# Pricing Private Education in Urban India: Demand, Use and Impact *

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**Abstract**

Private education services–including both private schools and after-school tutoring–forms a substantial part of the education sector in the developing world. We conduct a field experiment to study the role of prices in the market for tutoring in Delhi's slums. Using a two-part pricing design, we identify whether higher willingness to pay is associated with higher attendance in tutoring classes and whether prices have causal impacts on attendance and dropout. We find that higher willingness to pay is associated with higher attendance, but that lower prices reduce dropout. Using assigned prices as instruments for take-up of the classes, we find no evidence that tutoring impacts average test scores.

**JEL Classifications**: C93, D12, I25, L3, O15

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# 1 Introduction

Private provision of education forms an important and growing component of the education sector in developing countries. Across the developing world, 14 percent of primary and 20 percent of secondary students are enrolled in private schools, numbers comparable to developed countries (World Bank, 2018). Private tutoring is also prevalent. In India, for example, about 20 percent of students in grades 6-8 attend tutoring, and this number rises to over 30 percent at the secondary level (Azam, 2016).

Understanding the functioning of private education markets is crucial as they take an increasing role within the education sector. One important set of questions relate to the demand for private education and the role of prices in these markets. In the case of tutoring, for example, some argue that fees charged by providers exclude the poor from receiving tutoring, exacerbating inequality in education outcomes (Bray, 2009). This has led to calls for government regulation of fees (UNESCO, 2017). On the other hand, fees could allocate tutoring to those who will attend regularly, exert the most effort, and thereby benefit the most. The act of paying could also induce greater effort on the part of parents and children through sunk-cost effects (Thaler, 1980; Ketel et al., 2016).[1]

Understanding these mechanisms can help inform policies to subsidize or regulate within the tutoring market. For example, if prices simply serve to exclude the poor, then large subsidies may be justified. If, on the other hand, effort is higher when prices are higher, the optimal subsidy may be lower. Of course, optimal policy depends crucially on the effectiveness of tutoring in improving learning outcomes, and there is very limited evidence in this regard.

To shed light on these questions, this paper explores the interplay between prices of tutoring and take-up, attendance, and treatment effects of these services. We do this through field experiment in the market for tutoring (henceforth "tuitions") in 21 of Delhi's largest slum areas. In our experiment, we employ a two-part pricing design to introduce variation

1. Tooley (2009) suggests similar mechanisms in the market for private schools, noting that children in private schools attend more often than their counterparts in public schools.

in the price at which households are willing to enroll their children and random variation in the final, on-going price that households continue to pay. Households were initially offered tuition classes at random prices, and conditional on enrolling their children at that price, a random surprise discounted price was offered. We then measured students' attendance in the classes and test scores at the end of the school year.

Our methodology allows us to estimate several effects that are important inputs for forming pricing policy. First, we estimate the demand curve for tuitions and household characteristics related to demand. Second, we estimate whether the initial price screens out those who are less likely attend the classes. Third, conditional on the initial price, we estimate the causal effects of prices on continued attendance and dropout.*Ex ante*, there could be two competing forces driving the impact of the second price: (i) credit constraints, learning, or other factors dampen continued attendance when the price is high, or instead (ii) high prices induce continued attendance through sunk-cost effects. Finally, we use variation in offer prices as instrumental variables to estimate the impact of these classes on test scores.

Our analysis yields four key results. First, we find strongly downward sloping demand for enrollment as the initial price moves from zero up to the prevailing market price in the slums. We observe several sensible correlations with between demand and observable characteristics: parents of female children have lower willingness to pay, while prior experience with tuitions is correlated with higher willingness to pay. However, we do not observe a significant correlation between willingness to pay and household wealth.

Second, we find evidence that higher prices screen out those who use tuitions less intensively: those who enrolled at a price 100 Rupees higher attended 5 percentage points more classes. Average attendance is monotonically increasing across each of the four initial price groups.

Third, conditional on initial willingness to pay, we find that a higher ongoing price leads to a high number of dropouts and hence lower attendance in the classes. An ongoing price 100 Rupees higher is associated with 11-12 percent lower attendance over the year. This implies that any sunk-cost effects are ultimately outweighed by the negative effect of having to pay the higher on-going price in this market. This indicates that low prices may be required to prevent dropout over time.

Finally, we use our random price variation as instrumental variables to investigate the impacts of the tuition classes on math and language test scores. We find no evidence that the classes impact test scores on average. We provide evidence that this finding can partially be explained by substitution to other tuition providers. We also find evidence that children from poorer households and girls may benefit from the classes in English, but not in math.

Our paper relates to several strands of literature. Most broadly, it relates to the growing literature that explores the effects of pricing on demand, utilization and effectiveness of socially provided goods and services. Much of this literature focuses on health products (see Dupas and Miguel, 2017, for a review). In general, these studies find low willingness to pay, and mixed evidence that prices serve screen out those with the least potential to benefit. In contrast to many of the products studied in this literature, the market for education services is relatively well developed, with many households accustomed to paying for these services. It is therefore an open question whether the broad conclusions from the health literature also apply to the education sector.

Our paper also contributes to a recent but growing literature on private education services in developing countries. This literature has thus far focused primarily on the characteristics and efficacy of formal private schools (e.g., Muralidharan and Sundararaman, 2015; Singh, 2015). A smaller literature examines the effectiveness of private tutoring in developing countries, yet many of these studies suffer from endogeneity issues (Dang and Rogers, 2008). A notable exception is Muralidharan, Singh and Ganimian (2018), who conduct a randomized evaluation of a tutoring program in India consisting of level-appropriate and adaptive teaching using computers, and which had very large impacts on test scores. Our study, by contrast, examines group-based tutoring with more traditional teaching methods.

Finally, our study contributes to the literature examining demand for private education – and tutoring in particular – in developing countries. Several studies examine the determinants of demand for tutoring using non-experimental methods (e.g., Dang, 2007; Azam, 2016; Liu and Bray, 2017). We add to this literature by using experimental variation in prices to rigorously identify how household characteristics vary by initial willingnes-to-pay, how willingness-to-pay signals a child's propensity to attend tutoring, and how the ongoing price affects attendance over the course of the year.

The remainder of the paper is organized as follows. Section 2 describes the contextual setting for the experiment. Section 3 describes the experimental design and our data. Section 4 describes each of the main results: demand and correlates of willingness to pay, selection effects, causal effects, and treatment effects of classes on test scores. Section 5 concludes.

# 2 Experimental Setting and Design

## 2.1 Setting and Program

The use of private tuitions is prevalent across India. According to the 2007-2008 National Sample Survey, 20 percent of children in grades 6 to 8 attended tutions in the past year. Urban students are more likely to attend than rural students, although the fraction of rural students attending is non trivial (28 percent in urban areas vs. 17 percent in rural areas). Use of tutions are prevalent among all income groups: 14 percent of students in households in the lowest expenditure quintile attended tuitions in the past year (Azam, 2016).

We conducted our field experiment in 21 of Delhi's largest slum areas. We focused on the Delhi area for two reasons: First, as India's largest metropolitan area, it is home to a large population of urban poor and, like the rest of India, has a very active private market for education services. In our sample, 82 percent had attended tuitions in the past year.

Our implementing partner for the project, Pratham, is an education non-governmental organization (NGO) that runs education programs across India. Their tuition centers in Delhi primarily serve children in primary and upper primary school. There was one Pratham tuition center located in each of the 21 slum areas in the study.[2]

2. Each of these slums were at far enough away from each other such that it would have been extremely unlikely for households to send their children to one of the other Pratham tuition centers in the city.

Topics taught at Pratham tuition centers cover standard school subjects, remedial skills, kindergarten, and some vocational skills for older children. Our study focused on "content" classes, which cover standard school subjects and are the most popular program at the tuition centers. The curriculum in these classes was based entirely on the official school curriculum. Classes were held 6 days per week, for 3 hours each day, during the school year. Each class consisted of at most 20 students and was segregated by gender.[3] Our study focused on content classes offered to students in grades 6 to 8.

While Pratham's content classes were free prior to 2010, the organization subsequently changed this policy and started charging a fee. The two main reasons cited by the NGO leaders were that (i) they wanted to raise revenue, and (ii) they felt (anecdotally) that students attended less regularly when classes were free. Pratham ultimately started charging fees in all tuition centers, but there was slight variation in the actual fees charged across centers. For our experiment, we worked with Pratham to come up with a "posted" price for the tuition classes: that is, the highest amount that Pratham would charge per month in the absence of a randomized discount. This fee amount was Rs 200 for grade 6, and Rs 250 for grades 7 and 8. The fees charged by Pratham were slightly below the average prevailing fees charged by other tuition providers in the local slums.

## 2.2 Experiment

The experiment was conducted over the 2014-2015 school year, from April 2014 through March 2015, with subsequent data collection that lasted through 2016. The core experiment consisted of assigned initial offers to students in grade 6 to 8 to attend the local Pratham tuition center at randomized prices. A second randomization of prices was then conducted for those who took up the initial offers and enrolled their children.

3. Public schools in Delhi are segregated by gender: girls attend in the morning, while boys attend in the afternoon. Since most children in the slum areas attend these public schools, group-based, private tuition classes in the city are also typically segregated by gender.

### 2.2.1 First-Price Offers

The protocol initial offers replicated (to the extent possible) Pratham's usual approach in recruiting students for their tuition classes. This approach involves teachers going door-to-door to each household located around the tuition center and providing parents with basic information about their classes: when and where they are held, what is taught, and how much the classes cost. We followed the same protocol, except for the fact that one of our enumerators accompanied each teacher to make the randomized offers and conduct surveys and tests.

When a household was approached, the enumerator first conducted a baseline household survey, during which time the enumerator administered English and mathematics tests to the child. These instruments are described in more detail in section 2.3 below. Once the data collection was complete, the Pratham teacher provided the standard information on the tuition classes. The initial offers were made at the end of the visit.

The offer prices were randomized across up to and including the posted price: Rs. 0, Rs. 75, Rs. 150, and Rs. 200 (6th grade) or Rs 250 (7th and 8th grades). A concern with randomly assigned prices for any good or service is that households may perceive a lower (higher) price to signal lower (higher) quality. In anticipation of this occurring, we designed the price offers in such a way that the channel of *price as a signal of quality* would be shut down to the extent possible. Price offers were made by using scratch cards (illustrated in Figure A1), which made the process appear truly random to households.[4] If the respondents asked, they were told the prices were randomly assigned and were not told the posted prices unless they asked (very few did).

Through acceptance of these offers and enrollment of students, we are able to determine a bound on households' willingness to pay (WTP) for the classes. While there are more precise methods of eliciting WTP (e.g., using the Becker-DeGroot-Marschak (1964) mechanism), we chose to implement take it or leave it (TIOLI) offers in order to mimic the status quo offers of

4. During pilots, there had also been some parents that did not want a "hand out" and had insisted on paying full price. It was therefore important for the assignment of prices to appear truly random.

the NGO as much as possible. The NGO's standard method involves providing pricing and other information to the household, letting them consider enrolling their children, and then enrollment and payment at the tuition center at a later date. Under BDM, purchases must be enforced at the randomly drawn price in order for the procedure to be incentive compatible. This would have been difficult in our context, where there is naturally a lag between the offer and enrollment, which could lead households to renege on purchase decisions.

Initial offers for the tuition classes took place over three rounds. Panel A of Table 1 presents the timing and details of each round. The first round of offers, conducted in April and May of 2014, was made to households of 892 children who had attended Pratham tuitions in the 2013-2014 school year. In this round prices were randomly pre-assigned separately, with stratification by tuition center and grade. Prices were assigned in equal proportions across the four prices in each grade.

Between June and September 2014, we made initial offers for students who had not been previously enrolled in Pratham tution centers. Eligible households were identified by going door-to-door in the slum around the tutoring center and asking if there was a student in grades 6-8 in the household. Offers to these new students were conducted over two rounds. The initial round of offers to new students took place in June through August 2014, in which 3390 children received offers. Because we did not have pre-existing lists of students for these rounds, households drew scratch cards from a bag to determine the offer price.[5] Prices were again stratified by tuition center and grade. Anticipating that take-up would be lower at higher prices, and in order to maximize power, more offers were made at higher prices in order to yield more even proportions of *accepted* offers across prices.

By August, the total number of accepted offers was lower than the capacity of Pratham's tuition centers, and a final round of offers was therefore conducted to fill the centers to capacity. Enumerators and Pratham staff approached households in a larger radius around each tuition center than in the earlier round. We made 1157 additional offers to new students

5. Included in this round were 101 students who had enrolled in Pratham's "Summer School" classes in June and were given pre-assigned prices.

in August and September. This time, the offers were made in equal proportions across prices to ensure that enough children would enroll to fill the centers to capacity.

### 2.2.2 Second-Price Offers

Once a child was enrolled in the tuition classes and payments were made for 1-3 months (depending on when the first offer had been made), the household was visited again. The second price offer was then made, which would apply through the end of the school year in March 2014. Following the procedure for first price offers, scratch cards were once again used to make these offers. Prices were randomly assigned across the same four price groups as the first prices, in amounts up to and including the student's first price. Because students with an initial price of 0 were not eligible for further discounts, they were not approached. For the analysis, students with a first price of 0 are coded as having a second price of 0 if they met the enrollment and attendance criteria for their group. There were 544 such students.

Panel B of Table 1 presents the details of the second-price offers. Second prices were assigned in two batches. In each batch, the randomization was pre-assigned and stratified by first price and grade in equal proportions up to the initial offer price. Children who received an initial offer in the first four rounds were eligible for a second-price offer if they attended the classes in August. There were 843 such children, and their second-price offers were made at the end of September and beginning of October. For the fifth round of initial offers, eligibility for a second price offer was determined based on attendance in September.[6] Two hundred twenty-seven children from this round received second-price offers.

## 2.3 Data Collection

As described above, baseline household surveys and a pre-test (in math and English) took place in conjunction with the first-price offers. The surveys collected basic household

6. In order to avoid anticipation of discounts on the part of households, the enrollment period for the second batch closed before second-price offers were made for the first batch. Thus, it was not possible for students to enroll and get a discount after the first second-price offer was made.

demographic information, as well as current and prior experience with tuitions for all children in the household.

The math and English exams were based on the school syllabus for the child's grade. These, in turn, followed the content taught in Pratham's tuition classes. These exams were administered at home while the baseline surveys were taking place and took about one hour to complete.[7]

In addition to the baseline household surveys and education tests, we collected daily child-wise attendance data from the Pratham tuition centers throughout the 2014-2015 school year. In order to ensure the accuracy of these data, project staff conducted several unannounced checks at the centers to verify that recorded attendance matched actual attendance. We did not find any evidence of over-reporting of attendance. The few discrepancies we found were mainly due to teachers completing attendance registers later in the class, particularly when students arrived late.

Endline surveys and education tests were conducted April through June of 2015 for the entire sample of households who received a first-price offer. Because many households were away during the summer, revisits continued through September. In all 3996 (91 percent) of households were successfully surveyed.

Column 1 of Table 2 displays baseline characteristics of the sample. There are, on average 5.8 individuals in each household. Mother's education is relatively low at 3.7 years on average, with over half of mothers having zero education.[8] About 10 percent of students were in private school. As noted in Section 2.1 above, 82 percent of students attended tuitions in the previous year. This is only partially driven by students who had attended Pratham tuitions previously: among new students, 78 percent had attended tuitions in the prior year (not shown in table).

Table 2 also tests for balance of the sample by the randomly assigned prices. Column 2 regresses the first price on the characteristics shown, controlling for stratum dummies. Of 11

7. Pratham also conducts its own assessments at the beginning and end of the school year, and the tests in our study were broadly similar in coverage to the Pratham assessments.

8. As expected, father's education is higher at 6.6 years on average (not shown in the table).

characteristics examined, one is significant at the 10 percent level: children offered a price Rs. 100 higher had 0.015 standard deviations higher durables ownership, on average. The characteristics are jointly insignificant, with a p-value on the F-statistic that all coefficients are zero of 0.35. Columnn 2 regresses the second price on these characteristics, again controlling for stratum. One out of 11 coefficients is significant at the 10 percent level, and the of the test that all coefficients are zero fails to reject at conventional levels (p-value = 0.54).

# 3 Results

## 3.1 Demand

We begin by estimating basic demand for Pratham tuitions. Since the assignment of the of the first price was random, to estimate demand, we simply regress a dummy for take-up of the tuition classes (that is, enrollment), on the offer price:

$$Enrol_{igc} = \beta_0 + \beta_1 first_{igc} + S'_{igc}\psi + X'_{igc}\lambda + \epsilon_{igc} \tag{1}$$

Where $Enrol_{igc}$ is a dummy for enrollment of child $i$ in grade $g$ in tuition center $c$, where a child is coded as enrolled if the initial payment was made and the child attended on at least one day. $first_{igc}$ is a continuous variable for the initial offer price, $S_{igc}$ are dummies for strata (grade, tuition center, and round), and $X_{igc}$ are child and household-specific controls.

Table 3 shows the results of this estimation. At a price of 0, nearly 69 percent of students enroll. Demand is strongly downward sloping: the point estimate implies that a 100 Rs. higher price results in 17 percent lower take up. At a price of 75 Rs., this implies an elasticity of demand of 0.27.

We also estimate a flexible specification, where we replace the $first_{igc}$ with dummies for each price, with the price of zero as the omitted category. The coefficient estimates are provided in Columns 3 and 4 of Table 3 and are displayed graphically in 2. As shown, demand is monotonically decreasing across all 4 offer prices.

## 3.2 Correlates of Willingness-to-Pay

Next, we examine how willingness-to-pay for the tuitions correlates with observable student- and household-level characteristics. This allows us to examine, for example, whether willingness-to-pay is related to household wealth, child gender, ability, or other characteristics.

We model WTP for $i$ in grade $g$ in center $c$ to be linear in characteristics:

$$WTP_{igc} = \beta_0 + X'_{igc}\beta_1 + S'_{igc}\psi + \epsilon_{igc} \tag{2}$$

where $S_{igc}$ are dummies for grade for a child $i$ in grade $g$ in center $c$, and $X_{igc}$ are child and household-specific controls.

The TIOLI nature of our experimental pricing design does not allow us to measure the willingness to pay directly. Instead, what we observe is take up: $Enrol_{igc}$, which takes value 1 if $WTP_{igc} \geq first_{igc}$, and 0 otherwise, where $first_{igc}$ is the initial offer price.

Based on Equation (2), we can express enrollment as a function of the latent variable $WTP$:

$$\begin{aligned} Enrol_{igc} &= 1(WTP \geq first_{igc}) = 1(WTP - first_{igc} \geq 0) \\ &= 1(\beta_0 + X'_{igc}\beta_1 + S'_{igc}\psi + \epsilon_{igc} - first_{igc} \geq 0) \end{aligned} \tag{3}$$

We estimate this discrete choice model using a constrained probit regression.[9] We convert $first_{igc}$ to 100's of rupees and normalize its coefficient to be -1 so that the other coefficients are directly interpretable in relation to WTP in 100's of rupees. The sample consists of all households that were approached with the first price offers.

The results are presented in Table 4. While some of variables are not significantly predictive of willingness-to-pay, we observe several sensible correlations with these characteristics.

9. The results are similar for a logit model, and in fact, the effect sizes are even larger. We present these results in Appendix Table A1.

Having a female student is negatively correlated with willingness to pay: a household is willing to pay 10 Rs.less on average, for a female child. Household size and attending private school are negatively associated with willingness to pay, while prior experience with Pratham tuition classes is a strongly positively correlated with WTP. Finally, attending private school is also very strong predictor of lower take up: having a child enrolled at a private school reduces willingness to pay by approximately Rs. 50. This suggests that parents view private school and private tuitions as substitutes. Importantly, there is no evidence of a relationship between wealth and WTP. This suggests that, within our sample, credit constraints may not be a key factor in the initial take-up decision.

## 3.3 Attendance

We next analyze attendance over the course of the year among students who enrolled in the Pratham tuitions. To motivate the analysis, Figure 3 displays the average percentage of classes attended, by month. As shown in the figure, attendance was generally declining over the school year. This was driven primarily by new students, but also occurred to a lesser extent among old students.

Figures 4 and 5 further examine these patterns by examining any attendance in a month (the extensive margin) and the percent of classes attended, conditional on any attendance (the intensive margin). As shown in the figures, while the proportion of students attending at all is declining across months, the fraction of classes attended among those attending is relatively stable. This implies that the declining overall pattern in Figure 3 is driven by dropouts, rather than irregular attendance among those who did not drop out.

### 3.3.1 Selection Effects

In this section we test whether those with a higher initial willingness-to-pay for the tuition classes are also the ones that have higher attendance. To examine this, we start with the sample of students who took up the classes. Within this sample, those who took up at a higher initial price have higher WTP for the classes. We separate initial WTP from the causal effect of prices by controlling flexibly for the second price. In order to do this, we further restrict the sample to households that were assigned a second price. That is, we exclude households that initially enrolled but dropped out before second prices were assigned. Our outcome of interest is the percentage of all classes attended between the second-price offer and the end of the school year in March. The model we estimate is:

$$Y_{igc} = \beta_0 + \beta_1 first_{igc} + \sum_{p=0}^{250} \delta_p 1(second_{igc} = p) + S'_{igc}\psi + X'_{igc}\lambda + \epsilon_{igc} \tag{4}$$

Here, $Y_{igc}$ represents the percentage of classes attended, and $first_{igc}$ is the continuous variable for the offer price. We control for dummy variables for the second price assignment, $second_{igc}$. This estimates the relationship between the first price and attendance, *conditional* on the second price. We also estimate a flexible specification where we replace $first_{igc}$ with dummies for each of the four prices that were offered as first price.

The results are shown in Table 5. There is strong evidence for selection: paying a Rs. 100 higher price is associated with 5 percentage points more classes attended. Figure 6 displays the estimates for the flexible specification graphically, with corresponding estimates in Columns 3 and 4 of Table 5. These results show that attendance is monotonically increasing across all 4 initial price groups.

### 3.3.2 Causal Effects

Next, we investigate how the *ongoing* (that is, the second) price influences continued use of the tuition classes. We define this effect as the "causal" effect. Given the dynamic nature of continued payments over the entire academic year, there are several sources of causal effects. On one hand, if households make decisions to continue with the classes on an ongoing basis, a higher price may make them more likely to dropout. However, this negative effect could potentially be offset by a sunk-cost or psychological effect, in which a higher price induces higher attendance.

We explore this net causal effect of the second price on attendance, by estimating a model similar to the equation used to estimate selection effects above. Using the sample of students who received a second price offer, we estimate:

$$Y_{igc} = \beta_0 + \beta_1 second_{igc} + \sum_{p=0}^{250} \delta_p 1(first_{igc} = p) + S'_{igc}\psi + X'_{igc}\lambda + \epsilon_{igc} \tag{5}$$

Each of the variables in this equation is defined as before, with the only change being that we include a continuous variable for the second price and control from the first price a set of dummy variables. We also estimate a flexible specification where we replace the continuous variable for second price with dummies for each of the four prices that were offered.

The results are presented in Table 6 and Figure 7. We find strong negative effects of the second price on subsequent attendance: according to the estimates in Columns 1 and 2, a higher price by Rs. 100 is associated with 12 percentage points lower attendance. Columns 3 and 4 provide estimates for the flexible specification (displayed graphically in Figure 7), and we see that attendance is monotonically decreasing in price. These results imply that any potential sunk cost effects are more than outweighed by the negative effect of the higher price.

### 3.3.3 Irregular Attendance vs. Dropout

We next examine the effects of the first and second prices on the intensive and extensive margins of attendance. This can shed light on whether selection or causal effects operate primarily through irregular attendance (the intensive margin) or dropout (the extensive margin).

To examine these impacts, we arrange our data by month and child and construct two measures of attendance. The first, representing the extensive margin, is a dummy variable indicating any attendance in a given month for that child. The second measure, representing the intensive margin, equals the percent of classes attended in that month for that child, conditional on any attendance for that month. That is, for this latter measure we code non-attendance in a month as missing. We then regress each measure on first and second prices, following the regressions in equations (4) and (5) above.

The results are shown in Table 7. As shown in the first row, the first price has a positive and significant relationship with both the intensive and extensive margins of attendance. By contrast, the second price only has a significant negative impact on the extensive margin. This implies that those with higher initial WTP both attend more regularly and are less likely to drop out, while the ongoing price primarily influences dropout.

## 3.4 Treatment Effects

Finally, we estimate the impacts of Pratham's tuition classes on test scores. The basic model is one where student test scores depend on attendance in the classes:

$$Y_{igc} = \beta_0 + \beta_1 Enrol_{igc} + S'_{igc}\psi + X'_{igc}\lambda + \epsilon_{igc} \tag{6}$$

Where $Y_{igc}$ is the student's test score and $Enrol_{igc}$ represents enrollment and any attendance in the Pratham classes, as defined before. Once again, $S_{igc}$ are dummies for grade for a child $i$ in grade $g$ in center $c$f, and $X_{igc}$ are child and household-specific controls.

Ordinary-least-squares estimates of this specification are presented in Columns 1 to 4 of Table 8. Attending the Pratham classes is associated with about a .08 standard deviation higher English test score, and a 0.06 standard deviation higher score on the Math test. These estimates may be biased however, since they rely on non-random variation in attending Pratham's classes. In order to address this endogeneity, we instrument attending Pratham's tuition classes with the first price that was offered. From the demand estimation above, we already know that a lower price is strongly associated with higher take up. This implies a strong first stage for the instrument. We therefore instrument $Enrol_{igc}$ with a set of dummies for the first price offer and present the results in Columns (5) to (8) in Table 8. Surprisingly, find no evidence for effects of attending the Pratham classes on either English or math scores using this instrumental variables strategy, for the average student.

Before exploring mechanisms for the IV results, we discuss several potential explanations for the differences between the OLS and IV results. First, the IV are considerably noisier than the OLS estimates: that the standard errors of the IV estimates are approximately three times the standard errors of the OLS estimates. Using the IV estimates, we cannot reject positive effects equal in magnitude to the OLS estimates. Second, the OLS estimates could be influenced by selection. In the OLS estimation, enrollment is correlated WTP, and we have seen previously that WTP is correlated with both household characteristics and a child's propensity to attend. Thus, the selected nature of the enrolled sample could be driving the OLS results.

The following subsections investigate mechanisms behind the lack of effects in the IV estimation.

### 3.5 Substitution to Other Tuition Providers

One potential mechanism for the lack of impacts observed in the previous section is substitution across tuition providers. As discussed previously, the market for private tuitions in Delhi's urban slums is thick, with many providers in addition to Pratham.

To test whether children substituted across tuitions, we first check whether the first price predicts takeup of non-Pratham tuition services. We estimate Equation (1), where the dependent variable is defined as attendance in a non-Pratham tuition over the school year, measured by of the endline survey. The results are shown in Columns 3 and 4 of Table 10. The first price has a positive and significant effect on attending non-Pratham tuitions. The magnitude indicates that a 100 rupee higher price increases the likelihood of attending non-Pratham tuitions by about 5 percent. This suggests some degree of substitution to other tuitions, but note that the magnitude is smaller that the effect of price on take-up of Pratham tuitions (shown in Columns 1 and 2 of Table 10 for comparison). This implies that on net, a higher price still induced lower take-up of *any* tuitions over the school year. Indeed, when we regress use of any tuition on first price (Columns 5 and 6 of Table 10, the coefficient is still negative and highly statistically significant.

If we assume that Pratham and non-Pratham tuitions have the same impact on test scores, we can estimate the impact of attending *any* tuition class on test scores. We do this by estimating Equation (6) with the dependent variable as a dummy for whether a child attended *any* tuition in the 2014-15 school year. Again, we instrument attendance with the first price as in the previous section. Columns 3 and 4 of Table 10 presents the results, with Columns 1 and 2 repeating the initial treatment-effects specification from above for comparison. As expected, we again observe statistically insignificant impacts on test scores, but the standard errors have increased. Taken together, these results suggest that substitution could contribute to the lack of treatment effects that we observe on the full sample.

## 3.6 Heterogeneity in Treatment Effects

To further explore treatment effects estimated above we examine heterogeneity by student and household characteristics. We begin by examing heterogeneity in test scores. One hypothesis for the lack of treatment effects in the full sample is the curriculum of the Pratham classes. Because many children in our sample are behind grade-level, and because the Pratham tuitions focused on the school syllabus, the curriculum may have been too advanced for most students in the sample. To examine whether this was the case, we estimate impacts separately for students with below- and above-median pretest scores. In the case where the curriculum was too advanced, we would expect treatment effects for students with higher pretest scores. Panel A of Table 11 displays the results. [10] For both English and math test scores, we do not observe any evidence for impacts for either subgroup, and we fail to reject that the impacts are equal across subgroups. Thus, this analysis does not support the hypothesis that the curriculum targeted only more advanced students. We note, however, that this test is not definitive: for example, the curriculum may have been too advanced for the vast majority of students, in which case we would not expect heterogeneity by above- and below-median pretest scores.

10. The estimation is implemented by interacting dummy variables for each subgroup with indicators for each first price group and using the resulting interactions as instruments for take-up in the two subgroups.

To examine the distributional effects of the classes, Panels B and C Table 11 display heterogeneity by child gender and household wealth, respectively. Although there is no evidence of heterogeneity in math impacts, the impact in English is positive and significant for girls (estimate = 0.13; s.e. = 0.073). We reject that the impacts are the same for boys and girls at the 10 percent level (p-value = 0.070). We also observe heterogeneity in impacts on English test scores by wealth: children from poorer households experience increases in English scores by 0.15 standard deviations as a result of attending.

# 4 Conclusion

We conduct a randomized trial among existing and potential clients for the NGO Pratham's tuition services among upper primary schoolchildren across 21 slum areas in Delhi. In order to disentangle selection by initial WTP and causal effects of prices, we employ a two-part pricing methodology. Combining randomized offer prices, enrollment data, and test scores, we are able to rigorously estimate the effects of Pratham tuitions on children's test scores.

We observe downward-sloping demand, along with sensible correlates of willingness-to-pay. We further find that after enrollment, those with higher willingness to pay attend more often conditional on the ongoing price. However, conditional on initial willingness to pay, a higher ongoing price increases the likelihood of dropout.

Taken together, the results highlight a trade-off between intensity of attendance and retention of students that an NGO faces in setting the price of the classes. However, the causal effect of higher ongoing prices more than offsets the initial selection effect. This implies that a higher price, applied throughout the year, would lead to higher dropout among those who initially took up. One potential policy implication is that prices may indeed serve as a useful screening mechanism, provided that a the NGO can offer subsequent discounts in order to retain students who initially took up.

Importantly, however, we find no evidence that the tuitions increased test scores on average: using our randomized prices as instruments, we find no effects of the tuition classes on test scores over the full sample. Exploring mechanisms for this result, we find some evidence that households who faced higher prices were more likely to enroll their children in other tuitions. This can account for some, of the null treatment effects on the full sample. We also explore whether the level of Pratham tuitions was too high – focusing on the school syllabus rather than on lower level skills. However, we find no effects on students with higher baseline test scores, suggesting that even those who could keep up with the material covered in the classes did not benefit on average.

Our study has focused on household demand for tuitions, children's attendance patterns, and impacts of tuitions on children's test scores. At the same time, there is limited research on the behavior of private suppliers, such as the determinants of entry decisions and pricing strategies of providers. Future work could examine supplier behavior to better understand the private tutoring market as a whole.

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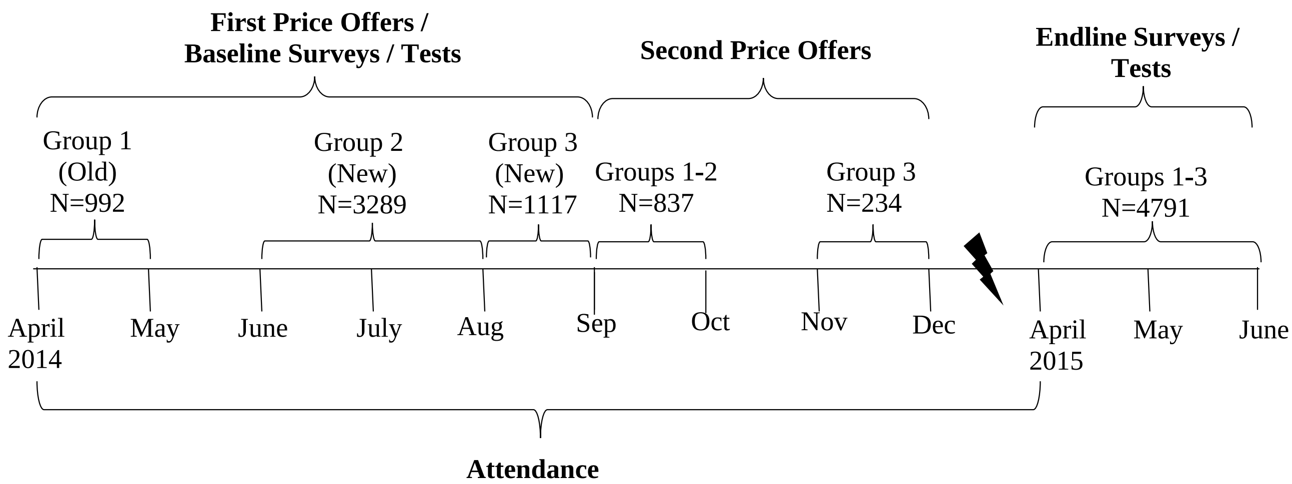
# Figures

Figure 1: Timeline of Experiment




*Notes:* Groups 1 and 2 had to be enrolled by August to be included in second-price randomization. Group 3 had to be enrolled by September to be included in the second-price randomization.

Figure 2: Demand by First Price

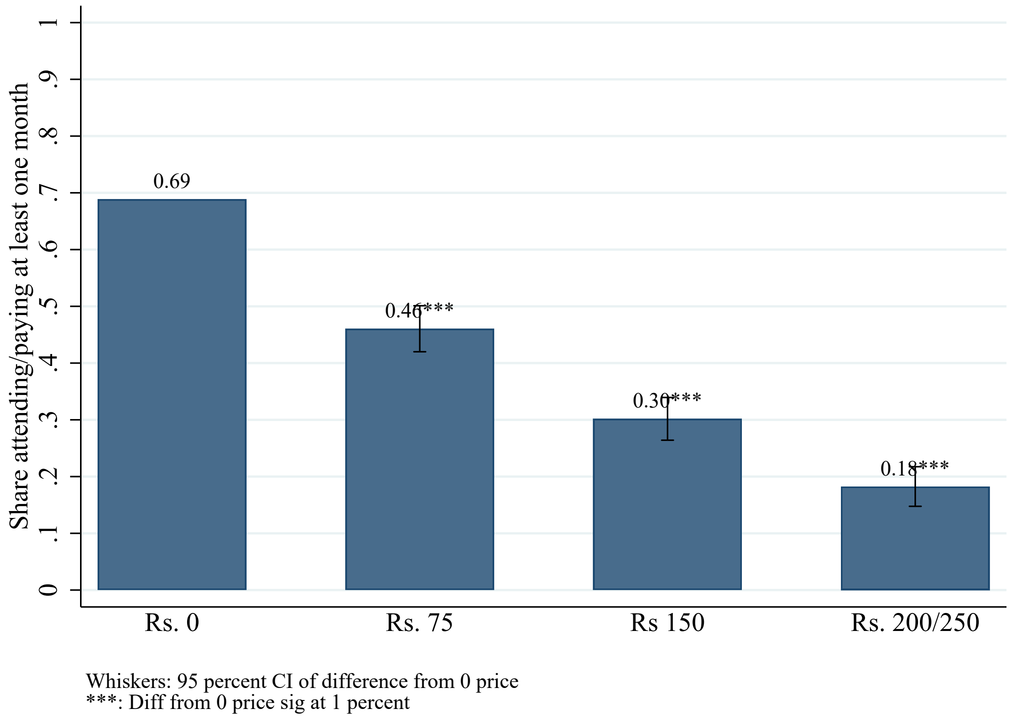


Figure 3: Monthly Attendance by Offer Group

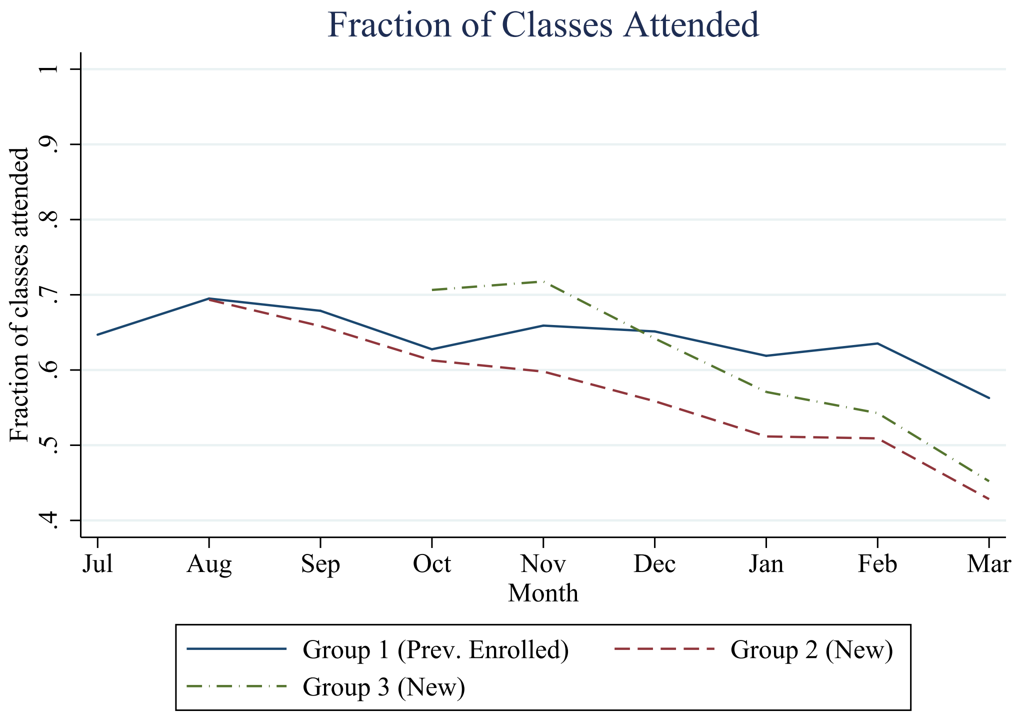


Figure 4: Fraction of Students Attending by Month

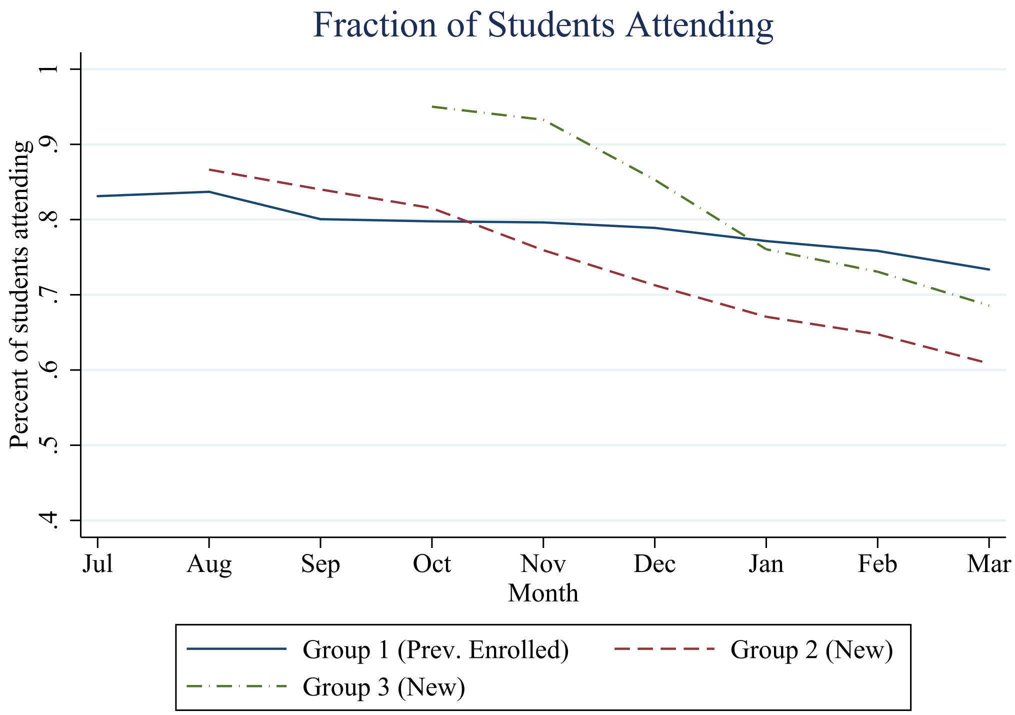


Figure 5: Monthly Attendance Conditional on Attending in a Month

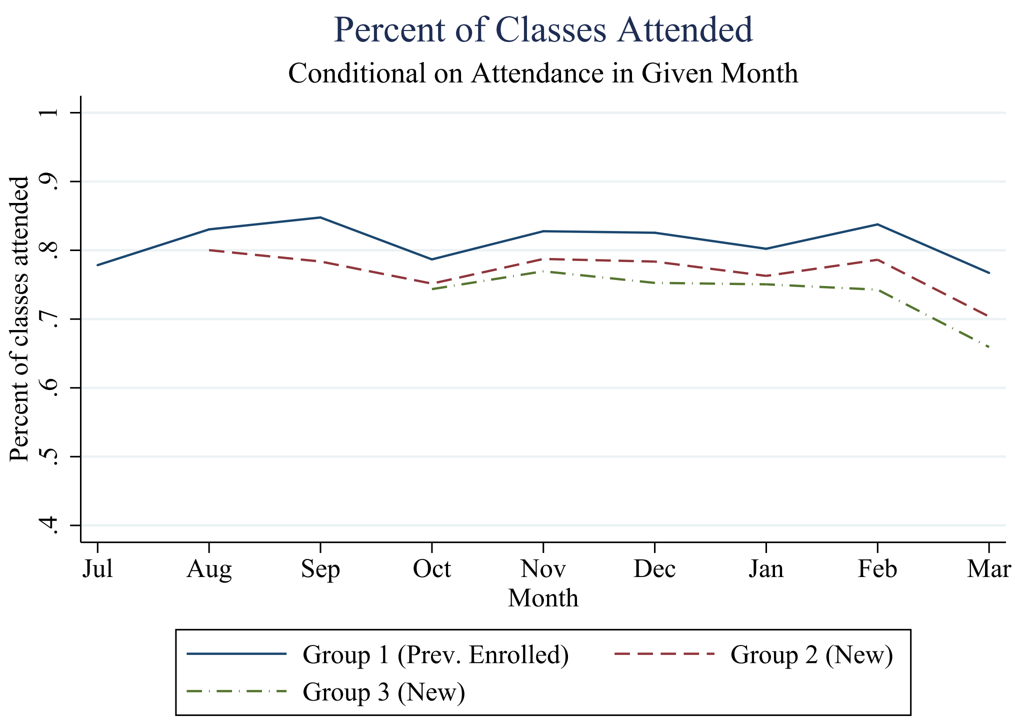


Figure 6: Percent Classes Attended by First Price

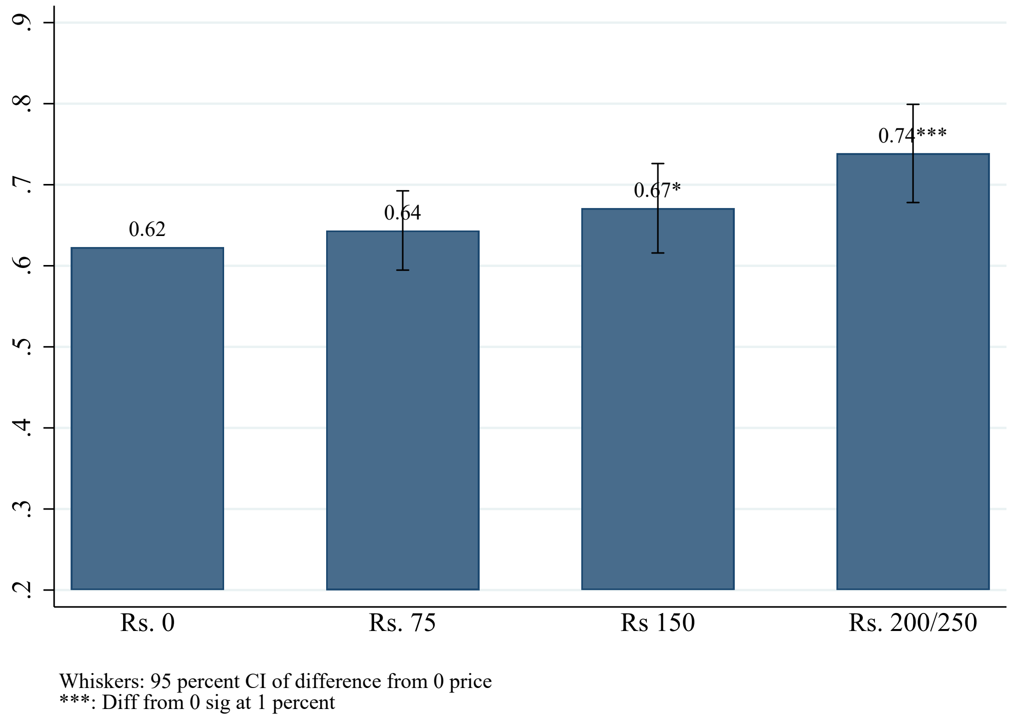
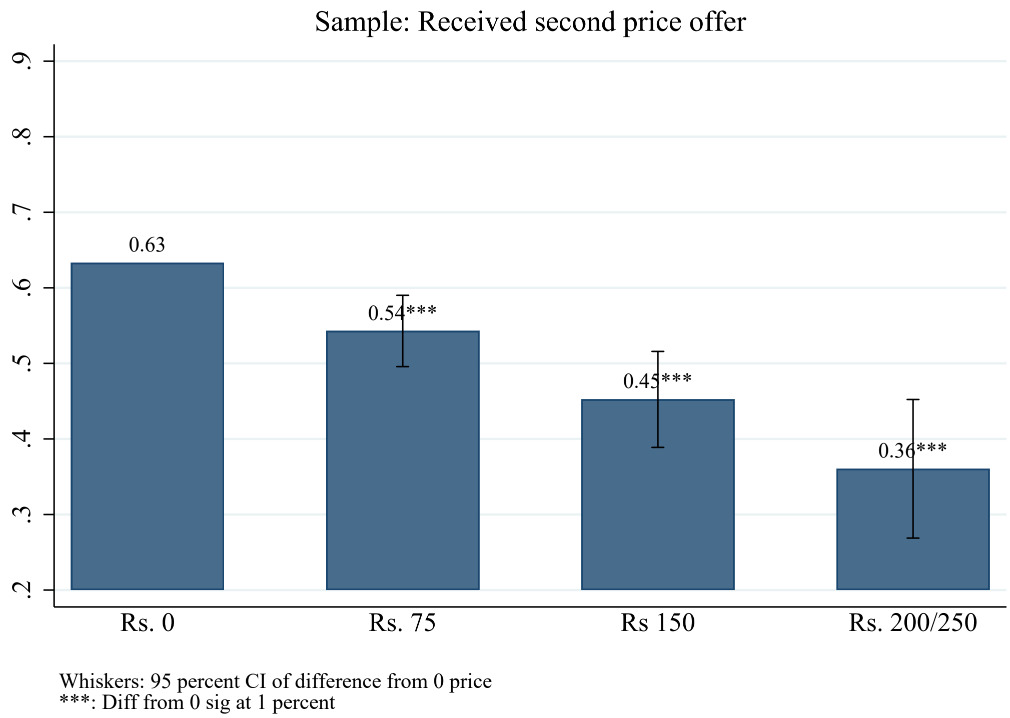


Figure 7: Percent Classes Attended by Second Price



# Tables

Table 1: Offer Details

| *Panel A: First-price offers* | | | |
|---|---|---|---|
| Round | Offer Dates | No. Offers | Pre-Assigned? |
| (1) Old | Apr-May | 892 | Yes |
| (2) New 1 | Jun-Aug | 3390 | No |
| (3) New 2 | Aug-Sep | 1157 | No |
| *Panel B: Second-price offers* | | | |
| Round | Offer Dates | No. Offers | Pre-Assigned? |
| (1), (2) | Sep-Oct | 837 | Yes |
| (3) | Nov | 234 | Yes |

Notes: This table provides details of how the first and second price offers were made to households in 2014. "Old" refers to the sample of students that had been enrolled at Pratham in the previous (2013-14) academic year. "New" students are those that were approached for the first time. Round 2 includes 101 students who had been enrolled in Pratham's "Summer School" in June 2014. Prices for these students were pre-assigned.

Table 2: Summary Statistics and Balance check

| | | Dependent Variable | |
|---|---|---|---|
| | Sample Mean | First Price | Second Price |
| | (1) | (2) | (3) |
| # HH Members Age 19+ | 2.62 | 0.00987 | 0.0117 |
| | [1.25] | ( 0.0102) | ( 0.0134) |
| # HH Members Age 15-18 | 0.656 | 0.0143 | -0.0104 |
| | [0.801] | ( 0.0166) | ( 0.0219) |
| # HH Members Age 6-14 | 2.38 | -0.0124 | 0.00396 |
| | [1.01] | ( 0.0124) | ( 0.0154) |
| # HH Members Age 0-5 | 0.329 | -0.00295 | -0.00260 |
| | [0.649] | ( 0.0193) | ( 0.0239) |
| 1st PC of Durables Ownership | 0.00636 | 0.0151* | 0.00490 |
| | [1.66] | ( 0.00843) | ( 0.0104) |
| Mother education (years) | 3.72 | -0.00297 | -0.00456 |
| | [4.22] | ( 0.00310) | ( 0.00382) |
| Female | 0.486 | 0.00215 | 0.0164 |
| | [0.500] | ( 0.0242) | ( 0.0300) |
| Attends Private School | 0.107 | -0.0659 | -0.0443 |
| | [0.309] | ( 0.0440) | ( 0.0612) |
| Attended Tuition Past Yr | 0.820 | -0.0194 | 0.0222 |
| | [0.384] | ( 0.0327) | ( 0.0447) |
| Normalized Math Score | 0.00562 | -0.0138 | 0.0181 |
| | [1.00] | ( 0.0140) | ( 0.0171) |
| Normalized English Score | 0.00358 | 0.00717 | 0.0312* |
| | [1.00] | ( 0.0151) | ( 0.0185) |
| Observations | 5439 | 5067 | 1512 |
| P-value: all coefs 0 | | 0.347 | 0.538 |

Notes: Notes: This table provides summary statistics of houshold characteristics measured in the baseline survey and a check of the balance of the randomized prices in terms of those characteristics. Column (1) presents means over the sample approached for initial offers. Column (2) presents a regression of the first price (in 100s of rupees) on the characteristics listed, controlling for stratum dummies. Column (3) regresses the second price (in 100s of rupees) on the characteristics listed, controling for dummies for first price and stratum. Standard deviations are in square brackets, and standard errors are in parenthases.

Table 3: Demand for Pratham Tuition Classes

| | Dependent Variable: Attended (1/0) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Price in 100's | -0.172*** | -0.171*** | | |
| | (0.00658) | (0.00683) | | |
| Price=Rs.75 | | | -0.196*** | -0.228*** |
| | | | (0.0186) | (0.0207) |
| Price=Rs.150 | | | -0.339*** | -0.387*** |
| | | | (0.0175) | (0.0192) |
| Price=Rs.200/250 | | | -0.426*** | -0.506*** |
| | | | (0.0166) | (0.0178) |
| Controls | NO | YES | NO | YES |
| Mean of Dep. Var | 0.686 | 0.689 | 0.686 | 0.689 |
| R2 | 0.341 | 0.347 | 0.345 | 0.212 |
| N | 5439 | 5067 | 5439 | 5067 |

Notes: This table provides estimates for equation (1) in Columns 1 and 2. In Columns (3) and (4), we estimate a flexible specification, where we replace the first price with dummies for each first price that was offered. The omitted category in this case is a price of 0. Controls include all variables listed in Table 2.

* significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent

Table 4: Correlates of WTP-Constrained Probit Model

| | Dependent Variable: Attended Any Class | |
|---|---|---|
| | (1) | (2) |
| # HH Members Age 19+ | -0.00559 | -0.0215 |
| | (0.0191) | (0.0205) |
| # HH Members Age 15-18 | -0.144*** | -0.160*** |
| | (0.0311) | (0.0333) |
| # HH Members Age 6-14 | 0.0214 | 0.0227 |
| | (0.0228) | (0.0243) |
| # HH Members Age 0-5 | 0.0184 | 0.00982 |
| | (0.0354) | (0.0378) |
| 1st PC of Durables Ownership | -0.0102 | -0.0102 |
| | (0.0155) | (0.0166) |
| Mother education (years) | 0.00164 | 0.00249 |
| | (0.00569) | (0.00602) |
| Female | -0.130*** | -0.0998** |
| | (0.0444) | (0.0472) |
| Attends Private School | -0.514*** | -0.480*** |
| | (0.0830) | (0.0887) |
| Attended Tuition Past Yr | 0.0919 | 0.0740 |
| | (0.0615) | (0.0649) |
| Normalized Math Score | 0.0414 | 0.0343 |
| | (0.0254) | (0.0274) |
| Normalized English Score | 0.0425 | 0.0191 |
| | (0.0277) | (0.0297) |
| Attended Pratham Tuition Prior Year | 1.279*** | |
| | (0.0625) | |
| Grade 7 | 0.102* | |
| | (0.0528) | |
| Grade 8 | 0.113** | |
| | (0.0539) | |
| Stratum Dummies | NO | YES |
| Mean of Dep. Var | 0.329 | 0.319 |
| N | 5067 | 4968 |

Notes: This table provides estimates for a probit model for estimating the parameters for equation (2), with equation (3) as the latent model. Enrollment is regressed on characteristics and offer price using a probit model, with the coefficient on offer price constrained to be -1. This scales coefficients relative WTP in '00s of rupees.
* significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent

Table 5: Selection Effects

| Sample: | Attended Any Class After Second Price Offer | | | |
|---|---|---|---|---|
| Dependent Variable: | Fraction of Classes Attended | | | |
| | (1) | (2) | (3) | (4) |
| First Price in 100's | 0.0481*** | 0.0501*** | | |
| | (0.0126) | (0.0129) | | |
| Price=Rs.75 | | | 0.0339 | 0.0204 |
| | | | (0.0243) | (0.0250) |
| Price=Rs.150 | | | 0.0436 | 0.0479* |
| | | | (0.0274) | (0.0281) |
| Price=Rs.225/250 | | | 0.113*** | 0.115*** |
| | | | (0.0302) | (0.0309) |
| Controls | NO | YES | NO | YES |
| Mean of Dep. Var | 0.604 | 0.602 | 0.604 | 0.602 |
| R2 | 0.272 | 0.305 | 0.272 | 0.305 |
| N | 1625 | 1512 | 1625 | 1512 |

This table provides estimates for equation (4) in Columns 1 and 2. In Columns (3) and (4), we estimate a flexible specification, where we replace the first price with dummies for each first price that was offered. The omitted category in this case is a price of 0. Controls include all variables listed in Table 2.

* significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent

Table 6: Causal Effects

| Sample: | Attended Any Class After Second Price Offer | | | |
|---|---|---|---|---|
| Dependent Variable: | Fraction of Classes Attended | | | |
| | (1) | (2) | (3) | (4) |
| Second Price in 100's | -0.114*** | -0.119*** | | |
| | (0.0162) | (0.0166) | | |
| Price=Rs.75 | | | -0.0819*** | -0.0886*** |
| | | | (0.0235) | (0.0241) |
| Price=Rs.150 | | | -0.178*** | -0.181*** |
| | | | (0.0316) | (0.0324) |
| Price=Rs.225/250 | | | -0.257*** | -0.269*** |
| | | | (0.0455) | (0.0468) |
| Controls | NO | YES | NO | YES |
| Mean of Dep. Var | 0.604 | 0.602 | 0.604 | 0.602 |
| R2 | 0.275 | 0.307 | 0.275 | 0.307 |
| N | 1625 | 1512 | 1625 | 1512 |

Notes: This table provides estimates for equation (5) in Columns 1 and 2. In Columns 3 and 4, we estimate a flexible specification, where we replace the second price with dummies for each second price that was offered. The omitted category in this case is a price of 0. Controls include all variables listed in Table 2.

* significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent

Table 7: Price Effects on Intensive and Extensive Margins

| | Number of Months | Percent Attendance if Enrolled |
|---|---|---|
| | (1) | (2) |
| First Price in 100's | 0.0428*** | 0.0299*** |
| | (0.0116) | (0.00593) |
| Second Price in 100's | -0.144*** | -0.000800 |
| | (0.0173) | (0.00813) |
| Mean of Dep. Var | 0.814 | 0.781 |
| R-squared | 0.214 | 0.189 |
| N | 8502 | 6917 |

In Column 1, the dependent variable is a dummy indicating attendance in a given month. In Column 2, the dependent variable is the percent of classes attended in a given month, only including observations where the student attended at least one class. The unit of observation is a student-month. Standard errors are clustered at the student level.

* significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent

Table 8: Treatment Effects of Attending Pratham Tuition

| Dependent Variable: | OLS Estimates | | | | Instrumental Variable Estimates | | | |
|---|---|---|---|---|---|---|---|---|
| | English Score | | Math Score | | English Score | | Math Score | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Attended any Pratham class | 0.0787*** | 0.0768*** | 0.0687** | 0.0627** | 0.0506 | 0.0251 | -0.0286 | -0.0810 |
| | (0.0198) | (0.0203) | (0.0279) | (0.0287) | (0.0575) | (0.0590) | (0.0807) | (0.0833) |
| Baseline English Score | 0.792*** | 0.754*** | 0.352*** | 0.335*** | 0.792*** | 0.753*** | 0.351*** | 0.335*** |
| | (0.00968) | (0.0108) | (0.0136) | (0.0152) | (0.00969) | (0.0108) | (0.0136) | (0.0153) |
| Baseline Math Score | 0.0517*** | 0.0477*** | 0.354*** | 0.350*** | 0.0521*** | 0.0484*** | 0.355*** | 0.351*** |
| | (0.00985) | (0.0100) | (0.0138) | (0.0141) | (0.00988) | (0.0100) | (0.0139) | (0.0142) |
| Controls | NO | YES | NO | YES | NO | YES | NO | YES |
| Mean of Dep. Var | 0.00363 | 0.00292 | 0.00417 | 0.00966 | 0.00363 | 0.00292 | 0.00417 | 0.00966 |
| R2 | 0.698 | 0.707 | 0.398 | 0.408 | 0.642 | 0.649 | 0.345 | 0.349 |
| N | 4887 | 4625 | 4903 | 4640 | 4887 | 4625 | 4903 | 4640 |

Notes: This table provides estimates for equation (6) in Columns 1 to 4. In Columns 5 and 8, we estimate equation (6), using first price as an instrumental variable. Controls include: number of household members aged 6-14, the first principle component of an asset index, mother's years of schooling, a dummy for whether the student is female, whether the student attends private school, and whether he/she attended tuition in the past year.

* significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent

Table 9: Demand for Pratham and Non-Pratham Tuition Classes

| | Dependent Variable | | | | | |
|---|---|---|---|---|---|---|
| | Attended Pratham Tuition | | Attended Non-Pratham Tuition | | Attended Any Tuition | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Price in 100's | -0.171*** | | -0.0451*** | | -0.0756*** | |
| | (0.00683) | | (0.00771) | | (0.00725) | |
| Price=Rs.75 | | -0.209*** | | -0.0725*** | | -0.102*** |
| | | (0.0194) | | (0.0219) | | (0.0206) |
| Price=Rs.150 | | -0.342*** | | -0.0649*** | | -0.130*** |
| | | (0.0182) | | (0.0206) | | (0.0194) |
| Price=Rs.200/250 | | -0.429*** | | -0.119*** | | -0.194*** |
| | | (0.0174) | | (0.0196) | | (0.0185) |
| Controls | YES | YES | YES | YES | YES | YES |
| Mean of Dep. Var | 0.329 | 0.329 | 0.680 | 0.680 | 0.723 | 0.723 |
| R2 | 0.347 | 0.351 | 0.157 | 0.158 | 0.190 | 0.191 |
| N | 5067 | 5067 | 5067 | 5067 | 5067 | 5067 |

Notes: This table provides estimates for equation (1) in Columns 1 and 2. In Columns (3) and (4), we estimate a flexible specification, where we replace the first price with dummies for each first price that was offered. The omitted category in this case is a price of 0. Controls include all variables listed in Table 2.

* significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent

Table 10: TREATMENT EFFECTS OF ATTENDING ANY TUITIONS

| | Pratham Tuitions | | Any Tuitions | |
|---|---|---|---|---|
| Dependent Variable: | English Score | Math Score | English Score | Math Score |
| | (1) | (2) | (3) | (4) |
| Attended Tuition | 0.0251 | -0.0810 | 0.0619 | -0.234 |
| | (0.0590) | (0.0833) | (0.154) | (0.225) |
| Controls | YES | YES | YES | YES |
| R2 | 0.649 | 0.349 | 0.650 | 0.329 |
| N | 4625 | 4640 | 4625 | 4640 |

Notes: This table provides estimates of equation (6), using first price as an instrumental variable. Controls include all variables listed in Table 2.

* significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent

Table 11: HETEROGENEITY IN TREATMENT EFFECTS

| | Math | English |
|---|---|---|
| | (1) | (2) |
| *Panel A: Pretest Score* | | |
| Below Median Pretest Score | -0.0439 | 0.0550 |
| | (0.102) | (0.0642) |
| Above Median Pretest Score | -0.0347 | 0.0295 |
| | (0.108) | (0.0883) |
| p-value: Bottom=Top | 0.945 | 0.791 |
| N | 4903 | 4887 |
| *Panel B: Gender* | | |
| Female | -0.0633 | 0.132* |
| | (0.101) | (0.0726) |
| Male | 0.0163 | -0.0326 |
| | (0.103) | (0.0733) |
| p-value: Male=Female | 0.531 | 0.0696 |
| N | 4899 | 4883 |
| *Panel C: Wealth* | | |
| Below Median Wealth | -0.0571 | 0.151** |
| | (0.0966) | (0.0689) |
| Above Median Wealth | -0.0251 | -0.0778 |
| | (0.113) | (0.0806) |
| p-value: Poorest=Wealthiest | 0.806 | 0.0136 |
| N | 4855 | 4840 |

Notes: Controls include all variables listed in Table 2.

* significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent

# Appendix

Figure A1: Scratch Cards

Table A1: Correlates of WTP-Constrained Logit Model

| | Dependent Variable: Attended Any Class | |
|---|---|---|
| | (1) | (2) |
| # HH Members Age 19+ | -0.0119 | -0.0367 |
| | (0.0311) | (0.0337) |
| # HH Members Age 15-18 | -0.217*** | -0.264*** |
| | (0.0513) | (0.0553) |
| # HH Members Age 6-14 | 0.0367 | 0.0431 |
| | (0.0374) | (0.0403) |
| # HH Members Age 0-5 | 0.0285 | 0.0226 |
| | (0.0577) | (0.0619) |
| 1st PC of Durables Ownership | -0.0293 | -0.0232 |
| | (0.0254) | (0.0274) |
| Mother education (years) | 0.00302 | 0.00457 |
| | (0.00937) | (0.01000) |
| Female | -0.190*** | -0.134* |
| | (0.0729) | (0.0780) |
| Attends Private School | -0.720*** | -0.636*** |
| | (0.139) | (0.148) |
| Attended Tuition Past Yr | 0.0820 | 0.0872 |
| | (0.0997) | (0.106) |
| Normalized Math Score | 0.0803* | 0.0604 |
| | (0.0415) | (0.0452) |
| Normalized English Score | 0.0568 | 0.0224 |
| | (0.0455) | (0.0490) |
| Attended Pratham Tuition Prior Year | 2.084*** | |
| | (0.102) | |
| Grade 7 | 0.0774 | |
| | (0.0868) | |
| Grade 8 | 0.0950 | |
| | (0.0886) | |
| Stratum Dummies | NO | YES |
| Mean of Dep. Var | 0.329 | 0.319 |
| N | 5067 | 4968 |

Notes: This table provides estimates for a logit model for estimating the parameters for equation (2), with equation (3) as the latent model. Enrollment is regressed on characteristics and offer price using a logit model, with the coefficient on offer price constrained to be -1. This scales coefficients relative WTP in '00s of rupees.
* significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent