Can Model Public Schools in India Expand Access to a High-Quality Education?

BY

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THESIS
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For Dr. Nirmalanandanatha Maha Swamiji, my beloved guru and my source of inspiration. For my parents, to whom I owe everything.

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TABLE OF CONTENTS

CHAPTER PAGE

TABLE OF CONTENTS (continued)

TABLE OF CONTENTS (continued)

LIST OF TABLES

LIST OF TABLES (continued)

LIST OF FIGURES

FIGURES | PAGE

LIST OF FIGURES (continued)

LIST OF ABBREVIATIONS

2SLS	Two-Stage Least Squares
AITT	All India Trade Test
ASER	Annual Status of Education Report
CGA	Cumulative Grade Average
CID	Crime Investigation Department
DISE	District Information System for Education
DPUE	Department for Pre-University Education
EBB	Educationall Backward Blocks
GM	General Merit
IAS	Indian Administrative Service
IB	International Baccalaureate
IGCSE	International General Certificate of Secondary Examination
IPS	Indian Police Service

LIST OF ABBREVIATIONS (continued)

ITI	Industrial Training Institute
KSEEB	Karnataka Secondary Education Examination Board
LATE	Local Average Treatment Effect
NTC	National Trade Certificate
OBC	Other Backward Class
PPE	Per Pupil Expenditure
RDD	Regression Discontinuity Design
RTE	Right to Education
SC	Scheduled Caste
SES	Socio-Economic Status
SSLC	Secondary School Leaving Certificate
ST	Scheduled Tribe

SUMMARY

Chapter 1: Public School Quality and Student Outcomes: Evidence from Model Public Schools in India

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 have superior infrastructure, high accountability, English as the medium of instruction, and contract teachers. The model schools admit students into sixth-grade 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. I find that attending a model school has large positive effects on math, science, social science test scores, and a positive effect on the probability of joining pre-university. Lastly, turning to the costs, the per-pupil annual expenditure in model schools is comparable to that of the traditional public schools.

Chapter 2: Do Effects of Model Public Schools Differ by Prior Learning Levels and Gender?

Abstract: I use the within year and within school variation in the 1,300 school-by-category cutoffs from 3 cohorts of model schools to determine the effects of attending a model school based on prior learning levels and relative position within class respectively. I estimate multiple local average treatment effects and find that model schools have a similar positive effect across the ability (as measured by entrance exam score) distribution. I explore heterogeneity in effects by gender and the results suggest that model schools work for girls as well as boys.

Chapter 3: School Type, Career Aspirations and Information Gaps: Descriptive Evidence from Different Public School Systems in India

Abstract: In India, the interaction of attending a public school and low socioeconomic status is correlated with low career aspirations (Arulmani, Van Laar, and Easton, 2003) and narrow occupational categories (Munshi and Rosenzweig, 2006; Krishna, 2017.) Using survey data from 2,842 students at 49 schools, I compare the career aspirations of students across four different systems of public schools that vary in quality. The findings are not casual as students can sort to schools. The objective of this paper is to identify and document the differences in career aspirations and information gaps to aid future research. I find that attending a system of higher quality public schools is associated with an increase in the likelihood of having a socially desirable career aspiration such as doctor or engineer. Although 45 percent of the sample aspire to be a doctor or engineer, I find that students across all four systems of schools lack knowledge on the college admission determinants to pursue medicine or engineering.

1 PUBLIC SCHOOL QUALITY AND STUDENT OUTCOMES: EVIDENCE FROM MODEL PUBLIC SCHOOLS IN INDIA

1.1 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.[2] 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.[3] Second, many families with the capacity to pay for a private school are switching their children to the private sector.[4] Thus, an important question for public policy is whether raising the quality of public schools has any prospect of succeeding in developing countries. In

[2]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), and Heckman, Humphries, and Veramendi (2018). For developing countries, see Peet, Fink, and Fawzi (2015).

[3]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.

[4]For literature on private schooling phenomenon, see Muralidharan and Kremer (2006) and Kingdon (2017) for India, Tooley, Dixon, and Amuah (2007) for Ghana, Rose (2003) for Malawi, and Alderman, Orazem, and Paterno (2001) for Pakistan.

this paper, I exploit a natural experiment in India to examine the effects of an attempt to create 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.[5] 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.[6] 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 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 and families. The model schools admission structure allows

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

[6] 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.

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 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.[7] 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.[8]

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.[9] This cutoff score for admission into a model school is not known to the school or to the potential students

[7] 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.

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

[9] 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, the principals said 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.

beforehand. Thus, whether students near the cutoff fall to the right or the left 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 that applied to 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 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, 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 a statistically 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.

1.2 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 low-income students an opportunity to attend a high-quality public 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 an 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 within the Hindu religion, which makes up nearly 80 percent of the population.[10] Castes are hereditary and are arranged hierarchically, with 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) which are educationally or socially disadvantaged– about 41 percent.[11] There is substantial evidence documenting inequality in education, employment, and income across these castes.[12]

India has been trying to address the inequalities present across social classes through reservations in higher education and central government jobs.[13] 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.”[14] 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

[10] Caste is also referred to as jati.

[11] 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.

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

[13] 15 percent for SCs and 7.5 percent for STs.

[14] Kothari Commission Report (1964-66)

– 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).[15]

Model schools program. With the intention of improving primary and secondary education, India designated 3,479 out of 5,564 blocks as educationally backwards.[16] 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."[17] To accomplish this, it was proposed that the 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

[15]See *Swelling support for common schools* by Summiya Yasmeen for an excellent summary of the Kothari Commission Report and her description of the three tiers of Indian schooling.

[16]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 had rural female literacy rates of less than 45 percent, irrespective of the gender gap. Additionally, 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.

[17]Speech Transcript

the model schools program. I have obtained data for Karnataka, a southern state in India, and hence, analyze model schools in that state.[18]

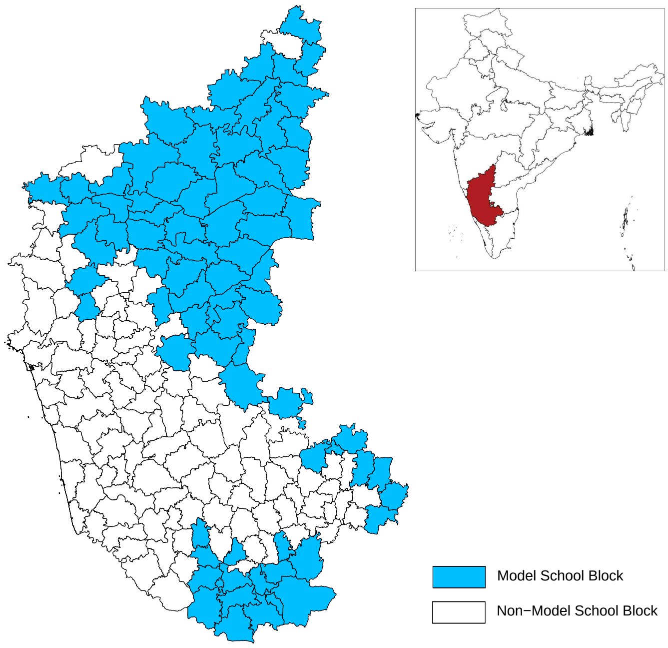
The Indian education system consists of three parts– elementary, secondary, and tertiary education.[19] Elementary education includes primary school (grades 1 through 5) and upper-primary school (grades 6 through 8). Secondary education begins with high school (grades 9 and 10), and then students may choose to either enter the labor market or continue on with their education. Students who pursue further education may attend senior-secondary school (a two-year, pre-university track, equivalent to 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 an undergraduate degree. Students choosing to attend a diploma college earn a diploma in engineering upon successful completion. Those who choose to attend an ITI can appear for the All India Trade Test (AITT) at the end of two years, wherein successful candidates will receive the National Trade Certificate (NTC). The latter two paths typically lead to labour market entry.[20]

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

[19]See Cheney, Ruzzi, and Muralidharan (2005) for an excellent summary of the Indian education system.

[20]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.

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.

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 the Selection, Eligible, and Rejection lists. 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.[21] 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 the model school.

The selection and eligible lists are then sent to each model school to begin the admission process. In theory, if all 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 later sections. In such a case, the principal will admit students from the eligible list, in descending order, based on their entrance exam score.

[21] In the list of 80 students, under each caste category, the students are listed 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 may not both be admitted. 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.

1.3 Data

In this section, I describe the three sources of administrative data that allow me to track those who appeared for the model schools entrance exams at two future points: the end of high school (tenth grade) and the 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) in 10^{th} grade. I discuss the attrition and it's effect on the interpretation of findings in the results section.

1.3.1 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, 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. The data are available 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.

Upon completion of 10^{th} grade, if students choose to continue some form of education, they have three options, as described in Section 2 above. 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$^{\text{th}}$ grade exam in the years 2016-17, 2017-18, and 2018-19 respectively.[22]

1.3.2 Merging of Data Sets

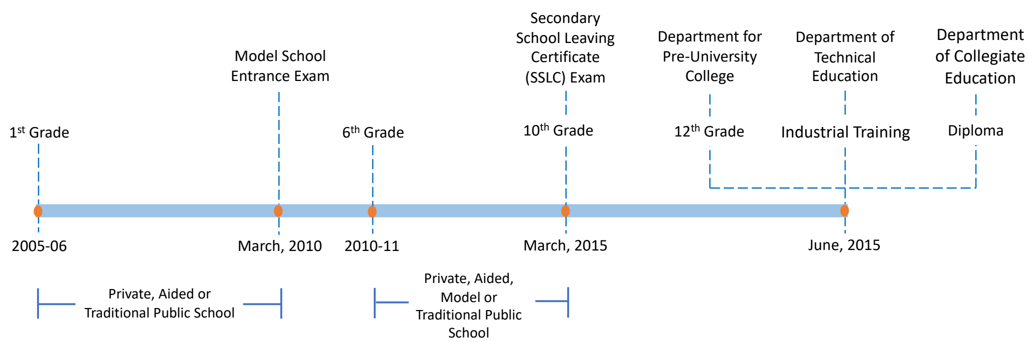
Fuzzy string matching. Figure 2 shows the potential progress path for a typical student who wishes to attend a model school in cohort 1. This figure also facilities understanding of which data set(s) are used at each stage. The first objective is to track students who took the entrance exam in the 10$^{\text{th}}$ grade data set. Although, there is no unique identifier that is common to the entrance exam data and the 10$^{\text{th}}$ 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$^{\text{th}}$

[22]The first and second cohort appeared for their 12$^{\text{th}}$ grade exam in 2017 and 2018 respectively. The third cohort would have appeared for 12$^{\text{th}}$ 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.

grade. Five years later, I am able to find 63,442 (approximately 77 percent) of those students in the 10th grade data.[23]

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 5th grade and Secondary School Leaving Certificate (SSLC) exam at the end of 10th grade. After 10th 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.

Attrition. I anticipated that not everybody who took the model school entrance exam can be found in the 10th-grade exam. However, I cannot simply assume that those students must have dropped out of school, as there are two other possible reasons.[24] First, students could have migrated to blocks other than the 74 model school blocks. My data is limited to the 74 EBBs

[23]The matching rate varies for students who attended model schools versus non-model schools. Of the 11,906 students who appeared for the 10th-grade state-standardized exam from model schools, I was able to find the entrance exam scores for 11,262 (∼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 10th grade results for 52,181 (∼74 percent) of them.

[24]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.

with model schools. 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 2 percent between within district and neighboring district matched samples suggests that there is very little between-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.[25] 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 but took the 10th-grade exam at a school that does not follow the state-standardized syllabus. However, as model schools are built in educationally

[25]Each state designs its own syllabus that is to be followed by all public and aided schools. Therefore, public and aided schools cannot choose their syllabus. The primary purpose of the state-standardized syllabus is to facilitate the use of the regional language as the 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 syllabi, 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.

backward blocks, only a small fraction of students that appeared for the entrance exam might be attending a central or international syllabus school.[26]

In the results section, I assess the concerns related to attrition and demonstrate the robustness of the results.

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^{th} grade exam from either a traditional or aided public schools, suggesting that they are the go-to schools in these EBBs. As anticipated, private schools have the lowest percentage of students belonging to the Scheduled Castes and Scheduled Tribes. Model schools have the highest 10^{th} grade mean score when compared with 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, which may be evidence of households' preference for boys' education in these blocks (Datta and Kingdon, 2019). The percent continuing traditional schooling after 10^{th} grade is comparable across all the schools types.

[26]Using District Information System for Education (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^{th} grade students in these schools could be about 5 to 7 percent of the total 10^{th} grade students. DISE data has serious accuracy issues and hence these are approximations only.

TABLE I: 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 (2A, 2B, 3A, 3B, C1)	66.2	67.8	62.9	69.3	68.4
	(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 (in years)	10.21	10.24	10.2	10.2	10.21
	(.97)	(1.01)	(.96)	(.97)	(.95)
English medium school in fifth-grade (percent)	8.6	16.3	2.3	19.7	2.6
	(28)	(37)	(15)	(39.8)	(15.8)
Average entrance exam score (out of 100)	49.98	63.35	44.48	52.7	46.21
	(17.64)	(16.26)	(15.98)	(16.63)	(15.99)
Panel B: Outcome variables					
Percent graduating high school	90.3	96.4	87.8	92.8	86.9
	(29.6)	(18.5)	(32.7)	(25.8)	(33.8)
10^{th} grade mean percentage	69.82	77.54	66.23	74.01	65.59
	(15.15)	(12.53)	(14.87)	(14.6)	(14.62)
Percent scoring A/A+ in tenth-grade	28.7	47.8	19.6	39.8	17.7
	(45.2)	(50)	(39.7)	(48.9)	(38.2)
Percent attending pre-college after tenth-grade	70.82	71.87	72.56	75.3	60.67
	(45.45)	(44.96)	(44.62)	(43.13)	(48.85)
Percent choosing Science stream	47.1	45.5	47.4	46.6	49.2
	(49.9)	(49.8)	(49.9)	(49.9)	(50)
Percent choosing Arts stream	26.5	28.3	25.2	26.5	28
	(44.1)	(45)	(43.4)	(44.1)	(44.9)
Percent attending private pre-college	33.1	33.7	34.1	34	29
	(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.

1.4 Empirical Strategies

I take advantage of the mechanism used to determine model school admissions. This extends the work of Pop-Eleches and Urquiola (2013), a study of Romanian secondary schools, because there is a separate cutoff for each caste category within each model school. As the cutoffs are not pre-determined and depend on the take-up rate, I determine a cut-off for each school-by-category for each year. To do this, I set the entrance exam score of the last student admitted in each year as the cutoff score for that school-by-category (denoted by $cutoff_{sj}$, for school s and category j).

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.[27] In such a case, using the lowest score as the cutoff would introduce measurement error.[28] For this reason, I reassign the cutoff score for a school-by-category combination based on the following rule: the gap between two consecutive model school attendants' scores is greater than 0.75 standard deviations of that school-by-category's entrance

[27] 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.

[28] 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.

exam score and the percent share of students who scored between the two scores is at least 10 percent.[29]

This method of constructing the cutoff scores gives me a total of 1,513 cutoffs across three cohorts.[30] The sample consists of 35,764 students below the cutoff and 25,385 students above the cutoff. In this section, I discuss the strategy to determine the effects of model schools by combining all the cutoffs.

1.4.1 Combining All Cutoffs

I combine all cutoffs under one framework by assuming homogeneity in effects across all cutoffs to determine the treatment effects. 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 within each category in the selection list chooses to attend model school. However, not everyone who is on the selection list of top students in each caste category chose to attend a model school, leading to imperfect compliance. Hence,

[29] 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 1,513 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.

[30] 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.

to determine the effects of attending a model school, I employ a “fuzzy” regression discontinuity design (Hahn, Todd, and Van der Klaauw, 2001; Lee and Lemieux, 2010).

In this context, the treatment is attending model schools and admission to a model school is conditional on the entrance exam score being above the appropriate 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 student's entrance exam score with the respective school-by-category cutoff score for each cohort ($C_i = EE_i - cutoff_{sj}$). 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 the students that are at the cutoff and the rest of the students 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 equal to one if 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 estimated even if factors that affect outcomes such as math scores are systematically related to applicants' entrance exam scores.

If, prior to the treatment, the students just above and just below the cutoff are similar, then those students just below the cutoff will serve as a valid control group for students just above the cutoff. In such a case, any differences in the 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 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 the asymptotically 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.

1.5 The First Stage & Threats to Identification

The identification strategy discussed above relies on the validity of the instrument and the identification assumption. First, the empirical strategy relies on entrance exam scores' ability to predict model school attendance. 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 cutoff are similar. The internal validity of the estimates fails if students on one side of the cutoff are systematically different from students on the other side. These potential threats can be assessed through various tests, a benefit of the RD design. In this section, 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.

1.5.1 First Stage: Probability of Attending Model School

In Figure 3, I present the basic first stage results for my data following equation (1). Here, the x-axis is the running variable – distance between 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, Cattaneo, and Titiunik (2014). Figure 3 shows a clear discontinuity at the cutoff, speaking to the validity of the instrument and the empirical design.[31] The vertical distance between the two solid lines at the discontinuity is analogous to $\hat{\rho}$ in equation (1).

[31] I omit the value 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 them in any of my analyses. Typically, there are 1 or 2 students at each cutoff and a total of 2,615 students for all 1,513 cutoffs.

Figure 3: 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, Cattaneo, and Titiunik (2014) (referred to as CCT, hereafter) optimal bandwidth test results. Each point represents the mean probability of attending a model-school in one-point bins. The solid lines represent the linear fit for the points, estimated separately on either side of the cutoff.

Table 2 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.

TABLE II: FIRST STAGE: PROBABILITY OF ATTENDING A MODEL SCHOOL

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

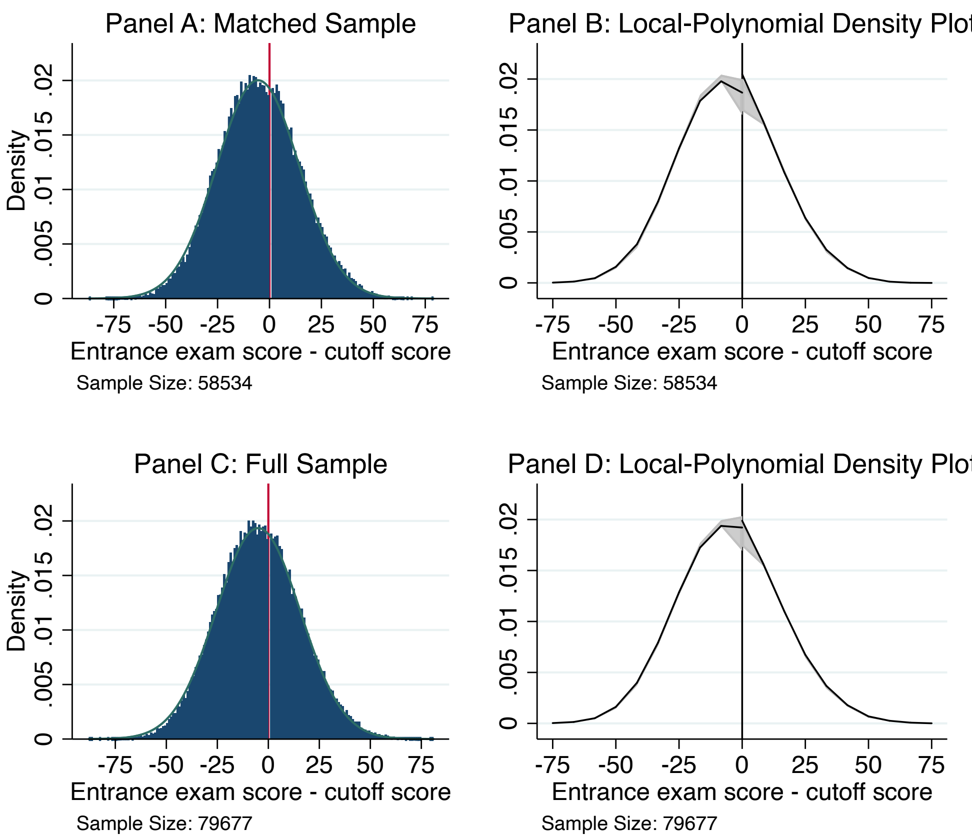
Notes: The above table reports the first stage results obtained from regressing an indicator for whether a student is attending model school on a dummy for whether a student's entrance exam score is greater than or equal to the relevant school-by-category cutoff. Regression also includes a vector of 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 large F-statistic suggests that the scoring above the cut-off strongly affects the probability of attending a model school. Standard errors clustered at school-by-category-by-year are in parentheses.

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

1.5.2 Tests to Assess Threats to Identification: 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 can perfectly manipulate their entrance exam score so as to be able to score just above the cut-off. However, perfect manipulation just 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 unknown until the exams are graded and depends on the students' take-up rate. Moreover, the cutoffs are block-, category-, and

Figure 4: Histogram Test



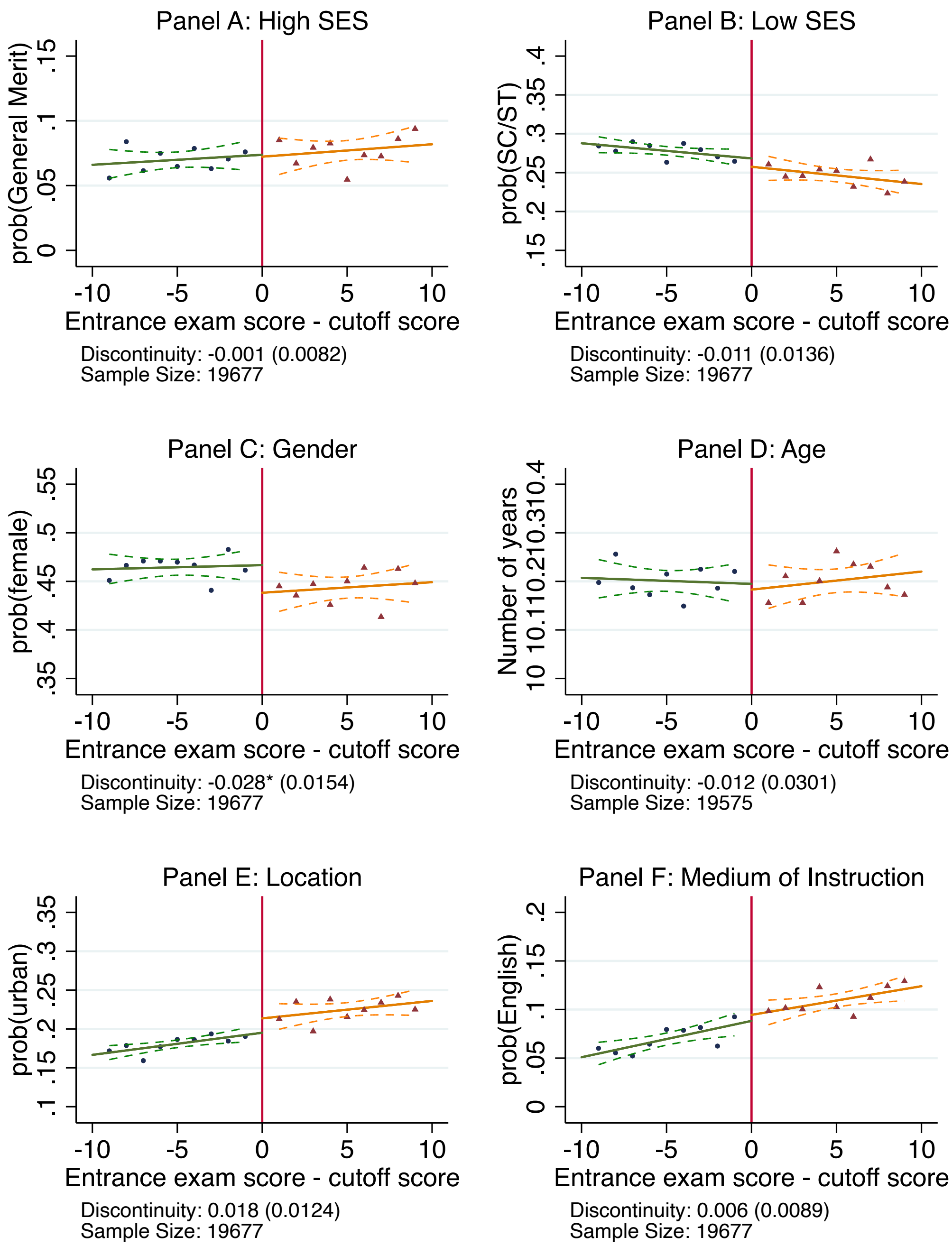
Notes: "Entrance exam score - cutoff score" is the entrance exam score minus the relevant school-by-category cutoff score. Panel A and panel C plot the distribution of the number of students by density in each point bin for matched and full sample, respectively. Panel B and panel D show the McCrary (2008)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

year-specific. Second, as the exams are prepared by the state government and are graded at district centers, the graders don't know the students. Third, the graders would need to be aware of the student's caste category, which does not appear on the exam. Lastly, Panels A and C in Figure 4 show the distribution of matched sample and full sample, respectively. The density of the running variable appears smooth around the discontinuity. Panels B and D in Figure 4 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 just below the cutoff. In Figure 5, I show the discontinuity plots for several student characteristics. As shown in Table 18 (in appendix), 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.[32] I find systematic differences for gender in the matched sample. However, the estimate is quite small and only significant at the ten percent level.

[32] 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.

Figure 5: Covariate Smoothness Test



Notes: In each panel the solid lines represent the linear fit of the dependent variable on the entrance exam score, estimated separately on either 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 5th grade. Each point is the mean of the of the dependent variable within non-overlapping one point bins.

1.6 Results

In this section, I present the estimates of the effect of attending model schools on various short and longer-term schooling 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: academic achievement as measured by test scores and final grades, educational attainment as measured by years of schooling, and career choice as measured by choice of major in pre-university.

I first find that model schools significantly improve math, science, and social science test scores, and increase the probability of graduating high school (10^{th} grade) with an A/A+ grade. Next, I show that attending a model school increases the probability of staying in school until 10^{th} grade, the probability of passing high school, and the probability of joining pre-university after high school. Performance grades in 10^{th} grade are 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 the increased test scores in math and science, the null effect on choosing science as a major is a puzzle.

1.6.1 Academic Achievement

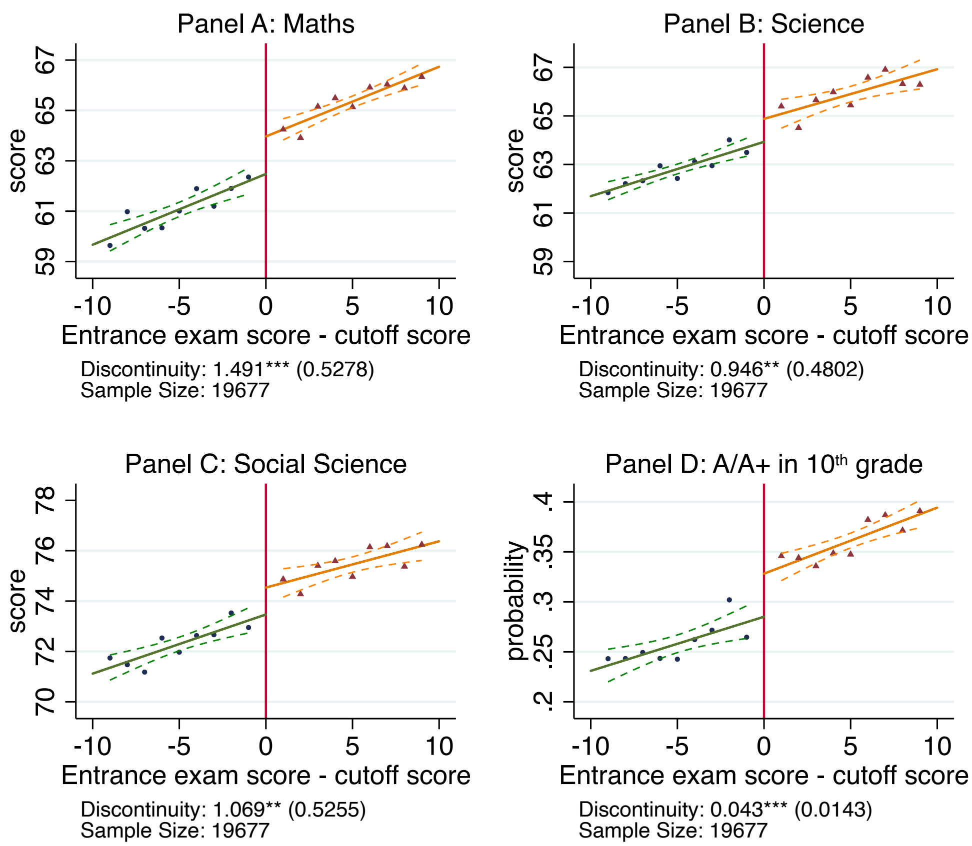
I begin by studying performance in the 10^{th}-grade exam that they appear for after being at model schools for five years. All students attending schools that follow the syllabus set by the state department of education appear for a state-standardized exam at the end of 10^{th} grade. It is the first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

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.[33] Depending on the first language, the second and third language is either English, Kannada or another local language. The content of the language-subject exams varies based on the school's medium of instruction. For example, English textbooks for an English-medium school are very different from English textbooks for a Kannada-medium school. However, the syllabi of math, science, and social science are the same irrespective of the medium of instruction. Therefore, the students cannot be compared across languages but can be

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

compared across core subjects to determine the effects of model schools on learning outcomes.

Figure 6: Reduced Form Graphs: Academic Achievement



Notes: In each panel the solid lines represent the linear fit of the dependent variable on the entrance exam score, estimated separately on either 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.

Mathematics, science, and social science test scores. Figure 6 presents the reduced form graphs for a fixed bandwidth and Table 3 presents the 2SLS estimates for a number of bandwidths in order to illustrate stability of estimates. Reduced form graphs in panels A, B, and C in Figure 6 provide graphical evidence for the causal effect of model schools on learning 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 3. As per column 2, attending a model school increases math scores by 6.8 points (0.38 sd), science scores by 4.1 points (0.26 sd), and social science scores by 4.7 points (0.26 sd), on average, after controlling for observable characteristics.

One way to think about these test score gains is to see how they impact the overall score and grade. On average, attendance at a model school increases scores in the core subjects by approximately 15 points. This equates to 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 major decisions.

Grade achieved in $\mathbf{10^{th}}$ grade. Students are given a letter grade for each subject and using all the six subjects' grades, the education department then determines the Cumulative Grade Average (CGA). A student can get an A+ by scoring above 90 percent and an A by scoring between 80 and 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 the science, arts, or commerce stream. Therefore, obtaining an A or A+ can be used as a signal for pre-college and hence, I look at the effect of model schools on the grade obtained in 10$^{\text{th}}$ grade.[34]

TABLE III: 2SLS ESTIMATES: ACADEMIC ACHIEVEMENT

Bandwidth	**+/-10**	**+/-10**	**+/-20**	**+/-20**	**+/-30**	**+/-30**
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Math score in 10th 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 10th 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 10th 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 10th 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)
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.

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

[34] Although the content of the language subjects varies based on what the first language is, 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.

Panel D in Figure 6 shows a clear discontinuity in the probability of graduating 10^{th} grade with an A or A+. The 2SLS regression estimates are shown in Panel D of Table 3. 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. Of the 300,000, 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 large considering the potential positive effects of scoring an A or A+ can have on a child's psychology and future career choices.

1.6.2 Attrition

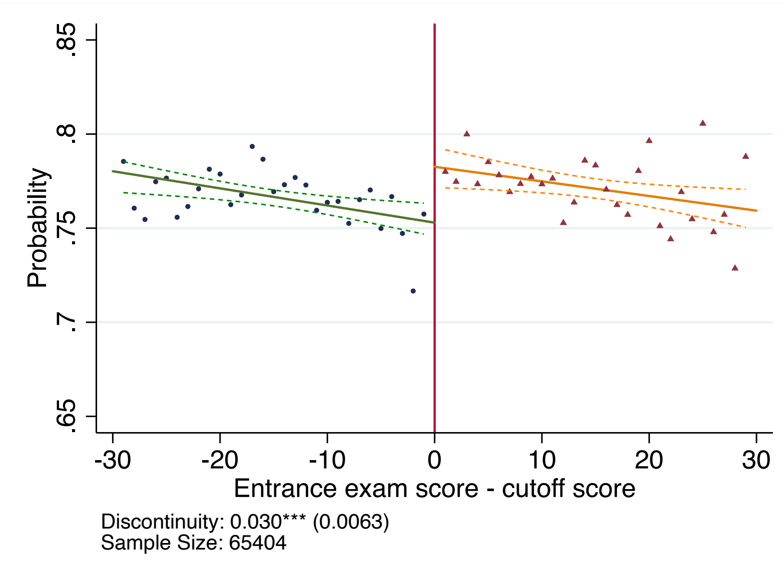
Recall that I am unable to track about 23 percent of the students who appeared for the model schools entrance exam in 10^{th}-grade. Missing 10^{th}-grade data can reflect two things: 1) dropping out of school; and 2) attrition from sample of students who remain in school. In this section I am going to describe attrition, construct bounds and investigate how the estimates change as I take additional steps to find those who attend schools further away.

The challenge is to learn more about the magnitude of the attrition issue and how it likely affects the estimates. First, attrition due to dropping out of school can be problematic if the level of attrition is different for those below and above the cutoff. Second, attrition from sample of students who remain in school can be problematic if attriters below the cutoff had more supportive families or migrated to join better schools in response to failing to be admitted. In both the scenarios, the concern is that the attriters below the cutoff had better outcomes than those above the cutoff.

(i) Level of attrition around the cutoff: The attrition can be a threat to the validity of the results if the likelihood of finding a match for students just below the cutoff is different from that of the students just above the cutoff. To first check for this, I plot the probability of finding a match below and above the cutoff (see Figure 7). The x-axis is the running variable and 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 within each bin. As shown, students with an entrance exam score that is above their respective school-by-category cutoff are about 3 percentage points more likely to be found in the 10^{th}-grade exam data set than those who scored below the cutoff.

Although the magnitude is small, the attrition can bias the estimates and the direction of the bias will depend on the characteristics of the attriters below the cutoff. First, if additional 3 percent that are missing below the cutoff are at the top of the 10^{th}-grade distribution, then the results discussed above

Figure 7: Attrition: Probability of Finding a Match



Notes: In each panel the solid lines represent the linear fit of the dependent variable on the entrance exam score, estimated separately on either 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.

(Table 3) will be upward-biased. To produce a lower bound estimate, I balance the attrition around the cutoff by dropping the top 3 percent of students within each of the above-cutoff bins. Alternatively, the attriters below the cutoff could be from the bottom of the 10^{th}-grade distribution. To determine the upper-bound estimates, I drop the bottom 3 percent of students within each of the above-cutoff bins.

I present the results in Appendix Table 19. The lower-bound estimate of math test scores and the likelihood of scoring an A/A+ is statistically significantly greater than zero. The lower-bound estimate of the science and social science test scores is positive and not statistically significant. The magnitudes of the lower bound estimates for the math and social science test scores, and the probability of obtaining A/A+ in 10^{th} grade exam are close to the main results even after dropping the top 3 percent of students within each of the above-cutoff bins. This suggests that the extent to which attrition due to dropping out of school affects the estimates is very small.

(ii) Magnitude of Attrition: The attrition is particularly concerning if those below the cutoff had more supportive families or migrated for education at different rates than those above the cutoff. In such a case, the main estimates will be upward-biased as the below-cutoff attriters would have scored higher than non-movers on the same exam. The search process that I adopt for finding students allows me to examine whether the attriters, who may have migrated for education, are likely to substantially bias the estimates.

In order to track students who appeared for the entrance exam in 5^{th} grade at 10^{th} grade, I carry out a fuzzy string matching process in three phases. First, I search for students in the 10^{th} grade exam data set within their entrance exam block. Using block-level matching, I am able to find matches for approximately 69 percent of the students. Second, to account for the possibility of within-district migration, I then search for non-matched students in the 10^{th} grade data set at the district level. Using district-level matching, I am able to find a match for approximately 75 percent of all students. Finally, to account for between-district migration, I conduct a last phase of search wherein I search for the remaining non-matched students in blocks that are adjacent to their own block but that are in a different district.[35] The final matched sample matches approximately 77 percent of the students, and I use this sample for the main analysis.

As a result, I have a data set that is matched at the block level with 8 percent fewer students than the final matched sample. If it is the case that the movers below the cutoff are scoring higher than the non-movers, then the results using the block-level sample will be different from the main results keeping everything else constant. First, I re-plot the probability of finding a match for the block-level sample. I find that the discontinuity in the likelihood of finding a match around the cutoff is 3.6 percent compared to the 3 percent for the final matched sample (see Panel A in Figure 18 in appendix). Second, I redo the analysis for all of the academic achievement outcomes using the block-level matched sample. The estimates are similar to the main results (see Table 20 in appendix). Finally, as per 2001 census, only about 1.1 percent of the total migrants in India reported education as the primary reason for migration (Bhagat, 2010). Therefore, it is unlikely that the attriters could have migrated for better schools and being able to track them would not have significantly affected the results.

[35] I am only able to search in the adjacent blocks that are also EBBs.

1.6.3 Effects on Educational Attainment

In this subsection, I look at the effect of attending a model school on the probability of graduating high school, and the probability of continuing traditional schooling. These outcomes help to determine whether model schools have an effect on overall educational attainment levels.

Graduating high school. 10^{th} grade signals the end of secondary schooling. 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 criterion 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.

There are two approaches to look at the high-school graduation probability. One is to limit the sample to those who take the 10^{th}-grade exam. Since virtually all of the students pass the 10^{th}-grade exam then this approach conditions on the outcome. Conditioning on taking the 10^{th}-grade exam means that any effect of model schools on the probability of dropping out prior to 10^{th}-grade are ignored. Second is to use the whole sample. Using the whole sample has the problem of attrition, wherein, I cannot distinguish between those that may have appeared for the 10^{th}-grade exam else where and those that have dropped out. But if I assume all attriters to be dropouts, I can estimate a range for the probability of graduating high-school.

I present the graphical evidence for both the approaches in Panels A & B of Figure 8. Panel A is for the matched sample consisting of only the students that have 10$^{\text{th}}$-grade scores. Panel B is for the full sample consisting of both the students that have 10$^{\text{th}}$-grade scores and attriters that do not have 10$^{\text{th}}$-grade scores. I assign the 10$^{\text{th}}$-grade pass indicator to be zero for attriters. Panel A suggests that there is no statistically significant discontinuity at the cutoffs. Panel B shows a clear discontinuity in the high-school graduation rate.

The corresponding regression estimates are in Panels A and B of Table 4. Based on Column 2's estimates, 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.[36] Although an effect of 31.6 percentage points appears to be big, the actual effect is more likely to be closer to 31.6 than 5.35 percentage points. However, this is an upper bound estimate given the evidence in subsection 1.6.2 showing that as I expand the geographic matching area the probability of being tracked at some school increases; presumably it would increase by more if geographic area were expanded further.

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

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 the labor force. I use the unique registration number assigned to students for the 10^{th}-grade exam to find them 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 while 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 face is whether to continue traditional schooling or to take up vocational courses.[37]

For the purpose of the analysis, I consider a student to have continued traditional schooling if they appeared for the 12^{th}-grade exam conducted by the Department of Pre-University Education.[38] Therefore, I look at the probability of continuing traditional schooling using an indicator for whether a student appeared for the 12^{th}-grade exam.[39] Similar to the high-school

[37]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.

[38]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".

[39]As I do not have twelfth-grade data for the third-cohort, I present results for the full matched sample with first and second cohort only in Table 21 in appendix. The table

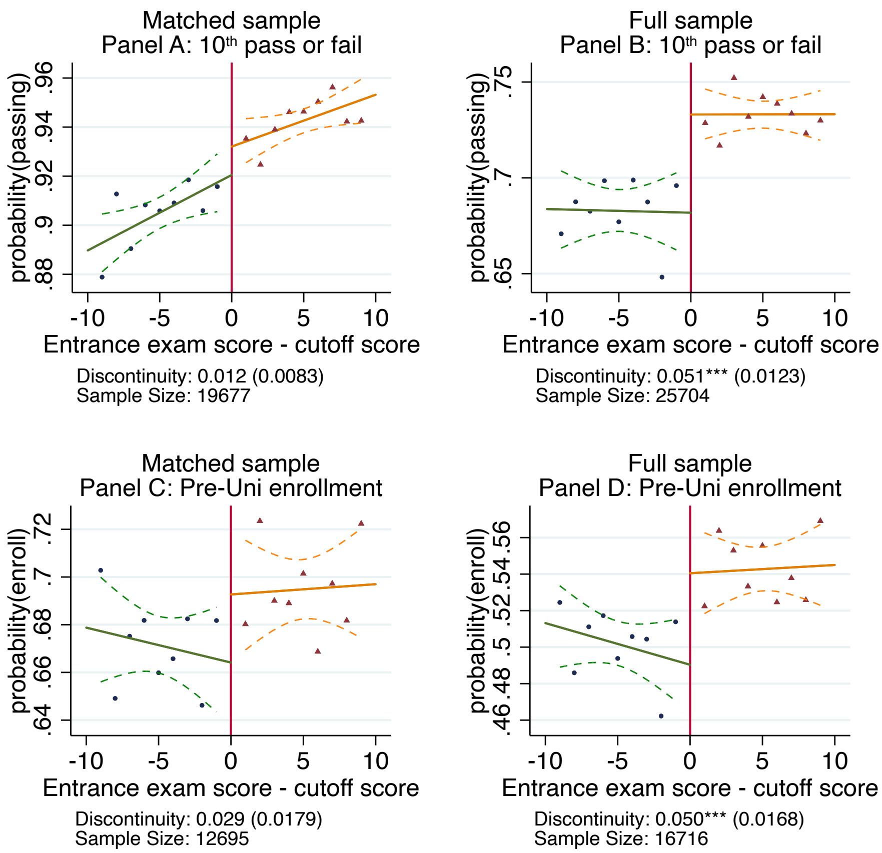
graduation outcome, I adopt two approaches to look at the probability of continuing schooling: (i) limit the sample to those who take the 10^{th}-grade exam; and (ii) use the whole sample and treat all attriters has dropouts. Therefore, I again estimate a range for the probability of continuing schooling using both the approaches.

I present the graphical evidence for both the approaches in Panels C & D of Figure 8. Panel C is for the matched sample and it shows a small change at the cutoff but the estimates are imprecise. Panel D is the for the full sample and shows a clear discontinuity. The corresponding regression estimates are in Panel C & D of Table 4 for matched and full sample, respectively. The matched sample estimate 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. The full sample estimate in Panel D suggests a 29.9 percentage points increase in the probability of continuing traditional schooling.

It is unclear what the actual estimate might be as the level of attrition changes when looking at outcomes beyond 10^{th}-grade. However, even the lower-bound estimate that is conditional on students appearing for the 10^{th}-grade exam is large and significant. This suggests that, at the least, model schools have a big positive effect on the likelihood of continuing schooling after exiting high-school.

shows that the effects are not driven by cohort 3 and that the estimates are consistent with the main results.

Figure 8: 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 cut-off. 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 represent the linear fit of the dependent variable on the entrance exam score, estimated separately on either 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 IV: 2SLS ESTIMATES: EFFECTS OF MODEL SCHOOL ATTENDANCE ON VARIOUS MEASURES OF EDUCATIONAL ATTAINMENT

Bandwidth	**+/-10**	**+/-10**	**+/-20**	**+/-20**	**+/-30**	**+/-30**
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: probability of passing 10th 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 10th 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.

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

1.6.4 Post-Secondary Outcomes

Those that join pre-university college need to decide which subject stream to specialize in and which 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.

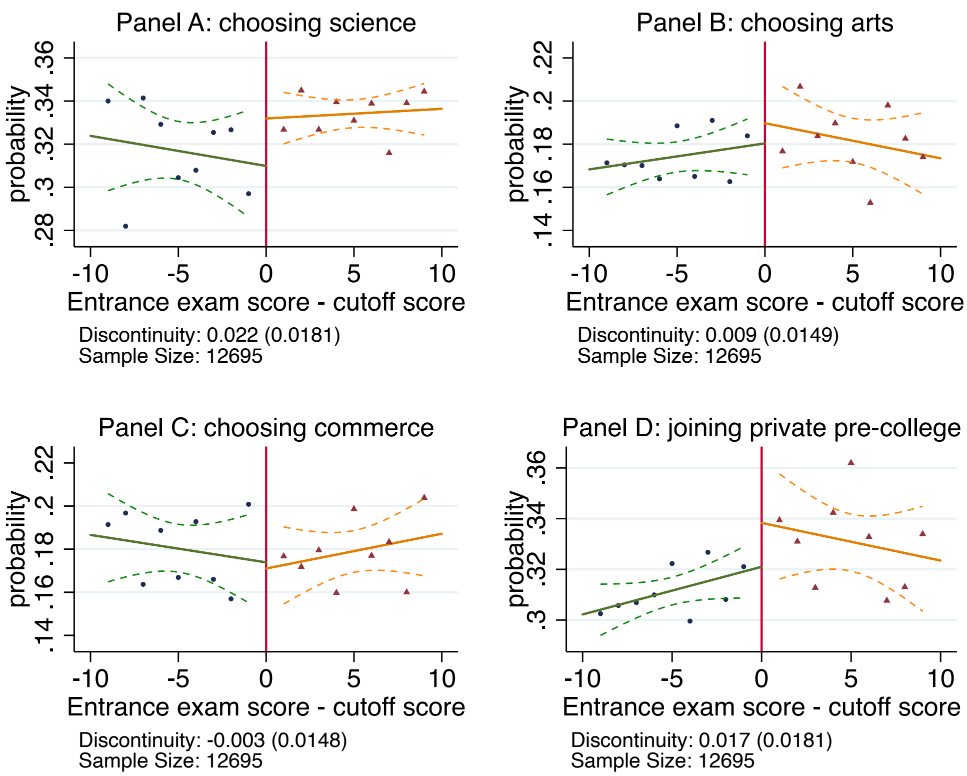
Major choice: science, arts, or commerce. While students have three majors or streams (science, arts, and commerce) to choose from, science has the highest demand as it is the mostly commonly chosen stream, followed by commerce, and then by the arts (humanities).[40] It is worth noting that the science stream, due to its popularity, has the highest cutoff for 10$^{\text{th}}$-grade exam scores. Therefore, students make their decisions based on their 10$^{\text{th}}$-grade subject exams. Additionally, the majority of PU colleges only offer a few subjects, restricting the movement of students between streams after the choice has been made.

I would expect model school students to be more likely to choose the science stream as attending a model school leads to significant gains in test scores and increases the probability of obtaining an A/A+ in the 10$^{\text{th}}$-grade

[40] 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.

exam. 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 9 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.

Figure 9: 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 represent the linear fit of the dependent variable on the entrance exam score, estimated separately on either 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 V: 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.

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

The corresponding regression estimates are presented in panels A, B and C in Table 5. Based on the estimates in column 2, attending a model school has no statistically significant effect on choosing either the science or the arts stream. The Panel C estimate suggests that there is no difference in the likelihood of choosing the 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 pursue the 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 succeeding 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 a third type where the management is private but the government provides a substantial amount of aid in return for charging low fees (aided). As of 2015, there were 1,378 public (approximately

29 percent), 795 aided (approximately 16.5 percent) and 2,621 private (approximately 54.5 percent) PU colleges in Karnataka.[41] Since model schools end in 10$^{\text{th}}$ 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 (public, private, or 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 9, I plot the probability of attending a private PU college. The figure suggests that students just above the cutoff are no more likely to attend a private PU college than are students just below the cutoff. The corresponding regression estimates are presented in Table 5, panel D. The estimates suggest a positive effect, but due to the large standard errors, the estimates are not statistically significantly different from zero.

1.7 Discussion

In this section, I explore 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 pri-

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

marily to teacher contract structure, school accountability and governance, and student effort/motivation, but peer effects also appear to be a contributing factor.

1.7.1 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 6). 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 become a permanent public school teacher (Muralidharan and Sundararaman, 2013; Duflo, Dupas, and Kremer, 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.[42]

[42] 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.

TABLE VI: 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%

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.

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. The improved governance ensures that model schools do not suffer form the same problems as traditional public schools such as high teacher absenteeism, low classroom activity. Good governance 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 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.[43] 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 school infrastructure may also make students believe that the education they are receiving is comparable to that of their private-school counterparts.[44]

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 could be contributing to the positive

[43] Azam, Chin, and Prakash (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).

[44] Visit Model Schools website for infrastructure visuals.

effects for those that are just above the cutoff. However, having better peers does not necessarily translate to better test scores (Beuermann and Jackson, 2018). 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 public schools' quality.

1.8 Cost Analysis

Traditional Public Schools. As per the Right to Education (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.

In conclusion, back of the envelope calculations imply that per-pupil expenditure in model schools is between 9,315 and 11,632 Indian rupees and per-pupil expenditure in traditional public schools is between 11,848 and 16,914 Indian rupees. Therefore, the costs of operating model schools is comparable to that of traditional public schools.

1.9 Implications for Policymakers

Numerous developing countries address low public school quality by implementing policies that subsidize private school attendance through vouchers and reservations. However, evidence on whether private schools provide higher learning gains is mixed (see Urquiola, 2016 for a review). In this paper, I look at the effects of creating a public good, i.e. improving public schools as opposed to subsidizing private schools. In this section, I briefly discuss the policy implications of the findings of this paper. Improving public schools can have significant positive effects on schooling outcomes and it has several advantages.

First, it provides access to quality education for low income children and children from lower castes. Research shows that higher levels of education lead to better employment opportunities and therefore income. Hence, improving public schools can have significant economic gains.

Second, the improved public schools can set an example for other public schools. Especially in the context of developing countries wherein policy implementation is poor and the potential benefits aren't fully realised. For instance, 12 out of 21 states with EBBs did not have functional model schools as of 2016 (see Table 23 in appendix).[45] 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 positive effects of improved public schools.

Third, the paper provides important evidence for the political economy debate of whether the status quo of traditional public schools should be changed to begin with. On one hand, several Indian states are creating new traditional public schools and/or consolidating the existing schools to improve the quality and the effectiveness. A common theme among these schools is to make English the default medium of instruction.[46] This proposed move has invited divided opinions. On one side, the pro-regional language activists and literary figures, along with 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 (i.e., SC/ST) are expressing their support to the government's move as the majority of their children rely on traditional

[45] For example, Odisha, an eastern state with 173 blocks out of 315 classified as EBBs, only implemented the model schools program in 2017.

[46] In one policy, Karnataka has introduced 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. Here is a recent article in the Indiatimes describing the policy.

public schools.[47] To that end, this paper provides crucial evidence on the potential benefits of improved public schools to aid the policymakers in such political scenarios.

1.10 Conclusion

In this chapter, 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, India on three dimensions: academic achievement, educational attainment, and career choice.

This chapter has two main findings. The first finding is that attendance at a model school raises academic achievement (as measured by test scores) and educational attainment indicators (as measured by years of schooling) significantly. The second finding is that attending a model school has no statistically significant effect on the probability of choice of major in pre-university college.

[47]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.

Finally, turning to the costs, back of the envelope calculations imply that the per-pupil annual expenditure in the model schools (9,315 – 11,632 Indian Rupees) is comparable to that of the traditional public schools (11,848 – 16,914 Indian Rupees).

2 DO EFFECTS OF MODEL PUBLIC SCHOOLS DIFFER BY PRIOR LEARNING LEVELS AND GENDER?

2.1 Introduction

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. In Chapter 1, I employ an econometric strategy to combine all 1,513 cutoffs under one framework to identify the local average treatment effect of model schools. In this Chapter, I extend the analysis to investigate the heterogeneity in model schools' effects using the same administrative data.

I start by attempting to estimate the effects of model schools based on students learning levels as measured by their entrance exam scores. I am able to investigate this using the differences in the magnitudes of the school-by-category cutoffs both within year and within school. In particular, I adopt to two approaches to categorize and estimate multiple local average treatment effects to identify differences in effects.

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. Therefore, I first exploit this variation to 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.

Although all students above each of the caste category's cutoff are barely admitted to a model school, they can be at different learning levels relative to their peers within their school. I exploit this variation to 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 20^{th} percentile entrance exam score.[48]

Note that there is nothing special about the median cutoff score or the 20^{th}-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. [49] I estimate the effects for each of the groups created based on the categorizations of the two approaches. As these two categorizations are correlated, I interact them to learn more about the differences in the effects of model schools.

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.

[48]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.

[49]I check for robustness by choosing 40^{th} and 60^{th} percentile cutoff score, and 15^{th} percentile and 25^{th} percentile student's cutoff score.

The two main findings from the above 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.

I further explore heterogeneity in program effects by gender, since geographic blocks were classified as educationally backwards based on the gender gaps in education. Households preference to pay for a boy's education over a girl's education is the status quo. However, getting admitted to a model school that is free to attend gives the girls access to improved public schools. Furthermore, as gender gaps is one of the primary motivators for model schools, I expect the environment to be more supportive for girls in model schools.

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 suggest that model schools work for girls as well as boys.

Preliminary results suggest that there is little variation by caste. This result is surprising given that the counterfactual schools for the lower castes are the traditional public schools that are of low-quality. However, the results are conditional on selection into taking the model school entrance exam. Therefore, the quality of students across all castes that select into taking the test might be comparable. For instance, of the eight cutoffs within each school, it is not the case that the lowest castes have the lowest cutoffs (Figure 17 in appendix). Additionally, small sample size for the Scheduled Tribes and General Merit caste categories prevent me from making any meaningful conclusions.

2.2 Empirical Strategy[50]

2.2.1 Variation in Cutoffs Within Year and Within School

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

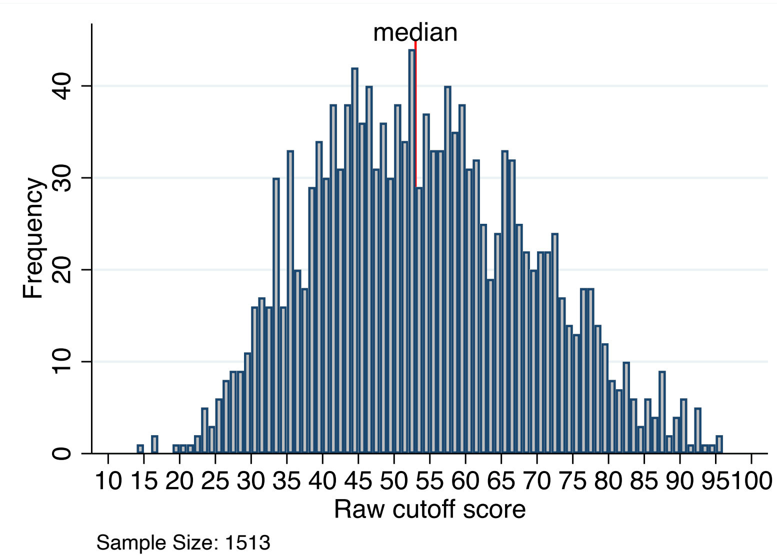
[50]Refer to Chapter 1 for details on Data and the Program.

(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 10, I show that the magnitudes of the 1,513 cutoff scores are in fact roughly normally distributed. Cutoff scores vary from 16 to 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 label them as "above median absolute learning level" (denoted by $\widetilde{A}$: *Above*). The rest of the categories are classified as "below median absolute learning level" (denoted by $\widetilde{A}$: *Below*). 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:

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

Figure 10: 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.

To check for the statistical significance of the difference in effects, I 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 also varies across schools. 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 7, the 10th percentile of median exam scores is 47.5, while the 90th percentile of median exam scores is 80. Just as prior achievement levels can matter for a student's performance, the student's relative position within her class can also affect her performance.

TABLE VII: 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: xth percentile score in each model school among those that were admitted. Column: yth percentile score within each xth percentile. First, I determine the 10, 20, 50, 70 and 90th percentile score within each model school among those that were admitted. Second, I determine the 10, 20, 50, 70 and 90th percentile within each of the percentiles. Therefore, each number is the yth percentile score within the xth percentile scores.

To determine the importance of relative learning levels, I group students into those with "low relative learning level" and "high relative learning level". Those in the first group are part of a category whose cutoff score was below the overall 20th percentile student's score in their school-year. Those in the second group are part of a category whose cutoff score is above the 20th percentile student's score in their school-year.[51] I will denote these

[51]Note that there is nothing special about the median cutoff score or the 20th percentile student's score that I have chosen as the reference points. This combination of the criteria allows me to have a large 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 40th percentile

two groups as $[\widetilde{R} : Low]$ and $[\widetilde{R} : High]$, 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:

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

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

Combination of absolute and relative criteria. As the above two categorizations are correlated, I interact them in order to learn more. Combining the two group classifications for each of the two factors gives a total of four groups: $[\widetilde{A} : Below\ \&\ \widetilde{R} : Low]$; $[\widetilde{A} : Below\ \&\ \widetilde{R} : High]$; $[\widetilde{A} : Above\ \&\ \widetilde{R} : Low]$; and $[\widetilde{A} : Above\ \&\ \widetilde{R} : High]$. 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 A for details on the empirical equations.

score and by changing the 20^{th} percentile student's score to the 25^{th} percentile student's score.

2.3 Results

I begin by exploring the effects for certain subsets of students based on initial learning levels and position within class using the empirical strategy discussed above. The main idea is to estimate multiple local average treatment effects so as to infer whether whether the effects differ by absolute and relative learning levels. The main conclusion from this analysis is that model schools have a similar positive effect for students across the ability distribution. I conduct a second heterogeneity analysis by gender. Since geographic blocks were classified as educationally backwards based on the female literacy and the gender gap in education. Overall, I find that model schools have same effects on females and males in academic achievement and a bigger effect on females in the likelihood of continuing schooling after 10^{th} grade. The key takeaway is that model schools work for girls as well as boys.

2.3.1 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 provides a unique opportunity to estimate multiple LATEs for different subsets of the population using the empirical strategy discussed in the above section.

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 estimates in Table 8. 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 major in science, as opposed to arts or commerce. 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 estimates in Table 9. First, model schools increase the probability of continuing schooling after 10th grade for those that are above the 20th percentile student. Second, irrespective of being below or above the 20th percentile student, model schools increase the probability 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 10. The regression shows the results relative to the base group, where the base group consists of those students with both low absolute prior learning levels and low relative position within their class. 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 20th-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 20th percentile student within ones school seems to really matter for the likelihood of continuing schooling after 10th grade. Third, those who start at a high absolute learning level but are below the 20th percentile student in their class score more points on math and are most likely to obtain an A/A+ in 10th grade.

TABLE VIII: 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 IX: 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 X: 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.

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

2.3.2 Effects by Gender

Evidence shows 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.[52] Therefore, I check for differential effects in all of the outcomes for females and males. As families are less likely to invest in their daughters' education than their sons' education, providing girls access to model schools could have strong positive effects on girls. I report the estimates in Table 11. 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. In general, these results suggest that model schools effects both males and females academic achievement outcomes positively.

The gender gaps between school enrollment levels increase with age in developing countries. For instance, in India, there is little to no gap between female and male enrollment at age 14, but by age 18, there is an observable

[52]For example, see Duckworth and Seligman (2006). In developed countries, evidence suggests that while females benefit from such interventions, males maybe be unaffected or become worse off (Jackson, 2010; Kling, Ludwig, and Katz, 2005; Hastings, Kane, and Staiger, 2006).

TABLE XI: 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 Female	0.0543	-0.212	-2.478	-3.878	0.563	0.262	0.008	-0.000
	(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 Female	-0.000	-0.0134	0.195	0.119
	(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 Female	0.183	0.139	-0.0519	-0.0754	0.0640	0.0562	0.226	0.188
	(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.

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

difference in enrollment in formal schooling between the genders.[53] 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 11, attending a model school increases the likelihood of girls continuing schooling after 10$^{\text{th}}$ grade by about three times more than it increases for boys. Similarly, estimates in Panel C of Table 11 suggests that the probability of girls choosing science as the major is about six times more than probability of boys choosing science as the major.

Effects by Caste. 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 as the results are conditional on selection into taking the model school entrance exam. For instance, of the eight cutoffs within each school, it is not the case that the lowest castes have the lowest cutoffs (Figure 17). Additionally, small sample size for the Scheduled Tribes and General Merit caste categories prevent me from making any meaningful conclusions. I present the results in Table 12.

[53]According to the Annual Status of Education Report (ASER 2017: Beyond Basics), by age eighteen, 31 percent of females are not enrolled in formal schooling while 28 percent of males are not enrolled.

TABLE XII: 2SLS ESTIMATES BASED ON CASTE

	Panel A: Academic Achievement			
	Math	Science	Social Science	10^{th}:A/A+
Model School	2.628	1.035	8.263	-0.128
	(5.835)	(5.583)	(6.313)	(0.154)
Model School x SC	2.471	-0.726	-3.235	0.292
	(7.012)	(6.764)	(7.837)	(0.187)
Model School x ST	15.62	18.99*	2.618	0.745***
	(10.78)	(10.55)	(11.09)	(0.269)
Model School x OBC	3.041	2.664	-4.884	0.327*
	(6.385)	(6.024)	(6.822)	(0.169)
Observations	19677	19677	19677	19677

Notes: The above table presents instrumental variable estimates for groups categorized based on caste. The table does not present estimates for other outcomes as the sample size for Scheduled Tribes and General Merit due to lack of sample size. 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 caste groups is used as an instrument for model school indicator interacted with a dummy for each of the groups. Notation: SC indicates Scheduled Caste; ST indicates Scheduled Tribe; and OBC indicates Other Backward Classes. 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 choice of major. All regressions include controls: gender, 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.

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

2.4 Conclusion

In this chapter, I examine the heterogeneity in the effects of model schools along several dimensions. First, I use the variation in the 1,513 cutoffs to identify whether the effects differ based on absolute initial learning levels across all schools and relative learning levels withing each school. The main finding is that model schools have a similar positive effect for students across the ability distribution.

Second, I explore heterogeneity in effects by gender since geographic blocks were classified as educationally backwards based on the gender gaps in education. The main finding is that model schools overall, have the same effect on females as well as males.

Chapters 1 and 2 relate 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, Kingdon, et al., 2010; Chudgar and Quin, 2012; Muralidharan and Sundararaman, 2015; Singh, 2015), but research on the effects of public schools is scant.[54] 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, Romania, Kenya, and China, respectively. While Lucas and Mbiti (2014)

[54] 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.

show that elite government schools in Kenya have no effect on test scores, the other three studies document positive effects on test scores.[55] 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 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 statewide implementation can be vital to their success. Chapters 1 & 2 provide crucial evidence on the potential benefits of improving public schools to the policymakers.

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

3 SCHOOL TYPE, CAREER ASPIRATIONS AND INFORMATION GAPS: DESCRIPTIVE EVIDENCE FROM DIFFERENT PUBLIC SCHOOL SYSTEMS IN INDIA

3.1 Introduction

Although the socially desirable careers are that of a doctor, lawyer and engineer, the highest positions achieved by the individuals in Indian villages, who primarily attend public schools, are dominated by that of soldiers, teachers, constables, and clerk typists (Krishna, 2017). The low socio-economic status and career beliefs of the students attending public schools help explain the narrow occupational categories (Arulmani, Van Laar, and Easton, 2003, Munshi and Rosenzweig, 2006). However, policies to improve public school quality have given an opportunity for students from low-socio economic status with higher career aspirations to sort to better public schools. In this paper, I use survey data to compare the career aspirations of 10$^{\text{th}}$-grade students attending different systems of public schools that vary in quality.

Different policies aimed at improving public school quality have resulted in multiple systems of public schools. I identify four systems of public schools. First, traditional public schools serve as the base as they are mandated to admit all students that seek admission.[56] Second are the social welfare schools, which are high quality public schools that admit students through an entrance exam. Social welfare schools were created in select census blocks to target students from the two lowest caste categories in India (scheduled caste and scheduled tribes). Third are the model schools; these schools also admit students through an entrance exam. Model schools were created in educationally backward blocks to serve as a model for traditional public schools to emulate. They admit students from all caste categories. Finally, aided schools are schools that are funded by the government and are free to attend but are privately managed. Aided school students often perceive themselves to be attending a private school. Households perceive private schools to be superior than traditional public schools (Muralidharan and Kremer, 2006; Kingdon, 2017).

I surveyed 49 schools in Karnataka, a southern state in India. Of the 49 schools I visited, 19 were public schools, eight were social welfare schools, nine were model schools, and 13 were aided schools. During each school visit, students were given a questionnaire and were instructed to fill their responses for all questions. Through this process, I obtained responses from 2,842 students.

[56] They are plagued with factors that hinder student learning; such such as high teacher absenteeism, lack of basic equipment and school supplies, poor infrastructure, weak governance (Chaudhury et al., 2006; Glewwe and Kremer, 2006).

The paper has three main findings. First, attending a higher quality system of public schools is associated with an increase in the likelihood of having a socially desirable career aspiration such as doctor, engineer, civil servant. Second, although 45 percent of my sample indicated that they aspire to be either doctor or engineer, I find that students across all four systems of schools lack knowledge on the academic requirements to pursue medicine or engineering. Third, *perceived* self-earnings of students at improved public schools is higher that of students at traditional public schools.

The justification for any kind of information interventions by researchers depends on the difference between the information perceived and the actual information. For example, Nguyen (2008) and Jensen (2010) study the effects of providing information on actual returns to education to students who perceived lower returns to education in Madagascar and Dominican Republic respectively. This study hopes to provide baseline estimates for designing information interventions that involve career orientation, information on academic requirements and returns to education. Currently, the most related literature to this in India is a study by Chari and Maertens (2014), which measured households' perceived returns to education for sons and daughters and they find distinct gender differentials. To the best of my knowledge, there is no study that has tried to measure public school students' perceptions about the academic requirements to attend college. This is also the first study to document the differences in career aspirations of students across different systems of public schools.

3.2 Background

In this section, I briefly describe the structure of the Indian education system that has resulted in children having to make their college degree choices immediately after 10^{th}-grade. I highlight the stark differences in the characteristics of students and families that attend private sector schools along with the advantages of attending a private school that influence the decision-making process. I then turn to the public schools sector to describe four systems of schools that vary in overall quality and along the following characteristics: location, medium of instruction, admission procedure, and target group. I discuss the possibility of children attending the different systems of public schools having different career aspirations and career beliefs.

When career decisions are made:

The Indian education system differs from that of the traditional system in most developed countries. Traditionally in developed countries, students decide on their college major only after enrolling in college and are typically older than 18 at the time. In contrast, students in India often must commit to the subjects they wish to studying in college immediately after 10^{th} grade (aged around 13-14 years old). As a result, students need to make a choice early in life and the amount of information they have on career options often depends on the type of school they attend, their peers, and parents education level. The interaction of making a decision early in life and inadequate information either due low school quality or low parent's education levels can contribute to children dropping out of school. In 2015, the gross enrollment rate in tertiary education in India was only 27% (World Bank Education Statistics).

School type, career beliefs, and career aspirations:
In India, the public and private school sectors vary greatly by quality; private schools are considered far superior to public schools as they are more productive in improving student outcomes (Singh, 2015; Muralidharan and Sundararaman, 2015). Since private schools are for-profit fee-charging schools, only those households that are able to afford will send their children to private schools. Therefore, private school students are exposed to better school resources, better informed peers, their parents have higher levels of education and they typically take courses to prepare for college admission. Thus, the career beliefs and career aspirations of those that attend private schools differ from those that attend public schools.[57]

Variation in public school quality:
Over the last decade, several policies have been implemented to improve the quality of public schools. As a result of these policies, different systems

[57] I do not compare the career aspirations of children to public schools to children in private schools.

of public schools have been formed. Although the systems are different, the schools are still funded by the government and are free to attend. I identify four different public school systems that vary along the dimensions of school quality (infrastructure, medium of instruction), peer composition, and admission procedures. I list the four systems below.

First, traditional public schools are of the lowest quality and carter to all students. These schools are located at the village and census block levels following the regional language as the medium of instruction to make them accessible to all students. I use traditional public schools as the base comparison group.

Second, social welfare schools are public residential schools that are built in certain census blocks to provide quality education to students either based on caste or gender. Social welfare schools mainly focus on providing quality education to those belonging to Scheduled Caste (SC) and Scheduled Tribe (ST) categories and rural females. These schools have superior infrastructure when compared with traditional public schools and they admit students to 6^{th}-grade based on their performance on an entrance exam. While some schools follow English as the medium of instruction, there are several schools that follow regional language as the medium of instruction. These schools are primarily attended by students that were at traditional public school until 6^{th}-grade. Several case studies suggest that social welfare schools are in fact of higher quality and the students attending these schools perform better than their counterparts at traditional public schools.

Third, model schools are located in educationally backwards blocks to serve as a model for the traditional public schools to emulate. There is one model school in each of the educational backward blocks. Institutionally, they are similar to social welfare schools as they share the same objective of providing quality education. These schools admit students into 6^{th}-grade under all caste categories based on their performance in an entrance exam. Model schools follow English as the default medium of instruction. Evidence presented in Chapters 1 and 2 suggests that model schools improve student outcomes. Chapter 1 also shows that about 70 percent of the children that attend model schools were at traditional public schools until 6^{th}-grade.

Finally, aided schools are schools funded by the government but controlled by a private management. These schools cater to a variety of students as they are free and often considered to be on par with private schools. For all purposes, aided schools are restricted by all the rules that apply to the public schools. However, students attending aided schools often perceive that they are attending a private school due to the private management. The medium of instruction can be either English or the regional language.

One of the consequences of varying public school quality is that career aspirations of students can vary by the system of schools that they attend. Two scenarios occur if policies aimed at improving public school quality are working. First, students with higher career aspirations that were at traditional public schools until 6^{th}-grade can now attempt to sort to social welfare or model schools by appearing for the entrance exam. Second, students that do not necessarily have high career aspirations but perform well on the entrance exam may change their career beliefs and have higher career aspirations as a result of attending a social welfare or model school.

Apart from having differential career aspirations, students across different schools may also vary in their knowledge on what it takes to pursue their career aspirations. Specifically, depending on the type of public school that students attend, they may either presume that their chances of attending a good college are small or they may lack information on the determinants of college admissions.

3.3 Methodology

I begin this section by describing the approach used to select the three districts in which survey was conducted. Following the districts selection procedure, I describe the characteristics of the schools and students surveyed under each of the four systems of public schools noted in the above section. I then explain the instruments used in the survey to capture the following from the students: intention to continue schooling, time preferences, career aspiration, college admission determinants, and perceived returns to education. I end this section by noting that the results found in this paper are not casual as students can sort to schools. The objective is to identify and document the differences in career aspiration across the four systems of public schools.

3.3.1 Sample Selection:

The survey took place between January and March 2018 in Karnataka. Karnataka consists of 30 districts, the central-level geographic election unit. The 30 districts were broken into 3 groups based on each district's 10^{th}-grade pass percentage in 2016-17. I then selected one district from each of the three groups. The number of schools to be surveyed in each district was based on the percent share of schools across all 3 districts. By default, all blocks will have only one model school and one social welfare school (if any). The number of traditional public schools and aided schools to be surveyed in each block was based on the percent share of schools within each district.

Participants

Schools: I visited 49 public schools to collect responses to a questionnaire from 2,842 students who were in 10^{th}-grade. Of the 49 schools I visited, 19 were public schools, eight were social welfare schools, nine were model schools, and 13 were aided schools. Table 13 shows the summary statistics for some of the schools' characteristics. The majority of the model and aided schools are in urban areas. Whereas, the majority of the traditional public schools and social welfare schools are in rural areas.[58] Twenty percent more teachers have a graduate degree at social welfare, aided and model schools as compared to traditional public schools.

Students: Of the 2,842 students that were surveyed across the 49 schools, 47 percent of them were from traditional public schools indicating that the majority of students rely on traditional public schools; 9 percent were from social welfare schools, 16 percent were from model schools, and 28 percent were from aided schools. About 50 percent of the students are female. The summary statistics of students are presented in Table 14. As mentioned in section 3.2, regional language is the default medium of instruction in traditional public schools. In line with this, 82 percent of the traditional public school students chose "Kannada" as the medium of instruction. Whereas, 91 percent of students from social welfare and all students from model schools indicated English as the medium of instruction.

The new public school systems with improved school quality are supposed to improve equity by providing access to students that cannot afford fee-charging private schools. However, both the average father's and mother's income increases as we go from traditional public schools to aided schools. Similarly, 50 percent of the parents that send their children to model schools

[58] As there is only one model school per block, they are mainly located in urban areas so as to make them easily accessible. Social welfare schools on the other hand are residential and requires more space.

have an education level greater than 10$^{\text{th}}$-grade. On the other hand, the majority of the parents of the children that attend traditional public schools and social welfare schools have an education level that is below 10$^{\text{th}}$-grade. In line with the income story, a higher percentage of students attending model and aided schools report on having various households items (fridge, bike, car, tv) when compared to traditional public schools and social welfare schools.

TABLE XIII: SUMMARY STATISTICS – SCHOOL LEVEL

School Characteristics	All Schools	Public Schools	Social Welfare Schools	Model Schools	Aided Schools
Urban	43.1	15.6	9.6	77.8	80.9
(percentage of schools)	(49.5)	(36.3)	(29.6)	(41.6)	(39.4)
Average Number of Classrooms	3.508	2.891	4.963	4.361	3.461
(per school)	(2.422)	(2.341)	(3.134)	(1.625)	(2.268)
Free Meals in School	100	100	100	100	100
(percentage of schools)	(0)	(0)	(0)	(0)	(0)
Library in School	93.8	89.7	85.2	100	100
(percentage of schools)	(24.2)	(30.4)	(35.6)	(0)	(0)
Number of Male Teachers	4.839	5.197	5.748	3.481	4.757
(per school)	(2.228)	(1.704)	(2.211)	(1.292)	(2.911)
Number of Female Teachers	4.359	5.803	3.319	3.282	2.909
(per school)	(3.515)	(3.874)	(2.531)	(2.104)	(2.804)
Percent of Teachers with Graduate	73.3	61.1	86.1	82	80.2
Degree & Above (per school)	(33.6)	(32.3)	(20.4)	(33.9)	(33.6)
Percent of Teachers with	99.1	98.8	98.1	100	99.2
Professional Degree (per school)	(2.8)	(3.1)	(4.2)	(0)	(2.7)
Received Free Text Books	92.2	100	100	100	72
(percentage of schools)	(26.8)	(0)	(0)	(0)	(44.9)
	49	19	8	9	13

Note: The above table presents the descriptive statistics of all the schools that were surveyed. The schools surveyed were matched to the 2016 DISE data using the unique DISE school code. Standard errors are in parenthesis. **Source:** For DISE raw data- `www.schoolreportcards.in/SRC-New/`.

TABLE XIV: SUMMARY STATISTICS – STUDENT LEVEL

	All Schools	Public Schools	Social Welfare Schools	Model Schools	Aided Schools
Student Characteristics (mean):					
Female	49.9	48.6	54.8	43.9	53.9
	(50)	(50)	(49.9)	(49.7)	(49.9)
Kannada as Medium of Instruction	56.6	82.4	9.6	0	61.6
	(49.6)	(38.1)	(29.6)	(0)	(48.7)
Father's Education (10th grade or Below)	74.2	87.6	84.1	56.8	58.4
	(43.8)	(33)	(36.7)	(49.6)	4(9.3)
Mother's Education (10th grade or Below)	84.3	91.7	95.2	80.5	70.4
	(36.4)	(27.6)	(21.4)	(39.7)	(45.7)
Father's Income per Month (Indian Rupees)	13311.14	8592.196	10785.12	13027.97	22337.85
	(23914.66)	(10057.03)	(15522.88)	(15600.49)	(39518.05)
Mother's Income per Month (Indian Rupees)	6879.666	4255.41	5987.611	7874.766	13791.23
	(13249.71)	(4033.94)	(5225.575)	(8485.46)	(25212.12)
Household Items:					
Fridge (Percentage of students)	31.9	18.8	17.8	44.8	51.4
	(46.6)	(39.1)	(38.3)	(49.8)	(50)
Bike (Percentage of students)	61.9	49.9	63.7	69.4	77.2
	(48.6)	(50)	(48.2)	(46.1)	(42)
Cot (Percentage of students)	78.1	71.2	76.3	86.3	85.8
	(41.3)	(45.3)	(42.6)	(34.5)	(35)
Car (Percentage of students)	13.4	8.4	8.5	9.5	25.4
	(34)	(27.8)	(28)	(29.4)	(43.6)
TV (Percentage of students)	86.7	81.8	83.7	91.6	93.1
	(34)	(38.6)	(37)	(27.8)	(25.4)
Mobile (Number of mobiles)	2.437	2.18	2.442	2.576	2.783
	(1.45)	(1.358)	(1.425)	(1.276)	(1.609)
Fan (Number of fans)	1.817	1.467	1.45	2.042	2.396
	(1.414)	(1.083)	(1.189)	(1.128)	(1.837)
N	2842	1327	270	451	794

Note: The above table presents the descriptive statistics of all the students that were surveyed by each school type. The averages were computed using the data obtained through the questionnaire. Standard errors are in parenthesis.

3.3.2 Instruments

Intention to continue schooling and time preferences: At the end of 10th-grade, the majority of students exit their current schools and decide on whether to continue some form of schooling or join labor force. Evidently, the highest dropout rate is after 10th-grade. Therefore, in an effort to gauge students' intentions, students were asked a question on whether they plan to attend pre-college after 10th-grade. They were given five options: Definitely, yes; Mostly, yes; Don't Know; Mostly, No; Definitely, No.

Present bias, wherein agents discount the future heavily, is one of the main reasons for why children drop out of school early or enter the labor force early. There are several approaches to measuring time preferences but there is no single approach that is widely accepted and some are easier than others to implement. I follow the most commonly used method wherein students are asked to choose between receiving monetary payments early or later in time (Andersen et al., 2008; Andreoni and Sprenger, 2012). I asked the students to choose between accepting 900 rupees today or accepting 9000 rupees after 5 years.

Career aspirations and college admission determinants: The survey included a question that asked what the students wish to become when they grow up. There were several options to choose from and a blank space to write down their choice if it was not present in the list. Following which, students were asked questions about the college degree choice and the academic requirements needed to pursue their choice of career.

Perceived returns to education: Following the approach adopted by Nguyen (2008) and Jensen (2010), I asked questions on what the students think they would earn if they were to find work after 10^{th}-grade, 12^{th}-grade, and after receiving a college degree to measure *perceived* self-returns to education. It is possible that students perceive themselves to be different than others and hence, can perceive oneself to earn more or less than the average person for a given level of education. Therefore, I asked the students what they think an average person would earn for the same three levels of education.

Reverse causality

The objective of this paper is not to determine whether policies aimed at improving school quality improves career aspirations. Rather, the objective is to identify and document the differences in career aspirations across different systems of public schools that vary in quality.

When determining whether policies aimed at improving school quality improve career aspirations, the main concern is reverse causality. It is highly probable that students with higher career aspirations sort to higher quality schools by choosing to write the entrance exam. Selection through an entrance exam means that better qualified students get to attend better quality schools on average. Additionally, students with lower career beliefs or aspirations can sort to traditional public schools as the admission procedure does not involve an entrance exam. Due to these concerns, the findings of the paper should not be interpreted in a causal sense. Rather, the findings of this paper are descriptive in nature.

3.4 Results

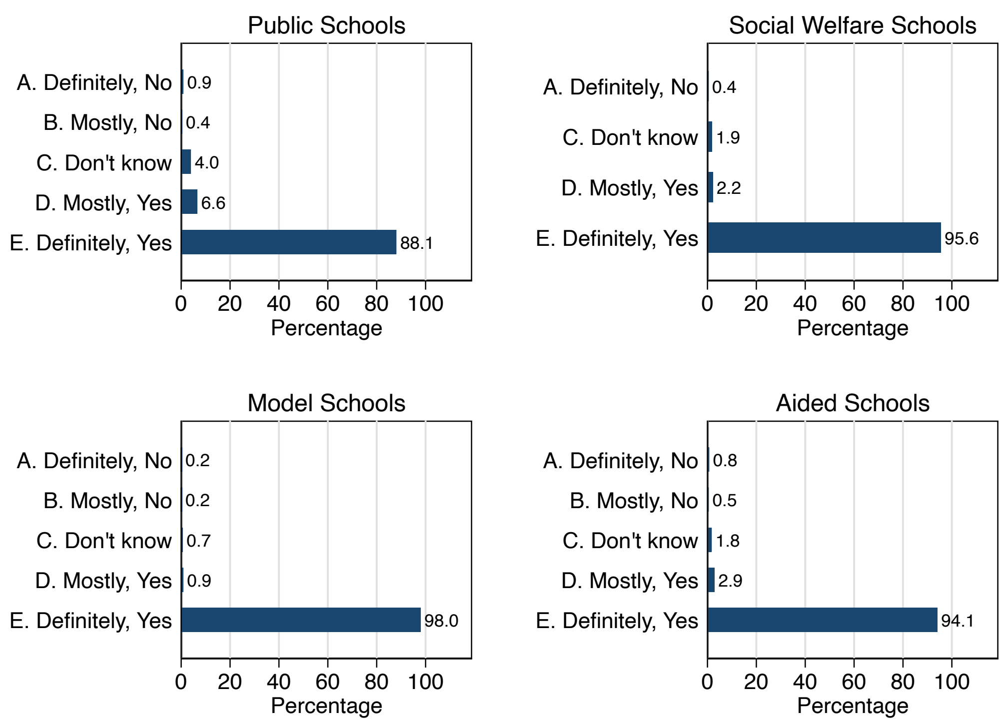
3.4.1 Intention to Continue Schooling and Time Preferences

The response of students regarding intentions to continue schooling after 10^{th}-grade by public school-type is presented in Figure 11. The majority of students across all schools either answered "Mostly, Yes" or "Definitely, Yes", suggesting that the majority of students surveyed intend to continue schooling after 10^{th}-grade. However, students' revealed preferences through the time preference question tell a different story.

As seen in Figure 12, at least 50 percent of the students across all types of schools chose either "Definitely 900 Rupees" or "Mostly 900 Rupees", suggesting that they value the present more. This is in line with the finding that students focus too much on the present (Bettinger and Slonim, 2007; Lavecchia, Liu, and Oreopoulos, 2016).

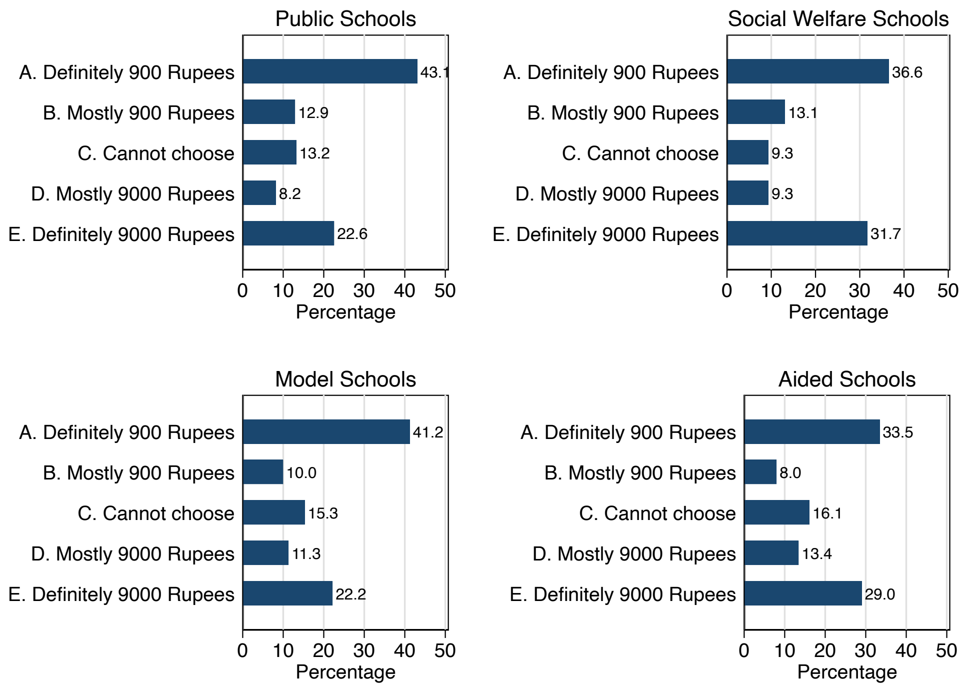
Present-biased behavior or short-term thinking can have serious long run implications on student outcomes due to sub-optimal decision making. The effects can include opting into easy classes instead of hard classes, spending time with friends instead of looking for scholarships or studying, and choosing easy majors over high-paying majors (Solomon and Rothblum, 1984; Steel, 2007). Different ways of improving self-control, patience, and focus among students could help reduce present-bias and lead to optimal educational investments.

Figure 11: Intention to Continue Schooling After 10$^{\text{th}}$-grade



Notes: The following question was asked: *"Are you planning to attend pre-college (PUC, Diploma, ITI) after SSLC?"*. The mean percentage of children choosing each of the five options is presented in this figure.

Figure 12: Time Preferences of Students

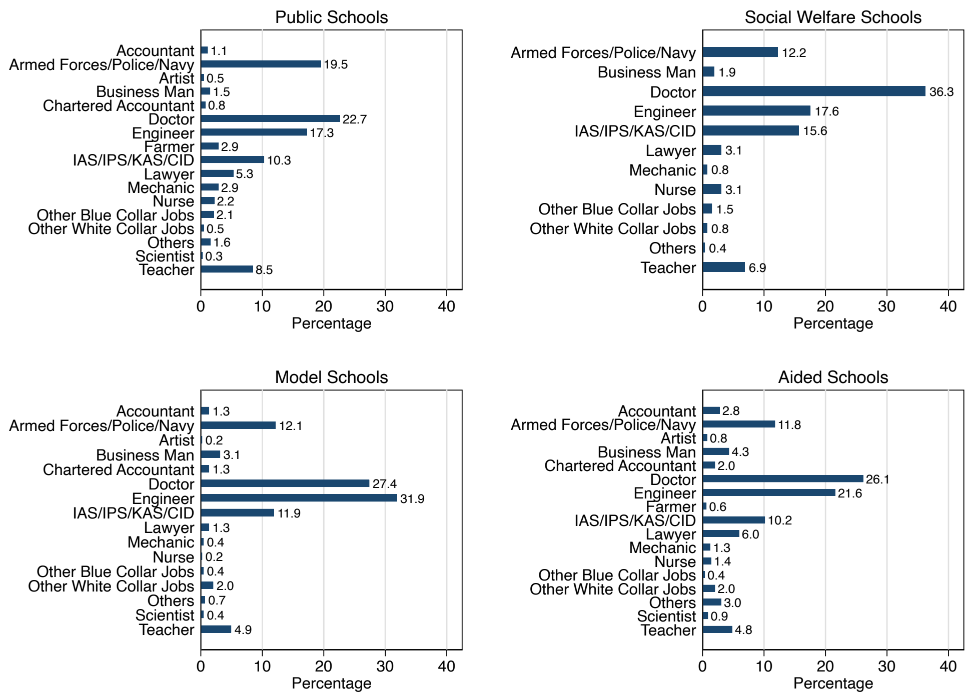


Notes: The following question was asked: *"If you had to choose between accepting 900 Rupees today or accepting 9000 Rupees after 5 years, what would you choose?"* The mean percentage of children choosing each of the five options is presented in this figure.

3.4.2 Career Aspirations and College Admission Determinants

To begin with, I show the break down of career aspirations by school type in Figure 13. Across all four systems of schools doctor and engineer are the most sought after careers. The percent of students that aspire to join armed forces or become a teacher varies across schools.

Figure 13: Career Aspirations by School Type



Notes: The following question was asked: *"What do you wish to become when you grow up?"*. The mean percentage of children choosing each of career options is presented in this figure.

In Table 15, I present the correlation regression results for four categories of ambitions for each school type. I run the following regression:

$$Y_i = \beta_0 + \beta_1[social\_welfare\_school] + \beta_2[model\_school] + \beta_3[aided\_school] + \epsilon$$

where, Y is an outcome (ambition) and each school represented as a binary indicator. The omitted group is the traditional public schools. Therefore, β_1, β_2, β_3 represent the difference in the likelihood of choosing a particular ambition for social welfare, model and aided schools respectively, when compared to the traditional public schools. I present the estimates in Table 15.

TABLE XV: CORRELATIONS: AMBITION AND SCHOOL TYPE

	(1)	(2)
Panel A: High Ambition=Doctor or Engineer		
Social Welfare School	0.139***	0.115***
	(0.0334)	(0.0339)
Model School	0.194***	0.129***
	(0.0271)	(0.0298)
Aided School	0.0779***	0.00594
	(0.0222)	(0.0250)
Panel B: Low Ambition=Police Force or Farmer		
Social Welfare School	-0.102***	-0.0716***
	(0.0252)	(0.0252)
Model School	-0.103***	-0.0592***
	(0.0204)	(0.0222)
Aided School	-0.0999***	-0.0414**
	(0.0168)	(0.0186)
Panel C: Moderate Ambition=Teacher		
Social Welfare School	-0.0161	-0.0234
	(0.0169)	(0.0172)
Model School	-0.0354***	-0.00689
	(0.0137)	(0.0152)
Aided School	-0.0366***	-0.0161
	(0.0113)	(0.0127)
Panel D: Very High Ambition=IAS/KAS/IPS/CID		
Social Welfare School	0.0535**	0.0485**
	(0.0212)	(0.0219)
Model School	0.0161	0.00253
	(0.0171)	(0.0193)
Aided School	-0.00151	-0.00404
	(0.0141)	(0.0162)
N	2815	2815
Controls	No	Yes

Note: The above table presents regression estimates for four categories of ambitions. Each column represents a regression wherein students at one type of school are being compared to the students at the rest of the schools using a binary dummy. Controls include: gender, family earnings as dummy for above median income, parents education as a dummy for above. 10^{th}-grade education, parents occupation. Standard errors in parentheses.

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

In panel A, I present the results for a student's ambition being a doctor or engineer, as 45 percent of my sample selected one of these two options. I consider these to be high ambitions as they require a highly competitive college degree. As per column 1, attending a social welfare school is associated with a 14 percentage points increase in the likelihood of aspiring to become a doctor or an engineer compared to the traditional public schools. Similarly, attending a model school school is associated with a 19.4 percentage point increase in the likelihood of aspiring to become a doctor or an engineer when compared to the traditional public schools. These relationships are significant at the 99 percent confidence interval even after controlling for gender, family income, parents' occupation, and parents' education.

In panel B, I present the results for a student's ambition being to join the police force or become a farmer as 17 percent of my sample picked one of these two options. I consider these to be low ambitions as they do not require a college degree. As per column 1, attending a social welfare school, model school, or an aided school is associated with a 10 percentage point decrease in the likelihood of aspiring to the join police force or become a farmer when being compared to traditional public schools.

In panel C, I present the results for the ambition of becoming a teacher as 7 percent of my sample aim to become a teacher. Although teacher as a profession can be considered in high regards, becoming a public school teacher in India is relatively easy as it only requires a teacher certification degree.

Therefore, I consider this to be a moderate ambition. Students attending public schools are known to sort themselves into the teaching profession in India due to job security and the non-monetary benefits of obtaining a government job. Attending a model or aided school is associated with a 4 percentage points decrease in the likelihood of aspiring to become a teacher when being compared to traditional public schools. However, these estimates move towards zero and are insignificant when controlling observables.

In panel D, I present the results for the ambition of becoming a high stature civil servant. A handful of government entities appointment people to work for the central and state governments at the highest level, namely, Indian Administrative Service (IAS), Indian Police Service (IPS), Crime Investigation Department (CID), and state level administrative services. The process of securing a job at one of these government bodies typically involves appearing for an entrance exam after the completion of a college degree. The number of people that attempt to obtain on of these jobs far exceeds the number of jobs available. As a result, it can take years of attempts before an individual gets the job and some people will give up deciding to pursue something else. Therefore, I consider this choice to be a very high ambition.[59] The estimates for model and aided schools are close to zero and insignificant. However, attending a social welfare school is associated with a statistically significant 5 percentage point increase in the likelihood of aspiring to be a

[59]It is important to note that students may or may not know the competitiveness of this career choice when thinking about their aspirations.

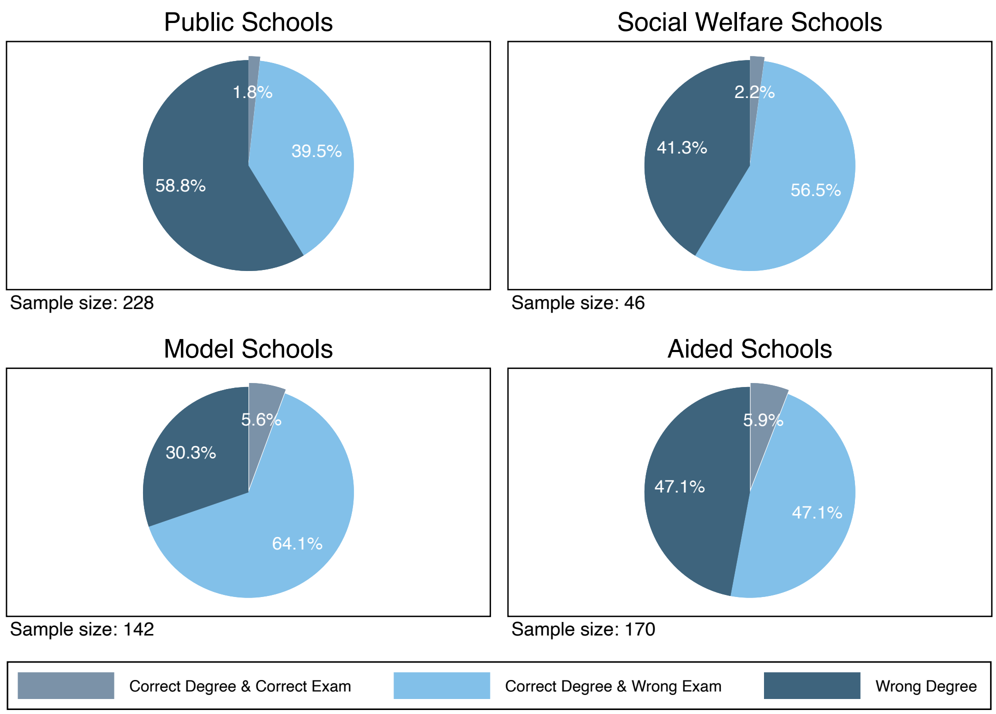
high profile civil servant. This finding is not surprising as anecdotal evidence suggests that social welfare schools inspire the children from low castes to pursue this high ambition. A major inspiration for these children is the father of the Indian constitution, Dr D. R. Ambedkar, who belonged to the scheduled caste and is known for fighting for the rights of lower social classes.

3.4.3 Knowledge About Academic Requirements for Career Choice

After students indicated their career aspirations, they were asked what college degree they needed to join and what entrance exam they needed to write to pursue their aspirations. Figures 14 & 15 illustrate the results of these questions for becoming a doctor and becoming an engineer respectively. The sample is restricted to those that indicated their ambition as engineer or doctor in each school system. I picked these two ambitions rather than checking for all the ambitions as 45 percent of my sample indicated that they either aspire to be an engineer or a doctor.

A total of 586 out of 2,842 students answered that they aspire to be an Engineer. There are two observations worth noting. First, a very small percent of the students are aware of the name of the degree and the entrance exam they have to write to seek admission into an engineering college across all school types. Second, this percentage increases slightly for model schools and aided schools.

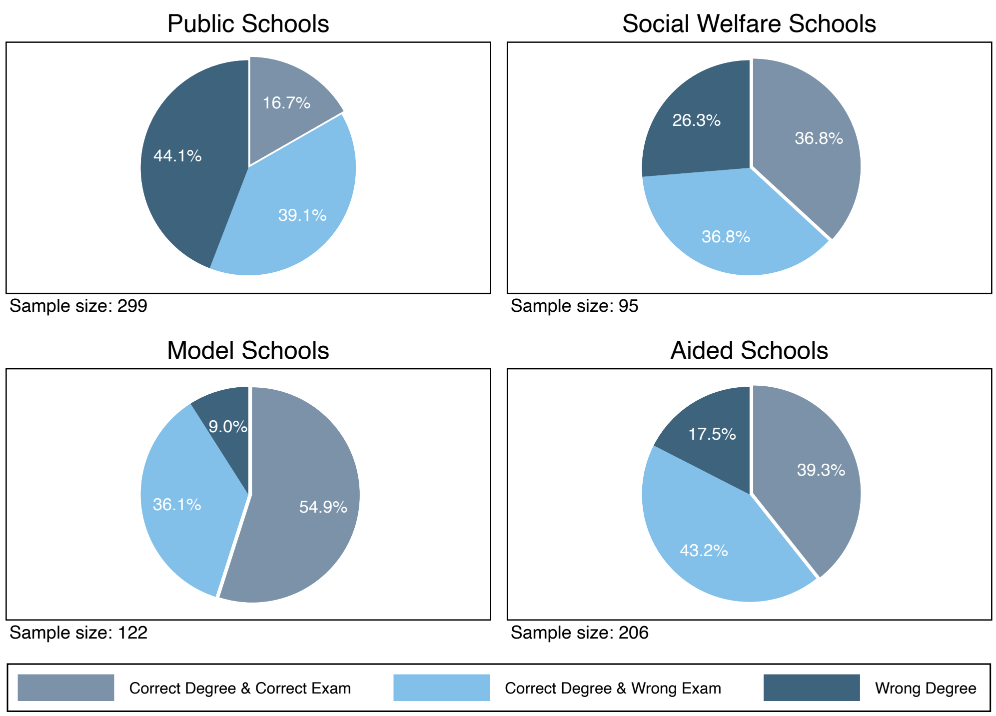
Figure 14: Knowledge on Degree and Entrance Exam for Engineering



Notes: In order to join an engineering college, student's need to appear for a state-standardized entrance exam. The figures gets at whether those who said they would like to become an engineer know the name of the entrance exam that they need to appear for.

A total of 722 students said becoming a doctor was their ambition. The percent share of students that know the name of the degree and entrance exam to attend a medical college is much greater when compared to the engineering degree. Medicine is one the most desired degrees in India and this finding is probably due to students being more familiar with the name of the exam. However, the demand for medical colleges far exceeds the supply and therefore, medicine is the most competitive degree in terms of admission rates. For instance, in order to be considered for admission to a medical college, students need to score above the 50^{th} percentile in the entrance exam.

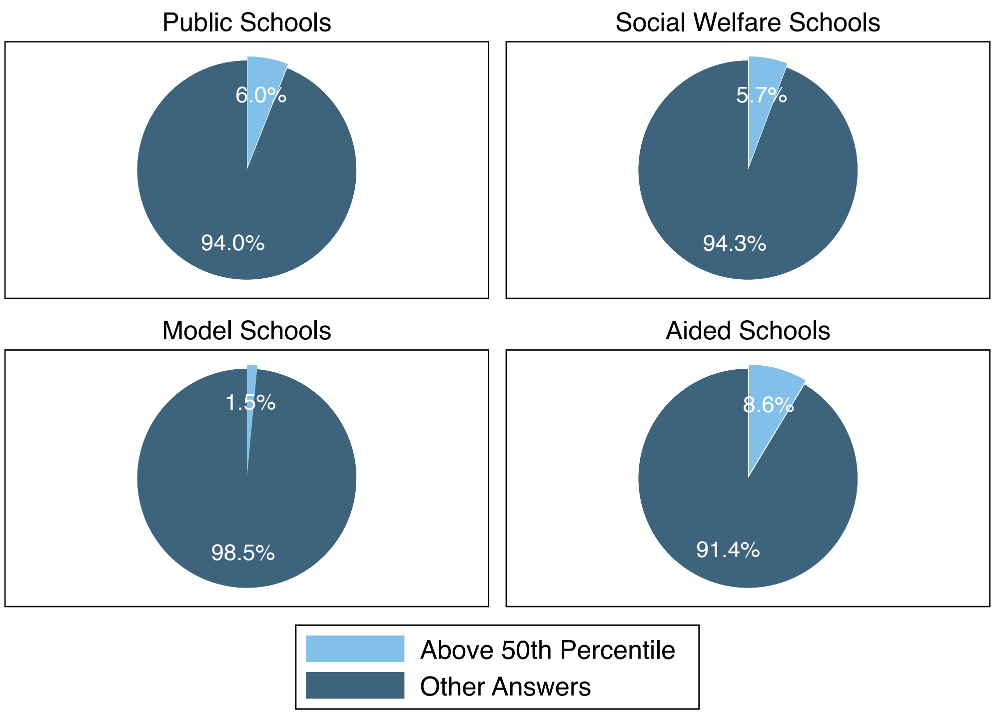
Figure 15: Knowledge on Degree and Entrance Exam to Become a Doctor



Notes: In order to join an medical college, student's need to appear for a national-standardized entrance exam. The figures gets at whether those who said they would like to become a doctor know the name of the exam that they need to appear for.

I extended the exercise for a medical degree by asking the students what they thought was the minimum score need to get a rank in the entrance exam. The results are shown in Figure 16. Of the 233 students who said they want to become a doctor and who knew the correct name of the degree and entrance exam, only 13 students across all schools knew that they had to score at the 50^{th} percentile or above to to receive a rank in the entrance exam.

Figure 16: Minimum Score Needed to get a Rank in the Medical College Entrance Exam



Source: Appearing for medical entrance exam is only necessary condition. The sufficient condition for becoming eligible to be admitted into a medical college, students need to score above the 50^{th} percentile. To check how many students know this, I asked the following question: *"What are the minimum marks required in the NEET exam to become eligible to seek admission into a medical college under General Merit (GM) category?"* This figure shows the percent of students that selected the correct response for each school type.

3.4.4 Perceived Returns to Education for Self and Others

Table 16 presents the average *perceived* returns to education (per month) for self and others for each school type. I first look at self-earnings. The perceived self-earnings increases when going from public schools to aided schools across all three levels of education. For example, the difference in perceived earnings for a college degree is 4,500, 6,000 and 8,000 Indian rupees for social welfare schools, model schools and aided schools respectively when compared to traditional public schools.

These differences could be due to the possibility that the actual returns to education vary across these schools. Another explanation is the pessimistic bias among traditional public school students as found in previous studies (Attanasio and Kaufmann, 2009; Jensen, 2010; Sequeira, Spinnewijn, and Xu, 2016).[60] As a result, the level of increase in *perceived* returns to education when going from one education level to another is correlated with school type. For instance, the difference between *perceived* earnings with 12^{th}-grade and earnings with 10^{th}-grade is about 7,000 Indian rupees for public schools. The same difference is about 9,000 Indian rupees for social welfare schools, 7,500 Indian rupees for model schools, and 9,000 Indian rupees for aided schools. There is similar pattern in the perceived earnings differences when college

[60] Under pessimistic bias, people overestimate the likelihood of negative things happening to them.

degree is compared to 12$^{\text{th}}$-grade and when college degree is compared to 10$^{\text{th}}$-grade.

TABLE XVI: PERCEIVED EARNINGS BY EDUCATION LEVEL FOR SELF AND OTHERS

	All Schools	Public Schools	Social Welfare Schools	Model Schools	Aided Schools
Level of education: 10th-grade					
Self	11355.2	10103.13	10994.25	11493.86	13514.05
	(11089.18)	(8617.515)	(8869.837)	(9982.677)	(15073.68)
Others	13529.47	13498.67	14389.85	12596.29	13823.22
	(13640.65)	(13424.92)	(14155.52)	(13227.48)	(14046.43)
Level of education: Pre-University (12th-grade)					
Self	19307.65	17472.65	19931.94	18914.38	22455.86
	(14066.59)	(12842.36)	(12987.81)	(12703.82)	(16445.42)
Other	21663.82	20769.92	23002.7	20401.37	23432.98
	(16787.45)	(16160.5)	(17937.71)	(16557.3)	(17391.14)
Level of education: College Degree					
Self	34006.32	30418.65	34916.09	36133.11	38717.81
	(22757.32)	(20913)	(23421.65)	(21786.27)	(25087.08)
Other	35759.78	31660.94	35951.71	39419.91	40465.13
	(27021.89)	(23668.45)	(26970.85)	(29351.52)	(29762.22)

Note: The above table presents the perceived self and others earnings by school type. The averages were computed using the data obtained through the questionnaire. Standard errors are in parenthesis.

For instance, the difference between *perceived* earnings with 12$^{\text{th}}$-grade and earnings with 10$^{\text{th}}$-grade is about 7,000 Indian rupees for public schools. The same difference is about 9,000 Indian rupees for social welfare schools, 7,500 Indian rupees for model schools, and 9,000 Indian rupees for aided schools. There is similar pattern in the perceived earnings differences when college degree is compared to 12^{th}-grade and when college degree is compared to 10^{th}-grade.

When looking at others earnings, students across all school systems perceive self-earnings to be lower than average individual's earnings for all levels of education. Pessimistic bias could again explain this if we think that students across all schools are treating the students at private schools to be in the "others" category.

3.5 Conclusion

In this paper, I use survey responses from students at four systems of public schools in India to study the career aspirations of 10^{th}-grade students. The first finding is that attending a high quality system of public schools is associated with an increase in the likelihood of having a socially desirable career aspiration such as doctor, engineer, and civil servant. Second, although 45 percent of my sample indicated that they aspire to be either doctor or engineer, I find that students across all four systems of schools lack knowledge on the academic requirements to pursue medicine or engineering. Third, *perceived* self-earnings of students at improved public schools is higher that of students at traditional public schools.

These findings are not casual in nature as students can sort to schools. This study hopes to provide baseline estimates to researchers for designing information interventions that rely on differences between the information perceived and the actual information. The primary objective of this study is to provide information that reflects the differences in career aspirations among students and schools.

The study also has implications to policymakers. First, the lack of knowledge of academic requirements may hinder good decision-making. Second, the dispersion in perceived returns to education may affect the decision of staying in school or dropping out.

CITED LITERATURE

Abdulkadiroğlu, Atila, et al. 2011. "Accountability and flexibility in public schools: Evidence from Boston's charters and pilots". *The Quarterly Journal of Economics* 126 (2): 699–748.

Alderman, Harold, Peter F Orazem, and Elizabeth 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.

Andersen, Steffen, et al. 2008. "Eliciting risk and time preferences". *Econometrica* 76 (3): 583–618.

Andreoni, James, and Charles Sprenger. 2012. "Estimating time preferences from convex budgets". *American Economic Review* 102 (7): 3333–56.

Angrist, Joshua, et al. 2002. "Vouchers for private schooling in Colombia: Evidence from a randomized natural experiment". *American Economic Review* 92 (5): 1535–1558.

Arulmani, Gideon, Darren Van Laar, and Simon Easton. 2003. "The influence of career beliefs and socio-economic status on the career decision-making of high school students in India". *International Journal for Educational and Vocational Guidance* 3 (3): 193–204.

Attanasio, Orazio, and Katja Kaufmann. 2009. *Educational choices, subjective expectations, and credit constraints.* Tech. rep. National Bureau of Economic Research.

Azam, Mehtabul, Aimee Chin, and Nishith Prakash. 2013. "The returns to English-language skills in India". *Economic Development and Cultural Change* 61 (2): 335–367.

Bettinger, Eric, and Robert Slonim. 2007. "Patience among children". *Journal of Public Economics* 91 (1-2): 343–363.

Beuermann, Diether W, and C Kirabo Jackson. 2018. *Do parents know best? the short and long-run effects of attending the schools that parents prefer.* Tech. rep. National Bureau of Economic Research.

Bhagat, Ram B. 2010. "Internal migration in India: are the underprivileged migrating more". *Asia-Pacific Population Journal* 25 (1): 27–45.

Bharti, Nitin Kumar. 2018. "Wealth Inequality, Class and Caste in India, 1951-2012".

Bold, Tessa, et al. 2017. "Enrollment without learning: Teacher effort, knowledge, and skill in primary schools in Africa". *Journal of Economic Perspectives* 31 (4): 185–204.

Calonico, Sebastian, Matias D Cattaneo, and Rocio Titiunik. 2014. "Robust nonparametric confidence intervals for regression-discontinuity designs". *Econometrica* 82 (6): 2295–2326.

Card, David. 1999. "The causal effect of education on earnings". In *Handbook of labor economics*, 3:1801–1863. Elsevier.

Chakraborty, Tanika, and Shilpi Kapur Bakshi. 2016. "English language premium: Evidence from a policy experiment in India". *Economics of Education Review* 50:1–16.

Chari, AV, and Annemie Maertens. 2014. "Gender, productive ability and the perceived returns to education: Evidence from rural India". *Economics Letters* 122 (2): 253–257.

Chaudhuri, Kausik, and Susmita Roy. 2009. "Gender gap in educational attainment: evidence from rural India". *Education Economics* 17 (2): 215–238.

Chaudhury, Nazmul, et al. 2006. "Missing in action: teacher and health worker absence in developing countries". *Journal of Economic perspectives* 20 (1): 91–116.

Cheney, Gretchen Rhines, Betsy Brown Ruzzi, and Karthik Muralidharan. 2005. "A profile of the Indian education system". *Prepared for the New Commission on the Skills of the American Workforce*.

Chudgar, Amita, and Elizabeth Quin. 2012. "Relationship between private schooling and achievement: Results from rural and urban India". *Economics of Education Review* 31 (4): 376–390.

Cullen, Julie Berry, Brian A Jacob, and Steven Levitt. 2006. "The Effect of School Choice on Participants: Evidence from Randomized Lotteries". *Econometrica* 74 (5): 1191–1230. doi:10.1111/j.1468-0262.2006.00702.x.

Datta, Sandip, and Geeta Gandhi Kingdon. 2019. "Gender Bias in Intra-Household Allocation of Education in India: Has It Fallen over Time?"

De, Anuradha, et al. 2011. "PROBE revisited: A report on elementary education in India". *OUP Catalogue*.

Deming, David J, et al. 2014. "School choice, school quality, and postsecondary attainment". *American Economic Review* 104 (3): 991–1013.

Desai, Sonalde, and Veena Kulkarni. 2008. "Changing educational inequalities in India in the context of affirmative action". *Demography* 45 (2): 245–270.

Dongre, Ambrish A, and Avani Kapur. 2016. "Trends in Public Expenditure on Elementary Education in India". *Economic & Political Weekly* 51 (39).

Duckworth, Angela Lee, and Martin EP 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, Esther, Pascaline Dupas, and Michael Kremer. 2015. "School governance, teacher incentives, and pupil–teacher ratios: Experimental evidence from Kenyan primary schools". *Journal of Public Economics* 123:92–110.

French, Rob, Geeta Kingdon, et al. 2010. "The relative effectiveness of private and government schools in Rural India: Evidence from ASER data". *London: Institute of Education.*

Glewwe, Paul, and Michael Kremer. 2006. "Schools, teachers, and education outcomes in developing countries". *Handbook of the Economics of Education* 2:945–1017.

Hahn, Jinyong, Petra Todd, and Wilbert Van der Klaauw. 2001. "Identification and estimation of treatment effects with a regression-discontinuity design". *Econometrica* 69 (1): 201–209.

Hastings, Justine S, Thomas Kane, and Douglas Staiger. 2006. "Gender, Performance and Preferences: Do Girls and Boys Respond Differently to School Environment?" In *American Economic Review Papers and Proceedings*, 96:232–236.

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

Heckman, James J, John Eric Humphries, and Gregory Veramendi. 2018. "Returns to education: The causal effects of education on earnings, health, and smoking". *Journal of Political Economy* 126 (S1): S197–S246.

Hsieh, Chang-Tai, and Miguel Urquiola. 2006. "The effects of generalized school choice on achievement and stratification: Evidence from Chile's voucher program". *Journal of public Economics* 90 (8-9): 1477–1503.

Jackson, C Kirabo. 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.

Jensen, Robert. 2010. "The (perceived) returns to education and the demand for schooling". *The Quarterly Journal of Economics* 125 (2): 515–548.

Kingdon, Geeta Gandhi. 2017. "The private schooling phenomenon in India: A review".

Kling, Jeffrey R, Jens Ludwig, and Lawrence 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.

Krishna, Anirudh. 2017. "Attitudes, Experiences, and Information". In *The Broken Ladder: The Paradox and Potential of India's One-Billion*, 128–149. Cambridge University Press. doi:10.1017/9781108235457.006.

Lavecchia, Adam M, Heidi Liu, and Philip Oreopoulos. 2016. "Behavioral economics of education: Progress and possibilities". In *Handbook of the Economics of Education*, 5:1–74. Elsevier.

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

Lee, David S, and Thomas Lemieux. 2010. "Regression discontinuity designs in economics". *Journal of economic literature* 48 (2): 281–355.

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

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

Mbiti, Isaac, et al. 2019. "Inputs, incentives, and complementarities in education: Experimental evidence from Tanzania". *The Quarterly Journal of Economics* 134 (3): 1627–1673.

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

Munshi, Kaivan, and Mark Rosenzweig. 2006. "Traditional institutions meet the modern world: Caste, gender, and schooling choice in a globalizing economy". *American Economic Review* 96 (4): 1225–1252.

Muralidharan, Karthik, and Michael Kremer. 2006. "Public and private schools in rural India". *Harvard University, Department of Economics, Cambridge, MA*.

Muralidharan, Karthik, and Venkatesh Sundararaman. 2013. *Contract teachers: Experimental evidence from India.* Tech. rep. National Bureau of Economic Research.

— . 2015. "The aggregate effect of school choice: Evidence from a two-stage experiment in India". *The Quarterly Journal of Economics* 130 (3): 1011–1066.

Nguyen, Trang. 2008. "Information, role models and perceived returns to education: Experimental evidence from Madagascar". *Unpublished manuscript* 6.

Oreopoulos, Philip, and Uros Petronijevic. 2013. *Making college worth it: A review of research on the returns to higher education.* Tech. rep. National Bureau of Economic Research.

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

Park, Albert, et al. 2015. "Magnet high schools and academic performance in China: A regression discontinuity design". *Journal of Comparative Economics* 43 (4): 825–843.

Peet, Evan D, Günther Fink, and Wafaie 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, Cristian, and Miguel Urquiola. 2013. "Going to a better school: Effects and behavioral responses". *American Economic Review* 103 (4): 1289–1324.

Rose, Pauline. 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, Ankur, et al. 2015. "State of the Nation: RTE Section 12 (1)(c)".

Sequeira, Sandra, Johannes Spinnewijn, and Guo Xu. 2016. "Rewarding schooling success and perceived returns to education: Evidence from India". *Journal of Economic Behavior & Organization* 131:373–392.

Singh, Abhijeet. 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, Renu, and Protap Mukherjee. 2018. "'Whatever she may study, she can't 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.

Solomon, Laura J, and Esther D Rothblum. 1984. "Academic procrastination: Frequency and cognitive-behavioral correlates." *Journal of counseling psychology* 31 (4): 503.

Steel, Piers. 2007. "The nature of procrastination: A meta-analytic and theoretical review of quintessential self-regulatory failure." *Psychological bulletin* 133 (1): 65.

Tooley, James, Pauline Dixon, and Isaac Amuah. 2007. "Private and public schooling in Ghana: A census and comparative survey". *International review of education* 53 (4): 389–415.

Urquiola, Miguel. 2016. "Competition among schools: Traditional public and private schools". In *Handbook of the Economics of Education*, 5:209–237. Elsevier.

APPENDIX

A. Regression Equations for the Econometric Strategy in Chapter 2

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:

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

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:

$$Y = \psi_0\, run + \psi_1\, model\_school + \psi_2\, (run * model\_school) + \psi_3\, \widetilde{R} : High + \psi_4\, (run * \widetilde{R} : High) + \psi_5\, (model\_school * \widetilde{R} : High) + \psi_6\, (run * model\_school * \widetilde{R} : High) + \epsilon \quad (4)$$

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

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:

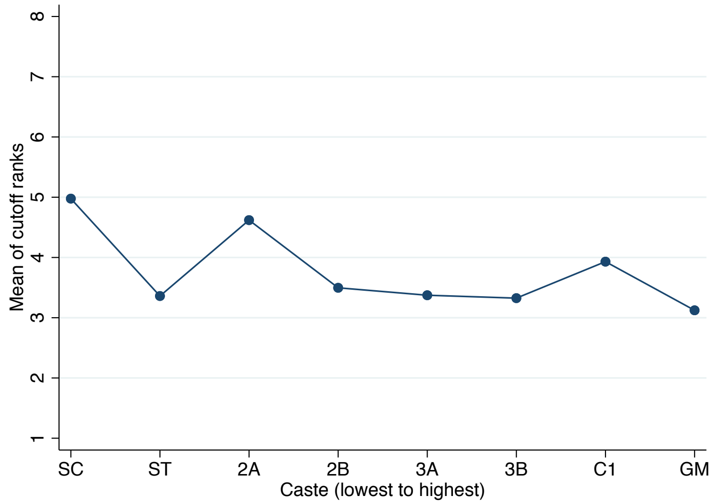
$$\begin{aligned} Y = {} & \beta_0\, run + \beta_1\, model\_school + \beta_2\, (run * model\_school) + \\ & \beta_3\, (run * (\widetilde{A} : Below\ \&\ \widetilde{R} : High)) + \beta_4\, (model\_school * (\widetilde{A} : Below\ \&\ \widetilde{R} : High)) + \\ & \beta_5\, (run * model\_school * (\widetilde{A}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

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 ($\widetilde{A}$: $Below$ & $\widetilde{R}$: Low) 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$^{\text{th}}$ 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$^{\text{th}}$ percentile student in their class.

Grouping based on within school and across schools variation in cutoffs

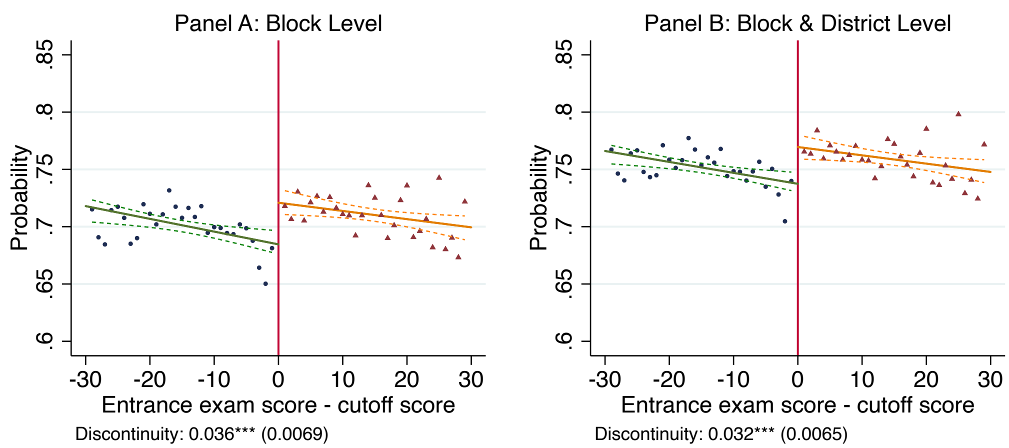
i	$< group_i >$	Description	Coefficients
-	$\widetilde{A}: Below$ & $\widetilde{R}: Low$	Students who have *low* prior learning levels and are *below* the 20$^{\text{th}}$ percentile student in their class	β_1
1	$\widetilde{A}: Below$ & $\widetilde{R}: High$	Students who have *low* prior learning levels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

Figure 17: Relationship Between Caste and Within School Ranking of the Cutoffs



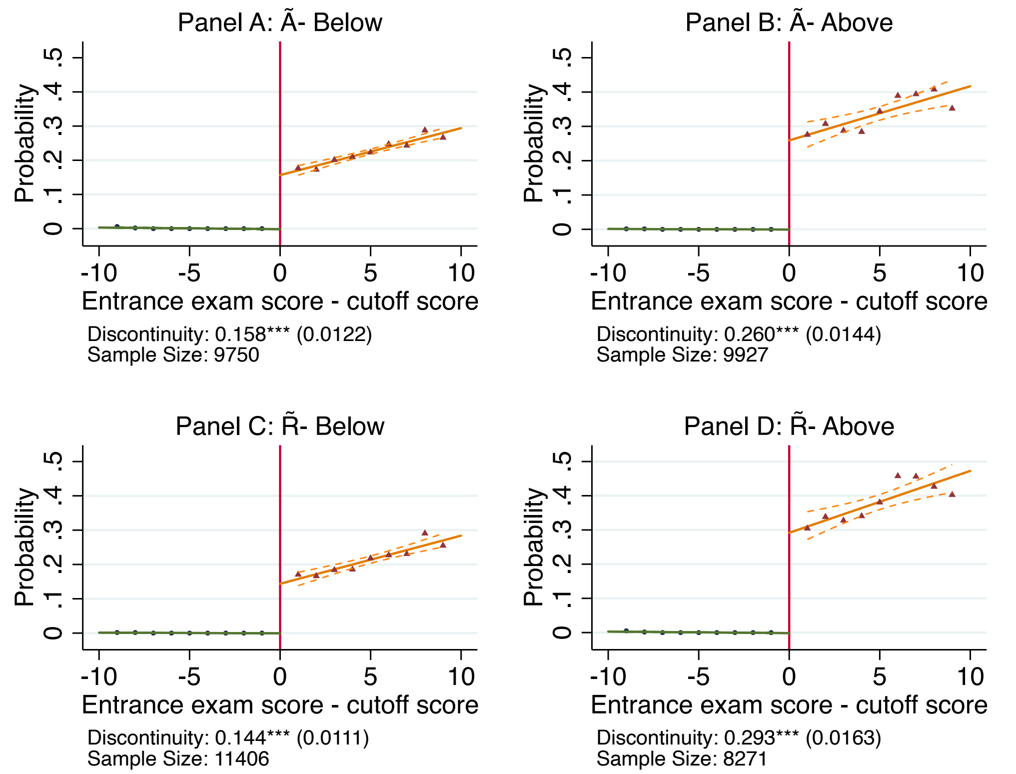
Notes: This figure shows the relationship between each caste and its cutoff's ranking within school. I first rank each of the possible eight cutoffs within a school from lowest (rank 1) to highest (rank 8). I then take the mean of these ranks across school for each caste. On the x-axis is the castes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

Figure 18: Attrition: Probability of Finding a Match



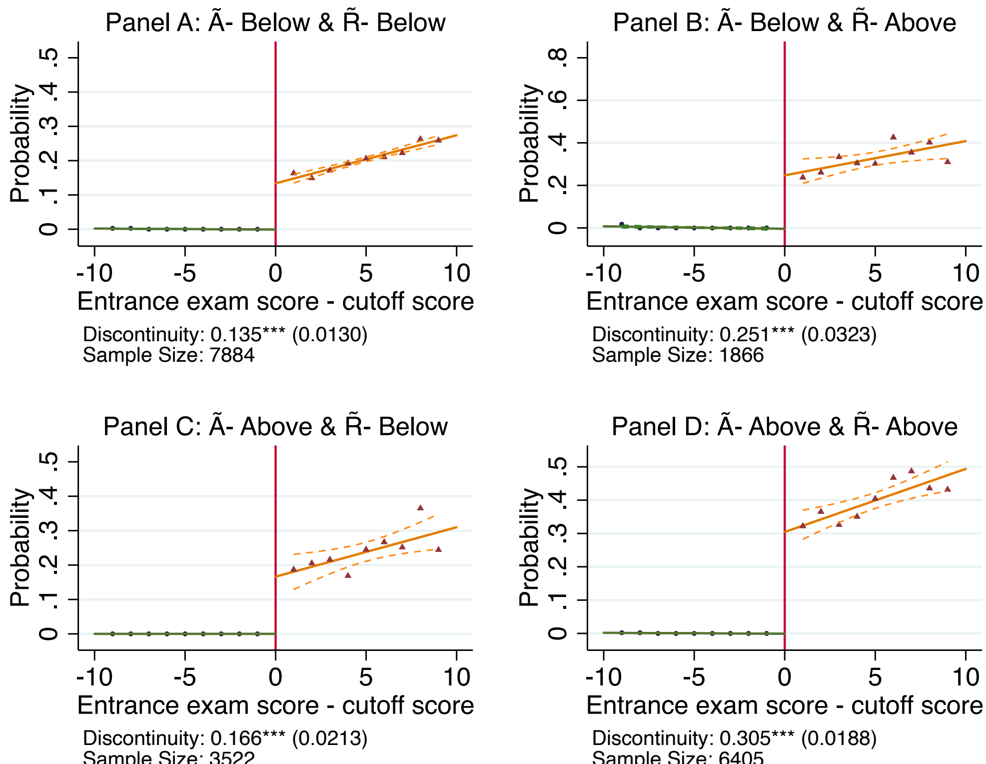
Notes: In each panel the solid lines represent the linear fit of the dependent variable on the entrance exam score, estimated separately on either side of the cutoff. Each point is the mean probability of finding a match within non-overlapping one point bins. "Entrance exam score - cutoff score" is the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

Figure 19: First Stage: Absolute learning levels and Relative Position Within the Class Separately



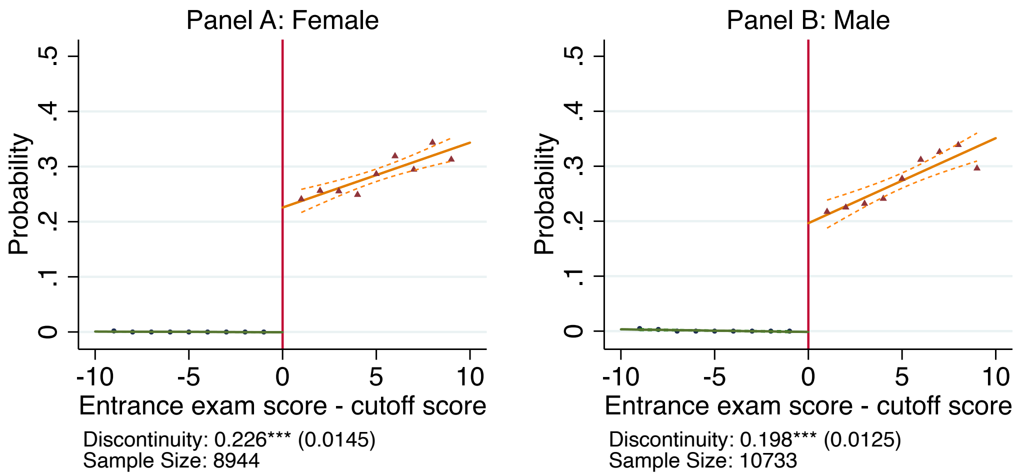
Notes: "Entrance exam score - cutoff score" is the entrance exam score minus the relevant school-by-category cutoff score. Notation: A-below indicates the group with categories whose cutoffs was below the absolute learning level as measured by the yearly median cutoff score. R-above indicates the group 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 20: 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 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 21: 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 XVII: 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	97.8	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
	(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 XVIII: 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 Instr-uction (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 5th grade. Standard errors clustered at school-by-category-by-year are in parentheses.

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

TABLE XIX: 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 XX: 2SLS ESTIMATES FOR BLOCK-LEVEL SAMPLE: ACADEMIC ACHIEVEMENT

Bandwidth	**+/-10**	**+/-10**	**+/-20**	**+/-20**	**+/-30**	**+/-30**
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Maths score in 10^{th} grade exam						
	7.546***	7.733***	5.885***	5.421***	7.557***	5.770***
	(2.018)	(1.880)	(1.318)	(1.229)	(1.189)	(1.105)
Panel B: Science score in 10^{th} grade exam						
	4.392**	4.764***	2.674**	2.548**	4.656***	2.934***
	(1.850)	(1.699)	(1.214)	(1.127)	(1.158)	(1.029)
Panel C: Social Science score in 10^{th} grade exam						
	4.837**	5.213***	3.053**	3.095**	4.662***	3.387***
	(2.038)	(1.951)	(1.345)	(1.302)	(1.276)	(1.212)
Panel D: prob. of obtaining A/A+ in 10^{th} grade exam						
	0.205***	0.213***	0.142***	0.136***	0.167***	0.131***
	(0.0523)	(0.0504)	(0.0334)	(0.0325)	(0.0312)	(0.0302)
Controls	No	Yes	No	Yes	No	Yes
Observations	17951	17951	34640	34640	45482	45482

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 XXI: 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 XXII: 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: Caste	GM	SC	ST	OBC
1{Entrance exam scorecutoff}	0.224***	0.187***	0.237***	0.207***
	(0.0367)	(0.0208)	(0.0369)	(0.0115)
Observations	1441	4025	1156	13055
F-Statistic	37.45	81.04	41.1	325.16
Panel C: 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 D: 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 E: 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 student's 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 XXIII: 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`

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EDUCATION

Ph.D., Economics, University of Illinois at Chicago, Illinois, USA, 2020

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RESEARCH

Public School Quality and Student Outcomes: Evidence from Model Schools in India. *Working Paper.*

Interventions to Improve Public School Children's Educational Outcomes in India. *Work in Progress.*

PROFESSIONAL PRESENTATIONS

Western Economic Association International annual meeting (WEAI), Canadian Economics Association (CEA), Illinois Economics Association (IEA), Annual Conference on Economic Growth and Development in Delhi (ACEGD).

TEACHING EXPERIENCE

Course Instructor, University of Illinois at Chicago, Chicago, Illinois

Microeconomics: Theory and Applications, Spring 2019, Spring 2020

Economics of Sports and Entertainment, Summer 2019

Teaching Assistant, University of Illinois at Chicago, Chicago, Illinois

Microeconomics: Theory and Applications, Fall 2015, 2017 & 2019; Spring 2016

Principles of Microeconomics, Fall 2016

Principles of Macroeconomics, Spring 2017

Freakonomics, Fall 2018

AWARDS AND HONORS

Graduate Winifred Geldard Memorial UIC Department Awards, Best Graduate Student Teaching, Chicago, Illinois, 2017, 2020

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