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Public Schools *Can* Improve Student Outcomes: Evidence from a Natural Experiment in India

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Abstract

I exploit a natural experiment in education policy in India to examine the effects of creating high-quality public schools. The "model" schools program established schools that admit students through an entrance exam. I estimate the effect of model schools on educational outcomes using a fuzzy Regression Discontinuity Design based upon the entrance exam cutoffs. With a data set of over 63,000 students, I consider three dimensions: (i) academic achievement; (ii) educational attainment; and (iii) career choice. For academic achievement outcomes, attending a model school increases test scores in math by 0.38 standard deviations, in science by 0.26 sd, and in social science by 0.26 sd on average. Attending a model school also increases the probability of obtaining an A in tenth-grade by 20 percentage points. For educational attainment indicators, model schools increase the probability of joining pre-university by 11.5 percentage points. However, attending a model school has no effect on the choice of major in pre-university college. Furthermore, I estimate multiple local average treatment effects and find that model schools have a similar positive effect for students across the ability distribution. Lastly, the per-pupil expenditure in model schools is comparable to that of traditional public schools. Overall, this paper provides suggestive evidence that the quality of public schools can be raised but other barriers persist.

Keywords: School quality, developing countries, public schools, India

JEL Codes: H52, I21, I24, I28

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1 Introduction

The widespread consensus on the importance of education and its impact on income and well-being has propelled developing countries to increase access to education.[1] However, the increase in quantity has not been simultaneously met by an increase in quality. This has two consequences. First, the learning levels of children in public schools are abysmally low so the expanded access is unlikely to have a major impact on future earnings or provide access to high-paying occupations.[2] Second, many families with the capacity to pay for a private school are switching their children to the private sector.[3] Thus, an important question for public policy is whether raising the quality of public schools has any prospect of succeeding in developing countries. In this paper, I exploit a natural experiment in India to examine the effects of creating high-quality public schools.

The model schools program, launched in 2009, established public schools that have a superior infrastructure, high accountability, English as the default medium of instruction, and contract teachers. The objective was to start one exceptionally good public school in each of the educationally backward blocks (EBB) that could serve as an archetype for traditional public schools to emulate.[4] A block is considered educationally backwards if its female literacy rate was below the national average and its gender gap in literacy was above the national average in 2001.[5] I look at Karnataka, a southern state in India, where model schools start at grade 6 and end at grade 10. Karnataka has a total of 74 EBBs and the first cohort of model schools was admitted in 2009.

Measuring school quality is difficult. The primary reason is that students may select schools based on certain unobservable characteristics that contribute to educational achievement such as own ability, parents' education, and income. Hence, any higher achievement in model schools or private schools could result not from better school quality but rather due to the differences in the students' families. The model schools admission structure allows me to overcome the endogenous selection challenge. Admission into a model school in Karnataka is determined through an entrance exam. The exam is out of a total of 100 points and students are tested on

[1] For literature on the effects of education on earnings, health, smoking, and other outcomes, see Card (1999), Long (2010), Oreopoulos and Salvanes (2011), Oreopoulos and Petronijevic (2013), Heckman et al. (2018). For developing countries, see Peet et al. (2015).

[2] For instance, in 2018, 55 percent of fifth-grade children in public schools in India could not read a second-grade textbook (ASER, 2018). See Bold et al. (2017) for a similar statistic for various African countries.

[3] For literature on private schooling phenomenon, see Muralidharan and Kremer (2006) and Kingdon (2017) for India, Tooley et al. (2007) for Ghana, Rose (2003) for Malawi and Alderman et al. (2001) for Pakistan.

[4] A block is an intermediate geographical cluster between a village and a district. A block is also called as 'taluk' or 'subdistrict'.

[5] The goal of improving the female literacy rate was not the primary motivation of placing the government-run model schools in EBBs. The model schools program was part of a broad initiative to improve the quality of public schools. See page 34 of the Eleventh Five Year Plan for further details.

languages, math, science, social science, general knowledge, and cognitive ability. The entrance exam is conducted at the block level; hence, students residing in a particular block compete for the model school in that block.[6] Moreover, students can apply to attend a model school under eight caste categories (SC, ST, 2A, 2B, 3A, 3B, C1, GM) and admission is based on their within-category performance.[7]

Each model school can admit up to 80 students. Using the admission lists prepared by the examination authority, the principal of each model school will admit students in descending order, based on their entrance exam score and caste category. The nature of the selection process creates a cutoff for each category within each model school, meaning that each model school can have up to eight school-by-category cutoffs.[8] This cutoff score for admission into a model school is not known to the school or to the potential students beforehand. Thus, whether students near the cutoff fall to the left or the right of the cutoff is as good as randomly assigned.

I assemble three restricted student-level administrative data sets to track the students who appear for the model school entrance exam in fifth-grade at two future points: tenth-grade and pre-university. With a data set of over sixty-three thousand students from 74 model schools across three cohorts, I am able to investigate three dimensions of schooling outcomes: (i) academic achievement as measured by test scores and final grades; (ii) educational attainment indicators using years of schooling; and (iii) career choice using choice of major in pre-university college.

My first econometric strategy combines all 1,513 cutoffs under one framework to identify the local average treatment effect of model schools. I adopt a Fuzzy Regression Discontinuity Design (RDD) to compare the outcomes of students who scored barely above and barely below the admission cutoff score within their block and caste category. Using the indicator for whether the entrance exam score is above the relevant school-by-category cutoff as an instrument for the model school attendance indicator, I find that attending a model school raises academic achievement and educational attainment indicators significantly.

For academic achievement, attending a model school increases math test scores by 0.38 standard deviations (sd), science test scores by 0.26 sd, and social science test scores by 0.26 sd on average,

[6] It is not compulsory for all students in a block to appear for the entrance exam and therefore I am unable to identify the average peer quality for non-model school attendants. By manually going through the fifth-grade school names (year prior to the entrance exam), I estimate that close to 70 percent of the students appearing for the entrance exam are from public schools.

[7] SC - Scheduled caste; ST - Scheduled tribe, OBC - Other Backward class (2A, 2B, 3A, 3B, C1), and GM - General merit. I discuss them in detail in the next section.

[8] I say "up to" as not every school has admitted students under each of the eight categories. Although there is a quota for each caste category, I was told by the principals that when there weren't enough candidates in one of the caste categories, they took students from another category. Thus, the quotas weren't strictly enforced in the first three years that I look at.

all statistically significant. Attending a model school also increases the probability of obtaining an A or A+ grade in tenth-grade by a statistically significant 20 percentage points. For educational attainment indicators, attending a model school increases the probability of passing tenth-grade by an insignificant 5.3 percentage points and increases the probability of joining pre-university college by a statistically significant 11.9 percentage points. However, model schools have no statistically significant effect on the probability of choosing either science, arts or commerce as a major in pre-university education.

On average, model school attendance improves educational outcomes; but an important issue is whether the effects vary by caste, gender or other dimensions especially given the explicit concerns about the inequality in access to quality schooling. Preliminary results suggest that there is little variation by caste. This is in part due to the absence of substantial caste differences in entrance exam scores. For instance, of the eight cutoffs within each school, it is not the case that the lowest castes have the lowest cutoffs (Figure A.1). Additionally, small sample size for the Scheduled Tribes and General Merit caste categories prevent me from making any meaningful conclusions. Therefore, I examine three other dimensions of heterogeneity.

I start by attempting to provide an insight into how model schools affect students across the ability distribution as measured by their entrance exam scores. I am able to investigate this using the differences in the school-by-category cutoffs both within year and within school. Depending on the magnitude of the cutoff scores, students near the cutoff can be starting model schools at different initial absolute learning levels in a given year. Additionally, although they were all barely admitted to model schools they can be at different learning levels relative to their peers within their school.

In my second econometric strategy, I estimate multiple local average treatment effects to identify differences in effects. First, I classify students' initial learning levels as above or below an absolute learning level. The absolute learning level is determined by the student's school-by-category cutoff relative to the median cutoff of all the school-by-category cutoffs in that year. Second, I classify students as above or below a relative learning level; where the relative learning level is the student's school-by-category cutoff relative to the student's school's 20th percentile entrance exam score.[9] I estimate the effects for both of the above criteria separately, and then combine both of the above criterion to further create four subgroups.[10] Conceptually, model

[9]The idea for using the school-by-category's cutoffs is so that the students above and below the cutoff in each of the category are always together.

[10]Note that there is no nothing special about the median cutoff score or the 20th percentile student's score. I picked these values as they allow for having enough sample size in each group to be able have meaningful results. I check for robustness by choosing 40th and 60th percentile cutoff score, and 15th percentile and 25th percentile student's cutoff score.

schools might affect the students in each of these groups differently for reasons such as big fish in a small pond, different outside options, differences in caste, or differences in control group students' peer qualities.

The two main findings from the second econometric strategy are as follows: (i) the effects of model schools for students that begin with high initial absolute learning levels (those scoring 52 points and above on the entrance exam) are not statistically significantly different from those that begin with low initial absolute learning levels; and (ii) model schools increase the likelihood of joining pre-university for those that are above the 20^{th} percentile student in their class irrespective of starting with a high or low initial absolute learning level. Broadly, the results suggest that model schools have a similar positive effect on all subgroups.

Lastly, I explore heterogeneity in program effects by gender since geographic blocks were classified as educationally backwards based on the gender gaps in education. I find that attending a model school increases girls and boys test scores in math and social science, and the likelihood of scoring an A/A+ by about the same amount. Interestingly, attending a model school has a positive effect on females when it comes to the probability of joining pre-university and choosing science as a major compared to an almost zero effect on males. However, they are not statistically significantly different. In general, the results suggests that model schools work for girls as well as boys.

This paper relates to two bodies of work in development economics. First, it relates to research on differences in quality of public versus private sector schools in India. There are several research papers in the literature on school quality in India that primarily focus on examining whether private schools improve student outcomes (Muralidharan and Kremer, 2006; French et al., 2010; Chudgar and Quin, 2012; Muralidharan and Sundararaman, 2015; Singh, 2015), but research on the effects of public schools is scant.[11] I contribute to this literature by providing the first piece of evidence on short and longer-term effects of creating high-quality public schools in India. To the best of my knowledge, this is also the first paper to study the effects of the model schools program.

Second, I contribute to an active recent literature investigating the variation in school quality within the public sector in non-OECD countries. Using Regression Discontinuity Design, Jackson (2010), Pop-Eleches and Urquiola (2013), Lucas and Mbiti (2014), and Park et al. (2015) ask whether attending an elite public school improves learning outcomes in Trinidad and Toabgo,

[11] See Angrist et al. (2002) and Hsieh and Urquiola (2006) for the effects of providing a voucher to attend private schools in Colombia and Chile respectively. Evidence on whether private schools provide higher learning gains is mixed (see Urquiola, 2016 for a review).

Romania, Kenya, and China, respectively. While Lucas and Mbiti (2014) show that elite government schools in Kenya have no effect on test scores, the other three studies document positive effects on test scores.[12] I add to this literature by attempting to look at outcomes beyond test scores and exploring the effects of high-quality public schools on students across the ability distribution in the Indian context.

The evidence found in this paper is also of relevance to the policy makers. First, the ambitious model schools scheme is yet to be either fully implemented or even adopted by all state governments. For instance, 12 out of 21 states with Educationally Backward Blocks did not have functional model schools as of 2016.[13] This paper hopes to inform policymakers the potential effects of model schools. Second, Karnataka is planning on introducing an English medium track starting from grade 1 in 1,000 traditional public schools in the 2019-20 academic year. In a separate policy, the Karnataka government has issued an official order to establish 173 Karnataka Public Schools (KPS) that start in grade 1 and go through grade 12, framed after the design of model schools.[14] To that end, this paper provides crucial evidence on the potential benefits of improving public schools to the policymakers.

2 Background and Policy Experiment

In this section, I briefly describe the caste system in India that has resulted in inequalities across social classes, as well as the unequal education system. I describe a policy which created a high quality public school in each of the Educationally Backward Blocks (EBB) in India, thus giving the poor students an opportunity to attend a high quality pubic school. I further explain the key features of the selection process for admitting students from all castes. In particular, students are selected based on their performance on a entrance exam within their caste and block.

Social stratification in India. People in India are divided based on caste, class, religion, region and sex. Of these, caste is the most divisive factor among the Hindu religion, which makes up nearly 80 percent of the population.[15] Castes are hereditary and are arranged hierarchically wherein there is a clear distinction between the top and the bottom. At the bottom are the "scheduled castes" (the SCs) and the "scheduled tribes" (the STs), who hold the lowest economic positions and are the most impoverished. The SCs and STs comprise of about 16.6 percent and 8.6 percent, respectively, of India's population. Finally, there are other backwards classes (OBC)

[12] In the context of developed countries, there are several high-quality research papers evaluating the effects of attending public schools that were already perceived to be better or elite. For United States, see Cullen et al., 2006; Hastings and Weinstein, 2008; Abdulkadiroğlu et al., 2011; Deming et al., 2014; Israel: Lavy, 2010.

[13] MHRD, India or Table A.6. This is the most recent statistic available.

[14] The National Education Policy 2019 (Draft) also suggests that such a framework will be adopted at the national level. See Chapter 7.

[15] Caste is also referred to as jati.

which are educationally or socially disadvantaged- about 41 percent.[16] There is substantial evidence documenting inequality in education, employment, and income across these castes.[17]

India has been trying to address the inequalities present across social classes through having reservations in higher education and central government jobs.[18] In the Report of the Education Commission (1964-66) chaired by D.S. Kothari, the commission condemned the separate, unequal school system which it accused of "increasing social segregation and perpetuating and widening grade distinctions."[19] Despite such early calls for change, the system on which the majority of primary and secondary school children rely on still suffers from fundamental problems such as high-teacher absenteeism, low classroom activity, weak governance and discriminatory attitudes of teachers towards the low castes (Chaudhury et al., 2006; Glewwe and Kremer, 2006; De et al., 2011).[20]

Model schools program. With the intention of improving primary and secondary education, India designated 3,479 out of 5,564 blocks as educationally backwards blocks (EBBs).[21] A block is considered educationally backwards if its female literacy rate was below the national average and its gender gap in literacy was above the national average. Addressing the state of EBBs and public education in India, the Prime Minister, Dr. Manmohan Singh, in his Independence day Speech in 2007, called for states "to give priority to education, as education alone is the foundation on which a progressive, prosperous society can be built."[22] To accomplish this, it was proposed that government would establish 3,500 "model" schools, one for each EBB. Although funding for the model schools program was split between the states and the federal government, state governments were responsible for the implementation of the model schools program. I have obtained data for Karnataka, a southern state in India, and hence, analyze model schools in that state.[23]

[16] See Census, 2011 for SC and ST population proportion and Table 20R of the National Sample Survey Organisation (NSSO) report for OBC population proportion. OBC generally consists of 2A, 2B, 3A, 3B, C1.

[17] See Desai and Kulkarni (2008) and Bharti (2018) for descriptive work on inequality in India.

[18] 15 percent for SCs and 7.5 percent for STs.

[19] Kothari Commission Report (1964-66)

[20] See *Swelling support for common schools* by Summiya Yasmeen for an excellent summary of the Kothari Commission report and her description on the three tires of Indian schooling.

[21] Initially the list was made up of 3,073 EBBs. Subsequently this list was expanded to include 406 more blocks, out of which 404 blocks were having rural female literacy rate of less than 45 percent irrespective of the gender gap. Besides, one SC concentration Block from West Bengal with SC rural female literacy rate of 19.81 percent and one ST concentration block in Orissa with ST rural female literacy rate of 9.47 percent were also included, taking the total number of EBBs to 3479.

[22] Speech Transcript

[23] Model schools are called, "Adarsha Vidyalayas" in Kannada, the regional language of Karnataka. It translates to "model schools" in English.

To provide additional context, I describe the Indian education system in general.[24] It consists of three parts- Elementary, Secondary, and Tertiary education. Elementary education includes Primary school (grades 1 through 5) and Upper-Primary school (grades 6 through 8). Secondary education includes high school (grades 9 and 10) and senior-secondary school (grades 11 and 12).[25] Upon completion of tenth grade, students who wish to continue their education can choose one of three paths: a two-year, pre-university track through senior secondary school (grades 11 and 12), a three-year diploma college, or a two year Industrial Training Institute (ITI). Students going through the pre-university track can seek admission into university for a undergraduate degree. Students choosing to attend a diploma college earn a diploma in engineering degree upon successful completion. Those who choose to attend an ITI, can appear for All India Trade Test (AITT) at the end of two years, wherein, successful candidates will receive the National Trade Certificate (NTC). The later two paths typically lead to labour market entry.[26]

Selection of students. Karnataka has a total of 74 EBBs and the first cohort of model schools was admitted in 2009 (see Figure 1). While model schools start at grade 6 and end at grade 10, admission into a model school in Karnataka is given through an entrance exam prepared by the examination authority of the education department. The entrance exam is conducted at the block level; hence, students residing in a particular block, can compete for the model school in that block only. Moreover, students can apply to attend a model school under eight categories: Scheduled Caste (SC), Scheduled Tribe (ST), Other Backward Classes (OBC)- 2A, 2B, 3A, 3B, C1 and General Merit (GM). The categorization is based on the caste classification system adopted by the state government and each category has its own quota on the number of students that must be admitted. Students who wish to attend model schools need to appear for the entrance exam in the month of March of their fifth-grade school year.

Upon completion of the entrance exam, the examination authority prepares three lists: Selection list, Eligible list, Rejection list. Each model school can admit up to 80 students in total. The selection list is the list of 80 students selected to be admitted into each model school.[27] The rejection list is a list of students who were absent for the entrance exam. The eligible list is comprised of all students who are neither on the rejection list nor the selection list. These students are eligible for admission if some students from the selection list choose not to attend

[24] See Cheney et al. (2005) for an excellent summary of the Indian education system.

[25] Senior-secondary education is also called as Pre-University (PU) education.

[26] While those who attend diploma colleges and ITIs typically seek a job, there is an option for lateral entry into undergraduate engineering colleges. For details, see Department of Technical Education for Diploma colleges and Department of Collegiate Education for ITIs in Karnataka. The pre-university colleges come under Department of Pre University Education.

[27] In the list of 80 students, under each school-by-category, the students are listed in the descending order based on their entrance exam score.

the model school.

The selection and eligible lists are then sent to each model school to begin the admission process. In theory, if all the 80 students in the selection list choose to attend the model school, there will be no need for additional rounds of admissions. However, not all students on the selection list choose to attend model schools as shown in the later sections. In such a case, the principal will admit students from the eligible list, in descending order, based on their entrance exam score.

The nature of the selection process creates a cutoff for each caste category within each model school. Just around the cutoff, being above or below is as good as random assignment. As a result of this admission process, nearly identical students are either admitted to or rejected from a model school. For example, if a school's cutoff score under the SC category is 70 points, a SC category student who scored 70 can attend the model school but a SC category student who scored 69 cannot. The cutoff score for each school-by-category is the entrance exam score of the last student admitted to the model school under each category. The construction of the cutoffs is discussed in detail in the empirical strategy section.

3 Data

In this section, I describe the three sources of administrative data that allow me to attempt to track those who appeared for the model schools entrance exams at two future points: end of high school (tenth-grade) and end of senior secondary school (pre-university). In particular, I exploit rich restricted data which include students' names, parents' names, date of birth to match across data sets and overcome the challenge of non-existence of a unique identifier in the India education system. Of the 82,793 students that appeared for the model schools entrance exam in the first three years, I am able to track 63,442 (approximately 77 percent) of them in 10^{th} grade. I will discuss the impact of attrition on the interpretation of findings in the results section.

3.1 Administrative Data

For this study, I rely on three restricted student-level administrative data sets: (i) Model schools entrance exam, (ii) Karnataka Secondary Education Examination Board (KSEEB), and (iii) Department for Pre-University Education (DPUE).

The model schools entrance exam data consist of the students' names, their parents' names, the students' dates of birth (dob), the students' caste-categories, the students' entrance exam score and several other student characteristics. This covers students who took the entrance exam in the years 2010 (cohort 1), 2011 (cohort 2) and 2012 (cohort 3). The KSEEB data contain the test scores of the state-standardized Secondary School Leaving Certificate (SSLC) exam that students appear for at the end of 10^{th} grade for all schools in the 74 blocks in which the model schools are present. Cohorts 1, 2 and 3 would have appeared for the 10^{th} grade exam in the academic years 2014-15, 2015-16 and 2016-17 respectively.

As discussed in the previous section, upon completion of 10^{th} grade, if students choose to continue some form education, they have three options to choose between. If they choose to continue traditional schooling, i.e. 11^{th} and 12^{th} grade, they will be in the DPUE data set. I use DPUE data to determine whether students continue traditional schooling or not after completing 10^{th} grade. Cohorts 1, 2 and 3 would have appeared for the 12^{th} grade exam in the years 2016-17, 2017-18 and 2018-19 respectively.[28]

3.2 Merging of data sets

Fuzzy string matching. Figure 2 shows the potential progress path for a typical student who wishes to attend a model school in cohort 1. This figure also facilities in understanding what data set(s) are used at what stage. The first objective is to track students who took the entrance exam in the 10^{th} grade data set. Although, there is no unique identifier that is common to the entrance exam data and the 10^{th} grade exam data, I am able to merge the two data sets using fuzzy string matching based on the student's name, their mother and father's names, the student's date of birth, block and district.

I start the matching process by searching for students within their entrance exam block. For those that did not find a match at the block level, I look within their district. Finally, I look for the remaining non-matched students in blocks that are outside their district but share the boundary with the block that the students took the entrance exam in. In the first three years, 82,793 students took the entrance exam to attend a model school for 6^{th} grade. Five years later, I am able to find 63,442 (approximately 77 percent) of those students in the 10^{th} grade data.[29]

Attrition. It is anticipated that not everybody who took the model school entrance exam can be found in the 10^{th} grade exam. However, I cannot simply assume that those students must have dropped out of school as there are two other primary reasons for why the students might

[28]The first and second cohort appeared for their 12^{th} grade exam in 2017 and 2018 respectively. The third cohort would have appeared for 12^{th} grade exam in the month of March in 2019. At the time of the data agreement (December 2018), the 2019 cohort's pre-university data was unavailable and hence I am only able to analyze pre-college outcomes for the first two cohorts.

[29]Using block level matching, I am able to find 57,459 ($\sim$69 percent) students. Using district level matching, I am able to find 62,288 ($\sim$75 percent) students. The matching rate varies for students who attended model schools versus non-model schools. Of the 11,906 students who appeared for 10^{th} grade state-standardized exam from model schools, I was able to find the entrance exam scores for 11,262 ($\sim$95 percent) of them. However, of the remaining 70,887 who took the entrance exam and did not attend a model school, I was able to find the 10^{th} grade results for 52,181 ($\sim$74 percent) of them. While I use the full matched sample for the main analysis, I also present results for both block and district level matched samples. My conclusions are not sensitive to merging at the block level versus merging at block and district level.

not have been found.[30] First, students could have migrated to blocks other than the 74 model school blocks. I am unable to search outside the 74 blocks due to data limitations. However, a difference of about 6 percent between block-level and district-level matching suggests that there is a lot of within-district migration. A difference of about of 2 percent between within district and neighboring district matched samples suggests that there is very little inter-district migration.

Second, students could have moved to schools that do not follow the state-standardized syllabus. In India, schools choose to follow one of three categories of syllabi at their inception: the state-standardized syllabus, the central syllabus, and the international syllabus.[31] Model schools, like traditional public schools, follow the state-standardized syllabus as they are government-run public schools. The data I use only contains information on schools and students that follow the state-standardized syllabus. Therefore, I am not able to track students who took the model school entrance exam and took the 10$^{\text{th}}$ grade exam at a school that does not follow the state-standardized syllabus. However, as model schools are built in educationally backward blocks, only a small fraction of students that appeared for the entrance exam might be attending a central or international syllabus school.[32] I assess the degree to which not being able to track everyone may bias the estimates in the results section.

Descriptive statistics. The descriptive statistics for a subset of variables for the full sample by school type is presented in Table 1. As shown, approximately 60 percent of the sample appear for the 10$^{\text{th}}$ grade exam from either a traditional or aided public schools, suggesting that they are the go to schools in these EBB blocks. With respect to the socio-economic status, as anticipated, private schools have the lowest percentage of students belonging to the Scheduled Castes (SC) and Scheduled Tribes (ST). The same for model schools is in between that of private and traditional public schools. Model schools have the highest mean percentage 10$^{\text{th}}$ grade is highest in as compared to traditional public, private and aided schools. While the gender ratio in public schools is about half and half, females are less likely to attend private schools suggesting

[30] Dropout rate of Upper-Primary schooling (grade 8) is around 4 percent and Secondary schooling (grade 10) is around 18 percent. See page 8 of DISE (2016) report.

[31] Each state designs its own syllabus that is to be followed by all public and aided schools. Therefore, public and aided schools do not have the option to choose the syllabus. The primary purpose of state-standardized syllabus is to be able to facilitate the use of the regional language as medium of instruction and to aid in conducting the state-standardized exam. In a similar manner, the central syllabus is created to meet the needs of the students whose parents are employed in the central government and are frequently transferred to different locations (Central Board for Secondary Education). The international syllabus, such as the International General Certificate of Secondary Examination (IGCSE) and IB (International Baccalaureate), are adopted by schools that are typically intended to serve the elite.

[32] Using DISE rawdata for the years 2014-15 and 2015-16, I find that percentage of schools that do not follow state-standardized syllabus in these 74 blocks could be anywhere between 4 to 6 percent and the percent share of 10$^{\text{th}}$ grade students in these schools could be about 5 to 7 percent of the total 10$^{\text{th}}$ grade students. DISE data has serious accuracy issues and hence these are approximations only.

households preference for boys education in these blocks. Percent continuing traditional schooling after 10^{th} grade is comparable across all the schools.

4 Empirical Strategies

Each model school admits students under eight different categories every year. For each school-by-category combination in each year, I set the entrance exam score of the last student admitted as the cutoff score (denoted by $cutoff_{sj}$, for school s and category j.) In other words, my approach builds on Pop-Eleches and Urquiola (2013) to determine each school-by-category's cutoff to be equal to the score of the applicant with the lowest entrance exam score.[33] This method of constructing the cutoff scores gives me a total of 1,513 cutoffs.[34] The sample consists of 35,764 students below the cutoffs and 25,385 students above the cutoffs.

Using my data, I exploit two types of variation to identify the effects of model schools: combine all cutoffs under one framework, and idiosyncratic differences in the magnitudes of the cutoffs within year and within school.

4.1 Combining all cutoffs

The first approach identifies the Local Average Treatment Effect (LATE) of attending a model school for those just above the cutoff. In theory, the compliance rate of the rule-based admission process would be 100 percent if every student in the selection list chooses to attend model school. However, not everyone who is in the list of top 80 students chose to attend a model school, leading to imperfect compliance. Hence, to determine the effects of attending a model school, I employ a "fuzzy" regression discontinuity design (Hahn et al., 2001; Lee and Lemieux, 2010).

In this context, the treatment is attending model schools and admission to a model school is

[33] Setting the lowest score as the cutoff can be problematic if some students with low entrance exam scores are admitted into model schools after the completion of the admission process. For instance, if a model school has a few vacant seats after the completion of the admission process, the principal of that model school may admit some students who would have otherwise not gotten in. In such a case, using the lowest score as the cutoff would be wrong. As an example, if a student with 30 points on the entrance exam is admitted into a model school and the next three highest scores are 50, 51 and 52 points, the cutoff should instead be 50 and not 30. For this reason, I reassign the cutoff scores for a school-by-category combination based on the following rule: if the gap between two consecutive model school attendants' scores is greater than 0.75 standard deviations of that school-by-category's entrance exam score and the percent share of students who scored between the two scores is at least 10 percent. The rule is only applied to groups with at least 35 students, the median number of students per group, in order to prevent making changes to small groups that do not have sufficient information. Following the rule, 255 out of 1,643 total school-by-category cutoffs are reassigned. Results are robust to changing the rule for score gaps from 0.75 SDs to 0.5 SDs and to changing the percent share of students from 10 percent to 15 percent.

[34] In theory, the total number of cutoffs should be 1,776 (74 model schools X 8 castes X 3 cohorts). First, not all schools have admitted students under all eight categories in each year. Second, I drop the categories within which all students who took the entrance exam were admitted to a model school as these categories will have no control groups.

conditional on the entrance exam score being above a cutoff. Therefore, the "first stage" is the effect of the being above the cutoff on the expected probability of attending a model school, conditional on the running variable. Since all 1,513 cutoff scores are not necessarily of equal magnitude, I construct the running variable (denoted as C_i) by subtracting each entrance exam year with the respective school-by-category cutoff score ($C_i = EE_i - cutoff_{sj}$). This gives a measure of how far each entrance exam score is from it's respective cutoff score. Therefore, the value of the running variable is zero for those that are at the cutoff and the rest get a value either above or below zero. As shown in the next section, results suggest that the probability of attending a model school is discontinuous when the running variable is equal to zero. The "reduced form", then, is the impact of scoring just above the model schools' entrance exam cutoff score ($C_i \geq 0$) on different outcomes. The "first stage" and "reduced form" equations will then take the form:

$$\text{First Stage} : E[D_i|EE_i] = \delta + \rho 1\{C_i \geq 0\} + f(C_i) + \eta \tag{1}$$

$$\text{Reduced Form} : Y_i = \alpha + \gamma 1\{C_i \geq 0\} + f(C_i) + \epsilon \tag{2}$$

where (1) is the "first stage" and (2) is the "reduced form". Y is an outcome, $1\{C_i \geq 0\}$ is an indicator for whether a student's entrance exam score, centered around zero, is greater than or equal to zero, $f(C_i)$ is a flexible control function of the running variable and D_i is the mean probability of attending a model school. Therefore, if admission to model schools changes discontinuously at $C_i = 0$, then the causal impacts of attending model schools can be identified even if applicant's entrance exam scores are systematically related to factors that affect outcomes such as math score.

Thus, suppose prior to the treatment, the students just below and above the cutoff are similar, students just below the cutoff will serve as an adequate control group for students just above the cutoff. In such a case, the differences in outcomes can be attributed to the effect of attending a model school. Then, "the second stage" regression takes the following form:

$$\text{Second Stage} : Y_i = \beta + \lambda E[D_i|EE_i] + f(C_i) + \epsilon \tag{3}$$

The treatment effect, λ, is then mathematically equal to the ratio of the reduced form coefficient (γ) and the first stage coefficient (ρ). Thus, I will adopt the two-stage least squares (2SLS) framework, wherein, scoring above the cutoff is used as an instrument for model school attendance. The estimate obtained is then the unbiased estimate of the local average treatment effect. More specifically, I estimate the effect of model schools on three dimensions: academic achievement using test scores and final grades, educational attainment indicators using years of schooling, and career choice using choice of major in pre-university college.

The econometric strategy described above identifies the overall effect of model schools on students that were barely admitted to model schools. This is an important input to evaluate whether the model schools work or not. However, it tells us little about the benefits to those who may not necessarily be at the bottom of their class or may not necessarily have adequate training prior to joining these schools.

4.2 Variation in cutoffs within year and within school

In the second approach, I estimate multiple LATEs using the idiosyncratic differences in raw cutoff scores. Recall that there are 74 model schools and each model school admits students under eight different categories. Therefore, depending on the magnitudes of the cutoff scores, students who are barely admitted to model schools (under each category in each school in each year) can be starting at different learning levels as measured by their entrance exam scores.

Absolute prior learning levels. In Figure 3, I show that the magnitudes of the 1,513 cutoff scores are in fact evenly spread out. Cutoff scores vary from a low of 16 points to a high of 96 points with a median of 53 points. Using this variation in the magnitudes of the cutoffs across categories, I create two groups to separate those with high initial learning levels from those with low initial learning levels. More specifically, I group the categories with cutoff scores greater than the yearly median cutoff score and call them "above median absolute learning level" (denoted by $\widetilde{A}:Above$) group. The rest of the categories are classified as "below median absolute learning level" (denoted by $\widetilde{A}:Below$) group. The first stage and reduced forms to determine the effects of model schools based on the absolute learning levels that students start are as follows:

$$
\begin{aligned}
\text{First Stage}: E[D_i|EE_i,\ \widetilde{A}:Above] &= \delta_1 + \rho_1 1\{C_i \geq 0\}\ + f_1(C_i) + \eta \\
E[D_i|EE_i,\ \widetilde{A}:Below] &= \delta_2 + \rho_2 1\{C_i \geq 0\}\ + f_2(C_i) + \eta \\
\text{Reduced Form}: Y_i = \alpha_1 + \gamma_1 1\{C_i \geq 0\} &+ f_1(C_i) + \epsilon_1 \quad \text{if } [\widetilde{A}:Above] = 1 \\
Y_i = \alpha_2 + \gamma_2 1\{C_i \geq 0\} &+ f_2(C_i) + \epsilon_2 \quad \text{if } [\widetilde{A}:Below] = 1
\end{aligned}
$$

To check for statistical significance of the difference in effects, I will adopt the two-stage least squares (2SLS) framework, wherein, scoring above the cutoff interacted with $[\widetilde{A}:Above]$ is used as an instrument for model school attendance interacted with $[\widetilde{A}:Above]$.

Relative position within school. As each school-by-category's cutoff can be different, the within school student composition can also be different across schools and it is. To show this, I first determine the 10, 20, 50, 70 and 90$^{\text{th}}$ percentile entrance exam score within each model school among those attending it. I then determine the 10, 20, 50, 70 and 90$^{\text{th}}$ percentile within each of the percentiles determined in the above step. As shown in Table 2, the 10$^{\text{th}}$ percentile of the 50$^{\text{th}}$ percentile scores in each model school is 47.5, whereas, the 90$^{\text{th}}$ percentile of the same is 80 i.e. the entrance exam score of the median student in each school can be different. Just as prior achievement levels can matter to a student's performance, the relative position of the student within her class can also also affect her performance. Therefore, to account for this, I classify each category as "below relative learning level" or "above relative learning level" by comparing each school-by-category's cutoff score to their respective within school 20$^{\text{th}}$ percentile entrance exam score. I will denote these two groups as $[\widetilde{R} : Below]$ and $[\widetilde{R} : Above]$ respectively. Similar to absolute learning levels, the first stage and reduced forms to determine the effects of model schools based on the relative position of students within their class are as follows:

$$
\begin{aligned}
\text{First Stage} : E[D_i|EE_i,\ \widetilde{R} : Above] &= \delta_3 + \rho_3 1\{C_i \geq 0\}\ + f_3(C_i) \\
E[D_i|EE_i,\ \widetilde{R} : Below] &= \delta_4 + \rho_4 1\{C_i \geq 0\}\ + f_4(C_i) \\
\text{Reduced Form} : Y_i = \alpha_3 + \gamma_3 1\{C_i \geq 0\} + f_3(C_i) + \epsilon_3 &\quad \text{if } [\widetilde{R} : Above] = 1 \\
Y_i = \alpha_4 + \gamma_4 1\{C_i \geq 0\} + f_4(C_i) + \epsilon_4 &\quad \text{if } [\widetilde{R} : Below] = 1
\end{aligned}
$$

To check for statistical significance of the difference in effects, I will adopt the two-stage least squares (2SLS) framework, wherein, scoring above the cutoff interacted with $[\widetilde{R} : Above]$ is used as an instrument for model school attendance interacted with $[\widetilde{R} : Above]$.

Combination of absolute and relative criterion. In summary, there are two factors that can influence a student's performance in a new school: absolute ability as measured by the prior achievement level and relative ability as measured by the position within the class. Combining the two-group classification for each of the two factors gives a total of four groups: $[\widetilde{A} : Below$ & $\widetilde{R} : Below]$; $[\widetilde{A} : Below$ & $\widetilde{R} : Above]$; $[\widetilde{A} : Above$ & $\widetilde{R} : Below]$; and $[\widetilde{A} : Above$ & $\widetilde{R} : Above]$. I then estimate the effects for each of the four groups in a manner similar to the the two groups criterion discussed above. See appendix B for details on the empirical equations.

Conceptually, model schools might affect the students in each of these groups differently for reasons such as big fish in a small pond, different outside options, differences in caste, or differences in control group students' peer qualities. Interestingly, it is not the case that low castes have the lowest cutoffs and high castes have the highest cutoffs (Figure A.1). Thus, the unique setup of model schools allows me to capture the effect of model schools based on students prior achievement levels and position within their class. Note that there is nothing special about the median cutoff score or the 20$^{\text{th}}$ percentile student's score that I have chosen as the reference points. This combination of the criterion allows me to have enough sample size in each of the four groups to get meaningful estimates. I check for robustness by changing the median cutoff score to the 40$^{\text{th}}$ percentile score and by changing the 20$^{\text{th}}$ percentile student's score to the 25$^{\text{th}}$ percentile student's score.

5 The First Stage & Threats to Identification

First, the identification strategies discussed in the previous section rely on entrance exam scores being a good predictor of attending model schools. I find a statistically significant jump in the probability of attending a model school at the cutoff, validating the instrument. Second, the key identifying assumption is that individuals on either side of the cutoffs are similar. The internal validity fails if students on one side of the cutoff are systematically different than students on the other side. One of the main attributes of the RD design is that it has tests to explore the potential threats to identification. Through the histogram smoothness test, I show that there is no manipulation of the running variable and through the covariates smoothness test, I show that there is no discontinuity at the cutoff for several of the covariates.

5.1 First Stage: Probability of Attending Model School

In Figure 4, I present the basic first stage results for my data following equation (1). Here, the x-axis is the running variable – distance between students entrance exam scores and the relevant school-by-category cutoff scores; the y-axis measures the probability of attending a model school. The sample is restricted to individuals with entrance exam scores within 10 points of the cutoff based on the optimal bandwidth test results obtained using Calonico et al. (2014). As seen, the model school entrance exam leads to a clear discontinuity at the cutoff, speaking to the validity of the instrument and the empirical design.[35] The vertical distance between the two solid lines at the discontinuity, is analogous to $\hat{\rho}$ in equation (1).

Table 3 presents the corresponding regression results following equation (1). The results are from regressing an indicator for whether students attend a model school on an indicator for whether their entrance exam score is above the relevant cutoff. The results suggest that, being just above the school-by-category cutoff increases the probability of attending a model school by 21 percentage points, a statistically significant jump.

[35] I omit the value for when the running variable is equal to zero. As the cutoff is determined using the students who attended model schools, I am forcing the students at the cutoff to attend a model school i.e. they are always takers. However, students who scored a point or two above the cutoff can choose whether to attend model school or not. Hence, by design, the mean probability of attending a model school at the cutoff will be larger than the mean probability of attending a model school just above the cutoff. Since, the students at the cutoff are forced to be always takers, I do not include them in the analysis. Typically, there are 1 or 2 students at each cutoff and a total of 2,615 students for all 1,513 cutoffs.

5.2 Regression Discontinuity Assumptions: Histogram and Covariates Smoothness

A primary threat to identification is the perfect manipulation of the treatment variable around the cutoff(s). In this context, it is a concern if students are able to perfectly manipulate their entrance exam score so as to be able to score just above the cutoff. However, perfect manipulation around the cutoff is unlikely for several reasons. First, in order to manipulate the score, one needs to know what the cutoff is going to be. Unlike GPA levels for college grades or income levels for tax benefits, the cutoff score for admission into a model school is not known until all exams have been graded and it depends on the students' take up rate. Moreover, they are block, category and year specific. Second, as the exams are prepared by the state government and are graded at district centers, the graders do not know the students. Third, manipulation by graders would require knowledge about student caste categories, and this information does not appear on the exams. Lastly, Panels A and C in Figure 5 show the distribution of matched sample and full sample, respectively. There is no visible jump in the density around the discontinuity. Furthermore, Panels B and D in Figure 5 show the McCrary (2008) density plots; as expected, there is no statistical evidence of systematic manipulation of the running variable.

I further check for the possibility of manipulation of the running variable by examining the observable characteristics of students prior to writing the entrance exam for model schools. It is a concern if there are discontinuities in observable characteristics as it would suggest the results might be confounded with unobservable differences between students just above and below the cutoff. In Figure 6, I show the discontinuity plots for several student characteristics. As shown in Table A2, there are no statistically significant differences in socio-economic status (using caste as proxy), gender, age, location and medium of instruction for both matched and full sample.[36] I find systematic differences for gender in the matched sample. However, the estimate is quite small and only significant at the ten percent level.

6 Results

In this section, I estimate the effect of attending model schools on various short and longer-term outcomes. In general, schools can affect several outcomes ranging from learning to social behavior. With the data available, I am able to investigate three dimensions: test scores and final grades as a measure of academic achievement, years of schooling as a measure of educational attainment, and choice of major as a proxy for career choice in the long run.

I first find that model schools significantly improve math, science and social science test scores,

[36] For the purpose of the covariates smoothness test, I divide the caste categories into two groups: (i) high SES (GM); (ii) low SES (SC/ST). I show the discontinuity plots for both of these groups.

and increase the probability of graduating high school (10^{th} grade) with the highest honor. Next, I show that attending a model school increases the probability of passing high school and the probability of joining pre-university after high school. Performance grades in 10^{th} grade is used by pre-university colleges to determine admission into different majors. However, I find that model schools have no statistically significant effect on choosing science, arts or commerce as a major in pre-university. With increased test scores in math and science, the no effect on science major choice is a puzzle.

6.1 Academic Achievement

I begin by studying students performance in the 10^{th} grade exam that they appear for after being at model schools for five years. All students attending schools that follow the syllabus set by the state department of education appear for a state-standardized exam at the end of 10^{th} grade to obtain the Secondary School Leaving Certificate (SSLC). It is the first state-standardized exam of any kind that students appear for in the schooling system. The state-standardized 10^{th} grade exam consists of six subjects - three languages (first, second and third language) and three core subjects (Mathematics, Science and Social Science).

Mathematics, science and social science test scores. The first language is usually the medium of instruction adopted by the school. Hence, English medium schools will have first language as English and Kannada medium schools will have Kannada as the first language.[37] Depending on the first language, the second and third language is either English, Kannada or another local language. The content of the language subjects vary based on whether it is the first, second or third language i.e. the syllabus of first language English textbook is not the same as that of the second language English textbook. However, the syllabi of math, science and social science is the same irrespective of the medium of instruction. Therefore, the students cannot be compared across languages but can be compared across core subjects (math, science and social science) to determine the effects of model schools on learning outcomes.

Reduced form graphs in panels A, B and C in Figure 7 provide graphical evidence for the causal effect of model schools in each of the core subjects. At the cutoff, there is a clear discontinuity in each of the subjects. The corresponding 2SLS regression estimates are presented in Panels A, B and C in Table 4. As per column 2, on average, after controlling for observable characteristics, attending a model school increases math score by 6.8 points (0.38 sd), science score by 4.1 points (0.26 sd) and social science score by 4.7 points (0.26 sd). One way to think about these test score gains is to see how they impact the overall score and grade. On average, model schools

[37] Occasionally, an English medium school may have Kannada has the first language but teach the core subjects in English.

lead to a student scoring about 15 points (in the core subjects) more than a traditional public, public-aided, or a private school student in the 10^{th}-grade state standardized exam. It is about 2.5 percent of the 625 total points that students can obtain in 10^{th} grade. Students use their scores in each subject to confirm their strength and inform their pre-university college stream decisions.

Grade achieved in 10^{th} grade. Students are given a letter grade for each subject and using all the six subjects' grades, a Cumulative Grade Average (CGA) is determined.[38] A student can get an A+ by scoring above 90 percent and an A by scoring above 80 percent but below 90 percent. The lowest possible grade is a C, for students scoring between 30 percent and 49 percent. These grades are used by pre-university colleges to determine whether to admit a student to science, arts or commerce stream. Therefore, obtaining an A or A+ can be used as a signal thereafter for pre-college and hence, I look at the effect of model schools on the grade obtained in 10^{th} grade.

Panel D in Figure 7 shows a clear discontinuity at the cutoff in the probability of graduating 10^{th} grade with an A or A+. The 2SLS regression estimates are shown in Panel D of Table 4. As per column 2, on average, attending a model school increases the likelihood of obtaining an A or A+ in 10^{th} grade by 19.8 percentage points. To put this into perspective, on average, about 300,000 students appeared for the 10^{th} grade exam from these 74 blocks in each of the three years. Out of which, only about 3 percent of the students scored 90 percent or above and only about 12 percent of the students scored 80 percent or above. Therefore, the magnitude of the effect is huge considering the potential positive effects scoring an A or A+ can have on a child's psychology and future career choices.

Attrition. Recall that I am unable to track about 23 percent of the students who appeared for the model schools entrance exam. This attrition can be a threat to the internal validity if the likelihood of finding a match for students just below cutoff is different from that of the students just above the cutoff. To check for this, I plot the probability of finding a match for all students below and above the cutoff (see Figure 8). The x-axis is the distance between the entrance exam score and the cutoff score. The y-axis is the mean probability of being able to track the students who appeared for the entrance exam in the 10^{th} grade exam within each point. As shown, students with an entrance exam score that is above the cutoff are about 3 percentage points more likely to be found in the 10^{th}-grade exam than those that scored below the cutoff.

Even though the magnitude is small, the attrition can bias the estimates and the direction of the bias depends on the characteristics of the additional 3 percent who are found above the

[38] I assume the level of difficulty of the first, second and third language exams to be the same irrespective of the school's first language.

cutoff. First, if the 3 percent are students who are the highest scorers, then the results discussed above are upward-biased effects of model schools. Second, if instead the 3 percent are students who are the lowest scorers, then the main results are downward-biased. Hence, I conduct a bounding exercise taking both of the above scenarios into consideration. To determine a lower bound estimate, I drop the top 3 percent within each of the above-cutoff bins. In a similar way, for the upper-bound estimates, I drop the bottom 3 percent of the students within each of the above-cutoff bins. I present the results in Appendix Table A.3. The lower-bound estimate of math test scores and the likelihood of scoring an A/A+ is statistically significantly greater than zero. However, the lower-bound estimate of science and social science test is not statistically significant.

6.2 Educational Attainment Indicators

In this subsection, I look at the effect of attending a model school on the probability of graduating high school, probability of obtaining an A/A+ grade ($\sim$ highest grades) in high school and the probability of continuing traditional schooling. These outcomes help to determine whether model school have an effect on overall education attainment levels.

Graduating high school. 10^{th} grade signals the end of secondary schooling, as in, all students will have to exit their current schools and make a decision thereafter based on their 10^{th} grade results, interests and various other factors. Passing 10^{th} grade is a minimum criteria either to continue schooling or to apply for a majority of government jobs. Therefore, I look at the high school graduation probability using an indicator for whether students pass the 10^{th} grade exam.

The graphical evidence presented in Panel A of Figure 9 suggests that there is no statistically significant discontinuity at the cutoffs. In order to account for the possibility that some students who did not find a match might have dropped out, I assign the 10^{th}-grade pass indicator to be zero for those that do not find a match. In Panel B of Figure 9, I plot the high school graduation for the full sample and the figure shows a clear discontinuity. The corresponding regression estimates are in Panel A and B of Table 5. Based on Column 2's estimates, the conclusion is that attending a model school increases the probability of graduating high school from anywhere between 5.35 percentage points and 31.6 percentage points. The estimates are robust to changing bandwidth and adding controls.[39]

Continuing schooling (pre-university). After 10^{th} grade, students exit their current schools and choose whether to continue traditional schooling, join vocational training or enter labor force. I use the unique registration number assigned to students for the 10^{th} grade exam to find them

[39] If I instead assume that all the attriters graduated high school, I find a zero.

after 10^{th} grade. Recall that the students have three options to choose from: a two-year pre-university track, a three-year diploma college, or a two year Industrial Training Institute (ITI). The two-year pre-university track is chosen by those who wish to pursue an undergraduate degree and the other two tracks are usually chosen by those who intend to enter the labor force upon completion of their respective courses. Therefore, the first decision that students are faced with is whether to continue traditional schooling or take up vocational courses.[40]

For the purpose of the analysis, I consider a student to have continued traditional schooling if they have appeared for the 12^{th} grade exam conducted by the Department of Pre-University Education.[41] Therefore, the outcome I look at is the probability of continuing traditional schooling using an indicator for whether a student appeared for the 12^{th} grade exam.[42] I present the graphical evidence in Panel C & D of Figure 9. The matched sample figure suggests a small but unclear change at the cutoff as estimates are imprecise. The corresponding regressions estimates are in Panel C & D of Table 5 for matched and full sample, respectively. The matched sample estimates in column 2 of Panel C suggests that attending a model school increases the likelihood of continuing traditional schooling by a statistically significant 11.5 percentage points.

6.3 Post-Secondary Outcomes

For those that join pre-university college, they need to decide what subject stream to specialize in, and what type of pre-university college to attend. Being able to observe students' decisions and outcomes post high school is important to identify the long-term effects of model schools.

Major choice: science, arts or commerce. While students have three options (science, arts and commerce) to choose from, science has the highest demand as it is the mostly commonly chosen stream, followed by commerce, and then by the arts (humanities).[43] Hence, it is worth noting that, science stream due to its popularity has the highest cut-off in terms of score required

[40] Due to data limitations, I am unable to observe those students who choose to join an ITI. Even though I can observe those that choose to join a diploma college, I need to know the students who have entered ITIs, in order to be able to observe "dropping out of school" as an outcome. Hence, I refer to this outcome as continuing traditional schooling rather than dropping out of school. About 4 percent of the sample in years 2014-15 and 2015-16 chose the diploma track.

[41] I do this in order to avoid misclassifying those who joined traditional schooling but drop out or switch tracks after 11^{th} grade as "continuing traditional schooling".

[42] As I do not have twelfth-grade data for the third-cohort, I present results for full matched sample with first and second cohort only in Table A.4. The table shows that the effects are not driven by cohort 3 and that the estimates are consistent with the main results.

[43] Choosing the science stream would mean that students almost always study mathematics, physics, and chemistry. Additionally, those intending to appear for medical school entrance exams choose biology/botany/zoology and those wishing to pursue engineering choose computer science. Similarly, students who choose the Commerce stream can choose to study economics, mathematics, commerce, or accounting. Lastly, those who choose the Humanities/Arts stream can choose to study subjects such as history, geography, philosophy, psychology, arts, music, languages, or political science.

in the 10^{th} grade exam. Therefore, students make their decisions based on their 10^{th} grade subject exams. Additionally, the majority of PU colleges only offer a few of the total subjects, restricting the movement of students between streams after the choice has been made.

For the reasons listed above, as attending a model school leads to significant gains in test scores and increases the probability of obtaining an A/A+ in 10^{th}-grade exam, I would expect them to be more likely to choose science stream. I check for this by looking at the probabilities of joining each stream as opposed to the alternative streams, separately. Panels A, B and C in Figure 10 plot the mean probabilities of choosing each stream for students just around the cutoff. There is no significant discontinuity at the cutoff in any of the figures. The corresponding regression estimates are presented in panels A, B and C in Table 6. Based on the estimates in column 2, attending a model school has no statistically significant effect on choosing science or arts stream. Panel C estimate suggests that there is no difference in the likelihood of choosing commerce stream between students just above and below the cutoff.

Two competing theories could explain this result. The first theory has to do with the perceptions of the students above the cutoff. Although they are doing better compared to the students below the cutoff, they might be comparing themselves with their peers when making their major choices. If they see themselves as being at a lower level compared to their peers, they might be less likely to choose science. A second theory has to do with the psychological mindset of the students. The notion of wanting to puruse science stream to become a doctor or an engineer is very strong among public school students in India. Often times, this notion leads to students making choices based on desire rather than their capability or chances of succeding in the field. Therefore, if all students regardless of their performance in 10^{th} grade attempt to pursue science, there would be no difference in the probability of joining science stream between the students just below and above the cutoff.

Pre-university (PU) college type: public, aided, private. Similar to the primary and secondary schooling system, PU colleges can have three different types of management. Some are private institutions and others are operated by the government. There is third type where the management is private but the government provides substantial amount of aid in return for charging low fees (aided). As of 2015, there were 1,378 government (∼29 percent), 795 aided (∼16.5 percent) and 2,621 private (∼54.5 percent) PU colleges in Karnataka.[44] Since model schools end in 10^{th} grade in Karnataka, the students who wish to continue on to pre-university have to choose the type of PU college they want to attend. This decision will depend not only on the cost of the PU college, as determined by the management type (government, private,

[44] Department of Pre-University Education, Annual report 2015-16.

aided), but also by the subjects that the PU college offers. Therefore, I look at the effect of model schools on the type of institutions the students join.

In panel D of Figure 10, I plot the probability of attending a private PU college. The figure suggests that there no difference in the likelihood of choosing to attend private PU college between students just above and below the cutoff. The corresponding regression estimates are presented in Table 6, panel D. The estimates suggest a positive effect, but due to the large standard errors, the estimates are not statistically significantly different from zero.

7 Heterogeneity Analysis

The main findings discussed in the above section are important when determining whether model schools work or not. However it tells us little about the average treatment effect of model schools. In this section, I begin by exploring the effects for certain subsets of students based on initial learning levels and position within class using the second empirical strategy discussed in section 3. The main idea is to estimate multiple local average treatment effects so as to be able to infer whether model schools work for all types of students. The main conclusion is from this analysis is that model schools have a similar positive effect for students across the ability distribution.

Geographic block were classified as educationally backwards based on the female literacy and the gender gap in education. Therefore, I explore the heterogeneity in program effects by gender. Overall, I find that females are in par with males in academic achievement and are more likely to continuing schooling after 10^{th} grade. The key takeaway is that model schools work for girls as well as boys.

7.1 Effects by variation in cutoff within year and within school

Studies that have applied regression discontinuity design to similar setups are essentially asking whether the students who are at the bottom in the treated schools perform better than the students who are at the top in the non-treated schools. The result is a local average treatment effect (LATE) estimate for a subset of the population. However, typical school admission setups do not provide variation to answer questions such as do two students admitted to the treated schools benefit equally if their initial learning levels are not the same? And does the effect differ depending on the relative positions of the students within their class? The model schools admission structure gives me an unique opportunity to estimate multiple LATEs for different subsets of the population using the second empirical strategy discussed in section 4.2.

Absolute prior learning levels. I test for whether model schools affect students starting with above median initial learning level differently from students starting with below median initial learning level as measured by their entrance exam scores. I report the estiamtes in Table 7.

Broadly, the two groups are not statistically significantly differently affected. However, when looking at just the magnitudes, the estimates suggest that the group starting with high initial learning level see a bigger increase in math, science and social science test scores. They also are more likely to choose science as opposed to arts or commerce as a major. The likelihood of joining a private pre-university for those starting with high initial learning levels is 17 percentage points more than those with low initial learning level and it is statistically significant at the 10 percent level.

Relative position within the class. I test for whether model schools affect students who are below the 20^{th} percentile student within their class differently from students who are above the 20^{th} percentile student within their class. I report the estiamtes in Table 8. First, model schools increase the probability of continuing schooling after 10^{th} grade for those that are above the 20^{th} percentile student. Whereas, model schools have a zero effect on those that are below the 20^{th} percentile student. Second, irrespective of being below or above the 20^{th} percentile student, model schools increase the likelihood of scoring an A/A+ by at least 13.5 percentage points for both groups.

Combining absolute and relative categorization. Finally, I test for heterogeneity in outcomes between four groups created using absolute prior learning levels and relative position within school. The estimates for all outcomes are presented in Table 9. The omitted group is the group with students below in both absolute and relative terms. Therefore, the regression I run checks if the three groups are significantly different from the omitted group. The estimates are imprecise and the standard errors are large due to the small sample size within each of the groups. Therefore, the results should be interpreted as suggestive evidence.

First, those who start at a low absolute learning level and are above the 20^{th} percentile student within their school are worse off in social science from attending model schools. Second, when looking at the magnitudes in Panel B, being above the 20^{th} percentile student within ones school seems to really matter for the likelihood of continuing schooling after 10^{th} grade. Third, those who start at a high absolute learning level but at below the 20^{th} percentile student in their class score more on math and are most likely to obtain an A/A+ in 10^{th} grade.

7.2 Effects by Gender

Evidence suggests that there are huge gender gaps in educational attainment in India (Chaudhuri and Roy, 2009; Singh and Mukherjee, 2018). Interventions such as these may affect females and males deferentially due to differences in gender characteristics such as self-discipline and parents characteristics such as mothers education.[45] Therefore, I check for differential effects in all of the outcomes previously discussed for females and males. As families are less likely to invest in their daughters' education than their sons' education, providing access to model schools to girls could potentially have strong positive effects on girls. I report the estimates in Table 10. As shown in Panel A, attending a model school increases boys and girls test scores in math and social science by the same amount. Model schools also increase the likelihood of scoring an A/A+ in 10^{th} grade by 19.6 percentage points for both males and females.

The gender gaps between school enrollment levels increases with age in developing countries. For instance, in India, there is little to no gap between female and male enrollment by age 14, but by age 18, there is an observable difference in enrollment in formal schooling between the genders.[46] There are several reasons for why girls may drop out of school earlier than boys. First, girls are expected to take on household chores, such as cooking and taking care of younger siblings, at a much earlier age than boys. Second, the distance to school can make it harder for girls to travel alone safely. As per the magnitudes in Panel B of Table 10, attending a model school increases the likelihood of girls continuing schooling after 10^{th} grade by about three times more than it increases for boys. In general, the results suggest that model schools effects both males and females positively.

8 Discussion

In this section, I begin by exploring the potential change mechanisms by pointing out the differences between model schools and other types of schools. Using administrative data on school characteristics, interviews, personal visits to schools, and anecdotal evidence, I attribute the effect of model schools primarily to teacher contract structure, school accountability and governance, and student effort/motivation, but peer effects are also a contributing factor. Following which, I highlight the poor state of implementation of the model schools program in other states in India and the policy implications of this paper's findings. More specifically, it is worth considering expanding the program in stages and exploring separately each of the components that make model schools successful.

[45] For example, see Duckworth and Seligman (2006). In developed countries, there is evidence suggesting that while females benefit from such interventions, males maybe be unaffected or become worse off (Jackson, 2010; Kling et al., 2005; Hastings et al., 2006).

[46] According to Annual Status of Education Report (ASER 2017: Beyond Basics), by age 18, 31 percent of females are not enrolled in formal schooling while 28 percent of males are not enrolled. As per the 2011 Census, 56 percent of the population of 18 year olds were not enrolled in school and the corresponding figure in 2001 is 74 percent.

8.1 Potential Change Mechanisms

The three factors that separate model schools from traditional public schools are as follows: teachers contract structure, school accountability and governance, and student effort or motivation (see Table 11). First, traditional public school teachers are civil-workers who are hired on a permanent basis and the model school teachers are recruited on a contract basis. From a pure effort-based perspective, the temporary-contract structure leads to model school teachers exerting high effort levels either to ensure the renewal of their contract or in order to be become a permanent public school teacher (Muralidharan and Sundararaman, 2013; Duflo et al., 2015).

Second, the primary objective for launching the model schools program was to create schools that could serve as an archetype for traditional public schools to emulate. Therefore, the Department of Education governed the model schools very closely by increasing the number of inspections, increasing the number of meetings with school principals, and holding the schools accountable for properly performing their daily functions.[47] Additionally, the targets set for model schools to achieve were much higher than those given to the traditional public schools. For example, during the meetings that I attended, traditional public schools' principals were asked to ensure that all students pass the 10^{th} grade exam. In a separate meeting with the model school principals, the main objective given was to ensure that the majority of students not only pass, but obtain distinctions (85 and above) on the 10^{th} grade exam. This complements the teacher contract structure, leading to the proper functioning of public schools, which is perhaps a predictor of students' performance (Mbiti et al., 2019).

Third, attending a model school can influence the student psychology in a positive way through the medium of instruction and infrastructure. First, unlike traditional public schools where the default medium of instruction is the regional language, the default medium of instruction in model schools is English. In multi-lingual India, English is the dominant language in higher education and governance and English as a medium of instruction has long been offered by elite private schools. There is well documented evidence suggesting high returns to learning in English.[48] Traditional public school students, who are mostly low-SES or low-income students, maybe demotivated by the prior belief that they cannot compete with their counterparts at private schools either for higher education or for high-level jobs. If this is the case, then learning in English in a model school may boost the esteem of public school students. Similarly, the improved

[47]For example, using DISE data, I estimate that Block Resource Coordinators, on average, visit model schools 5 times for every 3 times they visit traditional public schools.

[48]Azam et al. (2013) find that the hourly wages for men who speak English fluently is 34 percent higher and for men who speak a little English is 13 percent higher relative to men who do not speak English. They also point out that the return to being fluent in English is as large as the return to completing secondary school and half as large as the return to completing a bachelor's degree. For more evidence, see Chakraborty and Bakshi (2016).

school infrastructure may also make students believe that the education they are receiving is comparable to that of their private school counterparts.[49] Identifying the effect of each of these factors separately is beyond of the scope of this paper. Therefore, future work should attempt to disentangle the effects of each of these components so as to determine the extent to which each component can influence improving the public schools.

Model schools admit students based on their performance on an exam and thus the students who attend a model school are a selected set of students. The better peer quality of model schools certainly contributes to the positive effects for those that are just above the cutoff. However, the low take-up rate (40 percent), as demonstrated by the first stage, suggests that it is not strictly the top 80 students who are attending the model schools. As a result, several low performing students who would have been otherwise attending a traditional public school now attend a model school. Moreover, having better peers does not necessarily translate to better test scores (Beuermann and Jackson, 2018).

8.2 Implications to Policy Makers

First, the model schools scheme was a national level policy whose implementation was transferred to the states. However, the ambitious model schools scheme is yet to be fully implemented by all state governments. For instance, 12 out of 21 states with Educationally Backward Blocks (EBB) did not have functional model schools as of 2016 (see Table A.6). For example, Odisha, a eastern state with 173 blocks out of 315 classified as EBB only implemented the model schools program in 2017. Additionally, the government of India has stopped funding model schools and the decision to continue the program is left to the states. This paper hopes to inform policymakers the potential effects of model schools and act as a catalyst for the full implementation of the model schools scheme across all states.

Second, the timing of this paper is crucial. Karnataka is planning on creating new traditional public schools and/or consolidating the existing schools based on the model schools framework. In one policy, Karnataka is planning on introducing an English medium track starting from grade 1 in 1,000 traditional public schools in the 2019-20 academic year. The government plans to gradually add an English medium track to all public schools in future years.[50] This proposed move has invited divided opinions. On one side, the pro-regional language activists and literary figures, along with some politicians, are fiercely criticising it on the basis of wanting to preserve the regional language. On the other side, the leaders of low SES groups (SC/ST) are expressing their support to the government's move as the majority of their children rely on traditional public

[49] Visit Model Schools website for infrastructure visuals.

[50] Here is a recent article in the Indiatimes describing the policy.

schools.[51] In a separate policy, the Karnataka government has issued an official order to establish 173 Karnataka Public Schools (KPS) that start in grade 1 and go through grade 12, framed after the design of model schools.[52] The long-term objective of this project is to consolidate schools in order to improve efficiency in the use of teachers, and resources and improve school governance. In general, the public education system in India is moving towards having schools that go from grades 1 to 10 and/or grades 1 to 12 enabling students to complete schooling under one institution.[53] To that end, this paper provides crucial evidence on the potential benefits of improved public schools to the policymakers.

It is important to note that expanding this program means the average student quality may decrease with an increase in the number of students. But, in section 7.1, I show that model schools have a positive effect on students with both high and low initial learning levels. However, it is worth considering expanding the program in stages and exploring separately each of the components that make model schools successful. Future research should thus also focus on how to best expand the model schools network without compromising the quality aspect.

Finally, turning to the costs of running the model schools, back of the envelope calculations imply that per-pupil expenditure in model schools is between 9,315 to 11,632 Indian rupees and per-pupil expenditure in traditional public schools is between 11,848 - 16,914 Indian rupees. Therefore, the costs of operating model schools is comparable to that of traditional public schools (see Appendix A for cost calculations).

9 Conclusion

In this paper, I exploit a natural experiment in education policy in India to examine the effects of creating high-quality public schools. The model schools program was implemented to create one high-quality public school in each of the educationally backward blocks in India. Using three restricted administrative data sets, I examine the effect of attending a model school in Karnataka (a southern state in India) on three dimensions: academic achievement, educational attainment indicators and career choice.

The first finding is that attendance at a model school raises academic achievement and educational attainment indicators significantly. The second finding is that attending a model school

[51] Here are some recent articles in the newspapers summarizing the debate on the proposed policy: Deccan Herald, The Hindu, New Indian Express, The News Minute.

[52] Official government order. To learn more, visit Karnataka Public Schools website. See a Kannada newspaper article describing the proposed schools.

[53] See Chapter 7 of the National Education Policy 2019 Draft. For a general discussion on strategy for education in India, see page 10 of An Economic Strategy for India, put together by a non-partisan group of economists. For a detailed discussion on Education, see School Education Reforms in India prepared by Karthik Muralidharan.

has no statistically significant effect on the probability of choice of major in pre-university college. The third finding is that model schools have a similar positive effect for students across the ability distribution. The fourth finding is that model schools overall, have same effects on females as well as males, if not better on certain outcomes. Thus, my overall conclusion is that raising the quality of public schools can have significant positive effects on several dimensions of student outcomes.

With 75 percent (about 1 million) of schools being public schools and 65 percent (approximately 120 million) of the children who are in school attending a public school, quality of public schools in India is a first order policy issue. Improving the quality of public schools is at the core of the current education reforms that are being introduced by various state governments in India. Uncovering the effects of improved public schools prior to their state-wide implementation can be vital to their success. This paper provides crucial evidence on the potential benefits of improving public schools to the policymakers.

References

Abdulkadiroğlu, A., J. D. Angrist, S. M. Dynarski, T. J. Kane, and P. A. Pathak (2011). Accountability and flexibility in public schools: Evidence from boston's charters and pilots. The Quarterly Journal of Economics 126(2), 699–748.

Alderman, H., P. F. Orazem, and E. M. Paterno (2001). School quality, school cost, and the public/private school choices of low-income households in pakistan. Journal of Human resources, 304–326.

Angrist, J., E. Bettinger, E. Bloom, E. King, and M. Kremer (2002). Vouchers for private schooling in colombia: Evidence from a randomized natural experiment. American Economic Review 92(5), 1535–1558.

Azam, M., A. Chin, and N. Prakash (2013). The returns to english-language skills in india. Economic Development and Cultural Change 61(2), 335–367.

Beuermann, D. W. and C. K. Jackson (2018). Do parents know best? the short and long-run effects of attending the schools that parents prefer. Technical report, National Bureau of Economic Research.

Bharti, N. K. (2018). Wealth inequality, class and caste in india, 1951-2012.

Bold, T., D. Filmer, G. Martin, E. Molina, B. Stacy, C. Rockmore, J. Svensson, and W. Wane (2017). Enrollment without learning: Teacher effort, knowledge, and skill in primary schools in africa. Journal of Economic Perspectives 31(4), 185–204.

Calonico, S., M. D. Cattaneo, and R. Titiunik (2014). Robust nonparametric confidence intervals for regression-discontinuity designs. Econometrica 82(6), 2295–2326.

Card, D. (1999). The causal effect of education on earnings. In Handbook of labor economics, Volume 3, pp. 1801–1863. Elsevier.

Chakraborty, T. and S. K. Bakshi (2016). English language premium: Evidence from a policy experiment in india. Economics of Education Review 50, 1–16.

Chaudhuri, K. and S. Roy (2009). Gender gap in educational attainment: evidence from rural india. Education Economics 17(2), 215–238.

Chaudhury, N., J. Hammer, M. Kremer, K. Muralidharan, and F. H. Rogers (2006). Missing in action: teacher and health worker absence in developing countries. Journal of Economic perspectives 20(1), 91–116.

Cheney, G. R., B. B. Ruzzi, and K. Muralidharan (2005). A profile of the indian education system. Prepared for the New Commission on the Skills of the American Workforce.

Chudgar, A. and E. Quin (2012). Relationship between private schooling and achievement: Results from rural and urban india. Economics of Education Review 31(4), 376–390.

Cullen, J. B., B. A. Jacob, and S. Levitt (2006). The effect of school choice on participants: Evidence from randomized lotteries. Econometrica 74(5), 1191–1230.

De, A., R. Khera, M. Samson, A. Shiva Kumar, et al. (2011). Probe revisited: A report on elementary education in india. OUP Catalogue.

Deming, D. J., J. S. Hastings, T. J. Kane, and D. O. Staiger (2014). School choice, school quality, and postsecondary attainment. American Economic Review 104(3), 991–1013.

Desai, S. and V. Kulkarni (2008). Changing educational inequalities in india in the context of affirmative action. Demography 45(2), 245–270.

Dongre, A. A. and A. Kapur (2016). Trends in public expenditure on elementary education in india. Economic & Political Weekly 51(39).

Duckworth, A. L. and M. E. Seligman (2006). Self-discipline gives girls the edge: Gender in self-discipline, grades, and achievement test scores. Journal of educational psychology 98(1), 198.

Duflo, E., P. Dupas, and M. Kremer (2015). School governance, teacher incentives, and pupil–teacher ratios: Experimental evidence from kenyan primary schools. Journal of Public Economics 123, 92–110.

French, R., G. Kingdon, et al. (2010). The relative effectiveness of private and government schools in rural india: Evidence from aser data. London: Institute of Education.

Glewwe, P. and M. Kremer (2006). Schools, teachers, and education outcomes in developing countries. Handbook of the Economics of Education 2, 945–1017.

Hahn, J., P. Todd, and W. Van der Klaauw (2001). Identification and estimation of treatment effects with a regression-discontinuity design. Econometrica 69(1), 201–209.

Hastings, J. S., T. Kane, and D. Staiger (2006). Gender, performance and preferences: Do girls and boys respond differently to school environment? In American Economic Review Papers and Proceedings, Volume 96, pp. 232–236.

Hastings, J. S. and J. M. Weinstein (2008). Information, school choice, and academic achievement: Evidence from two experiments. The Quarterly journal of economics 123(4), 1373–1414.

Heckman, J. J., J. E. Humphries, and G. Veramendi (2018). Returns to education: The causal effects of education on earnings, health, and smoking. Journal of Political Economy 126(S1), S197–S246.

Hsieh, C.-T. and M. Urquiola (2006). The effects of generalized school choice on achievement and stratification: Evidence from chile's voucher program. Journal of public Economics 90(8-9), 1477–1503.

Jackson, C. K. (2010). Do students benefit from attending better schools? evidence from rule-based student assignments in trinidad and tobago. The Economic Journal 120(549), 1399–1429.

Kingdon, G. G. (2017). The private schooling phenomenon in india: A review.

Kling, J. R., J. Ludwig, and L. F. Katz (2005). Neighborhood effects on crime for female and male youth: Evidence from a randomized housing voucher experiment. The Quarterly Journal of Economics 120(1), 87–130.

Lavy, V. (2010). Effects of free choice among public schools. The Review of Economic Studies 77(3), 1164–1191.

Lee, D. S. and T. Lemieux (2010). Regression discontinuity designs in economics. Journal of economic literature 48(2), 281–355.

Long, M. C. (2010). Changes in the returns to education and college quality. Economics of Education review 29(3), 338–347.

Lucas, A. M. and I. M. Mbiti (2014). Effects of school quality on student achievement: Discontinuity evidence from kenya. American Economic Journal: Applied Economics 6(3), 234–63.

Mbiti, I., K. Muralidharan, M. Romero, Y. Schipper, C. Manda, and R. Rajani (2019). Inputs, incentives, and complementarities in education: Experimental evidence from tanzania. The Quarterly Journal of Economics 134(3), 1627–1673.

McCrary, J. (2008). Manipulation of the running variable in the regression discontinuity design: A density test. Journal of econometrics 142(2), 698–714.

Muralidharan, K. and M. Kremer (2006). Public and private schools in rural india. Harvard University, Department of Economics, Cambridge, MA.

Muralidharan, K. and V. Sundararaman (2013). Contract teachers: Experimental evidence from india. Technical report, National Bureau of Economic Research.

Muralidharan, K. and V. Sundararaman (2015). The aggregate effect of school choice: Evidence from a two-stage experiment in india. The Quarterly Journal of Economics 130(3), 1011–1066.

Oreopoulos, P. and U. Petronijevic (2013). Making college worth it: A review of research on the returns to higher education. Technical report, National Bureau of Economic Research.

Oreopoulos, P. and K. G. Salvanes (2011). Priceless: The nonpecuniary benefits of schooling. Journal of Economic perspectives 25(1), 159–84.

Park, A., X. Shi, C.-t. Hsieh, and X. An (2015). Magnet high schools and academic performance in china: A regression discontinuity design. Journal of Comparative Economics 43(4), 825–843.

Peet, E. D., G. Fink, and W. Fawzi (2015). Returns to education in developing countries: Evidence from the living standards and measurement study surveys. Economics of Education Review 49, 69–90.

Pop-Eleches, C. and M. Urquiola (2013). Going to a better school: Effects and behavioral responses. American Economic Review 103(4), 1289–1324.

Rose, P. (2003). From the washington to the post-washington consensus: the influence of international agendas on education policy and practice in malawi. Globalisation, Societies and Education 1(1), 67–86.

Sarin, A., S. Kuhn, B. D. Singh, P. Khanghta, A. A. Dongre, E. Joshi, A. Sengupta, and F. Rahman (2015). State of the nation: Rte section 12 (1)(c).

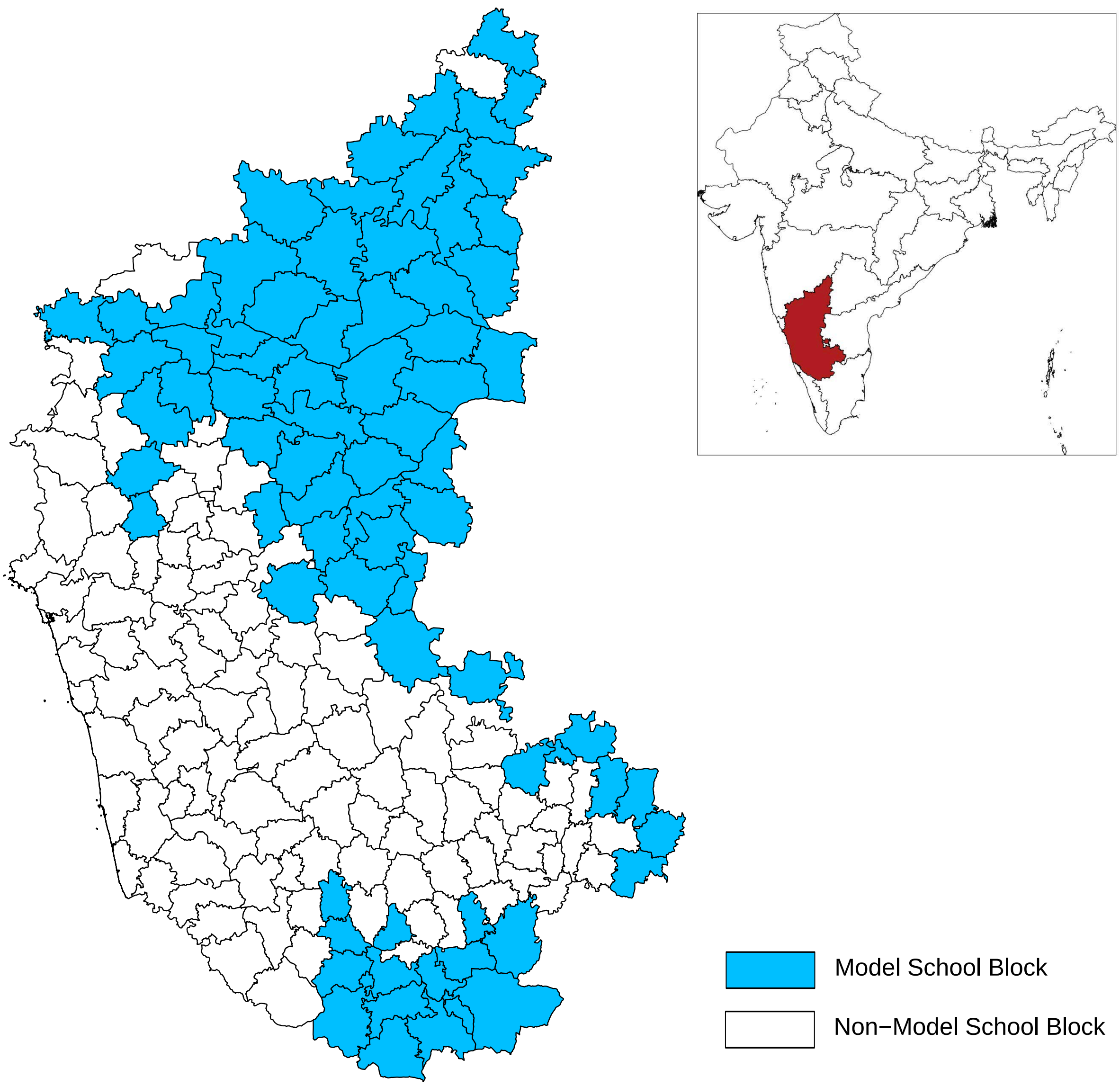
Singh, A. (2015). Private school effects in urban and rural india: Panel estimates at primary and secondary school ages. Journal of Development Economics 113, 16–32.

Singh, R. and P. Mukherjee (2018). whatever she may study, she cant escape from washing dishes: gender inequity in secondary education–evidence from a longitudinal study in india. Compare: A Journal of Comparative and International Education 48(2), 262–280.

Tooley, J., P. Dixon, and I. Amuah (2007). Private and public schooling in ghana: A census and comparative survey. International review of education 53(4), 389–415.

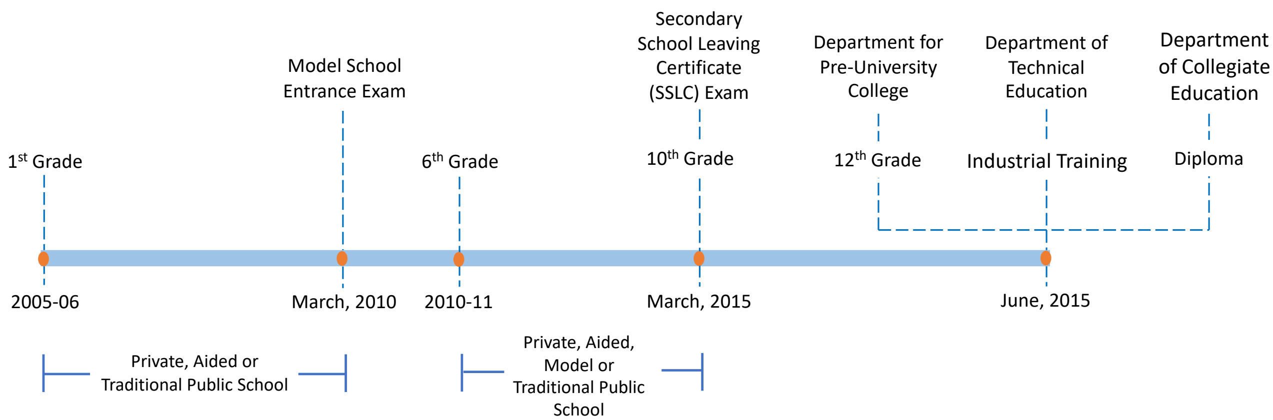
Urquiola, M. (2016). Competition among schools: Traditional public and private schools. In Handbook of the Economics of Education, Volume 5, pp. 209–237. Elsevier.

Figure 1. Model Schools Blocks in Karnataka, India



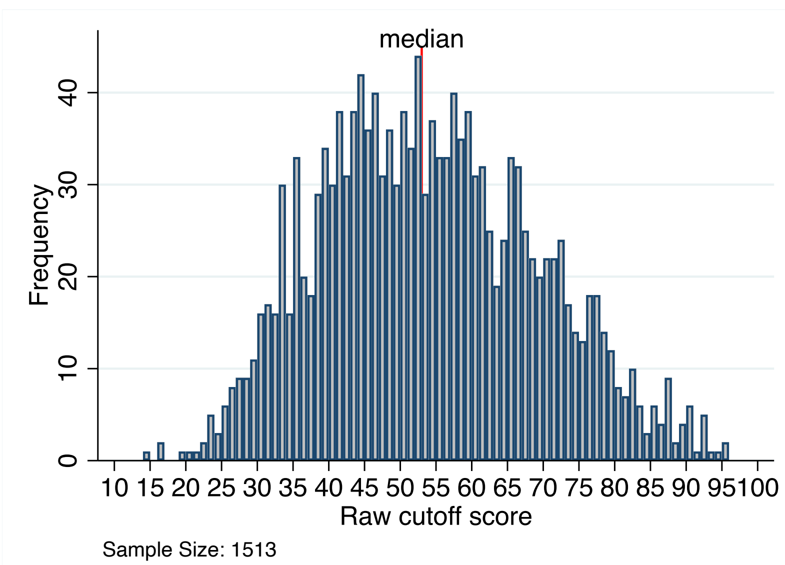
Notes: The figure shows boundaries of blocks with model schools in blue in Karnataka, a southern state in India.

Figure 2. A Time Line of Schooling for the First Cohort of Model Schools



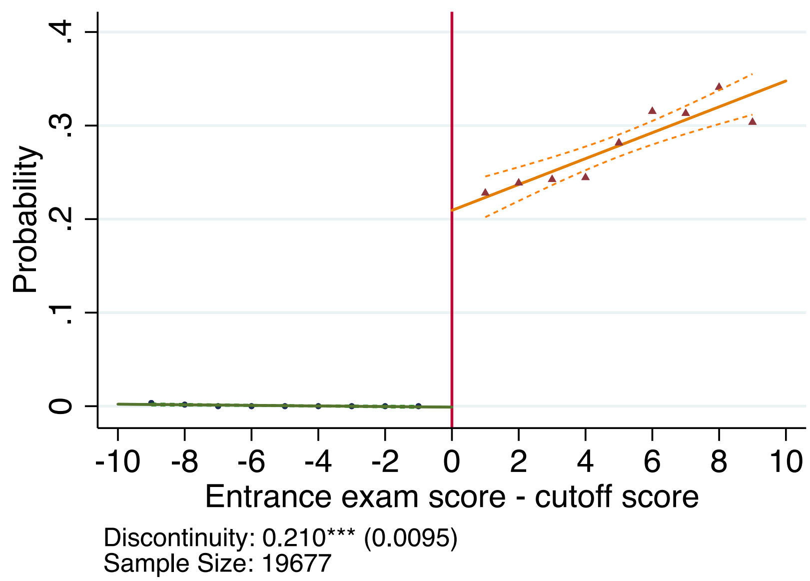
Notes: The figure illustrates the timeline of schooling for a student who could have entered model school in the first year. Students appear for the model schools entrance exam at the end of 5^{th} grade and Secondary School Leaving Certificate (SSLC) exam at the end of 10^{th} grade. After 10^{th} grade, students choose to attend either Pre-University College (PUC), Diploma college or Industrial Training Institute (ITI). PUC is considered to be traditional schooling has it is pursued by those who wish to attend college for an undergraduate degree.

Figure 3. Distribution of Cutoff Scores



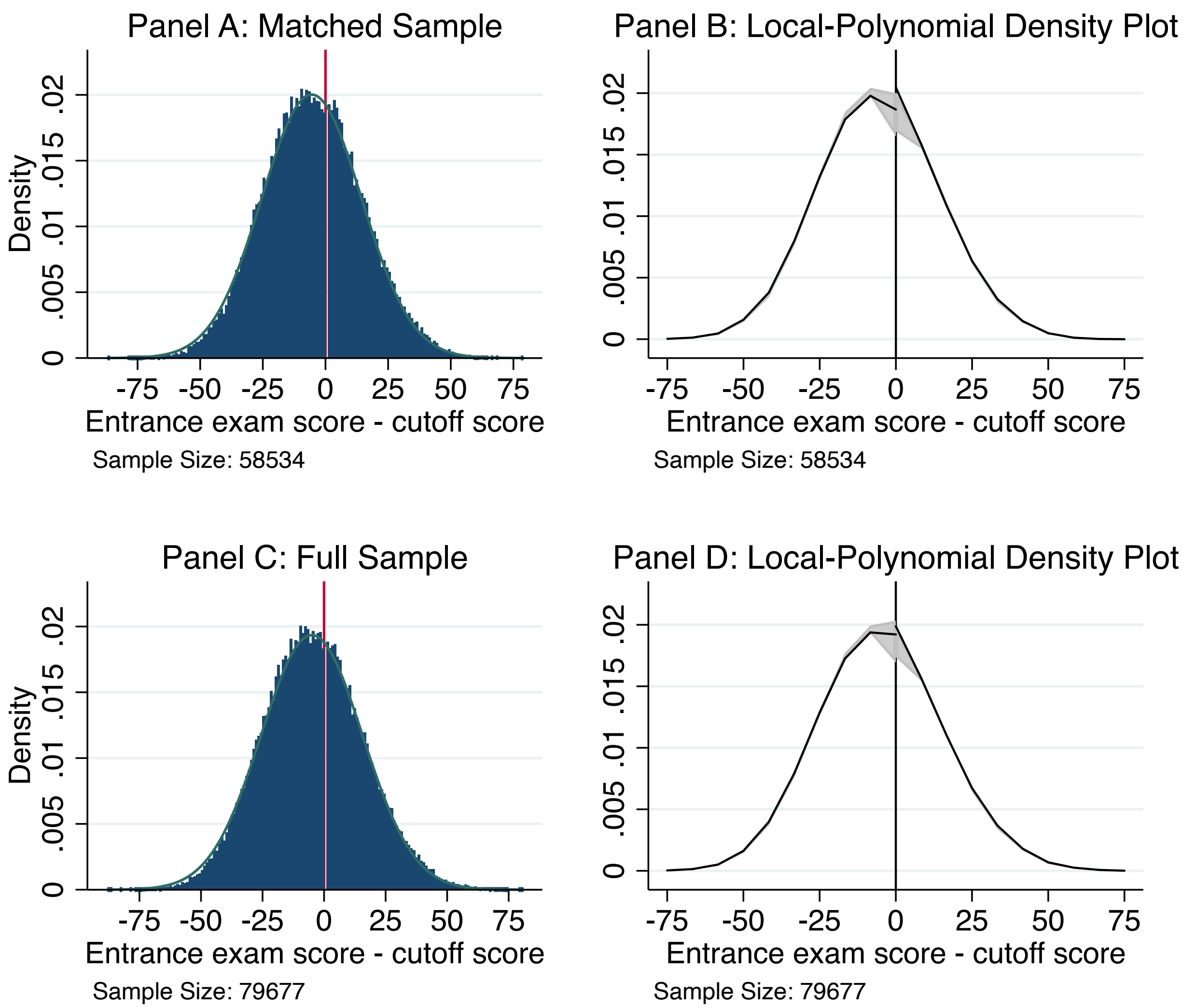
Notes: The figure plots the distribution of the cutoff scores. It shows that the magnitudes of the cutoff scores can be very different. Therefore, although students just above the cutoff in each of the categories are attending a model school, the starting point of each student can differ depending on the raw cutoff score of the category that the student is admitted under.

Figure 4. First Stage: Probability of Attending Model School



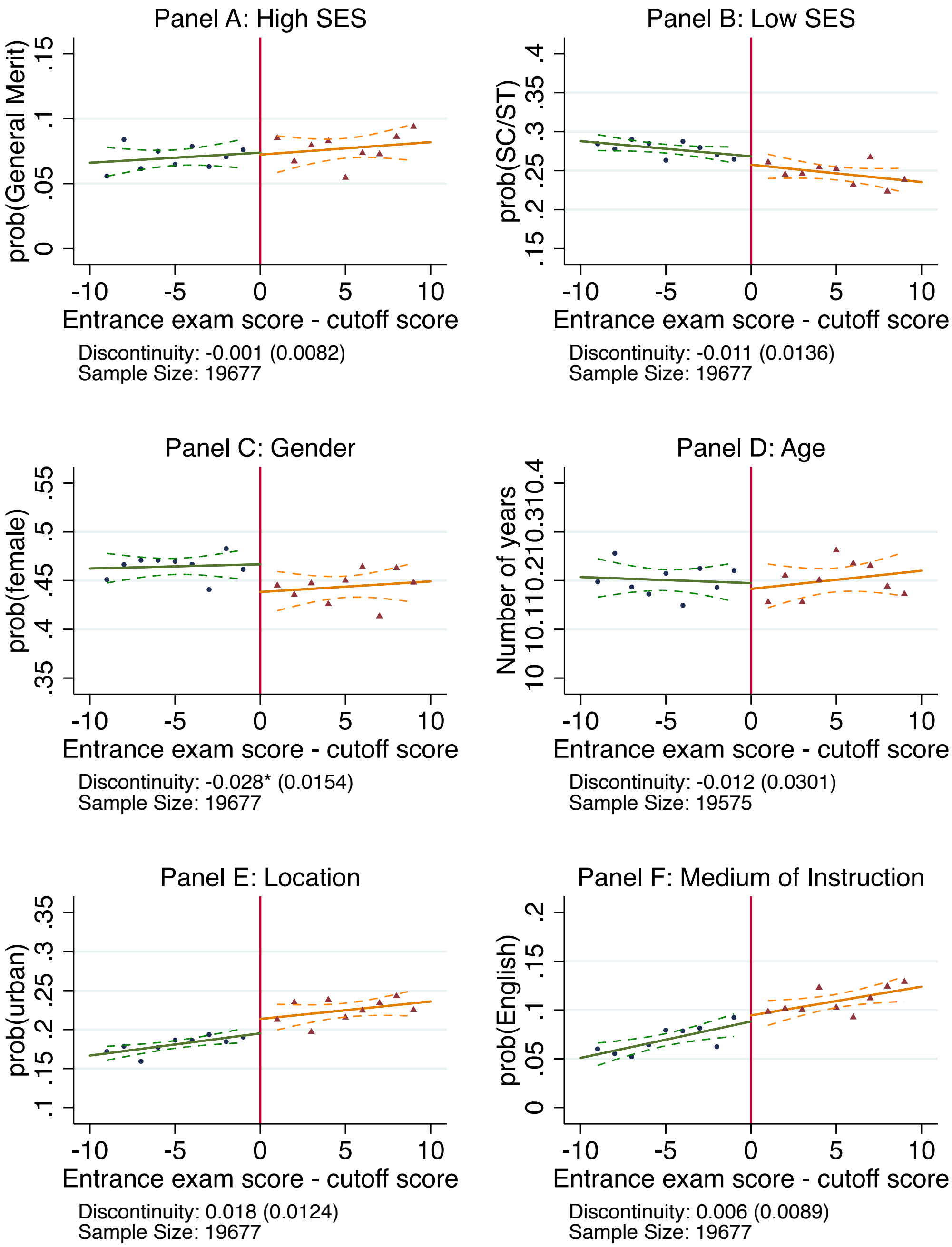
Notes: "Entrance exam score - cutoff score" is the entrance exam score minus the relevant school-by-category cutoff score. The sample is restricted to individuals with entrance exam scores within 10 points of the cutoff based on the Calonico et al. (2014) (referred to as CCT, hereafter) optimal bandwidth test results. Each point is the mean of the probability of attending a model school within non-overlapping one point bins. The solid lines are fitted values from a linear specification, separately estimated on each side of the cutoff.

Figure 5. Histogram Test



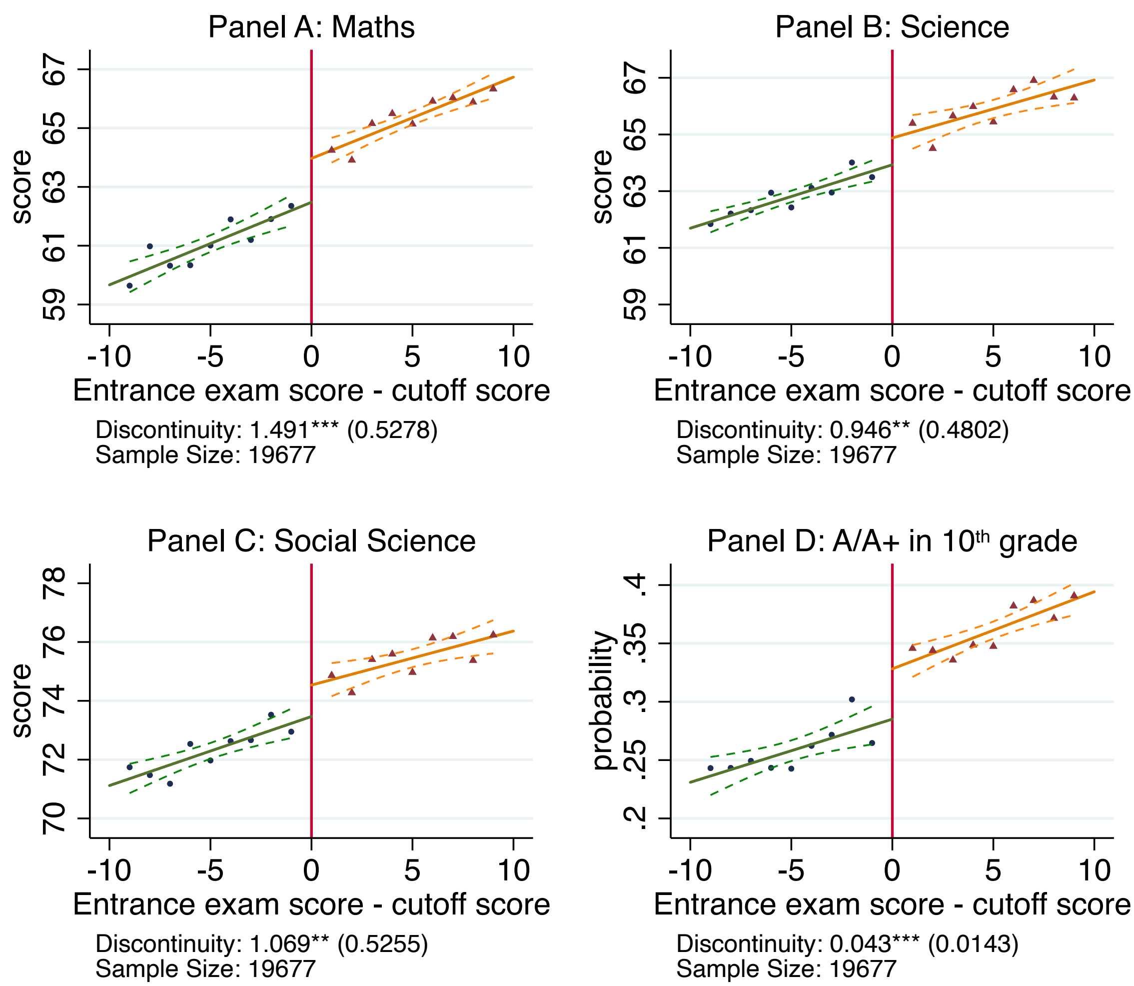
Notes: "Entrance exam score - cutoff score" is the entrance exam score minus the relevant school-by-category cutoff score. Panel A and panel C plot the distribution of the number of students by density in each point bin for matched and full sample, respectively. Panel B and panel D show the McCrary (2008) plots for matched and full sample, respectively. There is no visible jump in the density around the discontinuity; as expected, there is no statistical evidence of systematic manipulation of the running variable.

Figure 6. Covariate Smoothness Test



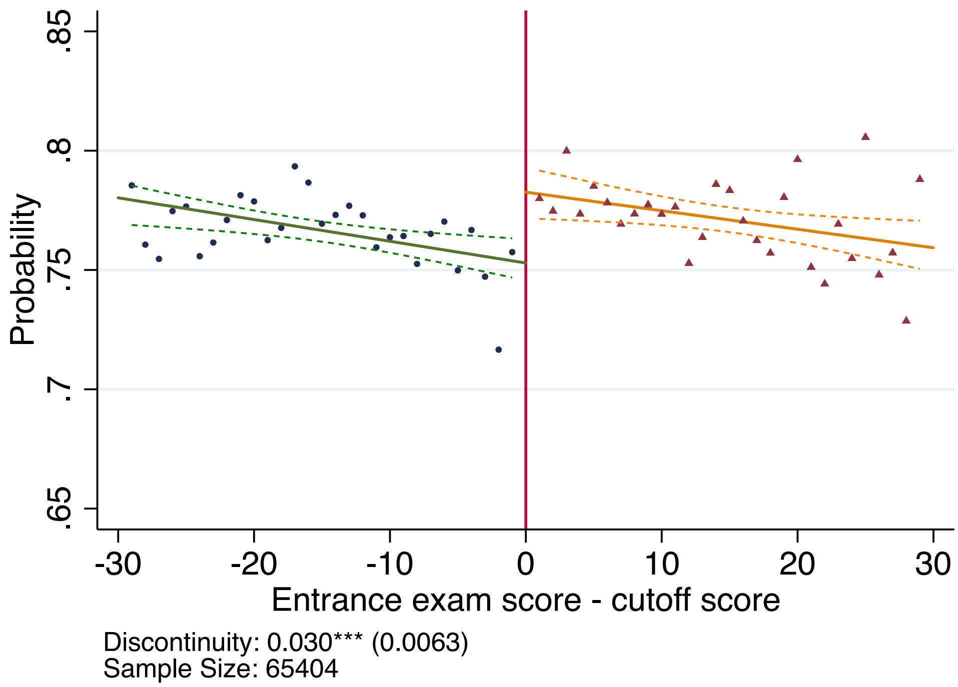
Notes: In each panel the solid lines are fitted values of regressions of the dependent variable on a linear trend in the entrance exam score, estimated separately on each side of the cutoff. The dependent variable in panels A and B is the socio-economic status grouped into two categories: (i) General Merit (GM); (ii) Scheduled Caste (SC) & Scheduled Tribe (ST), respectively. The dependent variable in Panel C is probability of being a female; the dependent variable in Panel D is the age of students; the dependent variable in Panel E is the probability of living in a urban area and the dependent variable in Panel F is the probability of studying in a English medium school in 5^{th} grade. Each point is the mean of the of the dependent variable within non-overlapping one point bins.

Figure 7. Reduced Form Graphs: Academic Achievement



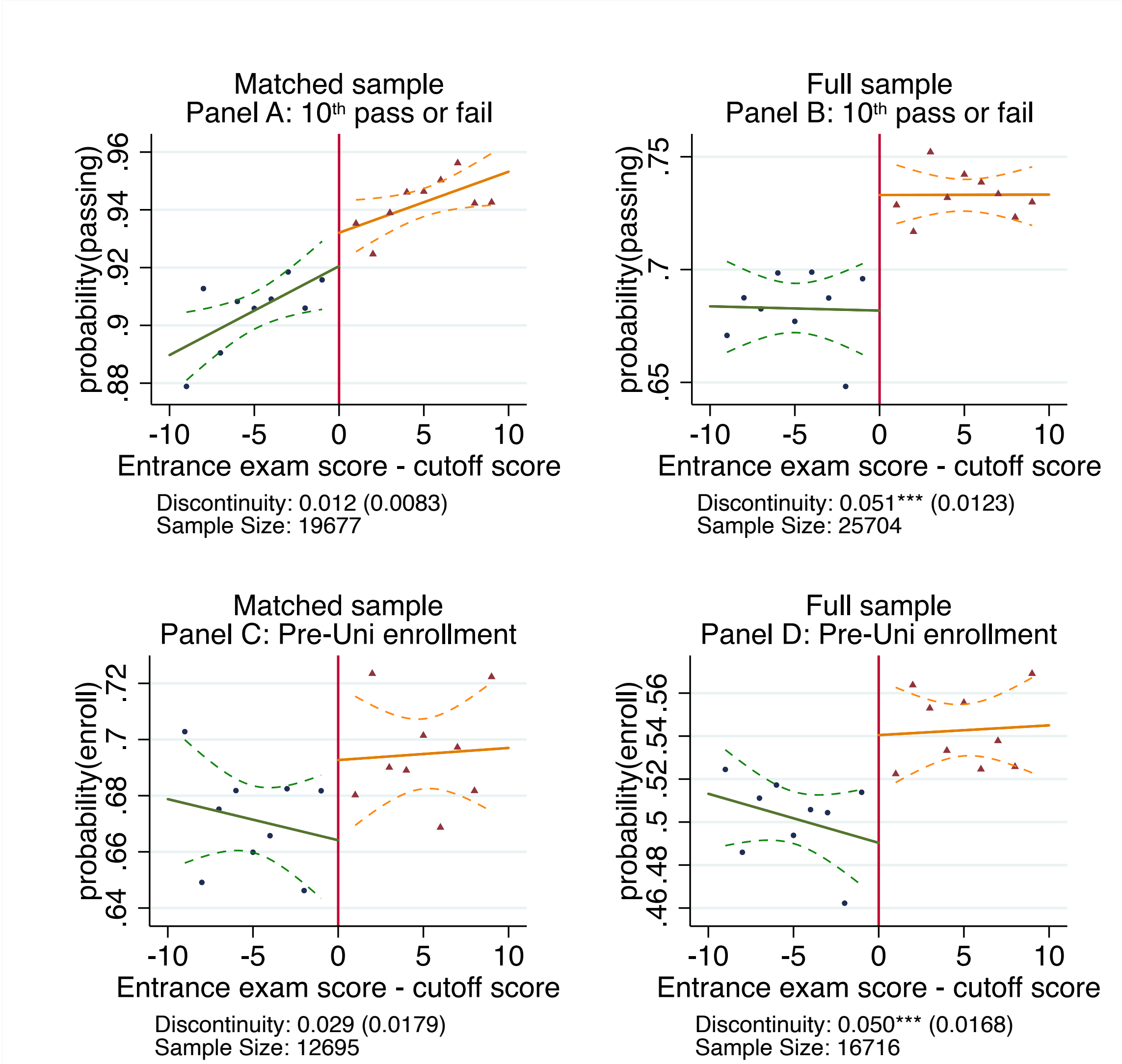
Notes: In each panel the solid lines are fitted values of regressions of the dependent variable on a linear trend in the entrance exam score, estimated separately on each side of the cutoff. Each point is the mean of the score of the dependent variable within non-overlapping one point bins. "Entrance exam score - cutoff score" is the entrance exam score minus the relevant school-by-category cutoff score.

Figure 8. Attrition: Probability of Finding a Match



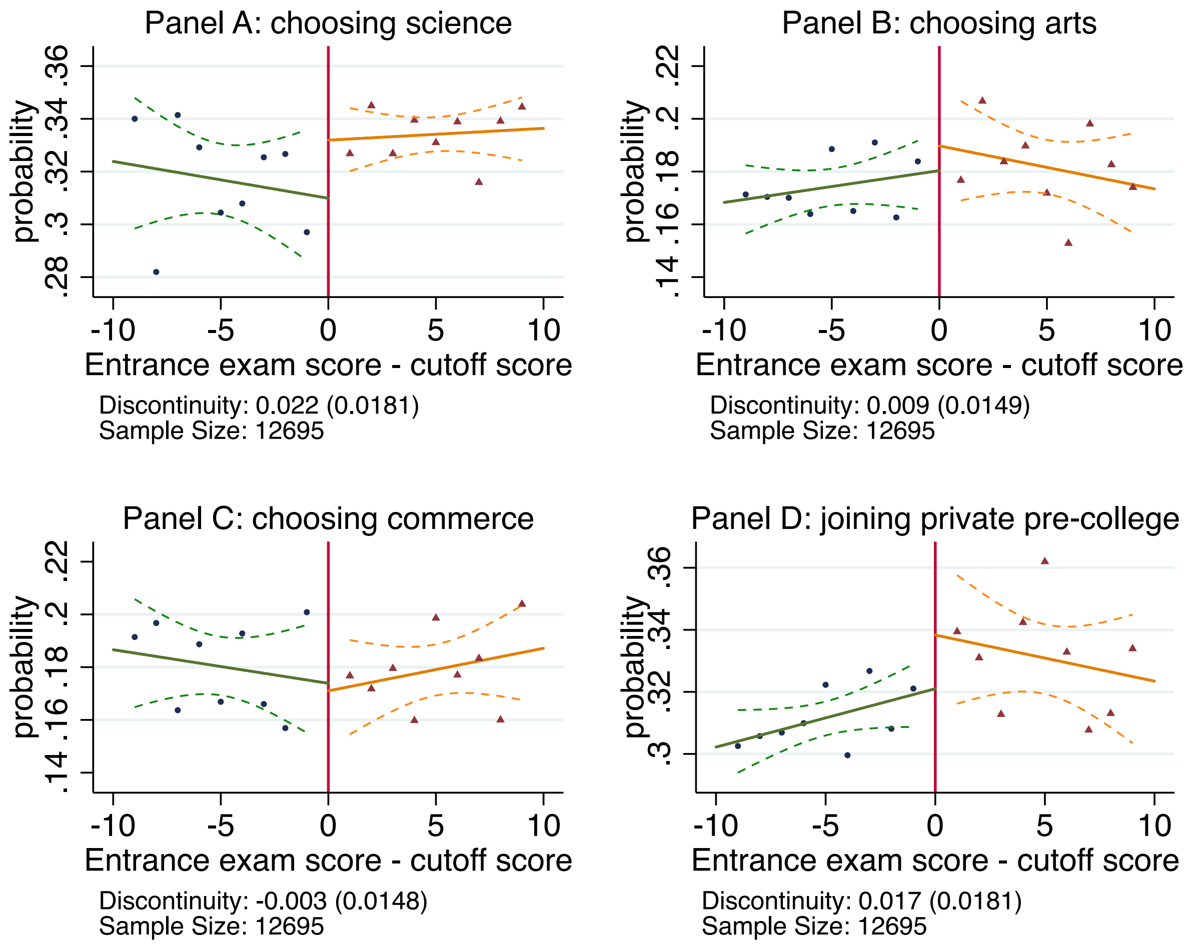
Notes: In each panel the solid lines are fitted values of regressions of the dependent variable on a linear trend in the entrance exam score, estimated separately on each side of the cutoff. Each point is the mean probability of finding a match within non-overlapping one point bins. "Entrance exam score - cutoff score" is the entrance exam score minus the relevant school-by-category cutoff score.

Figure 9. Reduced Form Graphs: Educational Attainment Indicators



Notes: Each panel represents the outcome variable, and restrict observations to individuals with entrance exam scores within 10 points of a school-by-category cutoff. The dependent variable in panel A and B is the probability of graduating high school. Panel A restricts the analysis to students who took the model school entrance exam and found a match in the tenth-grade exam. Panel B includes all students who appeared for the model school entrance exam and assigns a zero for graduating high school for a student that didn't find a match in the tenth-grade exam. For Panel C, I consider a student to be continuing schooling if they appeared for the 12^{th}-grade state-standardized exam. In each panel the solid lines are fitted values of regressions of the dependent variable on a linear trend in the entrance exam score, estimated separately on each side of the cutoff. Each point is the mean of the probability of the dependent variable within non-overlapping one point bins. "Entrance exam score - cutoff score" is the entrance exam score minus the relevant school-by-category cutoff score.

Figure 10. Reduced Form Graphs: Choice of Major and Pre-University College Type



Notes: Each panel represents the dependent variable, and restrict observations to individuals with entrance exam scores within 10 points of a school-by-category cutoff. In each panel the solid lines are fitted values of regressions of the dependent variable on a linear trend in the entrance exam score, estimated separately on each side of the cutoff. Each point is the mean of the probability of the dependent variable within non-overlapping one point bins. "Entrance exam score - cutoff score" is the entrance exam score minus the relevant school-by-category cutoff score.

Table 1. Descriptive Statistics, Administrative Data: 2009-2011 Cohorts

	School Type				
	All	Model Schools	Public Schools	Private Schools	Aided Schools
Panel A: Observable Characteristics					
Socioeconomic Status (percent)					
Scheduled Caste (SC)	18.6	18.1	21.8	13.9	17.1
	(38.9)	(38.5)	(41.3)	(34.5)	(37.7)
Scheduled Tribe (ST)	6.8	5.5	8.7	4.9	5.9
	(25.2)	(22.8)	(28.1)	(21.7)	(23.5)
Other Backward Classes	66.2	67.8	62.9	69.3	68.4
(2A, 2B, 3A, 3B, C1)	(47.3)	(46.7)	(48.3)	(46.1)	(46.5)
General Merit (GM)	8.5	8.6	6.6	11.9	8.6
	(27.8)	(28.1)	(24.8)	(32.4)	(28.1)
Percent female	45.5	44.9	49.2	39.1	44.7
	(49.8)	(49.7)	(50)	(48.8)	(49.7)
Age	10.21	10.24	10.2	10.2	10.21
(in years)	(.97)	(1.01)	(.96)	(.97)	(.95)
English medium school in	8.6	16.3	2.3	19.7	2.6
fifth-grade (percent)	(28)	(37)	(15)	(39.8)	(15.8)
Average entrance exam	49.98	63.35	44.48	52.7	46.21
score (out of 100)	(17.64)	(16.26)	(15.98)	(16.63)	(15.99)
Panel B: Outcome variables					
Percent graduating	90.3	96.4	87.8	92.8	86.9
high school	(29.6)	(18.5)	(32.7)	(25.8)	(33.8)
10^{th} grade mean	69.82	77.54	66.23	74.01	65.59
percentage	(15.15)	(12.53)	(14.87)	(14.6)	(14.62)
Percent scoring A/A+	28.7	47.8	19.6	39.8	17.7
in tenth-grade	(45.2)	(50)	(39.7)	(48.9)	(38.2)
Percent attending pre-college	70.82	71.87	72.56	75.3	60.67
after tenth-grade	(45.45)	(44.96)	(44.62)	(43.13)	(48.85)
Percent choosing Science	47.1	45.5	47.4	46.6	49.2
stream	(49.9)	(49.8)	(49.9)	(49.9)	(50)
Percent choosing Arts	26.5	28.3	25.2	26.5	28
stream	(44.1)	(45)	(43.4)	(44.1)	(44.9)
Percent attending private	33.1	33.7	34.1	34	29
pre-college	(47.1)	(47.3)	(47.4)	(47.4)	(45.4)
Number of Students	62,582	11,262	26,489	13,332	11,499
Number of Schools	4,257	74	1,993	1,393	798

Notes: Standard errors are in parentheses. Calculations are based on restricted administrative data sets provided by the Department of Primary and Secondary Education, Karnataka. Variables pertaining to pre-college are determined using the first two cohorts only (third cohort will complete pre-college in July, 2019). The corresponding number of students for each of the columns are 39,053; 7,264; 16,540 and 8,098 respectively. I include several other characteristics of schools in table A.1.

Table 2. Distribution of Entrance Exam Scores

	Percentiles				
	10	**20**	**50**	**70**	**90**
10	32	35	45	52	61.5
20	37	41.5	51	59	69
50	47.5	53	63	70	80
70	55	60	70	76	84
90	65	70	79	84	90

Notes: In this table, I summarize the distribution of the cutoffs. Row: x^{th} percentile score in each model school among those that were admitted. Column: y^{th} percentile score within each x^{th} percentile. First, I determine the 10, 20, 50, 70 and 90^{th} percentile score within each model school among those that were admitted. Second, I determine the 10, 20, 50, 70 and 90^{th} percentile within each of the percentiles. Therefore, each number is the y^{th} percentile score within the x^{th} percentile scores.

Table 3. First Stage: Probability of Attending a Model School

	Dependent Variable: Admitted to Model School
$1\{\text{Entrance exam score} \geq \text{cutoff}\}$	0.210^{***}
	(0.0123)
Constant	-0.049
	(.0271)
Observations	19,210
F-Statistic	291.03

Notes: The above table reports the first stage results obtained from regressing an indicator for whether a student is attending model school on a dummy for whether a students entrance exam score is greater than or equal to the relevant school-by-category cutoff. Regression also includes a vector of second-stage control variables: SES dummy variables, gender dummy, urban dummy, English medium dummy, block fixed effects and cohort fixed effects. The analysis restrict observations to individuals with entrance exam scores within 10 points of the cutoff based on the CCT optimal bandwidth test results. The F-statistic corresponds to a Wald test of a coefficient of zero on the instrument. Standard errors clustered at school-by-category-by-year are in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4. 2SLS Estimates: Academic Achievement

Bandwidth	**+/-10**	**+/-10**	**+/-20**	**+/-20**	**+/-30**	**+/-30**
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Math score in 10^{th} grade exam						
	6.600***	6.773***	5.511***	5.056***	7.529***	5.653***
	(2.137)	(2.012)	(1.353)	(1.261)	(1.231)	(1.141)
Panel B: Science score in 10^{th} grade exam						
	4.010**	4.141**	2.652**	2.321**	4.984***	3.016***
	(1.924)	(1.822)	(1.244)	(1.167)	(1.181)	(1.066)
Panel C: Social Science score in 10^{th} grade exam						
	4.531**	4.713**	3.069**	3.011**	5.087***	3.617***
	(2.166)	(2.086)	(1.406)	(1.354)	(1.310)	(1.246)
Panel D: probability of obtaining A/A+ in 10^{th} grade exam						
	0.191***	0.198***	0.137***	0.129***	0.176***	0.136***
	(0.0562)	(0.0543)	(0.0343)	(0.0333)	(0.0320)	(0.0310)
Observations	19210	19210	36966	36966	48538	48538
Controls	No	Yes	No	Yes	No	Yes
Observations	19677	19677	37744	37744	49520	49520

Notes: The above table presents instrumental variable estimates, where a dummy for whether a student's entrance exam score is greater than or equal to the cutoff is used as an instrument for model school attendance indicator. Columns 1 and 2 restrict observations to individuals with entrance exam scores within 10 points of the cutoff based on the CCT optimal bandwidth test results. Columns 3-6 tests for robustness in estimates within 20 and 30 points from the cutoff. Controls: SES dummy variables, gender dummy, urban dummy, English medium dummy, block fixed effects and cohort fixed effects. Standard errors clustered at school-by-category-by-year are in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5. **2SLS Estimates: Educational Attainment Indicators**

Bandwidth	**+/-10**	**+/-10**	**+/-20**	**+/-20**	**+/-30**	**+/-30**
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: probability of passing 10^{th} grade (Matched sample)						
	0.0513	0.0535	0.0752***	0.0755***	0.0750***	0.0643***
	(0.0351)	(0.0346)	(0.0217)	(0.0215)	(0.0215)	(0.0203)
Observations	19677	19677	37743	37743	49519	49519
Panel B: probability of passing 10^{th} grade (Full sample)						
	0.305***	0.316***	0.276***	0.294***	0.219***	0.239***
	(0.0622)	(0.0612)	(0.0394)	(0.0382)	(0.0363)	(0.0345)
Observations	25704	25704	49238	49238	64674	64674
Panel C: probability of joining pre-university (Matched sample)						
	0.119*	0.115*	0.0881*	0.0673	0.114***	0.0681*
	(0.0714)	(0.0677)	(0.0483)	(0.0444)	(0.0427)	(0.0365)
Observations	12695	12695	24369	24369	31748	31748
Panel D: probability of joining pre-university (Full sample)						
	0.286***	0.299***	0.266***	0.266***	0.249***	0.238***
	(0.0874)	(0.0845)	(0.0567)	(0.0536)	(0.0481)	(0.0447)
Observations	16716	16716	32019	32019	41786	41786
Controls	No	Yes	No	Yes	No	Yes

Notes: The above table presents instrumental variable estimates, where a dummy for whether a student's entrance exam score is greater than or equal to the cutoff is used as an instrument for model school attendance indicator. Columns 1 and 2 restrict observations to individuals with entrance exam scores within 10 points of the cutoff based on the CCT optimal bandwidth test results. Columns 3-6 tests for robustness in estimates within 20 and 30 points from the cutoff. Controls: SES dummy variables, gender dummy, urban dummy, English medium dummy, block fixed effects and cohort fixed effects. Standard errors clustered at school-by-category-by-year are in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6. 2SLS Estimates: Choice of Major and Pre-University College Type

Bandwidth	+/-10	+/-10	+/-20	+/-20	+/-30	+/-30
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: prob. of choosing Science stream (as opposed to Arts or Commerce)						
	0.0882	0.0871	0.0575	0.0452	0.0840**	0.0548
	(0.0749)	(0.0746)	(0.0476)	(0.0464)	(0.0399)	(0.0380)
Panel B: prob. of choosing Arts stream (as opposed to Science or Commerce)						
	0.0375	0.0289	0.0362	0.0266	0.0135	0.00148
	(0.0599)	(0.0593)	(0.0363)	(0.0360)	(0.0310)	(0.0304)
Panel C: prob. of choosing Commerce stream (as opposed to Science or Arts)						
	-0.00629	-0.00103	-0.00558	-0.00456	0.0162	0.0118
	(0.0591)	(0.0578)	(0.0356)	(0.0352)	(0.0305)	(0.0296)
Panel D: prob. of attending a private pre-university college						
	0.0683	0.0663	0.0631	0.0488	0.102**	0.0656*
	(0.0733)	(0.0723)	(0.0483)	(0.0462)	(0.0406)	(0.0384)
Controls	No	Yes	No	Yes	No	Yes
Observations	12391	12391	23848	23848	31108	31108

Notes: The above table presents instrumental variable estimates, where a dummy for whether a student's entrance exam score is greater than or equal to the cutoff is used as an instrument for model school attendance indicator. Columns 1 and 2 restrict observations to individuals with entrance exam scores within 10 points of the cutoff based on the CCT optimal bandwidth test results. Columns 3-6 tests for robustness in estimates within 20 and 30 points from the cutoff. Controls: SES dummy variables, gender dummy, urban dummy, English medium dummy, block fixed effects and cohort fixed effects. Standard errors clustered at school-by-category-by-year are in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7. 2SLS Estimates Based on Absolute Learning Levels

	Panel A: Academic Achievement							
	Math	Math	Science	Science	Social Science	Social Science	10^{th}: A/A+	10^{th}: A/A+
Model School	1.368	3.692	1.288	2.241	-0.368	1.547	0.0836	0.123
	(3.309)	(3.211)	(3.148)	(2.953)	(3.588)	(3.542)	(0.0789)	(0.0784)
Model School X	5.789	3.003	1.683	1.352	5.438	3.253	0.101	0.0619
$\widetilde{A}$: Above	(4.218)	(4.036)	(3.886)	(3.651)	(4.391)	(4.289)	(0.108)	(0.106)
Observations	19677	19677	19677	19677	19677	19677	19677	19677

	Panel B: Educational Attainment Indicators			
	10^{th}: P or F	10^{th}: P or F	Pre-Uni Enroll	Pre-Uni Enroll
Model School	0.00237	0.0294	0.0397	0.00539
	(0.0709)	(0.0696)	(0.128)	(0.123)
Model School X	0.0612	0.0302	0.109	0.169
$\widetilde{A}$: Above	(0.0777)	(0.0761)	(0.150)	(0.144)
Observations	19677	19677	12695	12695

	Panel C: Major Choice & Pre-University College Type							
	Science	Science	Arts	Arts	Commerce	Commerce	Private Pre-Uni	Private Pre-Uni
Model School	-0.0477	-0.0679	0.0264	0.0218	0.0609	0.0515	-0.100	-0.114
	(0.122)	(0.121)	(0.105)	(0.103)	(0.0959)	(0.0933)	(0.119)	(0.117)
Model School X	0.212	0.251	0.0162	0.0163	-0.120	-0.0987	0.266*	0.287*
$\widetilde{A}$: Above	(0.154)	(0.153)	(0.126)	(0.125)	(0.121)	(0.119)	(0.150)	(0.149)
Observations	12695	12695	12695	12695	12695	12695	12695	12695
Controls	No	Yes	No	Yes	No	Yes	No	Yes

Notes: The above table presents instrumental variable estimates for groups categorized based on the comparison of each cutoff score to the yearly median cutoff score. Each specification has two instruments: a dummy for whether a student's entrance exam score is greater than or equal to the cutoff is used as an instrument for model school attendance indicator; and a dummy where the above cutoff indicator interacted with a dummy for above absolute learning level group is used as an instrument for model school indicator interacted with a dummy for above absolute learning level group. Notation: $\widetilde{A}$-Above indicates the group with categories whose cutoffs was below the absolute learning level as measured by the yearly median cutoff score. Thus, the analysis is to determine whether "$\widetilde{A}$-Above" perform significantly different from "$\widetilde{A}$-Below". The analysis restrict observations to individuals with entrance exam scores within 10 points of the cutoff based on the CCT optimal bandwidth test results. Panel A provides results for academic achievement. Panel B provides results for educational attainment indicators. Panel C provides results for post-secondary outcomes. The regressions with controls include: SES dummy variables, urban dummy, English medium dummy, block fixed effects, cohort fixed effects. All of these controls interacted with "$\widetilde{A}$-Below" dummy are also added as controls. Standard errors clustered at school-by-category-by-year are in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8. 2SLS Estimates Based on Relative Position Within the Class

	Panel A: Academic Achievement							
	Math	Math	Science	Science	Social Science	Social Science	10^{th}: A/A+	10^{th}: A/A+
Model School	2.991	4.293	2.472	2.738	4.452	5.263	0.144	0.165^{*}
	(3.460)	(3.242)	(3.236)	(2.967)	(3.695)	(3.547)	(0.0892)	(0.0867)
Model School X	3.077	1.652	0.178	-0.0581	-2.810	-3.917	-0.00569	-0.0305
$\widetilde{R}$: Above	(4.260)	(4.014)	(3.926)	(3.632)	(4.413)	(4.240)	(0.112)	(0.108)
Observations	19677	19677	19677	19677	19677	19677	19677	19677

	Panel B: Educational Attainment Indicators			
	10^{th}: P or F	10^{th}: P or F	Pre-Uni Enroll	Pre-Uni Enroll
Model School	0.0233	0.0219	0.0192	0.00743
	(0.0656)	(0.0636)	(0.124)	(0.121)
Model School X	0.0295	0.0371	0.157	0.183
$\widetilde{R}$: Above	(0.0737)	(0.0719)	(0.149)	(0.142)
Observations	19677	19677	12695	12695

	Panel C: Major Choice & Pre-University College Type							
	Science	Science	Arts	Arts	Commerce	Commerce	Private Pre-Uni	Private Pre-Uni
Model School	0.0515	0.0414	0.0263	0.0217	-0.0587	-0.0557	-0.0116	-0.0160
	(0.128)	(0.127)	(0.101)	(0.0998)	(0.0984)	(0.0974)	(0.121)	(0.119)
Model School X	0.0558	0.0718	0.0166	0.0118	0.0848	0.0993	0.127	0.131
$\widetilde{R}$: Above	(0.155)	(0.155)	(0.124)	(0.123)	(0.122)	(0.120)	(0.151)	(0.149)
Observations	12695	12695	12695	12695	12695	12695	12695	12695
Controls	No	Yes	No	Yes	No	Yes	No	Yes

Notes: The above table presents instrumental variable estimates for groups categorized based on the comparison of each cutoff score to the 20^{th} percentile student's score within each school. Each specification has two instruments: a dummy for whether a student's entrance exam score is greater than or equal to the cutoff is used as an instrument for model school attendance indicator; and a dummy where the above cutoff indicator interacted with a dummy for above absolute learning level group is used as an instrument for model school indicator interacted with a dummy for above absolute learning level group. Notation: $\widetilde{R}$-Above indicates the group with categories whose cutoffs was below the absolute learning level as measured by the yearly median cutoff score. Thus, the analysis is to determine whether "$\widetilde{R}$-Above" perform significantly different from "$\widetilde{R}$-Below". The analysis restrict observations to individuals with entrance exam scores within 10 points of the cutoff based on the CCT optimal bandwidth test results. Panel A provides results for academic achievement. Panel B provides results for educational attainment indicators. Panel C provides results for post-secondary outcomes. The regressions with controls include: SES dummy variables, urban dummy, English medium dummy, block fixed effects, cohort fixed effects. All of these controls interacted with "$\widetilde{R}$-Below" dummy are also added as controls. Standard errors clustered at school-by-category-by-year are in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9. 2SLS Estimates Based on Absolute & Relative Learning Level

	Panel A: Academic Achievement			
	Math	Science	Social Science	10^{th}: A/A+
Model School	1.479	2.059	2.653	0.101
	(3.909)	(3.581)	(4.292)	(0.0935)
Model School x	6.666	-1.076	-7.595	0.0561
$\widetilde{A}$:Below & $\widetilde{R}$:Above	(6.579)	(6.101)	(7.168)	(0.167)
Model School x	7.091	1.091	6.578	0.172
$\widetilde{A}$:Above & $\widetilde{R}$:Below	(6.912)	(6.036)	(7.329)	(0.202)
Model School x	3.562	0.836	0.114	0.0256
$\widetilde{A}$:Above & $\widetilde{R}$:Above	(4.702)	(4.252)	(4.978)	(0.118)
Observations	19677	19677	19677	19677

	Panel B: Educational Attainment Indicators	
	10^{th}: P or F	Pre-uni enrol
Model School	0.00320	-0.0297
	(0.0848)	(0.146)
Model School x	0.0532	0.149
$\widetilde{A}$:Below & $\widetilde{R}$:Above	(0.142)	(0.263)
Model School x	0.0467	0.0757
$\widetilde{A}$:Above & $\widetilde{R}$:Below	(0.117)	(0.256)
Model School x	0.0564	0.224
$\widetilde{A}$:Above & $\widetilde{R}$:Above	(0.0905)	(0.165)
Observations	19677	12695

	Panel C: Major Choice & Pre-University College Type			
	Science	Arts	Commerce	Private Pre-Uni
Model School	-0.0677	0.0301	0.00792	-0.0977
	(0.148)	(0.123)	(0.116)	(0.140)
Model School x	0.0193	-0.0306	0.161	-0.0995
$\widetilde{A}$:Below & $\widetilde{R}$:Above	(0.251)	(0.226)	(0.182)	(0.258)
Model School x	0.302	-0.0344	-0.192	0.197
$\widetilde{A}$:Above & $\widetilde{R}$:Below	(0.290)	(0.205)	(0.210)	(0.266)
Model School x	0.215	0.0168	-0.00767	0.269
$\widetilde{A}$:Above & $\widetilde{R}$:Above	(0.178)	(0.145)	(0.142)	(0.171)
Observations	12695	12695	12695	12695

Notes: The above table presents instrumental variable estimates for groups categorized based on the comparison each cutoff score to the yearly median cutoff score and the 20^{th} percentile within school entrance exam score. Each specification has four instruments: one dummy for whether a student's entrance exam score is greater than or equal to the cutoff is used as an instrument for model school attendance indicator and a dummy for whether; three dummies where the above cutoff indicator interacted with a dummy for each of the groups is used as an instrument for model school indicator interacted with a dummy for each of the groups. Notation: A-below indicates the group with categories whose cutoffs was below the absolute learning level as measured by the yearly median cutoff score. R-above indicates the group with categories who cutoff was above the within school 20^{th} percentile entrance exam year. A-above is the opposite of A-below. Therefore, "A-below & R-above" is an indicator for a group with categories who cutoff was below on the absolute criteria and above the relative criteria. "A-above & R-below" and "A-above & R-above" should be interpreted in a similar manner. "A-below & R-below" is the omitted group. Thus, the analysis is to determine whether "A-below & R-above", 'A-above & R-below" and "A-above & R-above" perform significantly different from "A-below & R-below". The analysis restrict observations to individuals with entrance exam scores within 10 points of the cutoff based on the CCT optimal bandwidth test results. Panel A provides results for academic achievement. Panel B provides results for educational attainment indicators. Panel C provides results for post-secondary outcomes. All regressions include controls: SES dummy variables, urban dummy, English medium dummy, block fixed effects, cohort fixed effects. All of these controls interacted with each group's dummy are also added as controls. Standard errors clustered at school-by-category-by-year are in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10. 2SLS Estimates Based on Gender

	Panel A: Academic Achievement							
	Math	Math	Science	Science	Social Science	Social Science	10^{th}: A/A+	10^{th}: A/A+
Model School	6.955**	6.610**	5.540**	5.904**	4.579	4.485	0.198**	0.196***
	(2.975)	(2.867)	(2.644)	(2.534)	(3.047)	(2.961)	(0.078)	(0.076)
Model School X	0.0543	-0.212	-2.478	-3.878	0.563	0.262	0.008	-0.000
Female	(4.303)	(4.129)	(3.852)	(3.618)	(4.387)	(4.215)	(0.120)	(0.115)
Observations	19677	19677	19677	19677	19677	19677	19677	19677

	Panel B: Educational Attainment Indicators			
	10^{th}: P or F	10^{th}: P or F	Pre-Uni enroll	Pre-Uni enroll
Model School	0.0557	0.0560	0.0242	0.0598
	(0.0497)	(0.0493)	(0.0984)	(0.0920)
Model School X	-0.000	-0.0134	0.195	0.119
Female	(0.0648)	(0.0651)	(0.143)	(0.129)
Observations	19677	19677	12695	12695

	Panel C: Major Choice & Pre-University College Type							
	Science	Science	Arts	Arts	Commerce	Commerce	private pre-uni	private pre-uni
Model School	-0.0008	0.0203	0.0606	0.0728	-0.0356	-0.0333	-0.0385	-0.0183
	(0.104)	(0.104)	(0.0885)	(0.0888)	(0.0854)	(0.0845)	(0.101)	(0.0978)
Model School X	0.183	0.139	-0.0519	-0.0754	0.0640	0.0562	0.226	0.188
Female	(0.145)	(0.142)	(0.124)	(0.123)	(0.122)	(0.121)	(0.143)	(0.138)
Observations	12695	12695	12695	12695	12695	12695	12695	12695
Controls	No	Yes	No	Yes	No	Yes	No	Yes

Notes: The above table presents instrumental variable estimates, where a dummy for whether a student's entrance exam score is greater than or equal to the cutoff is used as an instrument for model school attendance indicator. Similarly, a dummy for whether a student's entrance exam score is greater than or equal to the cutoff interacted with a dummy for female indicator is used as an instrument for model school attendance indicator interacted with female dummy indicator. Thus, the analysis is to determine whether females perform significantly different from males. The analysis restrict observations to individuals with entrance exam scores within 10 points of the cutoff based on the CCT optimal bandwidth test results. Panel A provides results for academic achievement. Panel B provides results for educational attainment indicators. Panel C provides results for post-secondary outcomes. The regressions with controls include: SES dummy variables, urban dummy, English medium dummy, block fixed effects, cohort fixed effects. All of these controls interacted with gender dummy are also added as controls. Standard errors clustered at school-by-category-by-year are in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11. Key Differences Between Model Schools and Traditional Public Schools

	School Type		
	Model Schools	Public Schools	Private Schools
Teachers			
Contract structure	Temporary	Permanent (civil workers)	Temporary (contract teachers)
Accountability			
Target/objectives	High (ensure that majority of the students obtain distinctions)	Low (ensure that all students pass)	
Student effort & motivation			
Medium of Instruction (English)	Default	12.7%	46.8%
School expenditures			
Average per annum per pupil expenditure (Rupees)	9,315 - 11,632	11,848 - 16,914	

Notes: The above table lists the major differences between model schools and traditional public schools. The examples for high and low accountability is from author's observation notes during the meetings of education department officials with principals of different schools. For notes on the calculations of per pupil expenditure, please see the cost analysis section in the appendix.

Appendix

A. Cost Analysis

Traditional Public Schools

As per the RTE Act implemented in 2009, state governments are meant to set an upper limit for the reimbursement to private schools for admitting children under the 25 percent quota. The reimbursement is mandated to be equal to the per pupil expenditure (PPE) that the government incurs in its own schools. In 2013-14 & 2014-15, RTE reimbursement upper limit of per student expenditure to be reimbursed for children admitted to grade 1 in Karnataka was set to be 11,848 Rupees per annum (Sarin et al., 2015; GoK circulars) There are speculations on this being a serious underestimate (Kingdon, 2017). For Karnataka, as per Dongre and Kapur (2016), the PPE in 2014-15 was calculated to be 16,914 rupees. Therefore, the PPE in traditional public schools can be anywhere between 11,848 – 16,914 rupees.

Model Schools

Model schools go from grade 6 to grade 10. First cohort was admitted in 2010-11 (80 students per cohort). Which means, the first year in which the schools have students at all grades is in 2014-15 (400 students per school). An annual maintenance grant of 4750 Rupees per student was given in 2016 and 2017. The grant covers variety of costs such as schools repairs, laboratory consumables, school activities, maintenance of computers, medical care (see MHRD circular for a detailed list). The same was proposed for 2011-12 and therefore, for 2014-15, I will assume that the per-pupil annual maintenance grant is: 4,750 Rupees. In 2011, average salary that was paid out to the teachers teaching one of the six subjects (TGT) was 19,585 rupees. Physical education, drawing teachers were paid 10,379 rupees. Other workers such office helpers were paid 9,063 rupees (GoK circular). For 2014-15, inflation adjusted wages for teachers appointed in 2010 or 2011 would be 25,363 (at a rate of 1.09 percent). This is an over-estimate as the inflation adjustment should be somewhere around 4 percent assuming they were given a raise. Therefore, the per-pupil expenditure for model schools teachers comes up to 4,565 rupees per student. Combining this with the annual maintenance grant gives a total per student expenses of 9,315 rupees per annum. Including the salaries paid to non-traditional subject teachers (physical education, drawing, computer operator, etc) and non-teaching staff raises the total per student expenses to 11,632 per annum. Therefore, PPE in model schools could be anywhere between 9,315 – 11,632 rupees.

B. Regression Equations for the Second Econometric Strategy

Absolute prior learning levels
The following regression equation is used to check for whether the difference in effects between the two groups is statistically significant:

$$\begin{aligned} Y \ &= \theta_0\, run + \theta_1\, model\_school + \theta_2\, (run * model\_school) + \theta_3\, \widetilde{A} : Above + \theta_4\, (run * \widetilde{A} : Above) \\ &\quad + \theta_5\, (model\_school\ *\ \widetilde{A} : Above)\ + \theta_6\, (run\ *\ model\_school\ *\ \widetilde{A} : Above)\ +\ \epsilon \end{aligned}$$

Scoring above the cutoff is used as an instrument for model school attendance and scoring above the cutoff interacted with [$\widetilde{A}$: *Above*] is used as an instrument for model school attendance interacted with [$\widetilde{A}$: *Above*].

Relative position within school
The following regression equation is used to check for whether the difference in effects between the two groups is statistically significant:

$$\begin{aligned} Y \ &= \psi_0\, run + \psi_1\, model\_school + \psi_2\, (run * model\_school) + \psi_3\, \widetilde{R} : Above + \psi_4\, (run * \widetilde{R} : Above) \\ &\quad + \psi_5\, (model\_school\ *\ \widetilde{R} : Above)\ + \psi_6\, (run\ *\ model\_school\ *\ \widetilde{R} : Above)\ +\ \epsilon \end{aligned} \tag{4}$$

Scoring above the cutoff is used as an instrument for model school attendance and scoring above the cutoff interacted with [$\widetilde{R}$: *Above*] is used as an instrument for model school attendance interacted with [$\widetilde{R}$: *Above*].

Combination of absolute and relative criterion
The following regression equation is used to check for whether the differences in effects between the four groups is statistically significant:

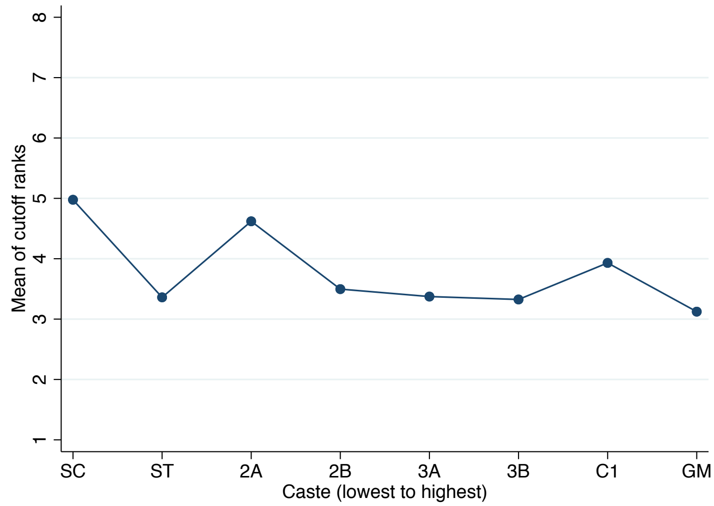
$$\begin{aligned} Y \ &= \beta_0\, run + \beta_1\, model\_school + \beta_2\ (run * model\_school) + \beta_3\, (run * (\widetilde{A} : Below\ \&\ \widetilde{R} : Above)) + \\ &\beta_4\, (model\_school * (\widetilde{A} : Below\ \&\ \widetilde{R} : Above)) + \beta_5\, (run * model\_school * (\widetilde{A} : Below\ \&\ \widetilde{R} : Above)) \\ &\quad +\ \beta_6\, ((\widetilde{A} : Below\ \&\ \widetilde{R} : Above))\ +\ \beta_7\, (run\ *\ (\widetilde{A} : Above\ \&\ \widetilde{R} : Below)) + \\ &\beta_8\, (model\_school * (\widetilde{A} : Above\ \&\ \widetilde{R} : Below)) + \beta_9\, (run * model\_school * (\widetilde{A} : Above\ \&\ \widetilde{R} : Below)) \\ &\quad + \beta_{10}\, (\widetilde{A} : Above\ \&\ \widetilde{R} : Below)\ + \beta_{11}\, (run\ *\ (\widetilde{A} : Above\ \&\ \widetilde{R} : Above)) + \\ &\beta_{12}\ (model\_school * (\widetilde{A} : Above\ \&\ \widetilde{R} : Above)) + \beta_{13}\ (run * model\_school * (\widetilde{A} : Above\ \&\ \widetilde{R} : Above)) \\ &\qquad + \beta_{14}\, (\widetilde{A} : Above\ \&\ \widetilde{R} : Above)\ + \epsilon \end{aligned}$$

Therefore, the above specification will have all four groups stacked together to estimate the differential effect for each group with respect to a reference group. $above\_cutoff$ is used as an instrument for $model\_school$. Similarly, ($model\_school\ *\ < group_i >$) is instrumented for using ($above\_cutoff\ *\ < group_i >$) for each of the three groups. The table below summarizes the groups and it's corresponding coefficients. By omitting the ($\widetilde{A}$: *Below* & $\widetilde{R}$: *Below*) group, the regression determines if each of the other three groups are statistically differently affected by model schools. This identification strategy therefore can be used to estimate four LATEs.

For instance, β_1 is the effect of model schools on students just above the cutoff who have a low prior absolute learning levels and are below the 20^{th} percentile student in their class. Whereas, $\beta_1 + \beta_4$ is the effect of model schools on those with high prior absolute learning levels and are below the 20^{th} percentile student in their class.

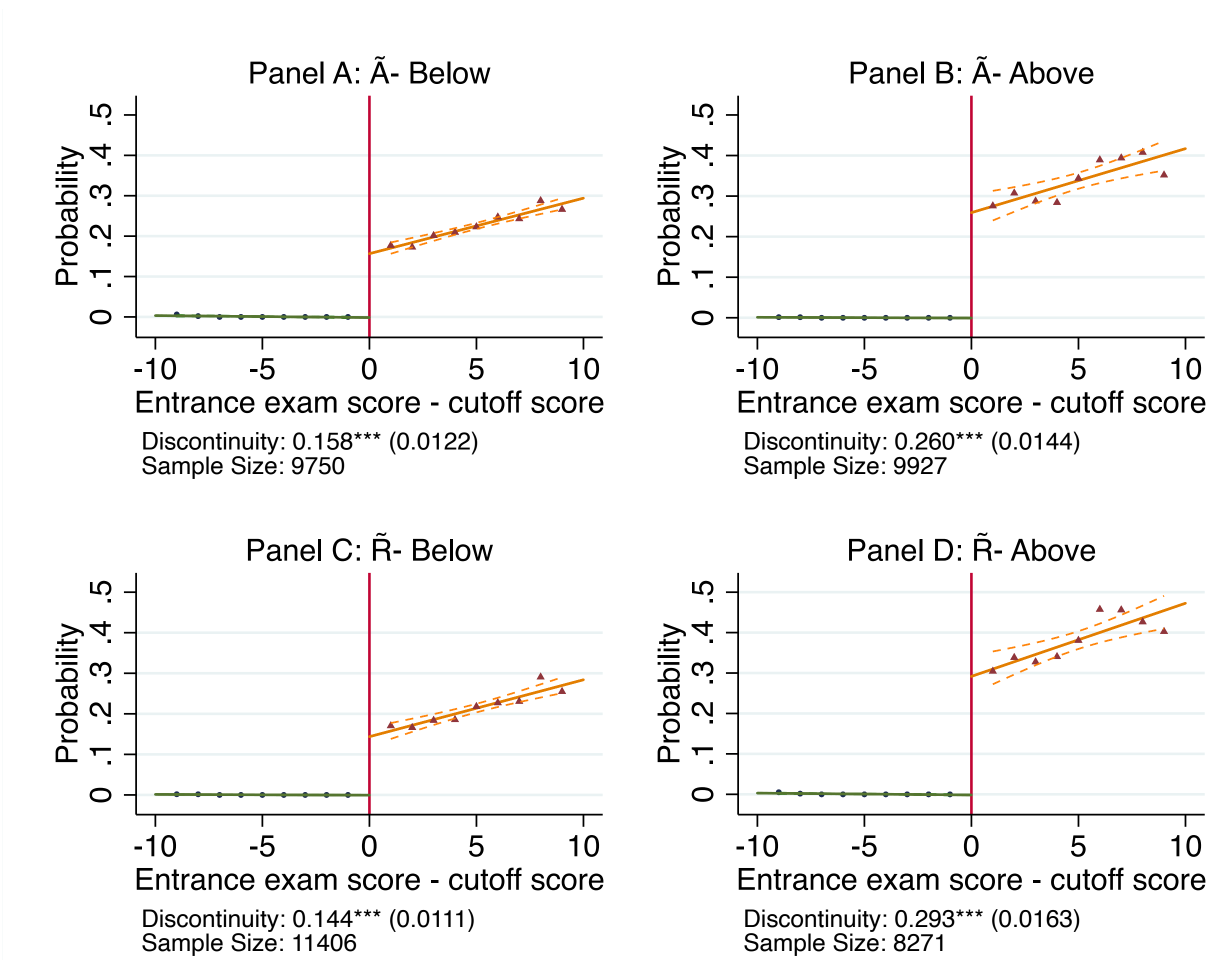
Grouping based on within school and across schools variation in cutoffs			
i	$< group_i >$	Description	Coefficients
-	$\widetilde{A}$: *Below* & $\widetilde{R}$: *Below*	Students who have *low* prior learning levels and are *below* the 20^{th} percentile student in their class	β_1
1	$\widetilde{A}$: *Below* & $\widetilde{R}$: *Above*	Students who have *low* prior learning levels and are *above* the 20^{th} percentile student in their class	$\beta_1 + \beta_4$
2	$\widetilde{A}$: *Above* & $\widetilde{R}$: *Below*	Students who have *high* prior learning levels and are *below* the 20^{th} percentile student in their class	$\beta_1 + \beta_8$
3	$\widetilde{A}$: *Above* & $\widetilde{R}$: *Above*	Students who have *high* prior learning levels and are *above* the 20^{th} percentile student in their class	$\beta_1 + \beta_{12}$

Figure A.1. Relationship Between Caste and Within School Ranking of the Cutoffs



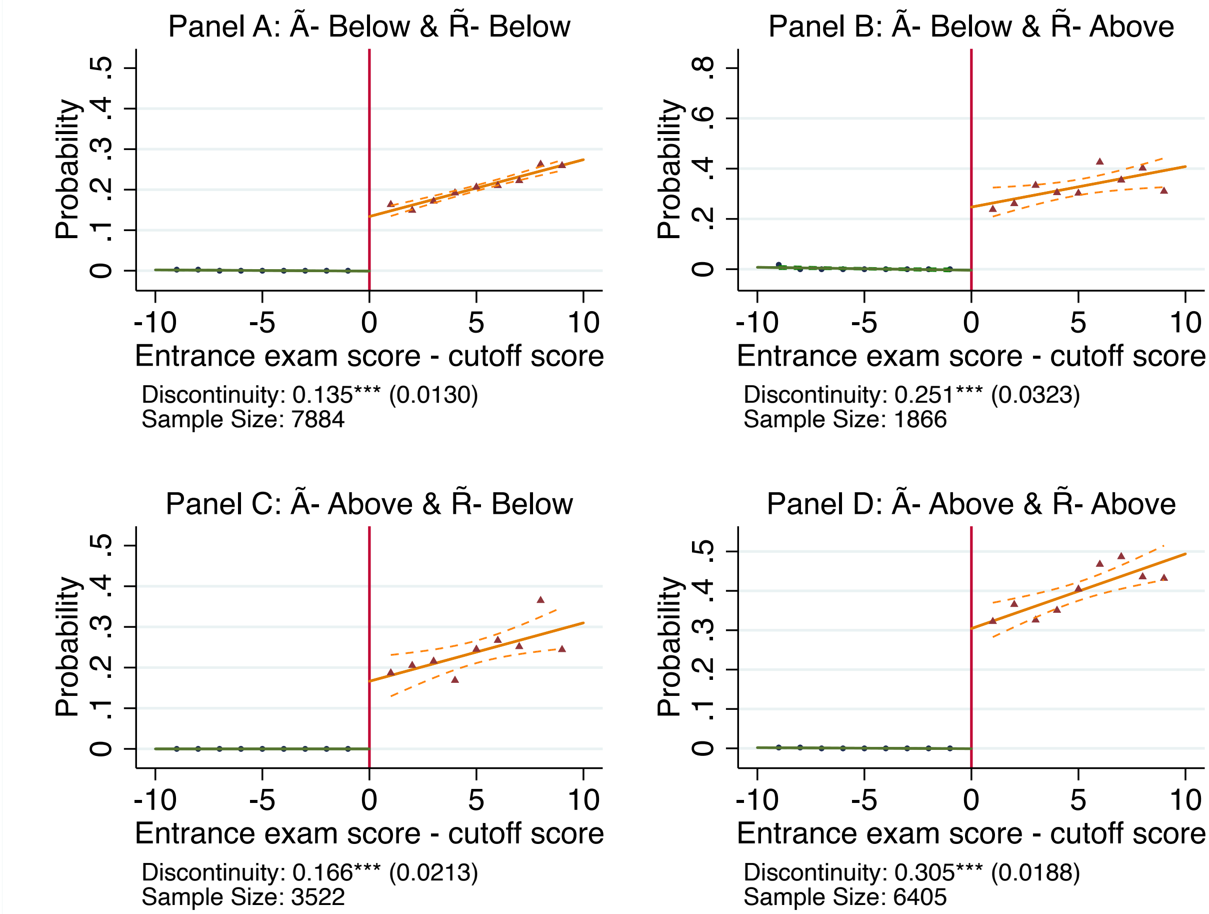
Notes: This figure shows the relationship between each caste and its cutoff's ranking within school. I first rank each of the possible eight cutoffs within a school from lowest (rank 1) to highest (rank 8). I then take the mean of these ranks across school for each caste. On the x-axis is the castes arranged in the order of social status from lowest to highest.

Figure A.2. First Stage: Absolute learning levels and Relative Position Within the Class Separately



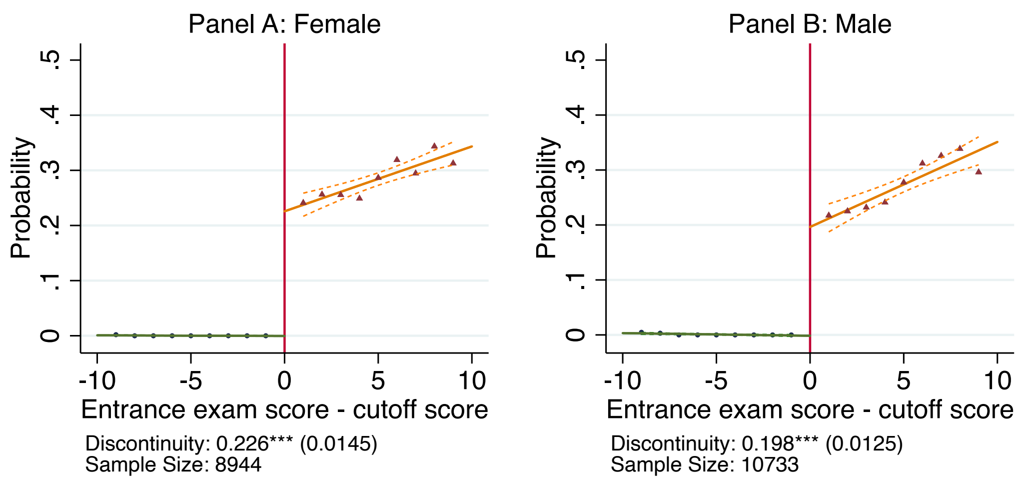
Notes: "Entrance exam score - cutoff score" is the entrance exam score minus the relevant school-by-category cutoff score. Notation: A-below indicates the group with categories whose cutoffs was below the absolute learning level as measured by the yearly median cutoff score. R-above indicates the group with categories who cutoff was above the within school 20^{th} percentile entrance exam year. A-above is the opposite of A-below. Therefore, "A-below & R-above" is an indicator for a group with categories who cutoff was below on the absolute criteria and above the relative criteria. "A-above & R-below" and "A-above & R-above" should be interpreted in a similar manner. "A-below & R-below" is the omitted group. Thus, the analysis is to determine whether "A-below & R-above", 'A-above & R-below" and "A-above & R-above" perform significantly different from "A-below & R-below". Each point is the mean of the probability of attending model school within non-overlapping one point bins. The solid lines are fitted values from a linear specification, separately estimated on each side of the cutoff.

Figure A.3. First Stage: Absolute Learning Levels and Relative Position Within the Class Combined



Notes: "Entrance exam score - cutoff score" is the entrance exam score minus the relevant school-by-category cutoff score. Notation: A-below indicates the group with categories whose cutoffs was below the absolute learning level as measured by the yearly median cutoff score. R-above indicates the group with categories who cutoff was above the within school 20th percentile entrance exam year. A-above is the opposite of A-below. Therefore, "A-below & R-above" is an indicator for a group with categories who cutoff was below on the absolute criteria and above the relative criteria. "A-above & R-below" and "A-above & R-above" should be interpreted in a similar manner. "A-below & R-below" is the omitted group. Thus, the analysis is to determine whether "A-below & R-above", 'A-above & R-below" and "A-above & R-above" perform significantly different from "A-below & R-below". Each point is the mean of the probability of attending model school within non-overlapping one point bins. The solid lines are fitted values from a linear specification, separately estimated on each side of the cutoff.

Figure A.4. First Stage for Gender



Notes: "Entrance exam score - cutoff score" is the entrance exam score minus the relevant school-by-category cutoff score. Each point is the mean of the probability of attending model school within non-overlapping one point bins. The solid lines are fitted values from a linear specification, separately estimated on each side of the cutoff.

Table A.1. Descriptive Statistics of Schools

	School Type				
	All	Model Schools	Public Schools	Private Schools	Aided Schools
Teacher Characteristics:					
Teachers with Graduate degree and above	56.6	69.6	63	49.1	47.3
	(41.3)	(39.7)	(39.3)	(42.9)	(41.1)
Teachers with Professional degree	9897.8	98.2	98.4	96.7	97.9
	(9.5)	(7.1)	(6.9)	(13.6)	(8.3)
Number of male teachers	6.02	4.34	6.31	5.12	6.75
	(3.6)(2.92)	(1.73)	(2.96)	(2.67)	(2.89)
Number of female teachers	3.16	3.14	3.3	3.73	1.74
	(3.03)	(1.77)	(2.48)	(4.1)	(1.89)
School Characteristics:					
Girls toilets	99.4	100	99.2	99.5	99.5
	(7.8)	(0)	(8.7)	(7)	(7)
Electricity	97.7	94.9	97.1	98.2	98.6
	(15.1)	(22.1)	(16.9)	(13.2)	(11.7)
Library	97.5	96.6	97.4	96.4	99.7
	(15.5)	(18.2)	(15.9)	(18.6)	(5.5)
Playground	87.3	62.5	82	91.3	97.8
	(33.2)	(48.6)	(38.4)	(28.2)	(14.8)
Water	58.3	54	54.4	61.5	64
	(49.3)	(50)	(49.8)	(48.7)	(48)
Meals in school	83.3	98.3	99.5	26.5	98
	(37.3)	(13.1)	(7.2)	(44.2)	(14.1)
School approachable by road	94.3	98.8	91.9	95.5	98.1
	(23.2)	(10.7)	(27.2)	(20.8)	(13.8)
Number of working days Secondary school	230.4	229.8	230.4	230.6	230.4
	(6.6)	(6.3)	(6.3)	(6.9)	(6.8)
Boundary wall	78	66.1	77.7	81.3	75
	(41.5)	(47.5)	(41.7)	(39)	(43.3)
Department Officials Visits:					
Visits by Block Resource Coordinators	1.46	2.42	1.5	1.33	1.46
	(1.95)	(2.78)	(2.1)	(1.74)	(1.74)
Visits by Cluster Resource Coordinators	3.36	4.1	3.43	3.13	3.46
	(3.99)	(4.16)	(4.19)	(3.56)	(4.08)

Notes: The above table summarises various characteristics of schools. Calculations are based on Unified-District Information System for Education (U-DISE) data. These are suggestive estimates only as several schools are either missing or have zeros for various characteristics on the DISE data. Standard errors are in parentheses.

Table A.2. Reduced Form Estimates of Covariates Smoothness Test

	High SES (General Merit) (1)	Low SES (SC & ST) (2)	Gender (Female) (3)	Age (Years) (4)	Location (Urban) (5)	Medium of Instruction (English) (6)
Panel A: Matched Sample						
	-0.0015	-0.011	-0.028*	-0.012	0.018	0.0062
	(0.0082)	(0.014)	(0.015)	(0.030)	(0.012)	(0.0089)
Observations	19677	19677	19677	19575	19677	19677
Panel B: Full Sample						
	-0.0059	0.00069	-0.016	-0.029	0.0082	-0.0030
	(0.0072)	(0.012)	(0.013)	(0.026)	(0.011)	(0.0079)
Observations	25893	25893	25893	25664	25893	25893

Notes: The above table presents the reduced form estimates for the covariates smoothness test, and restrict observations to individuals with entrance exam scores within 10 points of the cutoff based on the CCT optimal bandwidth test results. The dependent variable in columns 1 and 2 is the socio-economic status grouped into two categories: (i) General Merit (GM); (ii) Scheduled Caste (SC) & Scheduled Tribe (ST), respectively. The dependent variable in column 3 is probability of being a female; the dependent variable in column 4 is the age of students; the dependent variable in column 5 is the probability of living in a urban area and the dependent variable in column 6 is the probability of studying in a English medium school in 5^{th} grade. Standard errors clustered at school-by-category-by-year are in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.3. Bounding Exercise

	Bandwidth: +/-10					
	Lower Bound (drop top 3 percent)			Upper Bound (drop bottom 3 percent)		
	First Stage	Reduced Form	2SLS	First Stage	Reduced Form	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Math score in 10^{th} grade exam						
	0.206***	0.876*	4.093**	0.215***	2.970***	12.45***
	(0.0123)	(0.481)	(2.044)	(0.0125)	(0.479)	(2.038)
Panel B: Science score in 10^{th} grade exam						
	0.208***	0.263	1.214	0.212***	2.168***	8.977***
	(0.0122)	(0.434)	(1.845)	(0.0124)	(0.432)	(1.864)
Panel C: Social Science score in 10^{th} grade exam						
	0.206***	0.701	3.118	0.212***	2.743***	11.38***
	(0.0123)	(0.497)	(2.121)	(0.0124)	(0.488)	(2.115)
Panel D: prob. of obtaining A/A+ in 10^{th} grade exam						
	0.205***	0.0293**	0.137**	0.216***	0.0556***	0.239***
	(0.0122)	(0.0131)	(0.0560)	(0.0125)	(0.0132)	(0.0548)

The above table presents lower and upper bound first stage, reduced forms and 2SLS estimates for the sample when top 3 percent or the bottom 3 percent of the students within each of the above cutoff bins are dropped. A dummy for whether a student's entrance exam score is greater than or equal to the cutoff is used as an instrument for model school attendance indicator. For lower bound estimates, 3 percent of the toppers within each of the above cutoff bins are dropped. For lower bound estimates, 3 percent of the scorers at the bottom within each of the above cutoff bins are dropped. Columns 1 and 4 present the first stage estimate. Columns 2 and 5 present the reduced form estimates or in other word, intent to treat. Column 3 and 6 present the 2SLS estimates for each of the academic achievement outcomes. Controls: SES dummy variables, gender dummy, urban dummy, English medium dummy, block fixed effects and cohort fixed effects. Standard errors clustered at school-by-category-by-year are in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.4. 2SLS Estimates: 10^{th} Grade with First and Second Cohort Only

Bandwidth	**+/-10**	**+/-10**	**+/-20**	**+/-20**	**+/-30**	**+/-30**
	(1)	(2)	(3)	(4)	(5)	(6)
Academic achievement						
Panel A: Maths score in 10^{th} grade exam						
	7.348***	7.403***	6.785***	5.588***	8.015***	5.047***
	(2.579)	(2.365)	(1.662)	(1.498)	(1.540)	(1.380)
Panel B: Science score in 10^{th} grade exam						
	4.733**	5.207**	3.811**	2.905**	5.095***	2.546*
	(2.408)	(2.280)	(1.540)	(1.454)	(1.436)	(1.342)
Panel C: Social Science score in 10^{th} grade exam						
	3.689	3.678	4.180**	3.477**	5.294***	2.903*
	(2.607)	(2.457)	(1.705)	(1.598)	(1.622)	(1.511)
Panel E: probability of scoring 85 percent and above in 10^{th} grade exam						
	0.235***	0.248***	0.191***	0.172***	0.201***	0.142***
	(0.0691)	(0.0654)	(0.0403)	(0.0386)	(0.0382)	(0.0374)
Educational attainment indicator						
Panel D: probability of graduating high school						
	0.0322	0.0396	0.0730***	0.0674***	0.0782***	0.0584***
	(0.0363)	(0.0354)	(0.0240)	(0.0229)	(0.0245)	(0.0218)
Controls	No	Yes	No	Yes	No	Yes
Observations	12391	12391	23848	23848	31108	31108

Notes: The above table presents instrumental variable estimates, where a dummy for whether a student's entrance exam score is greater than or equal to the cutoff is used as an instrument for model school attendance indicator. Columns 1 and 2 restrict observations to individuals with entrance exam scores within 10 points of the cutoff based on the CCT optimal bandwidth test results. Columns 3-6 test for robustness in estimates within 20 and 30 points from the cutoff. Controls: SES dummy variables, gender dummy, urban dummy, English medium dummy, block fixed effects and cohort fixed effects. Standard errors clustered at school-by-category-by-year are in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5. First Stage Estimates for Heterogeneous Groups

	Dependent Variable: Admitted to Model School			
Panel A: Gender	Female	Male		
1{Entrance exam scorecutoff}	0.222***	0.198***		
	(0.0139)	(0.0128)		
Observations	8944	10733		
F-Statistic	256.28	238.85		
Panel B: Initial learning level				
	$\widetilde{A}$:Below	$\widetilde{A}$:Above		
1{Entrance exam scorecutoff}	0.157***	0.256***		
	(0.0155)	(0.0186)		
Observations	9750	9927		
F-Statistic	103.20	190.36		
Panel C: Relative position within class				
	$\widetilde{R}$:Below	$\widetilde{R}$:Above		
1{Entrance exam scorecutoff}	0.145***	0.291***		
	(0.0139)	(0.0208)		
Observations	11406	8271		
F-Statistic	108.75	194.27		
Panel D: Initial learning levels and position within class				
	A- Below & R- Below	A- Below & R- Above	A- Above & R- Below	A- Above & R- Above
1{Entrance exam scorecutoff}	0.134***	0.248***	0.164***	0.299***
	(0.0137)	(0.0316)	(0.0209)	(0.0173)
Observations	7884	1866	3522	6405
F-Statistic	96.81	61.32	61.47	299.06

The above table presents the first stage specification's estimate for each of the heterogeneous groups, where the key independent variable is a dummy for whether a students entrance exam score is greater than or equal to the relevant school-by-category cutoff. The analysis restrict observations to individuals with entrance exam scores within 10 points of the cutoff based on the CCT optimal bandwidth test results. Standard errors clustered at school-by-category-by-year are in parentheses. Notation: A-below indicates the group with categories whose cutoffs was below the absolute learning level as measured by the yearly median cutoff score. R-above indicates the group with categories who cutoff was above the within school 20$^{\text{th}}$ percentile entrance exam year. A-above is the opposite of A-below. Therefore, "A-below & R-above" is an indicator for a group with categories who cutoff was below on the absolute criteria and above the relative criteria. "A-above & R-below" and "A-above & R-above" should be interpreted in a similar manner. "A-below & R-below" is the omitted group. Thus, the analysis is to determine whether "A-below & R-above", 'A-above & R-below" and "A-above & R-above" perform significantly different from "A-below & R-below".

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.6. Model Schools Program Implementation Status by State as of 2016

States/UTs Name	Total No. of Blocks	EBBs	Non-EBBs	No. of schools approved	No. of schools functional
Andhra Pradesh	664	341	323	272	163
Arunachal Pradesh	79	40	39	0	0
Assam	178	81	97	77	0
Bihar	534	530	4	368	0
Chhattisgarh	146	76	72	74	74
Dadara & Nagar Haveli	-	-	-	-	-
Gujarat	224	85	139	84	84
Haryana	119	36	83	36	36
Himachal Pradesh	118	5	113	5	0
Jammu & Kashmir	-	-	-	-	-
Jharkhand	259	203	56	164	89
Karnataka	180	74	-	74	74
Kerala	-	1	-	-	-
Madhya Pradesh	313	201	112	201	201
Maharashtra	355	43	312	43	43
Manipur	35	5	30	0	0
Meghalaya	39	9	30	9	0
Mizoram	36	1	35	1	0
Nagaland	47	11	36	11	0
Odisha	315	173	142	162	0
Punjab	142	21	121	21	21
Rajasthan	254	186	68	134	72
Tamil Nadu	-	-	-	-	-
Telangana	464	396	68	317	192
Tripura	40	9	31	7	0
Uttar Pradesh	830	680	150	274	193
Uttarakhand	96	19	77	0	0
West Bengal	362	87	275	67	0

The above table is constructed using the reports published by MHRD at: https://mhrd.gov.in/model_school_state_ut