Evaluating the impacts of public student subsidies to low-cost private schools in Pakistan

Felipe Barrera-Osorio, and Dhushyanth Raju

This version: November 2014

Abstract: We examine the impacts of accountability-based public per-student subsidies provided to low-cost private schools in Punjab, Pakistan on student enrollment and school inputs. Program entry is contingent on achieving a minimum pass rate on a specially-designed academic test. We use regression discontinuity to estimate impacts on schools that joined the program in the last entry round (phase 4) before follow-up survey data collection. We find large positive impacts on school enrollment, number of teachers, and other inputs for program schools near the minimum pass rate.

JEL classification codes: I21, I28, O10

Keywords: education, accountability, Pakistan, regression discontinuity design, public subsidies, private schools

Contact information: Barrera-Osorio: Graduate School of Education, Harvard University, barrerfe@gse.harvard.edu; Raju: World Bank, draju2@worldbank.org. We thank the staff of the Punjab Education Foundation, in particular Usman Tariq Bhatti, Mian Kashif Ijaz, Shahid Hafiz Kardar, Allah Bakhsh Malik, Haroon Raheem, and Huma Rizvi for extensive discussions on program design and implementation and assistance with the program administrative data; HTSPE Pakistan for field survey administration; Corinne Saiens for assistance with the National Education Census data; Amit Dar, Michelle Riboud, Sofia Shakil, Huma Ali Waheed, and the Government of Punjab's School Education Department/Program Monitoring and Implementation Unit for encouragement and support; and Salman Asim, Elizabeth King, Leigh Linden, Richard Murnane, Quynh T. Nguyen, two anonymous referees, and participants at the 2009 NBER Program on Children Meeting for helpful comments and suggestions. Financial support from the World Bank's Education Program Development Fund and Bank-Netherlands Partnership Program Trust Funds is gratefully acknowledged. The findings, interpretations, and conclusions expressed herein are our own and do not necessarily represent the views of the World Bank, its Board of Directors, or any of its member countries. All remaining errors are our own.

1. Introduction

In 2012/2013, estimated net enrollment rates in Pakistan were 68% at the primary school level, 38% at the middle school level, and 26% at the high school level (2012/2013 Pakistan Social and Living Standards Measurement [PSLM] survey report, Pakistan Bureau of Statistics).¹ These levels are low in absolute terms, relative to other countries in the South Asia region, and relative to other developing countries at Pakistan's per capital income level. Given the trend to date, the United Nations Educational, Scientific and Cultural Organization (UNESCO) reports that Pakistan is unlikely to meet the United Nations' Millennium Development Goal of universal primary education by 2015 (UNESCO 2014). Initiatives that produce significant, sustained gains in school participation are therefore critical.

The public school system is the predominant provider of education in Pakistan, including in Punjab province, the site of our evaluation. In 2012/2013, 61 percent of primary school students in the province were in public schools (2012/2013 PSLM survey report, Pakistan Bureau of Statistics). Qualitative and quantitative evidence suggests that the public school system has been hampered in its ability to effectively and efficiently increase and improve schooling inputs—leave alone increase school quality and, in turn, education outcomes—mainly due to poor system governance and accountability (see, for example, Social Policy and Development Centre 2003).

Against this backdrop, the Punjab government has begun contracting the sizable and growing low-cost private school system in the province to deliver schooling with a minimum level of quality to poor households. Importantly, under these public-private partnership (PPP) initiatives, the government expects to hold private schools accountable for meeting contract terms.² The question that remains is whether the government succeeds in doing this when it has

largely failed to hold itself accountable for its own basic service delivery performance. Indeed, the effectiveness and efficiency of public budgetary allocations towards PPP initiatives in education depends on the answer.

In this paper, we evaluate the causal effects of an accountability-based public subsidy program to low-cost private schools in the province of Punjab, Pakistan on school enrollment and inputs. Administered by the Punjab Education Foundation (PEF), the Foundation Assisted Schools (FAS) program leverages the low-cost private school system in the province in an attempt to increase equitable access to schooling. The program offers a monthly per-student cash subsidy. To participate in the program, schools must offer free schooling to all enrolled children and achieve a minimum pass rate on a standardized academic test administered by PEF semiannually. Unlike standard subsidy programs which directly finance school inputs (Gauri and Vawda 2003), program schools are free to decide how to spend the subsidy.

The FAS program was initiated in November 2005 and expanded in phases. At the time of our follow-up field survey data collection in May 2009, the program had completed four phases of expansion, and covered 474,000 students in 1,082 low-cost private schools at the primary, middle, and secondary school levels in 18 of Punjab's 35 districts.³ In districts with the highest concentration of program schools, the program covered approximately one-fifth of all recorded private schools.

To the best of our knowledge, credible evidence on the impacts of public subsidies to private schools is limited. The study by Kim, Alderman, and Orazem (1999) is particularly pertinent as they evaluate a public subsidy program in Pakistan which shares some of the design elements of the FAS program. Using a difference-in-differences approach, Kim et al (1999) evaluated a public subsidy program in a randomly-selected subset of poor urban neighborhoods

in Balochistan province. They found that the program substantially increased both girls' and boys' school participation and that these increases were obtained at a lower cost than would be possible through the public school system. The few well-identified evaluation studies of the impacts of publicly-supported private schools contrast sharply with the rising use of such initiatives around the world (World Bank 2009).

Our study seeks answers to two questions. First, what is the causal effect of the FAS program on the number of students in program schools? Second, what is the causal effect of the program on inputs, namely the number of teachers, classrooms, and toilets, as well as student-teacher and student-classroom ratios in program schools? To answer these questions, we take advantage of the treatment assignment process for schools. Schools were either treated (a program school) or untreated (a rejected school) on the basis of their test pass rates relative to a cutoff. This assignment process allows us to use sharp regression discontinuity (RD) to identify the causal effect of the program. We validate the RD design using administrative data from the program application process. We estimate impacts on schools that entered the program in phase 4, the last entry round before our follow-up data collection, and were close to the test pass rate cutoff. Follow-up data were obtained from a field survey administered 17 months after phase-4 schools entered the program.

We find robust evidence of positive impacts on the number of students, teachers, and classrooms and negative impacts on student-classroom ratios for phase-4 program schools close to the pass rate cutoff. Program impacts were sizable both in absolute terms and relative to baseline means. Our conservative estimates indicate that, within 17 months, the program expanded schools by, on average, 137 students (+59%), 4 teachers (+46%), and 4 classrooms (+47%) and reduced student-classroom ratios by, on average, 4 students per classroom (−14%).

Our cost-effectiveness analysis indicates that the FAS program is among the cheapest interventions in developing countries for generating enrollment gains.

The estimated impact on enrollment must be interpreted cautiously given that we are unable to establish the extent to which the documented enrollment gains translate into school participation gains. If schools that join the program become more attractive vis-à-vis other schooling options, the program is likely to induce both displacement and diversion effects: some share of the new enrollment in the program school will likely come from students already enrolled in other schools or children that were initially considering enrolling elsewhere.

We are also unable to establish the aggregate household welfare effects of the program. The fact that enrollment has increased in program schools suggests that households have reoptimized their schooling decision in favor of program schools. Holding everything constant, we predict that the elimination of school fees in program schools raises aggregate household welfare. Information on student academic achievement (given a short evaluation window), school attainment, outcomes in labor and other markets, and outcomes related to quality of life (given a longer evaluation window) would be useful for ascertaining aggregate welfare effects across multiple, pertinent dimensions.

The remainder of the paper is organized as follows. Section 2 describes the education context at the time the FAS program was introduced. Section 3 describes the program. Section 4 presents our identification and estimation strategy. Section 5 describes the data and presents summary statistics. Section 6 presents our impact and cost-effectiveness estimates. Section 7 summarizes and interprets our main findings and discusses potential threats to internal validity, external validity, and welfare implications.

2. Context

The FAS program was conceived and introduced into an education landscape characterized by three major features: first, poor and inequitable school participation; second, a weak public school system, which remains the dominant service provider; and third, a rapidly growing private school system with the potential to address poor and inequitable school participation.

The education situation of Punjab—Pakistan’s most prosperous and populous province and the site of the FAS program—is by and large comparable to the rest of the country. At the time the FAS program was initiated, the estimated school participation rate for children ages 6 to 15 was 65.7% in the province.⁴

The public school system has been hampered in its ability to improve education outcomes due to, in large part, the lack of effective accountability and incentive systems which promote the legitimate and efficient use of allocated resources (Government of Pakistan 2009, Social Policy and Development Center 2003). While the public school system has struggled to enroll and educate children, the private school system has grown in both numbers and share of enrollment. In addition, responding to the broad demand for greater access and better quality, the system has evolved in character, becoming more egalitarian, less elitist, and increasingly reaching low-income and rural households.⁵ Using private school census data from 2000, Andrabi, Das and Khwaja (2008) found an exponential increase in the number of private schools in the 1990s, with more than one-half of current private schools established after 1995. Furthermore, they found that schools established before 1990 came up predominantly in urban areas, but, subsequently, schools have increasingly come up in rural areas.

The increase in the share of enrollment in private schools parallels the growth in the number of private schools. In 2004/05, 15.8% of children ages 6 to 15 were enrolled in private

schools in Pakistan; in Punjab, 18.5% of the corresponding population was enrolled in private schools. These percentages represent cumulative increases of 40.7% and 37.4%, respectively, since 1998/99. Andrabi et al. (2008) found that the growth rate in private school enrollment over the 1990s was highest among low-income households nationally, and among middle-income households in rural areas. In contrast, public school enrollment declined in both urban and rural areas and across the household income distribution over the same period.

Andrabi et al. (2008) also found that fees for private schools were generally low and constituted a small percentage of mean annual household expenditure. In 2000, median annual fees per student in all of Pakistan were 960 rupees (US\$23.4) in urban areas and 751 rupees (US\$18.3) in rural areas.⁶ The corresponding statistics for Punjab were lower, at 828 rupees (US\$20.2) and 600 rupees (US\$14.6), respectively. These private schools are affordable due to their low operating costs. One main cost component is labor: teachers. Private schools tend to be staffed by young, unmarried women with low levels of education and little or no formal training in teaching. Average pay for private school teachers is also paid substantially less than for public school teachers, even after accounting for differences in the characteristics of teachers between the two school types (Andrabi, Das, Khwaja, Vishwanath, & Zajonc, 2008).

Finally, there is growing evidence that private schooling is associated with higher student academic achievement in Pakistan (Alderman, Orazem, and Paterno 2001; Aslam 2003; Aslam 2009; Andrabi, Bau, Das, and Khwaja 2010; Andrabi, Das, Khwaja, and Zajonc 2011). Among these studies, Andrabi et al. (2010) identify the causal effect of private schooling on student academic achievement for primary-grade students in selected villages in Punjab via an instrumental variables strategy. They find that average student academic achievement in private schools is 0.8–1.0 standard deviations higher than in public schools.

3. The Foundation-Assisted Schools Program⁷

Program description: The FAS program is administered by PEF, a publicly-funded, semi-autonomous statutory organization established in 1991. PEF serves as the main institutional mechanism for education PPPs in Punjab. The organization's primary aims are to enable poor households to access private education with a minimum level of quality. PEF spent 1.1 billion rupees (US\$12.9 million) on benefits under the FAS program.⁸ This amount accounted for 61% of total expenditures by PEF in fiscal year 2007/2008. As of September 2008, the program had completed four entry phases, and covered 1,082 private primary, middle, and secondary schools in 18 out of Punjab's 36 districts. Of these, 945 program schools (87%) were located in just seven districts. This number of program schools represents a sizeable percentage of all private schools in these seven districts: using the 2005 National Education Census, a census of schools in Pakistan, we estimate that the program covered 21% of private schools in these districts.

The program was initially designed to target districts that ranked lowest in adult literacy rates based on data from the 2003/04 Multiple Indicators Cluster Survey (Government of Punjab 2004). In phases 1 and 2, however, this targeting strategy was not applied due to limited institutional and logistical capacity in PEF (Malik 2007). In phases 3 and 4, the targeting strategy was effectively applied. Consequently, 51% of program schools were located in districts ranked in the bottom-quarter, and 89% were located in those districts ranked in the bottom-half of literacy rankings.

Table 1 presents the distribution of program schools by selected characteristics measured in September 2008. Looking at all four phases together (Column 5), the mean school size was 351 students, 59% of schools were middle level, 83% were coeducational, 87% were registered with local government authorities, and 55% were rural. The distribution of program schools in

each phase (Columns 1 to 4) was roughly comparable, with the exception of the school's level. Phase-1 and phase-2 program schools were mainly secondary schools (65% and 73%), whereas phase-3 and phase-4 program schools were mainly middle schools (60% and 69%). School size appears to be decreasing with each phase: the mean size of phase-1 program schools was 561 students, whereas that of phase-4 program schools was 242 students. There may be many explanations for this pattern, among which is the length of exposure to the program.

Program benefits and eligibility: The main program benefit is an enrollment-related subsidy. The program school receives a monthly per-student cash subsidy of 300 rupees (US\$3.5) up to a maximum of 750 students.⁹ Given a mean school size of 215 students at the time of application to the program, the mean monthly subsidy payment to a program school was roughly 64,500 rupees (US\$759) at program entry. Enrollment information for determining the size of the subsidy was submitted by program schools to PEF on a monthly basis using standardized reporting forms. If enrollment increased by 50 students or more over one month, PEF visited the school to verify the information before raising the subsidy. PEF indicated that large changes in enrollment mostly occurred in April, at the start of the school year.

PEF reports that the subsidy level was set low for two reasons. First, it confines the attractiveness of the program to low-cost private schools. Second, it raises the political palatability of the program as the per-student subsidy amount is less than half of the estimated per-student expenditure in the public school system at the time the program was introduced.¹⁰ The subsidy benefit is paid for all twelve months of the year. To facilitate timely and regular payments, starting in August 2007, the benefit amounts have been transferred electronically to the bank accounts of program schools.

Entry into the program followed a three-step process. In step one, PEF issued a call for applications in newspapers. Eligibility was restricted to existing private primary, middle, and secondary schools with a minimum enrollment of 100 students from the districts listed in the call. With few exceptions, only schools that submitted properly-completed applications by the announced deadline were considered for the next step. In step two, PEF inspection teams visited schools to further screen them, a largely subjective exercise. In step three—introduced starting with phase 3—schools were required to take a test. All students in selected grades who were present in school on the day of the inspection were given a standardized academic test called the Short Listing Quality Assurance Test (SLQAT), a pared-down version of the Quality Assurance Test (QAT) used to determine continuing benefit eligibility once schools enter the program.¹¹ The SLQAT is 55-minute, written, curriculum-based test. It tests knowledge and comprehension in three subjects: English, Urdu, and mathematics. The grades to be tested were randomly selected by PEF and were not disclosed in advance. The school qualified for the program if at least 67% of tested students score 33% or higher on the SLQAT.

According to PEF records, of the 1,430 schools that submitted properly filled-in applications and were inspected in phase 4, 872 (61%) were offered the SLQAT. Of these schools, 431 (49%) achieved the minimum pass rate and qualified for the program.¹² And of these schools, 425 (98%) signed the program participation agreement.

Continuing benefit eligibility conditions and incentives: The program participation agreement stipulated multiple conditions for continuing benefit eligibility. Three conditions were stringently applied by PEF: the program school must (1) offer schooling without charge to its students; (2) place and maintain a PEF-issued signboard outside the school gate which notes, among other things, that the school offers free schooling and the contact information for PEF for

parents and the public to obtain additional information or register complaints; and (3) participate in the QAT and at least 67% of the tested students must score 40% or higher on the test.^{13 14}

Only a handful of program schools were disqualified for any reason, and only 28 out of the 1,111 program schools (2.5%) exited the program (Table 2). In addition, most disqualifications were due to two consecutive failures to achieve the minimum pass rate on the QAT. Importantly, for our study, only one phase-4 program school exited the program for any reason.¹⁵ Thus, program dropout was not an issue for phase-4 program schools.

The structure of the program (both the benefits and benefit maintenance conditions) can be expected to have a positive effect on education outcomes via multiple channels. First, setting the monthly subsidy in direct proportion to the number of children enrolled creates an incentive to draw in additional students. Second, conditioning the receipt of program benefits to the elimination of school fees—which lowers the costs of program schools in relation to competing private schools and matches public schools—is likely to raise the attractiveness of program schools, particularly for households for which school fees are a major constraint to sending children to private school. Third, public communication through the signboard placed outside the school gate is likely to raise public confidence in the program and, hence, the attractiveness of program schools.

Fourth, the program's structure can directly affect investments in the quantity and quality of school inputs and resources. For example, increases in enrollment induced by the per-student subsidy must be met by increased numbers of classrooms and teachers in order to comply with stipulated maximum student-teacher and student-classroom ratios. The mandated ratios require program schools that are out-of-compliance to build additional classrooms and hire additional teachers. Physical infrastructure and learning environment conditions require program schools to

conform to proper design and construction when they expand, and that they invest in teaching tools (for example, blackboards) and basic facilities (for example, toilets) as enrollment grows. These input-related conditions encourage schools to schedule investments and resources to either anticipate or accompany increases in enrollment. However, given that these conditions are not stringently applied, investments in school inputs and resources may lag behind enrollment increases, although, reportedly, lag-time was short.

4. Empirical strategy

Given that phase 4 was the last entry phase at the time we conducted the evaluation, schools that took the phase-4 SLQAT were either treated (a program school) or untreated (a rejected school) on the basis of their SLQAT pass rate relative to the cutoff (i.e., the probability of treatment jumps from 0 to 1 at the cutoff). This structure allowed us to apply a sharp regression discontinuity (RD) design.¹⁶ Under some mild regularity conditions, we identify the average causal effect of the treatment on the treated at the cutoff. We estimate the effect nonparametrically using local linear regression.

Identification: Following the exposition in Imbens (2004), Van der Klaauw (2008) and Todd (2007), let y_i denote the outcome of interest (for example, enrollment) in school i , and let the indicator variable $d_i \in \{0,1\}$ denote treatment assignment, where 1 denotes that the school is covered by the FAS program (treated), and 0 if not (untreated). In addition, let y_{0i} and y_{1i} denote the potential outcomes of school i in the untreated and treated states, respectively. The actual outcome observed for school i is given by

$$y_i = d_i y_{1i} + (1 - d_i) y_{0i} = y_{0i} + [y_{1i} - y_{0i}] d_i = y_{0i} + \alpha_i d_i, \quad (1)$$

where α_i denotes the treatment effect for school i .

To estimate causal effects we use an institutional feature of the program: eligibility is ultimately determined by the student pass rate obtained by the school on the SLQAT relative to the known pass rate cutoff of 67%. Given that virtually all schools that become eligible to participate in the program also chose to participate in the program, in practice, the cutoff determines program participation. Thus, program participation status is assigned based on the decision rule

$$d_i(z_i) = 1\{z_i \geq c\}, \quad (2)$$

where z_i denotes school i 's pass rate which is perfectly observed (z is more generally referred to as the assignment variable), c the known distinct cutoff pass rate, and $1\{\cdot\}$ an indicator function.

Under the assumptions that (1) the limit $\lim_{e \downarrow 0} E[y_{0i} | z_i = c + e]$ (where $e_i > 0$ denotes an arbitrarily-small number) is well defined; (2) $E[y_{0i} | z_i = c]$ is continuous in the assignment variable z at the cutoff (i.e., the conditional expectations of the outcome variable exhibits local smoothness at the cutoff in the absence of the treatment); and (3) the density of the assignment variable z is positive in the neighborhood of the cutoff, the difference in the mean outcomes between marginal passers and marginal failers,

$$E[\alpha_i | z_i = c] = \lim_{e \downarrow 0} E(y_{1i} | z_i = c + e) - \lim_{e \downarrow 0} E(y_{0i} | z_i = c - e). \quad (3)$$

identifies the average treatment effect on the treated at the cutoff (Hahn, Todd, and Van der Klaauw 2001; Todd 2007). A sharp RD design neatly fits the phase-4 SLQAT taker data, as the school's pass (eligibility) versus fail (ineligibility) status remains fixed given that phase 4 was the last entry phase before the follow-up data collection.

Estimation: Given that we are interested in estimating treatment effects at a single point using observations in its neighborhood, one suitable approach is local smoothing using

nonparametric regression. Following Hahn et al. (2001), we opt for local linear regression (a local polynomial of order one). Local linear estimation for a sharp RD design entails individually estimating the conditional expectations of the outcome y at the cutoff from below and above the cutoff, and then subtracting the two estimates. Standard errors, clustered at the district level, are derived following the robust procedure proposed by Calonico, Cattaneo, and Titiunik (2014).

Choice of kernel and bandwidth: Implementing local linear estimation requires specifying the kernel k , the weighting function, and bandwidth $h > 0$, the window width in which the kernel function is applied. We opt for the triangular kernel given that it is boundary optimal and, thus, well suited to RD problems (Cheng, Fan, and Marron 1997).¹⁷

The bandwidth is a relatively more important decision given the trade-off between estimation bias and variance. To select the optimal bandwidth, we use the data-driven procedure proposed by Imbens and Kalyanaraman (IK) (2012). We however check whether statistical inference is robust to alternative bandwidths around the optimal bandwidth, namely 75% and 125% of the optimal bandwidth.

5. Data and Sample

Data

Baseline data come from the phase-4 application records and SLQAT test records collected and maintained by PEF. The data are obtained from only properly-completed forms received by PEF before the announced deadline of July 2007. PEF collected 1,430 properly-completed application forms in phase 4.¹⁸

PEF constructed school-level electronic databases to store applicant information. The data included school characteristics (location, gender type, level, physical infrastructure, and registration status), total school enrollment by gender, total number of teachers and

administrative staff by gender, and the minimum and maximum monthly teacher salaries in the school.¹⁹ These databases serve as the source of baseline data for the following outcomes measured at the school level: number of students, teachers, classrooms, and toilets. School-level outcomes of student-teacher and student-classroom ratios were also constructed using the data on numbers of students, teachers, and classrooms. The databases also serve as the source of baseline data on school-level covariates, namely location, gender type, level, and registration status.

The SLQAT pass rate serves as the treatment assignment variable z . PEF constructed electronic databases for SLQAT takers, containing the total score for each test-taker. Student test scores were organized by school, and within each school, by grade. The school identification information in the databases included the school's name (and occasionally some address elements) and location (tehsil and district).²⁰ We use the student test score data to calculate our own school SLQAT pass rates. Our calculations and PEF's match almost perfectly, at 99.5%. We use our pass rates for the analysis.

Constructing a single electronic database for this analysis required linking the application data to the SLQAT data at the school level. School identification variables were not consistent across databases. Consequently, an iterative visual-matching process was used to link the two databases. First, schools were matched across databases using the district name and school name.²¹ Exact matching failed in a number of cases due to inconsistencies in spelling, word order, and completeness of the school's name. In these cases, we matched on the basis of key words and word patterns. In cases in which a unique school record could not be found, the set of matching variables was extended to include school address wherever possible. This extension helped resolve a number of questionable cases. On the basis of this exercise, 94% of school

records in the SLQAT databases were linked to school records in the application database, yielding a sample size of 830 schools. We call this sample the “SLQAT sample”.

Follow-up data come from a field survey administered to schools with SLQAT pass rates between ± 15 percentage points of the cutoff in May 2009, 17 months after phase-4 program schools received their first subsidy payment. The school sample size within the selected pass rate range is 319 schools. This number constituted 38% of the SLQAT sample and is referred to as the “cutoff neighborhood sample”.

At each sample school, the field survey interviewer collected information from school administrators or head teachers on the number of students, teachers, classrooms, and toilets, among other variables. Out of the 319 schools in the cutoff neighborhood sample, 303 schools (95%) participated in the field survey. The remaining schools were visited but were found to be permanently or temporarily closed. Closure rates of marginal failers and marginal SLQAT passers are similar.

Sample

Table 3 presents the distribution of schools by selected characteristics measured at baseline for the SLQAT sample, the full cutoff neighborhood sample, $z \in [52, 82]$, and a narrower cutoff neighborhood sample, $z \in [62, 72]$. Two patterns are evident. First, across the three samples, the distributional patterns for the characteristics are broadly comparable. For example, the majority of schools are middle schools (69%–72%), coeducational (83%–87%), officially registered (81–84%), and rural (59%–61%). Second, the distributional patterns for the characteristics are similar for the two cutoff neighborhood samples.

Table 4 presents means and standard deviations for the outcomes of interest measured at baseline, again separately for the SLQAT sample and the two cutoff neighborhood samples. In the SLQAT sample, schools had, on average, 222 students, 9 teachers, 8 classrooms, and 3 toilets. Average student-teacher and student-classrooms ratios were 26:1 and 28:1, respectively. These ratios were already at baseline below the stipulated maximums required for program participation. Relative to the SLQAT sample, schools in the cutoff neighborhood samples appear to be slightly larger. Mean outcomes are similar across the two cutoff neighborhood samples.

6. Results

A. Model specification tests

The literature on RD estimation suggests several specification tests (see, for example, Imbens and Lemieux 2008). First, we test whether there is any discontinuous change in the conditional probability of treatment at the SLQAT pass rate cutoff, given that the suitability of the RD model hinges on this feature of the data. Second, we test whether the density function of the SLQAT pass rate exhibits local smoothness at the cutoff. Third, we test the identifying condition that the conditional mean untreated outcomes at the cutoff exhibit local smoothness using our baseline data on outcomes.

Discontinuity in the probability of treatment at the cutoff

Figure 1 plots local linear regression functions for the probability of treatment estimated separately above and below the cutoff for schools in the cutoff neighborhood sample using the follow-up survey data. As expected, the probability of treatment jumps discontinuously from 0 to

1 at the cutoff. This pattern in the conditional probability of treatment motivates our selection of a sharp RD design for the phase-4 SLQAT sample.

Local smoothness in the density function of SLQAT pass rates

Rejection of local smoothness in the density of pass rates at the cutoff may suggest manipulation of pass rates. To assess this, we implement a test proposed by McCrary (2008) by separately estimating kernel density regressions below and above the cutoff point. We cannot reject smoothness in the density of pass rates at the cutoff.²²

Local smoothness in conditional mean outcomes at baseline

As a direct test of the identifying assumption, we examine whether mean outcomes measured at baseline satisfy local smoothness at the cutoff. Table 5 reports RD impact estimates of baseline mean outcomes at the cutoff based on local linear regressions for the optimal bandwidth (Column 1) and, as a robustness check, for 75% and 125% of the optimal bandwidth (Columns 2 and 3, respectively). Accompanying the table, Figure 2 plots the estimated local linear regressions for the outcomes, using the optimal bandwidth. In general, we do not find robust evidence to reject local smoothness at baseline. The one exception is classrooms: independent of the bandwidth (75%, 100% and 125% of optimal bandwidth), we find robust evidence that marginal failers have more classrooms on average than marginal passers at baseline.

B. RD impact estimates

Table 6 presents our RD impact estimates using the follow-up field survey data. The estimations are based on local linear regressions for the optimal bandwidth (Column 1), as well as for 75%

and 125% of the optimal bandwidth (Columns 2 and 3, respectively). Accompanying the table, Figure 3 plots the estimated local linear regressions for the outcomes, using the optimal bandwidth.

We find robust evidence of significant positive impacts on the number of students, teachers, and classrooms among marginal passers. We also find robust evidence of a significant negative impact on student-classroom ratios among marginal passers. The figures show a discernible structural change in the mean levels for these outcomes marginally above and below the cutoff. The most conservative estimates of impacts at the cutoff across the alternative bandwidths are 136.6 additional students (or +59%, relative to the baseline mean for the outcome in the cutoff neighborhood sample), 4.3 additional teachers (+46%), and 4 additional classrooms (+47%) and 4 less students per classroom (−14%).

We do not find robust evidence of impacts at the cutoff on the number of toilets and student-teacher ratios. The lack of a positive impact on the number of toilets is a concern given the large expansion in enrollment for marginal passers. The finding may suggest that PEF does not emphasize adding toilets as much it does other types of physical infrastructure, such as classrooms. Given the expansion in enrollment in marginal passers, the lack of an impact on student-teacher ratios suggests that program schools have expanded the number of teachers in lock-step with enrollment increases. This behavior may be driven in large part by PEF's condition that program schools maintain these ratios below stipulated levels. The ratios were already below these levels at baseline.

Falsification test: RD estimates at false cutoffs

As a falsification test, we estimate RD impact estimates using the follow-up field survey data at two arbitrarily-selected false cutoffs: 57% and 77%. The estimations are based on local linear regressions for the optimal bandwidth, as well as for 75% and 125% of the optimal bandwidth. The false cutoffs are equidistant from the true cutoff of 67%. We expect to find local smoothness in the conditional mean outcomes at these cutoffs. The subsample for the investigation at 57% is schools with SLQAT pass rates between 52% and 66%. Likewise, the subsample for the investigation at 77% is schools with SLQAT pass rates between 67% and 82%. We do not find robust evidence to reject local smoothness in the conditional mean outcomes at both false cutoffs.²³

Cost-effectiveness estimates

We estimate the cost-effectiveness of the program in relation to enrollment gains using two alternative methods. First, using the conservative estimate of the impact on enrollment (137 students), we derive the annual rupee cost of one additional student in a program school *induced* by the program. Given a baseline mean school size of 232 students for schools in the phase-4 cutoff neighborhood sample (which we treat as the number of children who would have attended the program school in the absence of the treatment) and an annual subsidy amount of 3,600 rupees (US\$42.4) per student, it costs 9,696 rupees ($=3,600 \times (232+137)/137$) (US\$114) to induce an additional student per year.²⁴ In comparison, this cost is less than one-third of the cost of inducing an additional student per year through conditional cash transfers to female students in public secondary schools in Punjab (Andrabi et al. 2008).

Second, following the approach by Evans and Ghosh (2008), we calculate the program's cost-effectiveness by deriving the annual per-student cost of increasing enrollment in program

schools by 1%. Using an annual subsidy of 3,600 rupees per student and the impact estimate on enrollment of 59%, we estimate a cost-effectiveness ratio of 61 rupees ($=3,600/59$) (US\$0.72). This estimated cost-effectiveness ratio compares extremely favorably with ratios of other evaluated education interventions across the developing world as reported in Evans and Ghosh. In fact, the estimated ratio for the FAS program ranks among the very lowest.²⁵ What is more, our estimated ratio surprisingly mirrors Evan and Ghosh's estimated ratio for the per-student subsidy program in Balochistan, Pakistan (see Kim et al. 1999) noted in Section 1.

7. Conclusion

In this paper, we estimate the impacts of accountability-based public per-student subsidies to low-cost private schools in Punjab, Pakistan on student enrollment and school inputs. Given poor public sector accountability, whether the government can hold partnering private schools accountable for complying with program conditions is an open question. For SLQAT takers in phase 4, we find robust evidence from applying a sharp RD design to the data that the program significantly increased the number of students, teachers, and classrooms and reduced student-classroom ratios among marginal passers. The impact estimates at the cutoff are sizable: our conservative estimates indicate that, within 17 months, the program expanded marginal passers by, on average, 137 students (+59%, relative to the mean baseline value for the outcome for cutoff neighborhood sample), 4 teachers (+46%), and 4 classrooms (+47%) and reduced student-classroom ratios by, on average, 4 students per classroom (−14%). Cost-effectiveness estimates suggest that the program is among the cheapest interventions in developing countries for inducing enrollment gains.

Two potential threats to the internal validity of impact estimates are present. These threats arise from design and implementation features of the program. The first threat is from program spillovers to nonprogram schools (of which marginal nonpassers are but a specific subset) that operate in the same local schooling markets as program schools. Design features of the program such as the free-schooling condition to maintain program benefits can alter the terms of local market competition. By giving program schools a competitive edge vis-à-vis nonprogram schools, impact estimates may be upwardly biased if, for example, they induce students (and also teachers) to shift from nonprogram to program schools. This in turn would lead to the shrinking (or, at an extreme, the shutdown) of nonprogram schools and/or discourage investments in the quantity and quality of inputs. On the other hand, the altered terms could downwardly bias impact estimates if they induce nonprogram schools to adapt to the competition, for instance, by ratcheting up investments in the quantity and quality of infrastructure and staff and/or altering fee structures to retain existing students and attract new students. Both types of effects could be present simultaneously. Consequently, the direction of the net effect is theoretically ambiguous.

The second threat arises from anticipation of future treatment. Program entry is not a one-off event. To date, there have been nine calls for applications over an eight-year period. Given this pattern, it is conceivable that nonprogram schools interested in joining the program might alter their behavior in anticipation of a future call for applications in an effort to increase the likelihood of program entry. These actions could, for example, take the form of nonprogram schools investing in more and better quality inputs and resources. Anticipation in this case would result in impact estimates being downwardly biased. In particular, behavioral changes due to anticipation might be most applicable to nonprogram schools which failed to achieve the SLQAT

pass rate cutoff in an earlier phase of entry (our marginal failers), as we would expect that the marginal costs of investments and efforts required for failers from a previous phase are likely to decrease as one approaches the cutoff from below.

When the RD model is applied to the correct data designs, it yields internally-valid estimates. However, the generalizability of these impact estimates is likely to be limited given that, in principle, they are only valid for narrowly-defined subpopulations. In the case of the phase-4 SLQAT test takers, the RD impact estimates are valid for low-cost private schools that successfully applied to the program, cleared the physical inspection, and obtained pass rates near the SLQAT cutoff. Even if we generalize our estimated impacts to be the average over the full range of SLQAT pass rates, the further generalizability of the impacts is limited by sample selection, since the SLQAT pass rate is only available for those schools which followed the three-step application process in the seven main program districts. This sample of schools may not be representative of low-cost private schools in program districts, let alone the larger population of low-cost private schools nationally. Given what we know about the steps preceding the SLQAT, the extent to which the sample of SLQAT takers diverges from the population of low-cost private schools is largely determined PEF's physical inspection screening. Evidently, this screening has bite: as mentioned before, only 61% of schools inspected, cleared the inspection and took the SLQAT in phase 4.

To end, the estimated impact on enrollment must be interpreted cautiously given that we do not establish the extent to which the documented enrollment gains translate into school participation gains. If schools that join the program become more attractive vis-à-vis other schooling options, the program is likely to induce both displacement and diversion effects: some

share of the new enrollment in the program school will likely come from students already enrolled in other schools or children that were initially considering enrolling elsewhere.

Understanding whether the program has produced aggregate welfare gains for households requires more information than we were able to gather for this evaluation. It also requires a more complex analysis. Specifically, we would need to evaluate the welfare distribution of households in the schooling markets which marginal failers are part of vis-à-vis the welfare distribution of households in the schooling markets which marginal passers are part of, with a clean separation between the markets of marginal failers and the markets of marginal passers. Given free choice for households, the enrollment gain in program schools suggests a welfare gain from households reoptimizing (under their same constraints households originally faced) in favor of program schools. If welfare is measured in terms of say monetary costs of schooling, holding everything else constant, we predict that the elimination of school fees in program schools generates aggregate welfare gains for households. If welfare is measured in terms of say student academic achievement, holding everything else constant, we predict that higher student academic achievement—induced by, among other things, the minimum QAT pass rate condition for continuing program eligibility—also generates aggregate welfare gains for households.

¹ The net enrollment rates at the primary, middle, and high school levels cover enrollment in grades 1 to 5 by children ages 6 to 10, enrollment in grades 6 to 8 by children ages 11 to 13, and enrollment in grades 9 and 10 by children ages 14 and 15, respectively.

² PPP initiatives are increasingly perceived in international policy circles as a promising mechanism for attaining key education goals (World Bank 2009). In addition, opportunities for introducing PPP programs of medium to large scale are emerging in several developing countries (for example, India, Kenya, and Nigeria) as the private education sector matures and becomes an important player in service delivery.

³ Primary schools are composed of grades 1 to 5. Middle schools are composed of grades 1 to 8 or 6 to 8. Secondary schools are composed of grades 1 to 10, 6 to 10, or 9 to 10.

⁴ Own estimate based on data from the 2004/05 Pakistan Social and Living Standards Measurement survey.

⁵ It is conceivable that much of the growth and change in the private school system is a direct response to the rigidities and shortcomings in the public school system.

⁶ The exchange rate in 2000 was 41 rupees per US dollar.

⁷ The information on the program presented in the paper reflects program design and administration until 2009.

⁸ In this and following sections, the exchange rate used for the conversions is 85 rupees per US dollar (effective March 2011). When the program was introduced in 2005, the exchange rate was roughly 60 rupees per US dollar; the rupee has steadily weakened since then.

⁹ The program also offers two cash bonuses. The first is a teacher bonus for a high level of school test performance. Once every school year, in program schools where at least 90% of students in tested classes obtain a score of 40% or higher in the QAT, up to five teachers selected by the school's administration each receive an award of 10,000 rupees (US\$118). The second is a competitive school bonus for top school test performance. Once every school year, in each of the seven main program districts, the program school with the highest share of students with a score of 40% or higher in the QAT is awarded 50,000 rupees (US\$588).

¹⁰ The exact subsidy amount was guided by a survey conducted by PEF in 2005 in selected districts which showed that the vast majority of private schools that operate in rural areas and disadvantaged urban neighborhoods charge between 50 to 400 rupees per month (US\$0.6 to 4.7) in fees. Based on this information, the subsidy amount was set at the upper-segment of this price range (Malik 2007).

¹¹ For schools that entered the program in phases 1 and 2, step 2 was the final entry step.

¹² Our own tallies based on the SLQAT data deviate slightly from the above numbers. We find that 856 schools took the SLQAT and, out of these, 432 schools achieved the minimum pass rate in phase 4.

¹³ The QAT is a 65-minute, written, curriculum-based test. It is administered twice a year in October–November (in the first term) and February–March (in the second term). Tested subjects are English, Urdu, mathematics, and science (general science in grades 1–8 and biology, chemistry, and physics separately in grades 9–10). The same procedures used to administer the SLQAT are largely followed with the QAT. One important difference is that, unlike with the SLQAT, the program school receives formal advance notice of the date of the QAT, and at least 80% of its students are expected to be in school on the day of the test.

¹⁴ There are also other conditions for continuing benefit eligibility. These include (1) registering the school with the District Registration Authority within one year of joining the program; (2) conducting only one class in a classroom in any period; (3) maintaining or upgrading the quality of the school's physical infrastructure (for example, adequate classroom space, properly-constructed rooms and buildings, sufficient ventilation, and sufficient artificial and natural light); (4) acquiring and maintaining adequate furniture and teaching tools (for example, benches, desks, and blackboards); (5) providing monthly reports to PEF on enrollment counts; (6) keeping student-teacher and student-classroom ratios below 35:1; (7) keeping enrollment above 100 students; and (8) not holding after-hours classes or tutoring services at the school. These additional conditions are applied more leniently. Typically, when PEF detects a violation among this subset of conditions, schools are provided with a warning and a grace period within which to comply. To date, no program schools have been disqualified for repeated violations of these conditions.

¹⁵ PEF reports that the three schools were problematic from the outset; the schools were ejected from the program for general noncompliance and nonperformance.

¹⁶ Schools that took the phase-3 SLQAT and failed had another opportunity to seek entry when phase 4 was announced. As a result, some phase-3 SLQAT “failers” reapplied to phase 4, cleared the physical inspection, retook the SLQAT, and passed it. In the working paper, we also present fuzzy RD impact estimates for phase-3 program schools.

¹⁷ While more sophisticated kernels are available, they do not provide any significant gain in asymptotic bias reduction. In general, parameter estimates appear to be robust to the choice of kernel (Imbens and Lemieux 2008).

¹⁸ The total number of unique applications received by PEF is unknown as all rejected applications were discarded.

¹⁹ As part of this inspection, the information provided by the school on the application form was verified. These inspection data would have been useful for checking the accuracy of the application data. They were however collected in paper form and not entered into an electronic database. Consequently, these data are unavailable for the purpose of this study.

²⁰ Tehsil is the geographical unit of government administration one tier below district. There are 127 tehsils in Punjab.

²¹ Although information on the school's tehsil was also available in both the application and test databases, this information was error-ridden. Consequently, this information was not used in the cross-database matching exercise.

²² Test results are available from the authors upon request.

²³ Falsification test results are available from the authors upon request.

²⁴ The annual subsidy amount per student is roughly equal to the annual *program amount* per student, as the per-student amounts for program administrative costs and the teacher and school bonuses add less than 1% to the amount. This is principally due to the large number of students currently covered under the program.

²⁵ This result remains qualitatively unaltered if we precisely follow the currency conversion and inflation adjustments steps taken by Evans and Ghosh to fix all ratios in 1997 US dollars.

References

- Alderman, H., Orazem, P.F. & Paterno, E.M. (2001). School Quality, School Cost, and the Public/Private School Choices of Low-Income Households in Pakistan. *Journal of Human Resources* 36(2):304–326.
- Andrabi, T., Das, J., Khwaja, A.I., & Zajonc, T. (2011). Do value-added estimates add value? Accounting for learning dynamics. *American Economic Journal: Applied Economics* 3:29–54.
- Andrabi, T., Bau, N., Das, J., & Khwaja, A.I. (2010). Bad public schools are public bads: Civil values and test scores in public and private schools. Manuscript.
- Andrabi, T., Das, J., & Khwaja, A.I. (2008). A dime a day: The possibilities and limits of private schooling in Pakistan. *Comparative Education Review* 52(3):329–355.
- Andrabi, T., Das, J., Khwaja, A.I., Vishwanath, T., Zajonc, T. & LEAPS team. (2008). Pakistan Learning and Educational Achievements in Punjab Schools (LEAPS): Insights to inform the education policy debate. World Bank Working Paper No. 43750.
- Aslam, M. (2009). The relative effectiveness of government and private schools in Pakistan: Are girls worse off. *Education Economics* 17(3):329–354.
- Aslam, M. (2003). The determinants of student achievement in government and private schools in Pakistan. *Pakistan Development Review* 42(4):841–876.
- Calonico, S., Cattaneo, M.D., & Titiunik, R. (2014). Robust nonparametric confidence intervals for regression-discontinuity designs. *Econometrica*, forthcoming.
- Cheng, M., Fan, J., & Marron, J.S. (1997). On automatic boundary corrections. *Annals of Statistics* 25(4):1127–1160.
- Evans, D., & Ghosh, A. (2008). Prioritizing educational investments in children in the developing world. RAND Working Paper 587.
- Gauri, V., & Vawda, A. (2003). Vouchers for basic education in developing countries: A principal-agent perspective. World Bank Policy Research Working Paper No. 3005. Washington, D.C.: World Bank.
- Government of Pakistan (Ministry of Education). (2009). *National Education Policy 2009*. Islamabad: Government of Pakistan.
- Government of Punjab, Pakistan (Planning and Development Department). (2004). *Punjab District-based Multiple Indicators Cluster Survey 2003–04*. Lahore: Government of Punjab.

- Hahn, J., Todd, P., & Van der Klaauw, W. (2001). Identification and estimation of treatment effects with a regression-discontinuity design. *Econometrica* 69(1):201–209.
- Imbens, G. W. (2004). Nonparametric estimation of average treatment effects under exogeneity: A review. *Review of Economics and Statistics* 86:4–30.
- Imbens, G. W., & Kalyanaraman, K. (2012). Optimal bandwidth choice for the regression discontinuity estimator. *Review of Economic Studies* 79(3):933–959.
- Imbens, G. W., & Lemieux, T. (2008). Regression discontinuity designs: A guide to practice. *Journal of Econometrics* 142(2):615–635.
- Kim, J., Alderman, H., & Orazem, P.F. (1999). Can private school subsidies increase schooling for the poor? The Quetta urban fellowship program. *World Bank Economic Review* 13(3):443–466.
- Malik, A. B. (2007). *Freedom of choice: Affordable quality education in public private partnership*. Lahore, Pakistan: Maqbool Academy Press.
- McCrary, J. (2008). Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of Econometrics* 142(2):698–714.
- Social Policy and Development Centre. (2003). *Social Development in Pakistan: Annual Review 2002-03*. Karachi: Social Policy Development Centre.
- Todd, P. (2007). Evaluating Social Programs with Endogenous Program Placement and Selection of the Treated. In: *Handbook of Development Economics*, eds. T. Paul Schultz and John Strauss, Vol 4., UK: Elsevier B.V.:3847–3894.
- United Nations Educational, Scientific and Cultural Organization (UNESCO). 2014. *EFA Global Monitoring Report 2013/4: Teaching and Learning: Achieving Quality for All*. Paris, France: UNESCO.
- Van der Klaauw, W. (2008). Breaking the link between poverty and low student achievement: An evaluation of Title I. *Journal of Econometrics* 142(2):731–756.
- World Bank. (2009). *The role and impact of public-private partnerships in education*. Washington, DC: World Bank.

Table 1. Mean characteristics of FAS program schools

Characteristic	Phase 1	Phase 2	Phase 3	Phase 4	All phases
	(1)	(2)	(3)	(4)	(5)
Students	561.40	547.42	373.83	241.66	351.18
<i>Level</i>					
Primary	0.02	0.05	0.05	0.11	0.07
Middle	0.24	0.31	0.60	0.69	0.59
Secondary	0.73	0.65	0.35	0.20	0.34
<i>Gender type</i>					
Coeducational	0.69	0.86	0.83	0.82	0.83
Girls-only	0.20	0.11	0.09	0.11	0.11
Boys-only	0.11	0.03	0.07	0.07	0.07
<i>Registration status</i>					
Registered	0.91	0.97	0.89	0.81	0.87
Unregistered	0.09	0.03	0.11	0.19	0.13
<i>Location</i>					
Urban	0.36	0.45	0.48	0.42	0.45
Rural	0.64	0.55	0.52	0.58	0.55
<i>N</i>	45	133	480	424	1,082

Notes: Statistics exclude the three higher secondary schools that are program schools. Statistics are constructed from administrative data from September 2008.

Table 2. FAS program participation status, by phase

Phase	Entrants	Disqualified, all reasons	Disqualified, double QAT failure	Current participation
	(1)	(2)	(3)	(4)
1	54	9	7	45
2	150	16	13	133
3	482	2	0	480
4	425	1	0	424
Total	1,111	28	20	1,082

Notes: Disqualification also includes voluntary exits. Statistics reflect program school participation status at the time of the follow-up data collection in May 2009.

Table 3. Distribution of schools by selected characteristics at baseline, SLQAT and cutoff neighborhood samples

Characteristic	SLQAT sample	Cutoff neighborhood samples	
	$z \in [0, 100]$	$z \in [52, 82]$	$z \in [62, 72]$
	(1)	(2)	(3)
<i>Level</i>			
Primary	0.12	0.12	0.12
Middle	0.72	0.70	0.69
Secondary	0.16	0.18	0.19
<i>Gender type</i>			
Coeducational	0.87	0.86	0.83
Girls only	0.08	0.08	0.08
Boys only	0.05	0.06	0.08
<i>Registration status</i>			
Registered	0.81	0.83	0.84
Unregistered	0.19	0.17	0.16
<i>Location</i>			
Urban	0.41	0.41	0.39
Rural	0.59	0.59	0.61
<i>District</i>			
Bahawalnagar	0.11	0.09	0.07
Bahawalpur	0.20	0.21	0.18
Jhang	0.11	0.14	0.18
Lodhran	0.12	0.09	0.13
Multan	0.16	0.20	0.10
Muzaffargarh	0.20	0.17	0.18
Rajanpur	0.10	0.09	0.14
<i>N</i>	830	319	120

Table 4. Summary statistics of outcome measures at baseline, SLQAT and cutoff neighborhood samples

Outcome measure	SLQAT sample	Cutoff neighborhood samples	
	$z \in [0, 100]$	$z \in [52, 82]$	$z \in [62, 72]$
	(1)	(2)	(3)
Students	221.66 (104.87)	231.76 (108.17)	234.73 (108.12)
Teachers	8.99 (3.70)	9.31 (3.76)	9.35 (3.68)
Classrooms	8.42 (3.82)	8.6 (3.75)	8.79 (3.59)
Toilets	2.95 (1.94)	2.97 (1.75)	3.18 (2.24)
Student-teacher ratio	25.56 (9.00)	25.54 (8.25)	25.74 (7.88)
Student-classroom ratio	27.99 (11.58)	28.25 (11.50)	28.30 (12.11)

Notes: Standard deviations in parentheses. z denotes the treatment assignment variable, the SLQAT pass rate.

Figure 1. Probability of treatment, cutoff neighborhood sample

Table 5. Local smoothness in conditional mean outcomes at baseline

Outcome measure	Cutoff neighborhood sample		
	h (1)	$0.75 \times h$ (2)	$1.25 \times h$ (3)
Students	-26.976* (16.04)	-40.965*** (15.42)	-21.817 (15.87)
Teachers	-0.688 (0.55)	-0.781 (0.50)	-0.607 (0.58)
Classrooms	-1.029*** (0.34)	-1.414*** (0.48)	-0.839*** (0.29)
Toilets	-0.272* (0.14)	-0.321** (0.16)	-0.252 (0.16)
Student-teacher ratio	-0.017 (0.89)	-0.706 (0.97)	0.279 (0.86)
Student-classroom ratio	1.261 (1.40)	0.968 (1.35)	1.213 (1.34)

Notes: * denotes statistical significance at the 10% level; ** at the 5% level; and *** at the 1% level. Sharp RD impacts estimated via local linear regressions with triangular kernel. h denotes optimal bandwidth determined via the method proposed by Imbens and Kalyanaraman (2012). Robust standard errors clustered at the district level reported in parentheses.

Figure 2. Local smoothness in conditional mean outcomes at baseline

Table 6. Discontinuity estimates of conditional mean outcomes using follow-up survey data

Outcome measure	Cutoff neighborhood sample		
	h (1)	$0.75 \times h$ (2)	$1.25 \times h$ (3)
Students	138.52*** (39.55)	136.56*** (41.42)	151.66*** (39.33)
Teachers	4.77*** (1.61)	6.33*** (1.96)	4.25*** (1.46)
Classrooms	6.22** (2.45)	5.31** (2.84)	4.01** (1.89)
Toilets	0.86 (1.41)	-0.10 (0.57)	0.52 (0.76)
Student-teacher ratio	-1.42 (1.90)	-6.12*** (1.31)	1.00 (1.74)
Student-classroom ratio	-12.26*** (3.88)	-16.75** (7.68)	-4.00* (2.08)

Notes: * denotes statistical significance at the 10% level; ** at the 5% level; and *** at the 1% level. Sharp RD impacts estimated via local linear regressions with triangular kernel. h denotes optimal bandwidth determined via the method proposed by Imbens and Kalyanaraman (2012). Robust standard errors clustered at the district level reported in parentheses.

Figure 3. Local discontinuities in conditional mean outcomes using follow-up survey data