = q_{ij}^{e|o}(\epsilon) \cdot (1 - q_{ij}^{e|o}(\epsilon)) \cdot \frac{\partial \tilde{u}_{ij}^e(\epsilon)}{\partial y_j} \tag{A90}$$

$$\frac{\partial q_{ij}^e(\epsilon)}{\partial y_j} = q_{ij}^e(\epsilon) \cdot (1 - q_{ij}^e(\epsilon)) \cdot \frac{\partial u_{ij}^e(\epsilon)}{\partial y_j} \tag{A91}$$

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:

$$\bar{q}_{ij}^o(\psi + \nu_r)'\phi = \underbrace{\phi_1 \bar{q}_{ij}^o(\psi + \nu_r) + \phi_2 \bar{q}_{ij}^o(\psi + \nu_r)^2}_{f(\bar{q}_{ij}^o(\psi + \nu_r))} + \epsilon_{ij}^{\bar{q}} \tag{A92}$$

Thus, the utility gradients are now

$$\frac{\partial \tilde{u}_{ij}^e(\epsilon)}{\partial y_j} = \frac{\partial \tilde{u}_{ij}(\epsilon)}{\partial y_j} + f'(\bar{q}_{ij}^o(\psi + \nu_r)) \frac{\partial \bar{q}_{ij}^o(\psi + \nu_r)}{\partial y_j} \tag{A93}$$

$$\frac{\partial u_{ij}^e(\epsilon)}{\partial y_j} = \frac{\partial u_{ij}(\epsilon)}{\partial y_j} + f'(\bar{q}_{ij}^o(\psi + \nu_r)) \frac{\partial \bar{q}_{ij}^o(\psi + \nu_r)}{\partial y_j} \tag{A94}$$

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

$$\frac{\partial \tilde{u}_{ij}(\epsilon)}{\partial p_j} = 0 \tag{A95}$$

$$\frac{\partial \tilde{u}_{ij}(\epsilon)}{\partial \delta_j} = 1 \tag{A96}$$

$$\frac{\partial u_{ij}(\epsilon)}{\partial p_j} = \alpha_i \tag{A97}$$

$$\frac{\partial u_{ij}(\epsilon)}{\partial \delta_j} = 1 \tag{A98}$$

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

$$\bar{q}_{ij}^o(\psi + \nu_r) = \alpha^o \tilde{\pi}_{ij}(\psi + \eta^r) + \beta^o \bar{A} + X_{ij}^{o'} \gamma^o, \tag{A99}$$

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.

A7.3 Gradients of the offer probabilities

Given the approximation and simplification of q_{ij}^o in Eq. (A75), its gradient reduces to:

$$\frac{\partial q_{ij'}^o(\epsilon_1, \epsilon_2)}{\partial y_j} = \alpha^o \frac{\partial \tilde{\pi}_{ij'}(\epsilon_1)}{\partial y_j} + \beta^o \frac{\partial A(\epsilon_2)}{\partial y_j} \tag{A100}$$

and (because $\bar{A}$ is fixed) the gradient of the observed propensity score in Eq. (A99) reduces to:

$$\frac{\partial \bar{q}_{ij}^o(\psi + \nu_r)}{\partial y_j} = \alpha^o \frac{\partial \tilde{\pi}_{ij}(\psi + \eta^r)}{\partial y_j} \tag{A101}$$

where

$$\frac{\partial \tilde{\pi}_{ij'}(\epsilon)}{\partial y_j} = \begin{cases} \tilde{\pi}_{ij}(\epsilon)(1 - \tilde{\pi}_{ij}(\epsilon))\frac{\partial \tilde{u}_{ij}(\epsilon)}{\partial y_j} & \text{if } j = j', \\ 0 & \text{otherwise} \end{cases} \tag{A102}$$

$$\frac{\partial A(\epsilon)}{\partial y_j} = \frac{A_D(\epsilon)\beta^o(-\sum_{ij'} \frac{\partial \tilde{\Delta}_{ij'}}{\partial y_j}) - A_N(\epsilon)\alpha^o \left(\sum_{ij'} \tilde{\Delta}_{ij'} \frac{\partial \tilde{\pi}_{ij'}(\epsilon)}{\partial y_j} + \frac{\partial \tilde{\Delta}_{ij'}}{\partial y_j} \tilde{\pi}_{ij'}(\epsilon)\right)}{A_D(\epsilon)^2} \tag{A103}$$

$$A_D(\epsilon) = N - \beta^o \sum_{ij} \tilde{\Delta}_{ij}(\epsilon) \tag{A104}$$

$$A_N(\epsilon) = \alpha^o \sum_{ij} \tilde{\Delta}_{ij}(\epsilon)\tilde{\pi}_{ij}(\epsilon) + \sum_i k_i \tag{A105}$$

$$\frac{\partial \tilde{\Delta}_{ij'}}{\partial y_j} = \begin{cases} -\frac{\partial u_{ij}(\epsilon)}{\partial y_j} & \text{if } u_{ij} = u_i^m, \\ \frac{\partial \tilde{u}_{ij}(\epsilon)}{\partial y_j} & \text{if } u_{ij} \neq u_i^m \text{ and } \tilde{u}_{ij} > u_i^m \text{ and } j = j', \\ 0 & \text{otherwise} \end{cases} \tag{A106}$$

Finally, the gradient of the total offer probability is:

$$\frac{\partial q_i^o(\epsilon)}{\partial y_j} = \sum_{j'} \frac{\partial q_{ij'}^o(\epsilon)}{\partial y_j} \tag{A107}$$

A7.4 Gradients of the application probabilities

We have that

$$\frac{\partial q_i^a(\epsilon)}{\partial y_j} = q_i^a(\epsilon)(1 - q_i^a(\epsilon))\frac{\partial \Delta_i(\epsilon)}{\partial y_j} \tag{A108}$$

where

$$\frac{\partial \Delta_i(\epsilon)}{\partial y_j} = \sum_{j'} q_{ij'}^o(\epsilon)\frac{\partial \tilde{\Delta}_{ij'}}{\partial y_j} + \frac{\partial q_{ij'}^o(\epsilon)}{\partial y_j}\tilde{\Delta}_{ij'} \tag{A109}$$

A16

A7.5 Gradients of the enrollment probabilities given other offers

We have that

$$\frac{\partial q_{ij}^{o-,e}(v,\psi,\eta^r,\eta^a)}{\partial y_j} = \exp(u_{ij}(v,\psi))B_{ij}(v,\psi,\eta^r,\eta^a) + q_{ij}^{o-,e}(v,\psi,\eta^r,\eta^a)\frac{\partial u_{ij}(v,\psi)}{\partial y_j} \tag{A110}$$

where

$$B_{ij}(v,\psi,\eta^r,\eta^a) = \left[\beta^o\frac{\partial A(\eta^a)}{\partial y_j} + q_{ij}^{o-,e}(v,\psi,\eta^r,\eta^a)\frac{\partial u_{ij}(v,\psi)}{\partial y_j}\right] \tag{A111}$$
$$\times \sum_{j'\neq j}\frac{1}{\exp(\tilde{u}_{ij'}(v,\psi)) + \sum_{k\neq j'}\exp(u_{ik}(v,\psi))}$$

A7.6 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 defines new first-order conditions for school prices and qualities,$FOC_p(v')$ and $FOC_\delta(v')$, defined in Appendix A8 and Section 8. 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 $\{\|p_{jt}^k - p_{jt}^{k-1}\| < \kappa \text{ and } \|\delta_{jt}^k - \delta_{jt}^{k-1}\| < \kappa\} \text{ or } k < 1$ **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** $mc_{jt} < \overline{mc}_t$ **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**
>
> **end**

end

A7.7 Moment conditions for estimating the quality adjustment threshold

The school first-order condition on price implies:

$$p_{jt} - \mu_{jt}^p = mc_{jt}(\delta_{jt}) \tag{A112}$$

Applying the difference operator reduces to:

$$\Delta p_{jt} - \Delta \mu_{jt}^p = 1\{mc_{jt} < \overline{mc}_t\}(\Delta \gamma_{jt} \delta_{jt}) + \Delta c_{jt}) + 1\{mc_{jt} \geq \overline{mc}_t\}\Delta mc_{jt} \tag{A113}$$

$$\Delta p_{jt} - \Delta \mu_{jt}^p - 1\{mc_{jt} < \overline{mc}_t\}\Delta \gamma_{jt} \delta_{jt} = 1\{mc_{jt} < \overline{mc}_t\}\Delta c_{jt} + 1\{mc_{jt} \geq \overline{mc}_t\}\Delta mc_{jt} \tag{A114}$$

Multiplying by the IV reduces to:

$$\Delta z_{jt}[\Delta p_{jt} - \Delta \mu_{jt}^p - 1\{mc_{jt} < \overline{mc}_t\}\Delta \gamma_{jt} \delta_{jt}] = 1\{mc_{jt} < \overline{mc}_t\}\Delta z_{jt}\Delta c_{jt} + 1\{mc_{jt} \geq \overline{mc}_t\}\Delta z_{jt}\Delta mc_{jt} \tag{A115}$$

Taking expectations and inserting moment conditions implies:

$$\mathbb{E}\left[\Delta z_{jt}[\Delta p_{jt} - \Delta \mu_{jt}^p - 1\{mc_{jt} < \overline{mc}_t\}\Delta \gamma_{jt} \delta_{jt}]\right] = 0 \tag{A116}$$

$$\mathbb{E}\left[\Delta z_{jt}[\Delta p_{jt} - \Delta \mu_{jt}^p - 1\{mc_{jt} < \omega \cdot \text{arcsinh}(t)\}\Delta \gamma_{jt} \delta_{jt}]\right] = 0 \tag{A117}$$

A8 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 Eq. (50) to Eq. (53):

$$p_t^{sq} = p_t, \; \delta_t^{sq} = \delta_t, \; v_t^{sq} = v_t \tag{A118}$$
$$\Rightarrow \{CS(p_t^{sq}, \delta_t^{sq}, v_t^{sq}), PS(p_t^{sq}, \delta_t^{sq}, v_t^{sq}), GS(p_t^{sq}, \delta_t^{sq}, v_t^{sq})\}.$$

Under a no voucher counterfactual, voucher offers are set to zero. In addition, prices and quality are determined solving adjust firms' first-order conditions given by Eq. (37) and Eq. (42).[79] This new distribution of prices and vouchers under the no voucher counterfactual also generates consumer, producer, and government surplus:

$$p_t^{nv}, \; \delta_t^{nv}, \; v_t^{nv} = 0 \tag{A119}$$
$$\Rightarrow \{CS(p_t^{nv}, \delta_t^{nv}, v_t^{nv}), PS(p_t^{nv}, \delta_t^{nv}, v_t^{nv}), GS(p_t^{nv}, \delta_t^{nv}, v_t^{nv})\}.$$

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:

$$\Delta CS = CS(p_t^{sq}, \delta_t^{sq}, v_t^{sq}) - CS(p_t^{nv}, \delta_t^{nv}, v_t^{nv}), \tag{A120}$$
$$\Delta PS = PS(p_t^{sq}, \delta_t^{sq}, v_t^{sq}) - PS(p_t^{nv}, \delta_t^{nv}, v_t^{nv}),$$
$$\Delta GS = GS(p_t^{sq}, \delta_t^{sq}, v_t^{sq}) - GS(p_t^{nv}, \delta_t^{nv}, v_t^{nv}).$$

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:[80]

$$BCR = \frac{\Delta CS + \Delta PS}{|\Delta GS|}. \tag{A121}$$

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.

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79. 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.

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

A9   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 as 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.

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.

A10   Voucher Design and School Behavior

A10.1   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 $\{p_{jt}^f, \delta_{jt}^f\}$ that solve new first-order conditions:

$$p_{jt-}^f = p_{jt+}^f = mc_{jt} + \frac{\mathbb{E}[N_{jt}^{nv}]}{-\frac{\partial \mathbb{E}[N_{jt}^{nv}]}{\partial p_{jt}}} \tag{A122}$$

$$\delta_{jt-}^f = \delta_{jt+}^f = mc_{jt}^{-1}(\tilde{p}_{jt}) - \frac{\mathbb{E}[N_{jt}^{nv}] + \mathbb{E}[N_{jt}^v]}{\frac{\partial \mathbb{E}[N_{jt}^{nv}]}{\partial \delta_{jt}} + \frac{\partial \mathbb{E}[N_{jt}^v]}{\partial \delta_{jt}}}$$

with $\tilde{p}_{jt}$ defined as in Eq. (41).

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 $\{p_{jt}^f, \delta_{jt}^f\}$, 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.

A10.2 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 $\bar{v}$.[81] 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

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81. 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.

will set price and quality $\{p_{jt}^{tu}, \delta_{jt}^{tu}\}$ that solve schools' adjusted first-order conditions:

$$p_{jt-}^{tu} = mc_{jt} + \frac{\mathbb{E}[N_{jt}^{nv}] + \mathbb{E}[N_{jt}^{v}]}{-\frac{\partial \mathbb{E}[N_{jt}^{nv}]}{\partial p_{jt}}} \tag{A123}$$

$$p_{jt+}^{tu} = mc_{jt} + \frac{\mathbb{E}[N_{jt}^{nv}] + \mathbb{E}(N_{jt}^{v}; p_{jt}^{tu} - \bar{v})}{-[\frac{\partial \mathbb{E}[N_{jt}^{nv}]}{\partial p_{jt}} + \frac{\mathbb{E}(N_{jt}^{v}; p_{jt}^{tu} - \bar{v})}{\partial p_{jt}}]}$$

$$\delta_{jt-}^{tu} = mc_{jt}^{-1}(p_{jt}) - \frac{\mathbb{E}[N_{jt}^{nv}] + \mathbb{E}[N_{jt}^{v}]}{\frac{\partial \mathbb{E}[N_{jt}^{nv}]}{\partial \delta_{jt}} + \frac{\partial \mathbb{E}[N_{jt}^{v}]}{\partial \delta_{jt}}}$$

$$\delta_{jt+}^{tu} = mc_{jt}^{-1}(\tilde{p}_{jt}) - \frac{\mathbb{E}[N_{jt}^{nv}] + \mathbb{E}(N_{jt}^{v}; p_{jt}^{tu} - \bar{v})}{\frac{\partial \mathbb{E}[N_{jt}^{nv}]}{\partial \delta_{jt}} + \frac{\mathbb{E}(N_{jt}^{v}; p_{jt}^{tu} - \bar{v})}{\partial \delta_{jt}}}.$$

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).

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.[82] 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.

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82. 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.

A10.3 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:

$$v(p_{jt}) < mc_{jt}. \tag{A124}$$

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.[83]

Schools' first-order conditions under voluntary participation for price and quality $\{p_{jt}^{vp}, \delta_{jt}^{vp}\}$ 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 have an adjusted optimal price $p_{j+,e}^{vp}$ equal to the no voucher counterfactual:

$$p_{jt-}^{vp} = mc_{jt} + \frac{\mathbb{E}[N_{jt}^{nv}] + \mathbb{E}[N_{jt}^{v}]}{-\frac{\partial \mathbb{E}[N_{jt}^{nv}]}{\partial p_{jt}}} \tag{A125}$$

$$p_{jt+}^{vp} = mc_{jt} + \frac{\mathbb{E}[N_{jt}^{nv}]}{-\frac{\partial \mathbb{E}[N_{jt}^{nv}]}{\partial p_{jt}}}$$

$$p_{jt+,e}^{vp} = mc_{jt} + \frac{\mathbb{E}[N_{jt}^{nv}] + \mathbb{E}[N_{jt}^{v}]}{-[\frac{\partial \mathbb{E}[N_{jt}^{nv}]}{\partial p_{jt}} + \frac{\partial \mathbb{E}[N_{jt}^{v}]}{\partial p_{jt}}]}$$

$$\delta_{jt-}^{vp} = mc_{jt}^{-1}(p_{jt}) - \frac{\mathbb{E}[N_{jt}^{nv}] + \mathbb{E}[N_{jt}^{v}]}{\frac{\partial \mathbb{E}[N_{jt}^{nv}]}{\partial \delta_{jt}} + \frac{\partial \mathbb{E}[N_{jt}^{v}]}{\partial \delta_{jt}}}$$

$$\delta_{jt+}^{vp} = mc_{jt}^{-1}(\tilde{p}_{jt}) - \frac{\mathbb{E}[N_{jt}^{nv}] + \mathbb{E}[N_{jt}^{v}]}{\frac{\partial \mathbb{E}[N_{jt}^{nv}]}{\partial \delta_{jt}} + \frac{\partial \mathbb{E}[N_{jt}^{v}]}{\partial \delta_{jt}}}$$

$$\delta_{jt+,e}^{vp} = mc_{jt}^{-1}(p_{jt}) - \frac{\mathbb{E}[N_{jt}^{nv}] + \mathbb{E}[N_{jt}^{v}]}{\frac{\partial \mathbb{E}[N_{jt}^{nv}]}{\partial \delta_{jt}} + \frac{\partial \mathbb{E}[N_{jt}^{v}]}{\partial \delta_{jt}}}.$$

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.

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83. 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. Sanchez 2021 studies this entry problem in detail. Counterfactuals assume these schools always participate. Assuming they always exit further reduces the policy's BCR.

For consumers, voluntary participation in the voucher sector will reduce consumer surplus as students will have reduced choice in voucher offers.[84] 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.

84. 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_{ijt}^{vp}.

Table A1: 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	Mixed	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.

Figure A1: Private School Tuition Fees
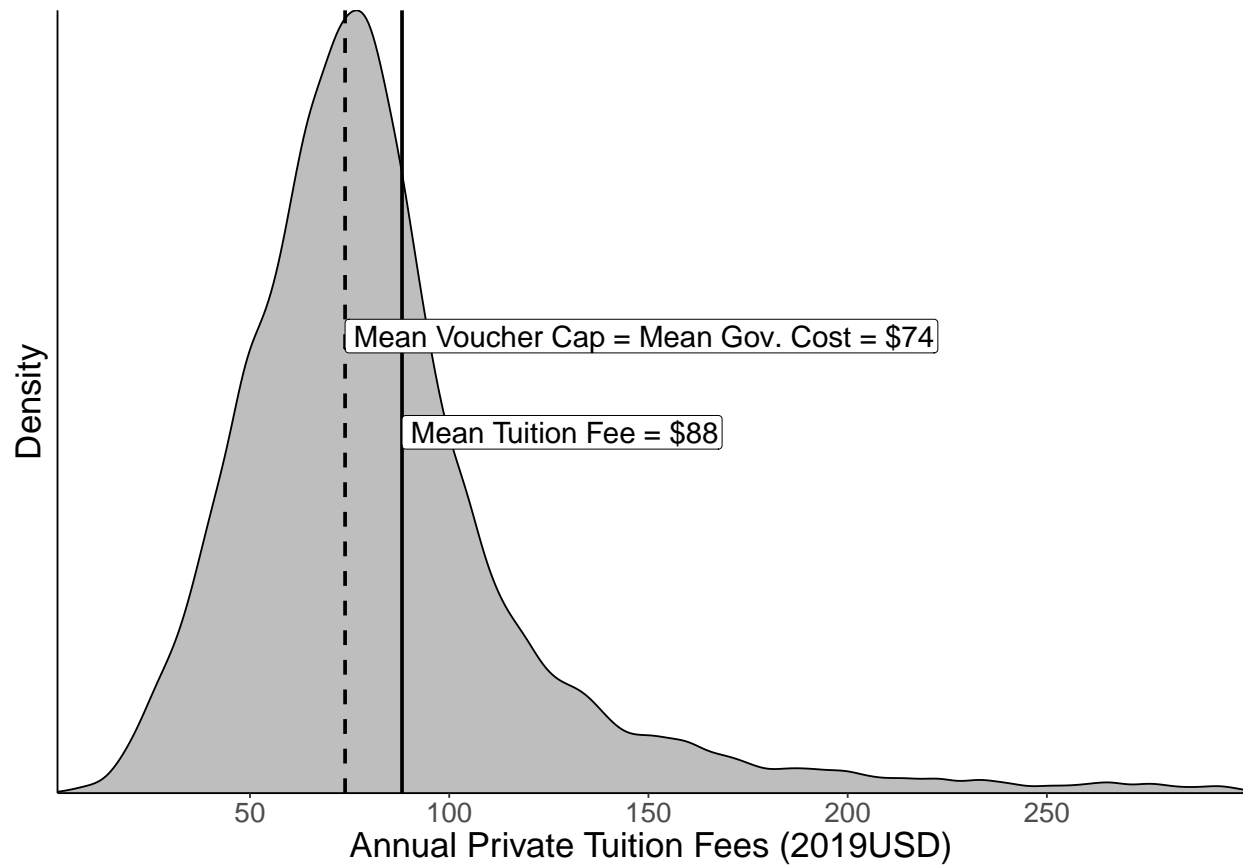
Notes: This figure presents the distribution of annual private school fees faced by students in Madhya Pradesh (MP) averaged across classes 1 to 8 from 2016 to 2018. The solid vertical line depicts the mean tuition fee. The dotted vertical line depicts the mean voucher cap, which is the average per-child expenditure among primary government schools in MP from 2016 to 2018.

Figure A2: Primary Schools Across Madhya Pradesh (Class 1)
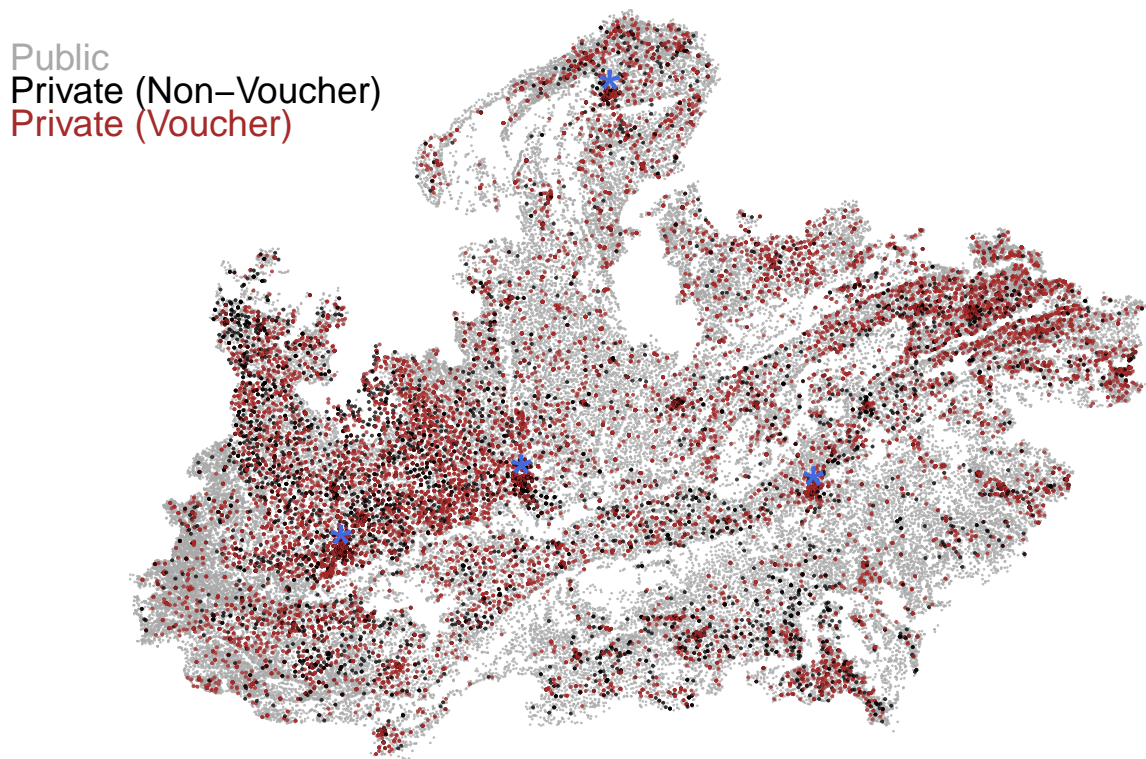
Notes: This figure shows a map of primary schools across Madhya Pradesh, restricted to those that offer class 1 instruction. The grey dots plot roughly 35,000 public schools; the black and red dots plot roughly 15,000 private schools; and the red dots plot roughly 13,000 private schools that receive 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 A3: School GPA and Standardized Exam Performance (2015)
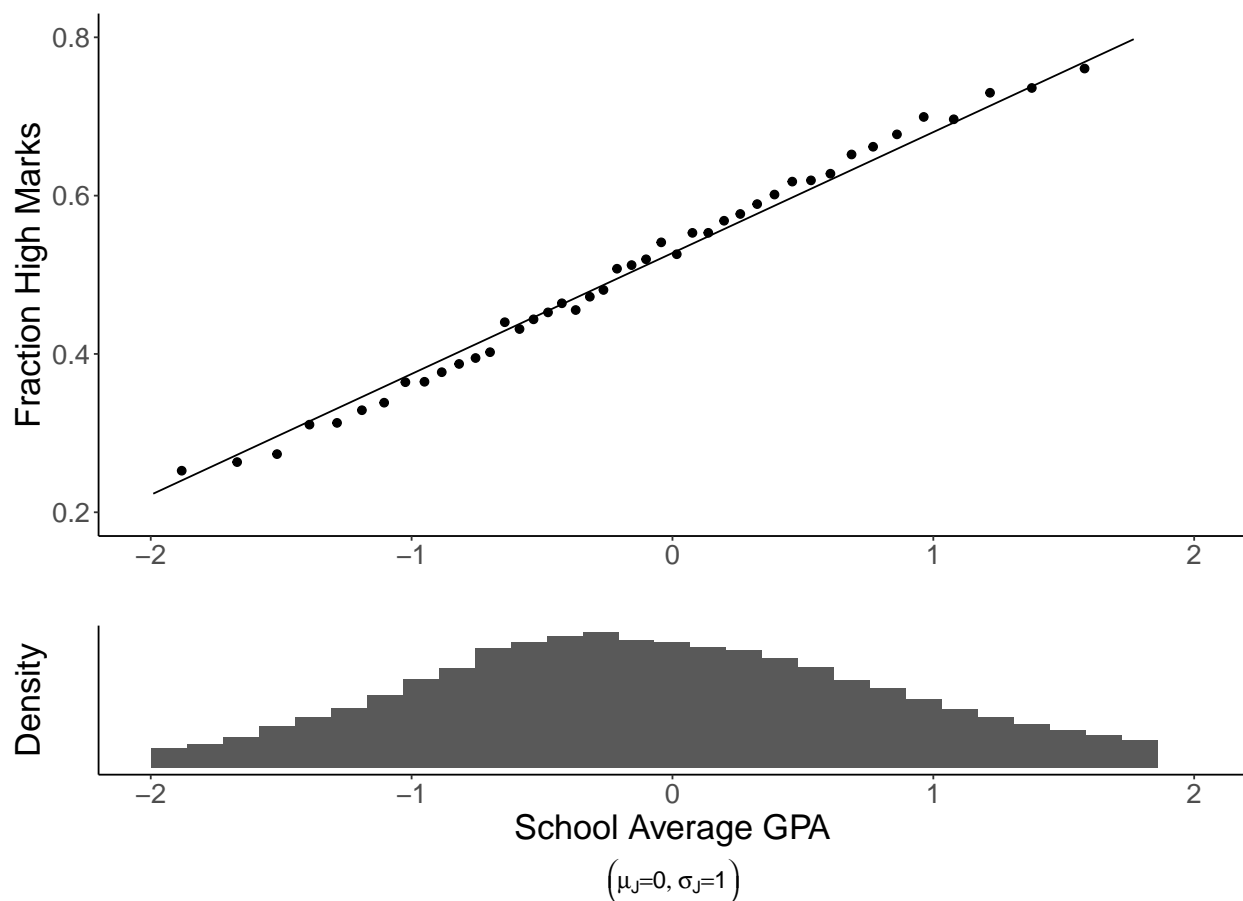
Notes: This figure describes the relationship between reported student GPA (x-axis) and standardized exam performance (y-axis) in 2015. The top panel presents a binscatter across schools and the bottom panel presents the distribution of average GPA across schools. "School Average GPA" refers to individual 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).

Table A2: Socio-Economic Status, GPA, and Value-Added Estimation

	GPA$_{it}$ ($\mu_I = 0, \sigma_I = 1$)			
	(1)	(2)	(3)	(4)
Female	0.04***	0.07***	0.04***	0.07***
	(0.00)	(0.00)	(0.00)	(0.00)
Below Poverty Line (BPL)	–0.12***	–0.07***		
	(0.00)	(0.00)		
Other Backward Caste (OBC)	–0.24***	–0.07***		
	(0.01)	(0.00)		
Scheduled Caste (SC)	–0.40***	–0.14***		
	(0.01)	(0.00)		
Scheduled Tribes (ST)	–0.59***	–0.21***		
	(0.01)	(0.00)		
Middle SES (SC/ST & Not BPL)			–0.31***	–0.10***
			(0.00)	(0.00)
Low SES (SC/ST & BPL)			–0.44***	–0.17***
			(0.00)	(0.00)
GPA$_{i,t-1}$		0.22***		0.23***
		(0.00)		(0.00)
School FE	No	Yes	No	Yes
Class$_{it}$ × Year FE	No	Yes	No	Yes
Class$_{i,t-1}$ × Year FE	No	Yes	No	Yes
Religion FE	No	Yes	No	Yes
Observations	1,741,356	1,741,356	1,741,356	1,741,356
Adjusted R^2	0.04	0.30	0.03	0.30

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. As described in Appendix A2, value-added is recovered as school (or school-by-year) fixed effects in the preferred specification in column (2).

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

Figure A4: Distance to School
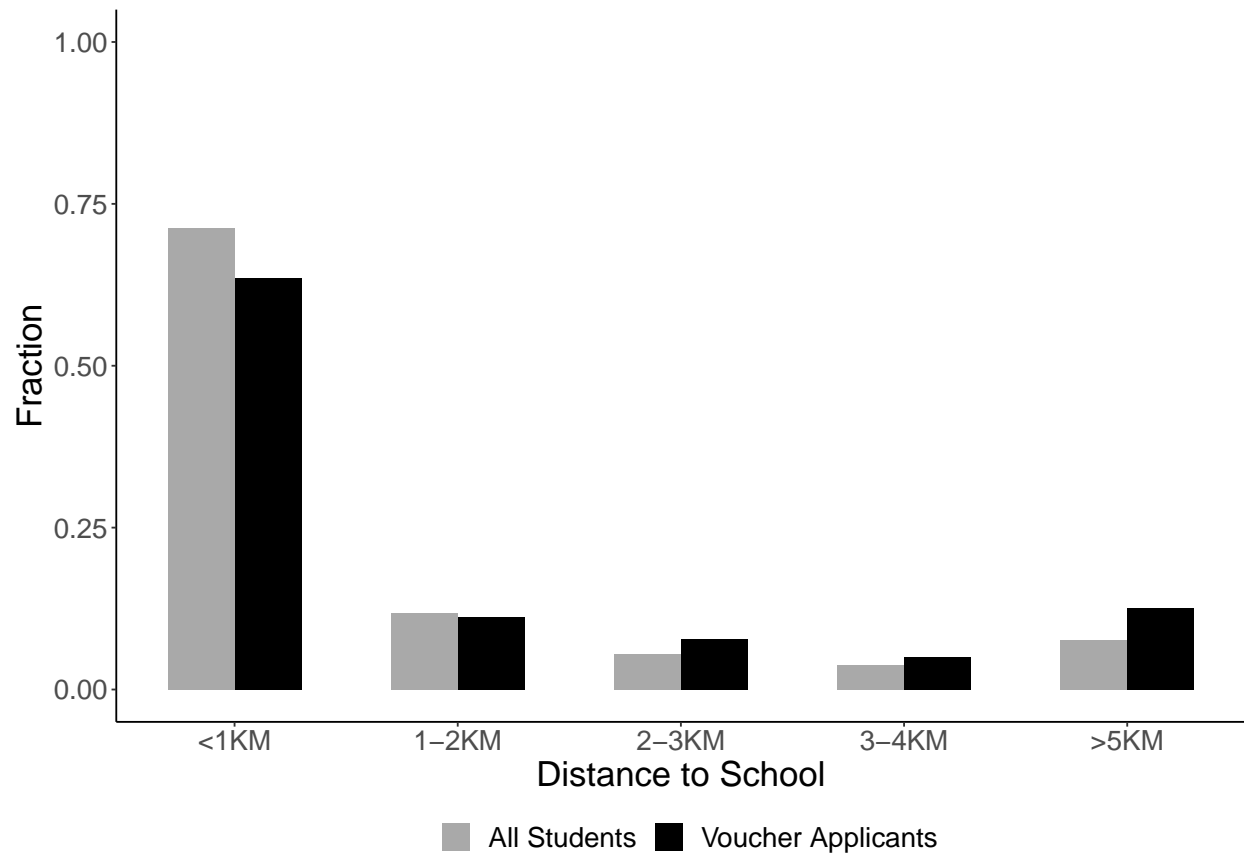
Notes: This figure reports the fraction of students who live a given distance from their school of attendance. Grey bars denote the fraction of all primary school students across Madhya Pradesh whose kilometer distance to school is within the given distance bin. Black bars denote the same fraction as 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.

	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.

Figure A5: Rank-Ordered Lists, Offers, and Takeup

(a) Rank Submitted

(b) Rank of Voucher Offer

(c) Voucher Takeup by Rank of Voucher Offer
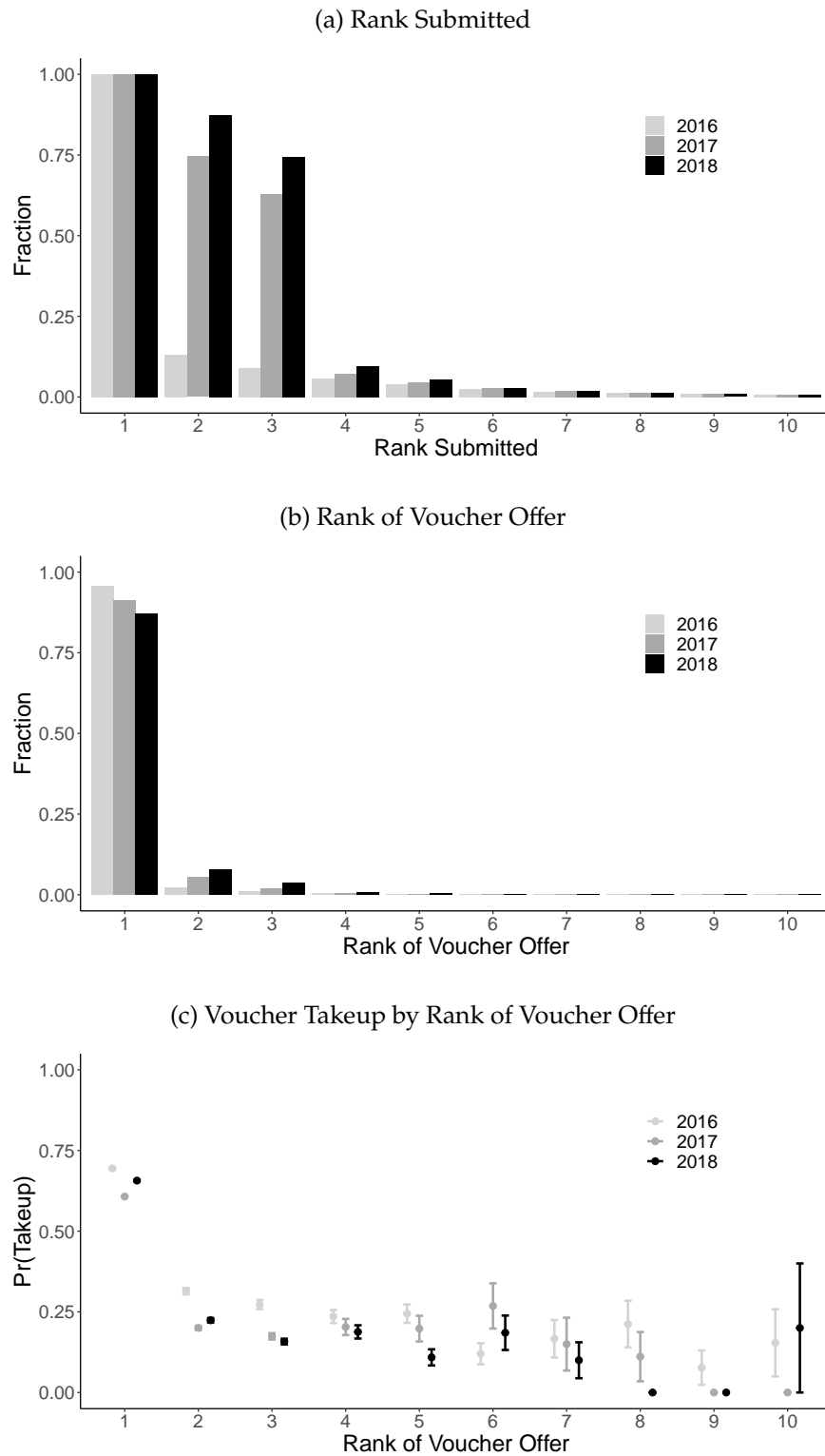
Notes: This figure presents data on rank-ordered lists, offers, and takeup for voucher applications for each application year from 2016 to 2018. Panel A reports the fraction of who applicants who submit a school for a given rank. In 2016, applicants could submit lists of any size. Starting in 2017 onward, 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 A6: Evidence of Deferred Acceptance Assignment

(a) Ranking Oversubscribed Schools
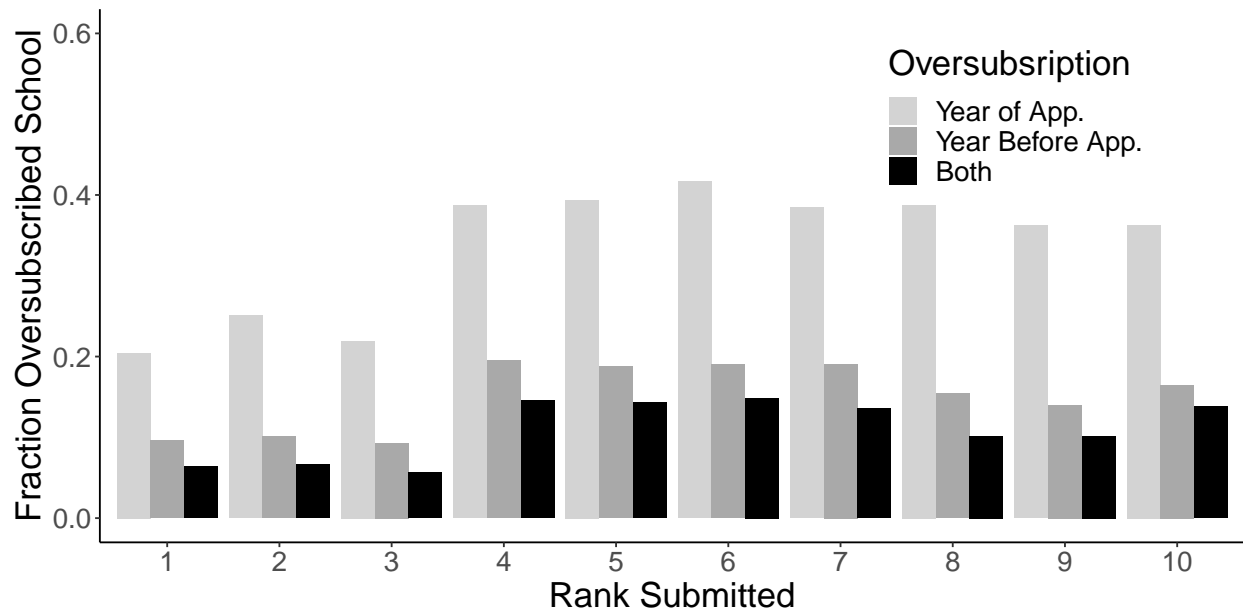
(b) Losing to Lower Ranked Applicants
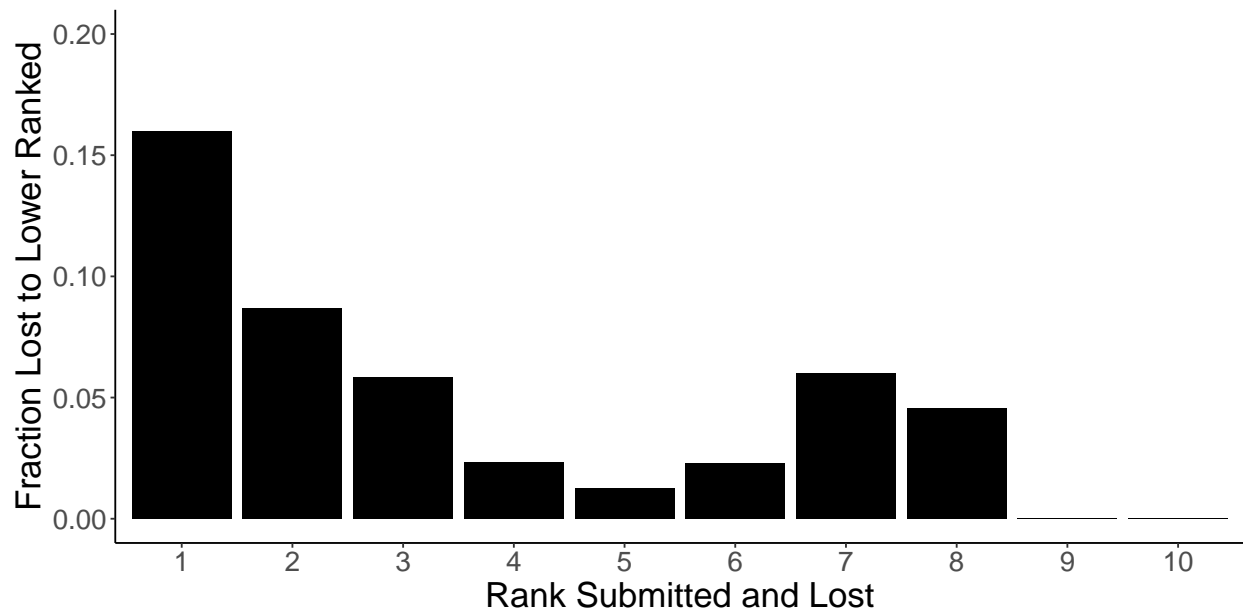
Notes: This figure presents evidence of the Deferred Acceptance assignment mechanism. Panel A reports the fraction of applicants who applied to an oversubscribed school with the given rank, conditional on submitting a rank-ordered list of the given size or greater. Light grey bars denote the fraction 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 A7: Voucher Offer Probabilities and DA Propensity Scores
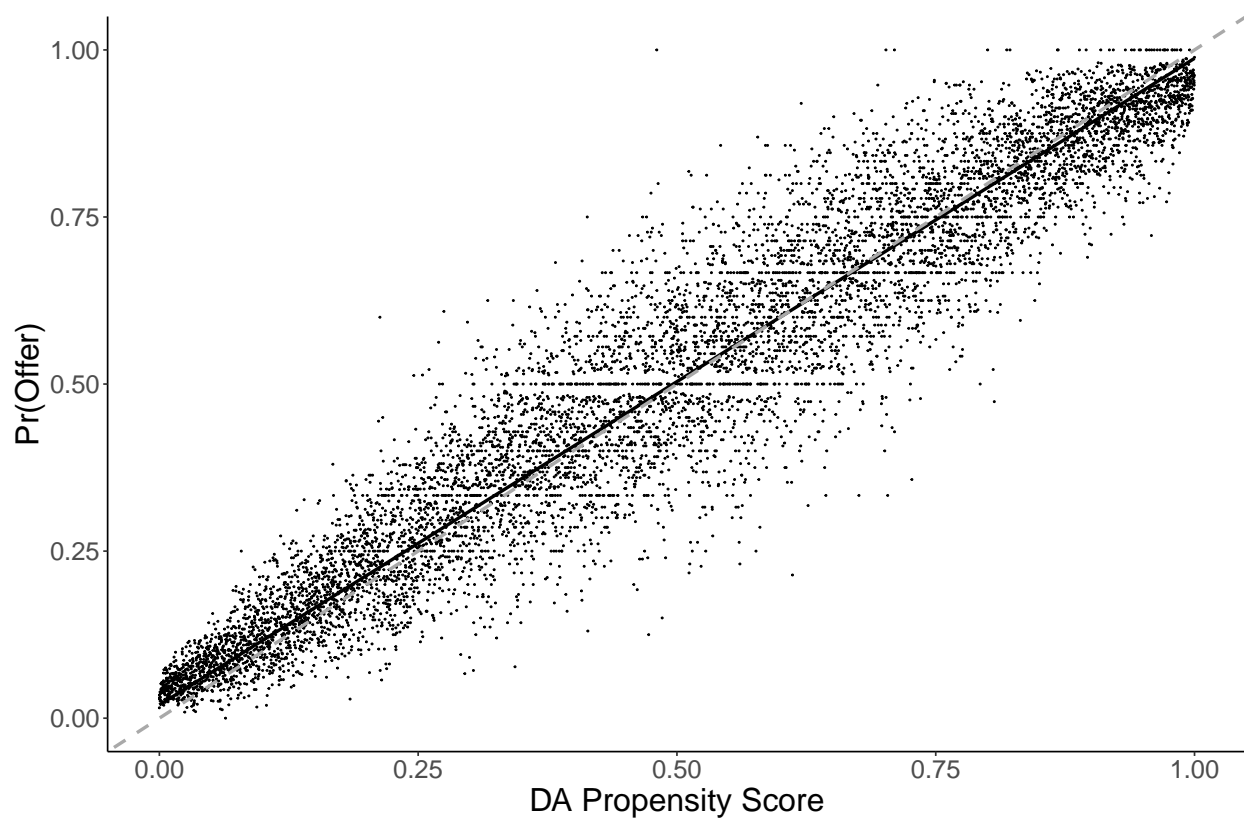
Notes: This figure describes the relationship between the simulated Deferred Acceptance (DA) propensity score (x-axis) and probability of winning a voucher offer (y-axis) across all applications from 2016 to 2018. For each propensity score π, each point denotes the fraction of applicant-school pairs 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.

Table A4: 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 A5: 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 A6: The Effects of First Choice Voucher Offers on Student and School Outcomes

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

	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	0.24	0.04***	0.27	0.03**	0.33	0.02	0.26	0.03***
		(0.01)		(0.01)		(0.02)		(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 and school outcomes (rows) for each year after application and over all years (columns). Panel A reports estimates for impacts to student achievement and Panel B reports estimates for impacts to assigned 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 Appendix A2. 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 A7: The Effects of Voucher Takeup: Robustness Across Specifications

Panel A: The Effect of Voucher Takeup on Student 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 School Outcomes

	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	0.37	0.04	0.36	0.04	0.30	0.10***	0.30	0.10***
		(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	2,587–3,261		2,572–3,208		2,311–3,018		2,305–3,010	
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 and school outcomes all years after application (rows) for different lottery fixed effect specifications (columns), using first-choice offer as an instrument specified by Eq. (1). Panel A reports estimates for impacts to student achievement and Panel B reports estimates for impacts to assigned 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 A2. 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 A8: 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.
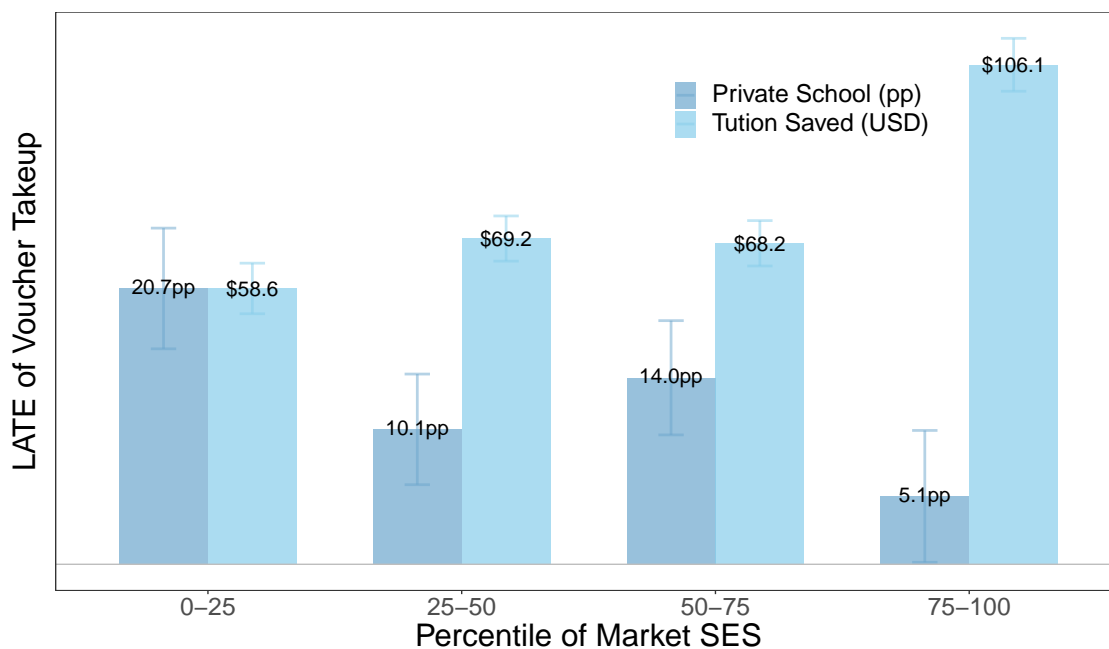 *10%, **5%, and ***1% significance level.

Figure A8: Market Heterogeneity in Voucher Takeup Effects

(a) Effect on Student Outcomes
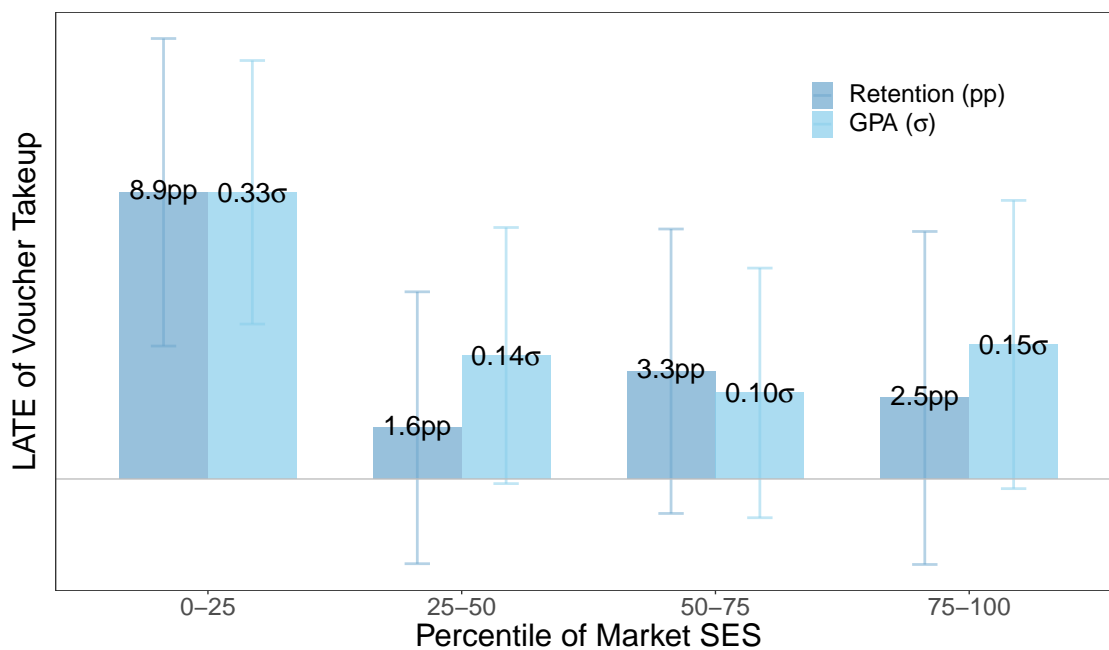
(b) Effect on School Outcomes

Notes: This figure presents LATE estimates of voucher takeup on outcomes over all years after application with additional interactions between takeup and market covariates as specified by Eq. (A2). 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 A9: Ex-Ante Exposure and Application Growth
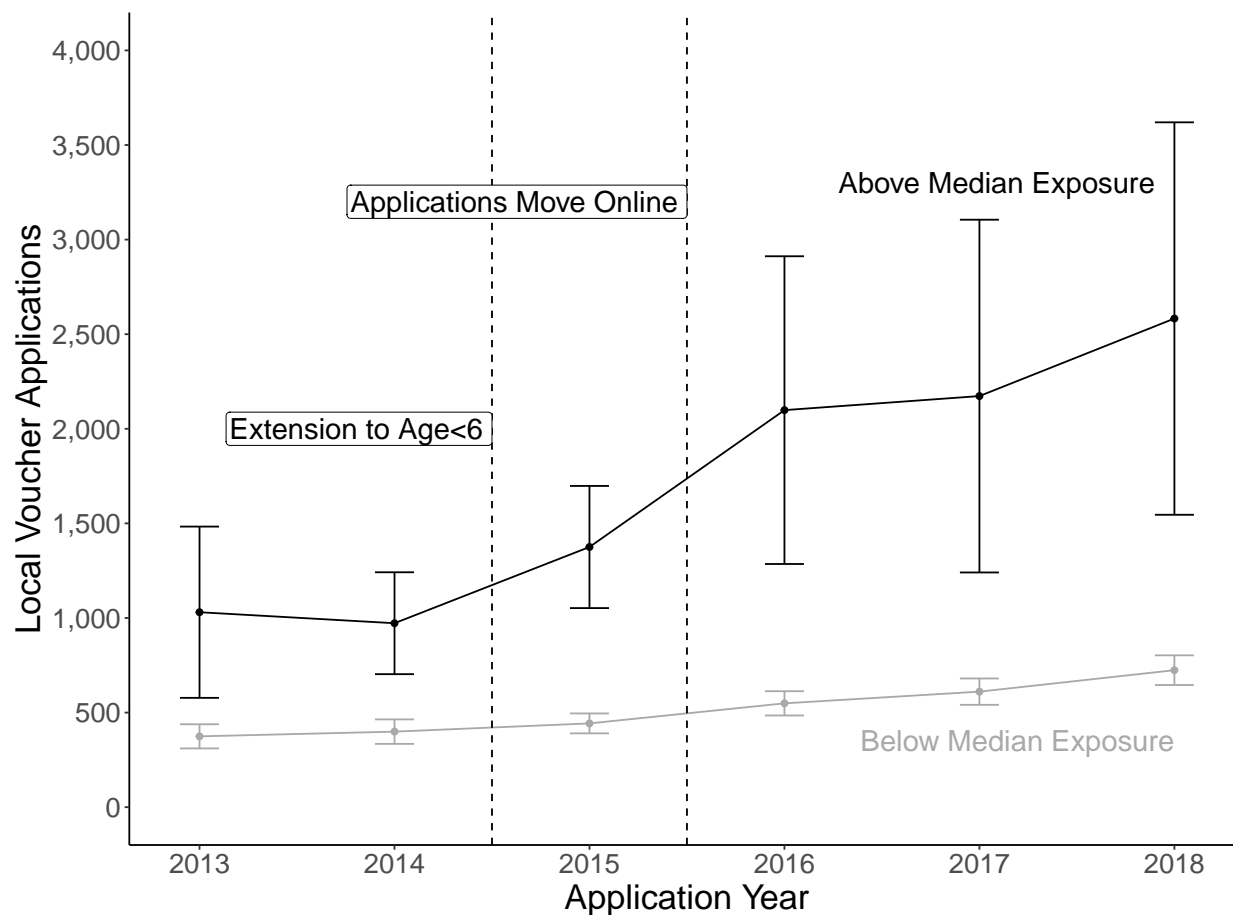
Notes: This figure presents the block-level average number of applications over time grouped by ex-ante exposure to application growth: blocks with greater or less than the median private market share for voucher eligible students (solid versus dashed). Panel B is restricted to schools in the modal bin 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. The dashed horizontal line denotes the average voucher cap over the sample period 2016 to 2018 of $74.47.

Table A9: The Effects of Voucher Applications on Private School Outcomes

2014 Price (USD)	Effect of Application Volume (1,000)					Range of Fit Statistics	
	Price (USD)	GPA Value-Added (σ)	Teachers per 10 Pupils	School Mean Utility (%)	School Exit (pp)	First Stage F-Stat	No. Obs.
<$34	4.97**	0.06	0.60	−0.06	−0.63	457−9,490	6,901−56,837
	(2.06)	(0.09)	(0.47)	(1.38)	(0.72)		
$34−$44	3.47***	0.07	0.42	2.48**	0.79	515−11,236	7,243−57,753
	(1.17)	(0.07)	(0.40)	(1.20)	(1.05)		
$44−$54	3.16**	0.15**	0.14	0.21	−0.02	920−12,393	8,970−71,004
	(1.23)	(0.07)	(0.37)	(0.82)	(0.49)		
$54−$64	2.43***	0.01	0.18	1.04*	0.05	2,103−27,447	17,097−144,397
	(0.63)	(0.04)	(0.24)	(0.62)	(0.17)		
$64−$74	1.18**	0.03	−0.08	0.58	0.68	1,283−19,041	10,890−100,298
	(0.52)	(0.02)	(0.13)	(0.46)	(0.47)		
$74−$84	0.41	−0.01	0.05	0.17	0.79	783−12,405	6,180−56,775
	(0.79)	(0.03)	(0.22)	(0.38)	(0.52)		
$84−$94	0.75	0.04	0.21	0.20	0.64	626−8,318	4,017−39,012
	(1.11)	(0.03)	(0.41)	(0.31)	(0.46)		
$94−$104	1.38	−0.09**	−0.23	1.09*	0.90	381−4,695	1,874−19,902
	(1.42)	(0.04)	(0.28)	(0.55)	(0.75)		
$104−$114	0.13	−0.01	−0.33	−0.00	−0.25	237−4,032	1,672−19,175
	(1.64)	(0.09)	(0.30)	(0.57)	(0.52)		
$114−$124	0.46	−0.01	0.01	−0.02	0.26	100−2,257	766−9,662
	(1.81)	(0.08)	(0.28)	(0.83)	(0.39)		
>$124	4.36***	−0.02	−0.39	0.65	0.19	360−11,440	1,414−46,278
	(1.44)	(0.05)	(0.44)	(0.63)	(0.41)		
Below Voucher Cap	2.49***	0.05*	0.16	0.87*	0.25	5,352−79,704	51,101−430,289
	(0.71)	(0.03)	(0.19)	(0.51)	(0.29)		
Above Voucher Cap	1.57	−0.01	−0.10	0.35	0.52	2,536−42,990	16,447−190,804
	(1.05)	(0.02)	(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 Eq. (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. "Prices" denotes the impact to school sticker prices for all classes up to class 8; "GPA Value-Added" is estimated as described in Appendix A2; "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 A10: The Effects of Voucher Applications on Village-Level Outcomes

| 2014 Average Village Price | Private Schools | | Public Schools | | | | | Range of Fit Statistics | |
	Entrants	Exiters	Entrants	Exiters	Avg. GPA Value-Added (σ)	Avg. Teachers per 10 Pupils	Avg. School Mean Utility (%)	First Stage F-Stat	No. Obs.
Below Median	−0.00	0.12	0.01	−0.15	0.01	−0.07	−0.99	111−966	2,307−21,870
	(0.08)	(0.10)	(0.04)	(0.17)	(0.05)	(1.58)	(1.28)		
Above Median	−0.15**	0.06	−0.01	−0.04	−0.04	0.48	−0.34	231−1,827	2,480−20,978
	(0.07)	(0.15)	(0.04)	(0.11)	(0.03)	(0.38)	(0.51)		
No Private Schools	0.12	−0.00	0.03	−0.01	0.09	0.20	−0.48	1,092−5,401	25,529−183,290
	(0.10)	(0.08)	(0.02)	(0.01)	(0.07)	(0.26)	(0.82)		
All	−0.06	0.06	0.01	−0.03	0.02	0.23	−0.50	3,584−9,448	68,377−214,773
	(0.07)	(0.11)	(0.02)	(0.05)	(0.04)	(0.25)	(0.58)		

Notes: This table presents IV difference-in-difference estimates of the impacts of application volume on village-level outcomes as specified by Eq. (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); "GPA Value-Added" is estimated as described in Appendix A2; "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). 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 A11: Demand Estimation Sample vs. 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.

Figure A10: School Mean Utility and GPA Value-Added
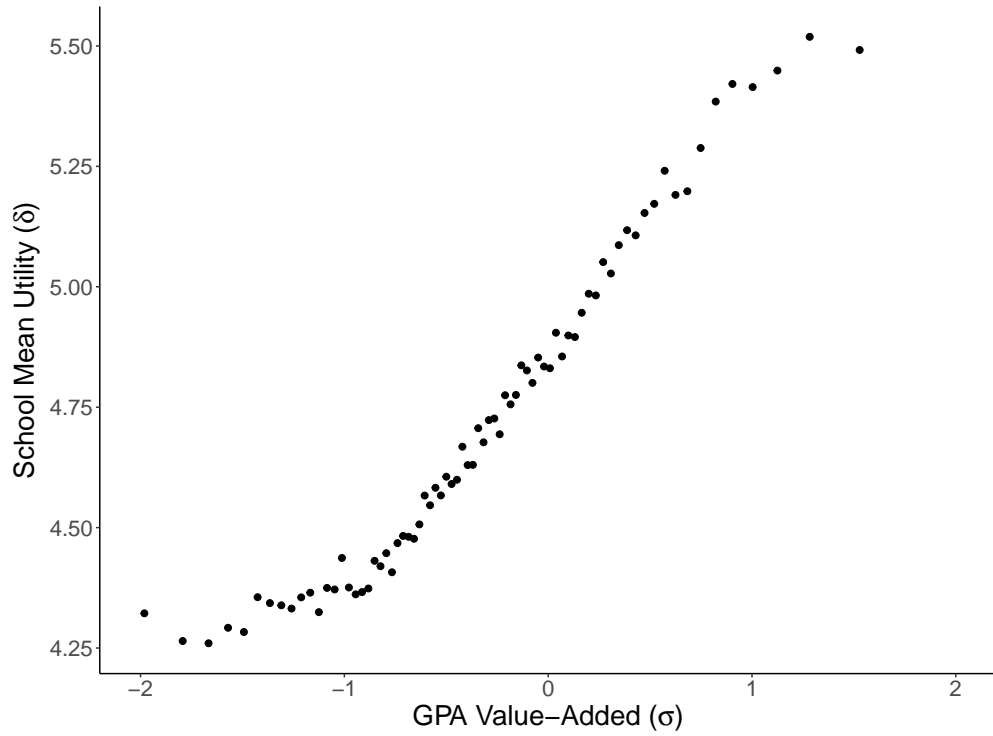
Notes: This figure plots a binscatter of school mean utilities (δ_{jt}) from the demand model as described in Section 6.1.2 against GPA value-added (q_{jt}) as described in Appendix A2. Initial estimation is restricted to a random sample of 200 markets from 2016 to 2018. School mean utilities δ_{jt} and application costs τ_t, τ_m are then estimated for other markets and years before 2016. See Appendix A5 for details of the estimation and extrapolation procedure.

Figure A11: Quality Adjustment Threshold and Sample Moment Conditions
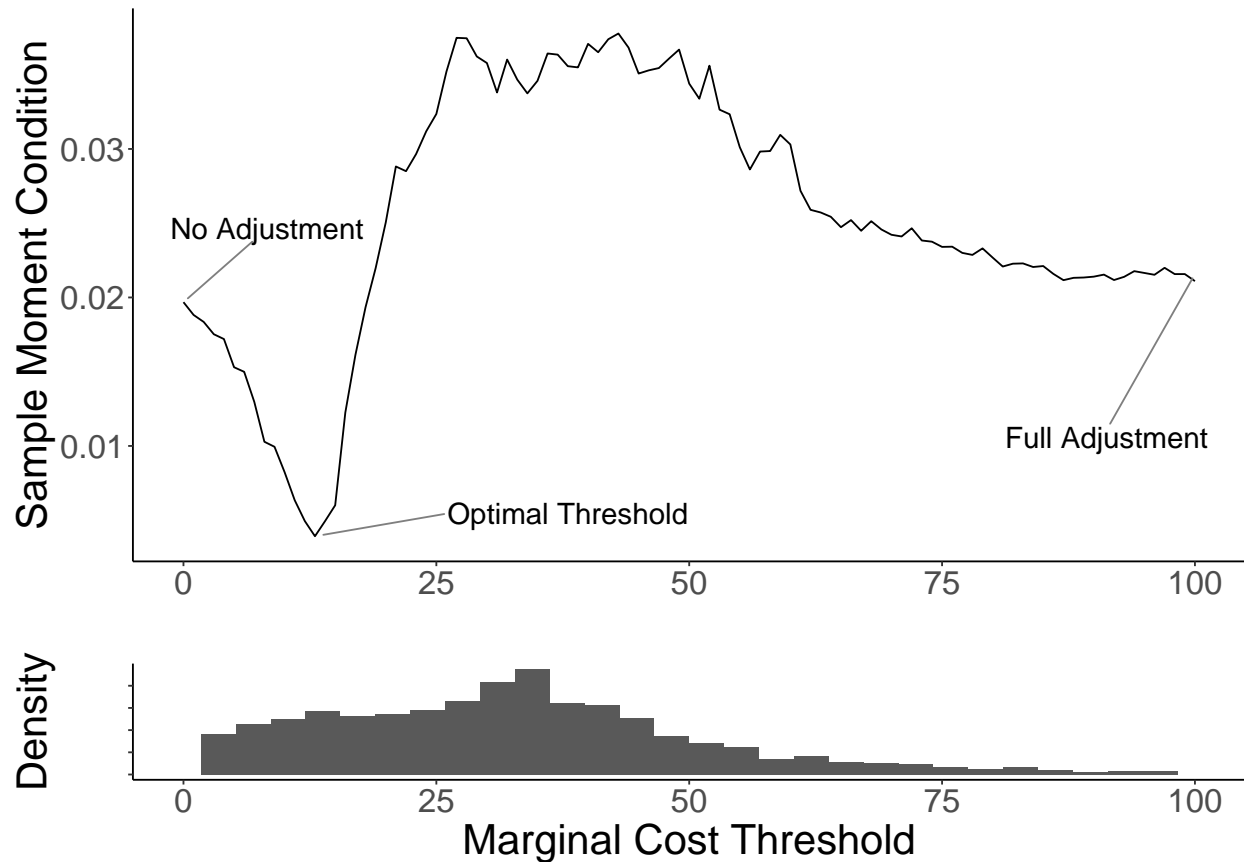
Notes: This figure presents sample moment conditions against candidate quality adjustment parameters as described in Section 6.2.3. The top panel plots the sample analogue to the moment condition (y-axis) for small increments of candidate threshold parameters ω (x-axis). The bottom panel plots a histogram 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 A12: Heterogeneity in Welfare Impacts
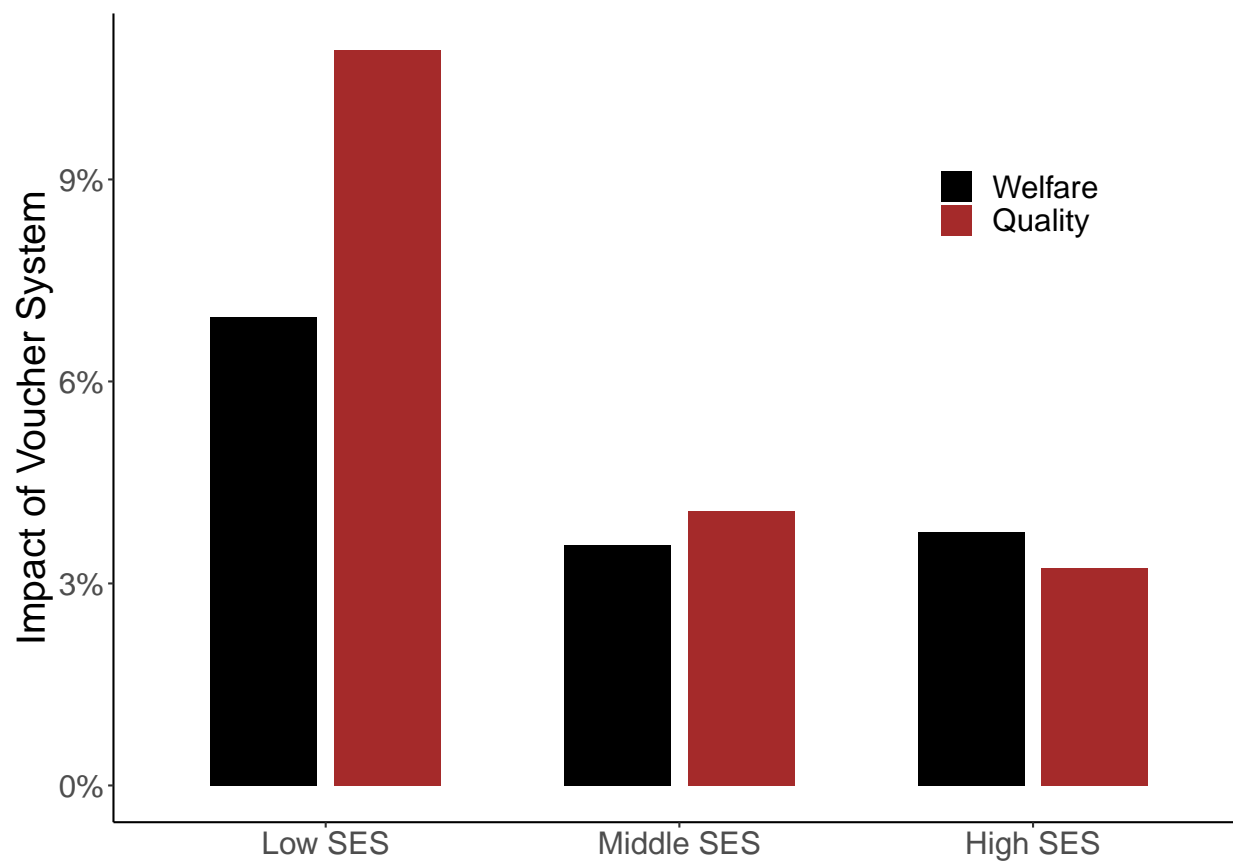
Notes: This figure presents estimates of the effects of India's voucher policy on student welfare *CS* and quality δ (y-axis), along the children's socio-economic status (x-axis). Black bars denote the percent change in consumer surplus from the status quo voucher system as described Section 7 and red 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.