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Introduction

Theoretical analysis on returns to education was pioneered by the works of Becker (1962), Mincer (1974), and Schultz (1961). Education or training was now treated as an investment rather than a consumption good with returns accruing in the future. The literature on returns to education has evolved tremendously over the years. The most recent estimates show that the global private rate of return to schooling is 10% for every year of schooling (Montenegro and Patrinos, 2014). Even though schooling has the potential to increase productivity by providing skills, there can be various circumstances which can lead to under-investment in education. For instance, borrowing constraints in financing education has been identified as one of the major market failure leading to inefficient and unequal education investments (Benabou, 1996; Checchi, 2006; Galor and Zeira, 1993). Due to this market failure governments in many developing countries have made huge investments in primary education. This significantly helped in bringing children to school with primary school enrolments reaching close to universal levels [1].

Though the rapid expansion helped many children to enter school, evidence on what they learn in school has been unsatisfactory. For instance, estimates from regional student assessments across the world reveal that millions of school going children have failed to acquire even the most basic literacy and numeracy skills.[2]. This has serious policy implications as recent studies have shown that the quality of education apart from quantity

[1]The net enrolment ratios in primary education increased by at least 20 percentage points from 1999 to 2012 in 17 countries, 11 of which were in sub-Saharan Africa (UNESCO, 2015a)

[2]Around 250 million children across the world are unable to acquire basic reading and mathematics skills and more than half of them have stayed in school for at least four years (Altinok et al., 2014; UNESCO, 2013)

is an important determinant of economic development (Hanushek and Woessmann, 2008; Schoellman, 2012). There also exists huge inequalities in educational opportunity across as well as within countries; in countries such as Ghana, India, Mozambique, Nigeria and Zambia, the poorest quintile accounts for 30% to 40% of the out-of-school population (UNESCO, 2009). Thus, much needs to be done to meet the SDG 4 of providing *inclusive and equitable quality education for all.*

The main objective of this dissertation is to understand how education policies affects quality and inequality in education. In Chapter 1, *"Look no farther: The impact of local contract teachers on student outcomes"*, my co-author and I explore the role of school quality more specifically teachers in enhancing human capital. The increasing number of contract teachers in developing countries has led to concerns about the effect of their employment on teacher quality. Contract teachers are in general less trained and qualified. However, they are more likely to be hired from the local community, which can positively affect student outcomes by reducing social distance or through better monitoring. This paper provides evidence on the difference in the impact of contract and regular civil service teachers with a special focus on the effect of being a local teacher or native of the village. Using a value-added estimation method, based on data from a unique survey in India, we find no statistically significant difference in the performance of contract and regular teachers for both grades 4 and 6. However, within contract teachers, we observe that local teachers have a significant and positive impact (0.24 standard deviation) on student learning for grade 6.

The next chapter, *"Retain or not to retain: Automatic promotion and student outcomes"*, deals with the issue of equity and efficiency in education. How does increase in access to education affect education quality? Does the effect vary by socio-economic background? A large scale education reform in India introduced automatic promotion in all elementary grades. This paper estimates the impact of automatic promotion on education outcomes. I use quasi exogenous variation in exposure to the policy due to initial differences in repetition rates across districts. I find that automatic promotion reduces dropout rates by 0.1 percentage points for children in the lower secondary age. However, the policy had a negative effect on learning outcomes. The probability that a primary age student could solve a basic reading and arithmetic task falls by 0.3 and 0.8 percentage points respectively. The negative effect was larger for children with a poor socio-economic background. I explore probable mechanisms for the decline in learning levels. I find that districts with congested government schools suffered more due to the policy.

In Chapter 3, *"Indian matchmaking: Impact of large scale education program"*, my co-authors and I look into marriage market returns to education. Marriage markets are important determinants of human capital investment and fertility outcomes. Marriage market outcomes, especially the age of marriage influence economic opportunities for women. In this paper, we study the impact of the large-scale education program in India, District Primary Education Program (DPEP), on female education and the marriage market. The program provides a regression discontinuity set-up to estimate the causal impact. The districts below the national average of female literacy were selected in the program. Preliminary results show that female education increases by 1.3 years. The program further reduces the age of marriage and increases partner's education.

Chapter 1

Look no farther: The impact of local contract teachers on student outcomes[1]

Many developing countries have made substantial progress in increasing enrollments in primary education since the 1990s. Nevertheless, this rise in demand for education has met with serious teacher shortages (UNESCO, 2015b). Evidence from both developed and developing countries shows that teachers play a critical role in improving the quality of education (Araujo et al., 2016; Bau and Das, 2020; Chetty et al., 2014b; Hanushek and Rivkin, 2006; Rockoff, 2004). With limited budget and institutional capacity, most of the developing countries find it difficult to hire good quality teachers. This problem is exacerbated by asymmetric information on teacher quality, as most of the observable characteristics such as qualification, training, salary, etc. explain little of the variation in their effectiveness.[2](Azam and Kingdon, 2015; Kane et al., 2008; Rivkin et al., 2005) Therefore, to ensure learning for millions of children in developing countries, identifying policies to hire quality teachers in a cost-effective manner is a matter of utmost priority.

Hiring contract teachers[3] has been advocated by many as one of the ways to improve

[1]This chapter is co-authored with Prof. Ana Balcão Reis.

[2]One exception is initial years of experience. Teachers perform more poorly on overage in the first few years of their teaching career, but there is no significant effect of teacher experience on student performance after accounting for initial years (Hanushek and Rivkin, 2006).

[3]Chudgar et al. (2014) use the term *alternative route* for *"any teacher hiring in which some element of the standard process has been diluted to allow school systems to fill vacant teaching positions."* We

teacher supply in a cost-effective manner for primary grades. In comparison to regular teachers, contract teachers have less stringent entry requirements in terms of teacher training and qualification certificates, are paid less, and are usually hired in a decentralized way from the local community (see Chudgar et al., 2014 for a detailed review on contract teachers). Earlier research has shown that teachers in developing countries face serious motivation problems with poorly incentivized contracts and lack of accountability (Chaudhury et al., 2006; Pritchett and Murgai, 2006). In an extensive review Kremer et al. (2013) highlight that reforms that improve accountability and incentives such as the local hiring of teachers on short-term contracts are effective in improving teacher effort. Contract teachers thereby provide an opportunity to improve student learning through (a) incentivized contracts and (b) better monitoring or accountability at the local level.

Existing evidence shows that contract teachers perform equally or even better than regular civil service teachers (Duflo et al., 2015; Muralidharan and Sundararaman, 2013), although the effusiveness might vary depending on the incentive structures, heterogeneity in student ability, and the level of accountability and management. For instance, Bourdon et al. (2010) use an extensive data set across three countries in Africa (Niger, Togo, and Mali) to analyze the effect of contract teacher policy. One of the main findings of their study is that contract teachers may do better than regular teachers in a low-ability context, whereas regular teachers might do better in a less disadvantaged student environment. The authors find that in Mali contract teachers had a positive effect on student outcomes since the system worked through the local communities. In the case of Niger the effect of contract teachers was negative. This may be explained by the fact that the system changed all contract teachers to centralized public employees, making them free from local monitoring. In another study, Atherton and Kingdon (2010) use a value-added method with school-fixed effects to estimate contract teacher effects on student test scores *within* schools in the Indian states of Bihar and Uttar Pradesh. They find a positive effect of

follow this broad definition when we refer to contract teachers throughout the paper. The diverse nature of hiring teachers through alternative methods makes it difficult to call them by a single name. In India, they are often termed *para teachers* while elsewhere they are called *contract teachers*.

contract teachers in the case of Uttar Pradesh, where contracts are renewed yearly, but no significant effect for the state of Bihar, where contract teachers are hired on a permanent basis. The data used for this paper are also for the Indian state of Bihar, where contract teachers are hired for life. Therefore, we do not expect to observe any impact on student outcomes through the incentive mechanism.

This paper provides additional evidence on the effect of contract teachers on student learning outcomes. Do contract teachers differ in performance from regular teachers? While most of the studies on contract teachers have focused on lower primary grades, this paper provides evidence for both grades 4 and 6. Additionally, we test if being a local/native teacher (born in the same village where school is located) explains variation in teacher quality. Earlier studies have focused on whether the hiring is centralized or decentralized to study the impact of local monitoring of teachers (Bold et al., 2018; Bourdon et al., 2010). We focus our analysis on the impact of teachers being local, i.e hired from the same village where the school is. The local nature of teachers is an important and distinctive feature that might induce them to exert more effort in difficult environments (remote areas, disadvantaged students) because of reduced social distance (Rawal, Kingdon, et al., 2010) or because they are more content to work in remote areas compared to regular teachers (Fagernäs and Pelkonen, 2011). To estimate the effect of a local teacher we take advantage of the fact that in our dataset not all contract teachers are hired locally. For better identification of local teacher effect, we look at variation in teacher quality among contract teachers only, as they form a more homogeneous group of teachers.

In order to answer the above questions, we make use of a unique dataset from a survey commissioned by the World Bank and the Government of Bihar in collaboration with ASER Centre, New Delhi (see Sinha et al. (2016) for a detailed description of the survey). The matched student teacher data from public schools have details on teacher and student characteristics, performance on tests (administered during the survey) for both teachers and students, and information on various classroom indicators. The survey spans four districts in the rural areas of the state of Bihar, India. Information was collected at three points in time over one academic cycle (2013-14). To estimate the difference in the effect of the two types of teachers we use value-added specification of an education production function.

We find that although contract teachers are very different from regular teachers when it comes to various observable characteristics (professional qualification, training, age, gender), there exists no statistically significant difference between the performance of the two types of teacher for both grades 4 and 6. Though earlier studies report a positive effect of contract teachers on student performance (Duflo et al., 2015) the 'no effect' in our study could be due to the fact that contract teachers in the state of Bihar are less incentivized (Atherton and Kingdon, 2010). They are hired for life and the school or the local community has no say in renewal or discontinuation of the contract. Our results raise similar concerns regarding large scale expansion of contract teacher hiring in public schools, as discussed by Bold et al. (2018). Due to political and administrative constraints (teacher unions etc.), most of the developing countries might find it difficult to implement flexible teacher contracts, which seems to be important for achieving learning gains.

Another mechanism through which contract teacher might have a positive affect on learning is local hiring. Comparing local and non-local contract teachers, we obtain a statistically significant and positive effect of a local teacher on student outcomes of 0.24 standard deviation for grade 6 only. The fact that hiring teachers from the local community might be important for their effectiveness in a rural setting invites further investigation with more detailed data to understand the mechanisms behind this finding.

The paper is divided into six sections. In the following section we provide a background of elementary education and teacher hiring policy in India. This is followed by data and descriptive statistics in Section 3. In Section 4 we discuss the estimation technique and Section 5 elaborates the result, followed by conclusion in the last section.

1.1 Education system and contract teachers in India

In India there exists a common school education structure (10+2), divided into four parts: primary, upper primary, secondary, and higher secondary. Primary (grades 1 to 5) and upper primary (grades 6 to 8) together constitute elementary education, corresponding to the age group 6-14 years. Table A.1 in Appendix A.2 outlines these levels along with the associated grades and ideal age range. The school system functions under a federal structure such that the control and management of schools is under the state governments. The central government is mainly responsible for laying down broad policy frameworks with a view to maintain uniform quality standards across the nation. The central government also provides funding to states through various centrally sponsored schemes to meet education development goals.

Since the 1990s India has witnessed continuous expansion in elementary education through various centrally sponsored programs like the District Primary Education Programme (DPEP) in 1994 and the Education for All Campaign (Sarva Shiksha Abhiyan, SSA) in 2002. In 2010 the Right to Education Act (RTE) was passed, making elementary education free and compulsory for all children 6-14 years old. Subsequently the country made considerable strides in achieving its goal of universal elementary education with the net enrollment ratio reaching 98% in 2009-10 (Government of India, 2013).

With a steady increase in enrollment rates across most parts of the country, the focus of the government has been shifting toward improving the quality of education (Muralidharan, 2013). Various studies in recent years have highlighted the dismal state of student performance across the country. A nationwide study by ASER Centre reported that the proportion of children in rural India in grade 5 who can read a grade 2 level text is 47% and only 25.6% can solve a 3-digit by 1-digit division problem (Pratham, 2014b). In 2009 the country ranked 73 out of the 74 nations that participated in the PISA study conducted by OECD. Closely related to the issue of quality of schools is the quality of the teaching workforce. The country is not only witnessing an acute shortage of teachers, but their lack of motivation has also been a major cause of concern (Chaudhury et al., 2006).

In India the practice of hiring contract teachers gained prominence during the 1990s with the thrust in policy toward more decentralized management of schools to meet the rising education demand in a cost-effective manner (Kingdon and Sipahimalani-Rao, 2010). Consequently, many states started to fill teacher vacancies through an alternative process of hiring teachers on a fixed term contract from the local community with less strict entry restrictions (Chudgar et al., 2014). Around 2000-01, the centrally sponsored scheme of universalizing elementary education (Sarva Shiksha Abhiyan (SSA)) laid down norms that further boosted the hiring of contract teachers.

By the year 2009-10 there were about 637,000 contract teachers working in the country, with their overall proportion in government schools reaching close to 14.4% (Mehta, 2009). The service conditions, qualifications, and salaries of contract teachers vary across the country as does the nomenclature – *shiksha mitra* in Uttar Pradesh, *shiksha sahayak* in Odisha, *niyojit shikshak* in Bihar, guest teachers in Delhi. However, recent regulations with insistence on professional training cut back the hiring of contract teachers, with many states struggling to find ways to absorb them effectively in the system (Chudgar, 2013).

In the state of Bihar, where this study was conducted, the *Panchayats* or the local self governance bodies were given the responsibility for the recruitment of contract teachers from the local communities around the year 2005-06. This led to a massive hiring drive following which about 300,000 contract teachers were hired, and the number of teachers in elementary schools almost doubled during the period 2006 to 2013 (Sinha et al., 2016).

1.2 Data

1.2.1 Background

The data for this study are derived form a survey that was commissioned by the World Bank and the Government of Bihar in collaboration with ASER Centre, New Delhi. The survey was conducted in 400 randomly selected government elementary schools in four districts in the rural areas of the state of Bihar in India.[4]

Bihar is the third most populous and one of the poorest states in India. Table 1.1 gives a brief overview of the four districts where the survey was carried out. Bihar has the lowest literacy rate in the country, with female literacy rate as low as 51.5% (Census, 2015). Over the last decade the state has achieved great success in increasing access to schooling but still performs poorly on various quality indicators. According to Pratham (2014a) the percent of children in grade 5 who can read a grade 2 level text fell from 65.4% in 2006 to 48.2% in 2014. It is also one of the states in India with lowest student attendance rates.[5] Our survey data also show that the average student attendance was as low as 57%.

Table 1.1: Description of Districts

District	Population (millions)	Lit. rate (all)	Lit. rate (female)	Female ratio[1]	Percent urban
Purnia	3.3	51.1	42.4	921	10.5
East Champaran	5.1	55.8	45.1	902	7.9
Jamui	1.8	59.8	47.3	922	8.3
Rohtas	3.0	73.8	63.0	918	14.5
State of Bihar	104	61.8	51.5	918	11.3
All India	1210	74.0	65.5	940	31.2

[1]Female per thousand male. Source: Census, 2015

In our survey data we find evidence of expansion in contract teacher hiring since 2005 (Figure 1.1). Overall, close to 73% of teachers are contract teachers and around 40% of

[4]According to The Annual Status of Education Report (Pratham, 2014b) 82.4% of children in the age group 6-14 years in rural region of Bihar were attending government schools.

[5]States like Uttar Pradesh, Bihar, Madhya Pradesh, and Jharkhand have student school attendance rates of below 60% in public schools (Government of India, 2013).

them are hired from the village where the school is. However, there is a steady decline in the number of contract teachers hired locally, from around 60% in 2005 to less than 10% in 2013 (Figure 1.1). The state of Bihar still faces huge teacher shortages.[6] Data from our survey reveal that in Bihar the average student-teacher ratio for all grades combined in our sample schools is close to 62. Also, there is a high incidence of multi-grade teaching, a practice in which students of different grades sit in the same classroom, mainly due to the shortage of teachers. In our data in almost 60% of schools children in grade 4 were found sitting with another grade during the field visits.

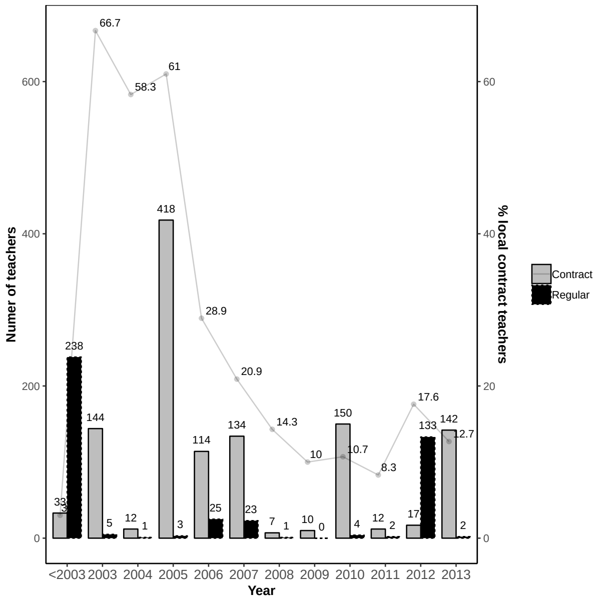


Figure 1.1: Number of contract and regular teachers by year of appointment and proportion of contract teachers who are native. Source: Authors' own calculation. The bar plot in the figure gives the number of contract and regular teachers by year of appointment. The line plot indicates the proportion of contract teachers that are hired locally, that is, from the same village where the school is located. Since the number of local regular teachers in very small, we do not plot it in the figure. Also, we add together the number of teachers appointed before 2003 because of low frequency for years before 2003.

[6]According to an answer given in the *Lok Sabha* (lower house of Parliament), of the approx. 907,000 total vacant teacher posts in government elementary schools across India, close to 22% (203,000) are in Bihar alone (MHRD, 2016).

1.2.2 Survey design and sample description

There were three phases of data collection whereby close to 400 randomly selected schools in four districts were tracked over a period of one year starting in September 2013. Information was collected through classroom and school observation formats, teacher interviews, and teacher and student assessments. The stages and periods of data collection are shown in Figure 1.2.

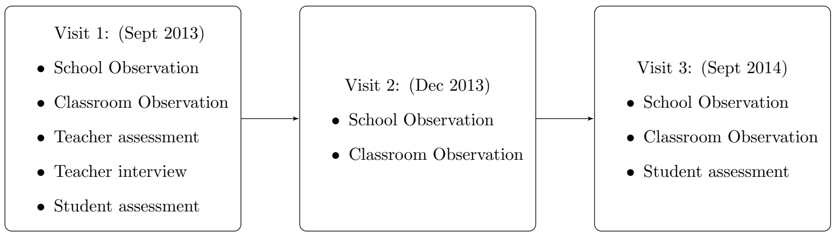


Figure 1.2: Stages of the survey

Of the 400 schools 214 are upper-primary in our survey data. For the purpose of our analysis we look at only these upper-primary schools since student assessments were conducted in these schools only. Ten children from grade 4 and ten from grade 6 in each upper-primary school were randomly selected and assessed in language and math at the beginning of an academic year (September 2013) and then at the beginning of the next academic year (September 2014). In Table 1.2 the details of the sample are given. The total number of children assessed is 4260 in baseline and 3927 in endline (Table A.2 in appendix A.2 compares the mean performance of those students that were tested in both visits and those that dropped out). A total of 1656 teachers were interviewed and assessed.

To calculate the teacher effect we need to match students uniquely to the teachers who taught them throughout the academic year. To uniquely match teachers to students of grades 4 and 6 we needed information from classroom observation. As part of the study, surveyors had to observe teaching-learning activities of language teachers in grades 4 and 6 during the lectures. Unfortunately, math teachers cannot be identified as they were not observed as part of the survey. There were three such classroom visits spread

Table 1.2: Survey sample data

District	Schools	Teachers	% Contract	% Native[1]	Student Assessments Grade 4		Grade 6	
					2013	2014	2013	2014
Purnia	60	427	73	34	600	548	600	538
E. Champaran	50	428	78	42	500	469	500	481
Jamui	53	345	79	27	530	483	530	479
Rohtas	51	456	65	36	500	465	500	464
Total	214	1656	73	36	2130	1965	2130	1962

[1]Perecent of contract teachers that are Native.

over the academic year (Figure 1.2). To make sure that children had the same teacher for most of the academic year, we include only those teachers who were found teaching language to the same students at least twice out of the three visits. Although this helps us to match students to teachers more confidently, it reduces our number of teachers to 339 (only language teachers) in a total of 199 schools. In Table A.3 in appendix A.2 we provide a comparison of characteristics of all teachers and those who are included in the final sample. For our main variables of interest we find no significant difference.

Table 1.3 provides a summary of the final data set that was used for analysis. Student z-scores were created by standardizing the language score for each grade and for each visit separately. Table 1.4 gives a detailed summary of student baseline and endline non-standardized scores by grade and subject. As stated earlier, students from grade 4 and 6 in upper-primary schools were assessed in language (Hindi) and math. One can see that the performance of students has improved over the academic year (Figures A.1 and A.2 in appendix A.1 give the density plots of total scores of students at baseline and the endline visits to schools).

More than half of the children (52%) in the age group 8 to 16 in government upper-primary schools are girls (Table 1.3). There is a high incidence of multigrade teaching (48%). One can also notice the prevalence of low student attendance (56%) and large classes with average class size of around 73 students. More than three-fourths of the teachers are contract teacher with an average age of around 38 years. Close to 31% of all

Table 1.3: Descriptive statistics

	N	Mean	St. Dev.	Min	Max
Student variables					
z-score baseline*	3,390	0.01	0.99	−1.78	2.33
z-score endline*	3,122	0.001	0.99	−2.48	1.87
Female=Yes	3,356	0.52	0.50	0	1
Age in years	3,241	10.89	1.37	8	16
Grade level variables					
Grade=6	339	0.51	0.50	0	1
Multigrade=Yes	338	0.48	0.50	0	1
% Attendance: grade 4,6 combined	336	56.20	18.46	4.55	96.67
Class size: grade 4,6 combined	337	73.3	50.0	15	396
Teacher variables					
Contract=Yes	334	0.75	0.43	0	1
Female=Yes	323	0.39	0.49	0	1
Age in years	321	37.52	9.00	20	78
Qualification					
Professionally qualified=Yes	313	0.49	0.50	0	1
Graduate or above=Yes	319	0.49	0.50	0	1
Experience (yrs.)	321	7.13	5.75	1	39
Training (days)	310	10.43	11.65	0	60
Math score	339	6.73	3.52	0	12
Hindi score	339	4.39	2.21	0	9
Work environment					
Native to village=Yes	320	0.31	0.46	0	1
Travel time (mins.)	320	38.33	55.71	0.00	720.00
Years in same school	320	5.43	3.47	1	24
No. of Transfers	317	0.35	0.82	0	4
Other activity=Yes	321	0.31	0.46	0	1
School variables					
Distance from HQ.	199	39.88	19.25	5	88
% Student attendance†	199	58.58	11.38	25.04	86.40
Infrastructure index **	199	5.08	1.46	1	7
Average Math score§	199	11.74	2.80	4.95	19.25
School size					
Total enrollment†	199	512.74	242.25	156.00	1,942.67
Total teachers†	199	8.78	3.65	2	22
Student teacher ratio †	199	61.79	23.88	19.50	156.25
Monitoring					
Principal in school=Yes	199	0.14	0.35	0	1
BRC visits‡	199	4.21	0.67	1.67	5.67
SMC meetings‡	199	3.78	0.69	1.00	5.00
Schools	199				
Teachers	339				
Students	3,390				

Notes: * z-scores were created by normalizing the total language score in each grade and in each visit
** Infrastructure index is a sum of seven indicators available in school: drinking water, toilet, separate girl's toilet, boundary wall, library, timetable, and mid-day meal menu displayed on wall.
§Average math score is calculated by taking a simple average of grade level mean math scores for grades 4 and 6.
† Student and teacher enrollment, percent attendace, and student teacher ratio were calculated by taking an average of the information from the three visits.
‡ BRC: Block Resource Co-ordinator, SMC: School management committee. The scale is average of three visits, higher value means meetings are held more often.

Table 1.4: Student score description by visit and grade

Statistic	N	Mean	St. Dev.	Min	Max
Grade 4					
Language baseline	1,660	8.1	4.8	0	18
Language endline	1,527	10.5	4.8	0	18
Math baseline	1,660	9.4	4.8	2	20
Math endline	1,527	11.5	5.1	0	20
Grade 6					
Language baseline	1,730	17.4	8.4	2	37
Language endline	1,595	21.2	8.4	0	37
Math baseline	1,730	14.2	6.0	2	28
Math endline	1,595	16.7	6.1	1	28

teachers are native to the village where the school is located. The proportion of teachers that are female is 39%. Almost half of the teachers are professionally trained and hold a graduate degree.

School variables were recorded three times over the academic year. Instead of using information from just one visit, we use a simple average over the three visits for certain variables such as student and teacher enrollment, attendance, and student teacher ratio. Similarly, for variables related to monitoring visits by the Block Resource Co-ordinator (BRC) and the School Management Committee (SMC) we create a scale that is an average of three visits. The questions that were asked to the primary respondent at school were (i) when was the last time the SMC had a meeting? (ii) when was the last time a CRC or BRC functionary visited the school? Based on the response category, scores were created such that a higher value indicates that meetings are held more often.[7]

We found that most of the schools were equipped with basic infrastructure facilities. On average schools had five of the seven basic amenities listed in the questionnaire.[8] On average there are eight to nine teachers in each upper-primary government school. The probability that there is a principal appointed in school is extremely low, at just 14%.

[7]The response category and corresponding scores are: *Never,Don't Know*=0, *More than 6 months ago*=1, *During the last 6 months*=2, *During the last 3 months*=3, *During the last month*=*4*, *During the last week*=5, and *Today*=6

[8]Infrastructure index is a sum of seven indicators available in school: drinking water, toilet, separate girl's toilet, boundary wall, library, timetable, and mid-day meal menu displayed on wall.

1.2.3 How different are the two types of teachers?

In this section we briefly discuss the difference between contract and regular teachers and local and non-local teachers. We also check the possibility that these different types of teachers are assigned to different types of classes. Thus, we look at their differences in terms of their own characteristics and also their work environment.

Table 1.5 presents several teacher characteristics by teacher type. It can be seen that there are significant differences between the two types of teachers. Regular teachers are professionally more qualified (difference of almost 43 percentage points) and trained. However, when it comes to educational qualification (graduate or above) the difference between the two is not significant. Regular teachers have higher scores in language test administered during the survey (0.69 points higher) but the difference is not significant in math.

Table 1.5: Difference in mean by teacher type-All teachers

	Contract	Regular	*Difference*	p.value[1]
%Female	44.63	23.46	21.17	0.00
Age in years	34.17	47.43	-13.26	0.00
%Professional qualified	38.03	81.01	-42.98	0.00
%Graduate or above	50.84	43.21	7.63	0.29
Experience	6.52	8.94	-2.42	0.04
Training (days)	8.58	15.65	-7.07	0.00
Math score	6.75	7.07	-0.33	0.44
Hindi score	4.29	4.98	-0.69	0.01
Teach Grade 6	47.22	62.20	-14.97	0.03
Multigrade=Yes	50.60	40.24	10.35	0.10
Class size	70.77	80.81	-10.05	0.12
Student attendance	55.87	56.43	-0.55	0.82
%Native to village	40.17	4.94	35.23	0.00
Travel time (min)	31.84	57.49	-25.65	0.02
Years in same school	6.26	2.99	3.28	0.00
Transfers	0.09	1.11	-1.02	0.00
BRC visits	4.26	4.06	0.20	0.03
SMC meetings	3.79	3.78	0.01	0.89
Principal in school=yes	15.08	12.20	2.88	0.64
N	252	82		

[1]p.value for t-test of difference in mean

We next look at the difference between the two types of teachers regarding various classroom and school level indicators. We find that contract teachers are less likely to teach upper primary grades (grade 6) compared to primary grades (grade 4) but they are not different when it comes to other classroom indicators such as the likelihood of teaching a multigrade class, class size, or class attendance. We also find that on average there are more monitoring visits (BRC visits) in the case of contract teachers than regular teachers. Another important point to notice from Table 1.5 is that there is a higher proportion of female contract teachers than regular teachers (21 percentage point difference), which is interesting as the state has been struggling to increase the number of female teachers in schools. Last, we find that contract teachers are much more likely to be hired from the same village as the school compared to regular teachers (35 percentage point difference).

Noticing the stark differences between contract and regular teachers, we go a step further and consider only contract teachers to obtain a more homogeneous group of teachers and then compare the difference between a native and a non-native teacher. In Table 1.6 we see that local teachers are mostly female who have been teaching in the same school for a longer period. More importantly, they are not very different from non-local teachers in terms of education and training or any grade or school level indicators, except for multigrade teaching. We take advantage of this fact to isolate the impact of being a local teacher.

1.3 Methodology

One of the major impediments to the estimation of the causal effect of teachers on student performance is the non-random allocation of students to schools and teachers. As a consequence, one needs to account for the selection of students into certain neighborhoods, schools, and teachers on unobservable student, family and school level components. One such specification is the value-added approach, which assumes that the lagged achievement score of students can account for the unobserved time-constant history of student and

Table 1.6: Difference in mean by locality (Native or not)- Contract teachers

	Native *(mean)*	Non-Native *(mean)*	*Difference in mean*	p.value[1]
%Female	62.50	32.87	29.63	0.00
Age in years	34.90	33.74	1.15	0.22
%Professional qualified	34.41	40.71	-6.31	0.41
%Graduate or above	50.00	51.77	-1.77	0.89
Experience	8.04	5.53	2.51	0.00
Training (days)	9.01	8.28	0.73	0.56
Math score	7.02	7.07	-0.05	0.91
Hindi score	4.34	4.58	-0.24	0.36
Teach grade 6	48.96	46.85	2.11	0.85
Teach Multigrade	37.50	57.75	-20.25	0.00
Class size	75.28	68.00	7.28	0.19
Class attendance	54.85	56.63	-1.78	0.46
Travel time (min)	15.49	42.94	-27.45	0.00
Years in same school	7.75	5.31	2.43	0.00
Transfers	0.09	0.09	0.01	0.85
BRC visits	4.24	4.29	-0.05	0.53
SMC meetings	3.83	3.80	0.03	0.69
Principal in school=yes	17.71	13.29	4.42	0.45
N Teachers	96	143		

[1]p.value for t-test of difference in mean

family inputs, as well as for time-varying historical student and school-based inputs (Sass et al., 2014; Todd and Wolpin, 2003). Thus, to estimate the difference in the affect of the two types of teachers we use value-added specification of an education production function.[9]

Based on the theoretical underpinning that child development is a cumulative process depending on the history of family and school inputs and her/his own endowment or ability, we start our model with the commonly accepted equation of the education production function.

$$A_{it} = A_t[X_i(t), F_i(t), S_i(t), \mu_{i0}, \epsilon_{it}] \tag{1.1}$$

where A_{it} refers to child $i's$ achievement at the end of t years in life. $X_i(t)$, $F_i(t)$, and $S_i(t)$

[9]For updated discussions on potential biases in value-added estimation one can look at Andrabi et al. (2011), Bau and Das (2020), and Chetty et al. (2014a).

refer to the histories of individual, family, and school inputs respectively. μ_{i0} represents the child's endowment or ability, which is inherited and does not vary with time, and ϵ_{it} is the error term.

As a first look at the difference in value-added by teacher type, we run a simple t-test for difference in average test scores of students. Table 1.7 reports the result of difference in difference of average student test scores in the first (baseline) and the last (endline) visit by teacher type for both grades separately. There are two main takeaways from this table: *first*, there is a significant difference in the average baseline scores (row 1) of students under contract and regular teachers (column 3 and 6). For instance, in grade 6 students under contract teachers perform 1.03 points lower on average compared to students under regular teachers. This is indicative of some sorting of teachers by student ability. Thus, it makes a strong case for isolating initial difference in performance to estimate contract teacher effect and justifies our use of a model in which we account for initial student performance. *Second*, the initial negative differences in average scores by teacher type are reversed for grade 4 (row 3 column 3). Students under contract teachers gain significantly more than students under regular teachers between the two test dates (0.69 points on average). For grade 6 there is no significant difference (row 3 column 6). These results provide some support for the existence of positive effect of contract teachers on student performance for grade 4 only.

Assuming that the arguments in equation 1.1 are linear and additively separable, the model to estimate the impact of contract teacher on student performance can be written as follows:

$$A_{ijkn,t} = \lambda A_{i,t-1} + \alpha X_i + \beta S_j + \gamma C_k + \delta(Contract)_n + \phi T_n + \eta_{ijkn} \tag{1.2}$$

This equation is a variation of the *partial persistence* model used in Sass et al. (2014). $A_{ijkn,t}$ is an indicator of current student performance or test scores. $A_{i,t-1}$ is the lagged test score, X_i, S_j, and C_k represent the current student, school, and grade characteristics respectively. $Contract_n$, the dummy for teacher type, which takes value one if the teacher is a contract teacher and zero otherwise, is our variable of interest. As a further step, we also include other teacher characteristics in the vector T_n to identify if other teacher-specific features (qualification, training, gender, and being local) explain any variation in student performance. The above specification uses $A_{i,t-1}$ to account for all previous inputs relevant for student outcomes. Estimates could still be biased due to the selection of teachers to schools and grades. It has been documented that contract teachers work in remote or more difficult areas compared to regular teachers. If teachers are selected into schools based on school quality, then our estimates of teacher-effect would be biased. Also, there can be sorting of teachers inside schools between or within grades. We saw in Table 1.7 that on average contract teachers receive students with poorer results. Therefore, before making causal inferences about the effect of teacher-type we take into account the possibility of non-random allocation of teachers to schools and grades.

Table 1.7: Difference in student language test scores by visit and teacher type: t-test

	Grade 4			Grade 6		
	Cont. (1)	Reg. (2)	*Diff.* (3)	Cont. (4)	Reg. (5)	*Diff.* (6)
Baseline	8.01	8.58	-0.57*	17.09	18.12	-1.03**
	(0.13)	(0.25)	(0.30)	(0.25)	(0.37)	(0.45)
Endline	10.55	10.47	0.09	20.67	22.38	-1.71***
	(0.14)	(0.25)	(0.31)	(0.26)	(0.37)	(0.46)
Difference	2.62	1.93	0.69**	3.54	4.20	-0.66
	(0.14)	(0.23)	(0.31)	(0.24)	(0.49)	(0.45)

Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

We first check if there is any selection of teachers on observable district, school, or grades level indicators (Table 1.8). We run a logistic regression with teacher type as the binomial dependent variable and various school and grade level indicators along with district dummies as the explanatory variables.

There are four important takeaways from the regression results in Table 1.8. *First*,

Table 1.8: Logit regression of contract teachers on school and grade factors

Dependent variable: Contract teacher dummy			
	(1)	(2)	(3)
Distance from HQ.	-0.005	-0.005	-0.005
	(0.007)	(0.007)	(0.008)
Total enrollment	-0.001*	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
Student teacher ratio	0.001	0.001	0.002
	(0.006)	(0.007)	(0.008)
Teacher attendace	0.011	0.007	0.006
	(0.011)	(0.011)	(0.012)
Infrastructure Index	-0.100	-0.006	0.032
	(0.106)	(0.104)	(0.111)
Principal=Yes	0.193	-0.114	-0.169
	(0.403)	(0.429)	(0.456)
BRC visits	0.530***	0.582***	0.626***
	(0.187)	(0.197)	(0.203)
SMC meetings	0.092	0.033	0.008
	(0.206)	(0.212)	(0.216)
Average math score	-0.108**	-0.066	-0.081
	(0.048)	(0.053)	(0.055)
Rohtas		-0.975**	-0.988**
		(0.428)	(0.453)
Purnia		-0.618	-0.679
		(0.418)	(0.427)
E. Champaran		0.801	0.770
		(0.535)	(0.540)
Teach grade 6=yes			-0.628**
			(0.316)
Multigrade=yes			-0.005
			(0.355)
Class attendance			-0.001
			(0.009)
Class size			-0.001
			(0.005)
Observations	334	334	330
Pseudo R^2	0.047	0.095	0.111

Jamui district is taken as base category. Standard errors in parentheses. We use robust standard errors. *p<0.1; **p<0.05; ***p<0.01

looking at the district dummies we find that contract teachers are less likely to be working in the district of Rohtas compared to Jamui (used as the base category). For other districts the difference is not significant. From Table 1.1 we know that Rohtas is the district with the highest literacy and urbanization rates compared to all other districts. This indicates that contract teachers are more likely to be present in resource constrained areas.

Second, we do not find any school quality variables explaining sorting of teacher to schools within district. In column 1 of Table 1.8 the variable *Average math score*, which we use as an indicator of initial school quality, is negative and statistically significant, implying that contract teachers are more likely to be in schools with lower student performance. But when we look at within-district variation *Average math score* is no longer statistically significant (columns 2 and 3). Thus, by including district dummies, we are more confident of our estimates of contract teacher effect, assuming that there is no sorting of teachers to schools within districts.

Third, in all specifications we notice that contract teachers are more likely to be in schools with better monitoring mechanisms. This is evident from the positive and statistically significant sign of the variable BRC visits. Contract teachers are thus more likely to be in schools that have frequent monitoring visits by the BRC (Block Resource Coordinator). *Fourth*, the regression specification in column 3 includes grade level indicators to check for sorting between grades. Although contract teachers are less likely to teach grade 6 compared to grade 4, other grade-level features such as multigrade teaching, class size, and student attendance do not vary significantly between the two types of teachers.

To summarize, we do not find evidence that within-districts teachers are selecting themselves or are otherwise placed in schools based on most of the observable school or grade level quality indicators except for monitoring. So, our main approach is to estimate equation 1.2 and include district dummies. However, there may still be selection of teachers to schools based on unobservables. One way to deal with the non-random allocation of teachers to schools on unobservable school factors is to focus on variation in teacher effect within schools by using school fixed effects. The school fixed effect model can be written as follows:

$$A_{ijkn,t} = \lambda A_{i,t-1} + \alpha X_i + \gamma C_k + \delta(Contract)_n + \phi T_n + (\nu_j + \eta_{ikn}) \tag{1.3}$$

where ν_j captures the unobserved school-level characteristics. In order to make sure that there exists variation within schools, we need at least two different teacher observations in each school. In our sample we have at most two teacher observations (one for grade 4 and another for 6). Although we can exploit this variation in teachers by grades to apply school fixed effect, we use this in our analysis only as a robustness check due to the small teacher sample size within schools.

In our sample schools the probability of selection within grades is negligible, as from the three classroom visits it was found that the incidence of multiple classes for a particular grade was very low in our sample schools. The proportion of schools with single class in grade 4 and grade 6 was 97% and 93% respectively. Thus, selection to classes within grades is not an issue.

In addition to the above models (equations 1.2 and 1.3) another way to look at the difference in the quality of contract and regular teachers is to estimate the distribution of teacher value added by teacher type. In order to obtain teacher value added we estimate the following equation:

$$A_{in,t} = \lambda A_{i,t-1} + \alpha X_i + \sigma Tid_n + \eta_{in} \tag{1.4}$$

where σ is the teacher fixed effect coefficient for every teacher Tid_n. We estimate teacher fixed effect $\hat{\sigma}$ and compare the distribution for different teacher types. We then estimate equation 1.5 below to determine if any of the teacher characteristics (T_n) explains variation in our estimated teacher fixed effect.

$$\hat{\sigma}_{njk} = \phi T_n + \eta_{njk} \tag{1.5}$$

One caveat to estimating teacher fixed effect from our data is that we do not have teacher observations for more than one year or different student cohorts over time. Therefore, we cannot isolate classroom level shocks from teacher fixed effect. However, we are able to control for grade characteristics and have seen that selection to classes withinin grades is not an issue in our sample of schools. Thus, we believe that our results are relevant to estimate the impact of local contract teachers. Lastly, earlier we saw that though contract and regular teachers differ along most of their observable characteristics, local and non-local contract teachers form a more homogenous or comparable group. Thus, to isolate the impact of a local teacher we estimate the above equation by focusing only on contract teachers.

1.4 Results

In Table 1.9 we present the results from the OLS value-added specification for each grade separately with endline z score as the dependent variable and baseline scores as one of the independent variables. We also include the results for both grades combined in columns 5 and 6. The last two columns report results from the school fixed effect model (equation 1.3). In columns 1 and 2 we present the results for grade 4 and in columns 3 and 4 for grade 6. As we move from left to right within each grade columns, we add other teacher characteristics to isolate the effect of contract teacher on student performance. For instance, column 1 (3, 5, and 7) is the basic specification with no teacher factors except the dummy for contract teacher. In column 2 (4, 6, and 8) we include other teacher characteristics.

There are some interesting things to note from Table 1.9. *First*, for grade 4 the effect of contract teacher on student performance is positive though only weakly statistically significant in column 1. The effect size is 0.16 standard deviation. However, once we include other teacher characteristics, the effect is no longer statistically significant (column 2). *Second*, for grade 6 we notice that once we include all factors, contract teacher is found to have a weakly statistically significant and negative effect on student performance (-0.15 standard deviation). Most importantly we find a positive and statistically significant coefficient for being local or native to the village (0.18 standard deviation). The weak significance of contract teacher effect for both grades (and no significant difference in the school fixed specification) imply that they are not much different from regular teachers in terms of student performance. This is in line with previous results reported in the literature.

Next, we turn to our main question of whether being a local teacher is beneficial for learning or not. In Table 1.10 we run the same specifications as in Table 1.9 but considering only contract teachers as we saw that they constitute a more homogeneous group. Looking at the results from full-specification in columns 2 and 4 of Table 1.10 with native teacher as the main variable of interest, we find that for grade 4 there is no significant impact of native teachers but for grade 6 there is a statistically significant and positive effect (0.24 standard deviation) of being a native teacher on student performance.

Finally, we calculate teacher fixed effects using equation 1.4. We then regress the estimated value-added of each teacher on teacher characteristics. We present grade-wise results of this analysis considering only contract teachers in Table 1.11. Once again, it can be seen for grade 6 that the effect of native teacher is significant and positive (column 4, 0.24 standard deviation). The relationship between native teacher and teacher fixed effect becomes clear when we plot the estimates of teacher value-added by splitting between local and non-local contract teachers in Figure 1.3. For grade 6 one can clearly see the difference in distribution of teacher fixed effect for contract teachers who are local and those who are not.

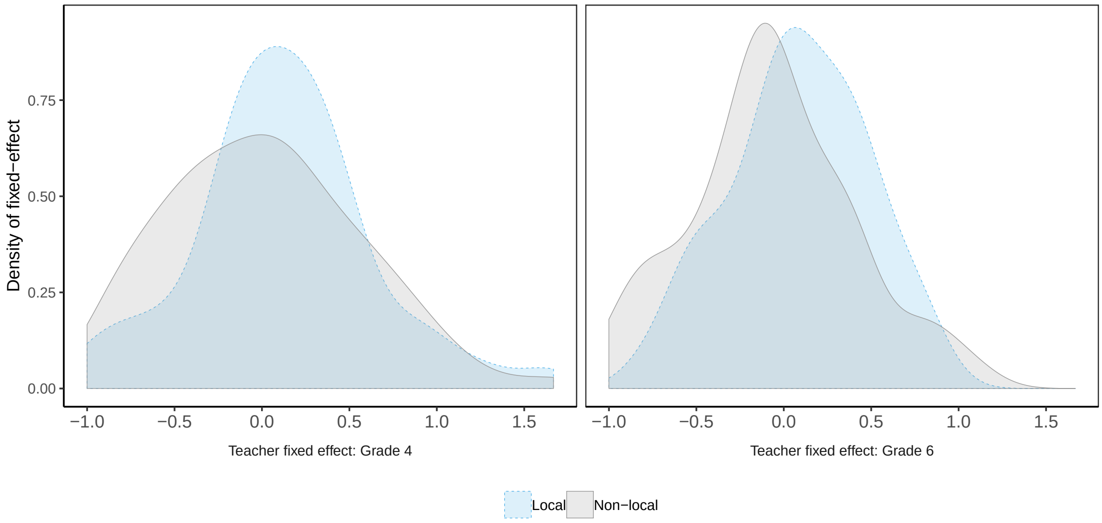


Figure 1.3: Density plot of teacher fixed effect by "Native" for contract teachers by grade

1.5 Conclusion

The increasing number of contract teachers in developing countries has led to concerns about its effect on teacher quality. Contract teachers are usually less professionally trained and qualified. However, they are more likely to be hired locally, that is, either from the local community and/or by the local administration. This can positively affect student outcomes by reducing social distance between the teacher and the student or through better monitoring of teachers. This paper provides additional evidence on the difference in the impact of contract and regular teachers on student learning outcomes focusing on the effect of being a local or a native teacher.

Using data form a survey conducted in the rural areas of the Indian state of Bihar, we find that although contract teachers are very different from regular teachers when it comes to various observable characteristics (professional qualification, training, age, gender), there is no statistically significant difference in student outcomes from having one or the other type of teacher, for both grades 4 and 6. Earlier research reports a positive effect of contract teachers on student performance (Duflo et al., 2015) the 'no effect' in our study could be due to the fact that contract teachers in the state of Bihar are less incentivized (Atherton and Kingdon, 2010). They are hired for life and the school or the local community has no say in renewal or discontinuation of the contract. Our results raise similar concerns regarding large scale expansion of contract teacher hiring by the government, as discussed by Bold et al. (2018). Due to political and administrative constraints (teacher unions etc.), most of the developing countries might find it difficult to implement flexible teacher contracts, which seem to be important for achieving learning gains.

The other mechanism through which contract teacher might have a positive effect on learning is local hiring. The local nature of these teachers is an important and distinctive feature that might induce them to exert more effort in difficult environments (remote areas, disadvantaged students) because of reduced social distance (Rawal, Kingdon, et al., 2010) or because they are more content to work in remote areas compared to regular teachers (Fagernäs and Pelkonen, 2011). To isolate the impact of a local teacher we restrict our analysis to contract teachers so that we have a more comparable group. We obtain a statistically significant and positive effect of a local teacher on student outcomes of 0.24 standard deviation for grade 6 only. The fact that hiring teachers from the local community might be important for their effectiveness in a rural setting invites further investigation with more detailed data to understand the mechanisms behind this finding.

Table 1.9: Value-added regression on teacher type - All teachers

	Dependent variable: Endline z- score							
	Grade 4		Grade 6		Both grades		School-fixed effect	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Contract teacher	0.16*	0.10	-0.10	-0.15*	0.01	-0.03	-0.06	0.004
	(0.08)	(0.10)	(0.08)	(0.09)	(0.06)	(0.07)	(0.07)	(0.08)
Native=yes		-0.01		0.18**		0.08		-0.06
		(0.10)		(0.09)		(0.07)		(0.08)
Female		0.10		-0.01		0.06		0.14*
		(0.09)		(0.09)		(0.06)		(0.08)
Graduate=Yes		-0.05		-0.04		-0.02		-0.04
		(0.10)		(0.07)		(0.06)		(0.07)
Professional qual=Yes		0.11		-0.06		0.03		0.12*
		(0.10)		(0.08)		(0.06)		(0.07)
Teacher test score		-0.01		-0.02		-0.01		0.003
		(0.02)		(0.02)		(0.01)		(0.02)
Experience >3 yrs.		0.02		-0.20*		-0.10		-0.10
		(0.08)		(0.11)		(0.07)		(0.09)
Training (Days)		-0.005		-0.0002		-0.002		-0.0005
		(0.005)		(0.003)		(0.003)		(0.004)
Previous year z score	0.47***	0.48***	0.46***	0.45***	0.47***	0.47***	0.48***	0.48***
	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
Child female	-0.07	-0.07	-0.03	-0.08*	-0.05	-0.08**	-0.03	-0.05
	(0.05)	(0.05)	(0.05)	(0.05)	(0.03)	(0.04)	(0.03)	(0.03)
Child age	-0.03	-0.04	-0.03	-0.01	-0.03*	-0.03	-0.01	-0.01
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
School factors	Yes	Yes	Yes	Yes	Yes	Yes	SFE	SFE
Grade factors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District dummy	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Observations	1,436	1,310	1,473	1,344	2,909	2,654	2,909	2,654
R^2	0.309	0.323	0.305	0.332	0.302	0.316	0.238	0.245
Schools (n)	158	144	161	146	191	184	191	184

Notes: This table reports results from the value-added specification to estimate contract teacher effect. Observations are at student level. Columns 1-2, 3-4, 5-6 report results for grade 4, grade 6, and both grades combined respectively. In columns 7-8 we report results from the school-fixed effect specification. The schools factors included are total school enrolment, student teacher ratio, infrastructure index, principal in school, BRC visits, SMC meetings, average math score. The grade factors included are multigrade, class size (columns 5-8 also include an indicator variable for grade). Standard errors are clustered at school level. *p<0.1; **p<0.05;***p<0.01

Table 1.10: Value-added regression on Native - Contract teacher

	Dependent variable: Endline z- score							
	Grade 4		Grade 6		Both grades		School-fixed effect	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Native=yes	-0.07	-0.08	0.14*	0.24**	0.06	0.08	-0.07	-0.13
	(0.10)	(0.11)	(0.08)	(0.10)	(0.06)	(0.08)	(0.10)	(0.10)
Female		0.11		0.03		0.09		0.11
		(0.10)		(0.11)		(0.07)		(0.12)
Graduate=Yes		-0.04		-0.01		-0.03		-0.14
		(0.11)		(0.09)		(0.07)		(0.12)
Prof. qual=Yes		0.09		-0.03		0.03		0.16*
		(0.11)		(0.08)		(0.07)		(0.08)
Teacher test score		-0.01		-0.03		-0.02		-0.01
		(0.03)		(0.02)		(0.02)		(0.03)
Exp >3		0.05		-0.32**		-0.10		-0.04
		(0.11)		(0.14)		(0.10)		(0.14)
Training (Days)		-0.003		-0.001		-0.003		-0.002
		(0.01)		(0.003)		(0.004)		(0.01)
Previous year z score	0.45***	0.46***	0.50***	0.49***	0.48***	0.48***	0.50***	0.50***
	(0.04)	(0.04)	(0.05)	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)
Child female	-0.08	-0.08	-0.06	-0.07	-0.06	-0.07*	-0.03	-0.04
	(0.06)	(0.06)	(0.06)	(0.06)	(0.04)	(0.04)	(0.04)	(0.04)
Child age	-0.05*	-0.06**	0.01	0.01	-0.03	-0.04	-0.03	-0.03*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
School factors	Yes	Yes	Yes	Yes	Yes	Yes	SFE	SFE
Grade factors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District dummy	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Observations	1,099	1,045	987	915	2,086	1,960	2,086	1,960
R^2	0.306	0.313	0.343	0.356	0.314	0.318	0.247	0.247
Schools (n)	121	115	106	98	163	157	163	157

Notes: This table reports results from the value-added specification to estimate native teacher effect. Observations are at student level. Columns 1-2, 3-4, 5-6 report results for grade 4, grade 6, and both grades combined respectively. In columns 7-8 we report results from the school-fixed effect specification. The schools factors included are total school enrolment, student teacher ratio, infrastructure index, principal in school, BRC visits, SMC meetings, average math score. The grade factors included are multigrade, class size (columns 5-8 also include an indicator variable for grade). Standard errors are clustered at school level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 1.11: Regression of teacher fixed effect by grade (Native)-Contract teacher

	Dependent variable=Teacher fixed effect σ				
	Grade 4		Grade 6		School Fixed effect
	(1)	(2)	(3)	(4)	(5)
Native	-0.01	-0.05	0.20*	0.24**	-0.11
	(0.12)	(0.12)	(0.11)	(0.11)	(0.10)
Female	0.09	0.08	0.04	0.01	0.09
	(0.11)	(0.11)	(0.12)	(0.12)	(0.12)
Graduate=Yes	-0.06	-0.06	0.04	0.001	-0.16
	(0.12)	(0.11)	(0.10)	(0.10)	(0.12)
Prof. qual=Yes	0.07	0.13	-0.04	-0.05	0.15*
	(0.11)	(0.12)	(0.10)	(0.10)	(0.08)
Teacher test score	-0.0005	-0.004	-0.02	-0.03	-0.01
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)
Exp>3	0.02	0.05	-0.29**	-0.28*	-0.05
	(0.12)	(0.12)	(0.13)	(0.15)	(0.15)
Training (Days)	-0.01	-0.003	-0.001	-0.001	-0.001
	(0.01)	(0.01)	(0.004)	(0.004)	(0.01)
School factors	No	Yes	No	Yes	SFE
Grade factors	Yes	Yes	Yes	Yes	Yes
District dummy	Yes	Yes	Yes	Yes	No
Observations	115	115	98	98	213
R^2	0.119	0.205	0.134	0.25	0.136

Notes: This table reports results from the teacher fixed effect specification to estimate its association with teacher characteristics. Observations are at teacher level. Columns 1-2, 3-4 report results for grade 4, grade 6 respectively. In column 5 we report results with school-fixed effect. The schools factors included are total school enrolment, student teacher ratio, infrastructure index, principal in school, BRC visits, SMC meetings, average math score. The grade factors included are multigrade, class size (column 5 also includes an indicator variable for grade). Standard errors are clustered at school level. *p<0.1; **p<0.05;***p<0.01

Chapter 2

Retain or not to retain: Automatic promotion and student outcomes[1]

2.1 Introduction

Many countries use retention as a tool to motivate students to work hard. In 2010, 32.2 million pupils repeated a grade in primary education globally (UNESCO, 2012). Retention is an expensive policy[2] and can even harm job market prospects in the long run (Eren, Lovenheim, et al., 2018). As opposed to retention some countries practice automatic promotion. Automatic promotion is a policy wherein students are promoted to the next grade without regard to achievement. Often termed as social promotion, this policy aims to keep students with their peer group.

This study uses quasi exogenous variation in exposure to a large scale education reform in India to estimate the effect of automatic promotion on access and quality of education. In 2009, India passed the Right to Education Act (RTE) making elementary

[1]I want to thank Bilal Barakat and Anna Cristina D'addio for their constant support and guidance. I also want to thank Ana Balcão Reis for her valuable suggestions. I am grateful to ASER Center for sharing their data. This paper is funded as part of the UNESCO fellowship for Global Education Monitoring report 2019.

[2]According toUNESCO (2009) repetition is estimated to cost around 12% of the education budget in Mozambique and 16% in Burundi

education free and compulsory for all[3] . The RTE Act has a no-detention policy clause that introduced automotic promotion in all elementary grades. The aim is to answer the following questions: *(a)* What is the effect automatic promotion on dropout rates? *(b)* What is the effect of automatic promotion on learning outcomes? Its not clear ex-ante how automatic promotion might affect student outcomes. It can decrease dropout rates by reducing the opportunity cost as well as physiological costs of retention. However, it might dis-incentivise students to work. Also, teachers might find it harder to work with more heterogeneous classes.

Evidence on the effect of retention on student outcomes is inconclusive [4]. Some studies find a positive effect of early grade retention on student achievement (Greene and Winters, 2007; Nunes et al., 2018; Roderick and Nagaoka, 2005; Schwerdt et al., 2017) while others show that retention is an ineffective tool to help weak students progress through school (Eren, Depew, et al., 2017; Greene and Winters, 2009; Jacob and Lefgren, 2009; Manacorda, 2012; Roderick, 1994). This study adds to the literature on retention by providing causal evidence of automatic promotion. What happens when the threat to repeat a grade is removed? More specifically, this study estimates the effect of removing the incentive associated with grade retention. This paper is closely related to Koppensteiner (2014) who provide evidence for automatic promotion in primary schools in Brazil. This study looks at both primary (grade 1-5) and lower secondary grades (grades 6-8) in India. This is important as recent studies have shown that the effect of retention might vary by age.

The RTE Act (2009) introduced the policy of automatic promotion in almost all states across India at the same time. This makes the creation of treatment and control groups difficult. In order to causally estimate the effect of automatic promotion on student outcomes this paper exploits the variation in exposure to the policy due to initial differences in behaviour across distrits with respect to repetition rates. I show that before 2009 there

[3] Elementary education in India comprises grades 1-8 or age group 6-14.
[4] Allen et al. (2009) and Allensworth (2005) provides an extensive review on this topic.

was a huge variation in repetition rates across states (figure 2.1). However, the repetition rates fell significantly after 2009 in almost every state (Shah and Steinberg, 2019). I compare districts with high repetition rates to districts with low repetition rates before and after 2009. The districts with high repetition rates in 2008 form the treatment group. While districts with low repetition rates in 2008 form the control group. The identification relies on the assumption that before 2009 the difference in outcome variables between districts with high repetition rates and districts with low repetition rates was constant.

I present results for primary (age 6-11) and lower secondary (age 12-16) separately. I find that for children in the primary age group there is no difference in the dropout rates between the treatment and control districts. However, the dropout rates for children in the secondary age group fell by 0.1 percentage points more in treatment districts compared to districts in the control group. I next present results for learning outcomes. I find that the policy had a negative effect on learning outcomes both for primary and lower secondary age groups. The probability that a primary age student could solve a basic reading and arithmetic task falls by 0.3 and 0.8 percentage points respectively. For children in the secondary age group there was no difference in reading levels between districts which got more treatment and districts which got less treatment. However, the math levels fell by 0.4 percentage points more for treatment districts compared to districts in the control group.

I test for heterogeneous impact of the policy depending on the socio-economic background of the child. I find that the negative effect was larger for children with a poor socio-economic background. I further explore probable mechanisms for the decline in learning levels. I find that districts with congested government schools (high pupil teacher ratios) suffered a larger decline in learning outcomes compared to those with less congested schools (low pupil teacher ratios.)

This study contributes to the rich literature on retention in two important ways. *First*, most of the evidence on retention looks at the effect of repeating a grade on repeaters or those who are at the highest risk of repeating a grade. In this study, I look at the aggregate effect of automatic grade promotion, as opposed to retention, on all students in the age cohort affected by the policy and not just repeaters. Heilig and Darling-Hammond (2008) and Jacob (2005) show that performance-based accountability measures can encourage efforts to 'game the system' by changing teaching practices (for example teaching to the test or focusing only on subjects that are being evaluated). This can negatively affect not just repeaters but also high performing students who are not directly affected by the policy. Also, due to automatic promotion, the class composition can become more heterogeneous making it more difficult for teachers to teach students at varying levels. Thus, more evidence is needed to understand how the change in incentives due to automatic promotion might affect the behavior of teachers and students.

Second, most of the evidence on retention in from developed country context [5]. Especially from the US where retention is usually followed by remedial programs or other instructional support which can help low-performing students catch up with their peers (Greene and Winters, 2007; Schwerdt et al., 2017). Unfortunately, most developing countries do not have such support mechanisms in place. Therefore, the impact of retention on student outcomes might be different in a developing country context.

The paper is divided into six sections. In the following section I provide a brief discussion on India's education system and the no-detention policy of the RTE Act 2009. Section three and four provide details of the data and empirical strategy respectively. In section five I discuss the results and probable mechanisms followed by conclusion in the last section.

[5] Except for (Manacorda, 2012) which provides evidence for Uruguay and (Glick and Sahn, 2010) which provides evidence for Senegal

2.2 Background

2.2.1 Elementary education in India

In India primary (grades 1 to 5) and lower secondary (grades 6 to 8) together constitute elementary education, corresponding to the age group 6-13 years. Table A.1 in appendix A.2 outlines these levels along with the associated grades and ideal age range. The school system functions under a federal structure such that the control and management of schools is under the state governments. The central government is mainly responsible for laying down broad policy frameworks with a view to maintain uniform quality standards across the nation. The central government also provides funding to states through various centrally sponsored schemes to meet education development goals.

Since the 1990, India has witnessed continuous expansion in primary education through various centrally sponsored programs like the District Primary Education Programme (DPEP) in 1994 and the Education for All Campaign (Sarva Shiksha Abhiyan, SSA) in 2002. Although the country has made remarkable progress in increasing enrolments at primary level, many students are still unable to complete the elementary grade cycle. Also, various studies in recent years have highlighted the dismal state of student performance across the country [6]. The government has thereby shifted its focus towards policies to improve the quality of education in elementary schools (Muralidharan, 2013). Recently, in a bid to increase accountability in the education system the Indian parliament passed a bill that allows states in India to chose whether or not they want to continue with automatic grade promotion in elementary grades. Evidence from this study could help states in understanding the impact of automatic promotion.

[6] A nationwide study by ASER Centre reported that the proportion of children in rural India in grade 5 who can read a grade 2 level text is 47% and only 25.6% can solve a 3-digit by 1-digit division problem (ASER 2014) In 2009 the country ranked 73 out of the 74 nations that participated in the PISA study conducted by OECD.

2.2.2 Right to Education Act 2009, and No detention policy

In 2009, the Right to Education Act (RTE) was passed, making elementary education free and compulsory for all children 6-14 years old. It was introduced in all states across India (except the state of Jammu and Kashmir). The RTE made various provisions related to access to schools, school infrastructure, teacher qualifications, and pupil-teacher ratios. Section 16 of the RTE Act stipulates that 'No child admitted in a school shall be held back in any class or expelled from school till the completion of elementary education'. The elementary stage of schooling covers grades 1 to 8. Coined as 'No-detention policy', this was considered an important feature of the act which was expected to remove the fear of failure and reduce drop out rates in elementary education. Also, instead of traditional exams the RTE aimed at using Comprehensive and Continuous Evaluation (CCE) to help children improve their learning.

Prior to the implementation of RTE in 2009, retention was a decision taken by the classroom teacher. The decision to pass or fail depends on a teachers analysis of academic performance, attendance and other behavioural traits of the students. Also, no provision for remedial help or additional instructional support was in place for those who fail. The students were required to repeat the same material again. This practice of retention is very different from the one based on *high stakes tests* where the decision to retain depends on objective criterion like scores on a standardised test. Also, repeaters are provided with additional support or remedial help [7].

The subjective nature of repetition in India is also reflected in the differences in repetition rates across states before the implementation of RTE. Table A.4 in appendix A.2 gives a snapshot of repetition policies followed by each state before 2009 (Bhukkal, 2015). Each cell represents the average repetition rates in each grade for the years 2005-2008. The cells that are red in colour represent those grades where retention was allowed according to state mandate. For instance, in Himachal Pradesh retention started from grade 6

[7] Allensworth (2005) notes this difference between the two kinds of retention policies and how one is more subjective than the other.

onwards whereas in Karnataka schools were not supposed to practice retention at all in any elementary grades. One would expect the repetition rate to be close to zero in grades where retention was not allowed. In table A.4 I do not see a clear pattern. For instance, even though most states are not supposed to retain students until grade 3, one can see that repetition rates are quite high in some states even for those grades. This indicates that before RTE the decision to retain students was more subjective rather than based on state policy. However, I find that the repetition rates decreased significantly since RTE was implemented in almost every state (see Figure 2.1.)

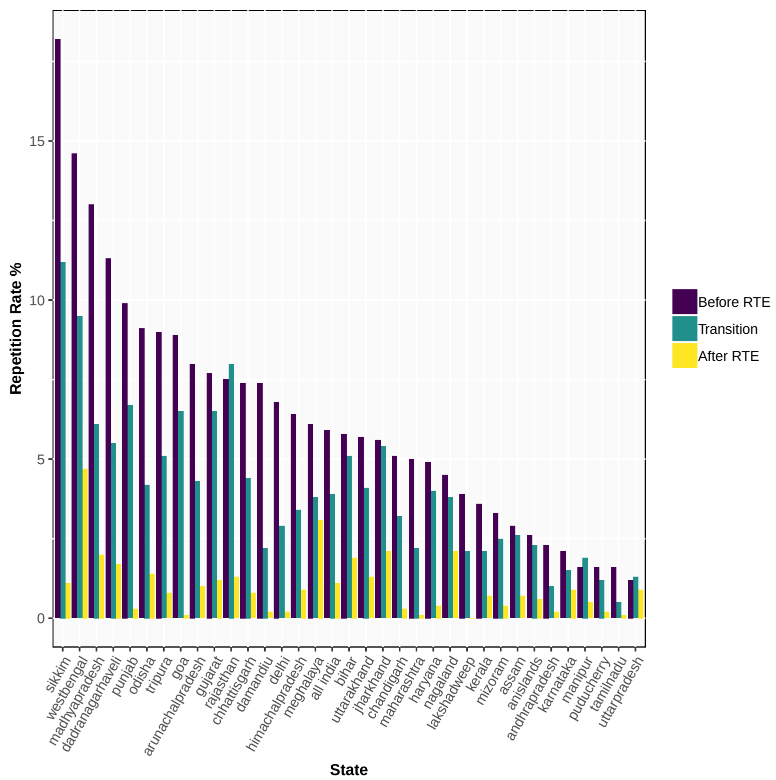


Figure 2.1: Trends in average repetition rates: The figure plots the average repetition rates by state and time category. The time category is before RTE (2005-2008), Transition (2009,2010) and after RTE (2011-2016). The dats is arranged in the descending order of average state repetion rates before RTE).

2.3 Data and Descriptives

The data for the analysis are drawn from two main sources. The District Information on Systems in Education (DISE 2005-2016) and Annual Status of Education Report (ASER, 2007-14). The DISE survey was initiated as part of the District Primary Education Programe 1994 (DPEP) by the Ministry of Human Resource Development (MHRD, India) and UNICEF, to collect school level information for successful implementation and monitoring of the program. This was later revised in 2001 to cover not just primary but all elementary grades for better monitoring of the SSA Program (Education for all Programe, 2001). The National University of Educational Planning and Administration is responsible for collecting and collating the data from all districts across the country. The schools (mostly head teachers) are responsible to supply information which is then aggregated at the district level. This annual survey has details on various indicators of elementary education (number of schools, enrolment, teachers ,infrastructure, school performance indicators and others). I use aggregate district level time-series data available from the DISE website for the years 2006-2016 [8].

ASER, on the other hand is a nation-wide household level annual survey conducted by the NGO Pratham since 2006. It collects information on schooling and basic learning status of children aged 5-16 from almost every rural district in the country. It is a citizen-led survey on education conducted in the household instead of schools.It therefore includes information on both enrolled and out of school children. Apart from basic reading and arithmetic tests, the survey also provides information on individual's education status (dropout, grade enrolled, school type etc.) and other household socio-economic indicators. As ASER does not follow the same individuals over time I use repeated cross section of individuals in the age group 6-16 years to create a pseudo-panel of individuals by age within each district. For my analysis I merge this data with the district level DISE data. Table 2.1 shows the descriptive statistics.

[8] School Report cards, DISE

The target group is children in the age group 6-16. Children in the age group 6-10 constitute the primary age group and children in the age group 11-16 constitute the lower secondary age group. The outcome variables include *Droprate*: whether or not the child dropped out of school , *Years of education*: the grade in which the child is currently enrolled, *Reading level*: whether a child can read simple text or not, and *Math level*: whether a child can do simple math operation or not.

Table 2.1: Descriptive statistics- Merged ASER and DISE data

	Mean	SD	Min	Max
ASER				
Dropout	0.04	0.19	0	1
Years of education	5.18	2.82	1	12
Reading level	0.47	0.50	0	1
Math level	0.54	0.50	0	1
Lower secondary age group	0.53	0.50	0	1
Child Age	10.72	3.02	6	16
Gender=Female	0.47	0.50	0	1
Mother Schooling	0.49	0.50	0	1
Years	2010.28	2.28	2007	2014
DISE				
Rep. rate 2008 Primary	4.93	4.09	0.0	19.9
Rep. rate 2008 Lower secondary	4.65	4.26	0.0	25.3
Repetition rate Primary	3.39	4.50	0.0	50.1
Repetition rate Lower secondary	2.96	4.48	0.0	80.2
Total teachers govt.	6703.47	4616.99	88.0	41044.0
Total rural govt. schools	1549.24	1051.63	0.0	8378.0
Total rural pvt. schools	288.63	297.75	0.0	2607.0
Total enr. govt.	182582.16	159885.83	0.0	1241336.0
One teacher schools	193.67	253.72	0.0	2951.0
Sch. enrol >50	603.24	575.95	0.0	5238.0
SDG grant	2830272.34	8128524.92	0.0	200702223.0
TLM grant	105762.14	495746.88	0.0	15799727.0
Years	2010.50	3.45	2005	2016

Notes: This table gives the summary statistics of ASER and DISE data. ASER is individual level repeated cross section data for children in the age group 6-16 from 2007-2014. DISE is district level panel data aggregated for all elementary grades 1 to 8 for years 2005-2016.

I use the average repetition rates in the year 2008 as a treatment intensity variable to create treatment categories. In Figure 2.2, I plot the trends in repetition rates by arranging the data in ascending order of quartiles of the intensity variable. It shows that the fall in repetition rates was largest for the districts in the top 25th (i.e 75-100) quartile.

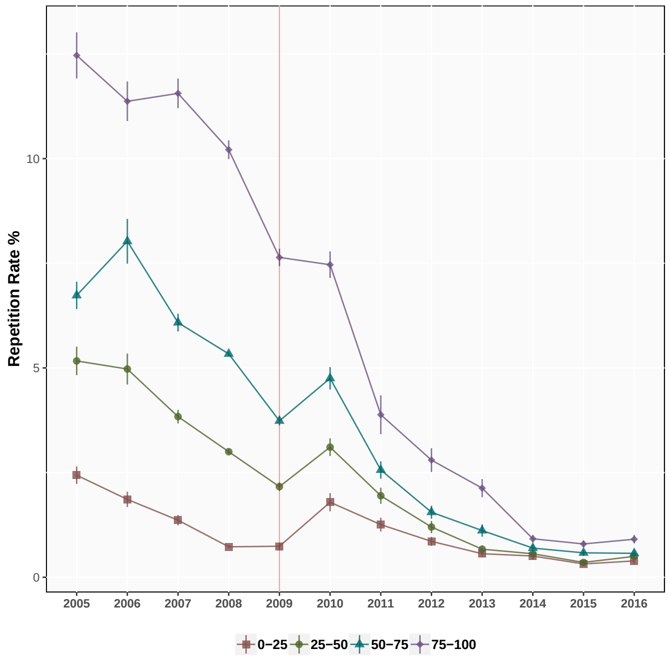


Figure 2.2: Trends in average repetition rates by arranging districts into quartiles categories derived from the intensity variable (Avg. repetition rate in 2008). This graph indicates how the repetition rate fell in each category specially for those districts in the highest quartile range (75-100)

2.4 Empirical strategy

The no-detention policy was rolled out across the whole country after the passage of the RTE Act in 2009. Prior to the implementation of the policy there was huge variation in repetion rates across districts. I use the average district level repetion rates in year 2008 to generate treatment and control groups. I call this the treatment intensity variable. Districts with high intensity (high average repetition rates) form the treatment group while districts with low intensity (low repetition rates) form the control group. After the introduction of automatic promotion there was a steep decline in repetition rates across the country, especially for those districts with pre-existing high repetition rates. In Figure 2.3 I present a scatter plot of repetition rate over the repetition intensity variable with a regression line fitted for each subgroup: pre (2005-2008) and post RTE years (2009-2016). The graph indicates that in the post-RTE period there was a significant fall in repetition rates and that the repetition rates decreased more in high intensity districts compared to low intensity.

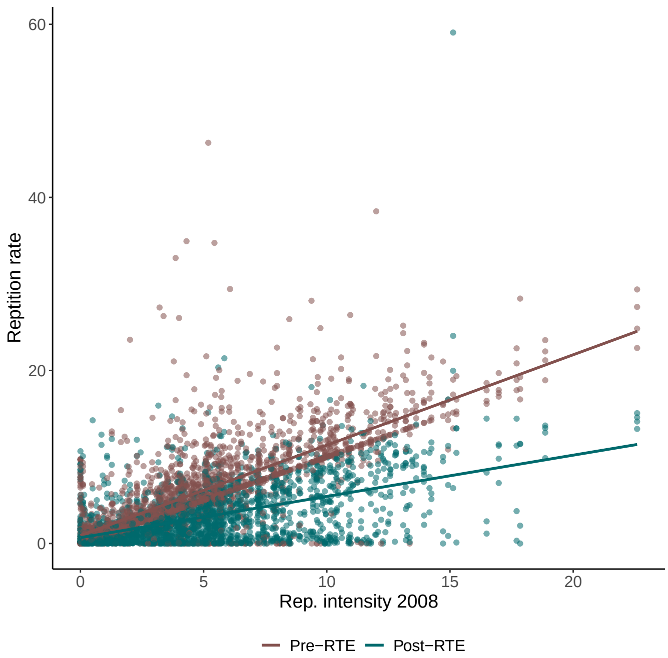


Figure 2.3: Scatter plot of repetition rate on intensity (Avg. repetition rate in 2008) by pre and post RTE category. The bold lines represent the fitted linear regression model. The graph shows how the change in repetition rates pre and post RTE varies by intensity (Avg. repetition rates in 2008). Post RTE, the repetition rates decreased more in high intensity districts compared to low intensity.

I exploit this difference in pre-existing behaviour across districts to employ a difference in difference framework wherein I compare districts with high repetition rates to districts with low repetition rates before and after the year 2009. The main idea is that the districts with high repetition rates will be affected more due to the sudden introduction of automatic promotion compared to those with low repetition rates. The identification strategy is to look at whether there is a break in any pre-existing differences in the trend of the outcome variables due to automatic promotion. In a regression framework in run the following specifications for each outcome variable:

$$y_{idt} = \alpha \ Post_t \ + \phi \ RR_d \ + \beta \ Post_t * RR_d \ + \gamma Dist_{dt} \ + \lambda X_i \ + \eta_d \ + \epsilon_{idt} \tag{2.1}$$

where y_{idt} is the outcome variable for individual i in district d, and year t. Equation 2.1 is the standard difference in difference specification where I interact a time dummy variable $Post_t$ (2007-2008 takes vale 0, 2009-2014 takes value 1) with a continuous intensity variable, RR_d, (the average district level repetition rate in the year 2008). The coefficient of $Post_t * RR_d$ is the main variable of interest which gives the difference between high and low intensity districts before and after RTE 2009. $Dist_{dt}$ are time-varying district level school education variables (like total schools, enrolment, teachers etc.), η_d represent district fixed effects and X_i refers to individual/family level co-variates. ϵ_{idst} is the error term.

2.4.1 Robustness

In this section I discuss some of the issues which need to be considered in order to establish a causal link between automatic promotion and student outcomes. *First*, the choice of the year 2008 to create treatment and control districts. In Figure 2.4, I show the density plot of the average repetition rates from 2005-2009. The figure shows how the distribution of repetition rates evolved over time prior to the implementation of the policy. One can notice a significant change in the distribution in the year 2009 when the RTE Act was passed. Therefore, the repetition rates in the year 2008 seemed a logical choice to create treatment categories.

Second, for establishing a casual link of automatic promotion it is important to test if prior to the implementation of RTE there was no change in the trends in behaviours regarding repetition rates in treatment and control districts. And that any divergence in behaviour occurred only after the year 2009.

I show that in this is in fact true. With the introduction of automatic promotion in 2009 there was a break in the pre-existing trends in the difference in repetition rates. In Figure 2.5, I plot the coefficient of the interaction between repetition intensity and year,

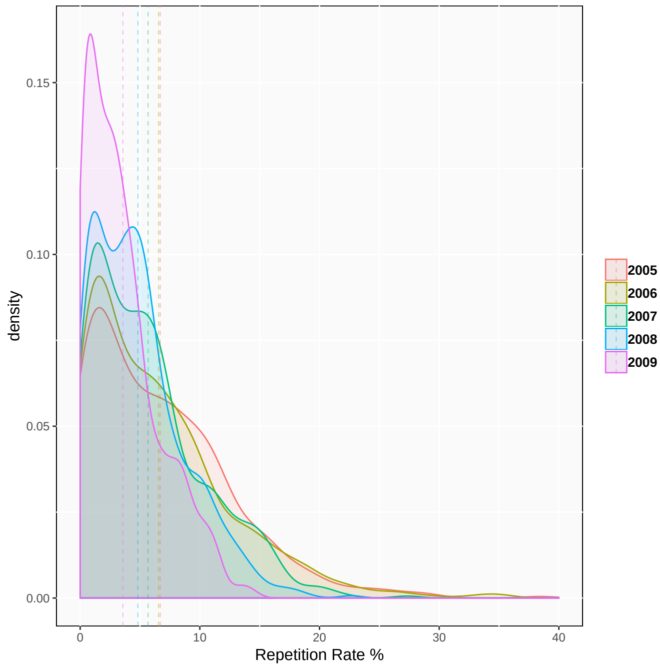


Figure 2.4: Density plot of repetition rates by year (2005-2009). The dotted line represents the mean. This figure shows how the distribution of repetition rates changed significantly in the year 2009.

β_t using equation 2.2 below.

$$y_{idt} = \sum_{t=2007}^{t=2014} \alpha_t \; Year_t \; + \phi \; RR_d \; + \sum_{t=2007}^{t=2014} \beta_t \; Year_t * RR_d \; + \gamma Dist_{dt} \; + \lambda X_i \; + \eta_d \; + \epsilon_{idt} \tag{2.2}$$

This is similar to equation 2.1 with the only difference that I interact the intensity variable with year instead of a time dummy. This will generate a β_t coefficient for each year which estimates the trend in the outcome variable. More specifically, taking 2007 as base year, β_t shows how the difference between high and low intensity districts changed over time without imposing any pre or post policy years. The results using equation 2.2 are presented graphically by plotting the β_t coefficient. As mentioned above, this interaction gives the change over time in the difference between high and low intensity district. Figure 2.5 plots the β_t coefficient using equation 2.2 with repetition rate as the outcome variable.

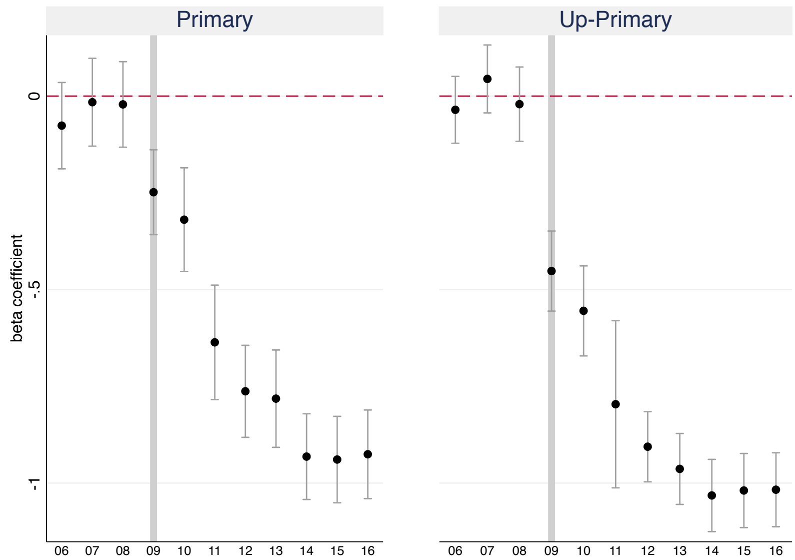
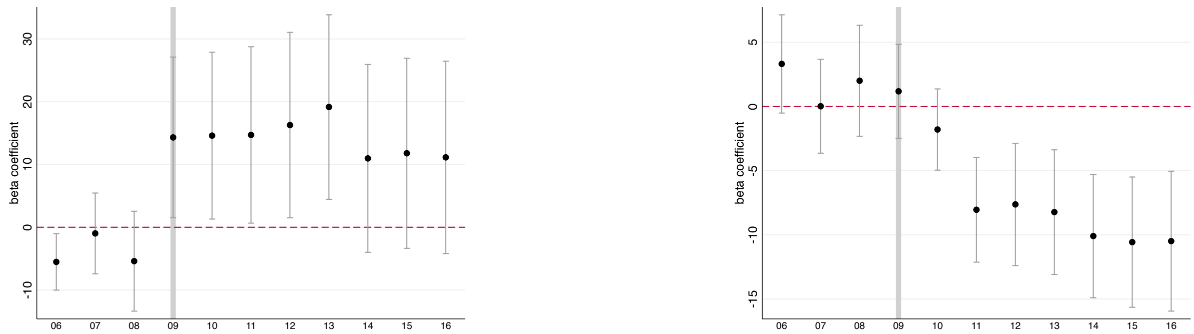


Figure 2.5: Trends in difference in repetition rates: This figure plots the β_t coefficient using equation 2.2 with repetition rate as the outcome variable. The grey vertical line indicates the year when RTE was passed.

The grey vertical line indicates the year when RTE was passed. It can be seen from the figure that before 2009 there was no change in the difference between repetition rates between high and low intensity groups but following the introduction of RTE in the year 2009 the coefficient of this interaction term becomes statistically significantly different from zero. The negative coefficient implies that the fall in repetition rates in high intensity regions was larger than the fall in repetition rates in low intensity regions, more so for lower secondary grades. This variation in behaviour can help me identify the impact of automatic promotion on education outcomes.

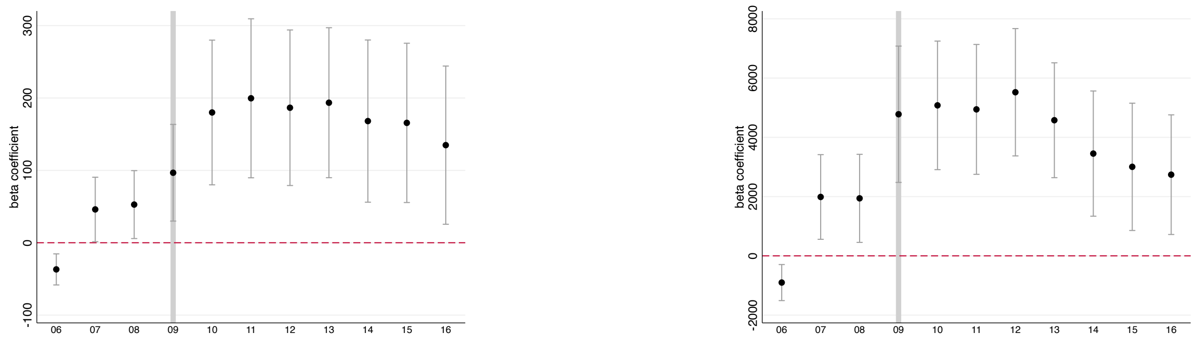
Third, it is true that repetition rates prior to the implementation of the policy are not randomly assigned. Differences in repetition rates across districts might be associated with the quality of education, institutional capacity or other socio-economic factors which can bias my estimates. To address the endogenity of my intensity variable I control for time-varying district level indicators of education institutional capacity (like total schools, total teachers, enrolment etc.) $Dist_{dt}$. I also use district fixed effects to account for time-unvarying unobservable factors η_d.

Fourth, another important issue which needs to be addressed to estimate the is that the passage of RTE 2009 introduced other policy reforms along with automatic promotion. These reforms can simultaneously affect education outcomes thereby making it difficult to identify the effect of automatic promotion. For instance, some of the major reforms introduced by RTE include (i) free and compulsory government schools for all children ages 6–14, (ii) reservation of 25 percent of private school seats for disadvantaged students in the local area, and (iii) providing minimum infrastructure and quality standards (like libraries, and girls' toilets, teacher qualifications and pupil-teacher ratios). I argue that even if these reforms had any effect on educational outcomes it should not bias our estimates of automatic promotion as long as these reforms did not differentially impact students in our treatment (high intensity districts) and control groups (low intensity districts). I check for differences in other inputs which might have changed due to RTE in Figures 2.6,2.7, and 2.8.



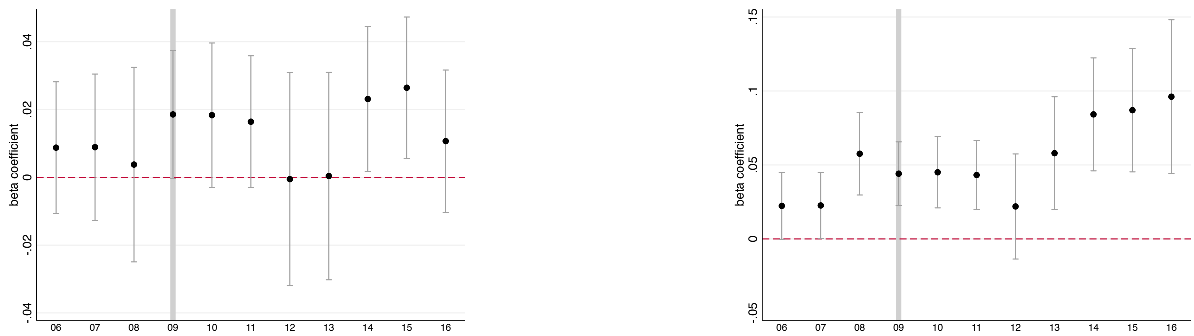
(a) Total government schools **(b)** Total private schools

Figure 2.6: Trends in difference in total schools in rural areas before and after RTE



(a) Total teachers, govt. **(b)** Total enrolment, govt.

Figure 2.7: Trends in difference in teachers and student enrolment before and after RTE



(a) Total grants for SDG **(b)** Total grants for TLM

Figure 2.8: Trends in difference in grants and teaching material before and after RTE

2.5 Results and discussion

In table 2.2, I present the results for primary age group and in table 2.3 for lower secondary age group. Each column reports the results for different outcome variables using equation 2.1. In columns 1-2 the outcome variable is dummy for dropout status, in columns 3-4 the outcome variable is dummy for whether the child is able to read a simple standard two level text while in columns 5-6 the outcome variable is whether the child can perform simple math operations. All specifications include time-varying district level variables. I also plot the beta coefficients from the OLS regression using equation 2.2 for each outcome variable separately in figures 2.9a, 2.9b, and 2.9c.

Primary age group

I find that the introduction of automatic promotion did not significantly affect the decision of primary age children to drop out of school or not (columns 1 and 2 of table 2.2).

The left hand panel in figure 2.9a plots the results for primary age group. It can be seen that the beta coefficient for dropout remains insignificant and close to zero for all years from 2008-2014 (figure 2.9a). Next, I present the results for the effect of automatic promotion on learning outcomes for primary age. I find that the introduction of automatic promotion lead to a significant decline in learning levels. The probability that a child can read a simple standard 2 level text decreases by around 0.3 to 0.4 percentage points (columns 3 and 4 of table 2.2) in a high intensity district relative to a low intensity district. The negative affect is even larger for arithmetic. The probability that a child in a high intensity district can solve a simple math problem decreases by around 1 percentage points more (columns 5 and 6 of table 2.2) compared to a low intensity district. I also plot the results in figures 2.9b and 2.9c. The left hand panel in figure 2.9b shows that following the introduction of automatic promotion the fall in the reading levels for high intensity districts was higher than the low intensity districts. Similarly, for math levels (left panel figure 2.9c) the difference between high and low intensity districts becomes

Table 2.2: Diffrence in Difference: Primary age group

	Droprate		Read level		Math Level	
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.001***	-0.002***	-0.017***	-0.016***	-0.024***	-0.011
	(0.000)	(0.000)	(0.006)	(0.005)	(0.008)	(0.006)
RepIntensity	-0.000		0.006***		0.010***	
	(0.000)		(0.001)		(0.001)	
Post*RepIntensity	-0.000	-0.000	-0.004***	-0.003***	-0.009***	-0.008***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Mother school	-0.006***	-0.006***	0.106***	0.095***	0.128***	0.110***
	(0.000)	(0.000)	(0.002)	(0.001)	(0.002)	(0.001)
Female	0.001***	0.001***	-0.002**	-0.001	-0.019***	-0.018***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
District fixed effect	No	Yes	No	Yes	No	Yes
R^2	0.005	0.008	0.141	0.169	0.185	0.223
No. of Obs.	1742148	1742148	1610943	1610943	1603796	1603796
No. of clusters	4216	4216	4216	4216	4216	4216

Notes: Difference in Difference: Dropout, reading and math level. In columns 1-2 the outcome variable is dummy for dropout status, in columns 3-4 the outcome variable is dummy for whether the child is able to read a simple standard two level text while in columns 5-6 the outomce variable is whether the child can perform simple math operations. All specifications include time-varying distrct level variaables: *Total teachers govt,Total rural govt. schools, Total rural pvt. schools, Total Enr govt, One teacher schools,Sch. enrol, log SDG grant and log TLM grant*. I use cluster robust standard errors at district year level.

large after the year 2009 and remains so until 2014.

Lower secondary age group

For children in lower secondary age I find that automatic promotion lead to a significant decline in the probability of dropout in high intensity districts of around 0.1 to 0.2 percentage points (table 2.3). The right hand panel in figures 2.9a plot the results for dropout rate in lower secondary age group. It can be seen that the beta coefficient for dropout becomes negative and significantly different from zero after the year 2009 (figure 2.9a). These results indicate that the effect of automatic promotion on dropout rates is larger for older children compared to younger children.

Finally, I present the results for the effect of automatic promotion on learning outcomes for lower secondary age. I find that for this age group the decline in reading levels is not that significant (columns 3 and 4 of table 2.3). Although the probability that a child can solve a simple math problem decreases significantly by around 0.4 to 0.6 percentage points (columns 5 and 6 of table 2.3) in a high intensity district relative to a low intensity district.

The results in figures 2.9b and 2.9c right hand panel also show that automatic promotion did not effect the reading levels of lower secondary age children however, for math the difference between high and low intensity districts becomes large after the year 2009 and keeps falling until the year 2014.

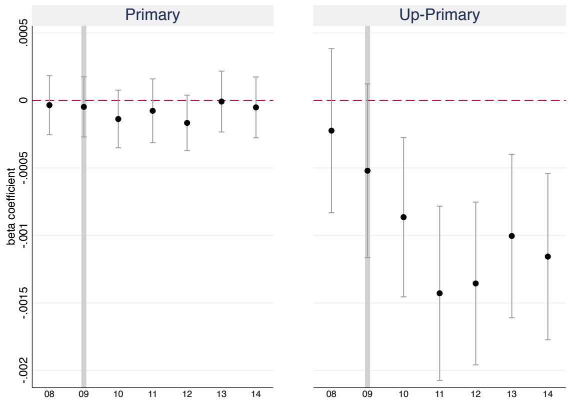
2.5.1 Mechanism

In table 2.4 I explore the probable mechanisms for the decline in learning levels after automatic promotion was introduced. I use the math level of primary age children as the dependant variable. In column 1 I use a triple interaction of time and intensity with the district level pupil-teacher ratio (or STR) and in column 2 I use a triple interaction of time and intensity with the dummy for the mother schooling. The triple interaction with STR is negative and significant which indicates that districts with a high student teacher

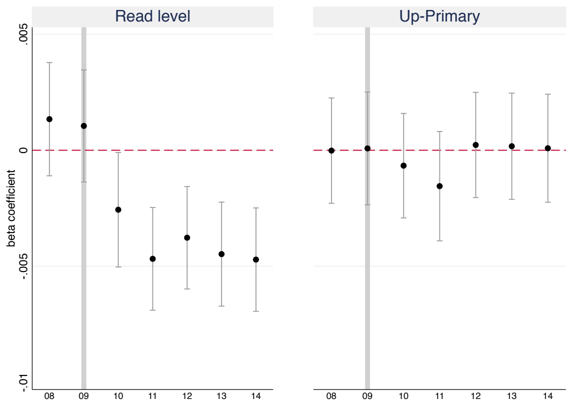
Table 2.3: Diffrence in Difference: Lower Secondary age group

	Droprate		Read level		Math Level	
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.001	-0.005***	-0.047***	-0.031***	-0.057***	-0.025***
	(0.002)	(0.001)	(0.006)	(0.005)	(0.007)	(0.005)
RepIntensity	0.001***		0.003***		0.005***	
	(0.000)		(0.001)		(0.001)	
Post*RepIntensity	-0.002***	-0.001***	-0.001	-0.001	-0.004***	-0.004***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Mother school	-0.055***	-0.051***	0.142***	0.129***	0.142***	0.126***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Female	0.009***	0.009***	-0.008***	-0.007***	-0.043***	-0.041***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.059	0.074	0.084	0.127	0.073	0.122
No. of Obs.	1973602	1973602	1788119	1788119	1784126	1784126
No. of clusters	4216	4216	4216	4216	4216	4216

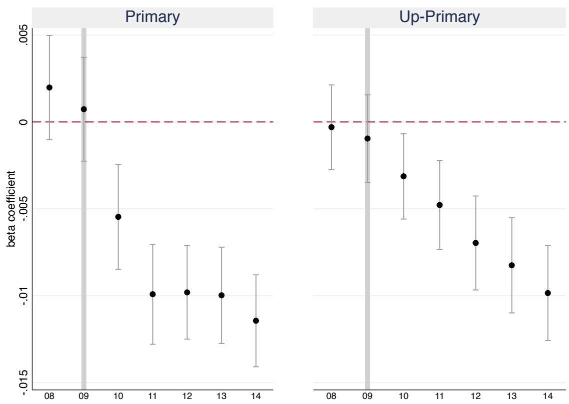
Notes: Difference in Difference: Dropout, reading and math level. In columns 1-2 the outcome variable is dummy for dropout status, in columns 3-4 the outcome variable is dummy for whether the child is able to read a simple standard two level text while in columns 5-6 the outomce variable is whether the child can perform simple math operations. All specifications include time-varying distrct level variaables: *Total teachers govt,Total rural govt. schools, Total rural pvt. schools, Total Enr govt, One teacher schools,Sch. enrol, log SDG grant and log TLM grant.* I use cluster robust standard errors at district year level.



(a) Dropout rate



(b) Reading level



(c) Arithmetic level

Figure 2.9: Difference in difference results: This figure plots the β_t coefficient) using equation 2.2 with different outcome variables.The grey vertical line indicates the year when RTE was passed.

ratio in government schools were more adversely affected by the policy.

Next, I show that students from disadvantaged backgrounds experience lower learning outcomes (math levels) compared to other students. I use mother's schooling variable as an indicator for child's socioeconomic background. The postive sign of the triple interaction with mother's schooling shows that student's whose mother went to school are better off compared to students whose mother never attended school.

Table 2.4: Heterogenous effects

	(1)	(2)
Post*Intensity*STR	-0.006***	
	(0.002)	
Post*Intensity*Motherschool		0.004***
		(0.001)
R^2	0.334	0.324
No. of Obs.	3414413	3414413
No. of clusters	4256	4256

Notes: Heterogeneous effects: The dependent variable in both columns is math level for all children in 6-16 age groups. I use district fixed effects and cluster robust standard errors at district year level.

There could be other reasons for the negative effect of automatic grade promotion on student outcomes. These include (a) less motivated students and teachers because of the removal of high stake exams or (b) inability to implement the new form of Continuous Comprehensive Evaluations (CCE) to assess student learning. More data on teachers and student assessments can help in understanding other mechanisms that lead to a decline in the quality of education after the policy.

2.6 Conclusion

The improvement in access to primary education across many developing countries has met with serious challenges to provide inclusive, quality education for all. Recent years have witnessed a shift in the focus of education policy towards improving the quality of education. For instance, the Indian parliament recently passed a bill that allows states to abolish social promotion in schools in a bid to improve declining quality of education. It is not yet clear though how this policy might affect educational opportunity and learning outcomes. This study thereby provides evidence on the effect of automatic promotion on educational outcomes.

In order to causally estimate the effect of automatic promotion on students' educational outcomes I use a large scale education reform in India, the Right to Education Act (2009) no-detention policy, that abolished the practice of retention for all elementary grades across the country. The difference in difference method allows me to estimate the effect of the policy on student drop-out rates, years of education and learning outcomes. I exploit variation in exposure to the no-detention policy due to differences in initial repetition rates across districts.

As intended the no-detention policy helped in reducing dropout rates in elementary education. I find that the policy helped in reducing the drop-out rates in post-primary education by 0.1 percentage points and increases the years of education by 0.07 years. However, the policy had a negative effect on learning outcomes. The probability that a primary age student could solve a basic reading and arithmetic task falls by 0.3 and 0.8 percentage points respectively. The negative effect was larger for children with a poor socio-economic background. I explore probable mechanisms for the decline in learning levels. The probable mechanisms for the negative effect of automatic promotion on learning outcomes are (a) less motivated students and teachers because of the removal of high stake exams (b) congestion or (c) inability to implement the new form of Continuous Comprehensive Evaluations (CCE) to assess student learning. I find that districts with congested government schools suffered more due to the policy. More data on teachers and student assessments can help in understanding other mechanisms that lead to a decline in the quality of education after the policy.

Chapter 3

Indian matchmaking: Impact of large scale education program[1]

3.1 Introduction

Investment in education can yield labor market as well as marriage market returns (Pierre-Andre Chiappori et al., 2009). In India, where the female labour force participation has been very low since 1980s (Klasen and Pieters, 2015), and marriage is universal the primary reason for investment in girl's education is to obtain returns on the marriage market (Adams and Andrew, 2019). Marital patterns have important implications for population growth, income inequality and allocation of intrahousehold resources among others (Becker, 1973). The age at marriage can influence the economic and physical well being of women and their children (Chari et al., 2017; Corno et al., 2020; Duflo, 2012; Field and Ambrus, 2008). The aim of this paper is to causally estimate the effect of female education on marriage market outcomes specially the age at marriage.

We start by establishing a causal link between the increase in women's education and her age at marriage. We exploit quasi-random variation in education induced by a large-scale education program in India, District Primary Education Program (DPEP), to

[1]This chapter is co-authored with Vikram Bahure `vikram.bahure@unige.ch` and Sayali Javadekar `sj2093@bath.ac.uk`

estimate its impact on female marriage market outcomes. DPEP was targeted to districts with low educational outcomes. Districts with an average female literacy rate below the national average of 39.3 (Census 1991) were eligible under the program. We exploit the discontinuity around the cut-off using regression discontinuity framework similar to Khanna (2015). Our estimates show that education increases by 1.5 years for women in the DPEP districts. We also find that, on an average DPEP causes a decrease in the women's age of marriage by 1.1 years. However, form our RDD estimates we cannot explain if the decrease in age at marriage is due to change in education of women in these districts. To check this channel, we use DPEP as an instrument for education to estimate the impact of increase in education on the age of marriage of the women. We find that the age of marriage decreases by 1.3 years for educated women in the DPEP districts. This finding is contrary to the existing evidence that finds a positive association between education and age at marriage (Breierova and Duflo, 2004; Brien and Lillard, 1994; Ikamari, 2005; Kirdar et al., 2009).

We provide a conceptual framework to understand the impact of education on the marriage market outcomes for woman. The theoretical underpinnings draw from Pierre-André Chiappori (2020) and Low (2014). We use a transferable utility framework in a unitary household model. Under transferable utility framework a stable match can be established by maximising the sum of utilities of the partners. In our model, men are characterised by income and woman are characterised by education and age. We assume men's utility to be decreasing in the age of the women at marriage. Men's family prefer younger brides due to longer reproductive life and less autonomy (Anukriti and Dasgupta, 2017; Caldwell et al., 1983; Jensen and Thornton, 2003; Wahhaj, 2015). In the context of India, where labour market returns are low for woman, our model predicts a negative association between woman's education and age of marriage. Given that educated and young brides are more desirable in the marriage market, woman with more education tend to improve their returns from marriage by finding a match at younger age.

Our first contribution is to the extensive literature on the marriage market returns to women's education. Women's education has been positively linked to husbands earnings and her own consumption through assortative mating in developed countries (Attanasio and Kaufmann, 2017; Pierre-André Chiappori et al., 2018; Lefgren and McIntyre, 2006). With the schooling expansion in developing countries, there is evidence on an increased educational homogamy in developing countries (Boulier and Rosenzweig, 1984; Permanyer et al., 2013; Smits and Park, 2009)[2]. There is also evidence on the diminishing returns to education as men do not place importance on the woman's intelligence or ambition over physical attributes (Fisman et al., 2006; Hitsch et al., 2010; Low, 2014). In countries with stricter social norms and low female labor force participation, parents invest in daughter's education only for a prospective match (Adams and Andrew, 2019). In this context, we provide causal evidence on the impact of schooling expansion on the marriage market outcome, specifically, the age at marriage.

The other main contribution of the paper is to build a conceptual framework to understand the impact of education of woman on the age of marriage. We add to the literature of matching in marriage markets (Pierre-André Chiappori, 2020; Low, 2014). In the two-sided market, we have bi-dimension for women in the model, education and age of marriage. We provide framework for the Indian marriage market where labour market returns are low for women and men have preference for young and educated brides. Considering the local social norms, we allow for dowry as a marriage payment in the model which is an important part of the Indian marriage market. The model predicts the negative association of age of marriage and education of the woman in the context of Indian marriage market.

In remainder of the paper proceeds as follows. Section 2 provides background information of the DPEP. Section 3 describes the data. Section 4 and 5 provides the estimation strategy and results respectively. Section 6 concludes the paper by discussing the paper's key findings and steps ahead. In Appendix we present the conceptual framework and the model.

[2]See (Anukriti and Dasgupta, 2017) for an excellent review on marriages in developing countries.

3.2 District Primary Education Program (DPEP)

The District Primary Education Program (DPEP) was a centrally sponsored scheme first launched by the Government of India in the year 1994. The scheme was run in partnership with the central government, the state governments and external donor agencies. The main objectives of the program were to increase access and quality of primary education as well as reducing gender and socio-economic inequality. The program focused on decentralised management of elementary education with districts as the main administrative unit. The program was targeted to districts with poor educational outcomes.

There were two main criteria which were used to select districts under the DEPP. First, those districts which had a female literacy rate below the national average of 39.3, and second, districts where the total literacy campaigns were successful. However, by 1994, the total literacy campaign had been implemented in almost all districts in India. Hence, the main selection criterion into DPEP was the below national average female literacy rate (Azam and Saing, 2017). The program was introduced in four phases across the country. The total number of districts covered by all DPEP phases (1994-2002) was 242 (273 with bifurcated districts) covering 18 states of India (MHRD, Government of India, 2002). Details of the districts covered under various phases is provided in figure 1.

THE DPEP is one of the largest donor assisted programs. Financing of the program was based on a 85:15 ratio with 85 percent given as a grant to the states by the central government (in partnership with international development agencies, World Bank, ECU, DFID, UNICEF) and 15 percent contributed by the state governments. In order to avoid crowding out of government investment in elementary education, the state governments had to maintain at least their existing levels of expenditure on elementary education. Overall, the project lead to an increase in the total allocation by the government for elementary education by about 17.5 to 20 percent. The project also laid strict guidelines regarding the proportions spent on civil works (24 percent) and management costs (6 percent) to ensure that a large part of the funds were spent directly on quality improvements

(Pandey, 2000).

According to the 16th Joint Review mission (MHRD, Government of India, 2002), DPEP covered around 51.3 million children and 1.1 million teachers in the school system. By the year 2002 around 39,500 new schools and more than 15,000 Early Childhood Centers were built. Apart from civil works the program interventions ranged from enrolment drives, community mobilization campaigns, establishing academic resource centers, to in service teacher training, textbook and curriculum renewal, and decentralized planning and monitoring (Sipahimalani-Eao and Clarke, 2003). Initial evidence showed that the program helped in improving access to primary education and progression into higher levels of education beyond primary (Jalan and Glinskaya, 2002). However, the effect was not uniform across states or socio-economic groups. More recent studies provide evidence on the long run effect of the policy on education levels after the completion of the program. (Azam and Saing, 2017) use difference-in-difference method to estimate the impact of the policy on the probability of completed primary education and years of schooling. They find a positive effect of the program both on probability of attending and finishing primary school and an increase in the years of schooling by 0.16 years.

Our paper is closely related to (Khanna, 2015) who uses an Regression Discontinuity Design to estimate the general equilibrium (GE) effect of the policy. The study finds that the program lead to an increase in the years of education and earnings in the targeted districts. It was also found that although the policy led to a significant decline in returns to skills, the overall welfare increased due to reduction in household's costs of education and increase in output. While (Khanna, 2015) provides evidence on the labor market returns of increase in education our paper looks at the non-labor market returns to education.

3.3 Data

The empirical analysis is carried out by combining data from various sources including: The National family and health survey IV (2015-16), The District Information on Systems in Education (DISE 2005) and Primary Census Abstracts 1991. The NFHS are nationally representative surveys carried out under the aegis of he Ministry of Health and Family Welfare (MoHFW), Government of India. The International Institute for Population Sciences (IIPS), Mumbai, acts as the nodal agency for all of the surveys. The main objective of the survey is to provide essential data on fertility, health and family welfare for the country. The NFHS-4 provide estimates for various indicators at the district, state and national levels. The sample is generated using the stratified two-stage sampling method with the 2011 census as the sampling frame. Primary Sampling Units consists of villages in rural areas and Census Enumeration Blocks (CEBs) in urban areas (Population Sciences - IIPS/India and ICF., 2017). For our analysis we use the Women's Questionnaire with detailed information on women's background characteristics (age, literacy, schooling, religion, caste/tribs), marriage and fertility decisions. A total of 723,875 eligible women age 15-49 were identified for individual women's interviews. Interviews were completed with 699,686 women, for a response rate of 97 percent.

To get information on schools The District Information on Systems in Education (DISE 2005) is used. The DISE survey was initiated as part of the District Primary Education Programe 1994 (DPEP) by the Ministry of Human Resource Development (MHRD, India) and UNICEF, to collect school level information for successful implementation and monitoring of the program. The National University of Educational Planning and Administration is responsible for collecting and collating the data from all districts across the country. The schools (mostly head teachers) are responsible to supply information which is then aggregated at the district level. This annual survey has details on various indicators of elementary education (number of schools, enrolment, teachers ,infrastructure, school performance indicators and others). I use aggregate district level data available from the DISE website for the years 2005 [3].

We also use Primary census abstracts for the year 1991 to get information on district

[3] School Report cards

level literacy rates and sex ratios [4]. The district level literacy for the 1991 will be used as the running variable for RDD estimation. Finally information on DPEP staus was collated manually using various GOI review reports published by NEUPA to map the progress of DPEP over the years[5].

Table 3.1 gives a brief description of the variables. The target group consists of women in the age group 15-40. Most women have finished primary education with the average years of education of around 7 years. Almost half of the women marry by the age 18 (average age at marriage for women is 18.5 years) and have their first child by age 20-21.

Table 3.1: Descriptive statistics- I, DHS data 2015-16

	N	Mean	SD	Min	Max
Marriage, Fertility					
Ever married	576,486	0.70	0.46	0	1
Age at marriage	383,926	18.47	3.51	10	29
Age at first birth	343,026	20.53	3.23	15	31
Marriage-first birth int.	332,671	25.51	18.96	0	129
Ever gave birth	576,486	0.62	0.49	0	1
Total children	576,486	1.55	1.62	0	15
Total children under 5	576,486	0.67	0.93	0	9
Partner					
Partner Age	67,992	34.31	7.44	15	70
Partner Education	70,512	7.92	4.89	0	20
Background					
Woman age	576,486	26.60	7.43	15	40
Education in years	576,486	7.32	5.07	0	20
Wealth index	576,486	5,090.88	97,595.39	−240,323	300,055
HHsize	576,486	5.92	2.69	1	41
District level					
Schools built until 1995	511,582	1343.87	819.25	16	5196
Female literacy cut-off	467,687	-3.12	17.074	-31.6	54.7
Sex ratio 1991	377,404	943.64	34.09	851.94	1079.71

Notes: DHS data 2015-16. Sample from woman questionnaire for all those who were young in 1994-2005. Total 632 districts (including splits) from DHS out of which 266 got DPEP and remaining did not.

[4] Census of India, 1991
[5] NEUPA Archives

3.4 Estimation Strategy

The decision of an individual to invest in education is correlated with various unobserved family, social and individual characteristics which might also effect their marriage and fertility outcomes. This makes it difficult to casually estimate the effect of education on marriage market outcomes. The District Primary Education Program (DPEP) provides a quasi-random variation in access to education that can be used to overcome the endogenity of education. DPEP was targeted to districts with low educational outcomes. Districts with an average female literacy rate below the national average of 39.3 (Census 1991) were eligible to get funding under the program. We exploit the discontinuity around the cut-off using regression discontinuity framework similar to Khanna (2015). The identification of the causal effects of DPEP program comes from the assumption that the potential outcomes are a continuous function of the fertility rates (Lee and Lemieux, 2010).

There is imperfect compliance to DPEP by female literacy rates. It was found that not all districts below the cut-off got the treatment while some districts that we not eligible (i.e above the cut-off) received the treatment. In a setting of imperfect compliance a "fuzzy" RD can be applied to estimate treatment effects. As opposed to a "sharp" RD where the probability of treatment jumps from 0 to 1, the fuzzy RD design allows for a smaller jump in the probability of treatment at the threshold (Lee and Lemieux, 2010). Due to the imperfect compliance we are estimating a LATE, i.e the effect relevant for the average-literacy district induced into taking up treatment.

Assuming that the treatment assignment is a good as random around the cut-off, the treatment effect recovered using fuzzy RD are similar to Wald formulation of the treatment effect in an instrumental variables (IV) setting. We estimate the first stage relationship between the running variable and treatment status in the close neighbourhood of the centered female literacy rate using equation 3.1 below.

$$T_{id} = \alpha + \gamma \mathbb{1}[X_{id} \leq c] + f(X_{id}) + \eta_i d, \quad c - h \leq X_d \leq c + h \tag{3.1}$$

whereX_{id} is the centered assignment variable (39.3-district female literacy rate). T_{id} is a dummy which takes value 1 if the individual belongs to a district which got DPEP. $X_{id} \leq c$ is an indicator for whether the individual lives in a district whose centered female literacy rate is less than c (where $c = 0$). $f(X_{id})$ is a function used to flexibly model X_{id}, the centered female literacy score. h_n is bandwidth selected using CCT methodology of *rdrobust* package (Calonico et al., 2017). In a standard IV setting the causal effects are estimated by assuming that the instrument affects the outcome only through its effect on treatment assignment. Similarly, we assume the indicator variable $X_{id} \leq c$ (analogous to an IV) has no impact on the outcome except by influencing the treatment status T_{id}.

In the second stage we estimate 3.2

$$Y_{id} = \beta + \tau_{FRD} \hat{T_{id}} + g(X_{id}) + \mu_i d, \;\; c - h \leq X_{id} \leq c + h \tag{3.2}$$

where T_{id} is the estimated probability of treatment from the first stage. τ_{FRD} is the main coefficient of interest which gives us the impact of DPEP on the outcome variable and $g(X_{id})$ is again a function used to flexibly model X_{id}.

3.4.1 Validity checks

In figure 3.1 we first show that there exists a discontinuity in receiving the treatment on the centered female literacy rate at the cut-off. The districts lying in the close neighbourhood around the cut-off show a significant difference in the probability of receiving the treatment. The probability of treatment assignment jumps by nearly 20 percentage points for districts just below the literacy cut-off.

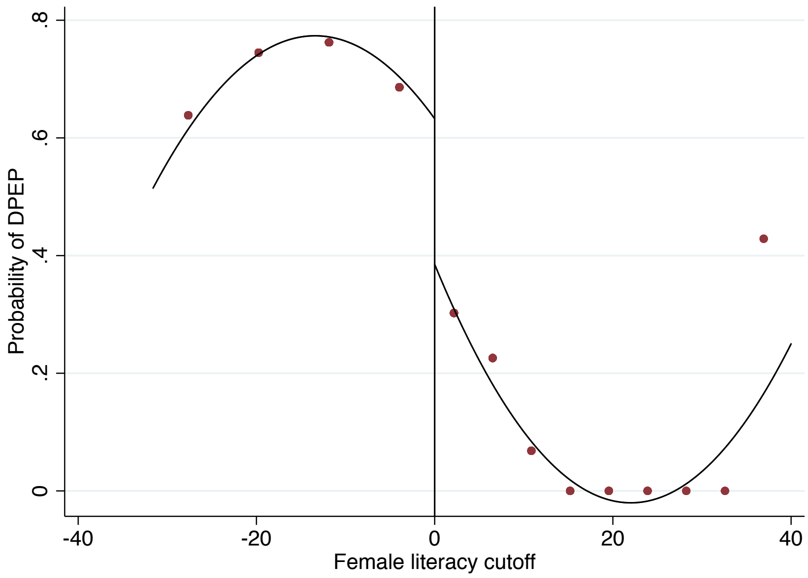


Figure 3.1: Probability of receiving DEPP

The validity of RD design requires that there is no manipulation of the assignment variable around the cutoff and. The DPEP program was introduced for the first time in the year 1994. As the criteria for being eligible for DPEP funding was based on a predetermined variable (female literacy rate as per 1991 census) individuals do not have precise control to select themselves into the program. We further provide a formal test to check whether the density of the assignment variable is continuous or not around the cut-off. In Figure 3.2 we can see that there is no discontinuity in the assignment variable. Also, to the best of our knowledge no other government program used female literacy rate for program eligibility.

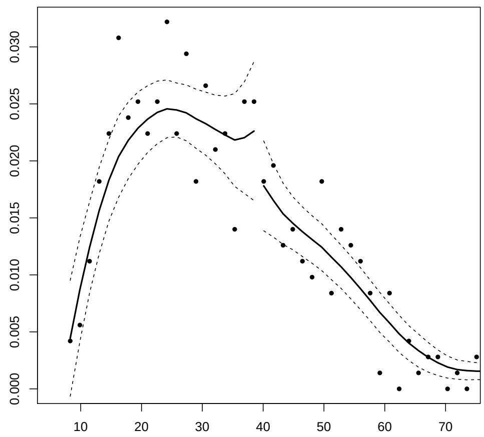


Figure 3.2: Mccrary Test

Finally, we provide balance test on predetermined variables that would otherwise bias the estimated parameters (Table 3.2). We use the district level data of DHS 1991-92 to estimate the difference in the pre-determined variables using the RDD method discussed above. We do not find the RDD coefficient to be statistically significantly different from zero.

Table 3.2: Balance test covariates, DHS data 1991-92

Initial covariates	RD Effect	Robust p-val
Schools built before 1995	-278.99	.888
Sex ratio 1991	14.47	.802
Age of woman	-1.941	.058
Education in years	-1.344	.275
HH size	1.137	.192
Age at first marriage	-.886	.465
Age at first birth	-.521	.593
Total children	.077	.984
Partner education	-1.245	.576

In all our specification standard errors are clustered at the district age level.

3.5 Results

Our main results examine the effect of education on woman's marriage market outcomes like age at marriage, age when first child was born, total fertility and partner's education. We first show that the DPEP lead to an increase in years of education of woman. Table 3.3 reports the estimated coefficient from our RDD specification in equation 3.2. The coefficient is column 1 gives the impact of DPEP on the years of education. As expected, the policy had a positive effect on years of education. The robust estimates show that on an average woman in the treated district complete 1.5 more years of education.

Table 3.3: Impact of DPEP on education-RDD estimates

	(1) Years of education
Conventional	1.480**
	[0.679]
Bias-corrected	1.475**
	[0.679]
Robust	1.475**
	[0.718]
Sample Mean	7.49
Obs.	467687
Effect. Obs.	88513
Bias	11.95
Bandwidth	4.71
VCE method	NNcluster
BW type	mserd

Notes: We use nn cluster robust standard errors at district age level. **$p<0.05$;***$p<0.01$

In Table 3.4 and 3.5 we report our main results. The estimates using the RDD method in table 3.4 show that the program lead to a decline in the age of marriage of woman by around 1.1 to 1.4 years (column 1). In column 2 one can see that the age of first birth also reduces by around half a year. We also find that woman on a average are marrying partners with more education (approx. 1.7 yeras). The RDD coefficient for total children ever born to the woman is not significantly different from zero.

Table 3.4: Women marriage outcomes-RDD

	(1) AgeMarr	(2) AgeFB	(3) Marr:FB(m)	(4) TotChild	(5) P.educ
Conventional	-1.120***	-0.510*	7.790***	0.082	1.723**
	[0.403]	[0.282]	[2.698]	[0.298]	[0.758]
Bias-corrected	-1.361***	-0.581**	8.506***	0.118	1.689**
	[0.403]	[0.282]	[2.698]	[0.298]	[0.758]
Robust	-1.361***	-0.581*	8.506***	0.118	1.689**
	[0.429]	[0.305]	[2.824]	[0.320]	[0.821]
Sample Mean	18.65	18.65	18.65	18.65	18.65
Obs.	309607	273355	266050	467687	55034
Effect. Obs.	66984	87076	47394	108395	11737
Bias	12.68	18.67	11.53	13.66	11.87
Bandwidth	5.37	8.70	4.23	5.80	5.39
VCE method	NNcluster	NNcluster	NNcluster	NNcluster	NNcluster
BW type	mserd	mserd	mserd	mserd	mserd

Notes: **p<0.05;***p<0.01

The RDD method gives us the average effect of the program on the treated districts. For instance, the estimates show that on an average, districts that got the treatment saw a decline in the age of marriage of woman. We are interested in the impact of the program on marriage outcomes of woman due to increase in education. Hence, to check if the age of marriage is falling due to increase in woman's education, we present the reduced form estimates using 2SLS in table 3.5. In the first stage we use DPEP as an instrument for education around the female literacy cut-off [6]. Table 3.5 shows the second stage results of the impact of education on age of marriage of the IV estimation. We also include female literacy cut-off ($flit$) as a control in the IV specification. We see that the the increase in education due to DPEP is associated with a fall in the age of marriage by nearly 1.4 years. We also see a similar decrease in the age at first birth. These results are similar to the RDD estimates in table 3.4.

[6] We use a bandwidth of 5 for the IV specification

Table 3.5: Women marriage outcomes-IV estimates

	(1) AgeMarr	(2) AgeFB	(3) Marr:FB(m)	(4) TotChild	(5) P.educ
Education	-1.351***	-1.250***	-0.644	-0.519***	-0.765
	[0.201]	[0.183]	[0.514]	[0.073]	[0.862]
Flit	0.102***	0.110***	-0.021	0.025***	0.029
	[0.017]	[0.018]	[0.044]	[0.004]	[0.049]
Constant	28.493***	29.500***	27.902***	5.426***	13.835**
	[1.452]	[1.291]	[3.578]	[0.588]	[6.298]
Observations	60867	52900	53020	94310	10950
Control Mean	19	21	23	1	8

Notes **p<0.05;***p<0.01

3.6 Conclusion

In this paper we estimate the effect of increased female schooling on the marriage market outcomes, specifically, the age of marriage of the woman. We exploit the quasi-random variation created by a large scale education intervention called DPEP that targeted districts with low female education. We build a transferable utility framework on the lines of (Low, 2014) wherein we assume that women are are characterised by their education and their age and men are characterised by their income. In our context, as there exists evidence on men's preference for younger brides, we let the men's utility decrease with women's age of marriage. Since, the labour market returns to education in India are low, our model predicts that women with more education will tend to improve their returns from marriage by finding a match at a younger age. Our empirical findings show that with an increase in female education due to DPEP, the age at marriage decreased by nearly 1.4 years. Contrary to existing evidence that shows a positive relation between female education and delay in marriage, our findings have important implications for policy. Our results indicate that surplus obtained from marriage is higher than that obtained from the labour market and so education leads to earlier marriage. In the future, we will look at the surplus obtained by educated women in marriages when they marry earlier.

3.7 Appendix

3.7.1 Conceptual framework: household problem

The utility for men and women is represented by subscript m and w respectively. Individuals value the private consumption, q, and children and household management as a public good, Q. The household production function follows Cobb-Douglas utility (qQ). The men's family has a preference for young brides. We add cost in the utility function which increases with age of the woman at marriage. $c(a_w)$ is an increasing function of age. Below is the utility for men and women both:

$$u_m = q_m Q - c(a_w)$$
$$u_w = q_w Q$$

We assume the investment in children depends on the parental human capital. The public good, Q, domestically produced from parental human capital is given by Cobb-Douglas utility function.

$$Q = H_m^{\alpha/2} H_w^{\alpha/2}$$

The budget constraint of the household will account for private consumption q and public good consumption i.e. child care. The sum of the consumptions will be equal to household income. We have husband's income, y, bride's income, z, and dowry payment, d. Dowry payment is one time usually around annual income of the husband. But we can consider it as small monthly payment over the life-cycle. Below is the budget constraint for the household. Here we assume the share of private consumption and public consumption is defined by β.

$$q_m + q_w + \beta Q = y + d + z$$

Dowry is an important part of Indian marriage market. It can exceed annual household income (Chiplunkar and Weaver, 2021). We introduce dowry in the model through budget constraint as an perpetuity monthly payment. For simplification, we assume dowry to be a constant amount.

In India, female labour force participation has stagnated around 30 percent and it has decreased in recent years. So the main investment is in the marriage market (Fletcher et al., 2017). Labour market returns are low for woman but they do increase with education. We assume similar logarithmic functional form for women's income. The labour market returns can be assumed to be low which means a low value of δ or z'_{H_w}.

$$z = \delta ln(H_w)$$

Here, we maximise the total household utility under the budget constraint. More specifically, we maximise the sum of utilities for men and women in the household, $u = u_m + u_w$. Below is the maximisation problem:

$$\max_{q,Q}.\ (q_m + q_w)(Q) - c(a_w)$$

$$s.t.\ q_m + q_w + \beta Q = y + d + z$$

We get equilibrium private consumptions and public good consumption. The equilibrium values for private and public good consumption are:

$$Q^* = \frac{(y + z + d + R)}{\beta + 1}$$
$$q^* = \frac{(y + z + d - R)}{\beta + 1}$$

where $R = \frac{2\delta}{\alpha}$.

3.7.2 Surplus function

From the optimal values we can get the joint utility for the household. Joint utility of the household, T, is the sum of utilities of men and woman as shown below:

$$T = q^* Q^* - c(a_w)$$
$$T = \frac{1}{(\beta + 1)^2}((y + z + d)^2 - R^2) - c(a_w)$$

Using joint utility we can define the surplus of the household. Surplus function is defined as joint utility minus the utility when the individuals are single. When they are single consume their own income. Using optimal values for private and public good consumption we get surplus function:

$$S(y, z, H_w, a_w) = \frac{1}{(\beta + 1)^2}((y + z + d)^2 - R^2) - c(a_w) - y - z$$

The surplus function depends on labour market income for men and women. It reduces with age of woman at marriage. As men's family prefer younger brides surplus decreasing in the age of woman. We also have surplus increasing in men's income.

3.7.3 Marginal rate of substitution

Using the surplus function, we estimate the rate of change of surplus with respect to age at marriage and education of the woman. Further, we comment on the marginal rate of substitution between age of marriage and education of the woman.

$$\frac{\partial S}{\partial H_w} = (\frac{2(y+z+d)}{(\beta+1)^2} - 1)z'_{H_w}$$

Given that we have the numerator positive we have surplus increasing in education of women. For that we need $2(y+z+d) > (\beta+1)^2$.

$$\frac{\partial S}{\partial H_w} > 0$$

Next, we estimate the rate of change of surplus with respect to age of marriage. Surplus of the household decreases as the age of woman increases.

$$\frac{\partial S}{\partial a_w} = -c'(a_w)$$

Further, we estimate the marginal rate of substitution ($MRS_{a_{H_w}}$) between age of marriage and education of woman. We estimate the MRS by taking a ratio between marginal surplus of education of woman and age of woman at marriage. If the labour market returns are low for woman then we get the MRS to be negative. The model predicts a negative association between education of woman and the age of marriage. There is demand for young and educated brides. Educated woman are able to find a match earlier after entering the marriage market.

$$MRS = \frac{\partial a_w}{\partial H_w} < 0$$

3.7.4 Household problem: quasi-linear utility

Here, we use similar set-up as the earlier problem. We use quasi-linear utility functional form where the private consumption does not depend on change in household income. We assume following functional forms:

$$u_m = q_m + ln(Q) - c(a_w)$$
$$u_w = q_w + ln(Q)$$

Another deviation from the above model is we assume dowry increases with education of women. There is evidence of positive correlation between dowry and education of woman (Anukriti, Kwon, et al., 2020). We assume dowry is an increasing function of education of woman. We take a specific logarithmic functional form in our specification. Dowry, d, depends on the woman's human capital, H_w, as shown below:

$$d = \gamma ln(H_w)$$

Keeping rest of the assumption similar to above household problem, we maximise the sum of utilities under the budget constraint. We get following equilibrium values:

$$Q^* = 2\frac{\alpha + \delta}{\alpha\beta}$$
$$q^* = (y + z + d) - 2\frac{\alpha + \delta}{\alpha\beta}$$

This provides us with the following surplus function which is independent of the income (y and z).

$$S(H_w, a_w) = \gamma ln(H_w) - 2\frac{\alpha + \delta}{\alpha\beta} + ln(2\frac{\alpha + \delta}{\alpha\beta}) - c(a_w)$$

The marginal rate of substitution between education of women and age of marriage has a negative relationship using this functional form as well.

$$\frac{\partial S}{\partial H_w} = \frac{\gamma}{H_w}$$
$$\frac{\partial S}{\partial a_w} = -c'(a_w)$$
$$MRS = -\frac{\gamma}{H_w c'(a_w)}$$

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Appendix A

Appendices

A.1 Figures

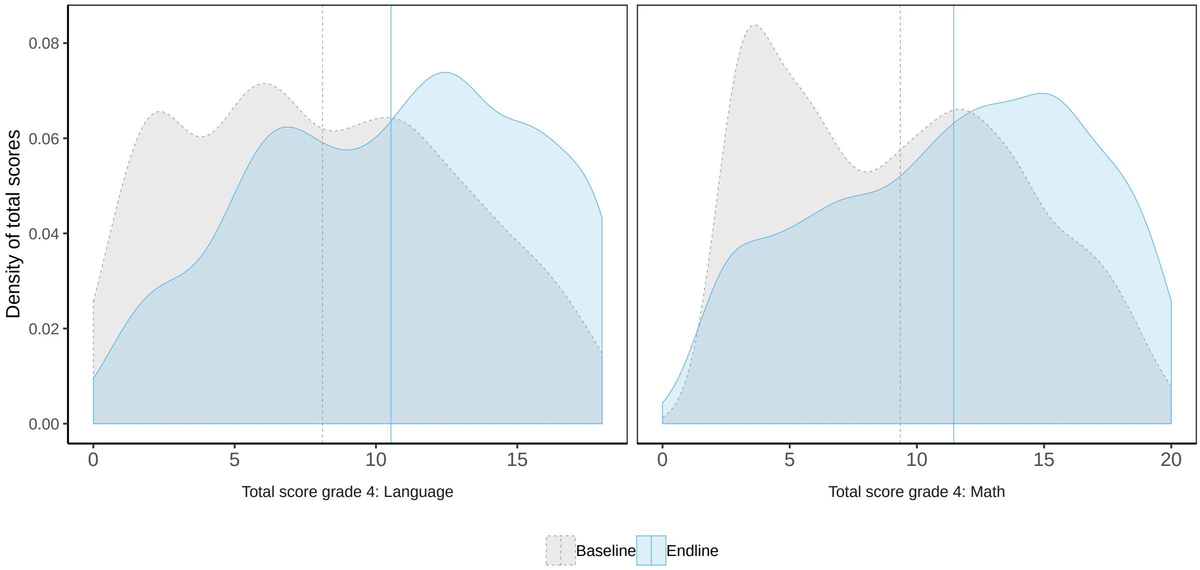

Figure A.1: Density plot total scores Grade 4

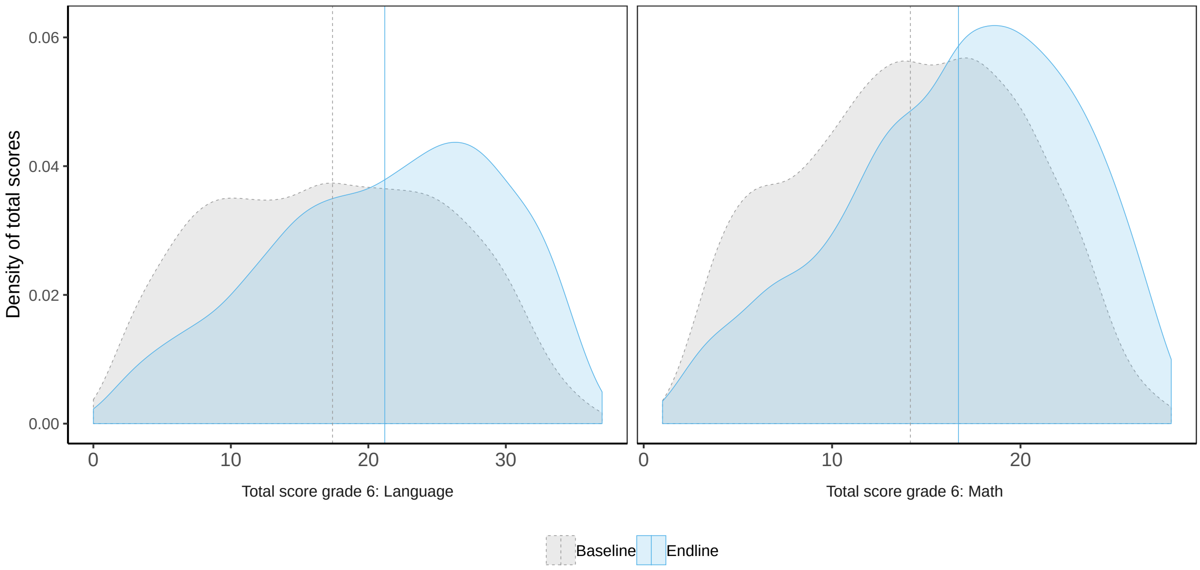

Figure A.2: Density plot total scores Grade 6

A.2 Tables

Table A.1: Levels of education

	Grades	Age
Primary	I-V	6-10
Lower secondary	VI-VIII	11-13
Secondary	IX-X	14-15
Higher Secondary	XI-XII	16-17

Table A.2: Difference in means of sample and dropped-out student

	Both visits	Dropped-out	Difference	p.value
	Grade 4			
Female=Yes	0.52	0.42	0.10	0.04
Age	10.02	10.35	-0.33	0.00
Lang. score baseline	8.03	9.01	-0.98	0.04
Math score baseline	9.30	9.84	-0.54	0.25
Contract teacher	0.81	0.83	-0.02	0.58
Native teacher	0.32	0.31	0.01	0.87
N	1527	133		
	Grade 6			
Female=Yes	0.54	0.43	0.11	0.02
Age	11.69	11.81	-0.11	0.10
Lang. score baseline	17.44	16.85	0.59	0.44
Math score baseline	14.24	13.18	1.06	0.06
Contract teacher	0.71	0.61	0.1	0.01
Native teacher	0.32	0.15	0.17	0.00
N	1595	135		

Table A.3: Difference in means of all and sampled teachers

	All	Sample	Difference	p.value
School variables				
Distance from HQ.	42.06	39.88	2.18	0.48
Student attendance	58.98	58.58	0.40	0.72
Teacher attendance	74.08	74.48	-0.40	0.74
Proportion contract	72.91	72.78	0.14	0.94
Infrastructure index	5.07	5.08	-0.01	0.94
Total enrollment	509.62	512.74	-3.12	0.90
Total teachers	8.71	8.78	-0.08	0.83
Student teacher ratio	61.81	61.79	0.02	0.99
Principal in school	0.15	0.14	0.01	0.80
BRC visits	4.21	4.21	0.01	0.90
SMC meetings	3.75	3.78	-0.03	0.66
Average math score	11.78	11.74	0.04	0.88
Teacher variables				
%Contract	0.73	0.75	-0.02	0.42
%Female	0.37	0.39	-0.02	0.50
Age in years	38.39	37.52	0.87	0.12
%Professional qualified	0.55	0.49	0.06	0.05
%Graduate or above	0.52	0.49	0.03	0.30
Experience	8.72	7.13	1.60	0.00
Training (days)	9.52	10.43	-0.91	0.20
Math score	7.14	6.73	0.41	0.05
Hindi score	4.61	4.39	0.22	0.09
%Native to village=yes	0.29	0.31	-0.02	0.36
Travel time (min)	38.42	38.33	0.08	0.98
Years in same school	5.77	5.43	0.34	0.14
Transfers	0.57	0.35	0.22	0.00
N Schools	214	199		
N Teachers	1656	339		

Table A.4: Grade repetition in states before RTE (2005-2008)

State	Grade 1	Grade 2	Grade 3	Grade 4	Grade 5	Grade 6	Grade 7	Grade 8
No grade repetion								
ANDHRA PRADESH	6.4	2.8	2.2	1.8	1.7	1.4	1.3	1.0
KARNATAKA †	2.1	2.0	2.0	2.0	2.5	2.5	1.9	1.9
ASSAM †	4.2	2.6	2.2	2.1	2.8	2.2	2.2	6.1
DELHI	5.1	5.6	5.3	5.7	2.6	14.3	8.9	7.3
MADHYA PRADESH	15.1	11.6	12.8	12.4	15.1	11.7	8.6	16.5
CHANDIGARH	3.3	3.2	2.8	2.8	4.7	6.7	6.7	10.7
HIMACHAL PRADESH	6.5	3.8	3.7	4.2	2.7	8.1	6.2	15.7
UTTARAKHAND	11.6	6.7	6.3	4.3	1.4	6.7	4.9	3.5
RAJASTHAN	14.7	9.2	6.6	3.9	3.3	8.2	5.4	8.3
BIHAR	16.1	7.5	6.0	4.8	3.9	3.1	2.7	2.3
ARUNACHAL PRADESH	10.0	9.6	9.3	7.5	6.9	6.9	5.8	8.3
JHARKHAND	16.5	7.2	5.3	4.1	3.4	3.2	2.8	2.6
ORISSA	20.8	8.7	7.5	6.2	5.9	6.4	8.4	8.7
TAMIL NADU	1.1	0.9	0.8	0.8	0.9	3.4	2.7	2.3
ANDAMAN& NICOBAR	3.5	2.0	1.5	1.8	1.5	3.9	3.1	3.3
WEST BENGAL†	18.0	8.0	6.6	6.6	22.2	18.5	18.7	18.4
PUNJAB	8.9	8.6	8.8	7.9	3.5	10.0	8.1	23.1
PONDICHERRY	0.5	0.3	0.3	0.3	1.7	3.9	2.5	3.1
TRIPURA	11.8	6.3	8.3	6.7	5.7	13.2	10.8	8.7
CHHATTISGARH	11.6	7.6	8.1	6.9	4.9	7.0	5.3	7.4
GOA†	4.1	2.5	2.3	5.7	13.0	11.6	10.8	21.0
HARYANA	3.9	4.4	6.4	6.0	3.4	4.0	3.9	7.2
UTTAR PRADESH	1.9	1.4	1.5	1.2	1.2	0.9	0.8	0.8
GUJARAT†	12.3	8.8	8.9	7.0	7.5	5.9	4.4	1.3
MAHARASHTRA†	7.6	5.1	4.7	3.4	5.2	4.5	3.9	5.9
LAKSHADWEEP †	3.0	3.6	2.9	2.4	3.0	3.1	5.1	8.3
KERALA†	0.5	3.5	3.3	3.4	3.6	3.6	5.3	5.8
SIKKIM	17.8	17.8	20.1	20.5	17.0	18.9	15.0	18.7
NAGALAND	4.8	4.3	4.4	4.0	4.6	4.4	4.4	5.5
MANIPUR	3.7	1.2	1.3	1.2	1.2	1.4	1.3	1.4
MIZORAM †	6.4	3.2	3.0	2.7	2.6	1.9	3.7	0.0
MEGHALYA †	7.6	5.8	5.4	4.9	7.3	5.8	5.9	5.6
DAMAN&DIU †	8.5	6.7	6.5	7.5	9.9	6.2	3.3	11.2
DADAR&NAGAR †	17.5	13.2	12.9	9.7	14.5	8.5	5.8	5.6

Note: India has total 36 states and union territory. I do not include the state of Jammu and Kashmir as it is not yet covered by RTE Act 2009. I include data for undivided Andhra Pradesh.
† Most states in India have grade 1 to 5 as primary and 6 to 8 as lower secondary. While some states which have 1 to 4 as primary and 5-7 as lower secondary include: Assam, DamanD̂iu, Dadar and Nagar, Lakshadweep, Meghalaya, Mizoram, West Bengal, Goa, Gujarat, Karnataka, Maharashtra and Kerala.